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ORIGINAL ARTICLE

Spatial and seasonal dynamics of rainfall in subtropical Brazil

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Abstract:

The mapping of rainfall is fundamental in the hydrological modeling process. In this sense, the importance of knowing the geographic and seasonal dynamics of average estimates of rainfall and associated uncertainties is evident. Thus, the present study aimed to predict the spatial and seasonal distribution of rainfall, with the estimation of related uncertainties, in the state of Rio Grande do Sul (RS). Average rainfall varies over the months of the year. In January, February, June, July, August, and September it rains more north and northeast. In March, April, May, October, November, and December it rains more northwest and north. In general, it rains a lot in October and little rain in August. From a geographical point of view, it is possible to highlight that greater volumes of rain occur in the northern part of the state of RS. The uncertainties associated with rainfall estimates show divergent temporal dynamics, with the greatest uncertainties tending to occur in January, February, September, and October and that the smallest uncertainties are observed in June, July, and August.

Keywords: Pluviometric precipitation; State of Rio Grande do Sul; Geostatistics; Kriging; Uncertainty.

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1. Introduction

Rainfall is the most important component of the hydrological cycle, with drastic spatial and temporal changes (MAHMOUDI-MEIMAND et al., 2015), generating an irregular distribution with high regional variability and heterogeneity. The volume, temporal variation and duration of rainfall are some of the characteristics that directly or indirectly affect the population, economy, and environment (BRITTO, BARLETTA and MENDONÇA, 2008).

In agriculture, among other aspects, knowing the local conditions of soil and rainfall, and their variation throughout the cultivation cycle, are essential to obtain better agricultural yields (SILVA et al., 2007; SILVA, PRELA-PANTANO and SANT'ANNA NETO, 2008). The state of Rio Grande do Sul is highlighted by agricultural production. The majority of municipalities have grain cultivation as their main production (RIO GRANDE DO SUL, 2021), making the study of the spatial-temporal variability of rainfall in RS essential.

Many studies were carried out in order to understand the behavior of precipitation in the territory of the state of Rio Grande do Sul (RS). Berlato and Fontana (1999) related the interannual variability of rainfall with the variability of soybean yields in the state of Rio Grande do Sul. Carmona and Berlato (2002) evaluated the effects of El Niño and La Niña on irrigated rice crops in Rio Grande do Sul. Berlato, Farenzena and Fontana (2005) evaluated the relationship between rainfall variability and corn yield in the state of RS. Britto, Barletta and Mendonça (2006) evaluated the seasonal and monthly behavior of maximum rainfall. Britto, Barletta and Mendonça (2008) studied the spatial and temporal variability of precipitation in RS. Baratto and Wollmann (2015) studied the topo-oro-pluviometric profile in RS. Gross and Cassol (2015) evaluated the rainfall anomaly index in the state of RS. Shumacher and Teixeira (2016) studied the relationship between instability indices and extreme rain in the state of RS. Ananias et al. (2021) performed the comparison of methods of spatial interpolation of mean, median and maximum precipitation in RS.

Rainfall monitoring over time and space is highly necessary to provide a precise estimate of regional rainfall, a fundamental requirement in water resource management (SALLEH, AZIZ and ADZHAR, 2019). For this, a well-distributed rainfall network with sufficient pluviometers is essential (MAHMOUDI-MEIMAND et al., 2015), given that rainfall networks are usually formed by a limited number of monitoring stations and this may affect estimate quality.

Geostatistics aims to characterize a variable of interest, from a spatial point of view, by studying spatial variability and determining associated uncertainties (YAMAMOTO and LANDIM, 2013). Geostatistical methods use sample sites and distances between locations to estimate spatial autocorrelation functions and weight the average estimates of the variable of interest. The geostatistical estimation is usually obtained by the ordinary kriging method, being an unbiased estimator with minimal variance (SOARES, 2006; YAMAMOTO and LANDIM, 2013).

