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Trabalho de Conclusão de Curso

Estimation of Agricultural Revenue Losses Due to Droughts in the State of Rio Grande do Sul

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Trabalho de Conclusão apresentado à comissão de Graduação do Departamento de Estatística da Universidade Federal do Rio Grande do Sul, como parte dos requisitos para obtenção do título de Bacharel em Estatística.

Orientador: Prof. Dr. Cristiano Lima Hackmann

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Este Trabalho foi julgado adequado para obtenção dos créditos da disciplina Trabalho de Conclusão de Curso em Estatística e aprovado em sua forma final pela Orientador e pela Banca Examinadora.

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"Nenhum outro planeta no sistema solar é uma boa casa para os seres humanos; temos esse mundo ou nada.". (Carl Sagan)

Agradecimentos

É inegável que uma trajetória acadêmica é construída com grande esforço individual. No entanto, esse esforço isolado não é suficiente para trilhar um caminho que exige propósito, renúncias e dedicação. Gostaria de expressar meus sinceros agradecimentos a todos que tornaram esta jornada mais leve, gratificante e enriquecedora.

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Resumo

Este estudo avalia o impacto da seca nos rendimentos médios de culturas agrícolas no Rio Grande do Sul, Brasil, com foco em arroz, milho e soja. Utilizando modelos de efeitos fixos e o Índice de Precipitação-Evapotranspiração Padronizado (SPEI) para definir as condições de seca, foram analisados os efeitos das secas moderadas, severas e extremas sobre os rendimentos das culturas. Os resultados mostram que as secas extremas têm o efeito negativo mais significativo sobre o logaritmo natural dos rendimentos médios, com coeficientes de -0,098 para o arroz, -0,070 para o milho e -0,097 para a soja. Isso indica que as secas extremas levam às maiores reduções nos rendimentos das culturas agrícolas. Além disso, foi estimado que as secas causaram perdas substanciais de receita entre 1974 e 2019, totalizando aproximadamente US$ 2,2 bilhões para o arroz, US$ 1,5 bilhões para o milho e US$ 3,5 bilhões para a soja, com as maiores perdas ocorrendo em 2012 para a soja e 1982 para o milho. Esses resultados destacam a necessidade crítica de medidas adaptativas e inovações tecnológicas para mitigar os efeitos adversos da seca na produtividade agrícola e na estabilidade econômica, enfatizando a importância de fortalecer a resiliência agrícola e garantir a segurança alimentar em meio ao aumento da variabilidade climática.

Palavras-Chave: Mudanças Climáticas, Secas, Perdas Econômicas.

Abstract

This study evaluates the impact of drought on crop yields in Rio Grande do Sul, Brazil, focusing on rice, maize, and soybeans. Using fixed effects models and the Standardized Precipitation-Evapotranspiration Index (SPEI) to define drought conditions, we analyze how moderate, severe, and extreme droughts affect crop yields. Our results show that extreme droughts have the most significant negative effect on the natural logarithm of average yields, with coefficients of -0.098 for rice, -0.070 for maize, and -0.097 for soybeans. This indicates that extreme droughts lead to the largest reductions in crop yields. Additionally, we estimate that droughts caused substantial revenue losses from 1974 to 2019, amounting to approximately US$ 2.2 billion for rice, US$ 1.5 billion for maize, and US$ 3.5 billion for soybeans, with the highest losses occurring in 2012 for soybeans and 1982 for maize. These findings underscore the critical need for adaptive measures and technological innovations to mitigate the adverse effects of drought on agricultural productivity and economic stability, emphasizing the importance of enhancing agricultural resilience and ensuring food security amid increasing climate variability.

Keywords: Climate Change, Drought, Economic Losses.

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Estimates of Agricultural Revenue Losses Due to Droughts in the State of Rio Grande do Sul

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Abstract

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Keywords: climate change, drought, economic losses.

1 Introduction

In addition to long-term climate changes, global warming is causing and will continue to cause alterations in the intensity, duration, and frequency of extreme weather events. Among these events, hydrological extremes, such as droughts, have been particularly frequent and have resulted in significant socioeconomic impacts across Brazil (Marengo and Espinoza, 2016; Marengo et al., 2011; Debortoli et al., 2017; Brito et al., 2018; Cunha et al., 2019).

For agriculture, the increasing intensity, duration, and frequency of drought events may heighten the occurrence of crop failures and livestock losses (Herrera-Pantoja and Hiscok (2015)). The rarity of such events complicates data collection and imposes challenges to monitoring and trend analysis (Debortoli et al., 2017).

One of the challenges in studying drought lies in defining the concept itself. Accurate drought definitions require considering variables such as precipitation, soil moisture, and groundwater levels across their temporal and spatial scales, as droughts can last from days to years and affect municipalities, regions, or entire countries. According to Mishra and Singh (2010), drought can be classified into four categories:

- **Meteorological Drought**: Characterized by the absence of precipitation over a relatively short period. Several studies investigating meteorological drought use monthly precipitation measures.
- **Hydrological Drought**: Refers to inadequate surface and groundwater resources to meet the demands set by a water management system. It can last days, months, or even years and generally occurs following a meteorological drought, given the time needed for aquifer and reservoir levels to be impacted.
- **Agricultural Drought**: Defined as a period during which soil moisture conditions decline to the point of compromising plant development and adversely affecting agricultural production.
- **Socioeconomic Drought**: Occurs when failures in the water resource system start to broadly affect human and economic activities, potentially resulting in the interruption of goods or services.

Addressing these challenges requires examining adaptive measures and technological innovations that may mitigate some of the adverse effects. Extreme hydrological events' impacts on agriculture might be alleviated through technologies such as irrigation or by developing crop varieties that are tolerant to heat and drought (Wreford et al., 2010; Olesen and Bindi, 2002). However, adaptive capacity is limited, as many long-term climatic changes are not easily reversible. In the future, rising temperatures and increased drought frequency may lead to the relocation of some agricultural crops inside Brazil (Assad et al., 2016).

Understanding the impacts of drought on agricultural yields and the associated economic repercussions is essential for formulating effective strategies to counteract the adverse effects of climate change. As global warming continues to influence the intensity, duration, and frequency of extreme weather events, agriculture is becoming increasingly vulnerable. In Brazil, where agriculture plays a pivotal role in the economy and involves diverse crop production, grasping these impacts is of critical importance.

The State of Rio Grande do Sul, a key producer of soybeans, maize, and rice, is particularly susceptible to drought events, such as the severe drought of 2012 (Carvalho et al., 2020). Since droughts can cause significant reductions in crop yields and lead to substantial economic losses, analyzing their effects on these essential crops offers valuable insights for regional policy-making and agricultural management.

This study utilizes a robust dataset covering several decades and 497 municipalities to estimate the impact of droughts on the average yields of soybeans, maize, and rice in Rio Grande do Sul. Additionally, it assesses the consequent effects on revenue losses across the state and its municipalities. Such an analysis aims to enhance understanding of how droughts affect agricultural productivity in this region, thereby informing strategies for adaptation and mitigation.

2 Effects of Drought on Agriculture

Empirical analysis of the economic impacts of droughts on agriculture has been conducted using a variety of methodological approaches, levels of data aggregation, spatial or temporal scopes, evaluated agricultural products, and quantitative characterizations of drought. Using a producer-level panel dataset and a fixed-effects econometric model, Schmitt et al. (2022) assessed the impact of extreme climate events on the average yield of grain production. Among the events analyzed, drought was identified as the primary factor reducing average yield.

Employing a panel dataset from 34 Sub-Saharan African countries covering the period from 1990 to 2020 and using Fully Modified OLS (FMOLS), Akpa (2024) found that the average yields of sorghum, maize, and rice are negatively affected not only by current floods and droughts but also by past events. The decline in average yield resulting from a drought year and its subsequent effect on income can also lead to the exit from agricultural activities. Using data from producers in a village in Maharashtra, India, and applying cross-sectional and panel data linear models, Harshan (2023) examined the impact of drought years on the income of smallholder farmers. The results suggest that after a drought year, households tend to shift from agricultural to non-agricultural occupations, as the latter are less vulnerable to extreme events.

Currently, drought events are already causing significant damage to agricultural production in various regions of Brazil. Using longitudinal municipal data from 2009 to 2017 and a fixed-effects model, Costa et al. (2020) assessed the impact of drought on the cultivated area and production value of beans, maize, sugarcane, and coffee in Brazil's semi-arid region.

Carvalho et al. (2020) analyzed the impacts of droughts and other extreme events on the production of rice, coffee, cassava, wheat, and soybeans. The authors developed a loss index based on the difference between planted and harvested area data provided by the Brazilian Institute of Geography and Statistics (IBGE) and insurance payments to producers due to these events. Their main findings indicate that droughts or dry spells, such as those experienced in the Brazilian semiarid region or in the state of Rio Grande do Sul in 2012, were responsible for significant production losses and increased insurance payouts across Brazil.

The studies highlighted previously use different strategies to define drought events. To isolate the effect of drought, Schmitt et al. (2022) created variables that capture extreme events based on critical thresholds of climate variables according to the phenological stages of the analyzed crops, Akpa (2024) used the number of drought events recorded annually by the International Disaster Database from the Centre for Research on the Epidemiology of Disasters and Harshan (2023) did not create a specific variable but instead used data from the year of the event and the subsequent year.

In studies focusing on Brazilian regions, Carvalho et al. (2020) collected information on extreme events from the Federal Government's National Plan of Disaster Risk Management and Response and the National Center for Monitoring and Early Warning of Natural Disasters. Meanwhile, Costa et al. (2020) quantified the effects of drought by measuring deviations from historical precipitation averages.

Drought indices such as the Standardized Precipitation Index (SPI), developed by McKee et al. (1993), the Palmer Drought Index, created by Palmer (1965), and the Standardized Precipitation-Evapotranspiration Index (SPEI), developed by Vicente-Serrano et al. (2010), have been employed as tools to monitor drought duration and intensity. Recently, the relationship between droughts identified by these indices and fluctuations in agricultural production has begun to be explored (Jabbi et al., 2021; Thomasz et al., 2024; Hamal et al., 2020; Mohammed et al., 2022; Kheyruri et al., 2023).

Mohammed et al. (2022) used SPI and SPEI at 3- and 6-month scales to assess the impact of droughts on standardized residuals of average maize and wheat yields in various regions of Hungary. Hamal et al. (2020) evaluated the effects of droughts on agriculture in Nepal, considering the same crops and response variable, but only using historical SPEI series at different time scales. Both studies found negative and spatially heterogeneous effects of droughts in their respective countries.

The SPEI, at 1- and 3-month scales, was also utilized by Jabbi et al. (2021) to analyze the impact of droughts occurring between 1990 and 2019 on maize, rice, millet, and sorghum production in three regions of The Gambia. The results indicated that over this period, there were increasing trends in temperature and SPEI, along with declining average yields in the three regions. In a study conducted in Iran, covering 30 provinces from 1995 to 2005, Kheyruri et al. (2023) identified drought periods using SPI and the Standardized Streamflow Index (SSI), which led to price increases and decreased production. These effects were more pronounced in areas with higher drought severity and lower levels of irrigation.

Thomasz et al. (2024) emphasized the importance of converting the biophysical losses generated by droughts into economic outcomes, specifically variations in cash flow and revenue losses. By identifying drought periods using the Palmer Index, Thomasz et al. (2024) assessed the impact of these events on the average yields of soybeans and maize in Argentina. Projected yield deviations were used to quantify the losses in monetary terms. Estimates suggest that losses across the 183 departments in the country from 1970 to 2020 amount to US$21 billion, which at that time represented more than half of the country's foreign exchange reserves.

3 Material and Methods

3.1 Data

The climate data used in this study were obtained from the Brazilian Weather Gridded Data (BR-DWGD), developed by Xavier et al. (2022) . The BR-DWGD is a gridded weather dataset for Brazil, providing daily values for precipitation (pr), maximum temperature (tmax), minimum temperature (tmin), solar radiation (Rs), relative humidity (RH), and evapotranspiration (ETo). This dataset features a spatial resolution of 0.1° x 0.1° and covers the period from 1961 to 2020.

The BR-DWGD dataset was constructed using data from 1,252 weather stations and 11,473 rain gauges, sourced from two Brazilian institutions: the National Water Agency (Agência Nacional de Águas - ANA) and the National Institute of Meteorology (Instituto Nacional de Meteorologia - INMET). Following data processing, daily gridded values for the aforementioned climate variables were computed using two interpolation methods: Inverse Distance Weighting (IDW) and Angular Distance Weighting (ADW). These methods were selected based on their superior performance during a cross-validation process. The spatial interpolation was delineated at the river basin level, encompassing major Brazilian river basins, including the Amazon River, the Tocantins River, the North Atlantic region, the São Francisco River, the Central Atlantic region, the Paraná River, the Uruguay River, and the South Atlantic region.

