MATEUS PEREIRA LAVORATO

ASSESSING THE FEASIBILITY OF A WEATHER INDEX INSURANCE FOR THE SEMI-ARID REGION OF BRAZIL

Tese apresentada à Universidade Federal de Viçosa, como parte das exigências do Programa de Pós-Graduação em Economia Aplicada, para obtenção do título de *Doctor Scientiae*.

Orientador: Marcelo José Braga

Coorientador: Vitor Augusto Ozaki

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ABSTRACT

LAVORATO, Mateus Pereira, D.Sc., Universidade Federal de Viçosa, September, 2020. **Assessing the feasibility of a weather index insurance for the semi-arid region of Brazil.** Adviser: Marcelo José Braga. Co-adviser: Vitor Augusto Ozaki.

Weather index insurance (WII) has long been advertised as a viable alternative to overcome issues related to crop yield insurance products like information asymmetry and high transaction costs. WII products were firstly developed to assist climate-vulnerable farmers from developing countries where establishing a well-structured crop insurance market is expressively difficult due to the poor transport infrastructure and the prevalence of sparsely distributed small-scale farms. In Brazil, the semi-arid region stands out as the one that concentrates the ideal conditions for the implementation of a WII product since it houses thousands of climate-vulnerable family farmers. Seen this, the present study investigated the feasibility of a WII product for the Brazilian semi-arid region. A multidisciplinary approach based on meteorological, econometric and actuarial tools were employed, generating three distinct but complementary chapters. Firstly, it was shown that aridification is indeed a major threat to the livelihood of the population of the Brazilian semi-arid region. Secondly, it was identified that crop yield responses to weather conditions considerably vary in space and that an expressive portion of analyzed municipalities proved to have a low level of basis risk. Thirdly, a WII product was designed, priced and evaluated, proving to be effective in decreasing farmers' downside risk. It is concluded, therefore, that it would be indeed feasible to establish a WII product in the semi-arid region of Brazil.

Keywords: Feasibility. Weather Index Insurance. Brazil.

RESUMO

LAVORATO, Mateus Pereira, D.Sc., Universidade Federal de Viçosa, setembro de 2020. **Assessing the feasibility of a weather index insurance for the semi-arid region of Brazil.** Orientador: Marcelo José Braga. Coorientador: Vitor Augusto Ozaki.

O seguro paramétrico de índice climático (WII) é, há muito, propagandeado como uma alternativa viável para contornar os problemas relacionados ao seguro baseado em produtividade, como a assimetria de informações e os altos custos de transação. O WII foi inicialmente desenvolvido para ajudar os agricultores climaticamente vulneráveis residentes em países em desenvolvimento, onde o estabelecimento de um mercado de seguro rural bem estruturado é consideravelmente difícil devido à uma infraestrutura de transporte deficiente e à prevalência de pequenas propriedades esparsamente distribuídas. No Brasil, a região semiárida se destaca como aquela que concentra as condições ideais para a implantação de um produto WII por abrigar milhares de agricultores familiares climaticamente vulneráveis. Visto disso, o presente estudo investigou a viabilidade de um produto WII para o semiárido brasileiro. Para tanto, foi utilizada uma abordagem multidisciplinar baseada em ferramentas meteorológicas, econométricas e atuariais, dando origem a três capítulos distintos, porém complementares. Primeiramente, foi demonstrado que a aridificação é, de fato, uma grande ameaça à subsistência da população da região semiárida. Em segundo lugar, identificou-se que as respostas da produtividade agrícola às condições climáticas variam consideravelmente no espaço e que uma parcela expressiva dos municípios analisados apresentou um baixo risco de base. Em terceiro lugar, um produto WII foi projetado, precificado e avaliado, o qual provou ser eficaz na redução do risco enfrentado pelos agricultores. Conclui-se, assim, que seria de fato viável desenvolver um produto WII para o semiárido brasileiro.

Palavras-chave: Viabilidade. Seguro Paramétrico de Índice Climático. Brasil.

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GENERAL INTRODUCTION

Agriculture is inherently uncertain. In fact, it depends on such a wide variety of factors that it can be seen as one of the riskiest economic activities. In general, five are the risks faced by farmers, namely, production, marketing, financial, institutional and personal (FAO, 2008). They refer to possible income losses related, respectively, to the occurrence of adverse climatic events; to decreases in prices or increases in costs; to loan defaults; to changes in institutional rules; and to farmer’s illness or death.

Among all sources of risks, one could say that production risks stand out for agricultural activities. Differently than industry and service sectors, agriculture has a direct dependence on nature and its resources given the key role of weather and biological processes in its production and economic results. Crop failure caused by unpredictable natural events has negative effects on agriculture's economic and social performance given that it triggers relevant losses on farmers' income, on exports, and on rural employment (Buainain and Silveira, 2017).

Some relatively small variations in production and prices are considered normal to the agricultural activity, being directly managed by farmers. The losses related to infrequent but catastrophic events, in turn, cannot be handled by farmers on their own (OECD, 2011). Indeed, catastrophic events occurred between 2003 and 2013 caused $70 billion losses in crop and livestock production of developing countries (FAO, 2015). Such figure stresses the impact of risks on agriculture, especially for the countries where the sector has a prominent role on the gross domestic product (GDP) and the balance of trade, which is the case of Brazil.

Combating production risks and their effects on both the agriculture and the economy as a whole is only possible through the management of agricultural risks. An appropriate risk management can enable, at least in part, the control of the undesirable consequences of adverse events like droughts and floods (Hardaker et al., 2015). Considering production risks, risk transfer emerges as the mostly employed strategy worldwide, encompassing several instruments like financial derivatives, insurance and insurance-linked securities (Hohl, 2019).

Financial markets in developing countries such as Brazil and India are not as mature as those in developed countries, which hampers the use of derivatives by farmers to manage agricultural risks via hedge operations. In these countries, insurance schemes based on government participation have proved to be an interesting option for the management of agricultural risks. In the Brazilian case, farmers can apply for government subsidy through the *Programa de Subvenção ao Prêmio do Seguro Rural* (PSR).

It is necessary to highlight, however, that crop yield insurance schemes like the PSR are commonly plagued with some relevant issues, namely information asymmetry and significant transaction costs. These problems stem from the way in which payouts are determined. Indemnities are calculated through the direct assessment of crop losses, which implies higher transaction costs while allowing the emergence of asymmetric information in the form of adverse selection and moral hazard.

1. Research problem

Considering the adverse effects of both transaction costs and asymmetric information, literature started to propose and analyze alternative models of agricultural insurance. Among possible substitutes to crop yield insurance, great attention was given to weather index insurance (WII) products (e.g., Alderman and Haque, 2007; Barnett et al., 2008; Hazell et al., 2010; Mahul and Stutley, 2010). These studies focus on developing countries where establishing a well-structured crop insurance market is even more difficult than in developed ones.

In the case of crop yield insurance, the evaluation of losses and the determination of payouts are costly and time-consuming because of the need of on-farm investigation. For developing countries, where smallholders prevail and transport infrastructure is inherently poor, the local assessment of crop losses can have an even higher cost, which would translate into the charge of prohibitive premiums. Following these studies, there was the establishment of some pilot programs for WII products in developing countries like Ukraine, Ethiopia and Malawi, for example (UNDESA, 2007).

According to Skees et al. (1997), WII is an alternative scheme that uses an observable weather parameter as a proxy to crop yields. By conditioning payouts on the realization of an independent and transparent index instead of actual yield losses, WII products overcome key problems related to crop yield insurance (Conradt et al., 2015). Farmers cannot influence the payoffs of a WII due to the randomness of the underlying index, what mitigates information asymmetry (Shen and Odening, 2013). Moreover, administering costs are minimized as the on-farm assessment of losses are unnecessary (Stoppa and Hess, 2003).

Differently than crop yield insurance, WII contracts are written against specific perils that are defined and recorded at aggregate levels. In order to serve as a proxy for the total losses within the specified area, the (underlying) index need to be highly correlated with the regional agricultural production of the insured crop (CAO, 2004). Working on a regional level, index contracts are the same for all farmers that cultivates the same crop in the same region. Once the specified adverse event triggers the payment, all insured farmers receive the same rate of payment.

Despite the benefits mentioned above, WII products still have little application in agriculture (Heimfarth and Musshoff, 2011). It must be highlighted, however, that several are the constraints to the success of insurance initiatives of this kind. Among them, basis risk stands out. It arises when index realizations are decoupled from local crop yields. Since no index is perfectly correlated with crop yields, some farmers may obtain no compensation despite experiencing losses, while others may have no losses and still receive indemnity payments (Skees, 2008).

Considering the advantages and drawbacks of weather index insurance, several papers analyzed the viability of such type of insurance for different locations worldwide (e.g., Conradt et al., 2015; Choudhury et al., 2016; Adeyinka et al., 2016; Black et al., 2016; Poudel et al., 2016; Shi and Jiang, 2016; Kusuma et al., 2018; Nogales and Cordova, 2019; Shirsath et al., 2019; Williams and Travis, 2019; Boyd et al., 2020; Eze et al., 2020). In general, their results support the feasibility of investing in WII products as a mean of protecting vulnerable farms against crop losses caused by catastrophic events.

In Brazil, the semi-arid region (Figure 1) can be highlighted as the ideal area for the implementation of a WII product as it is routinely affected by drought episodes that jeopardizes the livelihood of poor smallholders that often exclusively depends on rainfed agriculture. The region’s climate, which is marked by an expressive spatial-temporal variability, is expected to become even more arid in the near future due to temperature increases, rainfall reductions, water deficits and longer dry spells (Marengo and Bernasconi, 2015). The desertification process, characterized by land degradation of arid areas, poses a severe threat to the semi-arid region of Brazil (Vieira et al., 2015). The agricultural lands served by public irrigation perimeters fed by the São Francisco River are the exception (ANA, 2017).

Ultimately, one can relate the climate of the Brazilian semi-arid region to the prevalence of poverty among its inhabitants, especially those living in rural areas. In fact, data from the 2017 Census of Agriculture show that farmers from the semi-arid region account for only 6.4% of Brazil’s agricultural production value despite operating more than 1/3 of country’s farms. Despite housing thousands of climate-vulnerable farmers who could benefit greatly from insurance products[1], the Brazilian semiarid region has long been neglected by the PSR as its farmers account for only 0.6% of program's operations (MAPA, 2020).

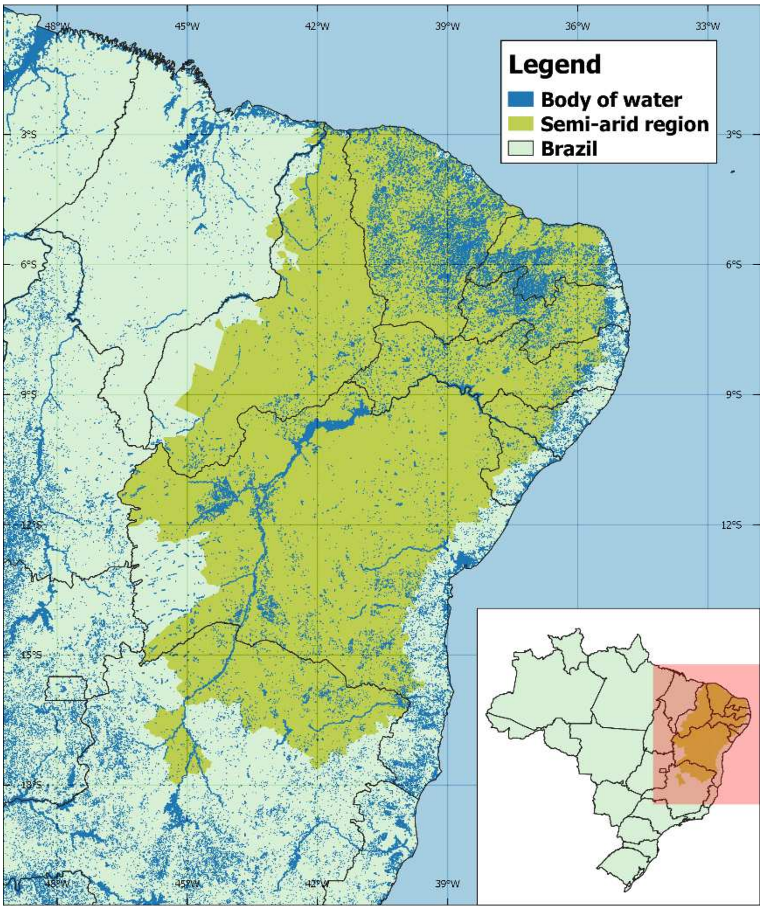

Figure 1. Location of the semi-arid region in the Brazilian territory.
Source: Elaborated by the author.

In view of the information presented so far, the present study relies on a multidisciplinary approach to address the following question: Is it feasible to implement a weather index insurance for the climate-vulnerable farmers from the semi-arid region of Brazil? Specifically, the investigation is divided into three distinct but complementary parts. The first chapter, in which meteorological tools are applied, analyzes the spatiotemporal variations of aridity in the Brazilian semi-arid. The second, in turn, conducts an in-depth econometric investigation of local crop yield responses to the degree

[1] It must be stressed that family farmers from the Brazilian semi-arid are currently served by the Garantia Safra Program. It works like an area-based crop insurance as farmers are compensated when crop yields measured at the municipal level fall below the long-term average. Although the participation fee is divided between federal, state and municipal governments, as well as the farmer himself, payouts are standardized to R$850.00, which are paid in five equal installments. This amount, however, is often not able to cover crop losses.

of aridity. The third and last chapter uses actuarial tools to design, price and evaluate an aridity index-based insurance.

The lack of assessments of this nature for Brazil is intriguing. The only piece of evidence provided so far is that of Raucci et al. (2019). These authors, however, conducted an analysis that is considerably different than the one we are suggesting to do here. The most remarkable of these differences regards the geographical scope of the analysis as they investigated municipalities in southern Brazil. Such region, however, currently concentrates the bulk of policies subsidized countrywide.

Therefore, examining a region like the semi-arid of Brazil, at least in our perception, makes a little more sense as this region is currently deprecated in terms of official subsidies to premium subsidies, concentrates a significant portion of Brazilian family farmers and is more sensible to adverse variations in weather conditions. Ultimately, the present study is expected to contribute both to the literature and to practitioners as it may inspire the investigation of the viability of this promising climate risk management tool for other vulnerable areas of the country.

2. Hypotheses

a) Aridity varies significantly in both space and time in the Brazilian semi-arid region.
b) Crop yields respond positively to declines in the local degree of aridity.
c) The weather index insurance product is effective in mitigating downside risk.

3. Objectives

The general objective of this thesis is to assess the feasibility of a weather index insurance for the semi-arid region of Brazil.

Specifically, the study aims to

a) generate a gridded dataset on the degree of aridity;
b) investigate spatial variations in crop yield responses to aridity;
c) identify locations for which basis risk could be minimized;
d) design and price a weather index insurance;
e) evaluate the effectiveness of the proposed product in mitigating downside risk.

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CHAPTER 1

Spatiotemporal variations of aridity in the semi-arid region of Brazil, 2000-2019

1. Introduction

Climate change is expected to decrease rainfall and rise temperature in several parts of the world, including Brazil. As a consequence, the expansion of areas with arid-like climates is identified as one of the main developments of global warming (Pour et al., 2020). In fact, the number of people living in arid lands worldwide may rise by more than 20% in the near future (Park et al., 2018). Therefore, evaluating and monitoring this phenomenon is of great importance, especially for regions where agricultural production corresponds to an expressive share of local economy (Pellicone et al., 2019).

Considering the Brazilian territory, the semi-arid region stands out in terms of the (possible) effects of climate change. Being primarily composed by municipalities from the Northeast region, the semi-arid of Brazil is, among the arid regions of the world, the most densely populated (Marengo, 2008). The region experiences great interannual variability in rainfall, which leads to the periodic occurrence of drought episodes (Marengo and Bernasconi, 2015). These phenomena have severe social, economic and environmental consequences (Silva, 2004), which are possibly driven by declines in the yields of crops—especially those grown by family farmers.

Rainfed agriculture predominates in the Brazilian semi-arid, surging the risk of crop frustration due to the climatic variability of the region. Ultimately, its residents, which often exclusively depend on the outcomes of agricultural production for their livelihood, face the challenge of achieving a sustainable rainfed production with an increasingly-limited water supply (Melo and Voltolini, 2019). Therefore, climate aridification poses a serious threat on people's livelihood. In order to address this issue, an in-depth analysis of spatiotemporal variations of aridity in the Brazilian semi-arid is conducted in the present chapter.

Monthly gridded data on accumulated precipitation and average temperature for the period between 2000 and 2019 were used in the construction of the aridity index proposed by De Martonne (1926), whose behavior was investigated using parametric and non-parametric approaches. Despite being developed at the beginning of the 20th century, De Martonne's aridity index is still widely used because of its efficiency in climate classification and minimal data requirement. Among the researches that applied this indicator, it can be highlighted the analyses conducted by Zarghami et al. (2011), Paltasingh et al. (2012) and Byakatonda et al. (2018).

The study of the spatiotemporal variation of aridity in the Brazilian semi-arid contributes to the literature by providing a piece of evidence on how recent climatic change has influenced the region's climate. Additionally, an aridity-based classification of the climate of the Brazilian semi-arid was also generated, which can later be used in future studies like those connecting the aridification process with the outcomes of the agricultural activity, offering relevant information that could be used by policymakers to conduct initiatives focused on addressing aridity-related problems, either by mitigating, transferring or coping with those risks.

The remainder of this paper is as follows. After this introduction, we describe the materials and methods, highlighting key aspects of data collection and manipulation. Next, we present the results for the spatiotemporal variation of aridity in the Brazilian semi-arid as well as the outputs of parametric and non-parametric approaches. Following, these findings are discussed, stressing its implication for the livelihood of local population. Lastly, we present the main conclusions of the chapter.

2. Materials and methods

2.1. Data

The data used in this article were collected from the website of the Brazilian National Institute of Meteorology (INMET, *Instituto Nacional de Meteorologia*). Specifically, we collected monthly data on accumulated precipitation (in millimeters) and average temperature (in degree Celsius) from 71 automatic weather stations distributed across the semi-arid region of Brazil, as depicted in Figure 1. These stations are most evenly distributed across the territory, making spatial interpolation results more reliable. Monthly data are gathered for 2000 onwards due to availability issues. In fact, reliable information is generally available only after that year as several automatic weather stations within the Brazilian semi-arid region were not operating before the 2000s.

