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Integration of Rural Insurance Data with Agricultural Zoning Data in Climate Risk Analysis: Case Study in Southern Brazil

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Abstract This paper presents a model to integrate agricultural zoning data into insurance risk analyses, focusing on the Southern region of Brazil. The methodology uses information from the Agricultural Zoning of Climatic Risk (ZARC) and insurance data provided by the Ministry of Agriculture, converting them into distributional variables for a Bayesian model. This allows detailed risk assessments, considering optimistic and pessimistic scenarios based on soil data from ZARC. These scenarios are combined with insurance information to generate more accurate risk distributions. The method allows for the comparison of risks between municipalities and agricultural crops, such as soybean and wheat, contributing to a robust risk classification in the Southern region. The proposed approach can significantly improve risk management in the agricultural sector, benefiting insurance companies, government and private agencies.Future studies could extend this methodology to conduct comparative analyses among insurance providers, assess risk dynamics in structured credit and insurance operations, and evaluate agricultural risks at the farm level. In a broader context, this research contributes to the development of a robust analytical framework that enhances risk assessment and supports more informed decision-making in the agricultural sector

Keywords risk management in crops; Bayesian Analysis; agricultural risk classification; Adverse selection; beta distribution

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1. Introduction

Extreme weather events, such as droughts, floods and storms, are the main causes of significant losses in agricultural production around the world (FAO, 2021). More than 60% of the variation in global productivity can be attributed to climate variability (Ray et al. 2015). Given the increasing unpredictability of the climate, agricultural risk management models, which are essential for both producers and governments, need to be adapted (Wilson et al. 2022). Producers are increasingly exposed to severe weather conditions, which increases the need for more effective risk mitigation programs. However, advancement in this area depends on integrating data into a comprehensive risk management strategy. Currently, most crop insurance methods do not adequately incorporate the factors that influence productivity. In Brazil, the agricultural risk management strategy is based on the Agricultural Climate Risk Zoning System (ZARC), although its potential is still underutilized.

This paper, based on the study *Enhancing Crop Insurance Analysis with Agricultural Zoning Data*, proposes an empirical Bayesian method that converts agroclimatic zoning and insurance claims data to refine crop insurance offerings. Taking inspiration from Shi & Irwin (2005), this study transforms ZARC projections into a priori distribution of production loss frequencies, updating them with information on insurance claims. This methodology creates a unified framework, allowing the assessment of deviations from ZARC predictions. To date, no research has directly established a connection between ZARC data and agricultural insurance claims, limiting its ap. This research seeks to fill this gap, with the potential to impact agricultural zoning systems and insurance markets globally.

Focusing on the southern region of Brazil, with emphasis on the states of Paraná, Santa Catarina and Rio Grande do Sul, the model demonstrates how agricultural technical data can improve risk assessment and, consequently, risk mitigation procedures for cash crops, soy and wheat.

2. Methodology and Mathematical Model.

The proposed methodology builds upon the findings of Martins and Signorini (2024), who identified soil characteristics as a key determinant in insurance rate calculations in the United States. It is important to note that in the United States the government determines the prices of agricultural insurance, while in Brazil, private companies operating in the insurance market set the rates. The type of soil is a criterion for risk selection by insurers in Brazil, and some companies choose not to offer policies for crops grown in sandy soils. This research framework shows how insurers can better assign risk levels at the municipal level considering soil type data from the agricultural zoning system, ZARC. When soil type is observed for a specific operation, insurers can employ a refined version of the framework under development to compare expected downstream distribution losses with expected county-level losses for the soil type of interest.

2.1 Agricultural zoning data

ZARC, an innovative resource for both producers and policymakers, is supported by a broad range of scientific disciplines such as agricultural climatology, soil science, crop science, and agricultural engineering (Gonçalves & Wrege 2018; Cunha et al. 2001a). Because growers must adhere to ZARC, historical data on crucial technical parameters become admissible inputs for risk evaluation and rating calculations (Liu & Ramsey 2022).

Recent advancements in ZARC's framework are driven by crop growth models, georeferenced datasets, historical climate records, and soil characteristics (Pandolfo et al. 2021).