Kriging allows generating estimates and assessing the associated uncertainties (CIGAGNA et al., 2015), given that kriging variance (or kriging standard deviation or standard error) is a measure of variability/uncertainty influenced by the arrangement of the sampling points, with regions with higher station densities tending to generate rainfall estimates with smaller errors. Recently, Salleh, Azis and Adzhar (2019) carried out a review of studies on optimizing rainfall monitoring networks, showing the use of kriging variance in the optimization process. Hence, a kriging standard deviation or variance map may provide subsidies for the more appropriate establishment of a sampling grid (CIGAGNA *et al.*, 2015) and enable the evaluation of the propagation of uncertainty over time.

In this sense, the importance of knowing the geographic and seasonal dynamics of average estimates of rainfall and associated uncertainties is evident, since both the configuration of monitoring stations in the study area and the variation of the months of the year, can influence the rainfall estimation process. Thus, the present study aimed to predict the spatial and seasonal distribution of rainfall, with the estimation of associated uncertainties, in the state of Rio Grande do Sul.

2. Material and Methods

Monthly rainfall data were collected from 1989 to 2018 (30 years) in rainfall stations located in the territory of the state of Rio Grande do Sul. Only rainfall stations with at least five years of data (at least 15% of data over 30 years) were considered for the study, totaling 277 stations in the period. We used 259 stations from the National Water Agency (ANA) and 18 stations from the National Institute of Meteorology (INMET). Thus, we guarantee the spatial-temporal representation of rainfall variability through monthly climatological averages and the annual general climatological average. Figure 1 shows the spatial distribution of rainfall stations in Rio Grande do Sul.

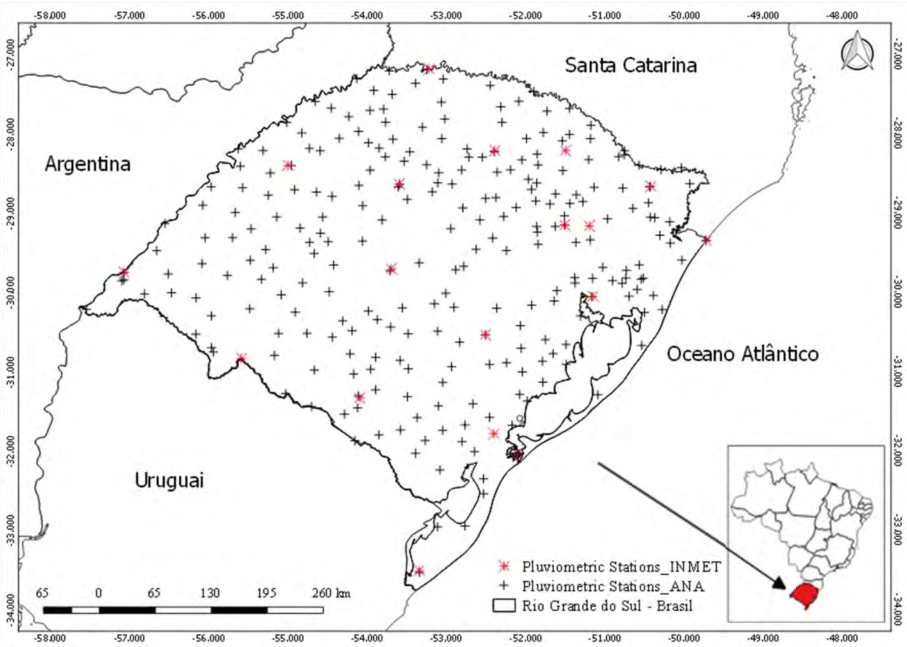

Figure 1: Map of the state of Rio Grande do Sul and spatial distribution of rainfall stations from the National Water Agency (ANA) and the National Institute of Meteorology (INMET).

To perform the data analysis, first, geostatistical analysis was used, through estimation of the robust semivariogram (CRESSIE and HAWKINS, 1980). Afterwards, a theoretical model is fitted to the sample semivariogram using the weighted least squares method. The spherical, exponential and Gaussian models were evaluated (ISAAKS and SRIVASTAVA, 1989; SOARES, 2006).