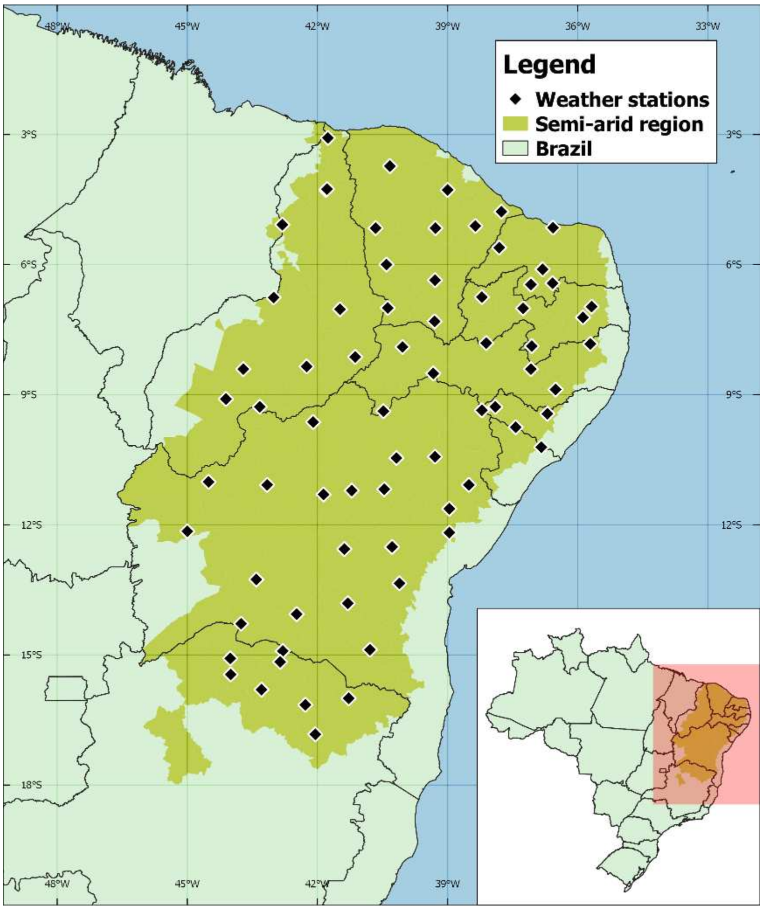

Figure 1. Geographical distribution of INMET's automatic weather stations across the semi-arid region of Brazil.
Source: Elaborated by the author based on data from INMET (2020).

2.2. Spatial interpolation of weather data

Three different methods were used to spatially interpolate the data gathered from the weather stations distributed across the semi-arid region of Brazil: inverse distance weighting (IDW), ordinary kriging (OK) and thin plate spline (TPS). IDW estimates the value for unsampled points as the weighted average of the actual points in its vicinity, where weights are a decreasing function of distance (Lu and Wong, 2008). OK estimates the value of a variable over a given region for which a variogram is known, assuming stationarity (Wackernagel, 2003). TPS smooths a scatter plot by fitting a nonparametric regression model that uses penalized least squares (Wood, 2003).

The accuracy of interpolation methods is evaluated by k-fold cross-validation. First, weather stations are randomly divided into k subsets. Second, spatial interpolation models are fitted to data from $k-1$ subsets and tested over the remaining subset. Third, considering y_i as the value recorded at station i and $\hat{y}_i$ as the value predicted via spatial interpolation, we calculate the mean absolute error $(\sum_{i=1}^{n}|\hat{y}_i - y_i|/n)$ and the root mean square error $\left(\sqrt{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2/n}\right)$. Fourth, the validation procedure is repeated k times. The overall accuracy of each interpolation method is obtained by averaging across the m months analyzed.

2.3. De Martonne's aridity index

The aridity index proposed by De Martonne (1926) is one of the most used indicators of the degree of water deficiency in a given region. In fact, despite being one of the oldest indexes developed to assess aridity levels, De Martonne's aridity index is still applied worldwide due to its efficiency and relevance in classifying regions in arid/humid climates (Pellicone et al., 2019). One of the main advantages of such aridity index regards data requirement, since it only demands information on precipitation and temperature.

In annual terms, the values for De Martonne's aridity index are given by

$$I_{DM}^{A} = \frac{P}{\bar{T} + 10} \tag{1}$$

where I_{DM}^{A} denotes the annual aridity index; P denotes the annual accumulated precipitation; and $\bar{T}$ denotes the annual average temperature. Due to the European origin of the index, 10 is added to the average temperature in order to avoid a negative denominator. Although this is not an issue for the region analyzed here, we chose to follow literature's standard.

In monthly terms, on the other hand, the values for the aridity index are calculated as follows

$$I_{DM}^{M} = \frac{P \times 12}{\bar{T} + 10} \tag{2}$$

where I_{DM}^{M} denotes the monthly aridity index; P denotes the monthly accumulated precipitation; and $\bar{T}$ denotes the monthly average temperature. Monthly precipitation is multiplied by 12 in order to make monthly values of the index compatible with the annual values previously described.

Following Araghi et al. (2018), one can use the De Martonne's aridity index to classify local climates according to the values presented in Table 1. It is observed that the lower the value of the aridity index, the more arid is the region under investigation. Considering interannual variations in the meteorological variables analyzed, it is noticed that the temperature level has varied modestly in practically all the investigated territory, whereas the volume of precipitation has been varying significantly both in space and time (see Figures 1A and 2A in the Appendix).

Table 1. Climate classification based on De Martonne's aridity index

Climate type	Range
Hyper-arid	$I_{DM} < 5$
Arid	$5 \leq I_{DM} < 10$
Semi-arid	$10 \leq I_{DM} < 20$
Mediterranean	$20 \leq I_{DM} < 24$
Semi-humid	$24 \leq I_{DM} < 28$
Humid	$28 \leq I_{DM} < 35$
Very humid	$35 \leq I_{DM} < 55$
Extremely humid	$I_{DM} > 55$

Source: Adapted from Araghi et al. (2018).

2.4. Trend analysis

Trend identification tests, which identify whether data series present downward or upward trends, are divided into two groups: parametric and non-parametric approaches (Şen, 2017). Here, tests of both natures are employed. The trend for the aridity level is parametrically estimated for each pixel using a classical regression approach, where the dependent variable is the De Martonne's index and the independent variable is time, which is measured chronologically. Specifically, the following linear regression is estimated

$$Y_t = \beta_1 + \beta_2 t + u_t, \tag{3}$$

where Y_t denotes the dependent variable; β_1 denotes the intercept; β_2 denotes the trend slope; t denotes the time; and u_t denotes the error term.

The trend slope, which is the parameter of interest in the present analysis, is obtained as follows

$$\hat{\beta}_2 = \frac{n\sum_{t=1}^{n} tY_t - \sum_{t=1}^{n} t \sum_{t=1}^{n} Y_t}{n\sum_{t=1}^{n} t^2 - \left(\sum_{t=1}^{n} t\right)^2} \tag{4}$$

where t = 1, 2, 3, …, n and n = 20 as time series comprises annual values from 2000 to 2019.

Among the non-parametric methods, two complementary approaches are considered here: the Mann-Kendall test (Mann, 1945; Kendall, 1946) and the Theil-Sen estimator (Theil, 1950; Sen, 1968). The former recognizes if a time trend exists, whilst the latter estimates its magnitude. Both methods are widely used in meteorological and hydrological analyses (e.g., Huang et al., 2016; Ahmed et al., 2019; Houmsi et al., 2019; Paniagua et al., 2019; Mutti et al., 2020; Pour et al., 2020). Tests of this nature do not require normality and are strong against outliers (Ti et al., 2018).

Specifically, the S statistic of the Mann-Kendall test is calculated as

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \operatorname{sgn}(x_j - x_k) \tag{5}$$

where n is the number of months, x_j and x_k are specifically months in the time series and $\operatorname{sgn}(x_j - x_k)$ is the following sign function

$$\operatorname{sgn}(x_j - x_k) = \begin{cases} +1, if\ x_j - x_k > 0 \\ 0, if\ x_j - x_k = 0. \\ -1, if\ x_j - x_k < 0 \end{cases} \tag{6}$$

When $n > 10$, the S statistic is normally distributed with variance given by

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i - 1)(2t_i + 5)}{18} \tag{7}$$

where m is the number of tied groups and t_i is the number of ties of extent i.

Finally, the standard normal test statistic Z is calculated as

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{Var(S)}}\ if\ S > 0 \\ 0\ if\ S = 0 \\ \dfrac{S-1}{\sqrt{Var(S)}}\ if\ S < 0 \end{cases} \tag{8}$$

where positive (negative) values of Z indicate a trend with increasing (decreasing) behavior. Trends are statistically significant when $|Z| > Z_{(1-\alpha/2)}$. Thus, if we consider the 5% significance level, the null hypothesis of no trend is rejected when $|Z| > 1.96$.

The Theil-Sen estimator, in turn, is calculated as follows. Initially, the slope of N data pairs are computed by

$$Q_i = \frac{x_j - x_k}{j - k} \quad \text{for} \quad i = 1, \dots, N \tag{9}$$

where x_j and x_k denote data values at times j and k, respectively, with $j > k$.

In specific, the magnitude of the time trend is estimated as the median of the N values previously calculated:

$$Q_{med} = \begin{cases} Q_{[(N+1)/2]}, & if\ N\ is\ odd \\ \frac{Q_{[N/2]} + Q_{[(N+2)/2]}}{2}, & if\ N\ is\ even. \end{cases} \tag{10}$$

where a positive (negative) value of Q_{med} indicates an increasing (decreasing) trend.

3. Results

3.1. Spatial interpolation

The accuracy of the spatial interpolation methods evaluated—inverse distance weighting, ordinary kriging and thin plate spline—is depicted in Table 2. Overall, IDW generated more accurate data than OK and TPS for both precipitation and temperature. Although literature has been showing that geostatistical techniques are better interpolators of meteorological variables than deterministic techniques (Pellicone et al., 2019), the results obtained here are still consistent as IDW also produced the best outcomes for Xavier et al. (2016), who investigated Brazil as well.

Table 2. Accuracy of spatial interpolation methods

Evaluation metrics	Interpolation method		
	IDW	OK	TPS
		Precipitation	
Mean absolute error	40.0170	46.0752	44.4311
Root mean square error	55.4365	60.2441	57.4798
		Temperature	
Mean absolute error	1.5945	1.9051	1.7966
Root mean square error	2.1029	2.3508	2.3313

Source: Research results.

It should be noted, especially for precipitation, that the accuracy of spatial interpolation was relatively low, i.e., both the mean absolute error and the root mean square error were quite high. This is possibly due to the sparse distribution of weather stations within the Brazilian semiarid and the high spatiotemporal variation of precipitation in the region. For temperature, in turn, the average absolute error calculated here was fairly close to that estimated by Xavier et al. (2016), indicating a good interpolation capacity.

3.2. De Martonne's aridity index

3.2.1. Temporal variation of annual aridity

Based on the results of the accuracy evaluation of spatial interpolation methods, IDW estimates of local precipitation and temperature were used for the construction of De Martonne's aridity index and the assessment of the aridity level of the semi-arid region of Brazil. Figure 2 displays the 20-year evolution of the degree of aridity in the analyzed territory. Considering that the spatial distribution of temperature has been relatively stable during the period of analysis, one could say that the aridity pattern is heavily influenced by changes in precipitation (see Figures 1A and 2A in the Appendix).

For the vast majority of years analyzed, orange tones—which indicate arid-like climates—prevail on the Brazilian semi-arid region. The climatic difference between the two decades analyzed is evident given that the years of the 2000s were, on average, more humid than those of the 2010s. In fact, one of the most severe droughts to ever affect the semi-arid region of Brazil started in 2012, which has caused a hyper-arid climate to be recorded in certain areas of the region since then.

The climate classification obtained via annual values of De Martonne's aridity index expressively varies both in space and time. During the 2000s, a significant portion of the semi-arid region experienced humid-like climates ($I_{DM} \geq 24$), especially the northern and southern parts of the territory. The situation changed dramatically in the 2010s, when arid-like climates ($I_{DM} < 20$) predominated across the analyzed area, with emphasis on the central part of the region. The wettest (driest) season was recorded in 2000 (2012), when 83% (95%) of the region presented humid-like (arid-like) climates.

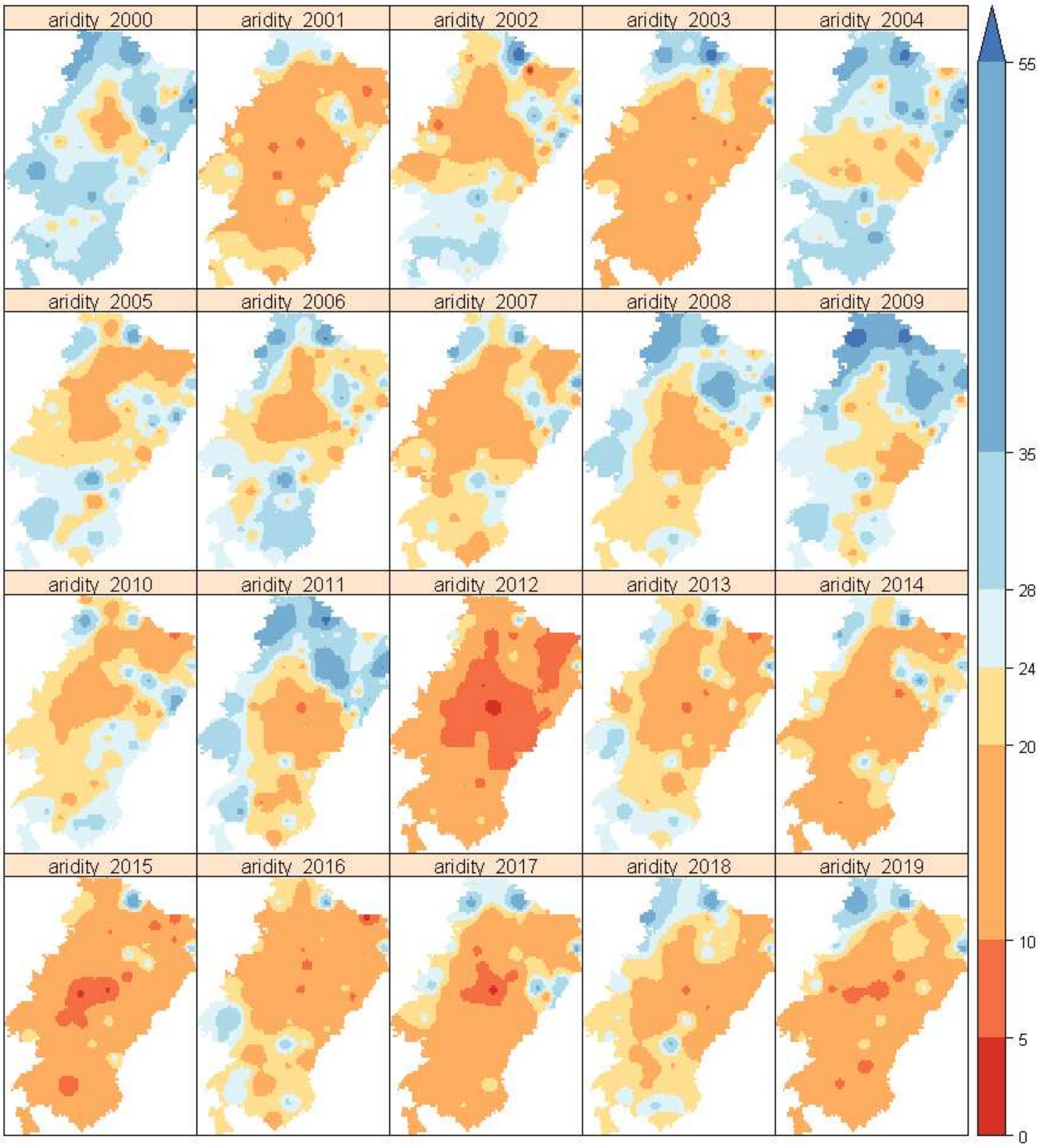

Figure 2. Temporal variation of annual aridity, Brazilian semi-arid, 2000-2019.
Note: Hyper-arid [0, 5); Arid [5, 10); Semi-arid [10, 20); Mediterranean [20, 24); Semi-humid [24, 28); Humid [28, 35); Very humid [35, 55); Extremely humid [55, ∞).
Source: Research results.

3.2.2. Spatial pattern of annual aridity

The 20-year average for the annual De Martonne's aridity index is depicted in Figure 3, which makes it possible to investigate the spatial pattern of annual aridity for the Brazilian semi-arid region. Considering the period between 2000 and 2019, it is observed that, on average, Semi-arid and Mediterranean climates predominate in the territory. In fact, even though Arid and Hyper-arid climates were not perceived, average values below 24 points for the aridity index were recorded in approximately 81% of the investigated area.

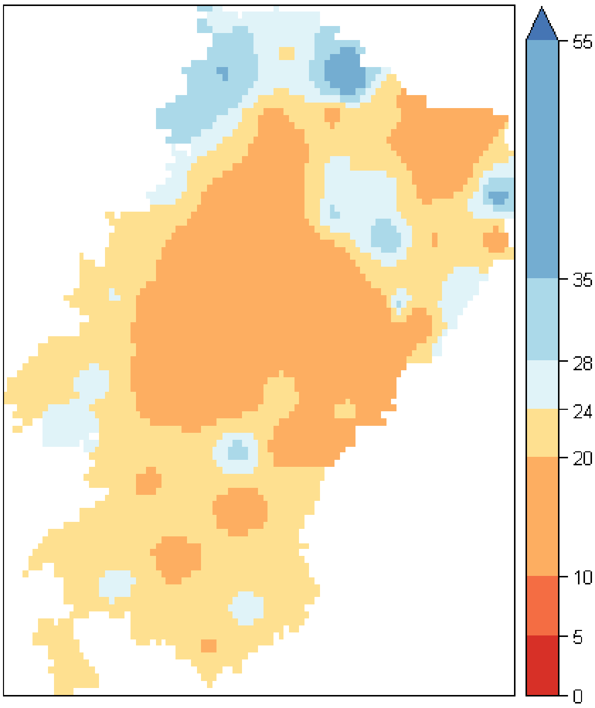

Figure 3. Spatial pattern of annual aridity, Brazilian semi-arid, 2000-2019 average.
Note: Hyper-arid [0, 5); Arid [5, 10); Semi-arid [10, 20); Mediterranean [20, 24); Semi-humid [24, 28); Humid [28, 35); Very humid [35, 55); Extremely humid [55, ∞).
Source: Research results.

Some isolated spots of humid-like climates are detected throughout the region, especially on the north. This is the portion of the territory that registered the highest average precipitation levels (> 1,000 mm per year) during the analyzed period. For most of the semi-arid region of Brazil, however, the average annual precipitation level was less than 1,000 mm, with some areas in the central part registering average values below 500 mm per year. Interestingly, the northern half of the region presents the highest averages for temperature as well (see Figures 3A and 4A in the Appendix).

