

Hourly-Scale Modeling of Storm Transitions in Southern Brazil with Markov Chains

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Abstract. Southern Brazil faces escalating flood risk, yet intraday storm dynamics remain under-characterized. This study aims to characterize the temporal dynamics of storm intensity and persistence at the intraday scale. To achieve this, we apply a season-resolved, intraday Markov chain framework for storm state transitions. Variable Length Markov Chain analysis (VLMC) of storm state transitions, using hourly precipitation from 15 INMET stations *in situ* from 2007 to 2024. Storms were identified and quantified by depth, duration, and intensity, then classified into Moderate, Strong, and Very Strong states. Peak mean intensities reach 9 to 11 mm h⁻¹ in mountainous units, compared with maxima near 7 mm h⁻¹ on the coast, where mean intensities are about 3 mm h⁻¹. Storms last roughly 11 to 13 hours in the Southern Plateau and Southern Shield, and 15 to 17 hours in the Central Depression and Coastal Plain, indicating greater lowland persistence. Transition probabilities indicate enhanced persistence of intense storms in orographic regions, while lowland areas exhibit faster dissipation. Upward transition probabilities increase in summer, with Moderate to Strong and Strong to Very Strong reaching about 0.20 in orographic areas, while persistence of Very Strong ranges from 0.10 to 0.20 in the Southern Shield. In winter, downward transitions to Moderate exceed 0.90 across most of the domain. Storm transitions show consistent behavior within each season and are well represented by a first-order Markov chain. Chi square diagnostics support first order, season-specific chains with stable transition structure. These intraday, spatially resolved probabilities link geomorphology to storm persistence and provide actionable inputs for early warning, zoning, and climate risk management.

Keywords: storm intensity, VLMC, orographic influence, climate variability.

1 Introduction

Precipitation is one of the most important atmospheric elements in the climatic context, with direct impacts on economic activities, water resources, and the daily lives of the population (Agel et al., 2015). In southern Brazil, especially in the state of Rio Grande do Sul, episodes of heavy rainfall and extreme storms have become increasingly frequent and severe, causing

flooding, landslides, and social and economic losses (Guedes et al., 2019; Junges et al., 2019; Minuzzi and Lopez, 2013; Ribeiro-Viana et al., 2009; Valente et al., 2023). The growing occurrence of these extreme events raises concerns about future changes in regional climate patterns (Avila-Diaz et al., 2020) and demands detailed analyses of their temporal and probabilistic characteristics. Recent studies at regional and national scales have documented an overall intensification of precipitation extremes—including very wet days (R95p), maximum 1-day precipitation (Rx1day), and precipitation intensity (SDII)—with particularly robust and consistent increases observed in southern Brazil (Regoto et al., 2021; de Souza et al., 2026). ~~Recent studies at regional and national scales have further documented intensification in precipitation extremes, including increases in indices such as R95p, Rx1day, and rainfall intensity, especially in southern Brazil~~ (Regoto et al., 2021; de Souza et al., 2026). These changes are consistent with broader patterns identified across southeastern South America, where long-term precipitation increases have been associated with modifications in large-scale circulation and moisture transport (Barros et al., 2008).

Previous studies have already demonstrated an increase in the frequency and intensity of extreme events in Rio Grande do Sul (Berlato et al., 2007; Junges et al., 2019; Melo et al., 2015). Valente et al., (2023), showed that, based on analyses of 20th-century events, years influenced by the El Niño phenomenon tend to exhibit positive precipitation anomalies, whereas La Niña years are associated with water deficits~~when analyzing events from the 20th century, observed that years influenced by the El Niño phenomenon tend to show positive precipitation anomalies, while La Niña years are associated with water deficits~~. This relationship between oceanic patterns and rainfall behavior was also evidenced by Santos; Barbosa-Diniz, (2014), who demonstrated the influence of oceanic indices on the variability of monthly precipitation in Rio Grande do Sul.

The occurrence of extreme precipitation events in southern Brazil is strongly influenced by a combination of atmospheric systems acting across multiple scales. Synoptic and mesoscale processes, such as frontal systems, Mesoscale Convective Complexes (MCCs), and the South American Low-Level Jet (SALLJ), play a central role in modulating moisture transport, convection, and rainfall persistence (Luiz-Silva et al., 2021; Martinez and Solman, 2022). These systems contribute to the development of intense and long-lasting precipitation events, particularly during the warm season, when enhanced moisture advection and atmospheric instability favor convective organization. In addition, the influence of large-scale climate modes such as ENSO has been widely documented, with El Niño phases typically associated with above-average precipitation and La Niña with deficits in the region (Santos and Barbosa Diniz, 2014; Valente et al., 2023). This combination of large-scale forcing and regional atmospheric dynamics helps explain the increasing frequency and severity of hydrometeorological extremes observed in recent decades.

Despite these advances, there are still gaps in understanding precipitation behavior on shorter time scales, such as hourly precipitation, and how these events are temporally organized. The growing use of high-frequency data in nowcasting applications highlights the importance of understanding precipitation dynamics at the hourly scale (Davis et al., 2014).

particularly for improving the characterization of storm evolution at intraday resolutions. In this context, the characterization of extreme events using statistical tools such as trend analysis, probability distributions, and Markov Chains allows not only for the description of observed patterns but also for the projection of likely future states based on the temporal dependence of the data (Junges et al., 2019).

Markov chains provide a useful framework for representing temporal dependence and persistence in precipitation processes, allowing the probabilistic characterization of transitions between rainfall states. Markov chains have been widely used to model rainfall data. The first known application was carried out by (Gabriel and Neumann, (1962) using rainfall records from Israel, and numerous applications have been developed since then. More recently, Wilks (2011) consolidated these methods, emphasizing their value for simulating precipitation sequences in atmospheric sciences. Previous studies have used Markov chains to analyze precipitation in Brazil. For example, Back (2017) applied a stochastic Markov chain model to study daily precipitation in the state of Santa Catarina, in southern Brazil, describing geographical patterns of rainfall. Similarly, Jale et al., (2019) examined rainfall on a daily scale in three states (dry, humid, and rainy) for the state of Paraíba, in northeastern Brazil. In their study, they reported transition probabilities between states, equilibrium probabilities, and expected durations for the different states. More recently, Vargas; Corso; Vallejos, (2022) applied Markov chains to assess how normal climate patterns may shift to altered states in the future for the city of Caxias do Sul, in the state of Rio Grande do Sul. They used the results of Markov modeling to support agricultural planning in the context of climate change.

The present study proposes an integrated analysis of the temporal and probabilistic behavior of storms in southern Brazil, with an emphasis on the eastern portion of the Rio Grande do Sul state, consists of the Jacuí Basin, the São Gonçalo Basin, and rivers that flow directly into the Atlantic Ocean - Drainage Area of the Lagoons (DAL), using hourly precipitation data from the Instituto Nacional de Meteorologia (INMET). The study aims to characterize storms and model the transitions through Markov chains.

Recent hydrometeorological disasters in southern Brazil, including the September 2023 crisis and the unprecedented rainfall of April to May 2024, expose systemic vulnerabilities in flood preparedness and motivate analyses that resolve storm evolution at intraday scales (Alvalá et al., 2024; Collischonn et al., 2025). Most regional climatologies emphasize annual signals (Berlato et al., 2007; Guedes et al., 2019; Junges et al., 2019; Minuzzi and Lopez, 2013), monthly or seasonal behavior (Britto et al., 2006; Marques and Möller, 2008; Santos and Barbosa Diniz, 2014; Valente et al., 2023), or daily statistics (Dorneles et al., 2020; Melo et al., 2015; Sanches et al., 2019; Schumacher et al., 2016; Teixeira and Prieto, 2020a), leaving intraday persistence and transition dynamics underexplored. This gap is particularly critical, as flood generation processes are strongly influenced by sub-daily rainfall organization, which cannot be fully captured at coarser temporal resolutions.

100 ~~In this context, the objective of this study is to characterize the temporal dynamics of storm intensity and transitions at the intraday scale in southern Brazil. Addressing this gap, To achieve this,~~ we use hourly precipitation from 15 stations from 2007 to 2024 to identify storms, quantify depth, duration, and intensity across contrasting physiographic units, and estimate season-specific transition probabilities among intensity states ~~w~~using a Markov chain framework~~ith Variable Length Markov Chains~~. This intraday, state-based framework yields spatially and seasonally resolved metrics of intensification and
105 persistence that can feed early warning, strengthen risk mapping, and support the revision of hydrologic design criteria in flood-prone basins.

~~The structure of the document is organized as follows. Chapter 2 presents a description of the study area and the precipitation data used. Chapter 3 details the methodology applied for storm characterization and Markov chain modeling. Chapter 4, presents and maps the results, followed by a discussion in light of the existing literature. Finally, Chapter 5 provides the main conclusions of the study.~~

2 Study area and precipitation data

The study area is located in southern Brazil, in the state of Rio Grande do Sul (see Figure 1a). The eastern portion consists of the Jacuí Basin, the São Gonçalo Basin, and rivers that flow directly into the Atlantic Ocean (see Figure 1b).
115 Collectively, we refer to this as the Drainage Area of the Lagoons (DAL). In this region, rivers drain into the large lagoons of southern Brazil, including Lagoa dos Patos, Lagoa Merín, and Lagoa Mangueira (Marques; Möller, 2008).

The Jacuí Basin discharges its waters into Lagoa dos Patos via the Guaíba River, on which the city of Porto Alegre is located (see Porto Alegre station in Figure 1), the main city in southern Brazil. The São Gonçalo Basin, in turn, acts as a natural channel connecting Lagoa dos Patos and Lagoa Mirim, regulating water flow in the lower part of the system (Marques; Möller,
120 2008).

A total of 15 weather stations with hourly data from 2007 to 2024 were used. These data are publicly available from the ~~Instituto Nacional de Meteorologia (INMET)~~ at <https://portal.inmet.gov.br/dadoshistoricos>. The spatial distribution of the stations is evenly spread across DAL, as shown in Figure 1c, and the statistical basic data of the stations are presented in Table 1.