The choice of the best model was based on the evaluation of the correlation between semivariogram values and values predicted by the model ($corr[\hat{\gamma}(h), \gamma(h)]$). To assess the magnitude and classification of the spatial dependence structure, the Spatial Dependence Index (SDI) (SEIDEL and OLIVEIRA, 2016) and the Spatial Dependence Measure (SDM) (APELL NETO et al., 2020) were used. Based on the best-fitted model, rainfall was estimated in non-sampled locations using the ordinary kriging estimator, as per expression 1:

$$\hat{Z}(s_0) = \sum_{i=1}^{n} \lambda_i . Z(s_i) \tag{1}$$

where λ_i are the kriging weights ($\sum_{i=1}^{n} \lambda_i = 1$) for each of the points s_i and $Z(s_i)$ is the value of rainfall at the sampling point s_i, $i=1,2,\ldots,n$.

Afterwards, uncertainties were estimated through the kriging variance of rainfall. The kriging variance is estimated, at a non-sampled point, by expression 2:

$$\hat{\sigma}^2(s_0) = \sum_{i=1}^{n} \lambda_i . \gamma(s_i, s_0) + \mu \qquad (2)$$

where are the kriging weights ($\sum_{i=1}^{n} \lambda_i = 1$) for each of the points s_i, $\gamma(s_i, s_0)$ is the value predicted by the semivariogram model for the distance between the points s_i and s_0 and μ is the Lagrange multiplier, $i=1,2,\ldots,n$.

Monthly kriging prediction and kriging variance maps were generated for rainfall. With the exception of February, in all other months it was necessary to first model the first-order trend as a function of the latitude and longitude coordinates and then carry out the estimation by kriging.

Afterwards, to carry out an evaluation of candidate regions to receive new pluviometric stations, the estimation of the kriging variance for the annual average pluviometric precipitation was carried out.

All analyzes were performed using geoR package (RIBEIRO JR; DIGGLE, 2001) of the R software (R DEVELOPMENT CORE TEAM, 2019).

3. Results and Discussion

The fits of the semivariogram models are adequate, efficiently describing the behavior of the spatial variability structure, with correlation coefficients (between semivariances and the values predicted by the model) of at least 0.94, indicating optimal fits. The exceptions are the months of March and December, for which there are correlation coefficients of 0.73 and 0.87, respectively, which indicates slightly less efficient adjustments, but still good adjustments (Table 1).

Based on the SDI and SDM indices, a moderate to strong spatial variability structure occurs in February, April, May, June, July, September, and October (Table 1). Moderate and strong spatial dependencies indicate kriging interpolation results in good quality maps (PAZINI et al., 2015; OLDONI and BASSOI, 2016; APPEL NETO et al., 2018). On the other hand, weak structures of spatial variability are observed in January, March, August, November, and December, which can generate lower quality estimates on the maps. Appel Neto et al. (2020) suggest that the SDI and SDM indices should be used together to improve the process of description and classification of the spatial variability structure. Assessing the mean and median annual rainfall in RS, Ananias et al. (2021) observe a strong degree of spatial dependence.

March and December are the months of greatest concern in the assessment of the spatial variability of rainfall, as they have lower correlation coefficients (between semivariances and the values predicted by the model) and are classified as having weak spatial dependence.

Table 1: Model of semivariogram, Nugget effect, Contribution, Range, Correlation (between semivariogram values and the values predicted by the model), Spatial Dependence Index (SDI) and Spatial Dependence Measure (SDM), for month.

Month	Model*	Nugget effect	Contribution	Range	Correlation	SDI**	SDM***
January	Gaus	217.01	125.03	1.23	0.98	5.76 (w)	10.64 (w)
February	Exp	123.24	253.10	2.48	0.98	13.44 (s)	21.81 (m)
March	Sph	28.68	215.88	0.37	0.73	3.11 (w)	3.95 (w)
April	Sph	195.63	163.77	7.73	0.97	17.09 (s)	30.17 (s)
May	Sph	189.66	198.68	3.33	0.99	16.24 (s)	27.06 (s)
June	Gaus	135.68	213.39	3.78	0.99	29.60 (s)	42.28 (s)
July	Sph	86.51	271.16	2.70	0.99	19.51 (s)	26.70 (s)
August	Gaus	135.27	75.45	1.87	0.98	8.58 (w)	16.01 (w)
September	Gaus	234.97	223.33	2.06	0.99	12.86 (m)	20.57 (m)
October	Exp	201.35	406.46	3.90	0.99	21.01 (s)	34.20 (s)
November	Gaus	194.15	76.37	1.15	0.94	4.16 (w)	8.74 (w)
December	Sph	171.74	94.65	1.31	0.87	4.44 (w)	8.87 (w)