3.2.3. Spatial pattern of monthly aridity

Differently than the previous analysis, the De Martonne's aridity index is now considered in a monthly basis as Figure 4 displays the 20-year average of the degree of aridity for each month of the year. A clear pattern arises as humid-like climates predominate during the first quarter, covering almost 90% of the territory in January, February and March. Arid-like climates, in turn, prevail during the remaining quarters, especially the third. In fact, on average, August and September stand out as 69% and 71% of the analyzed region experiences a hyper-arid climate during these months.

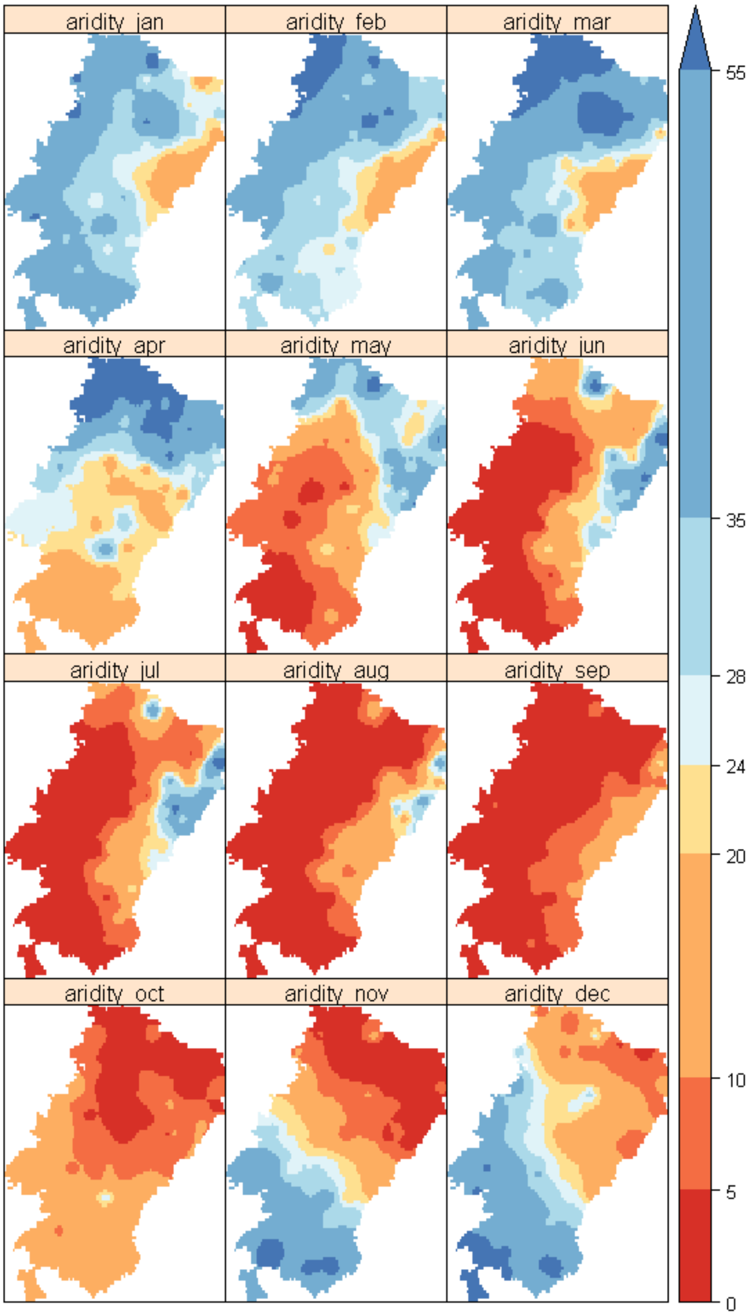

Figure 4. Spatial pattern of monthly aridity, Brazilian semi-arid, 2000-2019 average. **Note:** Hyper-arid [0, 5); Arid [5, 10); Semi-arid [10, 20); Mediterranean [20, 24); Semi-humid [24, 28); Humid [28, 35); Very humid [35, 55); Extremely humid [55, ∞). **Source:** Research results.

During the first quarter, arid-like climates are concentrated in the central-eastern portion of the Brazilian semi-arid. As of the second quarter, the Hyper-arid climate begins to advance from the south, evolving along the western strip of the region until reaching almost the entire territory in the end of the third quarter. In sequence, Hyper-aridity starts to give way to humid-like climates, with the expansion occurring from the south to the north. Ultimately, the spatial variation of monthly aridity is heavily influenced by changes in the precipitation level throughout the year (see Figures 5A and 6A in the Appendix).

3.3. Trend analysis

3.3.1. Annual aridity trends

Figure 5 depicts the spatial distribution of trend identification for the degree of aridity in the semi-arid region of Brazil. Both parametric (regression analysis) and non-parametric (Mann-Kendall test) approaches present similar results. There is no location with statistically significant (at the 5% level) positive trends. Even the locations with nonsignificant positive trends (pink spots) correspond to a quite small portion of the investigated area (roughly 1%). As higher index values are related to wetter climates, there is no tendency to increase the degree of humidity within the Brazilian semi-arid.

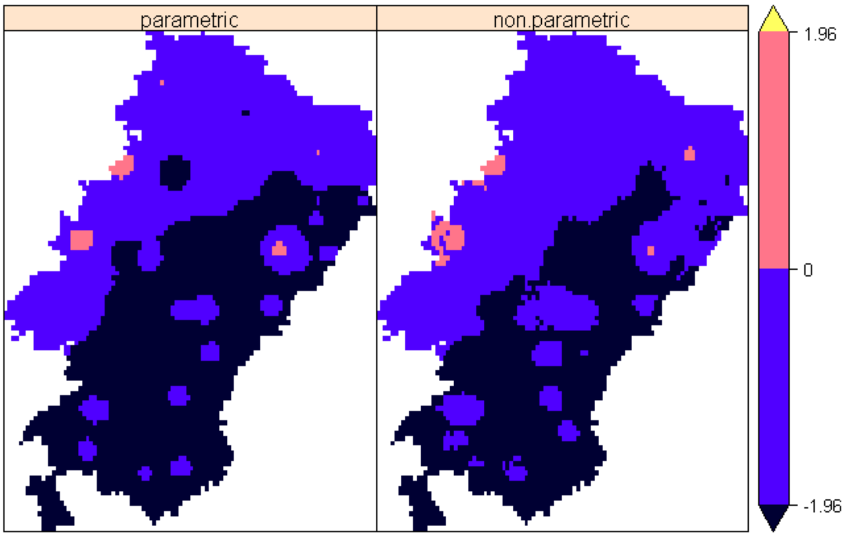

Figure 5. Results for parametric (regression analysis) and non-parametric (Mann-Kendall test) approaches of trend identification, Brazilian semi-arid, 2000-2019.
Note: Yellow (positive significant); pink (positive not significant); blue (negative not significant); black (negative significant).
Source: Research results.

On the other hand, statistically significant (at the 5% level) negative values were found for an expressive portion of the territory. In fact, a tendency for aridification was confirmed for roughly 51% (41%) of the semi-arid region according to the parametric (non-parametric) approach. These locations are mainly concentrated in southern and central-eastern areas. Although the regression analysis has identified a larger area with significant positive trends than the Mann-Kendall test, the coefficients of determination of individual estimates are generally quite low (see Figure 7A in the Appendix)

Focusing on the areas for which a statistically significant (at the 5% level) negative trend was found facilitate the investigation of the aridification process that has occurred in the semi-arid region of Brazil from 2000 to 2019. In specific, Figure 6 displays the magnitude of trends calculated using both parametric and non-parametric approaches. For virtually all locations for which a tendency towards aridification was identified, the aridity index of De Martonne decreased by an annual rate of less than one index-point per year.

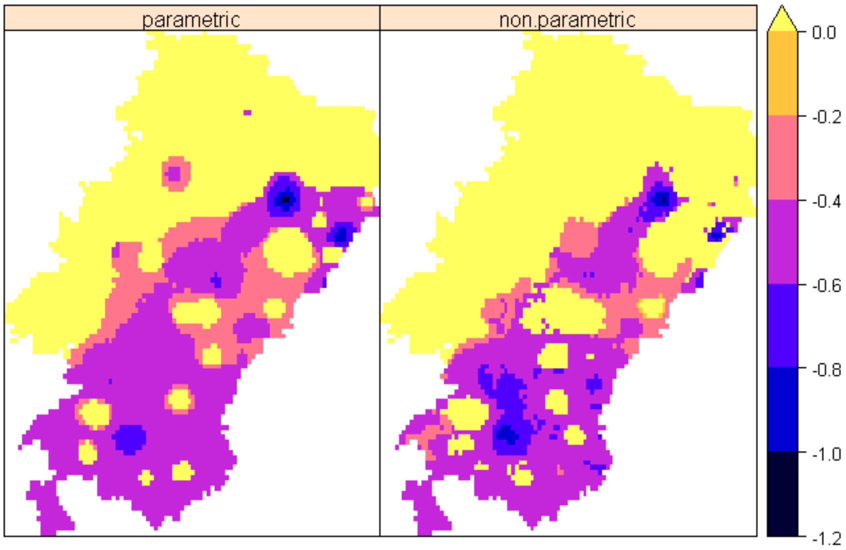

Figure 6. Results for parametric (regression analysis) and non-parametric (Theil-Sen estimator) approaches of trend measurement, Brazilian semi-arid, 2000-2019.
Source: Research results.

3.3.2. Monthly aridity trends

Now, the analysis of aridity trends is broken down in terms of the months of the year. Figures 7 and 8 indicate that both approaches provide similar results, although some minor differences are perceived. For instance, only the non-parametric method detected areas with a negative and statistically significant trend for January. For both approaches, in turn, areas with a statistically significant tendency to aridification prevail in June, August and September. It is also worth noting that a positive and statistically significant trend was identified for southern locations in June and July, which translates into an increase in the degree of humidity in those areas.

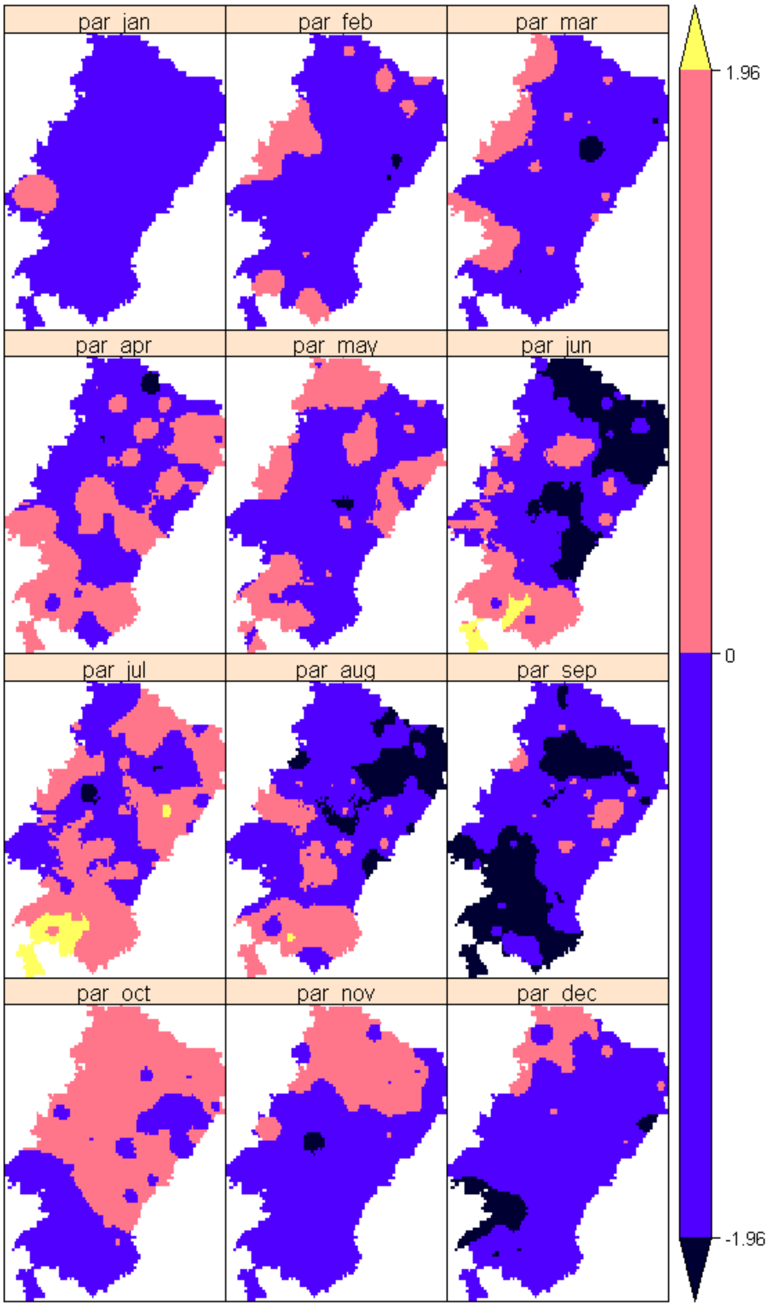

Figure 7. Results for the parametric (regression analysis) approach of trend identification, Brazilian semi-arid, 2000-2019.
Note: Yellow (positive significant); pink (positive not significant); blue (negative not significant); black (negative significant).
Source: Research results.

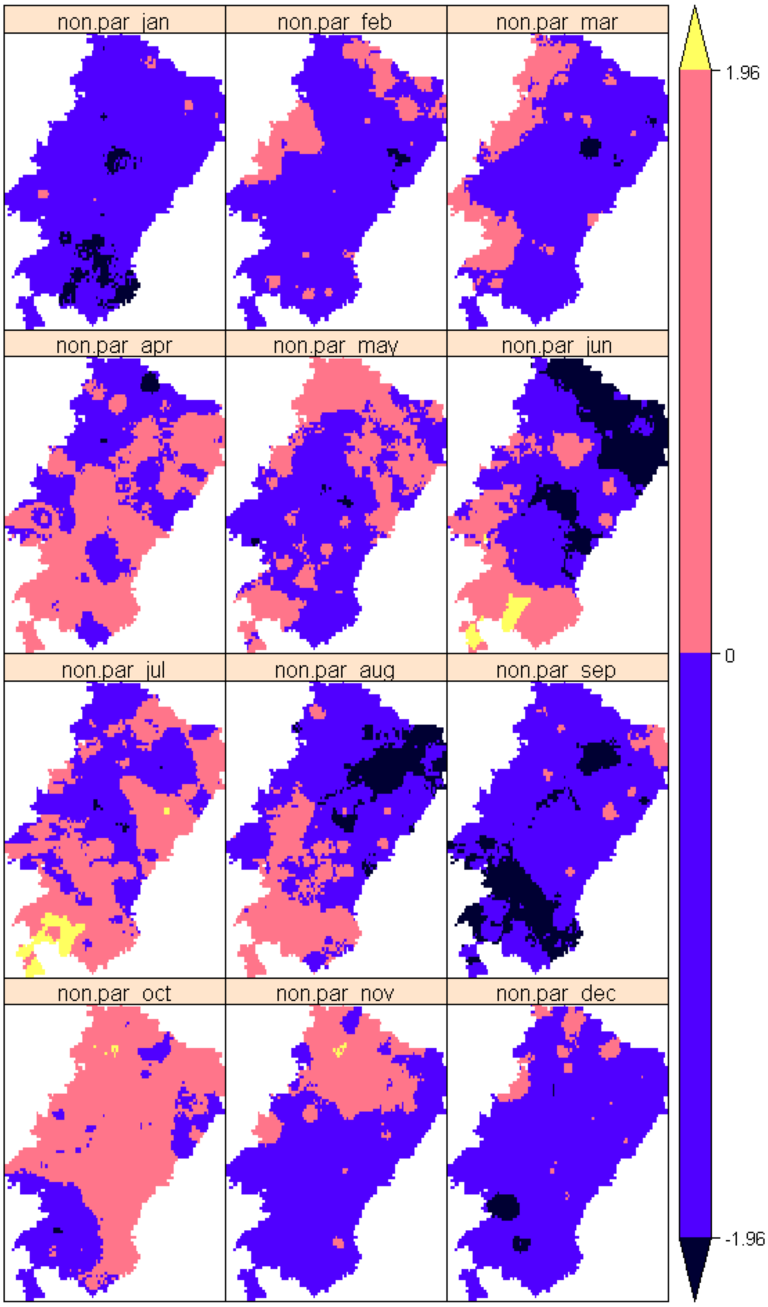

Figure 8. Results for the non-parametric (Mann-Kendall test) approach of trend identification, Brazilian semi-arid, 2000-2019.
Note: Yellow (positive significant); pink (positive not significant); blue (negative not significant); black (negative significant).
Source: Research results.

Contrary to what was observed in the annual analysis, the magnitude of the decrease in the De Martonne's aridity index is remarkable when a monthly basis is considered. In fact, the analysis of Figures 9 and 10 shows that there are some areas in which the aridity index decreases at annual rates greater than 4 index-points per year. Specifically, the highest magnitudes were recorded for December and January in the southern part of the territory and for April and June in the northern portion of the Brazilian semi-arid region.

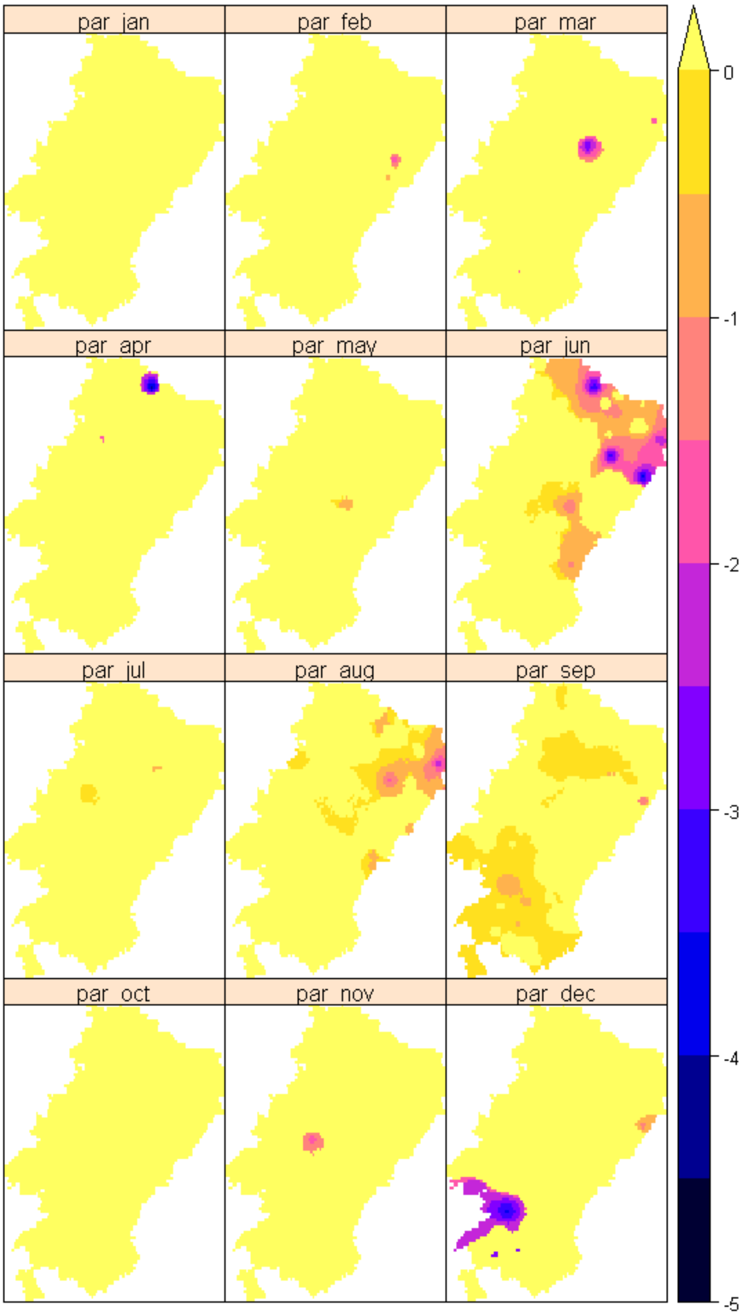

Figure 9. Results for the parametric (regression analysis) approach of trend measurement, Brazilian semi-arid, 2000-2019.
Source: Research results.