ZARC estimates probabilities (□□□) as the ratio of unfavorable events (□) to the crop cycle duration, segmented into 10-day sowing windows. These probabilities are computed using 30 years of historical data and are standardized for all cropping systems and municipalities included in ZARC. The general formulation is given by:

□□□=p(u)

where □□□ represents the simulated probability of production loss for soil texture □ and 10-day sowing period □. The soil textures are categorized as follows:

j = 1 when the clay content is greater than 10% and less than 15%.

j = 2 when the clay content is between 15% and 35%, and the sand content is less than 70%.

j = 3 when the clay content is greater than 35%.

Recommendations were used for soil types to identify risk thresholds for risk analysis in this study. The approach to simulating risk assessments was based on theoretical assumptions about a weighted average distribution of best and worst case scenarios. The ZARC labels risk classes using maximum threshold probabilities. Reported estimates of $\mathbf{z_{ij}}$are 20% for $\mathbf{z_{ij}} \leq 0.2$, 30% for $0.2 \leq \mathbf{z_{ij}} \leq 0.3$, 40% for $0.3 \leq \mathbf{z_{ij}} \leq 0.4$, and “-” when zij ≥ 0.4. In other words, ZARC makes it clear to producers that sowing is not recommended in periods of 10 days marked with a “-” sign.It is worth noting that ZARC forecasts are frequencies of production losses and do not capture the severity of occurrences. To obtain premium subsidies through the PSR, producers who meet the standards are those who sow crops in reported windows with a maximum loss frequency of 20%, 30% or 40%.For the development of the research, ZARC estimates were adjusted to create a priori distribution of production losses in three stages.

a) Conversion of loss frequencies to expected frequencies

$$\mathrm{E}(\Theta) = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \bar{\mathrm{z}}_{\mathrm{ij}}$$

where □(Θ) represents the expected production loss frequency considering different sowing periods and soil textures.

b) Weighting loss frequencies based on planting behavior

Farmers tend to avoid high-risk sowing periods, preferring lower-risk windows. Thus, planting progress data is incorporated to refine loss probabilities.

c) Estimation of Beta distribution parameters

The final expected frequency of production loss is computed for each maturation group □, soil type j, and municipality□:

α_kjm= E(Θ) x n

β_kjm= n-α_kjm

where □□□□ and □□□□serve as parameters for the Beta distribution, a widely used probabilistic model for insurance loss estimation.

The Beta distribution is particularly useful for modeling agricultural risk because it is flexible, allowing different probability shapes depending on the values of □ and □.In this study, if Y follows a Beta distribution, denoted as:

□∼Beta(□,□)

then the **probability density function (pdf)** is given by:

$$f(\theta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \theta^{\alpha-1}(1-\theta)^{\beta-1} \text{ para } 0 \leq \theta \leq 1$$

where:

- α and β are distribution parameters that were normalized to follow the ZARC proportions, they were multiplied by 100.
- Γ(·) is the Gamma function.
- θ is the random variable representing the frequency of production loss.

Since each municipality □ has its own set of where □□□□ and □□□□values, we compute the state-level estimates by averaging across all municipalities:

$$A_k = \frac{1}{M} \sum_{m=1}^{M} \alpha_{km} \text{ e } B_k = \frac{1}{M} \sum_{m=1}^{M} \beta_{km}$$

where:

- □□represents the average □α value across all municipalities in the state.
- □□represents the average □ value across all municipalities in the state.

The Beta distribution derived from ZARC is used as a prior in Bayesian modeling. By integrating historical crop insurance claims data, the posterior distribution is computed, resulting in a refined risk estimation that incorporates both climatic risk (ZARC) and real insurance loss frequencies.

This approach enhances agricultural risk modeling, providing more accurate risk predictions that can be used by insurance companies, policymakers, and farmers to improve decision-making in agricultural insurance programs.

2.2 Insurance data and transformation

Historical data on insurance contracts with subsidized premiums in Brazil are publicly available on the federal government's "open data" platform. In this study, data were retrieved from individual insurance policies for soybeans and wheat, grown in the southern region of Brazil, in the states of Paraná, Santa Catarina and Rio Grande Do Sul between the 2017/18 and 2021/22 harvests. The complete set has 21 variables for all states, but the focus was on five variables: municipalities, culture, compensation amount and policy year. During the period analyzed, compensation granted in the States of Paraná (PR), Rio Grande do Sul (RS) and Santa Catarina (SC) were examined, focusing on soybean and wheat crops. The total amount paid in compensation reached the expressive sum of R$2,908,700,184.58, distributed across 42,625 compensation payments. These payments were made based on 263,762 policies taken out in the three States. The variable that reports compensation amounts is of central interest. When the compensation payment is greater than zero for a given contract, we assign value 1 or 0otherwise.