125 The mountainous region of DAL is concentrated in the north, in the Souther Plateu, reaching a maximum elevation of 1,373 meters above sea level (m a.s.l.) (See Figure 1). In the south, the terrain features slightly lower mountains, around 300 m a.s.l., in the Souther Shield. Meanwhile, the lowland areas are prone to prolonged flooding, particularly in the Central Depression and Coastal Plain (Valente et al., 2023).

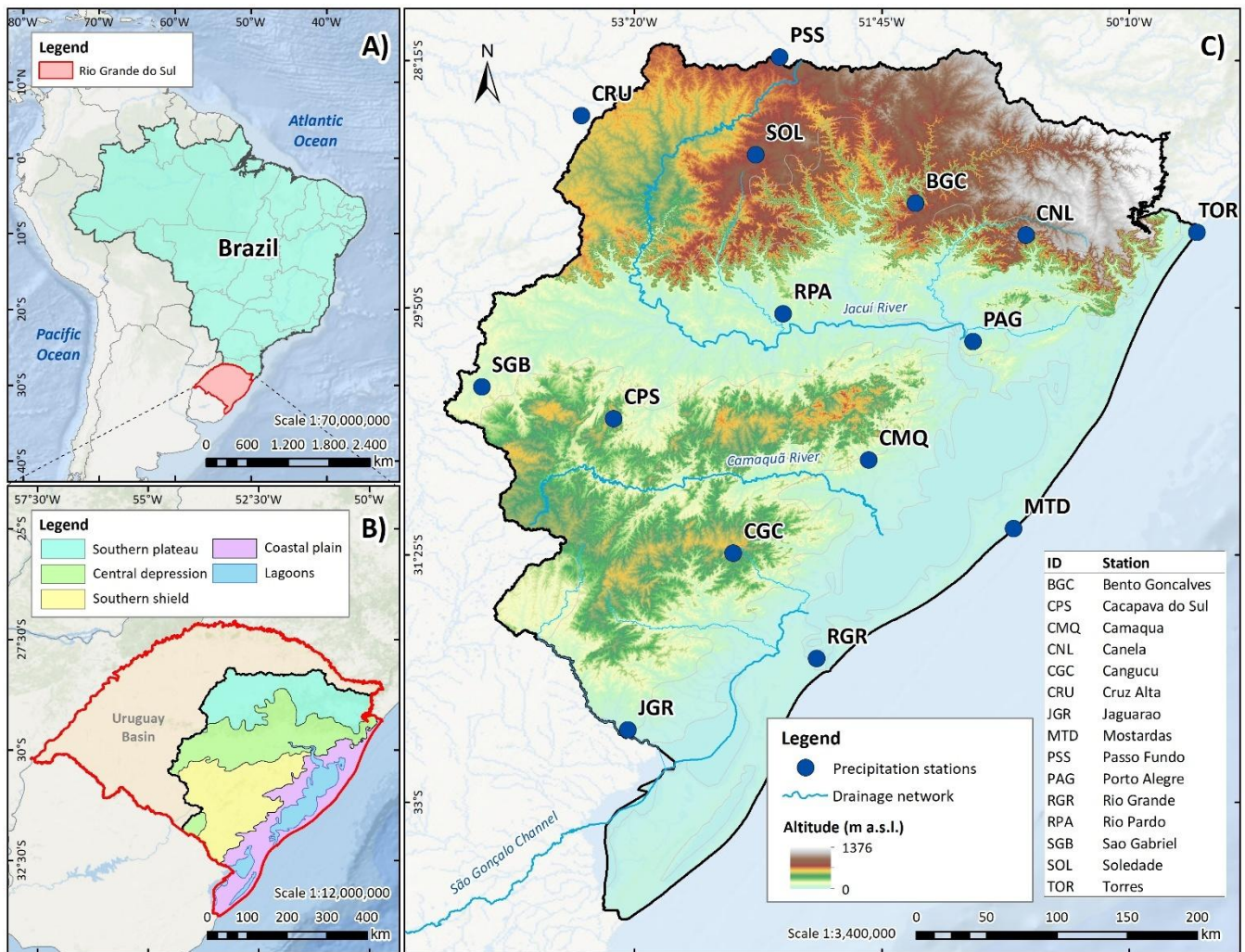


Figure 1. Localization of the Drainage Area of the Lagoons (DAL) and weather stations

Table 1. Basic statistical description of the rainfall stations with hourly data used

Station	ID	Mean <u>hourly</u> <u>precipitation</u> (mm)	Maximum <u>precipitation</u> <u>hourly</u> <u>precipitation</u> (mm)	<u>Standard</u> <u>deviation</u> <u>Desvest</u> <u>of</u> <u>hourly</u> <u>precipitation</u> (mm)	Missing data (%)
Bento Goncalves	A840	0.19	56.8	1.19	3.46
Cacapava do Sul	A812	0.2	45.8	1.26	3.05
Camaqua	A838	0.18	51.4	1.08	5.66
Canela	A879	0.25	59.4	1.22	15.29

Cangucu	A811	0.18	46.4	1.1	8.98
Cruz Alta	A853	0.2	47	1.32	5.04
Jaguarao	A836	0.16	48.8	1.09	6.75
Mostardas	A878	0.13	30.4	0.91	19.62
Passo Fundo	A839	0.21	47.8	1.27	1.23
Porto Alegre	A801	0.18	37.8	1.12	0.75
Rio Grande	A802	0.14	85.8	1.09	7.97
Rio Pardo	A813	0.19	46.4	1.18	4.88
São Gabriel	A832	0.17	76.8	1.21	11.24
Soledade	A837	0.21	47.4	1.33	10.85
Torres	A808	0.18	50	1.09	10.29

3 Methodology

The study utilized 15 hourly precipitation stations provided by INMET. Storm characterization was conducted using the hourly precipitation data as recommended by (Lamjiri et al., 2017). From the characterization of storms, the following variables were obtained: total storm precipitation, storm duration, maximum storm intensity, and average storm intensity.

The maximum storm precipitation data, which is a categorical variable, was taken, and the 95th and 99th percentiles were estimated to define the states: Moderate, Strong, and Very Strong Storms. These were the states used for Markov chain modeling.

For each station, four season-specific Markov chains were fitted to account for seasonal differences in storm-intensity transitions. Before modeling, the order of the chains was verified with a chi-square test and the homogeneity of the time series. The general scheme of the methodology can be seen in Figure 2.

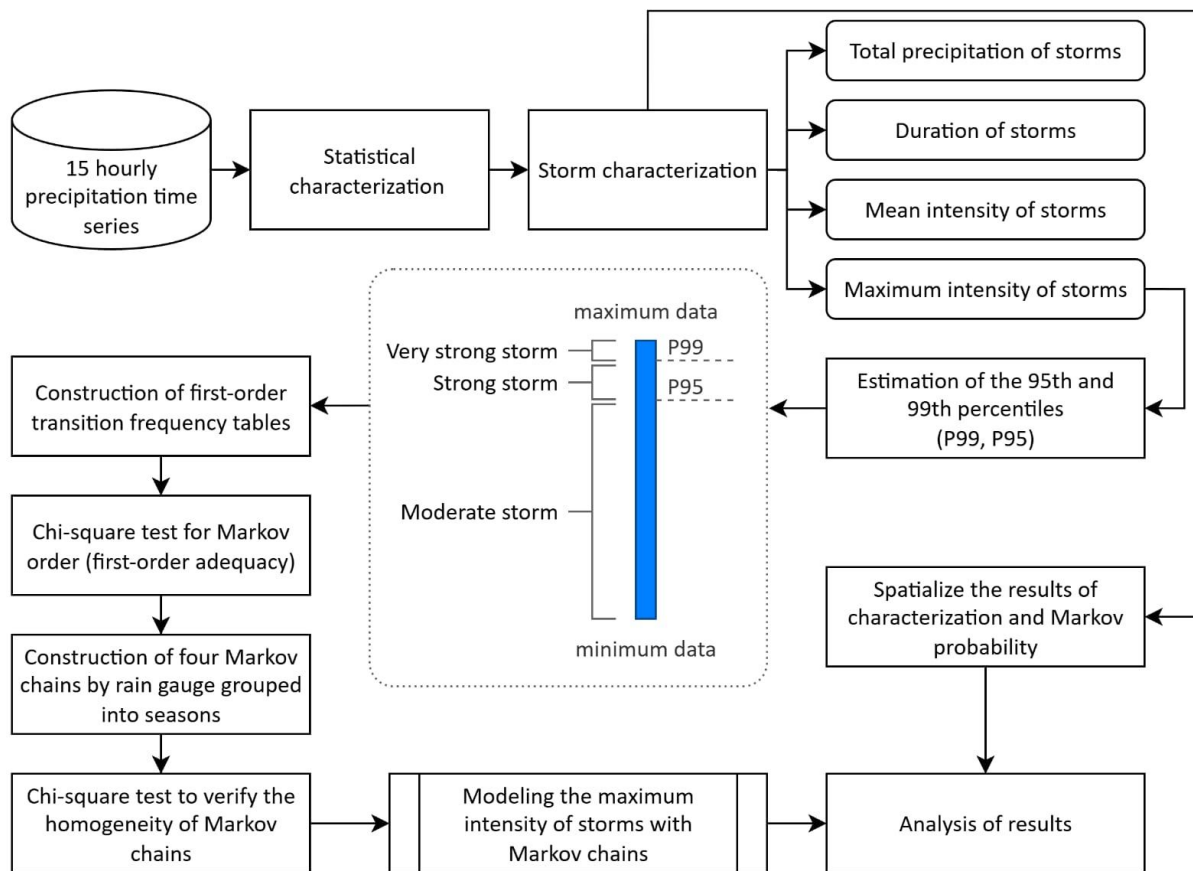


Figure 2. General methodology for storm analysis at hourly scale

145 3.1 Characterization of storms

In this study, hourly precipitation data were used to identify "storms". A storm is defined as a continuous stretch of precipitation separated by at least 6 hours of zero precipitation, with a minimum total precipitation of 5 mm. This criterion for defining a storm was adopted from previous studies to ensure comparability (Lamjiri et al., 2017; Palecki et al., 2005). For each storm, the total precipitation (mm) was estimated as the sum of hourly precipitation values from the start to the end of the event. The storm duration (h) was defined as the number of hours with a minimum total precipitation of greater than 5 mm, from the beginning to the end of the event. The average storm intensity (mm h^{-1}) is the total precipitation divided by the storm duration. Finally, the maximum storm intensity (mm h^{-1}) is the highest hourly precipitation rate observed from the beginning to the end of the event (see Figure 3). The variables characterizing the storm, as defined above, were spatialized as an average over the study basin.