The selection of BR-DWGD dataset is based on its use in a variety of research studies focusing on climate change and climate extremes (Jeferson De Medeiros et al., 2022; Lucas et al., 2021; Costa et al., 2020). Furthermore, the database developed by Xavier et al. (2022) is recognized for offering a more accurate representation of rainfall in Brazil compared to other available datasets (Lucas et al., 2021). This superior performance has been particularly verified in agroclimatic research, where agrometeorological models are employed to analyze and predict the yield of agricultural products (Duarte and Sentelhas, 2020; Rasera et al., 2023).

In addition to the climate data, municipal data series on production, planted area, and average yield of maize, rice and soybean were obtained from the Municipal Agricultural Production (Produção Agrícola Municipal - PAM) survey. PAM is produced and made available annually by the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatísticaaa - IBGE) and contains annual data at the municipal level on the main temporary and permanent agricultural products cultivated in Brazil. For this study, data were downloaded for the 497 municipalities in the State of Rio Grande do Sul, covering the period from 1974 to 2020.

3.2 Definition and Calculation of Droughts

In recent decades, several meteorological indices have been developed to monitor the intensity and frequency of drought events. Some of these indices are relatively simple to construct, relying solely on historical precipitation data for a specific geographic area (McKee et al., 1993). More sophisticated indices, however, incorporate additional climatic variables, such as temperature and evapotranspiration (Palmer, 1965; Vicente-Serrano et al., 2010). The choice between a univariate or multivariate index depends on the research question and the availability of climatic data for the region of interest.

Among the most well-known indices are the Standardized Precipitation Index (SPI) developed by McKee et al. (1993), the Palmer Drought Severity Index (PDSI) created by Palmer (1965), and the Standardized Precipitation Evapotranspiration Index (SPEI) developed by Vicente-Serrano et al. (2010). The SPI relies exclusively on historical precipitation data and can be used for spatial comparisons and monitoring drought events across various time scales. This allows the SPI to capture both short-term droughts affecting soil moisture and long-term droughts impacting water reservoirs (Ren et al., 2008). However, the SPI does not account for temperature or evapotranspiration, which limits its capacity to characterize these extreme hydrological events comprehensively.

To address this limitation, the PDSI incorporates both precipitation and temperature, and can also include variables reflecting soil moisture. Despite its advantages, the PDSI has drawbacks, such as low sensitivity to abrupt climatic changes, making it less effective for capturing short-term droughts (Guttman, 1998).

In this study, the SPEI was chosen as an alternative to the univariate SPI approach. The SPEI is a multi-temporal index based on the SPI, which considers both precipitation and potential evapotranspiration (Vicente-Serrano et al., 2010). Like the SPI, the SPEI is suitable for monitoring short-, medium-, and long-term drought events. The inclusion of evapotranspiration enables it to account for increasing evaporative demands over time, making it particularly suitable for studies addressing the impacts of climate change.

Following the methodology presented by Vicente-Serrano et al. (2010), the SPEI is calculated by first estimating Potential Evapotranspiration (PET) using the formula from Thornthwaite (1948), which relies solely on a monthly temperature data series:

$$PET = 16K \left(\frac{10T}{I} \right)^m \tag{1}$$

Where:

- T is the mean monthly temperature (in °C).
- I is the annual heat index, which is the sum of the 12 monthly i values with:

$$i = \left(\frac{T}{5}\right)^{1.514} \tag{2}$$

- m is a coefficient that depends on I:

$$m = 6.75 \cdot 10^{-7} \cdot I^3 - 7.71 \cdot 10^{-5} \cdot I^2 + 1.79 \cdot 10^{-2} \cdot I + 0.492 \tag{3}$$

- k is a correction coefficient obtained as a function of latitude and month:

$$k = \left(\frac{N}{12}\right)\left(\frac{NDM}{30}\right) \tag{4}$$

NDM is the number of days of the month, and N is the maximum number of sunshine hours, calculated using:

$$N = \left(\frac{24}{\pi}\omega_s\right) \tag{5}$$

Where ω_s is the hourly angle of sunrise and can be obtained by:

$$\omega_s = \arccos(-\tan\phi\tan\delta) \tag{6}$$

The value of ϕ is the latitude in radians for the region of interest, and δ is the solar declination in radians, which can be calculated using:

$$\delta = 0.4093\sin\left(\frac{2\pi J}{365} - 1.405\right) \tag{7}$$

Where J is the average Julian day of the month. After calculating the value of PET, the value of the Hydrological Surplus or Deficit D_i is obtained as the difference between Precipitation P_i and Potential Evapotranspiration PET_i in month i:

$$D_i = P_i - PET_i \tag{8}$$

The values of D_i can be accumulated over different time scales. For example, the accumulated difference for a given month j and year i, considering a time scale of $k = 12$ months, would be:

$$X_{i,j}^{k} = \sum_{l=13-k+j}^{12} D_{i-1,l} + \sum_{l=1}^{j} D_{i,l} \qquad se\ \ j < k \tag{9}$$

$$X_{i,j}^{k} = \sum_{l=j-k+1}^{j} D_{i,l} \qquad se\ \ j \geq k \tag{10}$$

Where $D_{i,l}$ is the difference $P - PET$ in the first month of year i in millimeters. To make the SPEI comparable spatially and temporally, the values of D_i must be adjusted to a probability distribution so that they follow a normal distribution with a mean of 0 and a standard deviation of 1. The distribution that best standardizes the values of D_i and works with negative values is the Log-Logistic distribution (Vicente-Serrano et al., 2010). The probability density function of a three-parameter log-logistic distribution can be defined as:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left[1+\left(\frac{x-\gamma}{\alpha}\right)\right]^{-2} \tag{11}$$

where α,β, and γ are the scale, shape, and location parameters, respectively, for $D < \gamma < \infty$. Using the L-moment procedure, the parameters of a log-logistic distribution can be defined as:

$$\beta = \frac{2w_1 - w_0}{6w_1 - w_0 - 6w_2} \tag{12}$$

$$\alpha = \frac{(w_0 - 2w_1)\beta}{\Gamma(1+1/\beta)\Gamma(1-1/\beta)} \tag{13}$$

$$\gamma = w_0 - \alpha\Gamma\left(\frac{1+1}{\beta}\right)\Gamma\left(\frac{1-11}{\beta}\right) \tag{14}$$

Here, $\Gamma(\beta)$ is defined as the gamma function of β. The values of w_s are the Probability-Weighted Moments (PWMs) of order s and can be obtained as:

$$w_s = \frac{1}{N}\sum_{i=1}^{N}(1-F_i)^S D_i \tag{15}$$

where F_i is the following frequency estimator:

$$F_i = \frac{i-0.35}{N} \tag{16}$$

where N is the number of data point and i is the range of observation organized in increasing order. The cumulative distribution function of the D series can be defined as:

$$F(x) = \left[1+\left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1} \tag{17}$$

Finally, the SPEI is calculated as the standardized values of F_i:

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \tag{18}$$

where

$$W = \sqrt{-2\ln(P)} \qquad for \quad P \leq 0.5 \tag{19}$$

and $P = 1 - F(x)$. If $P > 0.5$, then P is substituted by $1 - P$ and the sign of the SPEI is changed. The values of the constants are $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$.

The interpretation of the SPEI can be done following the same classification created by McKee et al. (1993) for the SPI (Table 1). Positive SPEI values indicate wet conditions, while negative values suggest drought conditions. The intensity of drought or wet conditions is measured by the magnitude of the index.

Table 1: Common Interpretation Scale of the SPEI

SPEI Range	Interpretation
≥ 2.0	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Normal conditions
-1.0 to -1.49	Moderate drought
-1.5 to -1.99	Severe drought
≤ -2.0	Extreme drought

Using climate data from the BR-DWGD database and the *SPEI* package developed by Beguería and Vicente-Serrano (2023) for R (R Core Team, 2024), monthly SPEI values were computed for the 497 municipalities in the State of Rio Grande do Sul, spanning the period from 1960 to 2020. The index values were calculated for a 6-month time scale, which is appropriate for capturing conditions of agricultural drought (Mishra and Singh, 2010).

Next, the months classified as experiencing moderate drought ($-1.5 < SPEI \leq -1.0$), severe drought ($-2.0 < SPEI \leq -1.5$), and extreme drought ($SPEI \leq -2.0$) were quantified and aggregated according to the production windows of the agricultural products considered in this study. For each crop, the count of months corresponding to these drought categories was determined based on annual intervals, beginning at the start of the planting window and ending at the conclusion of the harvest window.

The definition of the production windows was based on the agricultural calendar of the National Supply Company (Companhia Nacional de Abastecimento - CONAB) (Conab, 2022). According to this document, the growing season for rice and soybeans in Rio Grande do Sul starts in September and ends in May of the following year, while the growing season for maize begins in August and ends in June of the following year.

3.3 Effects of Drought on Average Yield

The effect of moderate, severe, and extreme drought events on the average yield of rice, maize, and soybeans was assessed using an unbalanced panel data set and a fixed effects econometric model. The linear regression model with fixed effects for time and cross-sectional units is a commonly used method for estimating causal effects when working with panel data (Imai and Kim, 2021). A panel data model that accounts for fixed effects for both units i and time t can be written as follows:

$$Y_{it} = \alpha_i + \lambda_t + \beta X_{it} + \varepsilon_{it} \tag{20}$$

where:

- Y_{it} is the dependent variable for unit i at time t.
- α_i represents the fixed effect specific to unit i.

- λ_t represents the fixed effect specific to time t.
- X_{it} is the vector of independent variables for unit i at time t.
- β is the vector of coefficients for the independent variables.
- ε_{it} is the error term.

Including fixed effects for units allows for controlling unobserved characteristics that are specific to each unit and invariant over time. On the other hand, controlling for time fixed effects accounts for potential systemic shocks that impact all units equally within a given period (Schmitt et al., 2022; Imai and Kim, 2021). Therefore, the simultaneous control of fixed effects for both units and time (two-way fixed effects) can reduce the bias from omitting unit-specific characteristics or temporal changes that affect Y_{it}.

The fixed effects model used in this study can be specifically described as follows:

$$Log(Y_{it}) = \alpha_i + \lambda_t + \beta_{MD}X_{1it} + \beta_{SD}X_{2it} + \beta_{ED}X_{3it} + \varepsilon_{it} \tag{21}$$

where:

- $Log(Y_{it})$ is the natural logarithm of the average yield of the crop (kg/ha) for municipality i in year t from 1974 to 2019.
- α_i represents the fixed effect specific to municipality i.
- represents the fixed effect specific to time t.
- β_{MD} is the coefficient associated with the moderate drought event
- X_{1it} is the number of months within the growing season that were classified as moderately dry according to the SPEI
- β_{SD} is the coefficient associated with the severe drought event
- X_{2it} is the number of months within the growing season that were classified as severely dry according to the SPEI
- β_{ED} is the coefficient associated with the extreme drought event
- X_{3it} is the number of months within the growing season that were classified as extremely dry according to the SPEI
- ε_{it} is the error term.

The model described by the Equation (21) was estimated individually for each of the crops assessed in this study, using the package *plm* developed by Croissant and Millo (2008) for R language.

3.4 Revenue Losses Due to Drought

The parameters estimated from Equation (21) for the three agricultural products were used to quantify the estimated average yield ($\widehat{Log}(Y_{1it})$) for each municipality in Rio Grande do Sul that experienced a drought event between 1974 and 2019:

$$\widehat{Log(Y_{1it})} = \widehat{\alpha}_i + \widehat{\lambda}_t + \widehat{\beta_{MD}} X_{1it} + \widehat{\beta_{SD}} X_{2it} + \widehat{\beta_{ED}} X_{3it} \tag{22}$$

Subsequently, to analyze the economic effect of these physical production losses, a counterfactual exercise was conducted assuming that a specific municipality i in year t did not experience the recorded drought event ($\hat{\beta_{MD}} = 0$ or $\hat{\beta_{SD}} = 0$ or $\hat{\beta_{ED}} = 0$). To this end, four additional average yield values were estimated for each municipality:

$$\widehat{Log(Y_{2it})} = \widehat{\alpha}_i + \widehat{\lambda}_t \tag{23}$$

$$\widehat{Log(Y_{3it})} = \widehat{\alpha}_i + \widehat{\lambda}_t + \widehat{\beta_{MD}} X_{1it} \tag{24}$$

$$\widehat{Log(Y_{4it})} = \widehat{\alpha}_i + \widehat{\lambda}_t + \widehat{\beta_{SD}} X_{2it} \tag{25}$$

$$\widehat{Log(Y_{5it})} = \widehat{\alpha}_i + \widehat{\lambda}_t + \widehat{\beta_{ED}} X_{3it} \tag{26}$$

While the result obtained with Equation (22) shows the combined effect of the three types of drought on the average yield for municipality i in year t, Equation (23) provides the estimated average yield ($\widehat{Log(Y_{2it})}$) assuming the municipality had not experienced any drought events. In contrast, Equations (24), (25), and (26) provide the estimated average yield for year t if the municipality had experienced only moderate drought ($\widehat{Log(Y_{3it})}$), severe drought ($\widehat{Log(Y_{4it})}$), or extreme drought ($\widehat{Log(Y_{5it})}$), respectively, in isolation. Therefore, the last three values capture the isolated effect of each drought category on the average yield.