Let y be the number of occurrences of compensation payments in all insurance contracts □ issued for the crop of interest in municipality □, such that Y ∈ {0, 1, 2,..., c}. To monitor and verify the loss of agricultural production, it can be plausibly inferred that the occurrence of compensation payments is conditional on the occurrence of loss. Therefore, the probability of Y conditional on the occurrence of production loss, P(Y|θ), follows a binomial distribution with parameters c and θ. In mathematical notation:

$$P(y|\theta) = (cy)\theta^{y}(1-\theta)^{c-y} Y \in \{0, 1, 2, \ldots, c\}$$

Knowing that the priori distribution of the frequencies of production losses, derived from ZARC, follows a beta distribution (□,□) and that the transformed data on the occurrence of compensation payments□ give rise to a conditional probability that follows a binomial distribution (□, θ) we can apply the Bayesian updating method to obtain the posterior predictive distribution of production losses. The calculation of the posterior distribution follows the procedure demonstrated by Hoff. (2009, pp. 35-38):

$$P(y) = \frac{P(\theta)P(y|\theta)}{P(y)}$$

$$P(y) = \frac{1}{P(y)} x \frac{(\alpha+\beta)}{(\alpha)(\beta)} \theta^{\alpha-1}(1-\theta)^{\beta-1} x \left(\frac{c}{y}\right)\theta^{y}(1-\theta)^{c-y}$$

$$P(y) = k(c, y, \alpha, \beta) x \theta^{\alpha+y-1}(1-\theta)^{\beta+c-y-1}$$

$$P(y) = \mathrm{beta}(\alpha+y, \beta+c-y)$$

The posterior beta distribution becomes a combination of the prior distribution and the transformed insurance claims data, resulting in easily recognizable raw moments.

$$E(\theta|y) = \frac{\alpha+y}{\alpha+\beta+c}$$

$$Var(\theta|y) = \frac{(\theta|y)E(1-\theta|y)}{\alpha+\beta+c+1}$$

Empirical calculations were carried out and then a system of equations was constructed to simulate alternative scenarios for different cultures and municipalities. The criteria developed in Martins and Signorini (2024) were used

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to validate the methodology and compare the power of predictability of the posterior distribution against the frequencies of production loss derived from the ZARC agricultural zoning system. The classification criteria were organized into three main categories and seven subcategories, based on the comparison of expected values and distributions for production scenarios: best (Ebst(θ) and Pbst(θ)), worst (Ewst(θ) and Pwst(θ)) and later (Epos(θ|y) and Ppos(θ|y)). The three risk categories are:

a) If Epos(θ|y) is smaller than Ebst(θ): if Epos is to the left of the 47.5% tail of the best scenario, it is classified as "A"; if you are in the 47.5% left tail, rate yourself as a "B".

b) If Ebst(θ) is less than Epos(θ|y) and Epos(θ|y) is less than Ewst(θ): if Epos is in the 47.5% tail to the right of the best scenario and to the left of the 47.5% tail of the worst case, it is classified as "C"; if it is in both tails, it is "D"; if Epos is in the 47.5% left tail of the worst case scenario, but not in the right tail of the best, it is classified as "E".

c) If Epos(θ|y) is greater than Ewst(θ): if Epos is in the tail of 47.5% to the right of the worst case scenario, it is classified as "F"; otherwise, it is rated “G”.

3. Results

Table 1 – Total number of policies, policies with losses and loss rates for crops of interest per analysis period

Analysis Period	Culture	Locality	Total Policies	National Representativity	Claims Policies	Percentage of Policies with Loss
2017/2018 até 2021/2022	Soja	Brasil	330.245	100,00%	46.921	14,21%
2017/2018 até 2021/2022	Trigo	Brasil	59.235	100,00%	12.493	21,09%
2017/2018 até 2021/2022	Soja	PR	148.916	46,82%	21.875	14,69%
2017/2018 até 2021/2022	Trigo	PR	31.337	58,76%	7.758	24,76%
2017/2018 até 2021/2022	Soja	RS	62.285	19,58%	12.718	20,42%
2017/2018 até 2021/2022	Trigo	RS	19.143	35,89%	3.119	16,29%
2017/2018 até 2021/2022	Soja	SC	11.924	3,75%	1.234	10,35%
2017/2018 até 2021/2022	Trigo	SC	1.874	3,51%	187	9,98%

Source: Prepared by the author based on insurance data collected from “dados abertos”.