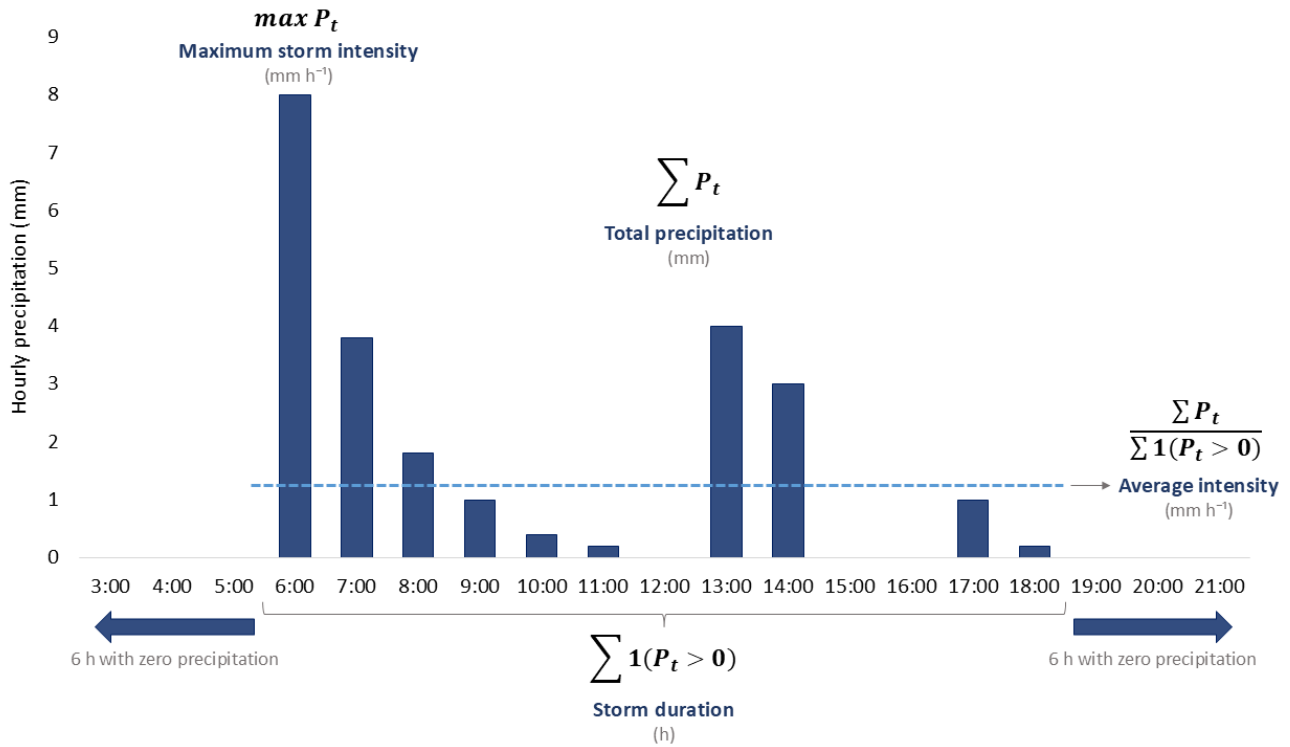


Figure 3. Graphical definition of storm-event metrics and detection criteria

3.2 Methodology for Calculating the Transition Probability Between Storm States using Markov Chains

3.2.1 Organization and discretization of storm intensity data

The variables resulting from the characterization of storms were examined statistically and graphically. An exploratory analysis was performed on the mean, median, standard deviation, and coefficient of variation (Table 1). Stations were compared using these descriptive statistics grouped according to these variables, frequency histograms and violinbox plots were generated to support the analysis. for them, and T the data were subsequently analyzed by season.

The seasons of the year were defined based on the dates of the solstices and equinoxes for the southern hemisphere. Summer was defined as December 21 to March 20 (of the following year), fall as March 20 to June 20, winter as June 20 to September 22, and spring as September 22 to December 21.

Considering the statistical analysis, the maximum storm intensity series at each rainfall station were modeled using Markov chains, grouped by season. The 95th and 99th percentiles of the intensity distribution were used as thresholds to define the state boundaries, as shown in Table 2, following approaches adopted by other authors (Gao et al., 2021; Jiang et al., 2023; Kemsley et al., 2024). This percentile-based approach is widely used in climate extremes analysis, particularly within the framework of the Expert Team on Climate Change Detection and Indices (ETCCDI), where indices such as R95p and R99p are employed to identify very wet and extremely wet events (Zhang et al., 2011).

Table 2. Classification of rainfall intensity states

States	Criterion
Moderate Storm	Intensity < 18 mm h ⁻¹
Strong Storm	Intensity ≥ 18 mm h ⁻¹ and ≤ 23 mm h ⁻¹
Very Strong Storm	Intensity > 23 mm h ⁻¹

175

3.2.2 Evaluation of assumptions for Markovian modeling

First-order dependency was evaluated by comparing observed and expected frequencies in the transition matrices. For each combination of station and season, first-order transition matrices were constructed, representing the probabilities of transitioning from one discrete rainfall intensity state to another in consecutive events. These matrices quantify the conditional probabilities (Eq. 1).

180

$$P(X_t = j | X_{t-1} = i) \quad (1)$$

where X_t denotes the discrete state of rainfall intensity at time t , and i, j are the possible states (Moderate, Strong, Very Strong).

This formulation embodies the Markovian dependence property (Norris, 1997; Ross, 2014), where the probability distribution of the current state depends only on the immediately preceding state (Eq. 2).

185

$$P(X_t | X_{t-1}, X_{t-2}, \dots, X_1) = P(X_t | X_{t-1}) \quad (2)$$

This assumption allows modeling the temporal dynamics through a single-step transition matrix, simplifying estimation and interpretation.

The transition matrix P was constructed by computing the relative frequencies of state transitions over consecutive events, as shown in Eq. (3).

190

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix} \quad (3)$$

Where each element P_{ij} represents the probability of transitioning from state i to state j . The assumption of a first-order Markov process implies that the future state depends only on the present state, simplifying the modeling of storm persistence and progression.

195 To investigate potential seasonal differences in transition behavior at each station, a chi-square test was applied to the corresponding transition matrices. Rather than treating the data as a single continuous series, the time series at each location was segmented into four separate Markov chains—one for each of the four seasons: summer, fall, winter, and spring. This approach made it possible to observe seasonal patterns more clearly and assess whether state transition probabilities remained stable within each period. Verifying this internal consistency was key, as it supported the decision to represent each season
 200 with a distinct transition matrix, thereby preserving the integrity of intra-seasonal dynamics while avoiding the distortion that could arise from mixing data across different times of the year. The chi-square test was applied to verify the temporal homogeneity of transition probabilities within each season, ensuring that the Markov chain assumptions of stationarity and first-order dependence were satisfied.

205 3.2.3 Estimation and Application of the Markov Model

The transition probability matrices were estimated by calculating the relative frequencies of transitions between discrete states. These matrices were used to quantify the conditional probability of observing a given rainfall intensity state, given the state of the preceding event (Gabriel and Neumann, 1962; Wilks, 2011). This approach allows simulating future sequences of rainfall intensity by sequential sampling from the estimated transition probabilities (Eq. 4).

$$210 \quad P(X_t = j | X_{t-1} = i) = \frac{N(i \rightarrow j)}{\sum_k N(i \rightarrow k)} \quad (4)$$

Where $N(i \rightarrow j)$ is the number of transitions observed from state i to j , and the denominator $\sum_k N(i \rightarrow k)$ is the total number of transitions departing from i across all possible states k , ensuring that each row of the matrix sums to one. This formulation ensures that the probabilities in each row of the transition matrix sum to one, forming a stochastic matrix. The model provides a framework to assess the likelihood of occurrence of *Moderate*, *Strong*, or *Very Strong* events conditioned on
 215 antecedent conditions, supporting the analysis of temporal persistence patterns. It is important to note that the Markov assumption implies that the process is memoryless beyond one lag and that the estimated probabilities are assumed constant across the observed period. The temporal homogeneity of transition probabilities within each season was explicitly evaluated using chi-square tests (see Appendix A1), supporting the use of time-homogeneous Markov chains.

To avoid linking events separated by long gaps, each seasonal series (summer, fall, winter, spring) was split by year, and transitions were computed only within the same seasonal block. Here s denotes the season and y the year of observation. At the start of each new season, the chain was “reset,” meaning that the first event of the season s in year y is treated as independent of the last event of season s in year $y - 1$ (Eq. 5).