*Gaus = Gaussian, Exp = Exponential, Sph = Spherical. **SDI classification: w = weak, m = moderate, s = strong spatial dependence (SEIDEL and OLIVEIRA, 2016). ***SDM classification: w = weak, m = moderate, s = strong spatial dependence (APPEL NETO, et al., 2020).

Figure 2 shows the kiging maps for the twelve months of the year, where it is observed that there is a greater amount of rain in the northern region of the state of RS. In January, February, June, July, August, and September, the highest average rainfall is predicted in the north and northeast of RS. In March, April, May, October, November, and December, rainfall is predicted with higher average volumes in the north and northwest of RS. The central and northern regions of RS form the significant agricultural area for the cultivation of corn (BERLATO, FARENZENA and FONTANA, 2005) and soybean (BERLATO and FONTANA, 1999). Berlato, Farenzena and Fontana (2005) highlight that the most important rains in the agricultural calendar for corn are from October to March in the state of RS. As for soybeans, rainfall variability is more relevant from December to March (BERLATO and FONTANA, 1999).

The smallest predicted volumes of precipitation are concentrated in the south and southeast of RS in January, October, November, and December. Further east, lower volumes occur in March and April. The smallest volumes of precipitation in the west of RS are observed in June, July, August, and September. The west and center-south form the rice-growing region of RS (CARMONA and BERLATO, 2002).

The mean annual precipitation in the state of RS is higher in the north (BRITO, BARLETTA and MENDONÇA, 2008; RIO GRANDE DO SUL, 2021) and in the northeast (RIO GRANDE DO SUL, 2021), indicating a direct relationship between precipitation and latitude (ANANIAS et al., 2021). Baratto and Wollmann (2015) note that there is an orographic effect on rainfall in RS, causing differences in the distribution of total rainfall to occur both in the South-North and West-Northeast direction, with a greater effect in the direction South-North.

The predicted rainfall varies, from the smallest to the largest predicted precipitation, from south-southwest to north-northeast in January, February, June, July, August, and September. The predicted rainfall varies, from the smallest to the largest predicted precipitation, from South-Southeast to North-Northwest in March, April, May, October, November, and December.

The month of October stands out as having the highest predicted precipitation volumes. The month of August stands out as having the lowest predicted precipitation volumes.

Figure 3 shows the kriging variance maps for the twelve months of the year, where it is observed that the January, February, September, and October stand out for presenting greater uncertainties (larger kriging variances) associated with the average estimates climatological, generating more heterogeneous rainfall estimates (maps with orange to red colors). Britto, Barletta and Mendonça (2006) observe that, in summer, it rains more in the Northeast region of RS, due to convective rains associated with the convergence zones of the South Atlantic, and that, in spring, it rains more in the Northwest of RS, where occur the mesoscale convective complexes. According to Campos and Eichholz (2011), the mesoscale convective complexes are associated with intense rainfall, strong gusts of wind, and hail, which leads to more heterogeneous rainfall.

Regarding the winter period, the months of June, July, and August have lower estimated uncertainties, with lower values for kriging variances (maps with yellow to white colors) (Figure 3). In winter, there is more rain on the coast and in the South-Central state of RS due to the frontal atmospheric system (BRITTO, BARLETTA and MENDONÇA, 2006). Frontal precipitations have a long duration and cover large areas, generating more homogeneous rainfall.