Table 1 provides a comprehensive view of the behavior of rural insurance policies for soybean and wheat crops in Brazil and in the states of Paraná (PR), Rio Grande do Sul (RS) and Santa Catarina (SC), with emphasis on the total number of policies issued, the number of policies that recorded losses and the corresponding percentage of lost policies. In national terms, it is observed that soy was the crop with the highest number of policies, totaling 330,245 contracts, of which 46,921 resulted in claims, representing a rate of 14.21% of policies with losses. On the other hand, wheat presented a higher percentage of claims, with 21.09% of its 59,235 total policies presenting claims, indicating a higher frequency of losses for this crop.

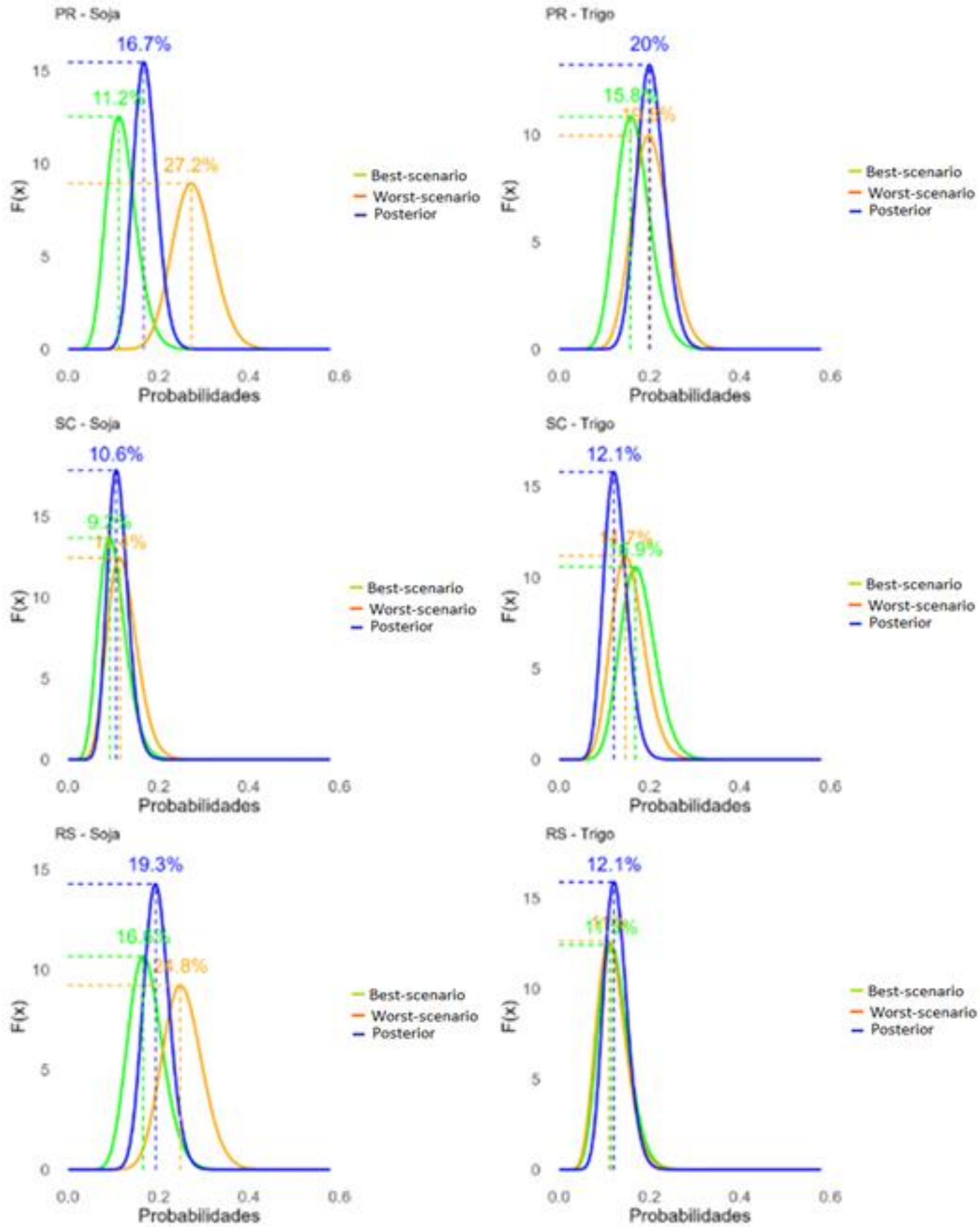

Figure 1 – Risk comparison for the states of Paraná, Rio Grande do Sul and Santa Catarina using the posterior distribution versus the best-scenario and worst-scenario distributions.

In Figure 1, probability distribution graphs for agricultural production losses in the states of Paraná, Rio Grande do Sul and Santa Catarina are presented, during the period from 2017/2018 to 2021/2022 for soybean (left) and wheat (right) crops. These distributions reflect the probabilities of agricultural losses according to Bayesian modeling and include different scenarios, namely:

- Orange Line: Represents the Worst Scenario, highlighting the greater probability of agricultural losses in adverse conditions.
- Green Line: Indicates the Best Scenario, reflecting the lowest probability of losses, considering more favorable conditions.

- Blue Line: Refers to the Posterior, which is the distribution adjusted by Bayesian modeling based on historical data. This curve reflects the average probability that is most representative of the real risk.

The analysis shows that later is a more reliable representation of the real risk of losses, considering historical data. In comparative terms, the results show that Paraná presents the highest adjusted risk for wheat, while Rio Grande do Sul stands out with the highest adjusted risks for soybeans. On the other hand, Santa Catarina presents the lowest adjusted risks for both crops, with a smaller range between scenarios, indicating greater stability. These findings are important to inform public policies and risk mitigation strategies in the agricultural sector, considering the particularities of each state and culture analyzed.

Table 2 – Count of municipalities by risk category.