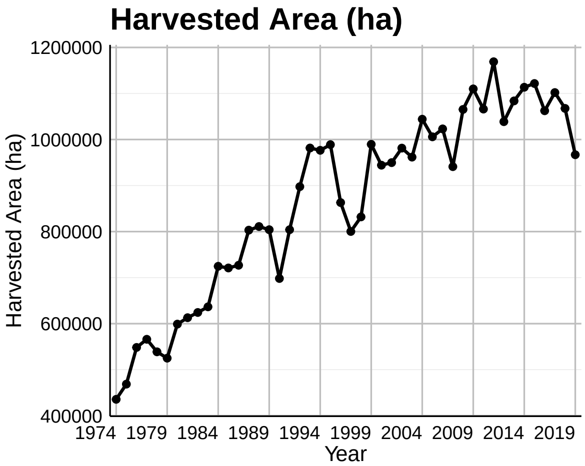
The average yield values obtained from Equations (22), (24), (25), and (26) were compared with the hypothetical average yield assuming no drought events had been observed, i.e., the average yield estimate provided by Equation (23). The differences obtained from these comparisons, along with the production data from PAM and the product sale price values obtained from the Center for Advanced Studies in Applied Economics (Centro de Estudos Avançados em Economia Aplicada - CEPEA) , were used to estimate the production and revenue losses for municipalities due to droughts.

4 Results

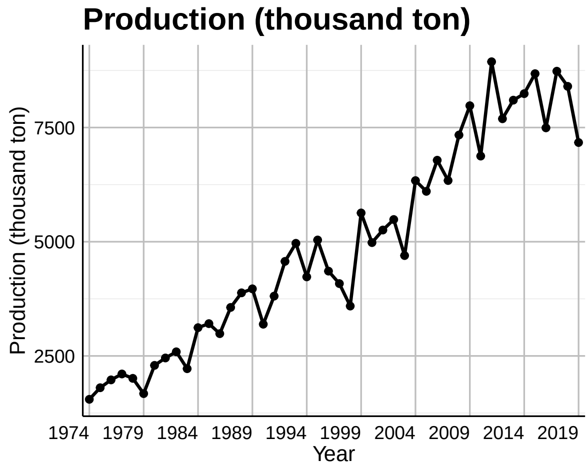
4.1 Production Characteristics

4.1.1 Rice

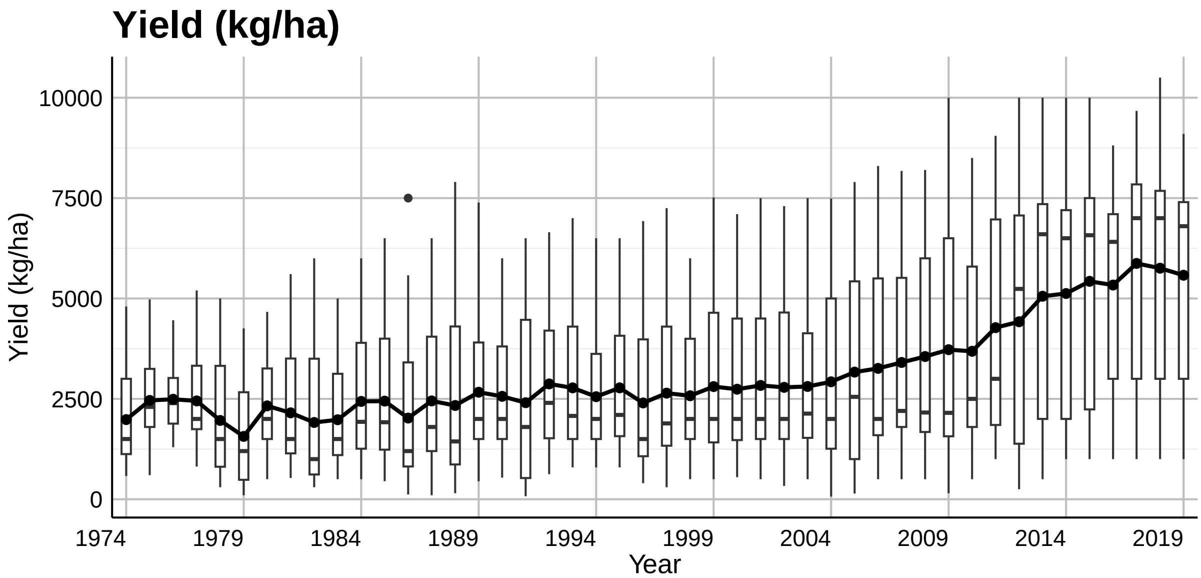
Brazil is the largest producer and exporter of rice in the world outside of Asia (USDA, 2024). Despite its significant role as an exporter, the majority of Brazilian rice production is aimed at domestic consumption. According to PAM (2024), about 70% of Brazil's rice production comes from the state of Rio Grande do Sul. Between 1974 and 2019, the harvested area of rice in Rio Grande do Sul increased by two and a half times, rising from 400,000 hectares to nearly 1 million hectares. During the same period, the amount produced more than tripled, growing from around 2 million tons to almost 7.5 million tons (Figure 1).



(a) Harvest area of rice



(b) Total production of rice



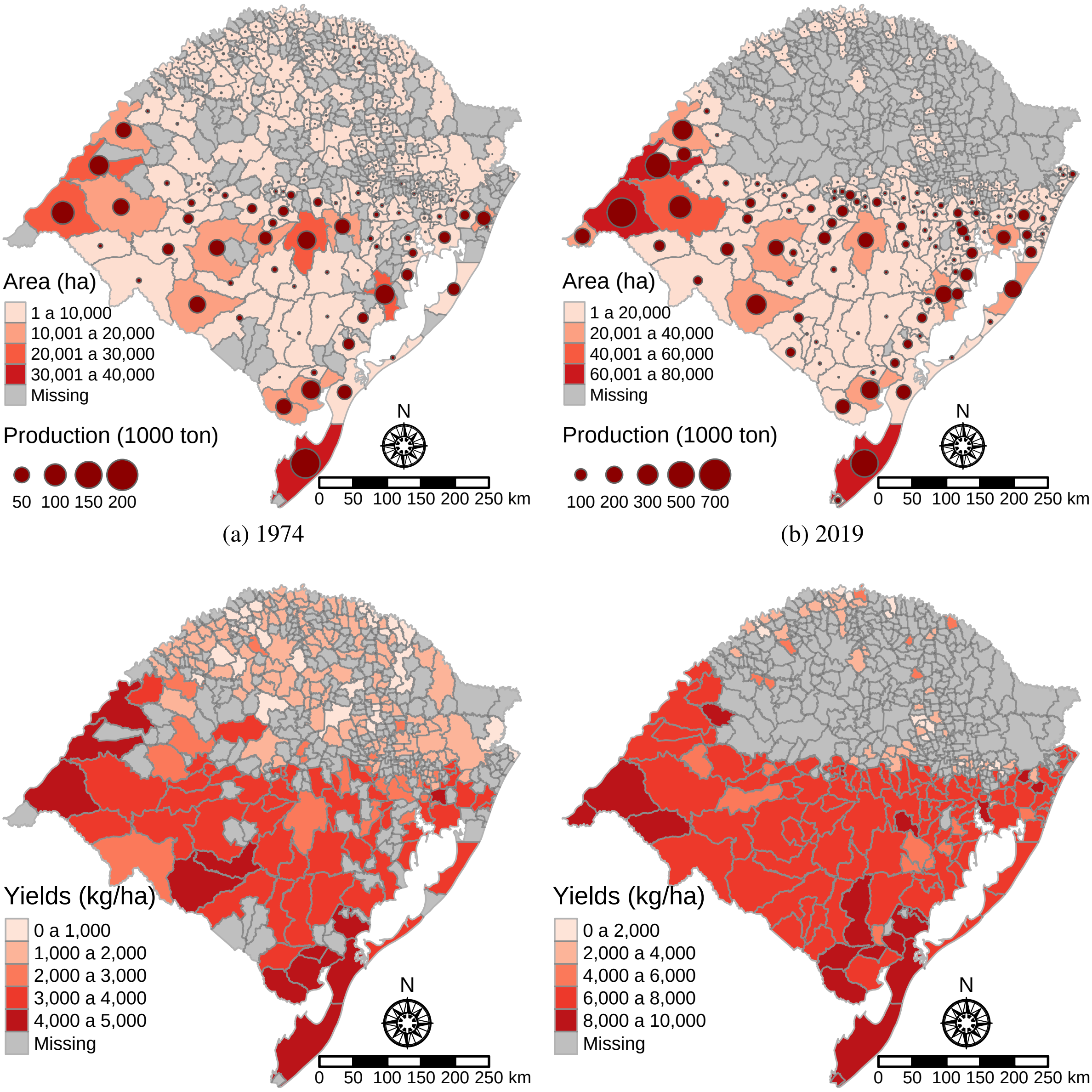
(c) Rice Yield

Figure 1: Evolution of rice production, harvested area, and average yield from 1974 to 2019

In addition to the incorporation of new production areas, the growth in production was also driven by the increase in average yield. This rise in yield was due to the adoption of mechanized, chemical, and biological production technologies, including machinery, agricultural implements, fertilizers, pesticides, herbicides, and new genetic varieties of rice. The average yield, which was around 2,500 kg/ha in 1974, increased to just over 5,000 kg/ha by 2019.

The increase in average yield over time was also accompanied by a greater range of values for this variable when considering all municipalities in the state of Rio Grande do Sul (Figura 1-c). This increase in variability resulted from a rise in production heterogeneity among the producing municipalities. In 2019, municipalities in the northwest of the state, such as Santo

Cristo and Machadinho, had average yields below 100 kg/ha. In contrast, leading production municipalities like Uruguaiana and Santa Vitória do Palmar, located in the southern part of the state, recorded average yields exceeding 8000 kg/ha (Figure 2).



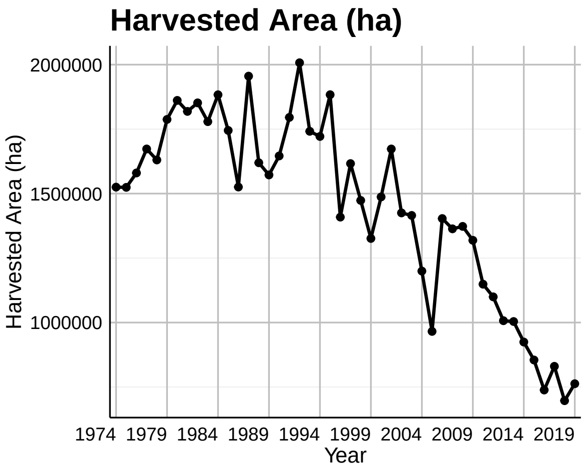
(a) 1974 (b) 2019

(c) 1974 (d) 2019

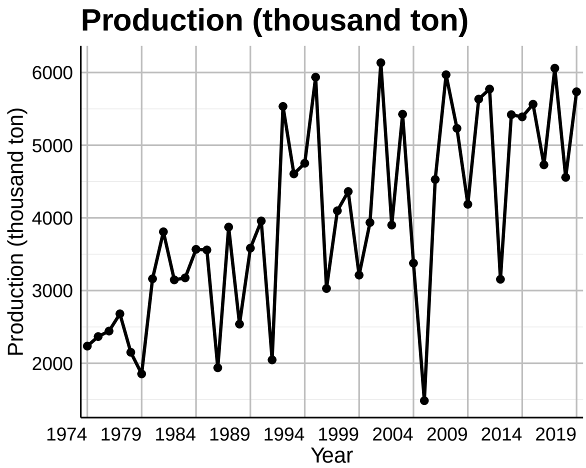
Figure 2: Production, harvested area, and average yield of rice in the State of Rio Grande do Sul for the years 1974 and 2019