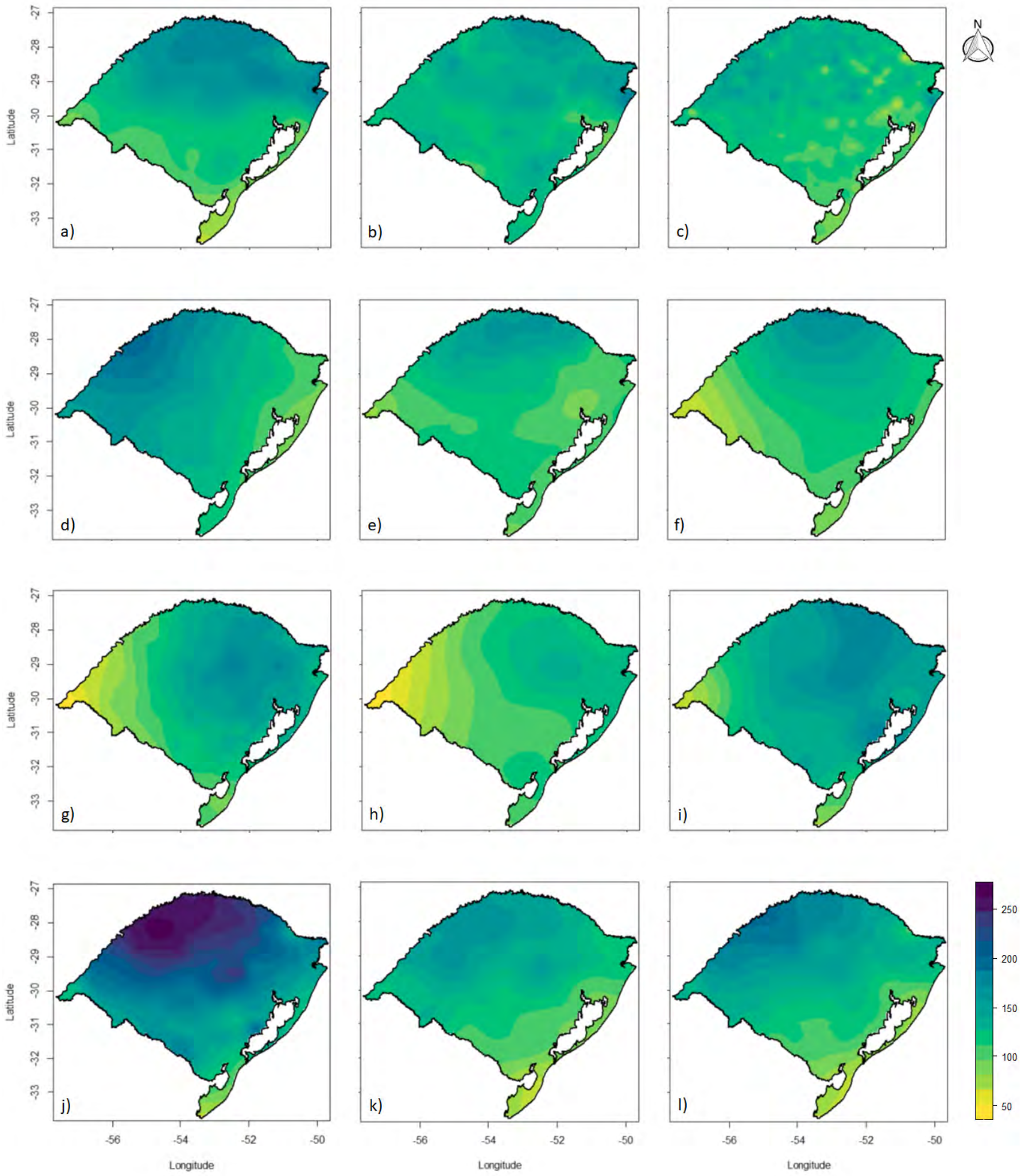

Figure 2: Kriging maps of the rainfall (mm) for the months of January (a), February (b), March (c), April (d), May (e), June (f), July (g), August (h), September (i), October (j), November (k) and December (l).