Culture	Period	UF	Risk							Total Number of Municipalities
			A	B	C	D	E	F	G	
Soja	2017/2018 a 2021/2022	PR	96	20	116	3	0	16	4	255
Trigo	2017/2018 a 2021/2022	PR	24	0	4	2	0	26	4	60
Soja	2017/2018 a 2021/2022	RS	43	20	18	7	11	22	18	139
Trigo	2017/2018 a 2021/2022	RS	20	2	0	0	0	18	1	41
Soja	2017/2018 a 2021/2022	SC	15	0	1	0	0	5	0	21
Trigo	2017/2018 a 2021/2022	SC	2	0	0	0	0	0	0	2

Source: Prepared by the author.

Table 2 provides a detailed overview of the count of municipalities in different risk categories for soybean and wheat crops in the states of Paraná (PR), Rio Grande do Sul (RS) and Santa Catarina (SC) in the period from 2017/2018 to 2021/2022. The risk categories, which range from "A" (minimum risk) to "G" (maximum risk), demonstrate the exposure of municipalities to possible losses, indicating differences in the risk profile between cultures and states.

In Paraná, soybeans show a wide risk distribution, with majority of municipalities in category "C" (116 municipalities), followed by category "A" (96 municipalities), which reflects a greater prevalence of intermediate and low risk levels. This pattern suggests a risk dispersion that, although it includes low-risk areas, presents a relevant contingent at moderate risk. On the other hand, the highest risk categories, such as "F" and "G", represent fewer municipalities, with 16 and 4 respectively. For wheat cultivation in Paraná, the concentration is greater in the high-risk categories, with 26 municipalities in the "F" category and 4 in the "G" category, while the lower risk levels (such as the "A" categories) represent a smaller total, with only 24 municipalities. These data indicate a greater exposure to risk for wheat crops in Paraná compared to soybeans.

In Rio Grande do Sul, soy presents a considerably balanced risk distribution, with a greater concentration of municipalities in category "A" (43 municipalities) and a notable presence in category "C" (18 municipalities). However, there is also a substantial number of municipalities high risk categories, such as "F" (22 municipalities) and "G" (18 municipalities), pointing to a diversification of the risk profile and significant exposure to higher risk levels. As for wheat in Rio Grande do Sul, the distribution is much more concentrated in low risk categories, with 20 municipalities in category "A" and a limited presence in the other categories, which suggests that wheat is less susceptible to losses in this state compared to soybeans.