$$P(X_1^{(s,y)} = j | X_{last}^{(s,y-1)} = i) = P(X_1^{(s,y)} = j) \quad (5)$$

This simple reset procedure, ~~inspired by the idea of Variable Length Markov Chains (VLMC) avoids linking events separated by long temporal gaps and ensures that transitions are evaluated within consistent seasonal blocks.~~ (Bühlmann and Wyner, 1999), ~~prevents spurious transitions between years and yields a more realistic picture of how storms evolve within each season.~~
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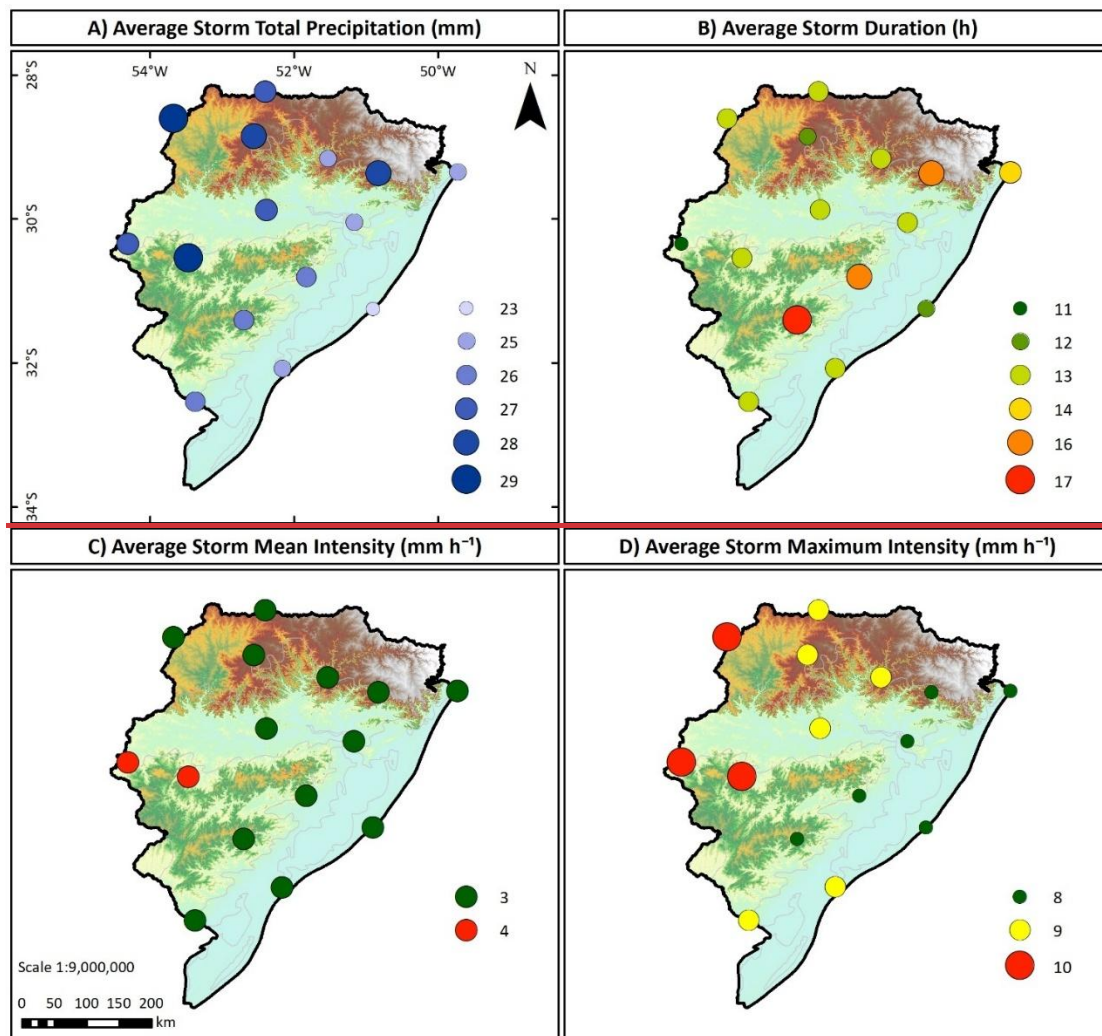
4. Results and discussion

4.1 Storm Characterization

The results of the storm characterization are presented in Figure 4. The highest precipitation amounts occur in the Southern Plateau, with average magnitudes of approximately 29 mm per event. Total precipitation shows a decrease, being greater in the Southern Plateau (north) and decreasing toward the Coastal Plain (south), with a slight increase observed in the mountainous region of the Southern Shield.

The average storm duration is shorter in the mountainous areas of the Southern Plateau and Southern Shield, ranging between 11 and 13 hours, whereas the longest-lasting storms occur in the ocean-facing foothills of the Central Depression and Coastal Plain, ranging between 14 and 17 hours.

Rainfall intensities are higher in the western part of the DAL and lower near the ocean. Consequently, maximum intensities are also greater in the west, particularly in the mountainous zones of the Southern Plateau and Southern Shield, where average peak values range from 9 to 10 mm h⁻¹. In contrast, precipitation intensities are lower in the Coastal Plain, with mean values of 3 mm h⁻¹ and maximum intensities averaging around 8 mm h⁻¹.



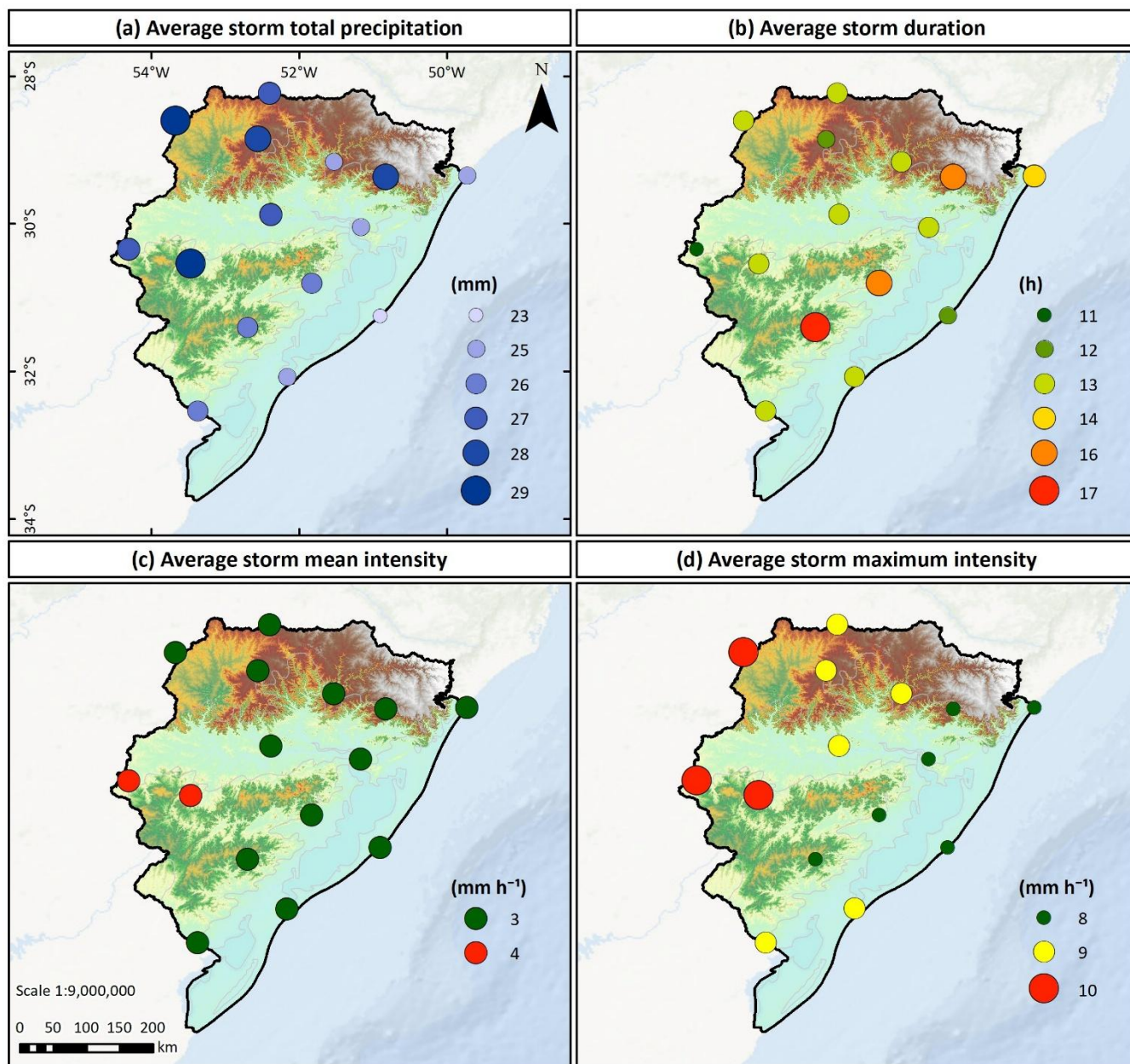
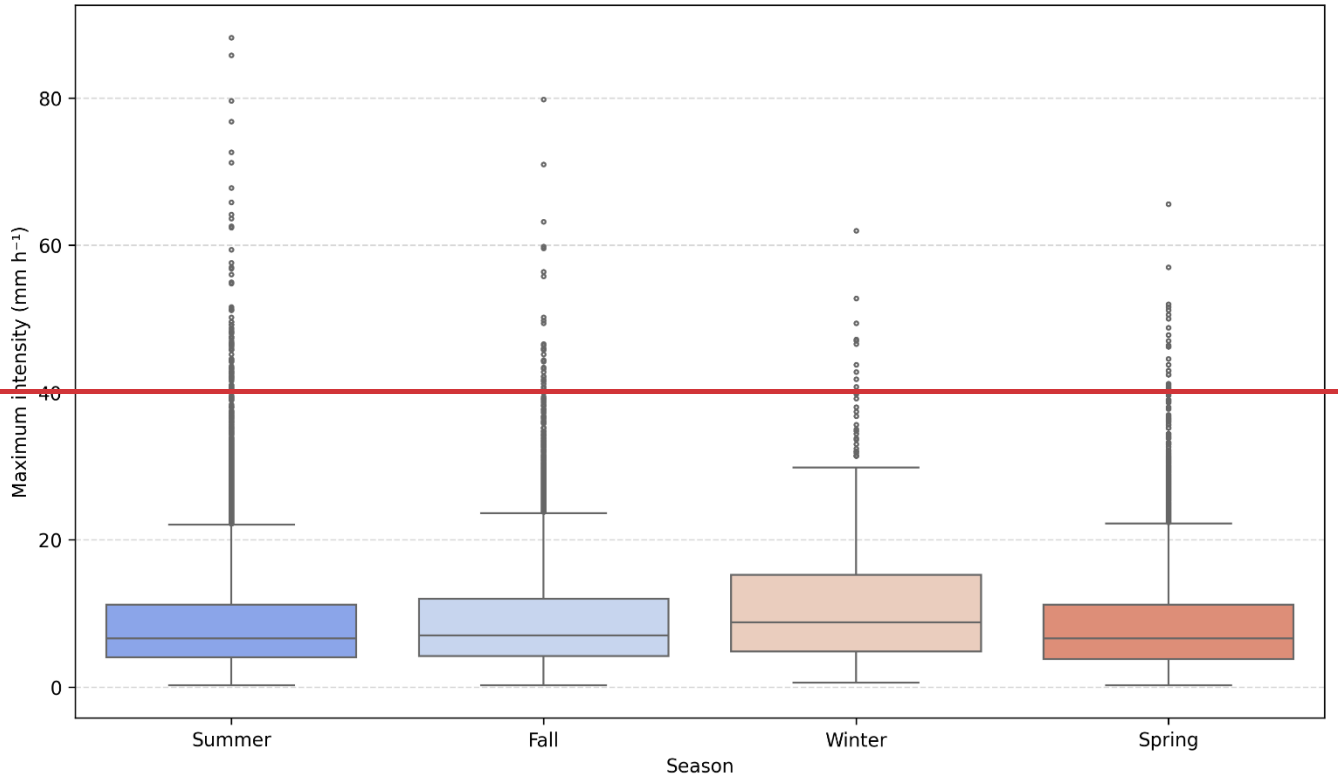