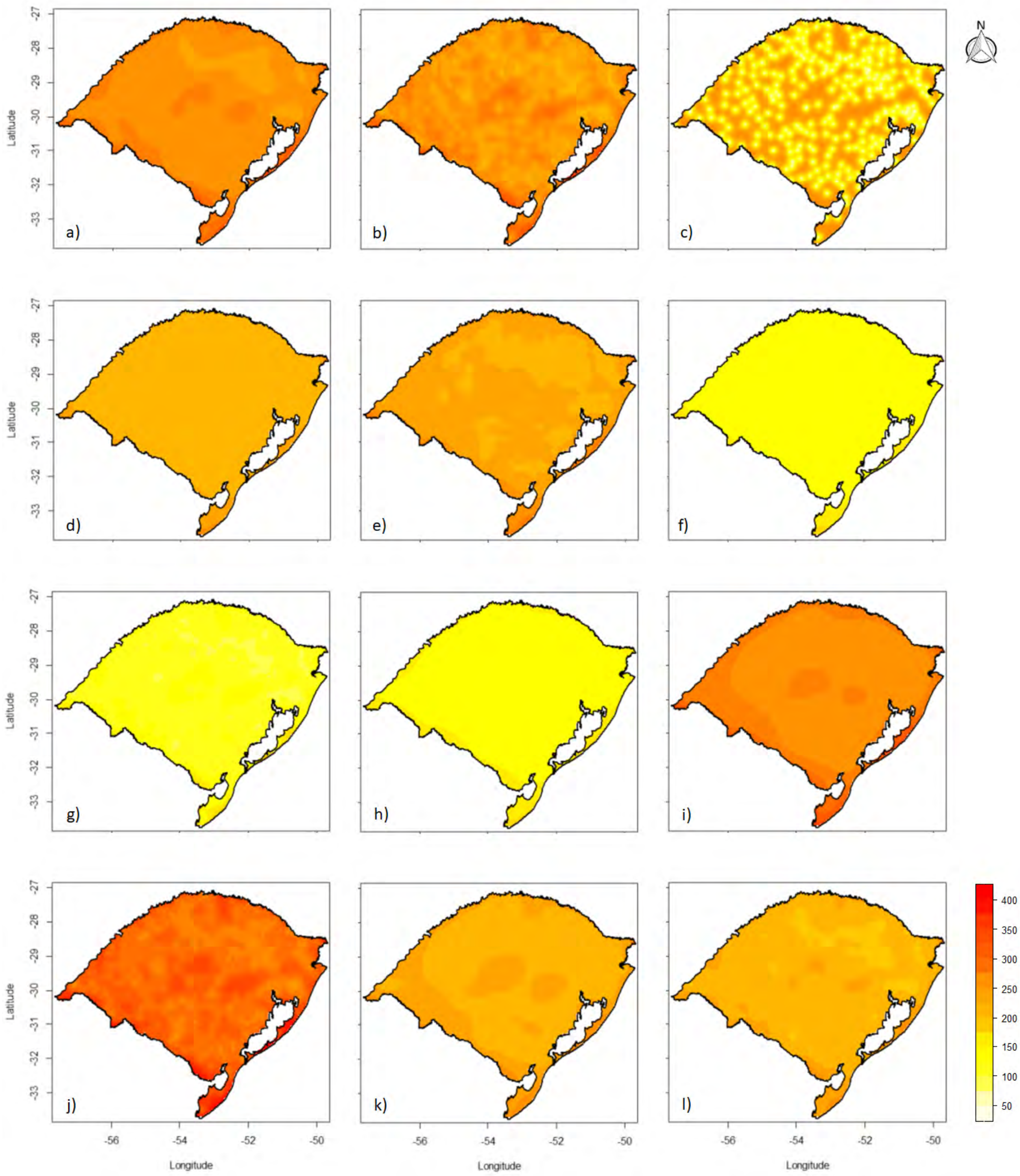

Figure 3: Kriging variance maps of the rainfall (mm²) for the months of January (a), February (b), March (c), April (d), May (e), June (f), July (g), August (h), September (i), October (j), November (k) and December (l).

Figure 4 shows the behavior of kriging (mean and amplitude) and kriging variance (average and amplitude), in each month of the year, in the state of Rio Grande do Sul.