4.1.2 Maize

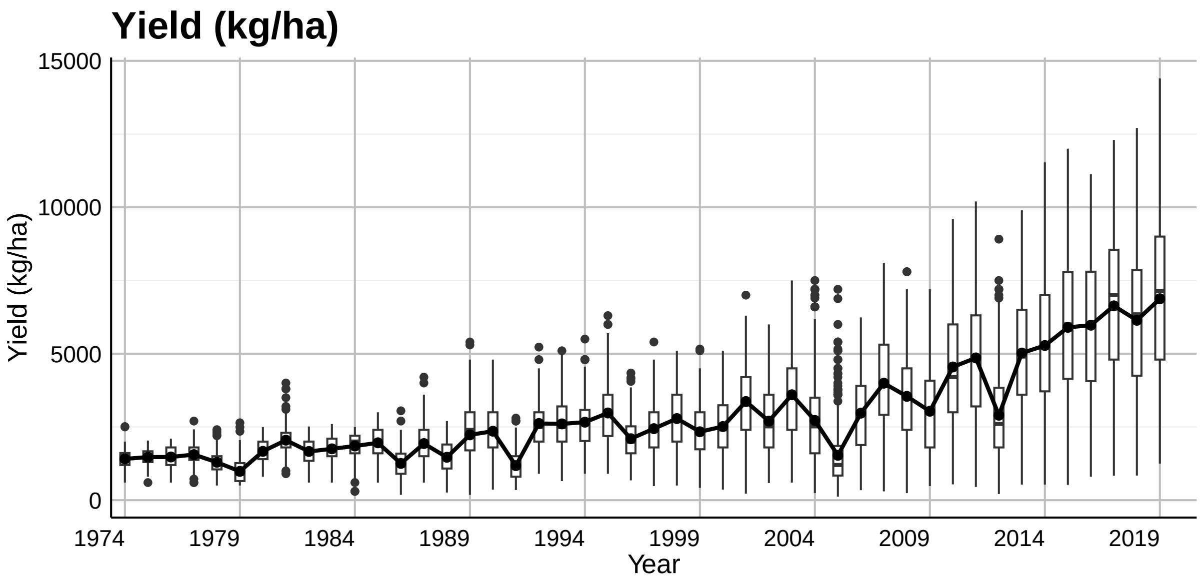
Currently, Brazil is the third largest producer and the largest exporter of maize in the world. Approximately 75% of maize production in Brazil is cultivated primarily between January and March. Along with the state of Minas Gerais, Rio Grande do Sul is among the top producers of the first crop, which is mainly grown between October and December (USDA, 2024). In recent decades, a decline in the area cultivated with maize in Rio Grande do Sul has been observed. This decline has not been matched by a similar decrease in production levels, due to the nearly consistent increase in average yield levels (Figure 3).



(a) Harvest area of maize



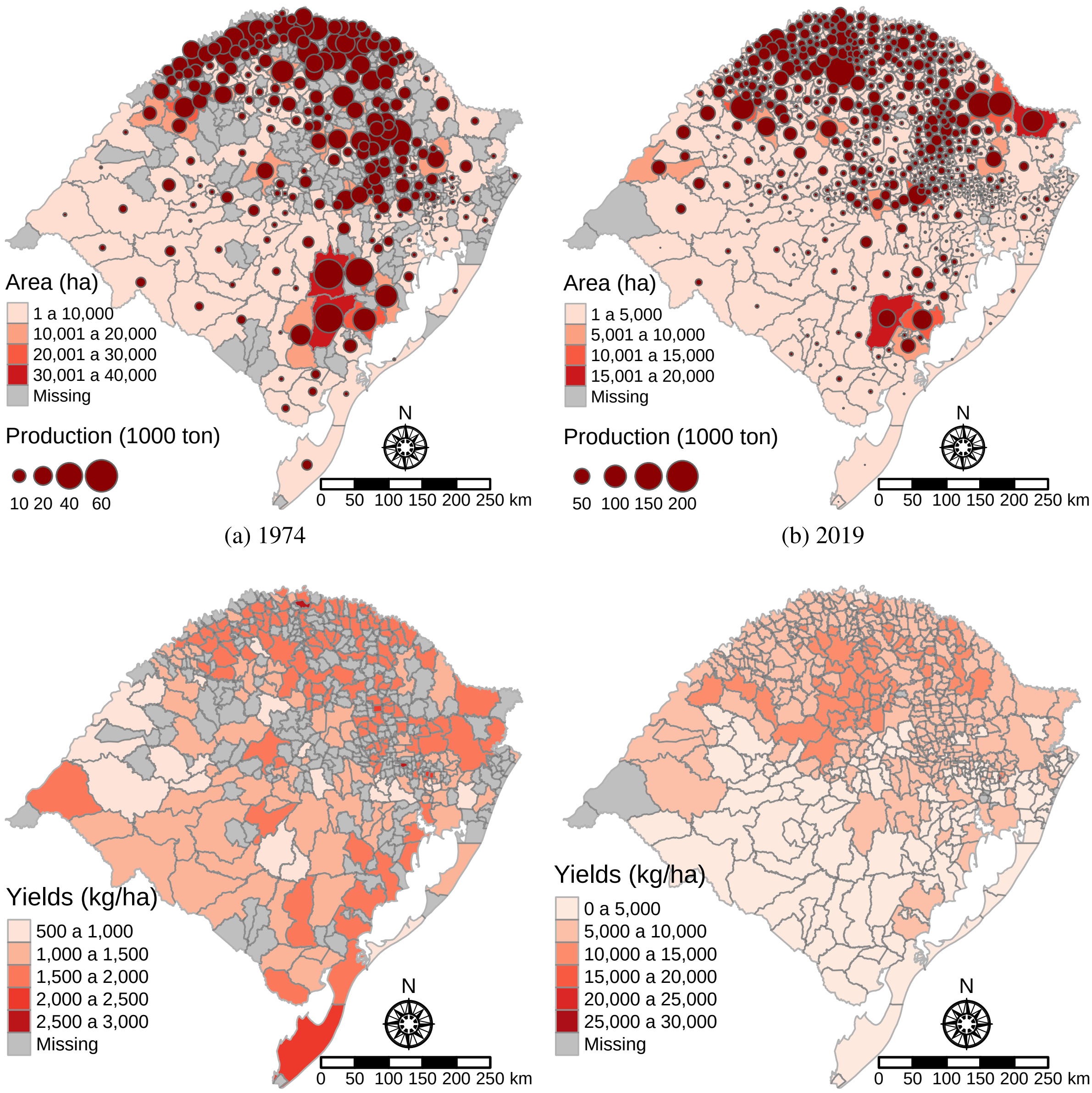
(b) Total production of maize



(c) Maize Yield

Figure 3: Evolution of maize production, harvested area, and average yield from 1974 to 2019

Similar to rice, the growth in average maize yield has been accompanied by an increase in the heterogeneity of production patterns and, consequently, greater variability in average yield among municipalities. Although maize is cultivated throughout Rio Grande do Sul, the highest average yield and production levels are observed in the northern part of the state, particularly in the northwestern region (Figura 4). The growth in the area cultivated with soybeans in this region, which has long been the state's primary production area, may partially explain the significant decline in the area cultivated with maize.



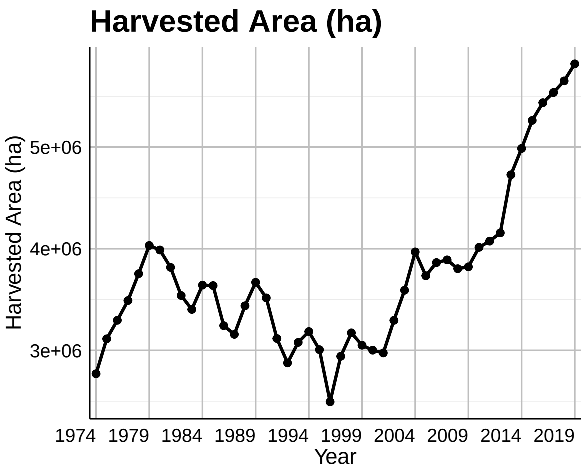
(a) 1974 (b) 2019

(c) 1974 (d) 2019

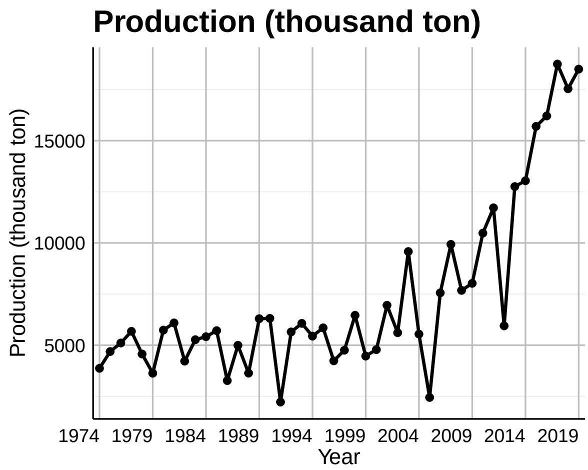
Figure 4: Production, harvested area, and average yield of maize in the State of Rio Grande do Sul for the years 1974 and 2019

4.1.3 Soybean

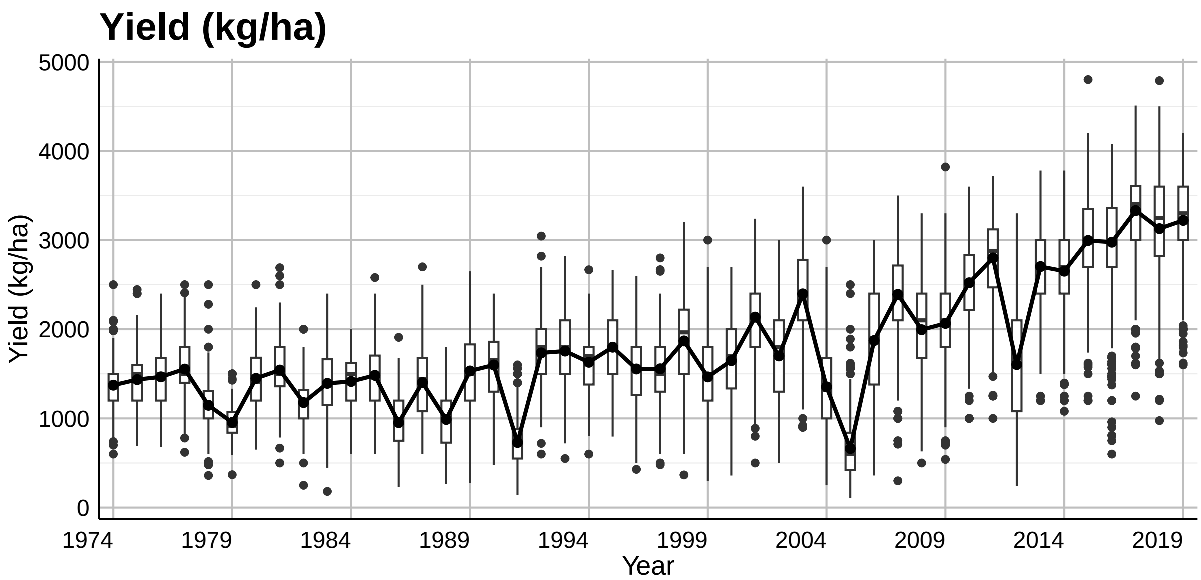
Brazil is the world's leading producer and exporter of soybeans. Within the country, Rio Grande do Sul ranks as the third-largest soybean-producing state, following Mato Grosso and Paraná. Soybeans have been cultivated in Rio Grande do Sul well before their expansion into the Brazilian cerrado. Until the early 2000s, soybean production and average yield in the state remained relatively stable, while the cultivated area had been declining in previous decades. From the 2000s onward, however, soybean production began to grow, driven by both increases in average yield and the expansion of the cultivated area. (Figure 5).