In Santa Catarina, the risk distribution for soybeans is mostly concentrated in low-risk levels, with 15 municipalities in category "A", while higher risk categories, such as "F" and "G", have only 5 municipalities. This profile indicates that soybeans are a relatively low-risk crop in the state. For wheat in Santa Catarina, the number of municipalities is even smaller, with only 2 municipalities in category "A" and none in the other risk categories, demonstrating that wheat presents an even more restricted risk exposure in this state.

The results can be analyzed more clearly in Figure 2, which presents the posterior distributions for soybean crops, according to the risk classification proposed by Martins and Signorini (2024). This model highlights a higher risk in the northwest, west and southwest regions of the states of Paraná and Rio Grande do Sul. In Santa Catarina, the highest risk areas are concentrated in the mountain plateau, in the West and in the Itajaí Valley. For wheat, risk patterns follow a similar trend, with a higher incidence in the northwest, west and southwest regions of Paraná and Rio Grande do Sul.

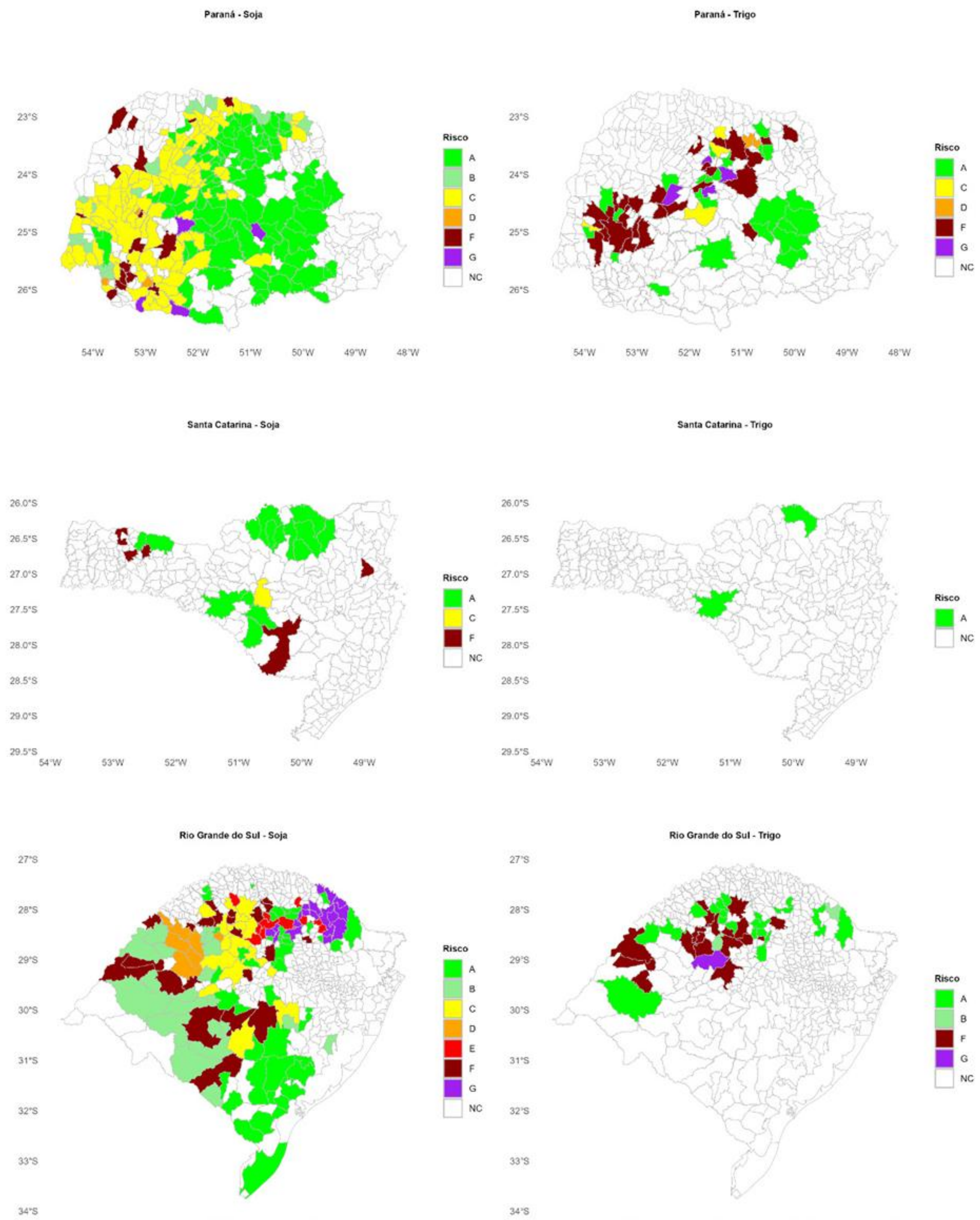

Figure 2 – Municipality Risk Map

This work highlights two important practical implications for policymaking that deserve concluding remarks. Firstly, winter crops are highly risky activities, as demonstrated by the results presented for wheat.

The results show that the proposed analytical framework is better equipped to study expected losses from the soybean insurance market than the agricultural zoning system alone. Generally, ZARC tends to overestimate the probabilities of production losses compared to our model for most locations. Production risk tends to be more spread out for wheat, leading analysts to recognize the importance of refining data granularity whenever possible.

Finally, our model captures the increase in risk much better than ZARC when unfavorable weather conditions occur. This was demonstrated by the shift right of expected losses for all crops analyzed.

4. Conclusions and recommendations

Furthermore, this research yields significant methodological insights. Notably, the integration of ZARC's recommended sowing windows with insurance data distributions has demonstrated effectiveness in enhancing risk assessment, reinforcing the utility of combining agroclimatic zoning data with empirical insurance records to refine agricultural risk management strategies. However, it is necessary to have a clear understanding of the potential of the methods light of the quantity and quality of information available. To mitigate this risk, analysts could consider being more stringent in allowing seeding window or even excluding some municipalities from zoning recommendations. When applying the Bayesian approach, it is usually based on assumptions about the probabilities of a given phenomenon. In theory, these assumptions can be subjectively obtained through expert assessments, as mentioned by Shi