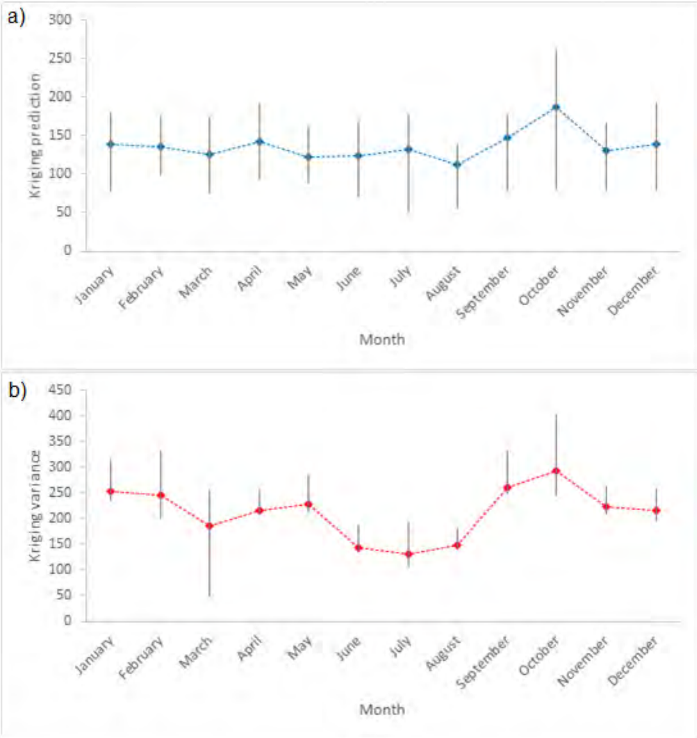

Figure 4: Behavior of kriging prediction (mean and amplitude) (mm) (a) and kriging variance (mean and amplitude) (mm^2) (b), in each month of the year, in the state of Rio Grande do Sul.

In Figure 4, the kriging predictions are similar, on mean, for all months of the year, except for October. October has the highest average predicted precipitation, but greater amplitude is also observed with places with minimum and higher rainfall.

Climatological normals indicate greater rainfall in September (data from 1961 to 1990) and in October (data from 1981 to 2010; data from 1990 to 2010) (INMET, 2022). The smallest precipitation volumes are observed in April (data from 1961 to 1990), in March (data from 1981 to 2010) and in August (data from 1990 to 2010) (INMET, 2022). According to the Climatic Atlas of Rio Grande do Sul (data from 1976 to 2005) (MATZENAUER, RADIN and ALMEIDA, 2011), it rains more in spring, corresponding to the months from September to December, with emphasis on the month of October as the rainiest month. Thus, it appears that there was a change over time in the behavior of monthly (seasonal) precipitation.

The smallest kriging variances, on average, occur in the winter months (Figure 4). This shows that the months of June, July, and August tend to have fewer uncertainties associated with rainfall. On the other hand, in the other months, there are greater variations in kriging (average and maximum), emphasizing the month of October, which presents the highest uncertainty estimate (Figure 4). Climatological normals indicate greater variability in August (data from 1961 to 1990) and in October (data from 1981 to 2010; data from 1990 to 2010) (INMET, 2022). Smaller variability is observed in May (data from 1961 to 1990; data from 1981 to 2010; data from 1990 to 2010) (INMET, 2022). Thus, it appears that there was a change over time in the month with greater variability.

Gross and Cassol (2015) observed greater negative rain anomalies in spring and summer and greater positive anomalies in the autumn and winter. These findings indicate fewer rain events in the hot months and more rainfall in the cold months of the year, which corroborates the results of greater kriging variances in the hot months and smaller kriging variances in the cold months. Furthermore, Gross and Cassol (2015) highlighted the month of October as having the highest number of negative rain anomaly events, a fact that coincides with our observation of greater kriging variances in October.