Figure 4. Spatialization of the average storm behavior in terms of (a) magnitude, (b) duration, (c) average intensity and (d) maximum intensity of storms

4.2 Verification of Markov Chain Assumptions and Seasonal Rainfall Intensity Analysis

The time series modeled with Markov chains corresponds to the ~~Average~~ Maximum ~~Rainfall-Storm~~ Intensity of the storms characterized in the previous analysis. An exploratory graphical analysis was conducted to evaluate potential seasonal differences. Figure 5 presents ~~violin box~~ plots of the data grouped by season, ~~alongside the annual distribution for comparison.~~

The results highlight clear seasonal contrasts. During summer, rainfall intensities are higher in terms of magnitude (greater extreme values between 27 mm h⁻¹ and 90 mm h⁻¹), ~~higher~~ frequency (~~123 outliers~~), and variability (interquartile range between 5 mm h⁻¹ to 14 mm h⁻¹). In contrast, winter exhibits the lowest intensities (extreme values between 18 mm h⁻¹ and 48 mm h⁻¹), with fewer extreme events (~~63 outliers~~) and reduced variability (interquartile range between 4 mm h⁻¹ to 8 mm h⁻¹) compared to the other seasons. Spring and fall display intermediate behavior between the two opposite phases, with spring showing slightly higher rainfall intensities relative to fall. Compared to seasonal violin plots, the annual distribution appears smoother and more generalized, effectively integrating seasonal differences while maintaining the influence of extreme events. This reinforces the importance of analyzing seasonal behavior separately, as aggregation may mask distinct seasonal patterns in intensity and variability.



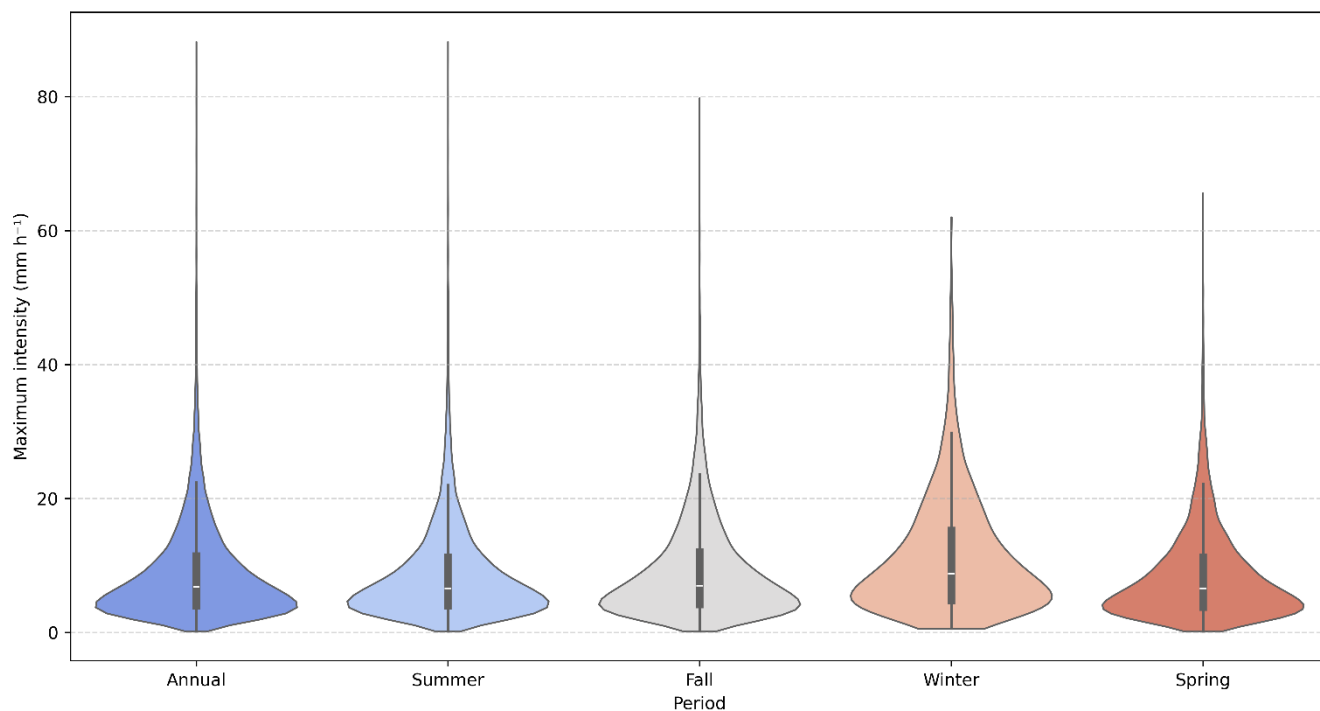


Figure 5. Violin Boxplots of the average maximum rainfall-storm intensity grouped for Annual, summer, fall, winter, and spring

Considering the seasonal differences highlighted in Figure 5, four separate time series were constructed, one for each season at every station. First-order transition matrices were then derived, and the order of each chain was verified. The chi-square values and corresponding p-values of this test are presented in Appendix A1. Additionally, the temporal homogeneity of the Markov chains defined by season was assessed through the transition matrices, with the chi-square statistics and p-values also reported in Appendix A1.

The results indicate that, for each station and season analyzed, the transition matrices exhibit homogeneous behavior consistent with first-order Markov chains. The chi-square statistics and their corresponding p-values were generally not significant ($p > 0.05$), suggesting that transition probabilities do not vary substantially within each station and can be considered stable over time. This outcome reinforces the suitability of applying Markov chains—~~considering the reset of the VLMC~~—and validates the results obtained from modeling extreme rainfall events using this approach.

275 4.3 Spatial Results of Markov Chain Modeling

In this chapter, the transition probabilities between rainfall intensity states are presented, grouped by season: spring (Figure 6), summer (Figure 7), winter (Figure 8), and fall (Figure 9). The interpretation of the transition maps follows this logic: the initial state corresponds to the rows, and the subsequent state to the columns. Therefore, Figures 6b, 7b, 8b, and 9b

illustrate the probability of transitioning from the Moderate state (row) to the Strong state (column). The same logic applies to
280 all other cells and figures presented in this chapter.

Figure 6 shows the transition probabilities between rainfall intensity states derived from the Markov chain modeling for spring. Upward transition probabilities, like Moderate to Strong (Figure 6b), Strong to Very Strong (Figure 6f), Moderate to Very Strong (Figure 6c) are relatively low, remaining below 0.2 across the entire study area. In contrast, there is a high probability of downward transitions to the Moderate state, like Strong to Moderate (Figure 6d) and Very Strong to Moderate
285 (Figure 6g), with values exceeding 0.7 throughout the region and particularly pronounced in the Coastal Plain.

Probabilities of transitioning to or persisting in the Strong state remain below 0.1 (Figures 6b, 6e, 6h), although slightly higher in the mountainous regions of the Southern Plateau and Southern Shield. In the lowland areas of the Central Depression and Coastal Plain, the probability of maintaining Strong conditions is nearly zero. The greater persistence of the Strong state in mountainous zones may be attributed to the role of topography in modulating orographic convection, which in
290 spring has not yet reached its peak development.