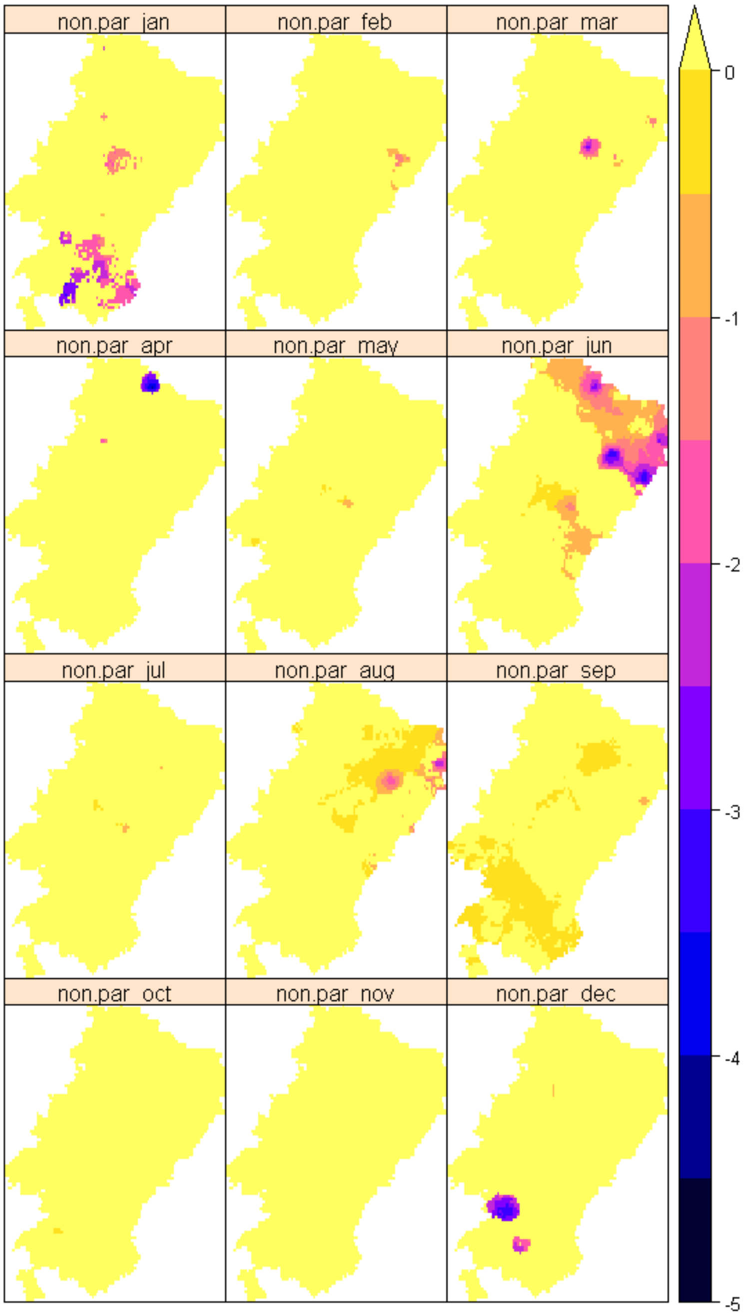

Figure 10. Results for the non-parametric (Theil-Sen estimator) approach of trend measurement, Brazilian semi-arid, 2000-2019.
Source: Research results.

4. Discussion

Spatiotemporal variations of aridity have some important implications for the Brazilian semi-arid region. As identified here, certain parts of the analyzed region have shown a decreasing trend in De Martonne's aridity index, which translates into a tendency towards the aridification of these locations. Such phenomenon can severely impact the livelihood of local population, especially in terms of water availability for human consumption as well as livestock and crop production. In fact, aridity negatively impacts ecosystems' biological and economic productivity, threatening hydrological and ecological processes (Marengo and Bernasconi, 2015). The results obtained, especially for the annual analysis, are highlighted precisely because the areas with a tendency to aridification usually are those with the lowest water availability. The situation gets worse the further away from the São Francisco River, the main body of water in the region.

Investigating climatic variability in northeastern Brazil, where most part of the semi-arid is located, Silva (2004) found that, at that time, significant decreasing trends in relative humidity and precipitation were observed in most of the weather stations analyzed. Therefore, changes in climatic variables associated with the aridification process have been affecting the semi-arid region of Brazil for a long time. Indeed, although drought episodes commonly affect the region, the drought experienced from 2012 to 2017—which, according to Marengo et al. (2017), was the most severe in decades—may be a direct consequence of such climatic changes.

If the present study demonstrated that certain parts of the semi-arid region of Brazil showed a tendency to aridification over the last two decades, the literature stress that this inconvenient scenario tends to get even worse. The results obtained by Marengo and Bernasconi (2015), for instance, indicate that the areas with the largest signal of drought increase are usually located where precipitation is projected to decrease. Their projections suggest that drought and arid conditions are expected to prevail by the second half of the 21st century due to temperature increases, rainfall reductions, water deficits and longer dry spells.

Family farmers, which heavily rely on rainfed agriculture, predominate in the semi-arid of Brazil (Angelotti and Giongo, 2019). Data from the 2017 Census of Agriculture show that most of these farmers grow temporary crops, which, due to the short production cycle, are more susceptible to climatic variations. Among these crops, beans and maize stand out. Greater water demand is observed during the planting season, which occurs during the less arid time of year. However, we identified some tendency to aridification for these months as well, which may impact crop yields and, consequently, the income and quality of life of farmers from the Brazilian semi-arid region.

The current scenario is already worrying, but the future tends to be disastrous for residents of the semi-arid of Brazil because of climate change and the consequent increase in the degree of aridity in the region. With this in mind, the government has already taken actions aimed at combating the effects of drought episodes that commonly plague the Brazilian semi-arid, such as the economic benefits granted to vulnerable smallholders through the so-called Bolsa Estiagem and the Garantia Safra Program (Alves, 2009). These initiatives help to mitigate the perverse effects of water shortage on the quality of life of local population.

5. Conclusion

This chapter examined the recent spatiotemporal variations of aridity in the semi-arid region of Brazil. To do so, parametric and non-parametric approaches were applied. Monthly weather data were employed in the construction of De Martonne's aridity index, which, in turn, was used to perform the climate classification of the region. The 20-year average indicated that local climate considerably varies between the months of the year. For example, for the third quarter, at least half of the territory has a hyper-arid climate, which is characterized by the virtual absence of rainfall.

In terms of the temporal changes in the aridity level, the Mann-Kendall trend test revealed that at least some portions of the Brazilian semi-arid present statistically significant negative trends for De Martonne's aridity index. Therefore, this result confirms the existence of a tendency towards aridification in the region. Complementing the trend analysis, the Theil-Sen's estimator indicated the magnitude of the aridification trend. In certain months, the aridity index has been decreasing at a faster pace in some locations. There, more humid climates usually predominate, indicating that different areas of the semi-arid can, in the long run, converge to an increasingly arid climate.

Ultimately, it is possible to conclude, based on the results obtained, that aridification is indeed a major threat to the livelihood of the population of the Brazilian semi-arid region. Guided mainly by the scarcity of rainfall that began to affect the region from the first years of the 2010s, the De Martonne's aridity index decreased across the region, translating into the predominance of arid-like climates, which jeopardizes agricultural activity and, consequently, impairs the ability of the local population to generate income due to persistent water deficits.

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Appendix

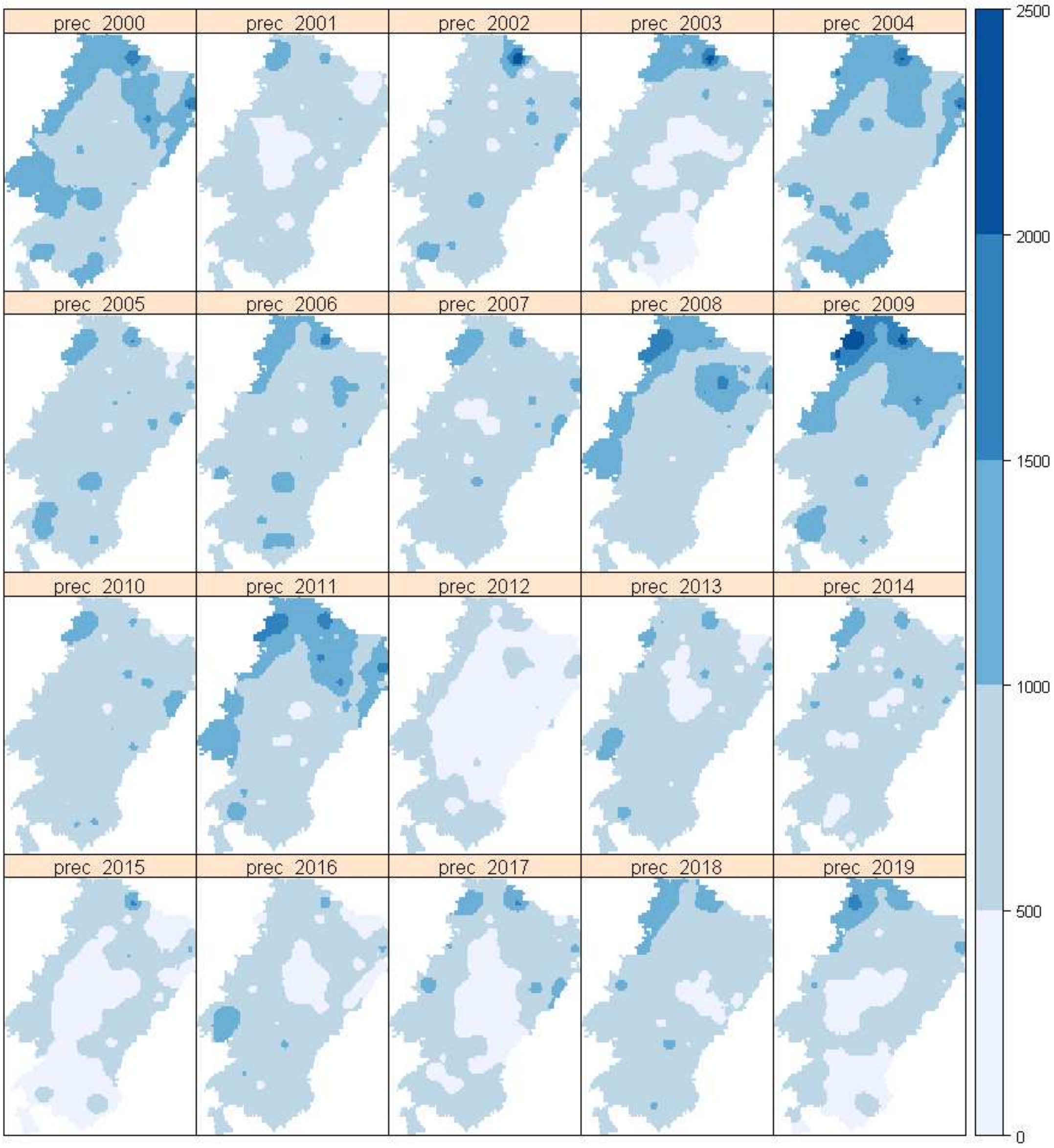


Figure 1A. Temporal variation of accumulated precipitation (mm per year), Brazilian semi-arid, 2000-2019.
Source: Research results.

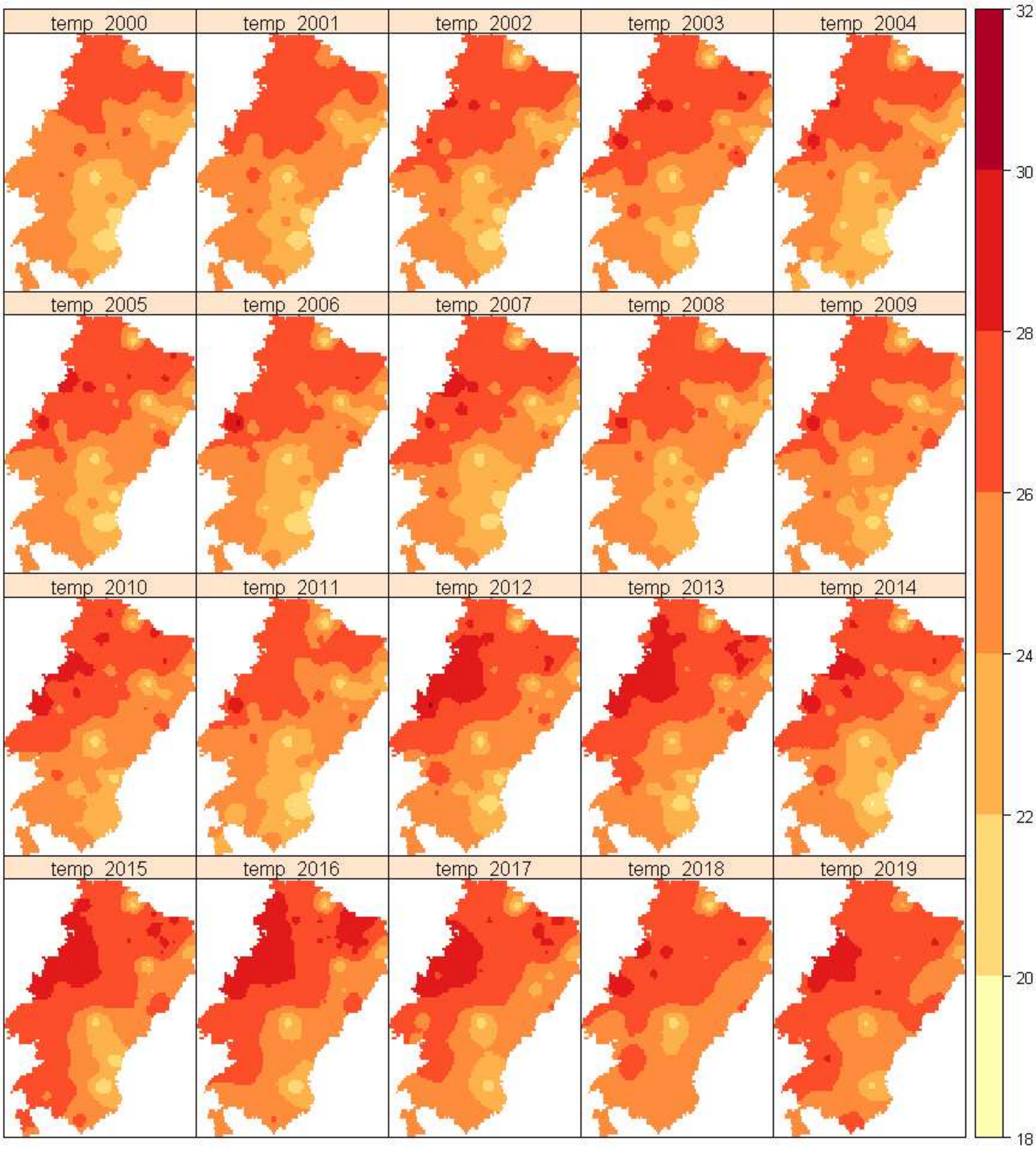


Figure 2A. Temporal variation of annual mean temperature (ºC), Brazilian semi-arid, 2000-2019.
Source: Research results.

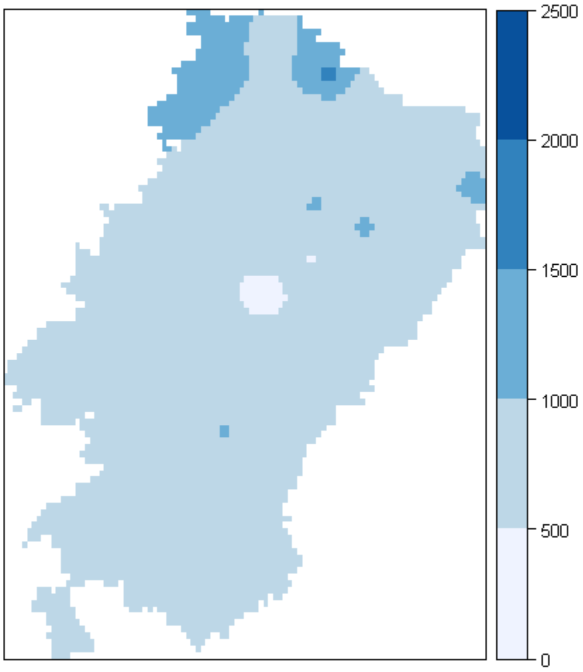


Figure 3A. Spatial pattern of accumulated precipitation (mm per year), Brazilian semi-arid, 2000-2019 average.
Source: Research results.

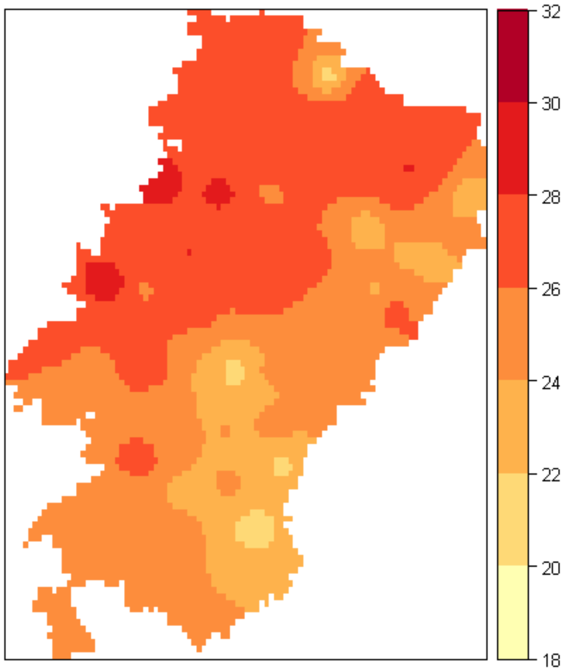


Figure 4A. Spatial pattern of annual mean temperature (ºC), Brazilian semi-arid, 2000-2019 average.
Source: Research results.