Figure 5 shows the behavior of the kriging prediction, in general, in the state of Rio Grande do Sul. Higher volumes of rain are observed in the north of RS, which is corroborated by the Climatic Atlas of Rio Grande do Sul (MATZENAUER, RADIN and ALMEIDA, 2011), which indicates greater annual precipitation in the northeast and north of Rio Grande do Sul.

It is observed that for higher predicted values, in general, there is a tendency for kriging variance to decrease, indicating that places with higher volumes of precipitation have less variability (Figure 5).

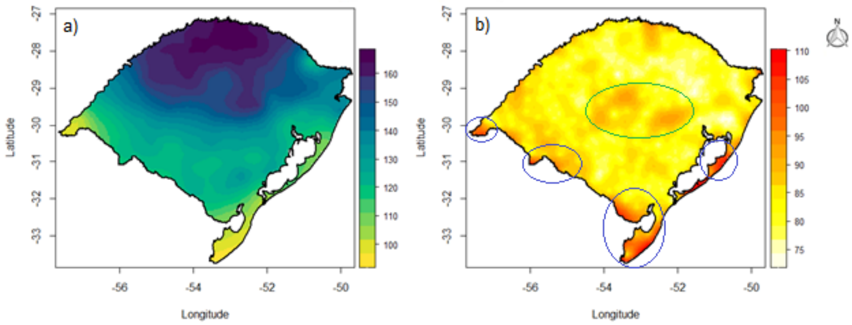

Figure 5: Average map of the kriging prediction (mm) (a), average map of the kriging variance (mm^2) and location of candidate sites to receive pluviometric stations (b).

In addition, Figure 5 shows the behavior of the estimated kriging variance, in general, and the location of possible candidate regions to receive new rainfall stations in Rio Grande do Sul. It can be seen that the areas close to the coast, to the south and west of RS, which are circled in blue on the map, are those with the greatest kriging variances, indicating greater uncertainties associated with rainfall estimates (orange to red color scale). Cigagna et al. (2015) comment that uncertainty increases as it moves towards the edges of the area where the sampling grid is smaller (less dense).

In this sense, one possibility is to use rainfall data from regions neighboring the state, such as ANA and INMET rainfall stations in southern Santa Catarina territory and western Argentina. Ceron et al. (2021), when carrying out the precipitation prediction in the La Plata Basin, which covers part of the territory of RS, showed that pluviometric precipitation data from stations located in Argentina can be used.

Furthermore, in Figure 5 the Central region (circled in green on the map) can be highlighted, with greater kriging variances. Thus, the Center, Coast, South and West regions of RS are candidates to receive new pluviometric stations or station reallocation.

Redundant stations with little or no contribution to reducing network variation can be eliminated or ideally located in areas of high network variability (SALLEH, AZIZ and ADZHAR, 2019). Thus, it is possible to optimize the development of a network rainfall with a smaller number of stations (MAHMOUDI-MEIMAND et al., 2015).

4. Conclusions

Greater volumes of rain occur in the northern part of the state of RS, and the average rainfall varies over the months of the year. In January, February, June, July, August, and September it rains more north and northeast. In March, April, May, October, November, and December it rains more north and northwest. It rains a lot in October and little rain in August.

The uncertainties associated with rainfall estimates show a divergent temporal dynamics between hot months, characterized by more heterogeneous rainfall, and cold months, characterized by more homogeneous rainfall. It is possible to highlight that the greatest uncertainties tend to occur in the months of January, February, September and October and that the smallest uncertainties are observed in the months of June, July and August.

It was possible to observe that the spatial configuration of the meteorological stations interferes in the uncertainties, and the regions located in the Coast, in the South, in the West and in the Center of Rio Grande do Sul, are regions that present high values of uncertainty associated with the rainfall. Such regions are candidates to receive new meteorological stations in the future in an attempt to minimize the uncertainties associated with the estimation of rainfall for the state of Rio Grande do Sul.

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AUTHOR´S CONTRIBUTION

A. Pisoni and E. J. Seidel conceptualized and designed the research. A. Pisoni and E. J. Seidel carried out data analyses. A. Pisoni, J. B. Pazini and E. J. Seidel drafted the manuscript. All authors read revised and approved the final manuscript.

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