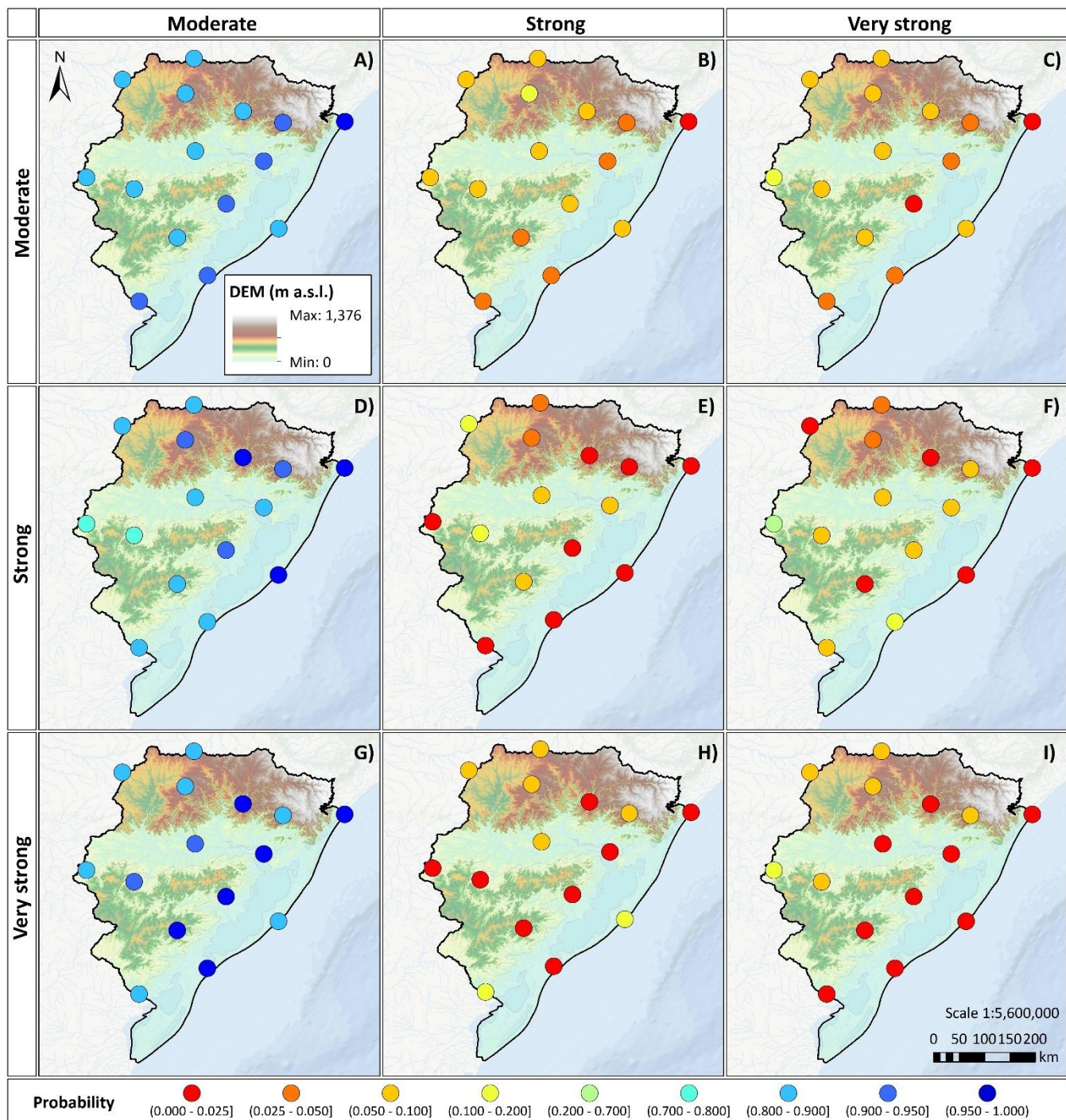


Figure 6. Spatial distribution of Markov transition probabilities between rainfall intensity states during spring. Rows represent the initial state and columns the subsequent state; thus, each panel shows the probability of transition between rainfall intensity classes. Panels along the main diagonal represent persistence probabilities. The same interpretation applies to Figures 7–9

Figure 7 shows the transition probabilities between rainfall intensity states for summer. The probability of maintaining a Moderate storm state ranges between 0.7 and 0.95 (Figures 7a, 7d, 7g), indicating strong persistence. In contrast, the probability of remaining in the Strong or Very Strong states is below 0.2 (Figures 7b, 7c, 7e, 7f, 7h, 7i). Upward transitions, like Moderate to Strong (Figure 7b), Strong to Very Strong (Figure 7f), and Moderate to Very Strong (Figure 7c) display higher probabilities in summer compared to the other seasons. The probability of a Moderate to Strong transition reaches up to 0.2 in the Southern Shield, while the probability of Strong to Very Strong transitions ranges from 0.025 to 0.2 across the Central Depression and Coastal Plain. Persistence of the Very Strong state can reach 0.2, particularly in the mountainous Southern Shield (Figures 7c, 7f, 7i).

The higher rainfall intensities in the mountainous regions coincide with the peak of convection in the area, where orographic effects enhance air uplift and favor more intense storms. Conversely, in the flat areas of the Central Depression and Coastal Plain, Very Strong events dissipate more quickly. This pattern reflects the typical behavior of plains, where the absence of topographic barriers reduces the persistence of convective systems.

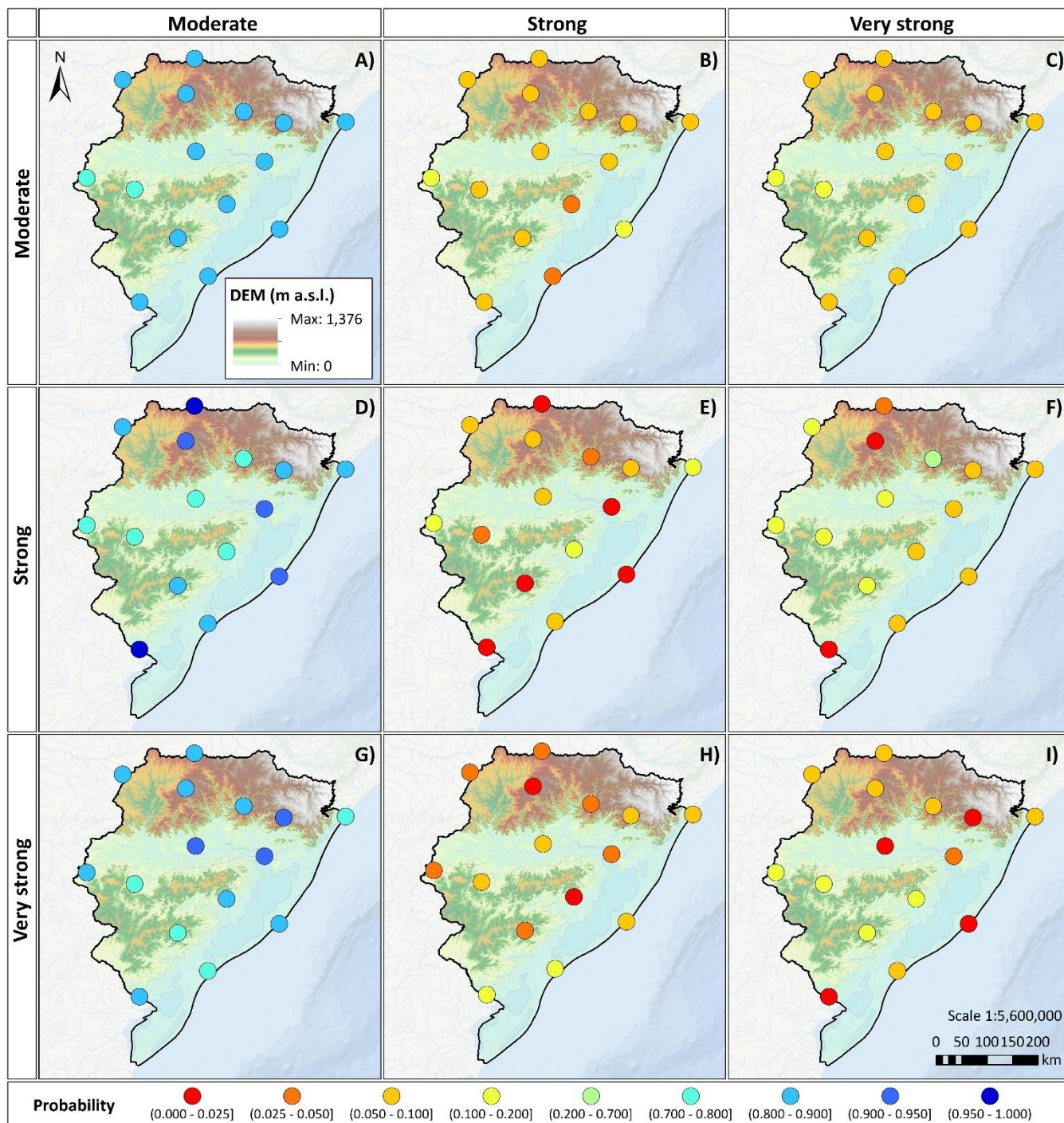


Figure 7. Spatial distribution of Markov transition probabilities between rainfall intensity states during summer

Figure 8 shows the transition probabilities between rainfall intensity states for winter. During this season, extreme events are less frequent, with downward transition probabilities reaching values close to 0.9 (Figures 8a, 8d, 8g). While Upward transition probabilities, like Moderate to Strong (Figure 8b), Strong to Very Strong (Figure 8f), Moderate to Very Strong (Figure 8c), remain near 0.025. The probability of transitioning from Strong to Very Strong (Figure 8f), or of persisting in the Very Strong (Figures 8c, 8f, 8i), is below 0.025 across the entire study area.

In contrast, downward transitions (Strong to Moderate, Very Strong to Moderate) are dominant, with probabilities exceeding 0.9 in most of the region. Unlike summer and spring, winter does not exhibit distinct spatial patterns in the behavior of extreme events, indicating a more homogeneous distribution of rainfall intensity across the study area.