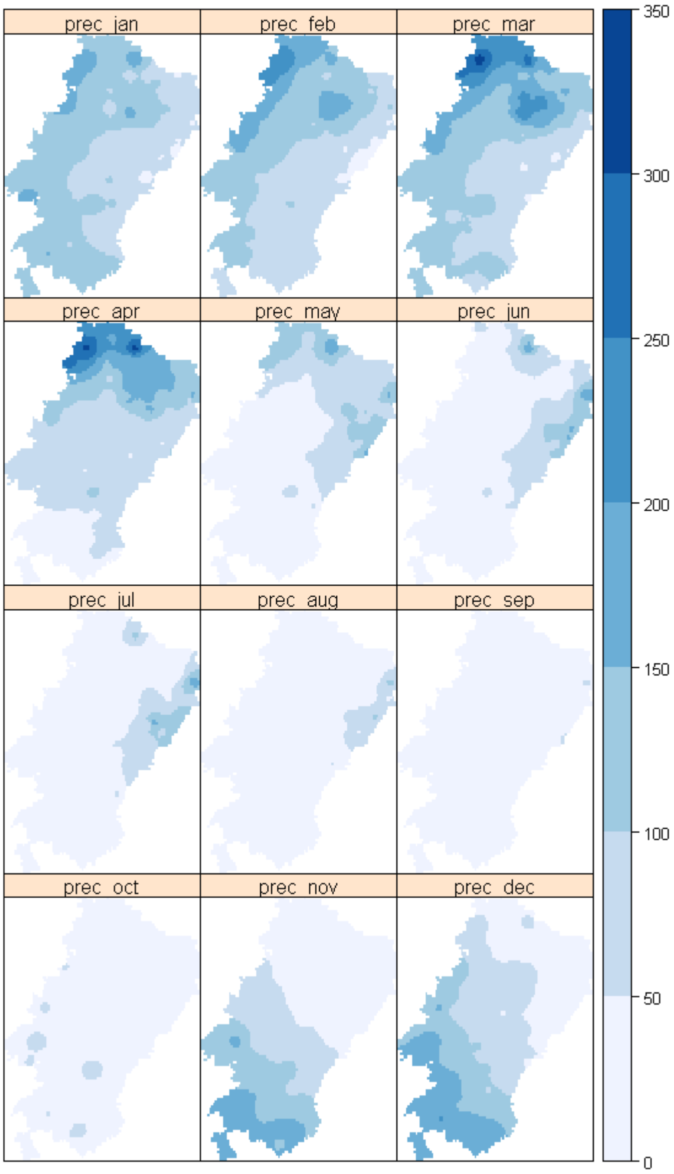


Figure 5A. Spatial pattern of accumulated precipitation (mm per month), Brazilian semi-arid, 2000-2019 average.
Source: Research results.

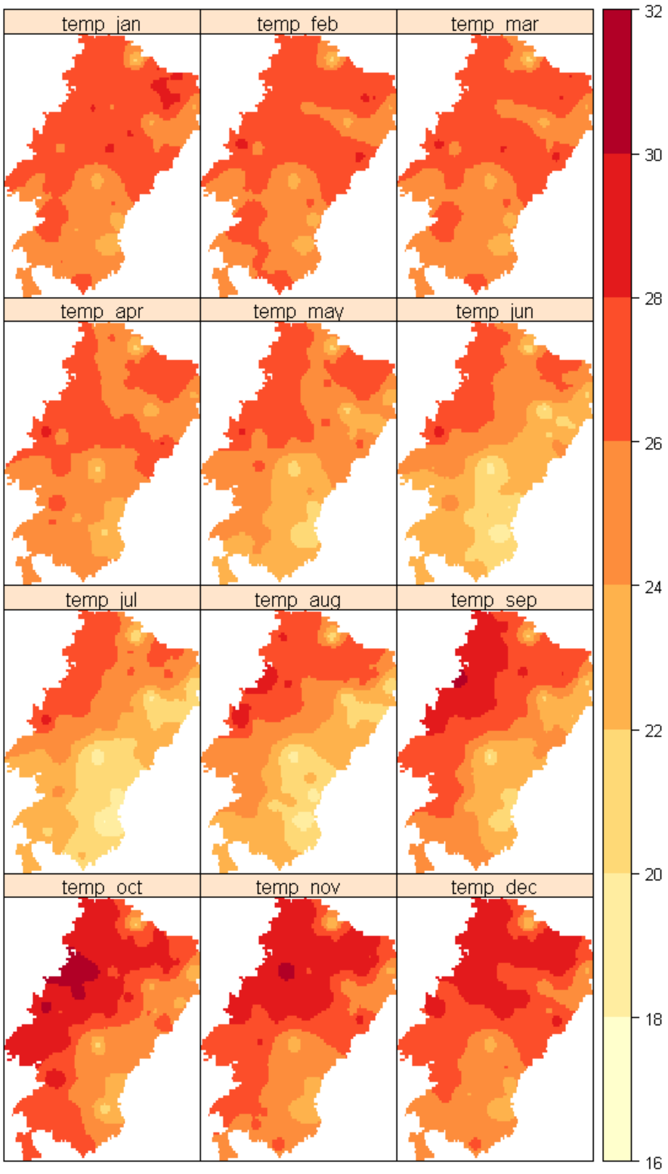


Figure 6A. Spatial pattern of monthly mean temperature (ºC), Brazilian semi-arid, 2000-2019 average.
Source: Research results.

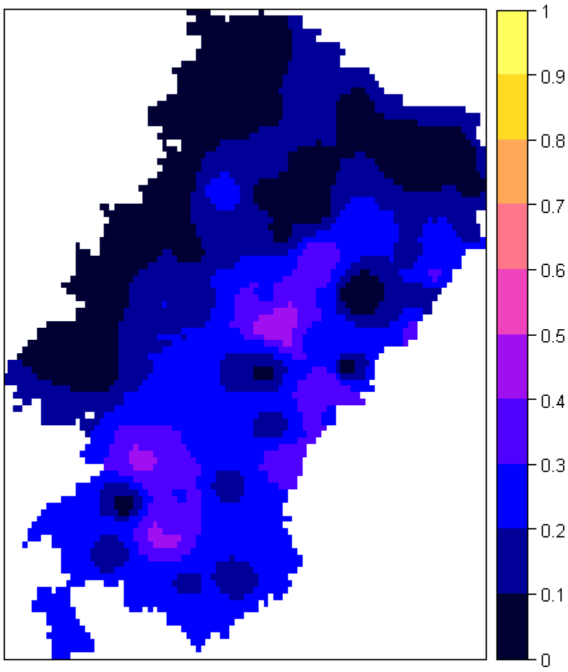


Figure 7A. Coefficient of determination for the regression of De Martonne's aridity index against a time trend, Brazilian semi-arid, 2000-2019.
Source: Research results.

CHAPTER 2

Crop yield responses to the degree of aridity in the semi-arid region of Brazil

1. Introduction

Weather index insurance (WII) has long been advertised as a major substitute for crop yield insurance. The latter determines claim payments based on actual losses, while the former considers the realizations of a pre-specified index. Since actual yields are not considered to payout determination, index-based products overcome some problems commonly related to indemnity-based ones, such as asymmetric information and high transaction costs. Ultimately, however, such issues are replaced by a different one, the so-called basis risk.

Basis risk, which arises when index realizations are decoupled from local crop yields, is often considered as the main obstacle to WII effectiveness (Miranda and Farrin, 2012). According to Chantarat et al. (2013), this mismatch may generate two important errors as insured farmers may be paid despite having no losses (type I error) or may not while experiencing crop failures (type II error). Therefore, a successful WII product heavily depends on the appropriate assessment of basis risk, making it crucial to correctly investigate the association between the weather parameter of interest and crop yields.

Such relationship, however, is usually investigated using econometric models that estimate global parameters, which could naively boost basis risk in a WII context. Some researchers, in turn, have explicitly recognized that the association between crop yields and weather inherently varies across space. For example, Cai et al. (2014), evaluated maize yield responses to weather for several counties within the United States, whilst Kusuma et al. (2018) assessed the relationship between rice yield and drought indicators for some Indonesian districts.

Following this same path, this chapter investigates crop yield responses to weather in the Brazilian semi-arid region. These responses are taken as indicators of basis risk and the implications for the design of a WII product in the region is discussed. A composite aridity index is used as a proxy for weather conditions and spatial non-stationarity is explicitly taken into account by the estimation of a Geographically Weighted Panel Regression (GWPR). The yields of beans and maize—two of the most cultivated crops throughout the semi-arid region of Brazil—are analyzed at the municipality level from 2003 to 2018.

The potential for climate aridification is one of the major consequences of global warming (Cherlet et al., 2018). In fact, future climate change projections suggest a desertification of the Brazilian semi-arid region (Fernandez et al., 2019). Such process leads to the increase of the degree of dryness of the climate, which jeopardizes the livelihood of vulnerable individuals, especially those dependent on rainfed agriculture. Therefore, the use of a composite aridity index as a proxy for local weather conditions is readily justified in a context of investigating crop yields.

The present analysis contributes to the literature by providing evidence on the spatially varying relationship between yields and weather conditions for two of the main crops cultivated in the Brazilian region that is most affected by catastrophic weather events. This information is highly relevant for the design of a WII product as estimates from the econometric model can indicate the existence—and perhaps the magnitude—of basis risk within the analyzed region, whose bulk of farmers are extremely vulnerable to climate changes.

The remainder of this paper is organized as follows. In the next section, the analytical framework considered is provided. After that, the methodology is characterized, in which the GWPR model is derived, data is detailed, estimation procedures are explained and model validation tests are exhibited. Subsequently, there are the presentation of results and its discussion in a context of weather index insurance products. Finally, the main conclusions are offered.

2. Analytical framework

Crop yield responses to the degree of aridity are scrutinized based on the relatively simple yet useful framework presented by Jensen et al. (2016), in which basis risk and its components are analyzed. If basis risk is not correctly addressed during the construction of an index insurance contract, there is no guarantee that by purchasing this product the farmer will be able to reduce his exposure to risk. On the contrary, poorly designed contracts could lead to undesired results for both farmers and insurers, leading to the failure of index insurance initiatives.

The derivation of the analytical framework starts with the definition of the municipality i as the geographic area covered by a single index insurance. Some farmer x, living in municipality i, experiences losses in year t at a rate $L_{x,i,t}$. Covariate losses, as those triggered by large-scale events such as droughts, can affect several individuals within a geographical area and are reflected in $\bar{L}_{i,t}$, which denotes the average of losses recorded in the municipality i at year t. Therefore, the losses suffered by farmer x can be divided in covariate losses $(\bar{L}_{i,t})$ and a remaining idiosyncratic component $(L_{x,i,t} - \bar{L}_{i,t})$.

Using the variance of loss rates as a metric of risk, the risk faced by farmer x can be decomposed into the variance of covariate losses, the variance of idiosyncratic losses and the covariance between them,

$$Var_t[L_{x,i,t}] = Var_t[\bar{L}_{i,t}] + Var_t[L_{x,i,t} - \bar{L}_{i,t}] + 2Cov_t[\bar{L}_{i,t}, L_{x,i,t} - \bar{L}_{i,t}], \tag{1}$$

where the more the losses of farmer x becomes similar to the municipality average $(L_{x,i,t} \rightarrow \bar{L}_{i,t})$, the more the risk faced by him are reflected in covariate risk $(Var_t[L_{x,i,t}] \rightarrow Var_t[\bar{L}_{i,t}])$.

In order to protect farmers against losses, an index insurance is available. The product determines indemnities according to the values of an index observed for each municipality i at every year t $(Index_{i,t})$. In the context of our research, this index captures weather conditions. The difference between the losses experimented by farmer x and the index $(L_{x,i,t} - Index_{i,t})$ is basis error. Its variance, in turn, denotes the risk farmer x faces when contracting the index insurance product, i.e., the so-called basis risk:

$$Var_t[L_{x,i,t} - Index_{i,t}] = Var_t[L_{x,i,t}] + Var_t[Index_{i,t}] - 2Cov_t[L_{x,i,t}, Index_{i,t}]. \tag{2}$$

The deviation of the index to covariate losses is the design error, whilst the variance of such difference $(Var_t[\bar{L}_{i,t} - Index_{i,t}])$ defines the so-called design risk. Such basis risk measure, according to Elabed et al. (2013), can be considered as an indicator of the quality of a given index insurance product. Thus, one can describe the risk faced by farmer x when index insurance is adopted by the sum of idiosyncratic risk, design risk and the covariance between design and idiosyncratic errors:

$$\begin{aligned} Var_t[L_{x,i,t} - Index_{i,t}] &\\ = Var_t[L_{x,i,t} - \bar{L}_{i,t}] + Var_t[\bar{L}_{i,t} - Index_{i,t}] &\\ + 2Cov_t[L_{x,i,t} - \bar{L}_{i,t}, \bar{L}_{i,t} - Index_{i,t}] & \end{aligned} \tag{3}$$

Ultimately, one could say that the idiosyncratic risk originates from divergences between the local climate at insured farms and the weather variables recorded at the station pre-specified in the contract. Therefore, it is an essentially geographic issue. Alternatively, insurance developers can use gridded weather data to determine policy parameters. In this case, the idiosyncratic risk can also be observed when the quality of interpolation results is not good enough.

Our analysis, in turn, focuses on the responses of crop yield to the degree of aridity and its implications to index insurance. Therefore, we are essentially investigating design risk. That is, the more the degree of aridity is able to reflect variations in crop yields, the lower the design risk. By minimizing design risk, the one that can be effectively addressed by insurance developers, the basis risk inherent to index insurance is also minimized and then the probability of success for the insurance product increases.

3. Methodology

3.1. Geographically Weighted Panel Regression

Crop yield responses to the degree of aridity are empirically modeled by means of a Geographically Weighted Panel Regression (GWPR). Conceptually, this model can be taken as a natural extension of the Geographically Weighted Regression (GWR) model as the only practical difference between them regards the explicit consideration of the time dimension by the former. In order to derive the GWR model and, ultimately, the GWPR model, one must first consider an ordinary linear regression (OLR) model (Fotheringham et al., 2002):

$$Y = X\beta + \varepsilon \tag{4}$$

where Y denotes the vector of crop yields; X denotes the matrix of weather conditions; β denotes the vector of parameters to be estimated; and $\boldsymbol{\varepsilon}$ denotes the vector of errors. Estimates of β, which is constant across observations, are given by

$$\hat{\beta} = (X'X)^{-1}X'Y. \tag{5}$$

The GWR model is obtained when local parameters are allowed:

$$Y_i = X_i\beta_i + \varepsilon_i \tag{6}$$

where i denotes a given location within the analyzed sample.

The vector of estimated regression coefficients, which now vary across observations, is

$$\hat{\beta}_i = (X'W_iX)^{-1}X'W_iY \tag{7}$$

where W_i denotes a n-by-n spatial weighting matrix whose diagonal elements indicate the weight assigned to each of the n observations for the regression point i.

The regression model presented in the Eq. 6 is calibrated via Weighted Least Squares (WLS), assuming that the closer an observation is to the regression point i, the greater its influence on the estimation of β_i. Spatial weighting matrices, in turn, are calculated by a kernel function and its respective bandwidth, which provides weights that are inversely related to distance. Therefore, the weighting process takes the assumption that spatial autocorrelation exists, possibly resulting in non-stationary patterns in estimated coefficients (Wheeler and Páez, 2010).

Finally, when the temporal component is considered, the GWPR model is obtained:

$$Y_{it} = X_{it}\beta_i + \varepsilon_{it} \tag{8}$$

where estimates of β vary across space but not across time. This occurs because the spatial relationship between locations does not change over time and thus both the bandwidth and the kernel function are time-invariant (Yu, 2010).

3.2. Estimation procedures

The key point in estimating the GWPR model regards the calculation of the matrix of local weights. As previously mentioned, W_i is calculated by a spatial kernel, a function that uses the distance between locations (d_{ij}) and a parameter of the bandwidth (b) to determine weights (Almeida, 2012). Here, an adaptive spatial kernel is used since data density varies considerably across space. In such kernel function, b is adjusted to data density so a fixed number of observations is considered in each subsample (Fotheringham et al., 2002).

The bi-square nearest neighbor kernel, specified below, is used in the weighting process:

$$\begin{aligned} w_{ij} &= \left[1 - \left(d_{ij}/d_{ik}\right)^2\right]^2 && \text{if } j \in Z_i(k) \\ &= 0 && \text{otherwise,} \end{aligned} \tag{10}$$

where w_{ij} denotes the weight assigned to j when calibrating the model for i; and $Z_i(k)$ denotes the set of kth nearest neighbors of i.

The reliability of GWPR estimates is directly influenced by the selection of b and the cross-validation (CV) criterion is considered in the optimization of the bandwidth. Specifically, the following 'drop-1' score is minimized:

$$CV = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(b)]^2 \tag{11}$$

where $\hat{y}_{\neq i}(b)$ is the estimated value of y_i when the location i is dropped.

As some time-invariant aspects specific to each unity of analysis can interfere in the relationship between crop yields and the degree of aridity, the use of a fixed effects specification is readily justified. Among such aspects, one could highlight both altitude and soil quality. The spatial rigidity of altitude is straightforward. For soil quality, in turn, this consideration is not so simple. However, for not-so-long time spans one could expect soil quality to remain relatively constant as both the degradation or correction of soil take some time to occur.

In spite of evidence showing that crop yields respond nonlinearly to the weather, only the linear term of the weather proxy is considered in the present study. Schlenker and Roberts (2009), for instance, found that nonlinearity is expected to occur only when temperature varies more than 10ºC across observations. Cai et al. (2014), however, argue that an expressive spatial variation is highly unlikely when applying a GWPR model since coefficients are estimated using geographically close subsets of data. Moreover, investigating only the linear aspects of the weather-yield relationship facilitates the discussion in an insurance context.

Ultimately, the following model is estimated:

$$yield_{it} = c_i + \beta_{1i} aridity_{it} + trend + \varepsilon_{it} \tag{12}$$

where $yield_{it}$, and $aridity_{it}$ respectively denote maize yield and the aridity index of location i in year t; c_i denotes location-specific, time-invariant fixed effects; $trend$ denotes a linear time trend; and ε_{it} denotes the error term.