(a) Harvest area of soybean



(b) Total production of soybean

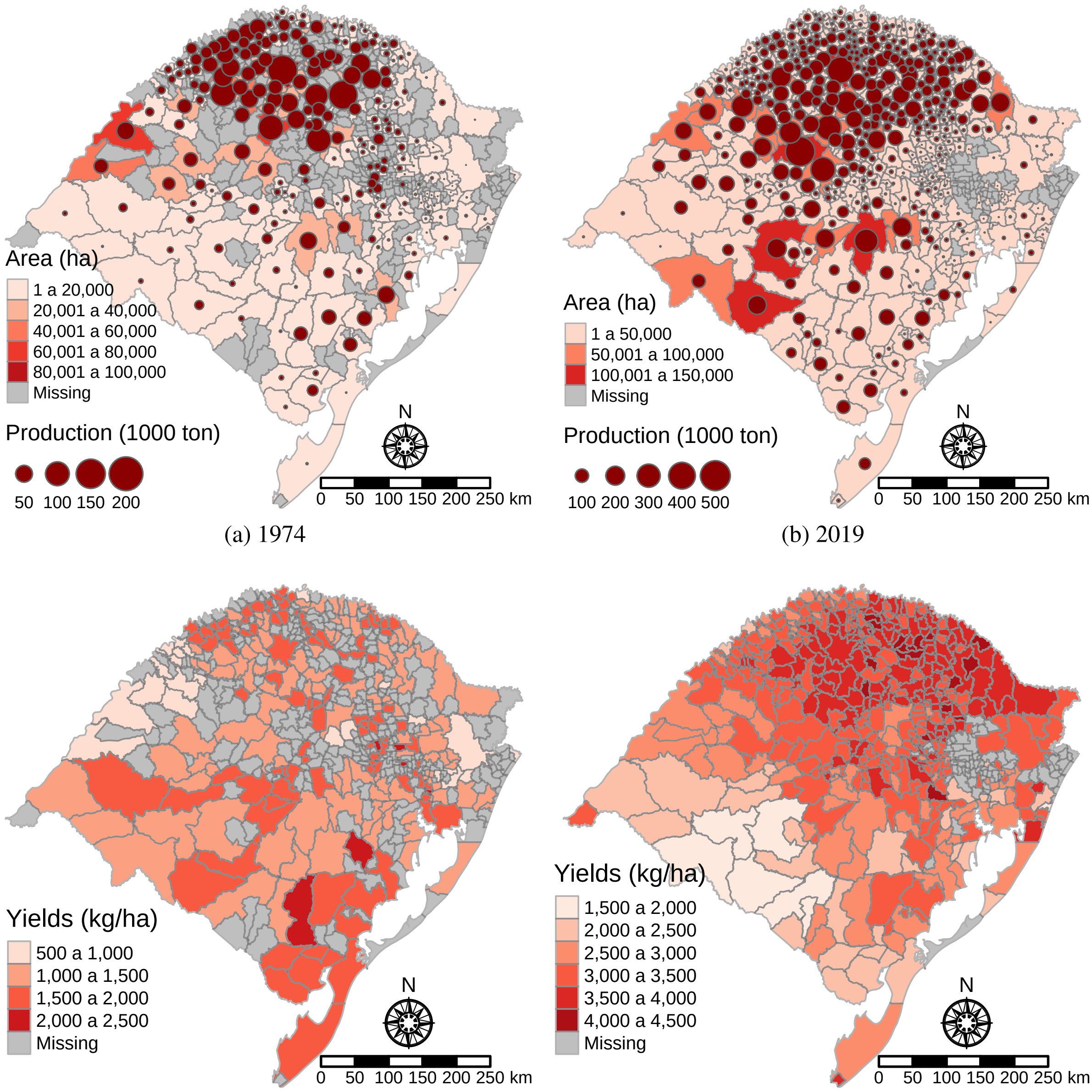


(c) Soybean Yield

Figure 5: Evolution of soybean production, harvested area, and average yield from 1974 to 2019

Unlike maize and rice, the growth in average soybean yield in Rio Grande do Sul has not been accompanied by a significant increase in the variability of this variable over the years. This suggests a pattern of adopting productive practices and technologies that has led to reduced production heterogeneity among municipalities in the state.

Production, which was more concentrated in the northwest of the state in 1974, has increasingly become significant in municipalities located in the southern part of the state, such as São Gabriel and Dom Pedrito (Figure 6). The rise in soybean production in these municipalities has been accompanied by stable productivity levels. The highest average yield levels in 2019 were observed in municipalities in the northern part of the state, such as Sertão and Três Palmeiras, with values exceeding 4000 kg/ha.



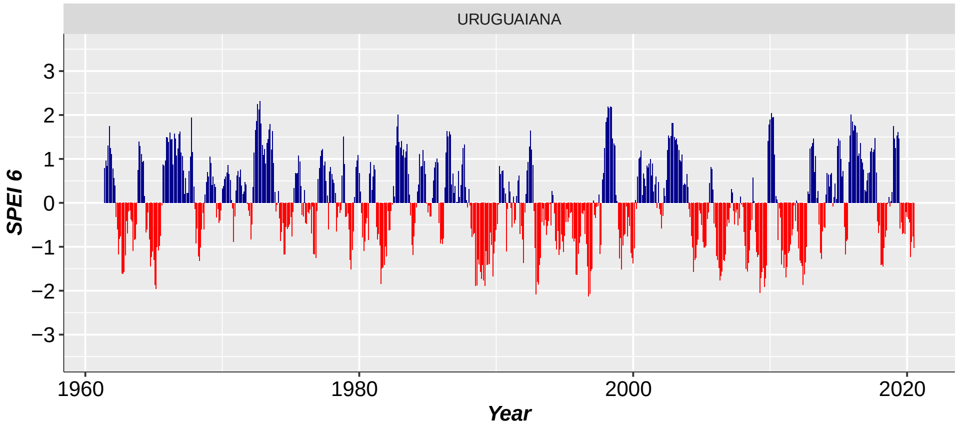
(a) 1974 (b) 2019

(c) 1974 (d) 2019

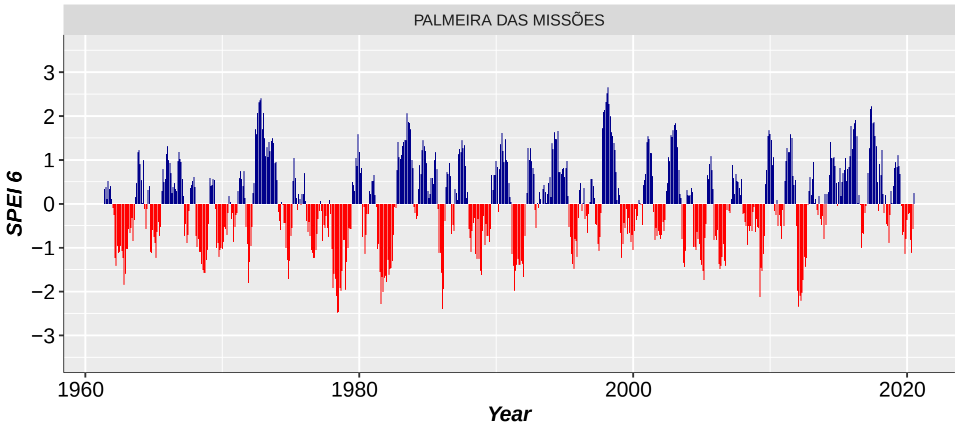
Figure 6: Production, harvested area, and average yield of soybean in the State of Rio Grande do Sul for the years 1974 and 2019

4.2 Drought Events in Rio Grande do Sul

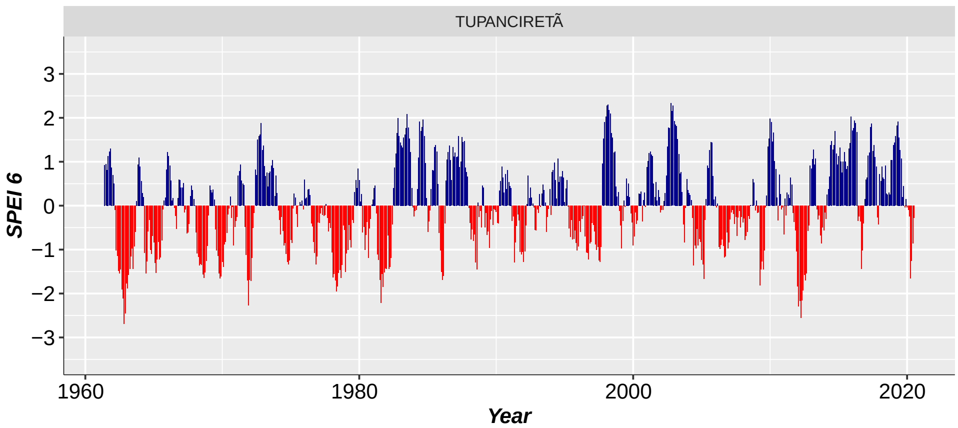
SPEI-6 series (six-month scale) were obtained for the 497 municipalities in Rio Grande do Sul, covering the period from 1960 to 2019 (Figure 7). The SPEI-6 was constructed from a longer climatic data series than the available production data (1974-2019). This choice was made because longer climatic series provide a more accurate indicator and are better suited to identifying patterns inherent to climate change. Additionally, longer series are more effective in detecting rare and extreme events, such as droughts.



(a)



(b)



(c)

Figure 7: SPEI Evolution for the Leading Rice(a), Maize(b) and Soybean-Producing (c) Municipalities in Rio Grande do Sul

The growing season for rice and soybeans in Rio Grande do Sul begins in September, in spring, and ends in May, at the end of autumn. To capture soil moisture conditions before planting begins, August was included at the start of the planting window. Thus, the SPEI-6 values considered for these two crops corresponded to the period from August of year 1 to May of year 2, totaling 10 months.

For the period 1974-2019, 450 monthly SPEI-6 values were obtained for each municipality in Rio Grande do Sul that cultivated rice or soybeans. Since drought is a rare event, few months were classified as moderately dry, severely dry, or extremely dry during this time interval (Figure 8).

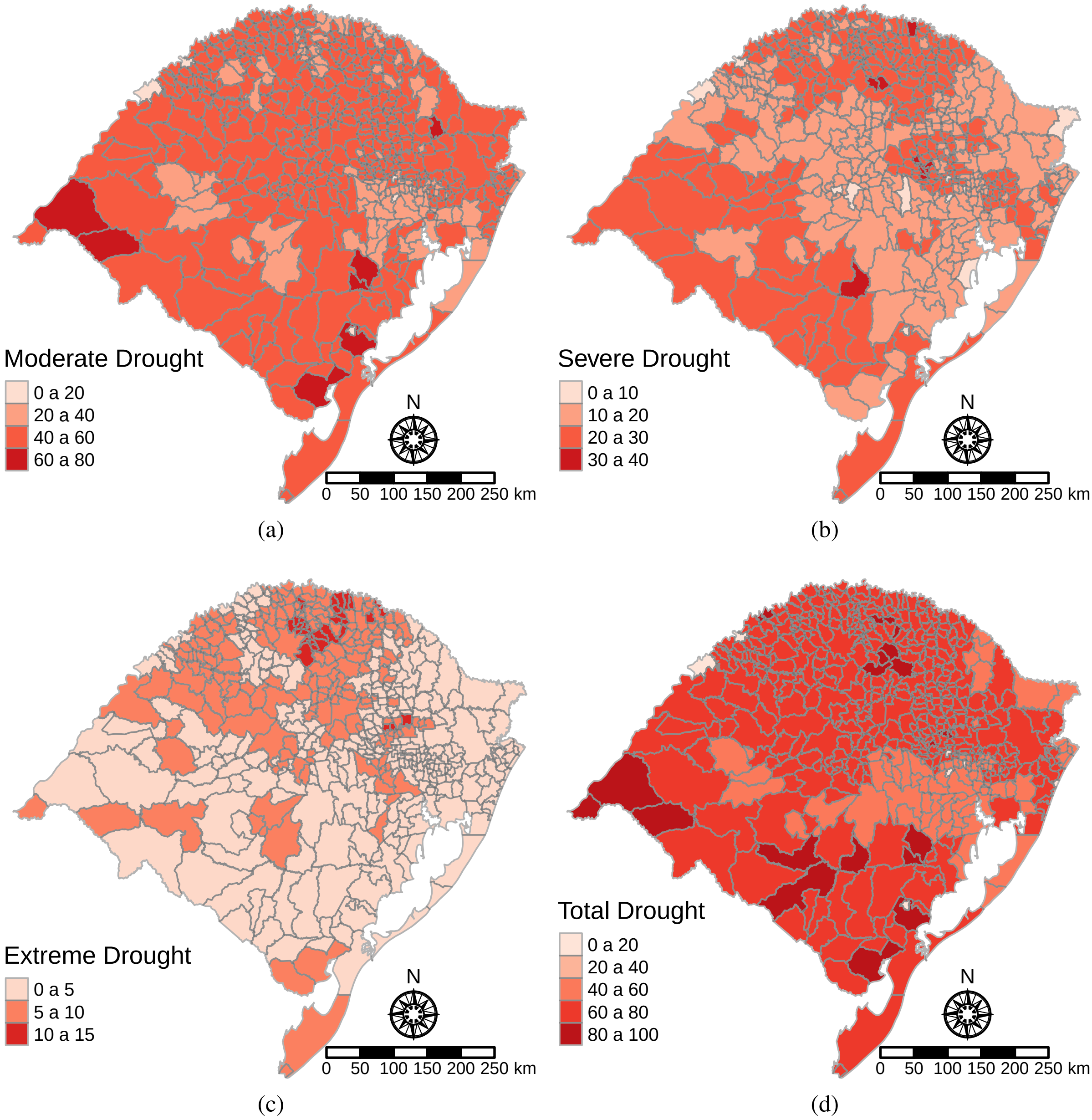


Figure 8: Number of months classified as moderately dry (a), severely dry (b), extremely dry (c) or dry in any SPEI category (d) between 1974 and 2019 for the growing seasons of rice and soybeans

For both rice and soybeans (Figure 8) and maize (Figure 9), most of the months in which drought occurred in the municipalities were classified as moderate, followed by severe, and finally extreme. This order reflects the expected inverse relationship between the intensity of the event and the number of observed events. A similarity in the drought cases identified in both growing seasons was the concentration of extreme drought events in municipalities in the northern part of the state.