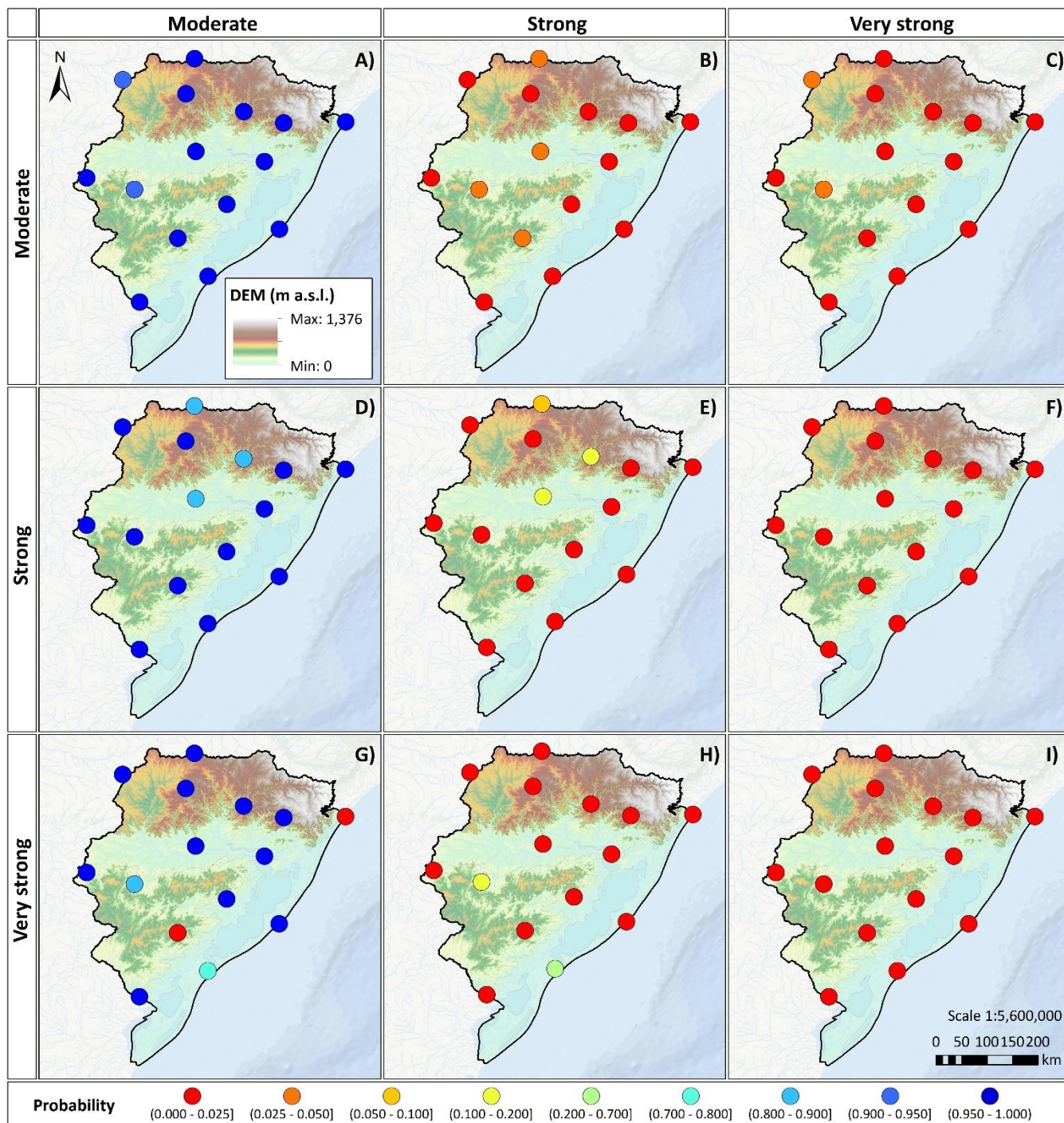


Figure 8. Spatial distribution of Markov transition probabilities between rainfall intensity states during winter

Figure 9 shows the transition probabilities between rainfall intensity states for fall. Upward transition probabilities, like Moderate to Strong (Figure 9b), Moderate to Very Strong (Figure 9c), remain below 0.1 across the study area. Similarly, transitions between the Strong and Very Strong states (Figures 9f, 9h) are generally below 0.2, with slightly higher values observed for the Strong to Very Strong transition (Figure 9f). This behavior reflects the transitional nature of fall, during which atmospheric conditions become less favorable for the development and intensification of convective systems. As a result, the escalation toward severe states is statistically rare, and storms tend to remain within moderate or weak intensity levels. This seasonal pattern indicates a shift from the convectively active regime of summer toward the more stable conditions characteristic of winter.

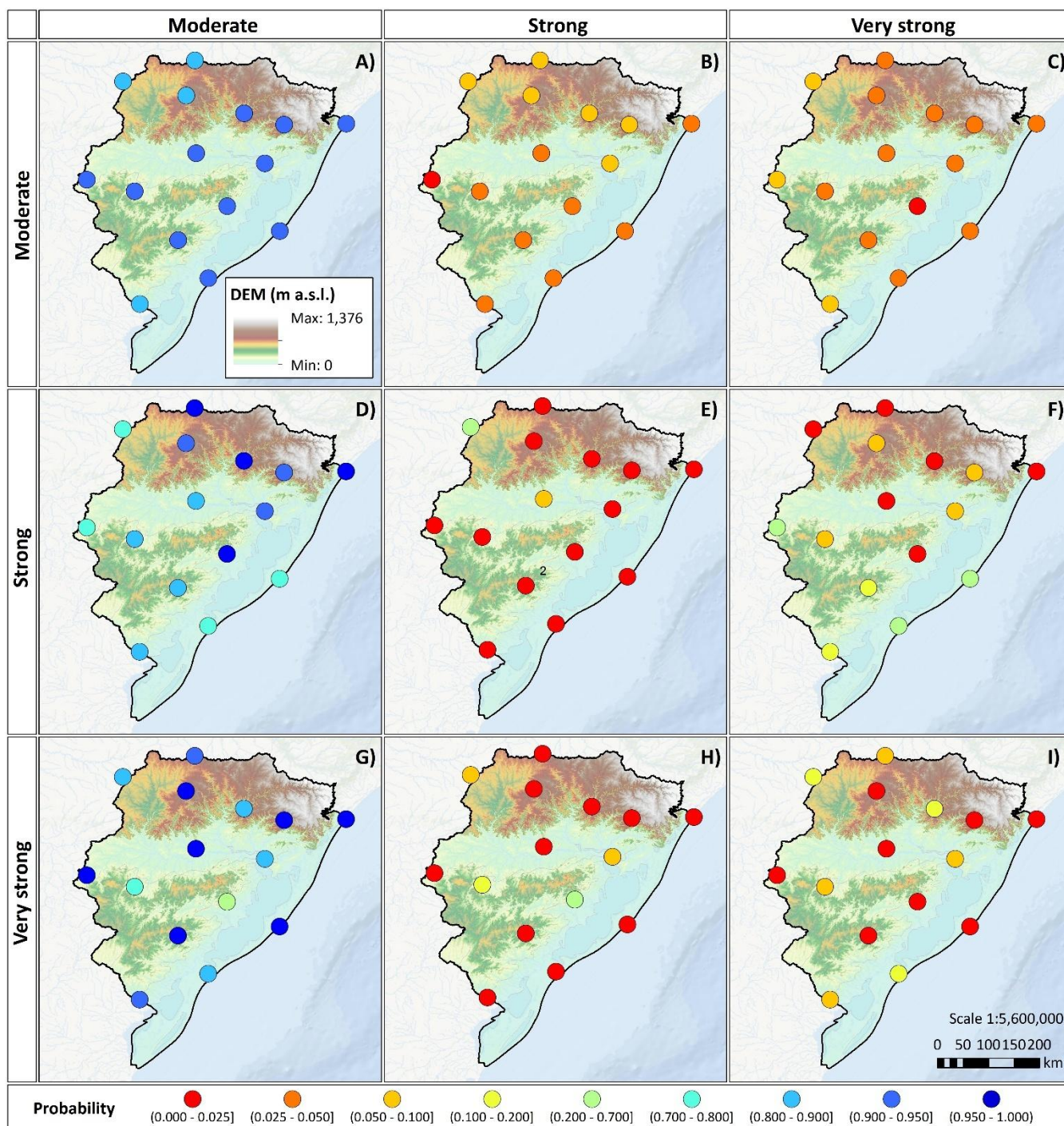


Figure 9. Spatial distribution of Markov transition probabilities between rainfall intensity states during fall

The comparative analysis of rainfall regimes throughout the year reveals well-defined patterns of persistence and transition in storm events, closely linked both to seasonal dynamics and to the particularities of regional topography. In spring, there is a marked tendency for rapid returns to moderate conditions after high-intensity episodes, a phenomenon especially evident in the Coastal Plain. By contrast, in the elevated areas of the Southern Plateau and Southern Shield, the Strong state persists more frequently, suggesting a significant influence of topography in modulating orographic convection. During summer, rainfall dynamics become more complex: upward transitions to more intense states—Moderate to Strong and Strong to Very Strong—are more frequent, particularly concentrated in the Southern Shield, where topographic conditions act as catalysts of repeated and intense convective processes. In the lowland regions, such as the Central Depression and Coastal Plain, Very Strong events tend to dissipate more quickly, consistent with the absence of orographic forcing mechanisms that sustain convective activity.

Fall, in turn, is characterized by a remarkable stability in rainfall regimes: Moderate events predominate with little variability, and transition probabilities between states remain considerably low. This regularity suggests a more predictable rainfall pattern, marked by a more uniform distribution of precipitation. In winter, downward transitions dominate, with probabilities exceeding 90%, and sequences of extreme events are rare. ~~by contrast, the highest downward transition rates are observed—exceeding 90%—and sequences of extreme events are rare.~~ This pattern is consistent with the predominance of frontal systems, which tend to generate less intense, more homogeneous, and shorter-lived rainfall.

Taken together, the findings highlight the decisive role of topography in enhancing the intensity and persistence of summer rainfall, as well as the concentration of prolonged flood risk in the lowland areas during winter. These seasonal and spatial differences are of strategic importance for hydrological modeling and for the design of risk management policies tailored to the specific characteristics of the territory.

4.4 Discussing of the results

Our findings indicate higher probabilities of upward transitions (e.g., Strong to Very Strong) during summer, consistent with synoptic studies in the region (Sanches et al., 2019; Schumacher et al., 2016; Teixeira and Prieto, 2020b), which highlight the intensification of the Low-Level Jet and moisture convergence in this season. Moreover, (Sanches et al., 2019) reported a significant increase in extreme events in December and a reduction in return periods, which aligns with the elevated upward transition probabilities observed in our study (up to 0.2 in the Southern Shield).

In winter, by contrast, our analysis shows dominant downward transitions (e.g., Very Strong to Strong), suggesting that frontal systems prevailing during this season are more stable and less convective, consistent with the findings of (Teixeira and Prieto, 2020a, b). However, this behavior is not solely related to the frontal systems themselves but also to the presence of more stable air masses associated with migrating anticyclones following frontal passages. This mechanism favors less intense rainfall and reduces the likelihood of consecutive extreme events, in agreement with (Britto et al., 2006), who documented the frequent passage of cold fronts. Our results extend this evidence by showing that such systems quickly return to moderate conditions.

The persistence of Strong and Very Strong events in mountainous areas confirms that orography modulates the rainfall regime, enhancing air uplift and storm continuity during summer. In contrast, the rapid dissipation of extremes in the Central Depression and Coastal Plain reflects the flat topography, where the absence of orographic barriers limits convective persistence. This is consistent with previous studies (Britto et al., 2006; Guedes et al., 2019; Teixeira and Prieto, 2020a) that identified persistent events associated with frontogenesis and slow-moving cyclogenesis in mountainous zones. Our results add detail by showing that these areas exhibit higher maximum intensities (9–11 mm h⁻¹) and greater persistence of Strong states, supporting the hypothesis that relief enhances both frontal and convective rainfall.