3.3. Robustness check and model validation

As an exercise of robustness check, three alternative econometric models are also estimated. Following Cai et al. (2014) and Kusuma et al. (2018), GWPR results are compared to those from non-spatial and spatial panel models. The non-spatial alternative refers to an OLR model. The spatial alternatives, in turn, are the spatial error model (SEM), in which error terms are correlated across locations, and the spatial lag model (SAR), in which crop yields of a given location are influenced by the yields of nearby locations.

In addition to checking for model robustness, two statistical tests for spatial non-stationarity are also applied. Under the null hypothesis that the GWPR and OLR models describe the data equally well, the first statistic (F_2) evaluates GWPR goodness of fit using analysis of variance. The second statistic (F_3), on the other hand, considers the null hypothesis that all local coefficients estimated via GWPR are statistically equal, testing if spatial non-stationarity indeed holds for the analyzed sample. These tests are demonstrated and explained in depth by Leung et al. (2000).

3.4. Data

The relationship between crop yields and the degree of aridity is investigated for two of the crops most cultivated in the semi-arid region of Brazil. The dataset comprises a large panel of municipality-level crop yields merged with grid-based information on the degree of aridity. Yield data were obtained from the Municipal Agricultural Production (PAM), an annual survey conducted by the Brazilian Institute of Geography and Statistics (IBGE), whilst data on aridification come from the first chapter of this study, in which monthly values for De Martonne's aridity index were calculated.

The inclusion of composite weather indexes—like the aridity index considered in the present study—into econometric models of the crop-weather association has been advocated at least since the 1960s (e.g., Stallings, 1960; 1961; Shaw, 1964; Oury, 1965). This is done in order to avoid functional misspecification of the relationship between crop yields and weather conditions. Since a higher index value translates into better conditions for agricultural production due to the increase in local humidity, crop yields are expected to be positively correlated with the realizations of aridity index.

Specifically, growing season values for De Martonne's aridity index are given by

$$I_{DM} = \frac{P \times \frac{12}{d}}{\bar{T} + 10} \tag{9}$$

where I_{DM} is the aridity index; P is the growing season accumulated rainfall; d is the duration of the growing season in months; and $\bar{T}$ is the growing season average temperature. Precipitation is multiplied by $12/d$ in order to annualize the values and 10 is added to the temperature in order to avoid a negative denominator—this goes back to the European origin of the index.

Figure 1 depicts the spatial distribution of De Martonne's aridity index over the Brazilian semi-arid. Values are averaged over the period from 2003 to 2018, being calculated for the growing season—more on this later—of (a) beans and (b) maize. Both crops seem to follow the same pattern as the highest values for the aridity index are concentrated in the municipalities with the lowest latitude. It is worth noting, however, that arid-like climates ($I_{DM} < 20$) are more prevalent during maize's growing season since it has a longer duration, reaching some of the driest months of the year.

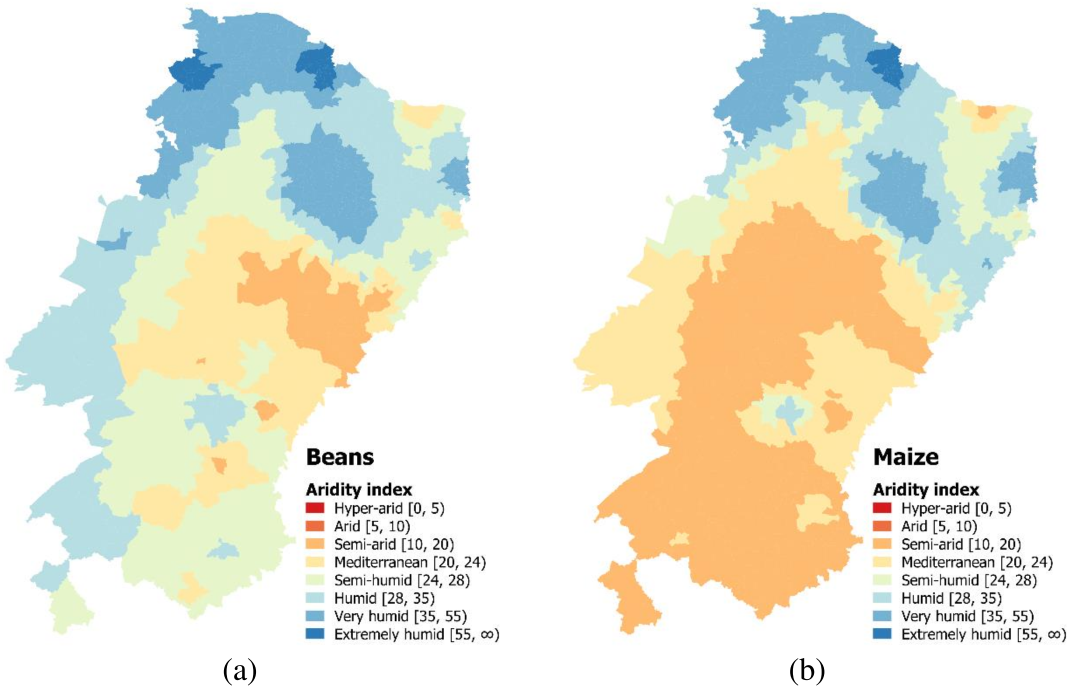
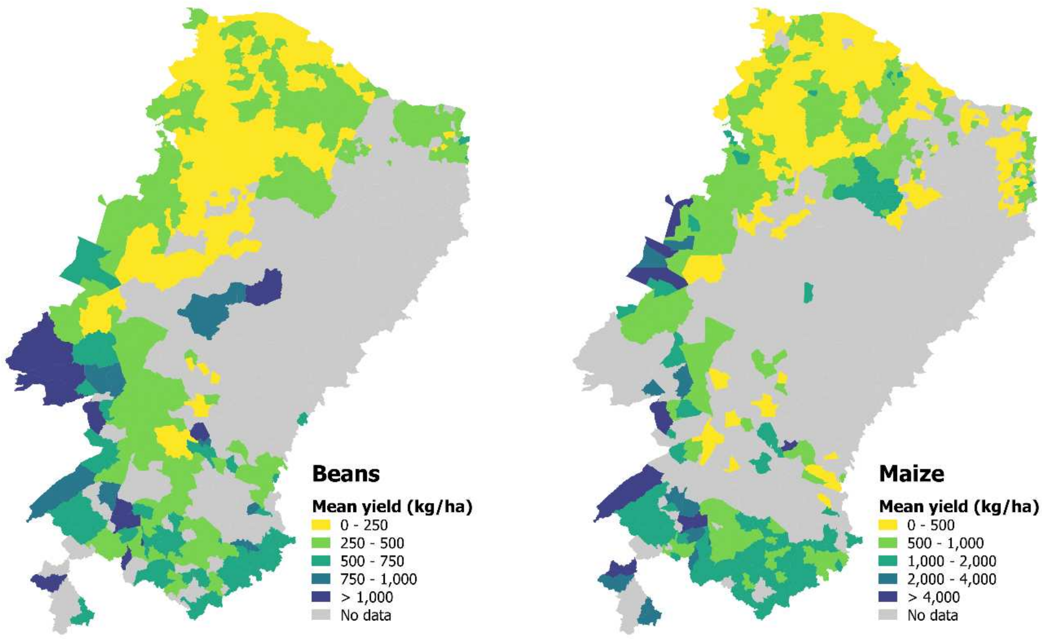


Figure 1. Mean values of De Martonne's aridity index for (a) beans and (b) maize, Brazilian semi-arid, 2003-2018.
Source: Elaborated by the author based on data from INMET (2020).

Measured in kilograms per hectare, crop yield data are gathered for beans and maize[2], covering a period of 16 years (2003 to 2018). According to data from the 2017 Census of Agriculture, these are some of the most cultivated crops throughout the semi-arid of Brazil. This is true especially for family farmers, which are the main target audience for weather index insurance. According to the schedule presented by the National Food Supply Company (Conab, 2019), maize's (beans') season are defined as ranging from January to August (December to June).

Although the Brazilian semi-arid comprises 1,262 municipalities within ten different states, only locations with consistent and complete information on crop yields are investigated as a balanced panel is required for the estimation of the GWPR model. While both crops are examined for the same time period of 16 years, each panel has a different spatial dimension. Specifically, 602 (47.7% of total) municipalities were considered for beans and 591 (46.8% of total) for maize. These locations are depicted in Figure 2, where mean yields for the crops investigated are presented.



(a) (b)

Figure 2. Mean yields for (a) beans and (b) maize, Brazilian semi-arid, 2003-2018.
Source: Elaborated by the author based on data from IBGE (2020).

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[2] Specifically, crop yield data refer to the first harvest of beans and maize as this is the most cultivated harvest for both crops in the analyzed region.

The econometric analysis[3] was conducted with the software R (R Core Team, 2019). As the GWPR model was estimated using the package 'spgwr' (Bivand and Yu, 2017), which is intended for cross-sections, demeaned data for crop yield and weather conditions were used in order to account for fixed effects via within transformation. As previously presented, additional models were estimated for robustness check. The OLR model was estimated using the package 'plm' (Croissant and Millo, 2008), whilst both SEM and SAR were estimated using the package 'splm' (Millo and Piras, 2018).

4. Results

Before delving into the results of the GWPR model, those of OLR, SEM and SAR are firstly analyzed (Table 1). Estimating a global parameter for the relationship of interest, these models provide robust evidence that crop yields indeed respond to variations in the degree of aridity within the semi-arid region of Brazil as all estimates are statistically significant at the 1% level. As expected, positive coefficients were estimated, indicating that increases in De Martonne's aridity index (decreases in the degree of aridity) leads to increases in crop yields.

Table 1. Estimation results for the Fixed Effects, Spatial Error and Spatial Lag panel data models, semi-arid region of Brazil, 2003-2018.

Crop yield	Panel Data Model		
(kg ha^{-1})	Fixed Effects	Spatial Error	Spatial Lag
		Beans (N = 9,632)	
$aridity$	4.4463*** (0.1984)	4.2438*** (0.3607)	2.0829*** (0.1723)
$trend$	0.2058 (0.2391)	0.1245 (0.4418)	0.0872 (0.2077)
rho		0.5302*** (0.0102)	
$lambda$			0.5309*** (0.0102)
		Maize (N = 9,456)	
$aridity$	11.2879*** (0.6452)	10.7238*** (1.0412)	6.2032*** (0.5926)
$trend$	2.0209*** (0.7504)	2.4397** (1.2203)	1.4199** (0.6892)
rho		0.4354*** (0.0115)	
$lambda$			0.4357*** (0.0115)

Notes: *, ** and *** represent, respectively, significance at the 10%, 5%, and 1% level. Standard errors are shown in parentheses. All models are estimated with municipality fixed effects.
Source: Research results.

When analyzing the OLR model, it is observed that, on average, a one-point increase in the aridity index is related to an increase of roughly 4.4 kilograms per hectare

[3] The author is grateful to Michael Oppenheimer, Danlin Yu and, mainly, Ruohong Cai for providing the necessary R script for the estimation of the GWPR model.

of beans. A greater influence of the degree of aridity is seen for maize as yields increase by 11.3 kilograms per hectare for each unit increase in the aridity index. SEM estimates were relatively close to OLR ones, while the smallest ones were found for SAR[4]. The spatial parameters (rho and lambda) were statistically significant for both crops, confirming spatial dependency[5].

Table 2 shows the results obtained by the GWPR model. Considering that one coefficient is estimated for each of the locations analyzed, estimates are presented by quantiles. As initially expected, coefficients vary considerably across the region. In fact, the interquartile range of estimates is considerably larger than the standard errors of the alternative models previously presented. This is an indication that crop yield responses are characteristically non-stationary in space[6], endorsing the validity of estimating local coefficients.

Table 2. Estimation results for the Geographically Weighted Panel Regression model, semi-arid region of Brazil, 2003-2017.

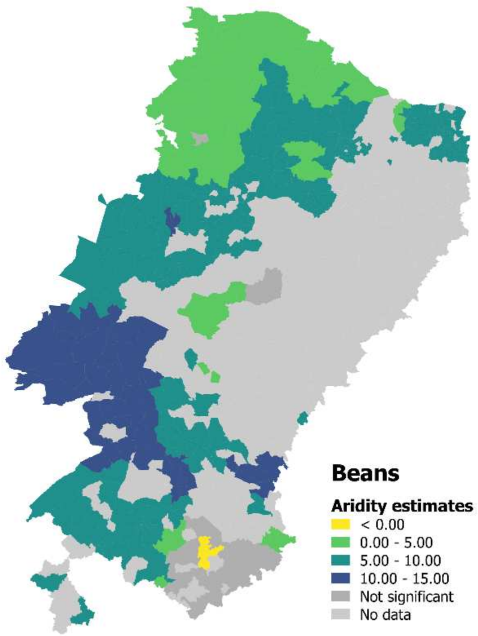
Crop yield	GWPR				
(kg ha^{-1})	Min	Q1	Median	Q3	Max
			Beans (N = 9,632)		
$aridity$	-3.8228	2.8194	5.5232	7.3921	14.9515
$trend$	-2.3394	-0.8261	0.2011	1.3008	3.9194
			Maize (N = 9,456)		
$aridity$	-49.5818	7.4768	11.6032	19.9774	63.0053
$trend$	-9.9721	-2.7182	0.1751	4.1529	47.3939

Source: Research results.

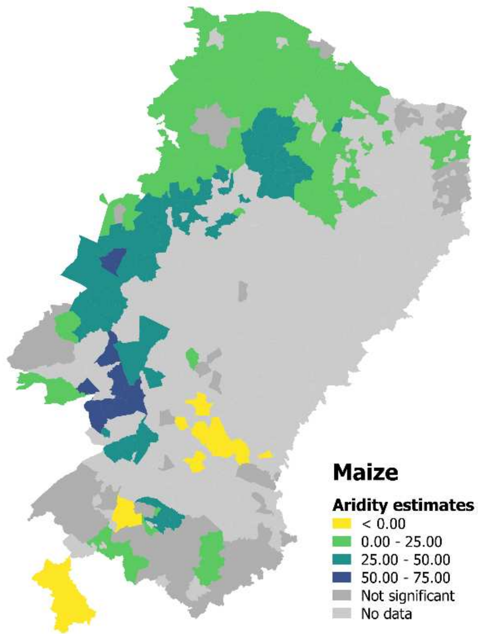
The median value of aridity coefficients estimated by the GWPR model for both crops is quite similar to those obtained by spatial and non-spatial models, i.e., there is strong evidence in favor of the robustness of the GWPR model in estimating crop yield responses to the degree of aridity. The vast majority of local estimates were positive, as expected. In fact, only 4% (6.6%) of locations had negative coefficients for beans (maize). Despite accounting for a small proportion of the sample, the presence of negative estimates is intriguing. It is hypothesized that in these locations the level of aridity is somehow optimal and any increase in the index is translated in yield losses.

[4] Cai et al. (2014) and Kusuma et al. (2018), who also used the GWPR model to examine crop yield responses to the weather, found a similar discrepancy between models' estimates for weather variables.
[5] By allowing for non-stationarity in the regression parameters, the GWR model—and, by extension, the GWPR—accounts for a large part of the autocorrelation observed in the error terms of a global model calibrated with spatial data (Fotheringham et al., 2002).
[6] Following Fotheringham et al. (2002), spatial non-stationarity refers to the case where the investigated process is not constant over space. In other words, the estimate of the relationship of interest depends on where the measurement is taken.

The proportion of municipalities for which aridity estimates were pseudo-significant[7] at the 5% level is 94% for beans and 74% for maize. Figure 3 indicates how these locations are spatially distributed over the Brazilian semi-arid region. The municipalities for which estimates were not pseudo-significant are primarily located in the southern part of the territory, the same area where the locations with negative coefficients are concentrated. As previously stressed, however, the bulk of estimates are positive and the largest ones are agglomerated in the west of the region for both crops.



(a)



(b)

Figure 3. Aridity estimates for (a) beans and (b) maize, Brazilian semi-arid.
Source: Research results.

Results obtained for Leung's tests validate the *a priori* preference for the GWPR model, as can be observed in Table 3. The calculated statistics make it possible to reject the two null hypotheses investigated at the 1% significance level. This is true for both beans and maize. Therefore, it is possible to state that, in the context of the present study, the GWPR model describes the data analyzed better than a given OLR model, whilst local coefficients estimated for the degree of aridity are not statistically equal, i.e., different locations indeed present distinct yield responses to the weather.

[7] Pseudo-significance, in this case, refers to the t-statistic for the coefficient of each regression point (Kusuma et al., 2018).

Table 3. Results for Leung's tests of spatial non-stationarity

Test	F statistic	p-value
	Beans	
F_2	3.9852	0.0000
$F_3(aridity)$	10.4396	0.0000
$F_3(trend)$	1.7096	0.0000
	Maize	
F_2	2.5852	0.0000
$F_3(aridity)$	6.3928	0.0000
$F_3(trend)$	1.8214	0.0000

Source: Research results.

As earlier discussed, adaptive bandwidths were optimized by cross-validation. For this kind of bandwidth, window size varies according to data density so the number of observations in each local regression is kept constant. Therefore, one could expect the proportion of municipalities considered in each local estimation to be inversely related to data density. For beans (maize), the number of data points used for the calibration of the GWPR model was 832 (346) over the 16 years of analysis—roughly 52 (22) municipalities per year.

5. Discussion

As previously described, it was found robust evidence that crop yields positively respond to changes in the degree of aridity, i.e., the less (more) arid (humid) a location is, as classified according to index values, more prone to the cultivation of both beans and maize it is. In fact, as stated by Hoogenboom (2000), in addition to solar radiation, precipitation and air temperature—which compose the index of aridity—are the key agrometeorological variables associated with agricultural production.

The difference observed across crops in terms of the magnitude of the estimated coefficients reflects the existing difference in water (humidity or moisture) requirement. As mentioned before, the lowest responses of crop yields to changes in the degree of aridity were observed for beans. As shown by Guerra et al. (2003), in certain parts of Brazil, beans require comparatively less water than maize during the growing season, with emphasis on the flowering stage of the plants.

In an index insurance context, two features of the obtained results worth highlighting. First, there is the proportion of observations for which the GWPR model provided positive and statistically pseudo-significant estimates. This result indicates the municipalities where the underlying index effectively works as a proxy for crop yield results. Moreover, the percentage of locations for which our GWPR model provided pseudo-significant coefficients are reasonably in line with the (scarce) literature on the same subject.

Investigating the production of rice in Indonesia with a GWPR model, Kusuma et al. (2018) found that half of their observations had pseudo-significant estimates for their main variable of interest, the Palmer Drought Severity Index (PDSI). Cai et al. (2014), who analyzed the responses of maize yields to weather conditions in the United States, found that 65% (53%) of analyzed locations were pseudo-significant for temperature (precipitation).