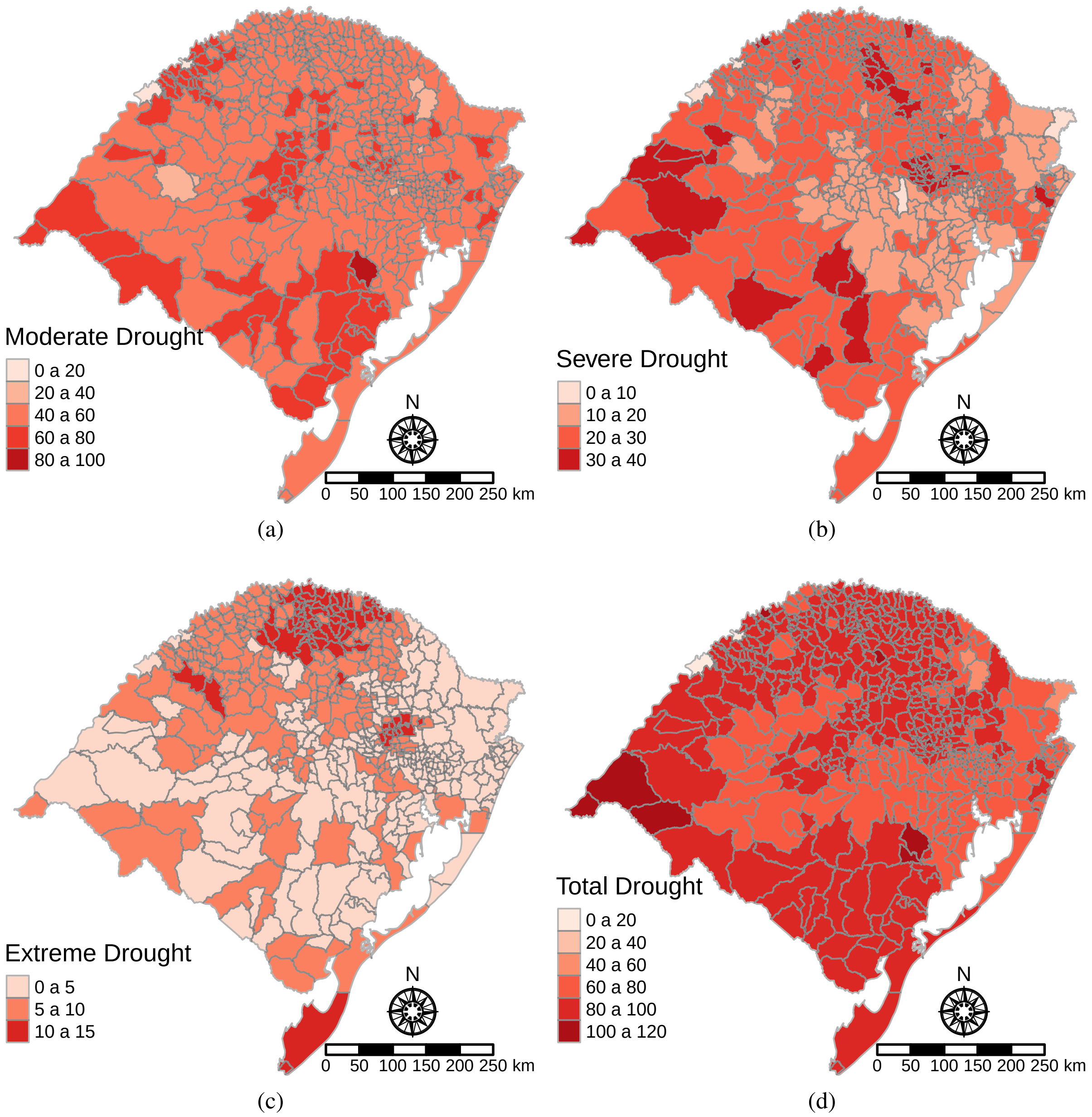


Figure 9: Number of months classified as moderately dry (a), severely dry (b), extremely dry (c) or dry in any SPEI category (d) between 1974 and 2019 for the growing season maize

The procedure applied to the growing season for rice and soybeans was also used for the maize, meaning that one month was added to the beginning of its growing window. Thus, to the official Conab window, which starts in August of year 1 and ends in June of year 2, July of year 1 was added to capture potential drought events just before the start of the planting season.

4.3 Droughts and Yields

The regression results show that drought negatively impacts the yields of the analyzed crops, with extreme drought having the most significant effect on average yields (Table 2). All three adjusted models are significant at the 1% level according to the F-test. Additionally, all coefficients obtained for the three models are significant at the 1% level. The R^2 values for the models are relatively low: 0.016 for rice, 0.018 for maize, and 0.021 for soybeans. These values indicate that drought variables explain only a small portion of the variability in crop yields. This result was expected, as average agricultural production yield depends on other factors not included in the model.

Table 2: Fixed Effects Regression Results for Rice, Maize, and Soybean Yields in Relation to Drought Conditions

	Dependent variable:		
		ln(yields)	
	Rice	Maize	Soybean
	(1)	(2)	(3)
Moderate Drought	-0.008^{***}	-0.013^{***}	-0.009^{***}
	(0.003)	(0.002)	(0.002)
Severe Drought	-0.036^{***}	-0.032^{***}	-0.034^{***}
	(0.004)	(0.003)	(0.003)
Extreme Drought	-0.098^{***}	-0.070^{***}	-0.097^{***}
	(0.009)	(0.006)	(0.006)
Observations	14,104	17,638	14,740
R^2	0.016	0.018	0.021
F Statistic	74.621^{***}	102.941^{***}	101.886^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

For rice, the coefficient associated with moderate drought is -0.008, indicating that each additional month of moderate drought reduces the natural logarithm of the average yield by 0.008 units. The effect of severe drought is even more pronounced, with a coefficient of -0.036, reflecting a decrease of 0.036 units in the natural logarithm of the average yield per additional month of severe drought. Extreme drought has the most intense impact, with a coefficient of -0.098, suggesting a reduction of 0.098 units in the natural logarithm of the average yield of rice for each additional month of extreme drought.

Similar interpretations can be made for maize and soybeans. For maize, moderate drought reduces the natural logarithm of the average yield by 0.013 units per month, severe drought decreases it by 0.032 units, and extreme drought reduces it by 0.070 units. These results also indicate a growing impact of drought on maize yield as its severity increases. For soybeans, moderate drought reduces the natural logarithm of the average yield by 0.009 units, severe drought decreases it by 0.034 units, and extreme drought reduces it by 0.097 units.

4.4 Revenue Losses

Using the fixed effects estimates and following the procedures outlined in section 3.4, estimates were obtained for the proportions of rice, maize, and soybean production that were lost due to droughts. Additionally, the monetary values of these production losses were estimated in millions of dollars. Both estimates were made for the entire state as well as for the municipalities of Rio Grande do Sul on an annual basis. To account for value fluctuations, the average dollar prices of the three crops over the past 4 years were used to estimate the monetary value of the losses.

Between 1974 and 2019, drought events led to substantial losses in the production of rice, maize, and soybeans in Rio Grande do Sul (Figure 10). In 2012, for example, it is estimated that approximately 24% of soybean production, 18% of maize production, and 13% of rice production were lost due to an extreme hydrological event. That year marked the highest relative loss in soybean production, although similar levels of loss were recorded for maize in 1978, 1979, 1982, and 1986, and for rice in 1982, 1989, 1990, and 1997.

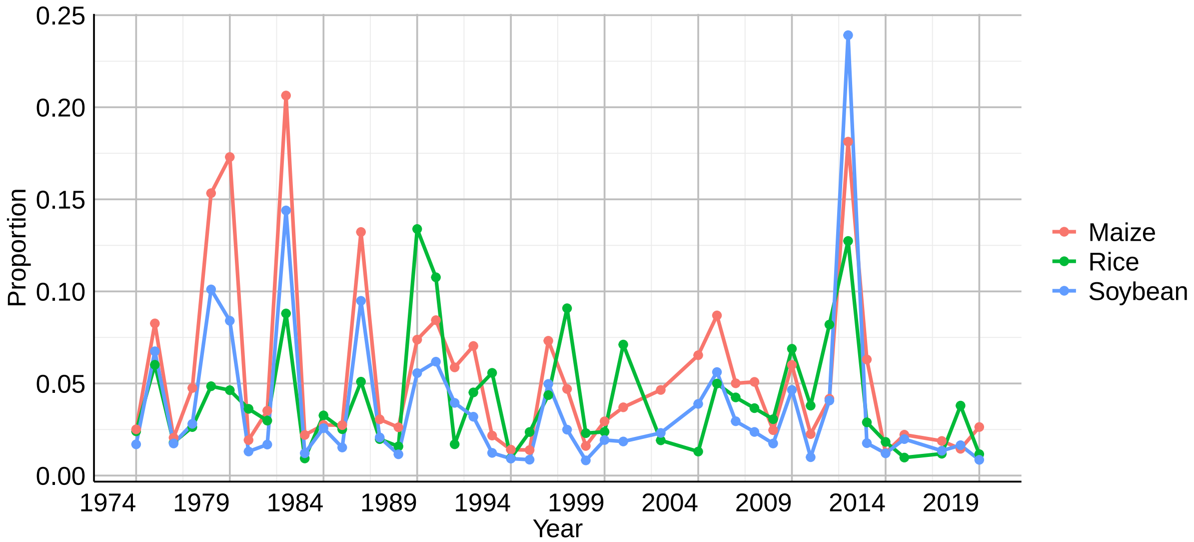


Figure 10: Estimated Proportion of Annual Production Lost Due to Droughts

The estimated loss values for rice, maize, and soybeans due to droughts amount to approximately US$ 2.2 billion, US$ 1.5 billion, and US$ 3.5 billion, respectively, between 1974 and 2019. The highest losses for soybeans occurred in 1978, 1982, and 2012, with values reaching US$ 268 million, US$ 363 million, and US$ 955 million, respectively (Figure 11). In 2012, the greatest revenue loss for rice was also observed, totaling US$ 346 million, surpassing the US$ 209 million recorded in 1989. For maize, the highest loss was registered in 1982 at US$ 197 million, followed by US$ 169 million in 2012.

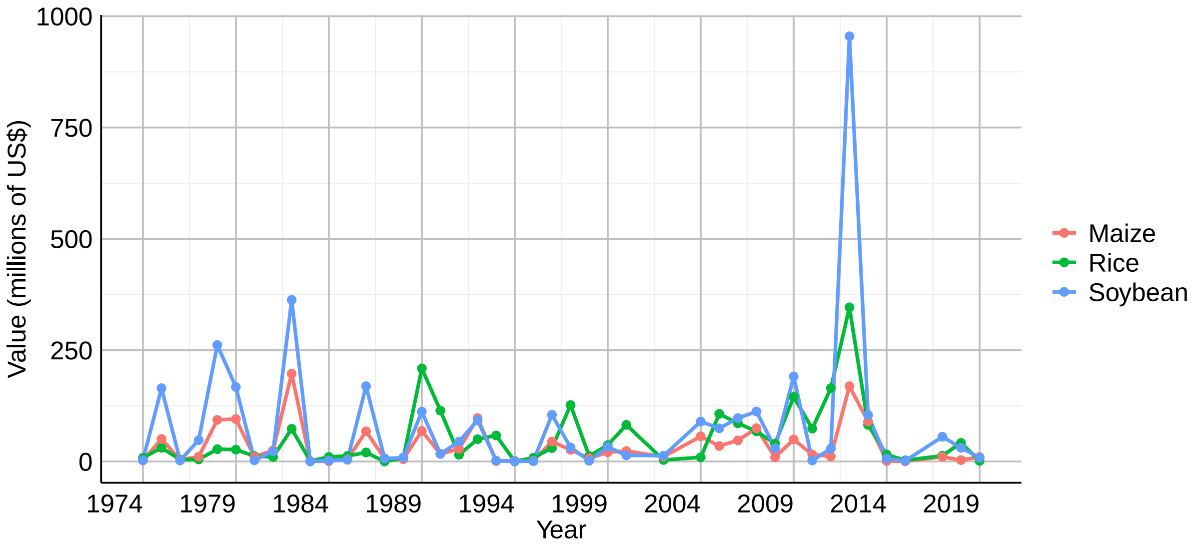
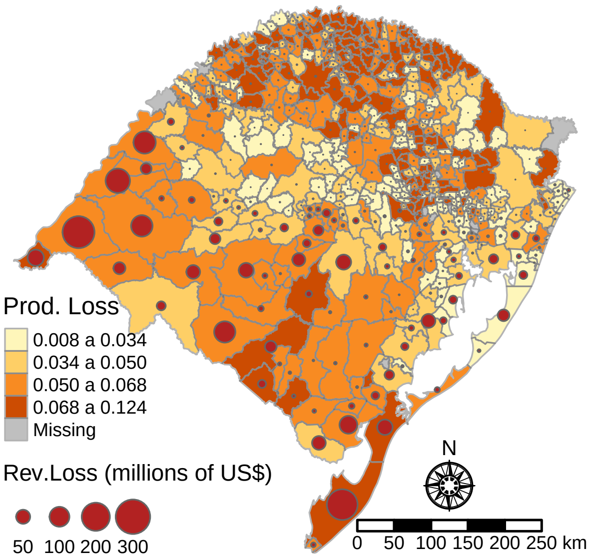