The higher upward transition probabilities observed in summer over the Southern Shield reflect mechanisms similar to those described for ~~Mesoscale Convective Complexes (MCCs)~~, where the Low-Level Jet (LLJ) and orography favor the persistence of intense rainfall. In addition, the katabatic flow from the Andes and its interaction with the LLJ enhance low-level moisture transport and convergence, creating favorable conditions for the development and maintenance of MCCs in the region (Salio et al., 2007). Ribeiro-Viana et al. (2009) reported 22 MCCs between October and December 2003, with an average duration of 18.6 hours, consistent with the persistence patterns identified in our study.

Storm characterization further revealed that rainfall events in lowland areas tend to last longer, which aligns with the increase in five-day precipitation totals (CMax5) documented by (Minuzzi and Lopez, 2013). This suggests that storm persistence is a key driver of seasonal rainfall accumulation. The marked geomorphological contrasts in the study area also help explain why trend analyses do not show consistent signals across all stations, as highlighted by (Melo et al., 2015). Orography not only influences trend detection but also affects the occurrence of extreme indices (R95p, R99p) (Melo et al., 2015) and the ICEXT index (Extreme Rainfall Intensity), analyzed by (Minuzzi and Lopez, 2013). ~~Both studies~~ showing that relief can either attenuate or intensify extreme rainfall occurrence, producing spatially contrasting responses. In this context, the spatial variability of storm transition dynamics identified in this study may also reflect differences in how local precipitation regimes respond to ongoing climate variability. Although the temporal homogeneity analysis performed in this study supports the assumption of stationary transition probabilities within the analyzed period, these results should be interpreted within the relatively short observational window

~~Furthermore~~ Furthermore, across southern Brazil, including Paraná, Santa Catarina, and Rio Grande do Sul, multi-model projections from CMIP6 indicate stronger precipitation extremes through mid to late century. Intensity-based indices rise, with increases in RX1day and RX5day, very-wet ~~days and extremely wet day totals~~ (R95p, ~~R99p~~), and the simple daily intensity index (SDII), alongside higher frequencies of heavy-rain days (R20mm) (Avila-Diaz et al., 2020, 2023) (Avila-Diaz et al., 2020). These projected changes suggest a potential shift in the underlying transition structure of storm dynamics, where probabilities associated with more intense states may increase over time. In this sense, while the current results support a stationary framework, future climate conditions may lead to non-stationary behavior in storm transition probabilities, reinforcing the need for extended analyses under changing climate scenarios.

The heterogeneous storm patterns driven by topography highlight the need for differentiated management strategies across physiographic units. The high persistence of rainfall in the Southern Shield indicates that this region may be an important

source of runoff and sediment, suggesting the need for reforestation and soil management practices to reduce flood peaks. In the plains, where extreme events may lead to prolonged flooding, priority should be given to wetland restoration and the reinforcement of early warning systems to mitigate risks. [Furthermore](#), (Marques and Möller, (2008), who studied water levels in the Lagoa dos Patos, emphasized that while storms dissipate in this ecosystem, water accumulation remains significant.

These management strategies are particularly relevant in light of evidence from previous studies pointing to an increasing trend in rainfall. [In this sense](#), (Guedes et al., (2019) reported that 50% of the stations they analyzed showed a significant increase in annual rainfall, linked to El Niño events. [Also](#), (Berlato et al., (2007) also demonstrated a generalized increase in precipitation in Rio Grande do Sul, associated with the higher frequency of El Niño. Such findings are concerning when considered alongside projections of increased El Niño frequency and intensity (Cai et al., 2014; Chen et al., 2024). Furthermore, Melo et al. (2015) estimated increases in R95p and R99p indices and projected up to 600 mm of additional annual rainfall above the 95th percentile by the end of the century in Rio Grande do Sul. Similarly, (Junges et al., (2019) found a significant increase of 6.3 mm/year in annual precipitation, with notable seasonal increases in spring (+2.5 mm/year) and winter (+1.9 mm/year).

5. Conclusions

[A key contribution of this study is the application of a state-based, intraday Markov framework to characterize storm behavior, providing a probabilistic description of intensity transitions that goes beyond traditional daily or seasonal analyses. This approach allows capturing the temporal structure of storms at the hourly scale, offering new insights into their persistence, intensification, and dissipation processes.](#)

The analysis revealed that summer is characterized by higher probabilities of transitions toward more intense storms, reaching values of up to 0.2, consistent with the intensification of the ~~LLJ~~Low-Level Jet and the enhancement of orographic convection reported in previous synoptic studies. Conversely, winter is dominated by downward transitions, with probabilities approaching 0.95, reflecting the influence of more stable and homogeneous frontal systems.

Topography was found to play a decisive role in the persistence and dissipation of storms. In the Central Depression and the Coastal Plain, storms tend to last longer, with [a](#) mean duration of 15 - 17 hours, but exhibit lower intensities, with average maximum values of 7 - 8 mm h⁻¹. In contrast, in the mountainous regions of the Southern Shield and the Southern Plateau, storms are more intense, ~~with maximum intensities of 10–11 mm h⁻¹~~, but shorter-lived, lasting on average 11 – 12 hours. This pattern reflects the direct influence of relief on rainfall dynamics. [In particular, the analysis reveals that the escalation toward high-intensity events is season-dependent and spatially heterogeneous, highlighting the combined influence of atmospheric circulation and terrain on storm evolution.](#)

Overall, the spatial and temporal characterization of storms developed in this study provides a solid foundation for advancing early warning systems, guiding land-use planning adapted to distinct physiographic units, and supporting the design of adaptation strategies in response to the projected increase in extreme precipitation events in southern Brazil.

435 From a practical perspective, the results provide relevant information for improving early warning systems, supporting risk mapping, and informing land-use planning and hydrological design in flood-prone regions. By identifying where and when storms are more likely to intensify or dissipate, the proposed framework contributes to more targeted and effective climate risk management strategies in southern Brazil.

440 **Appendix A1**

Temporal homogeneity test results and chain order determination for seasonal Markov models

Season	Station	Order		Homogeneity	
		Chi ²	p-value	Chi ²	<i>p-value</i>
Spring	Bento Goncalves	3.383	0.496	3.457	0.485
	Cacapava do Sul	3.493	0.479	3.148	0.533
	Camaqua	4.078	0.396	4.29	0.368
	Canela	1.936	0.748	1.893	0.756
	Cangucu	2.973	0.562	2.991	0.559
	Cruz Alta	2.758	0.599	3.035	0.552
	Jaguarao	3.195	0.526	3.173	0.529
	Mostardas	2.471	0.65	2.563	0.634
	Passo Fundo	0.108	0.999	0.123	0.998
	Porto Alegre	2.599	0.627	2.587	0.629
	Rio Grande	2.511	0.643	2.489	0.647
	Rio Pardo	1.381	0.847	1.284	0.864
	São Gabriel	4.569	0.335	4.535	0.338
	Soledade	1.911	0.752	1.878	0.758
	Torres	1.94	0.747	0.425	0.98
Summer	Bento Goncalves	6.551	0.162	8.522	0.074
	Cacapava do Sul	1.558	0.816	1.832	0.767
	Camaqua	5.816	0.213	5.128	0.274
	Canela	0.898	0.925	0.994	0.911
	Cangucu	5.301	0.258	5.395	0.249
	Cruz Alta	0.418	0.981	0.666	0.955
	Jaguarao	4.99	0.288	3.531	0.473
	Mostardas	2.826	0.587	3.109	0.54
	Passo Fundo	2.367	0.669	2.304	0.68
	Porto Alegre	2.077	0.722	2.293	0.682
	Rio Grande	3.606	0.462	3.784	0.436
	Rio Pardo	3.851	0.427	3.683	0.451
	São Gabriel	1.851	0.763	1.889	0.756

	Soledade	2.506	0.644	2.714	0.607
	Torres	2.98	0.426	2.086	0.72
Fall	Bento Goncalves	3.623	0.459	3.587	0.465
	Cacapava do Sul	6.007	0.199	5.865	0.21
	Camaqua	6.169	0.187	6.136	0.189
	Canela	2.382	0.666	2.58	0.63
	Cangucu	2.379	0.666	2.368	0.669
	Cruz Alta	8.196	0.085	8.138	0.087
	Jaguarao	1.766	0.779	2.109	0.716
	Mostardas	4.502	0.342	4.458	0.348
	Passo Fundo	2.574	0.631	2.593	0.628
	Porto Alegre	1.204	0.878	1.671	0.796
	Rio Grande	10.067	0.056	9.896	0.056
	Rio Pardo	1.547	0.818	1.531	0.821
	São Gabriel	3.89	0.421	3.852	0.426
	Soledade	2.432	0.657	2.357	0.67
	Torres	0.425	0.98	1.346	0.854
Winter	Bento Goncalves	3.778	0.437	3.837	0.429
	Cacapava do Sul	4.736	0.315	6.89	0.142
	Camaqua	0.07	0.999	0.07	0.999
	Canela	0.153	0.997	0.152	0.997
	Cangucu	0.523	0.944	0.083	0.995
	Cruz Alta	0.647	0.958	0.647	0.958
	Jaguarao	0.171	0.997	0.171	0.997
	Mostardas	0.079	0.999	0.079	0.999
	Passo Fundo	1.167	0.883	1.184	0.881
	Porto Alegre	0.219	0.994	0.217	0.995
	Rio Grande	9.564	0.052	9.605	0.052
	Rio Pardo	1.486	0.829	1.486	0.829
	São Gabriel	0.13	0.998	0.13	0.998
	Soledade	0.284	0.991	0.284	0.991
	Torres	1.3	0.861	0.079	0.98

Data availability

These data are publicly available from the ~~Instituto Nacional de Meteorologia (INMET)~~ at <https://portal.inmet.gov.br/dadoshistoricos>.

Author Contribution

445 Conceptualization: COM and JVS; data curation: COM and JVS; formal analysis: COM, JVS, JDMF, AAD, TAEF, DHM, and ASAS; Funding acquisition: COM; Methodology: COM, TAEF, DHM, and ASAS; Project administration: COM; Resources: COM; Software: COM and TAEF; Supervision: AAD and TAEF; Validation: TAEF, DHM and ASAS; Visualization: COM and JDMF; Writing (original draft preparation): COM, JVS, JDMF, and AAD; and Writing (review and editing): COM, JVS, JDMF, AAD, TAEF, DHM, ASAS.

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Competing Interest

The authors declare that they have no conflict of interest.

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580