The second feature that deserves mention is the magnitude of the local coefficients estimated. It indicates how the association between crop yields and the degree of aridity spatially varies within the semi-arid region of Brazil, providing evidence on spatial non-stationarity. As previously described, a certain pattern was found regarding the geographical distribution of estimates, given that negative coefficients and those that were not pseudo-significant were concentrated in the southern portion of the semiarid region. It was shown in the previous chapter that this is exactly the area that presented the greatest tendency to aridification over the last decades.

When insurance designers select a pool of municipalities within a region in which farmers would be able to access WII products, the magnitude of estimates is as important as its statistical significance. The latter, as explained above, indicates the locations for which the underlying variable would indeed capture variations in crop yields. The former, in turn, provides evidence on how much local crop yields would vary with a given variation in the underlying index, suggesting the municipalities in which farmers—and, consequently, insurers—would face higher risks.

6. Conclusions

In this chapter, it was investigated the association between crop yields and the degree of aridity for beans and maize in the semi-arid of Brazil. Accounting for spatial non-stationarity, a Geographically Weighted Panel Regression (GWPR) model was estimated for a sample of municipalities over a period of 16 years, from 2003 to 2018. Alternative models—fixed effects, spatial error and spatial lag panel data models—were also considered in order to check for the robustness of the GWPR estimates.

Although weather parameters were (indirectly) used to explain crop yield variations, assigning certain degree of randomness to the analysis, we opt for not claiming causality in the relationship estimated. In fact, given the background in which the examination is conducted—the implications of the crop-aridity association to index insurance—it is more interesting to control for spatial non-stationarity and statistical significance as a way of observing for which group of municipalities within the analyzed region implementing WII products would make sense.

In such context, the results of this study are meaningful for the semi-arid region of Brazil. Although some differences were observed between the crops analyzed, several municipalities obtained pseudo-significant coefficients for the response of crop yields to weather conditions. Based on the theoretical background presented, the statistical significance of GWPR estimates could be seen as a local indicator of the suitability of WII products, since at least one of the components of basis risk—design risk—would be minimized.

It should be noted, however, that the suitability of a given WII product for a certain region in terms of the minimization of basis risk does not guarantee the success of the initiative, especially with regard to the take-up level. In fact, among the other factors that affect the adoption rate of WII products, those related to the demand side stand out, such as the educational level of farmers, their understanding of insurance operations and their attitudes towards risk and uncertainty. Furthermore, it is also necessary to account for the idiosyncratic part of basis risk, which is related to the distance between weather stations and farms or the quality of weather data interpolation.

Ultimately, it is possible to conclude that, at some extent, the aridity index emulates region's weather conditions, presenting itself as a candidate for the underlying parameter in a WII product designed for the semi-arid region of Brazil. Despite being a composite index, the interpretation of de Martonne's index values and the recognition of its relationship with agricultural production are straightforward. Its utilization as a weather index, therefore, could in fact be taken into consideration by insurance designers due to its simple calculation, minimal data requirement and ease of comprehension.

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CHAPTER 3

Designing, pricing and evaluating a WII product for the semi-arid region of Brazil

1. Introduction

In countries and regions with comparatively lower levels of socioeconomic development, the establishment and development of well-structured crop yield insurance schemes is considerably complex. The spatial dispersion of small-scale rural properties and the characteristically poor transport infrastructure make on-site investigation of claims even more time-consuming and expensive than in developed countries. In this way, transaction costs often reach very high levels, which translates into the collection of prohibitive premiums.

It was precisely in order to circumvent such problems and offer to poor, vulnerable farmers the possibility to stabilize income and prevent asset losses that weather index insurance (WII) products were first conceived. According to Hellmuth et al. (2009), WII products can be designed to help poor farmers in overcoming poverty traps and achieve higher development levels or to assist governments and relief agencies in disaster management initiatives aimed at supporting the livelihood of vulnerable populations.

In Brazil, the semi-arid region stands out as the one that concentrates the ideal conditions for the implementation of a WII product. First, while average temperature does not show much oscillation, precipitation has a wide spatial-temporal variation, which facilitates the occurrence of severe drought episodes (Correia et al., 2011). Second, the rural population is mainly composed by family farmers whose livelihoods often exclusively depend on rainfed agriculture (Melo and Voltolini, 2019). Ultimately, these farmers are highly exposed to climate risks.

Around the world, several WII initiatives have been implemented for the last decade. Nevertheless, the effectiveness of potential index-based climate risk management tools continues to be analyzed for a variety of crops and countries[1] (e.g., Berg, Quirion and Sultan, 2009; Kellner and Musshoff, 2011; Zhu, 2011; Spicka and Hnilica, 2013; Conradt, Finger and Sporri, 2015; Choudhury et al., 2016; Adeyinka et al., 2016; Black et al., 2016; Poudel, Chen and Huang, 2016; Shi and Jiang, 2016; Kusuma, Jackson and

[1] A comprehensive review of the literature on weather index insurance is provided by Singh and Agrawal (2020).

Noy, 2018; Nogales and Cordova, 2019; Shirsath et al., 2019; Williams and Travis, 2019; Boyd et al., 2020; Eze et al., 2020).

The aforementioned papers vary considerably in terms of the scope of analysis as well as the geostatistical, econometric and actuarial methods employed. For Brazil, Raucci et al. (2019) is presumably the sole study investigating the development of a WII product. The authors designed a WII contract for soybean cultivation in selected locations of southern Brazil and evaluate hedging efficiency against lack of rainfall during the growing season. Our analysis differs to theirs in terms of geographical focus, scope and the methodology employed.

Specifically, the present study aimed at designing, pricing and evaluating the effectiveness of a WII product for municipalities in the Brazilian semi-arid region. Based on the finds of the previous chapter, the aridity index proposed by de Martonne (1926) was considered as the underlying variable guiding insurance payouts, which follows a proportional structure. The suggested product was priced via burning cost analysis and its effectiveness in stabilizing farmers' income was assessed through a mean-semivariance analysis and the Stochastic Efficiency with Respect to a Function (SERF) method.

This study contributes to the literature by providing evidence on the viability and effectiveness of developing and implementing a WII product for vulnerable farmers residing in one of the poorest areas of Brazil. Since the semi-arid has historically been neglected in terms of premium subsidies distributed through the crop yield insurance currently in force in the country, the suggested WII product may be viewed as a complement to that scheme, being explored in areas whose characteristics favor the implementation of this kind of climate risk management tool.

The remainder of this chapter is as follows. Next, the principles of weather index insurance are presented. In the third section, the methodology is described in detail, highlighting the criteria for defining the implementation area, the product design and pricing processes as well as the methods for evaluating its effectiveness in guaranteeing beans and maize farmers from the Brazilian semi-arid region against climate risk. Subsequently, research results are exhibited and discussed. Lastly, the main conclusions of the study are provided.

2. Principles of weather index insurance

The main feature of weather index insurance (WII) products regards the way in which payouts are set. Indemnity payments are determined with respect to the realization of a pre-specified index, which is based on a weather variable like precipitation, temperature or a composite index, as the aridity index used in the present study. The index works as a proxy for harvest failures, eliminating the need for on-site investigation of actual crop losses. Consequently, this kind of insurance enables the minimization of operational and transaction costs (IFAD, 2011).

WII policies are designed to protect vulnerable farmers against specific perils such as drought or flood. Additionally, these insurance products are usually defined and recorded at aggregate levels so the same set of parameters are offered to all farmers within a given region. In this sense, weather index insurance also minimizes information asymmetry, either in the form of adverse selection or moral hazard (World Bank, 2011). In fact, it is highly unlikely that individual farmers would be able to manipulate the realizations of the underlying variable.

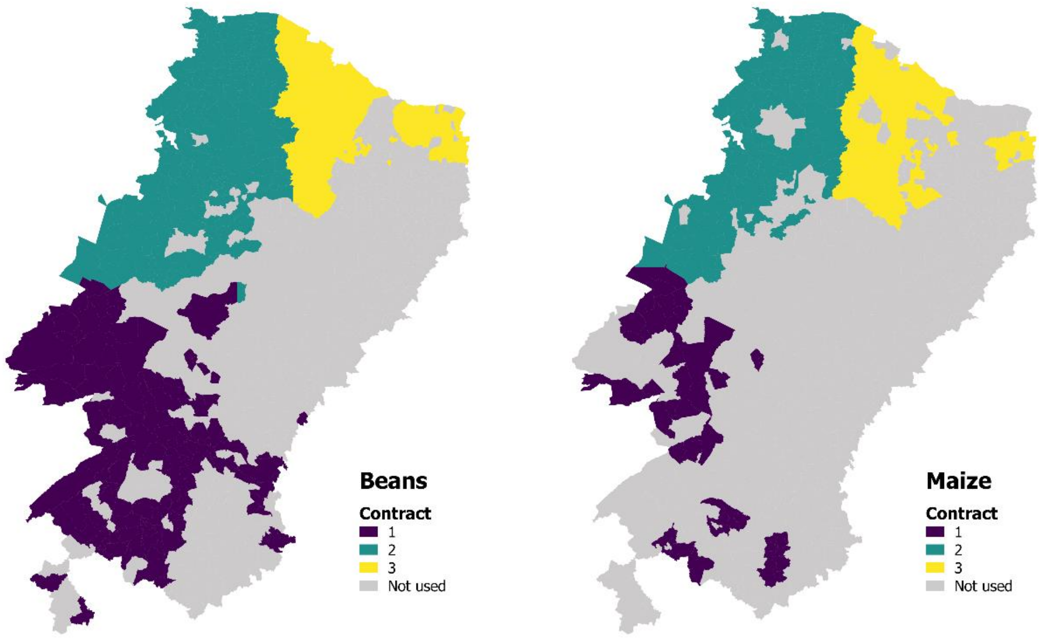
Among contract parameters, those governing the payout structure deserve great attention, namely the trigger and the exit point. The former indicates the point at which the contract starts to payout, whilst the latter defines the maximum payment. As stated by Hazell and Skees (2006), several are the existing payout structures. In a simple zero/one contract, indemnity corresponds to liability and is paid in full once the trigger is surpassed. A layered scheme, in turn, has a set of triggers and exit points. In proportional payment schedule, payouts increase proportionally as index realizations moves from the trigger to the exit point.

Despite being firstly developed with a focus on protecting smallholders, WII products can be applied at the micro, meso and macro levels (IFAD, 2010). At the micro level, for example, the insurance contract is commercialized with farmers in order to protect crops against specific perils such as drought or flood. At the meso level, on the other hand, financial institutions, input providers and traders present themselves as potential customers. At the macro level, WII facilitates disaster management by governments and development agencies.

3. Methodology

3.1. *Implementation area*

Following other studies that also investigated the feasibility of WII initiatives (e.g., Cai et al., 2014; Kusuma et al., 2018), the definition of the locations to be analyzed is based on basis risk minimization. Specifically, the results obtained in the previous chapter are used to select the municipalities for which basis risk is expected to be low, i.e., those whose estimates of the relationship between crop yields and the degree of aridity were positive and statistically significant. These locations are depicted in Figure 1. The semi-arid region is divided in three subregions according to geographical proximity[2] and a different WII contract is priced for each of them.



(a) (b)

Figure 1. Municipalities analyzed for (a) beans and (b) maize, by contract subregions.
Source: Research results.

3.2. Product design

As state elsewhere, the effectiveness of the underlying index in capturing variations in crop yields increases as the correlation between them also increases. Thus,

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[2] Specifically, subregions are determined by k-means clustering, using latitude and longitude as inputs.

following Stoppa and Hess (2003), we define the aridity index for year t (I_t) as a weighted average of monthly aridity values, as follows

$$I_t = \sum_{i=1}^{n} \omega_i DM_{it} \tag{1}$$

where the n is the total number of months in the growing season of each crop analyzed; ω_i is the weight assigned to the month i of the growing season; and DM_{it} is the De Martonne's aridity index for the month i of year t.

The weights are chosen to maximize the sample correlation between the aridity index and crop yields:

$$\max_{\omega_i} corr(I, Y) = \frac{\sum_t (I_t - \bar{I})\,(Y_t - \bar{Y})}{[\sum_t (I_t - \bar{I})^2]^{1/2}[\sum_t (Y_t - \bar{Y})^2]^{1/2}} \tag{2}$$
$$\text{subject to } 0 \leq \omega_i, \forall\, i.$$

where Y_t is the crop yield for year t, and $\bar{Y}$ is the average yield.

Among the possible types of indemnity functions, we opt for a proportional payout structure. In this case, the indemnity is paid in percentage terms when the index falls below a pre-specified threshold, which is known as strike level or trigger. In particular, the payout is governed according to the following scheme

$$Payout = \begin{bmatrix} 1 \;\; \text{if } I_t \leq I_E \\ \dfrac{I_T - I_t}{I_T - I_E} \;\; \text{if } I_E < I_t \leq I_T \\ 0 \;\; \text{if } I_T < I_t \end{bmatrix} \times Liability \tag{3}$$

where I_T denotes the trigger threshold, I_E denotes the exit threshold. When the value of I_t falls below the exit threshold no additional incremental payout is applied. In this case, maximum indemnity equals total liability.

The values of I_T and I_E are empirically determined in the same fashion as Choudhury et al. (2016). Specifically, a model-base clustering is employed in order to identify two heterogeneous groups regarding the weather index and crop yields, one possibly with high values of such variables, and another with low values. The trigger threshold, I_T, is defined as the average weather index of the low cluster, whilst the exit threshold, I_E, is defined as the lowest weather index observed for this same cluster.

The model-based clustering is conducted with R (R Core Team, 2019). Using the package 'mclust' (Scrucca et al., 2016), a model-based clustering built on parameterized finite Gaussian mixture models is estimated. Such models are estimated by the expectation-maximization (EM) algorithm, which is initialized by a hierarchical model-based agglomerative clustering. Subsequently, the optimal model is selected according to the Bayesian Information Criterion (BIC). Detailed information about this method can be found in Bouveyron et al. (2019).

3.3. Pricing approach

We rely on burning cost analysis for pricing the proposed weather index insurance product. This pricing method uses the empirical distribution of insurance losses to calculate the premium (Heimfarth and Musshoff, 2011). Burning cost analysis is often used for weather index insurance when a sufficient long time series of weather data can be used. In fact, Hohl (2019) states that such method is suitable if at least 15 years of weather data are available. As previously described, we work with 16-years long time series.

As observed by Parodi (2015), burning cost analysis is essentially a multi-step procedure. Accordingly, we follow four steps in the calculation of the risk premium rate. First, payouts are retrospectively calculated from 2003 to 2018. Second, both liability[3] and payout values are forwardly discounted at a 5% rate, which is usually used in the literature. Third, annual loss cost ratios are obtained by averaging the ratio of payouts to liabilities over locations. Fourth, the risk premium rate is computed by averaging the loss cost ratio over the analyzed years.

3.4. Product efficiency

The efficiency of the weather index insurance in guaranteeing farmers against climate risk is evaluated through the comparison of crop revenues with and without insurance adoption. When no insurance is contracted, per hectare revenue corresponds to the multiplication of crop yield (kg ha^{-1}) by postharvest crop price (R\$ kg^{-1}). For the case where index insurance is contracted, in turn, the premium is subtracted and the (possible)

[3] Liability is calculated as the expected yield times the coverage level. In order to account for operational costs, a deductible of 15% is considered and thus coverage level is set at 85%.

payout is added to the per hectare revenue previously presented. The approaches used to assess the efficiency of the insurance product are presented below.

3.4.1. Mean-semivariance

Since the seminal work of Markowitz (1952), the mean-variance (E-V) approach has been widely applied as the decision criterion for the selection of investment alternatives. Decision making, under this approach, considers (and compares) the mean and the variance of the different alternatives evaluated. The use of variance for risk measuring, however, is somehow questionable. In fact, variance is an appropriate measure of risk only if the underlying distribution is symmetric because deviations above and below the mean are weighted equally (Estrada, 2007).

The requirement of symmetry is overcome by the use of the mean-semivariance (E-S) approach. In this case, risk is measured through semivariance, which corresponds to the expected value of deviations below the mean (Mao, 1970). In other words, a zero weight is assigned to deviations above the mean as risk-averse individuals do not concern with these results. Conradt et al. (2015), Jensen et al. (2016) and Shi and Jiang (2016) can be cited as examples of studies that used the notion of semivariance to analyze insurance products. Mathematically, such risk measure is defined as

$$S_i = \begin{cases} E([R_i - E(R_i)]^2) & \text{for } R_i < E(R_i) \\ 0 & \text{for } R_i \geq E(R_i) \end{cases} \tag{4}$$

where S_i and R_i denote, respectively, the semivariance and the returns (revenue) of alternative i.

According to Porter (1974), E-S dominance can be defined in the same way of the E-V dominance; one must simply substitute the variance for the semivariance. In this study, crop revenues with insurance (I) are compared with those without insurance (N), so the former dominates the latter by the E-S rule if

$$\begin{gathered} E(R_I) > E(R_N) \text{ and } S_I \leq S_N \\ \text{or} \\ E(R_I) \geq E(R_N) \text{ and } S_I < S_N, \end{gathered} \tag{5}$$

where dominance implies that an insured farmer has a higher expected revenue and/or a lower risk exposition than one that is uninsured.

3.4.2. Stochastic efficiency with respect to a function

Among the existing approaches to decision making under uncertainty, many academics consider the subjective expected utility (SEU) hypothesis as the most satisfactory in normative terms (Fishburn, 1981). This approach, however, requires complete knowledge on decision maker's utility function for the evaluation of alternatives as the attitude towards risk is reflected on the shape of the utility function (Lien et al., 2007). Since the target group of the present analysis comprises hundreds of thousands of farmers, applying the SEU hypothesis is impractical.

When individual utility functions are not available, the literature often relies on efficiency analysis for the ranking of alternatives (Hardaker et al., 2015). Among the existing efficiency criteria, this study applies the stochastic efficiency with respect to a function (SERF) proposed by Hardaker et al. (2004), which has been widely applied in the agricultural context (e.g., Pendell et al., 2007; Maré et al., 2017; Adusumilli et al., 2020; Wang et al., 2020). This method identifies utility efficient alternatives for a range of risk attitudes as the assessed alternatives are ordered in terms of the certainty equivalents (CEs) calculated for a set of risk aversion coefficients.

Following the SEU hypothesis, farmers' utility of revenues depends on the degree of risk aversion, r, and the distribution of crop revenues, R, as follows:

$$U(R,r) = \int U(R,r)f(R)\mathrm{d}R \approx \sum_{j=1}^{m} U(R_j,r)P(R_j), \qquad (6)$$

where $U(\cdot)$, which denotes the utility function, is evaluated for risk aversion values ranging from r_{L} to r_{U}. The second term of (6) represents the continuous case, whilst the third term provides the discrete approximation, in which $P(R_j)$ denotes the probability of state j among the set of the m states for each alternative.