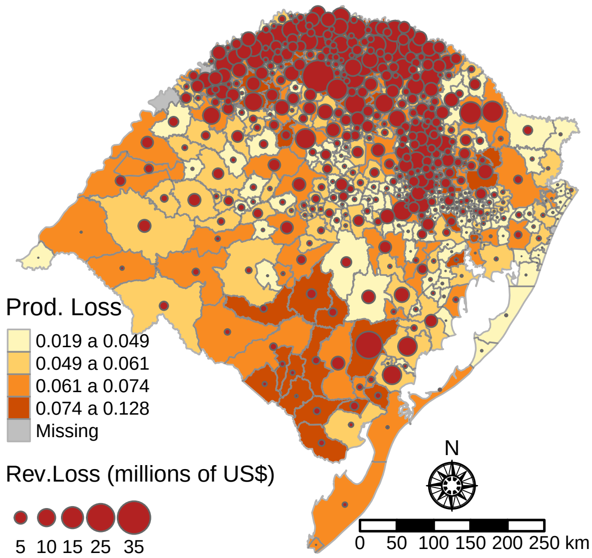
Figure 11: Estimated Value of Revenue Lost Due to Droughts

Between 1974 and 2019, the highest revenue losses for rice cultivation occurred in the southern part of the state, specifically in the largest producing municipalities of the period: Uruguaiana (US$ 258 million), Santa Vitória do Palmar (US$ 238 million), and São Borja (US$ 126 million) (Figure 12). The highest relative losses in produced quantity were recorded in the municipalities of Inhacorá (12.5%), Sarandi (12.3%) and Nonoai (11.4%).

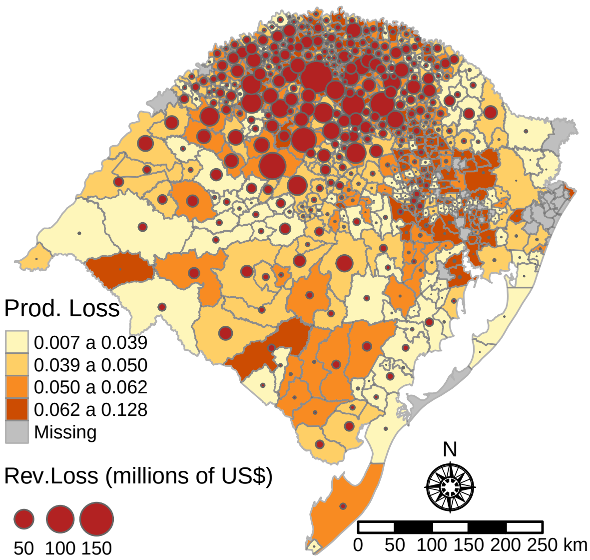
In the municipality of Palmeira das Missões, the largest producer of maize and soybeans during the period, the highest revenue losses for both crops were recorded, amounting to US$ 33 million for maize and US$ 141 million for soybeans. Significant revenue losses for soybeans were also estimated for the municipalities of Tupanciretã (US$ 96 million), Cruz Alta (US$ 85 million), and Passo Fundo (US$ 83 million). For maize, other municipalities with high revenue losses included Canguçu (US$ 24 million), Sarandi (US$ 19 million) and Erechim (US$ 16 million).



(a) Rice



(b) Maize



(c) Soybean

Figure 12: Estimation of Revenue and Proportion of Production Lost for Rice, Maize, and Soybeans Due to Droughts in the Municipalities of Rio Grande do Sul from 1974 to 2019

Similar to the pattern observed for rice, the municipalities with the highest revenue losses for maize and soybeans were also the largest producers in terms of accumulated production over the period. However, the greatest relative losses in production were found in municipalities with smaller production volumes. For soybeans, the highest proportion of production lost due to droughts was in municipalities such as Dois Irmãos (12.8%), Garibaldi (11.3%), Estância Velha (11.2%), and Carlos Barbosa (10.2%). For maize, the municipalities with the highest relative production losses were Nova Pádua (12.8%), Sarandi (12.2%), Constantina (12%), and Ronda Alta (11.9%).

5 Discussion

This study quantified the negative impact of drought on the yields of rice, maize, and soybeans. Specifically, similar to the approaches used by Mohammed et al. (2022), Hamal et al. (2020), Jabbi et al. (2021), Kheyruri et al. (2023), and Thomasz et al. (2024), this work employed a drought index to assess the effects of such extreme events on average agricultural yields.

The aforementioned studies utilized drought indices to identify drought periods or as quantitative variables. To evaluate the impact of different levels of drought on average yields, this study adopted a somewhat distinct approach by using annual quantifications of drought categories, as defined by McKee et al. (1993) from the SPEI, rather than the index itself, which is a continuous quantitative variable.

Similar to Schmitt et al. (2022), this study employed a fixed-effects panel data model for both municipalities and time. This approach provides more accurate estimates by controlling for unobserved variables that remain constant over time within municipalities and for time-specific trends and shocks that affect all municipalities simultaneously. Despite the advantages of this approach, this study did not account for spatial dependence in the variable estimates. Using a balanced panel, a requirement for some spatial econometric models, would limit the number of drought events in the dataset, which is problematic given that droughts are relatively rare events.

Equally important as evaluating the biophysical impacts of drought on agriculture, such as yield loss, is the capacity to estimate and communicate these negative effects in financial or economic terms. This approach helps broaden the discussion beyond agricultural experts to include a wider range of stakeholders and policymakers. Similar to Schmitt et al. (2022) and Thomasz et al. (2024), this study estimates not only the productive impacts of drought but also its economic consequences, specifically the revenue losses from agriculture due to various levels of drought that occurred between 1974 and 2019 in the State of Rio Grande do Sul.

One limitation of this study is the use of aggregated data due to the unavailability of historical production series at farm level. By utilizing municipal-level data, the internal variability among producers within this geographic unit may not be considered, potentially leading to underestimation of drought effects. However, this limitation is common in many studies. Works such as those by Schmitt et al. (2022) and Harshan (2023), which used farm-level data, are exceptions, with the use of aggregated data at the municipal, departmental, state, or provincial level being more typical (Mohammed et al., 2022; Hamal et al., 2020; Thomasz et al., 2024; Carvalho et al., 2020).

6 Conclusion

This study examined the impact of droughts on the yields and revenue losses of rice, maize, and soybeans in Rio Grande do Sul from 1974 to 2019. Although the variables associated with drought explain only a small portion of the variability in average yields in the adjusted models, the effects of these events remain significant and concerning. The fixed-effects model results revealed that droughts have a substantial negative impact on average crop yields, with extreme droughts presenting the most intense effects.

The findings indicate that for each additional month of moderate, severe, or extreme drought, average crop yields decrease significantly. For instance, an extreme drought reduces the natural logarithm of the average yield of rice by 0.098 units, representing a substantial loss in production. These patterns also apply to maize and soybeans, where more severe droughts result in increasing yield losses.

Furthermore, this study estimated the revenue losses associated with droughts, revealing substantial financial losses for all crops analyzed. Between 1974 and 2019, revenue losses amounted to approximately US$2.2 billion for rice, US$1.5 billion for maize, and US$3.5 billion for soybeans. The greatest losses were observed in years of extreme drought, such as 2012, when production and revenue losses were particularly high for soybeans.

Given ongoing climate changes, these results have implications not only for the State of Rio Grande do Sul but also for Brazilian agriculture as a whole. Rice, maize, and soybeans are crucial for both domestic food security and the country's trade balance. Droughts not only reduce crop yields but also lead to substantial financial losses that can severely impact the agricultural economy. Identifying the most affected areas and analyzing revenue losses provide a critical basis for developing effective mitigation and adaptation policies.

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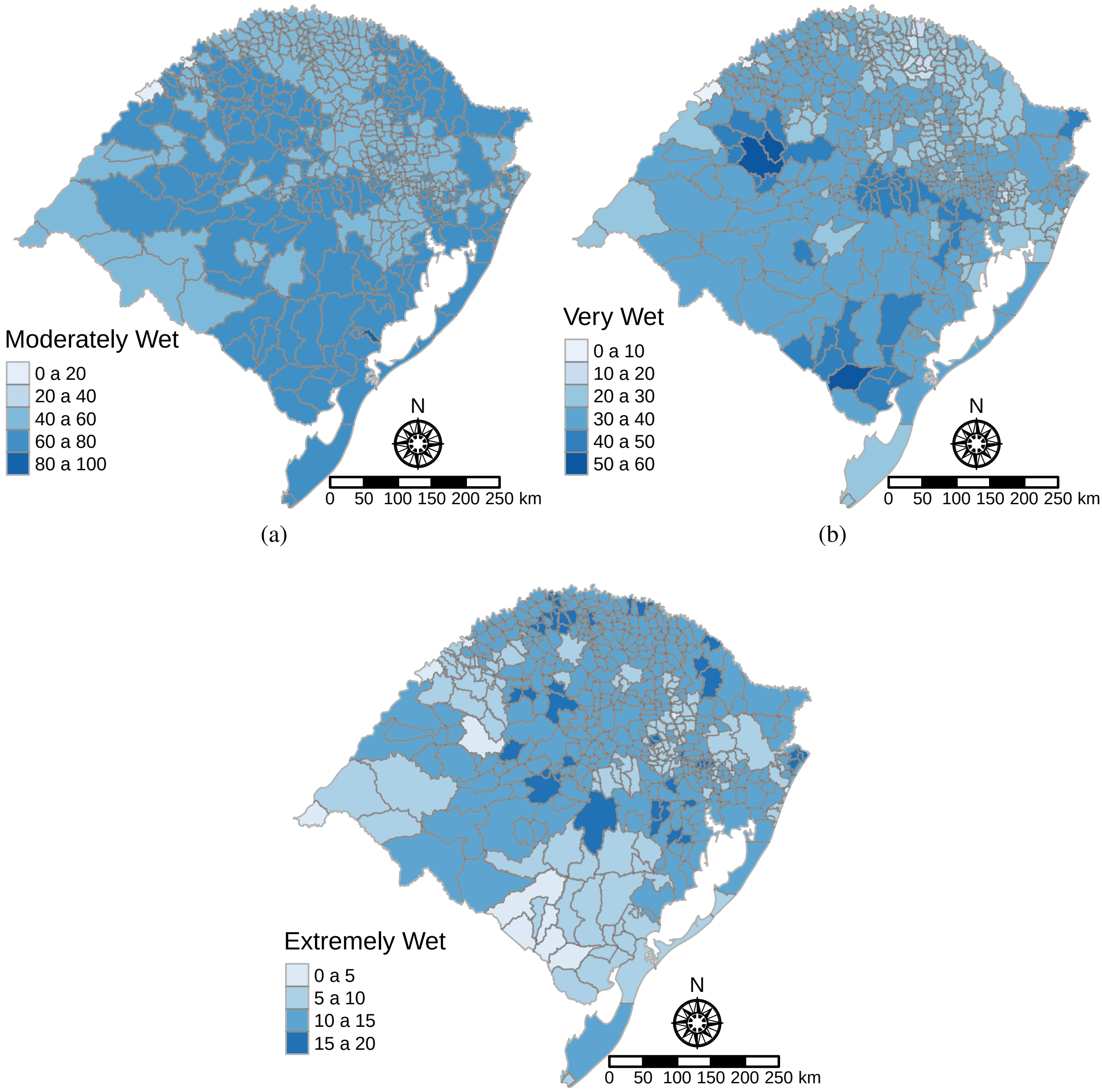
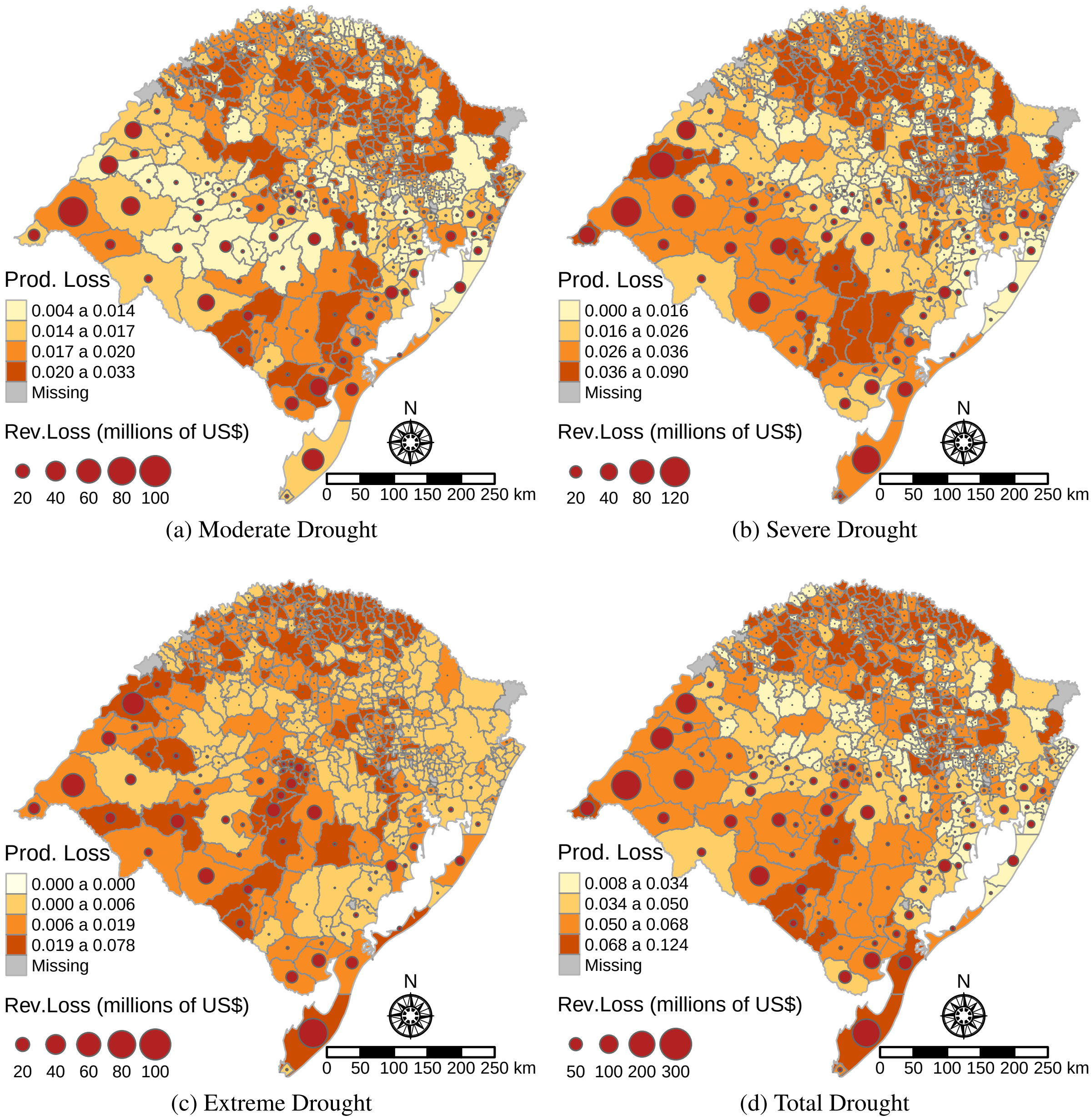
Appendix A Number of months classified as wet