and Irwin (2005). By choosing an appropriate model, these beliefs are adjusted as new data is incorporated, resulting in more accurate estimates. However, our application of the Bayesian approach differs slightly. We use information from the ZARC agricultural zoning system, which is not an uncertain set of beliefs about the probability of agricultural losses. As already discussed, this information is generated by a rigorous computational process, which includes georeferenced soil data and historical climate series. Thus, the ZARC information already constitutes a solid basis, and not just initial beliefs or empirical data that would need to be updated to generate more accurate estimates. The methodology presented in this article initiates a discussion on identifying situations where losses significantly exceed expectations, potentially leading to the development of a crop disaster management program. Future research could explore expanding the model to other crops and regions of the country, incorporating georeferenced soil analyses as an additional component in production risk classification to enhance the model's predictive capacity, as well as utilizing AD classification criteria to create scenarios and applying ZARC at the management level.

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Luciana Justina da Silva began her studies at CEFET-PR, where she completed a technical course in Electrotechnics. She then earned a degree in Electrotechnics Technology – Industrial Automation from UTFPR in 2006. Shortly after, she joined the Federal University of Paraná (UFPR), starting her Statistics degree in 2008 and graduating in 2013.In 2013, after working in data modeling at HSBC Bank, she became a public servant at the Paraná Court of Justice (TJPR), currently working in the Secretariat of Planning, in the Division of Data Analysis and Monitoring, where she remains to this day. In 2021, she began her master's studies in the Graduate Program in Numerical Methods in Engineering, with an expected completion in 2025.

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Gilson Martins is a professor at the Federal University of Paraná (UFPR) and was a visiting professor at Ohio State University (2022–2023). With extensive experience in multilateral projects, he has collaborated with private organizations, state departments, and ministries to shape public policies in agribusiness. He has coordinated forums on research, risk management, and innovation and led international promotion activities in multiple languages. Previously, he was a professor at PUC-PR and worked at the Organization of Cooperatives of Paraná (Ocepar). He has led studies for FAO, IDB, GIZ, CNA, and FAEP, and has collaborated with insurance companies and Brazil's Ministry of Agriculture on crop insurance and rural risk management. Gilson holds a Ph.D. from the University of Freiburg, and a master's and bachelor's in Forest Engineering from UFPR.

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