Partial ordering alternatives by CEs yields the same results as partial ordering through utility values since the former is given by the inverse of the utility function (Hardaker et al., 2004). Moreover, the utilization of CEs is advantageous due to the ease of interpretation as they are expressed in monetary terms (Lien et al., 2007). Specifically, CE is defined as the sure sum that yields the same utility as the expected utility of a given alternative (Lien; Hardaker; Flaten, 2007).

Only the alternatives with the highest CEs for some coefficient in the $[r_{\mathrm{L}}, r_{\mathrm{U}}]$ interval are utility efficient (Hardaker et al., 2004). The difference between the CEs of the two alternatives considered here yields the so-called utility weighted risk premium (UWRP), which corresponds to the minimal amount a farmer would receive to justify the non-adoption of the insurance product under a specific level of risk aversion (Wang et al., 2020). In mathematical terms,

$$UWRP(I, N, r_k) = CE(I, r_k) - CE(N, r_k), \tag{7}$$

where UWRP for a risk aversion level of k is obtained by subtracting the CE without insurance (N) from the CE with insurance (I).

Under SERF, the calculation of CEs—and, consequently, the UWRP—can be done using any kind of utility function for which its inverse can be obtained (Hardaker et al., 2004). Following Lien et al. (2007) and Fathelrahman et al. (2011), the monotonic concave ($U' > 0$ and $U'' < 0$) power utility function is used since farmers are assumed to be risk-averse, preferring more revenue to less. Specifically, the utility function considered here is given by

$$U(R) = \frac{R^{(1-r_r(R))}}{1 - r_r(R)} \tag{8}$$

where r_r denotes the coefficient of relative risk aversion. According to Anderson and Dillon (1992), the degree of (relative) risk aversion varies from 0.5 (hardly risk-averse) to 4 (extremely risk-averse). Therefore, this study considers that relative risk aversion coefficients varies within that interval, i.e., $r_\mathrm{L} = 0.5$ and $r_\mathrm{U} = 4$.

4. Results

Considering the set of municipalities selected for designing, pricing and evaluation of the suggested WII product, we calculated the weights to be assigned to each of the months that make up the growing season of the two crops investigated. The solution to the maximization problem, which considered average values of each subsample, is presented in Table 1. The weights assigned are highly heterogenous between crops as well as between contracts of a same crop. This result can be related to two facts. First, each crop follows its own season, having particular responses to the weather. Second, distinct climatic regimes and yield levels are observed among the analyzed subregions.

Table 1. Weights assigned to each month of crop's growing season

Contract	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
					Beans				
1	0.54	0.00	0.19	0.26	0.00	0.00	0.00	-	-
2	0.54	0.00	0.05	0.18	0.14	0.00	0.09	-	-
3	0.22	0.24	0.26	0.06	0.19	0.03	0.00	-	-
					Maize				
1	-	0.00	0.04	0.02	0.00	0.02	0.00	0.00	0.92
2	-	0.02	0.27	0.33	0.34	0.04	0.00	0.00	0.00
3	-	0.03	0.04	0.02	0.01	0.08	0.20	0.62	0.00

Source: Research results.

After generating weighted values for the aridity index, the burning cost analysis is conducted in order to determine the premium rate related to the contracts of each of the crops analyzed. The information presented in Table 2 shows how parameters vary between beans and maize. Averaging across contracts, the premium estimated for maize is higher than that calculated for beans, indicating that it is riskier to grow the former than the latter in the Brazilian semi-arid as the premium rate is expected to be directly proportional to risk exposure.

Table 2. Parameters of weather index insurance for the Brazilian semi-arid

Contract	Average liability (R$ ha^{-1})	Trigger (index points)	Exit (index points)	Average payout (R$ ha^{-1})	Premium (%)
			Beans		
1	1,324.29	33.15	7.68	167.80	14.93
2	541.51	30.53	4.09	42.04	9.90
3	649.78	21.14	1.66	39.41	6.83
			Maize		
1	436.68	48.14	13.84	34.47	12.79
2	713.60	4.71	1.21	90.86	16.77
3	397.46	4.58	0.62	52.59	17.57

Source: Research results.

Unlike for maize, the premiums calculated for beans vary considerably between its contracts. This is an indication that the analyzed subregions have different levels of risk exposure, which may be connected to the distinct weather patterns experienced the municipalities in these areas. Both trigger and exit points also vary substantially, especially for maize. This is due to differences in weight assignment and, consequently, to differences in the values used for the aridity index. For instance, August dominates index weighting for maize's contract of subregion 1, leading to weighted aridity values comparatively lower than those of the other subregions.

Finally, having defined the premium rate associated to each crop, it is possible to evaluate the effectiveness of the WII product in reducing unexpected variation in revenues of family farmers of the Brazilian semi-arid region. First, the notion of mean-semivariance is explored, comparing the insurance and no insurance scenarios in terms of mean revenue and its below-mean deviations, capturing downside risk. The results of the mean-semivariance approach, presented in Table 3, show that no dominance is identified as the introduction of insurance leads to declines in both risk and return. This is true for all contracts analyzed.

Table 3. Results of mean-semivariance approach for revenues of the contracts designed for beans and maize

Contract	Mean (R$ ha^{-1})			Semivariance (R$ ha^{-1})		
	Insurance	No insurance	Difference	Insurance	No insurance	Difference
			Beans			
1	1,528.03	1,557.98	-29.95	847.45	869.43	-21.98
2	625.52	637.07	-11.56	317.08	327.31	-10.23
3	759.48	764.44	-4.96	352.26	358.12	-5.86
			Maize			
1	492.36	513.74	-21.38	288.84	310.55	-21.72
2	810.72	839.53	-28.80	465.56	497.54	-31.97
3	450.36	467.60	-17.25	253.79	273.74	-19.95

Source: Research results.
Notes: Revenue is averaged across space and time and standard deviation is shown in parenthesis.

Secondly, in addition to the risk-return analysis, the SERF method is used to rank insurance and no insurance alternatives in terms of farmer's attitude towards risk. Figure 2 depicts the UWRP curve for risk aversion coefficients ranging from 0.5 to 4. Regardless of the contract analyzed, the insurance scenario becomes utility efficient as the level of risk aversion increases. In fact, the UWRP becomes positive when the risk aversion coefficient is around 1.5, which means that, from such point on, the CE calculated for the insurance scenario exceeds that of its counterpart. The CEs calculated for risk aversion coefficients ranging from 0.5 to 4 are found in the Appendix.

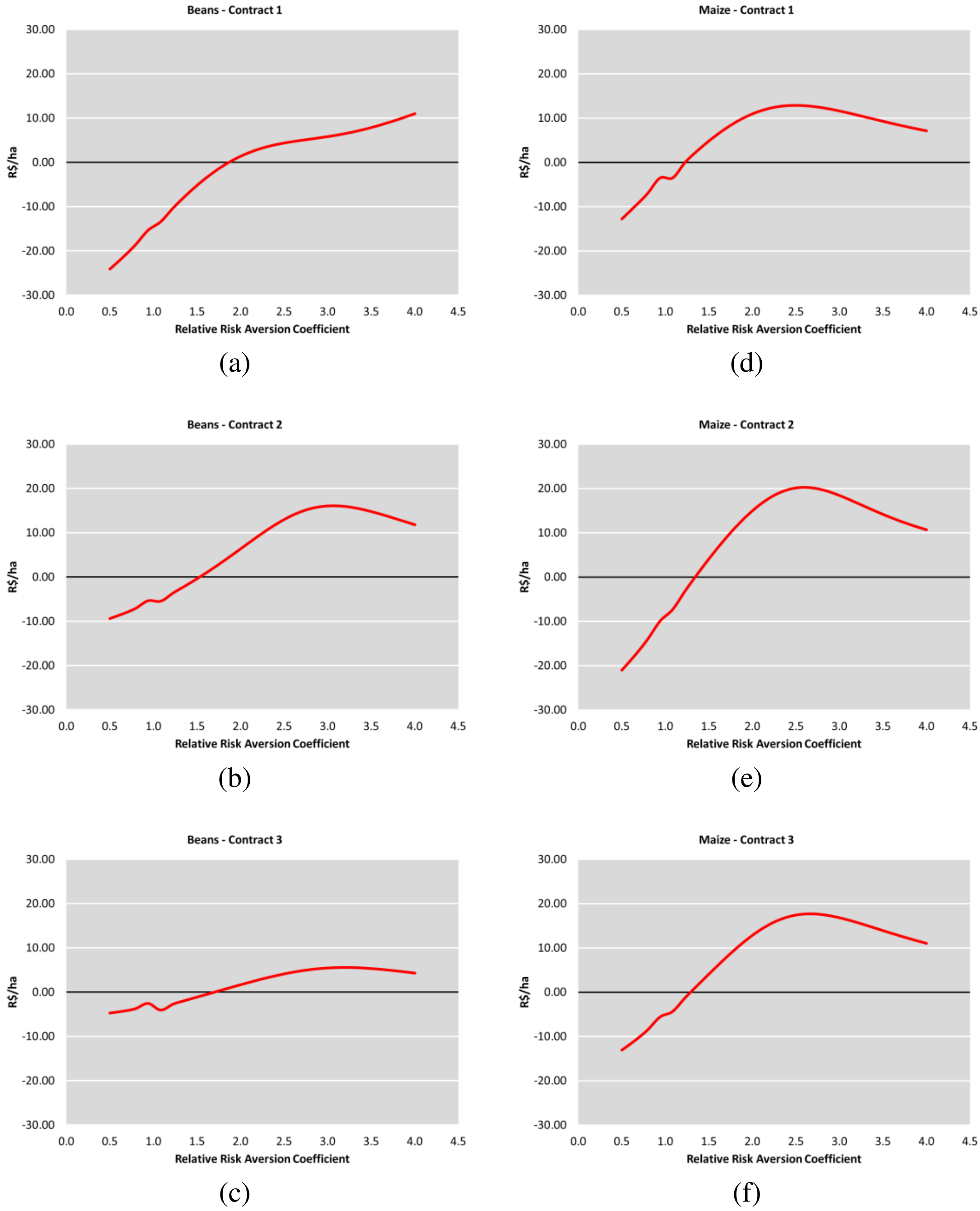

Figure 2. Utility Weighted Risk Premiums calculated for (a, b, c) beans and (d, e, f) maize, Brazilian semi-arid.
Source: Research results.

5. Discussion

Crop yield responses to weather conditions considerably fluctuate across the semi-arid region of Brazil. Accordingly, so do the parameters governing the payouts of the WII product designed in this study. Trigger and exit thresholds, as calculated through a model-based clustering algorithm, vary expressively among the different contracts designed for a same crop. This is, therefore, another piece of evidence on the spatially non-stationary nature of risk exposure to the weather, which corroborates the idea of offering different contracts to different parts of the Brazilian semi-arid.

With the payout parameters in hand, it was possible to calculate the premium rate of each contract by means of a burning cost analysis. Except for the region for which Contract 1 was designed, which comprises municipalities from the states of Piauí, Bahia and Minas Gerais, an expressive divergence regarding the premium rate was observed between the crops analyzed. In fact, the maize premiums calculated for Contract 2 and 3 are approximately twice as high as those computed for beans. For Contract 1, in turn, beans premiums are slightly higher.

As premiums are estimated in order to capture the risk faced by farmers, which ultimately are transferred to insurers, they provide an approximation of how much the farmers of a given crop in a given region are exposed to risk. According to the findings of this study, beans and maize farmers located in the southernmost part of the semi-arid do not have, between them, major differences in risk exposure. For the remainder of the region, however, maize production is much more susceptible to weather variations. In fact, as showed in the previous chapter, maize requires greater water availability than beans.

In regard of the effectiveness of the proposed WII product in protecting farmers against revenue variability, interesting features of the results achieved in this study worth highlighting. The mean-semivariance analysis showed that neither alternative dominates the other. In fact, the introduction of insurance leads to decreases in both downside risk and mean revenue. This result can be interpreted in light of the risk-return tradeoff. As defined by Markowitz (1952), a higher return is obtained at the expense of greater exposure to risk. Conversely, some fraction of expected return should be sacrificed in search of a lower level of risk.

The results of the mean-semivariance analysis are better understood when compared to those obtained through the application of the SERF method. For all the contracts analyzed, the insurance alternative becomes utility efficient as the relative risk aversion coefficient increases. For lower levels of risk aversion, on the other hand, the utility efficient alternative is the one with no insurance. As the introduction of this risk management tool leads to declines in both the mean and the semivariance of revenues, a less risk-averse farmer would not acquire the WII product developed here, thus guaranteeing a higher expected return.

6. Conclusion

In this chapter, a weather index insurance (WII) product was designed, priced and evaluated for beans and maize farmers of the Brazilian semi-arid region. The analyzed municipalities were chosen according to the results obtained in the previous chapter in order to mitigate the hazard of basis risk, being later divided in three groups according to geographical proximity. Consequently, a total of six contracts were evaluated—three for each crop. The parameters of a proportional payment schedule were estimated by a model-based clustering algorithm, contracts were priced via burning cost analysis and product effectiveness was evaluated using mean-semivariance analysis and the Stochastic Efficiency with Respect to a Function (SERF) method.

Reflecting the greater water requirement and, consequently, the greater production risk, the premiums calculated for maize were, on average, higher than those of beans. Averaging across contracts, the premium rate for beans (maize) was set at roughly 10.6% (15.7%). Ultimately, these figures may help explaining the incipience of crop insurance in the Brazilian semi-arid as the region accounts for only 0.2% (2.1%) of subsidized policies contracted by beans (maize) farmers countrywide (MAPA, 2020). The risk exposure may be such that insurers may be intimidated to operate in the region. In this case, government subsidies may play a crucial role even for a WII product.

Based on the results of the mean-semivariance analysis, it can be concluded that the WII product proposed for beans and maize farmers from the Brazilian semiarid would indeed be effective in protecting them from adverse variations in production revenue. Moreover, the results obtained through the application of the SERF method suggest that utility-maximizer farmers that are sufficiently risk-averse would prefer to adopt the WII product than to do not use this risk management tool. Assuming that farmers are generally risk-averse, one can ultimately conclude that the results of this study indicate that the contracts designed here would be commercially successful.

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Appendix

Table A1. Certainty equivalents for beans and maize, Brazilian semi-arid region

RRAC[1]	Contract 1		Contract 2		Contract 3	
	Insurance	No insurance	Insurance	No insurance	Insurance	No insurance
			Beans			
0.50	1,254.26	1,278.34	551.58	560.94	684.18	688.91
0.89	1,056.53	1,073.10	467.69	473.78	545.11	548.26
1.28	927.08	936.34	470.66	473.65	676.67	679.06
1.67	777.07	779.65	404.88	403.12	596.03	596.23
2.06	647.56	645.70	344.23	337.04	538.80	536.83
2.44	537.09	532.94	284.12	271.72	484.28	480.39
2.83	446.18	440.85	227.61	211.98	429.78	424.61
3.22	373.72	367.15	179.37	163.45	376.02	370.45
3.61	317.11	308.65	141.91	127.71	325.44	320.29
4.00	273.18	262.20	114.44	102.60	280.67	276.38
			Maize			
0.50	409.99	422.73	663.36	684.40	367.67	380.74
0.89	298.08	303.00	545.26	556.80	295.66	302.42
1.28	347.62	346.61	483.40	485.15	280.60	280.85
1.67	271.60	264.30	386.55	378.40	225.88	218.63
2.06	214.57	203.20	296.45	280.58	177.59	163.99
2.44	167.39	154.55	214.35	194.44	134.94	117.77
2.83	130.21	117.97	148.38	128.83	100.43	83.01
3.22	102.40	91.81	102.79	86.24	74.83	59.23
3.61	82.23	73.47	74.01	60.74	56.79	43.58
4.00	67.70	60.57	56.10	45.43	44.28	33.27

Note: [1] Relative Risk Aversion Coefficient.
Source: Research results.

FINAL REMARKS

The semi-arid region of Brazil is historically plagued by catastrophic events, among which stand out the droughts that severely threaten the livelihood of its residents. In fact, most of the population of this region is comprised by family farmers whose income directly depend on the small-scale, rainfed agricultural production. Despite this scenario, crop insurance adoption in the region is historically very low, even though the Federal Government has been providing premium subsidies for over a decade.

With this in mind, it is of great relevance to analyze the feasibility of implementing a weather index insurance (WII) scheme in the region. Such type of climate risk management tool is developed toward supporting the livelihood of vulnerable smallholders when catastrophes occur. As the payouts of WII products are driven by a pre-specified index, whose realizations depend on a given underlying weather variable, most of the issues that characteristically harm crop yield insurance schemes are addressed.

While mitigating asymmetric information and transaction costs, WII adds a different variable to this complicated equation. Basis risk arises in WII products because crop yield responses to the weather are inherently non-stationary across the area for which the contract is designed. Taking this into consideration, the association between crop yields and weather conditions was investigated through a Geographically Weighted Panel Regression (GWPR), a method that provides local estimates for the relationship of interest.

The results obtained by the GWPR model were scrutinized using such an analytical framework that the statistical significance of the coefficients estimated was taken as an indication of the minimization of design risk, the part of basis risk that can be effectively controlled by insurance designers. Within the set of municipalities analyzed for the production of beans and maize, the crops cultivated by the largest number of farmers in the Brazilian semi-arid, several locations had positive and statistically significant coefficients.

Based on the findings of the GWPR model, it was possible to define a sample of municipalities in the Brazilian semi-arid region for which a WII product was designed, priced and evaluated for effectiveness in mitigating downside risk. Considering parameters estimated through a model-based clustering algorithm, three crop contracts were developed for all the municipalities selected within the territory in order to address differences in local climate patterns.

Lastly, with all the necessary information, the effectiveness of the proposed WII product in mitigating downside risk were evaluated. To this end, mean-semivariance analysis and the Stochastic Efficiency with Respect to a Function (SERF) model were applied. Two scenarios were considered. In the first, farmers have no insurance. In the second, in turn, the WII product is adopted. As can be expected for a risk management tool, insurance adoption leads to decreases in downside risk, while also decreasing the expected return. Additionally, the WII product proved to be utility-efficient for risk-averse farmers within the Brazilian semi-arid.

The present analysis contributes to the literature and perhaps more importantly to practitioners. Based on investigations conducted worldwide, it was provided a simple yet powerful methodological framework in which both insurers and government agents may rely on to design and implement WII initiatives in Brazil. Moreover, monthly gridded data on the degree of aridity were generated, which can be used for several other purposes beyond the scope of this study. As a drawback, one must highlight the quality of interpolation results and the length of the time series of local crop yields, which may obstruct the development of more reliable insurance products.