(a) (b) (c)

Figure 13: Number of months classified as moderately wet (a), very dry (b) and extremely wet (c) from 1974 to 2019 according to the SPEI

Appendix B Estimates of Production and Revenue Losses



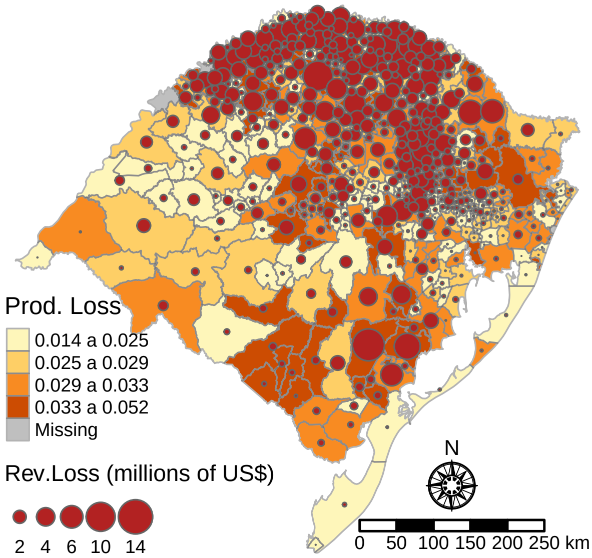
(a) Moderate Drought

(b) Severe Drought

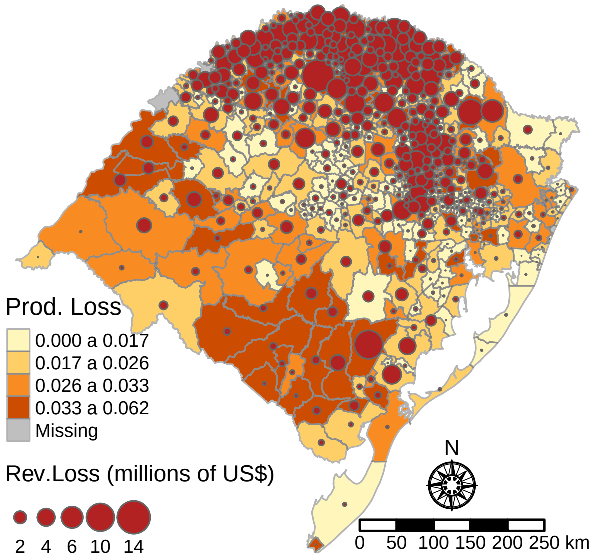
(c) Extreme Drought

(d) Total Drought

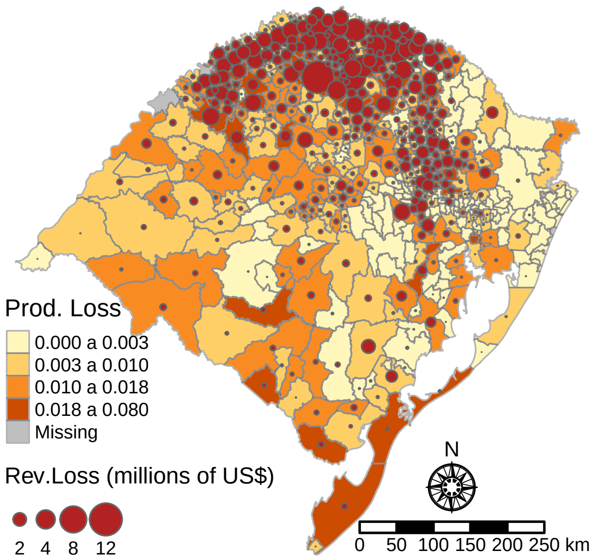
Figure 14: Estimates of Production and Revenue Losses for Rice (1974–2019) Based on Drought Classification



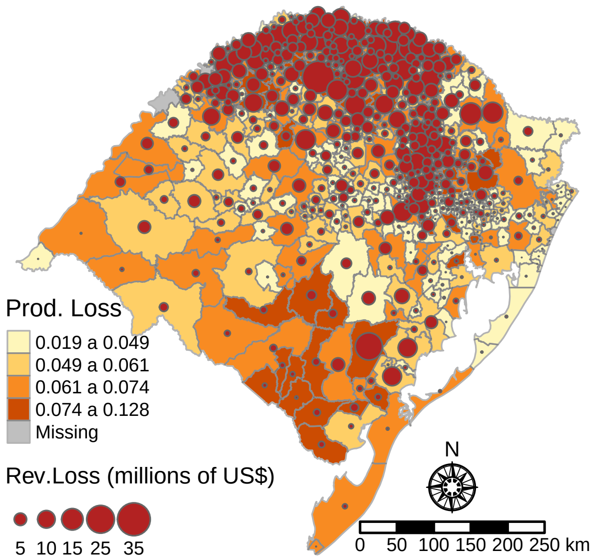
(a) Moderate Drought



(b) Severe Drought

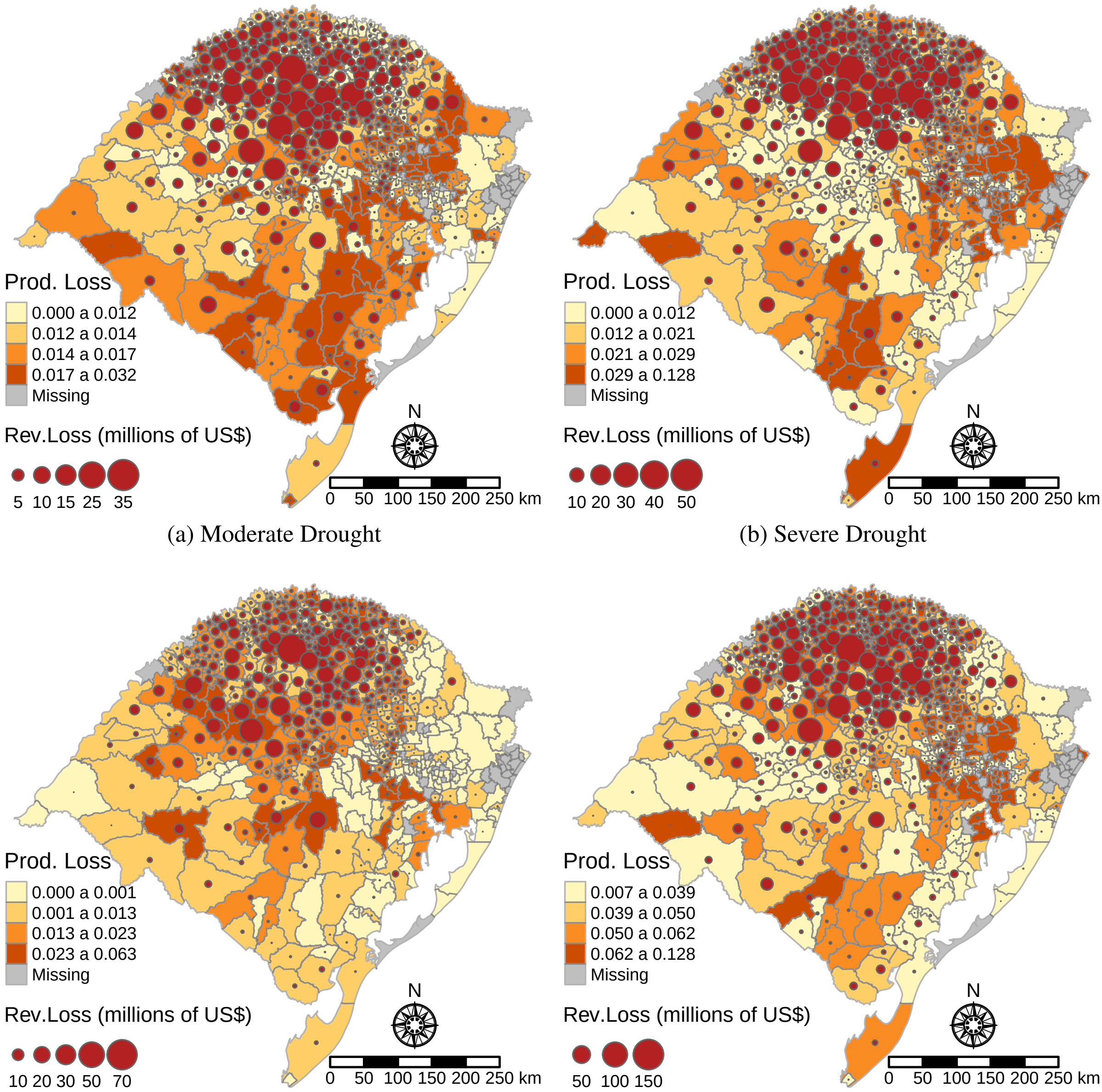


(c) Extreme Drought



(d) Total Drought

Figure 15: Estimates of Production and Revenue Losses for Maize (1974–2019) Based on Drought Classification



(a) Moderate Drought

(b) Severe Drought

(c) Extreme Drought

(d) Total Drought

Figure 16: Estimates of Production and Revenue Losses for for Soybean (1974–2019) Based on Drought Classification