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Assessing flood risks in the Taquari-Antas Basin (Southeast Brazil) during the September 2023 extreme rainfall surge



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This analysis delves into precipitation dynamics in the Bacia Taquari Antas region, with a focus on September 2023. Employing a multi-scale approach encompassing monthly, daily, and subdaily analyses, the study unveils a consistent precipitation distribution throughout the year. September 2023's anomaly, the second-highest in the dataset, prompts investigation into potential climatic variability. Notably, the daily analysis highlights September 4th, 2023, as significant, emphasizing the importance of historical context in evaluating weather event severity. Subdaily scrutiny of September 4th reveals intense, localized precipitation, raising concerns about hydrological impacts such as flash floods. Positive trends in Rx5day (maximum consecutive 5-day precipitation amount) and R25 (number of days in a year when precipitation exceeds 25 mm) indices indicate an increase in heavy precipitation events, aligning with broader climate change concerns. Shifting focus to flood extent and impact assessment in the Taquari-Antas Basin, a simulation model depicts the temporal evolution of the flood, reaching its peak on September 4th. Examination of affected areas, rainfall volumes, and impacts on census sectors, cities, and buildings furnishes critical data for disaster management. This study contributes to localized precipitation comprehension and broader issues of climate trends, flood risk evaluation, and urban vulnerability, providing a basis for informed decision-making and resilient planning strategies.

On September 3, 2023, the state of Rio Grande do Sul (Brazil) was on alert for the passage of a low-pressure system moving from central South America through the state toward the sea. The tragedy devastated cities in the Taquari Valley, resulting in 51 casualties and 8 people still missing. The low-pressure system would later develop into an extratropical cyclone the next day. Extratropical cyclones are low pressure systems with clockwise wind circulation on the Southern Hemisphere. They form in the extratropical and subtropical latitudes of the Earth. A short and comprehensible discussion of cyclones structure and formation can be found¹. Over southeastern South America, numerous studies show an important cyclogenetic region near Rio Grande do Sul^{2,3}. The formation of cyclones in this region commonly presents the expansion of a surface low pressure from the interior of South America towards the Atlantic Ocean⁴. This synoptic

pattern is clear in the low pressure occurred in the days analyzed in the present paper.

A persistent surface low pressure was present in central South America since, at least, September 01, and during September 03, it expanded toward the Atlantic Sea, directly influencing Rio Grande do Sul (figures not shown). The cyclone formation occurred on the evening of Monday, September 4. Throughout that day, when the cyclone center was located right at the Rio Grande do Sul Coast heavy rains had already affected more than 50 cities, with six casualties, primarily in the Northern region. In the early hours of Tuesday, September 5, the cities in the Taquari Valley were hit by the river's flooding that runs through the area. On this day, 15 fatalities were confirmed, all of them in the town of Muçum. A rescue operation was initiated to assist the affected and search for the missing individuals. As each day

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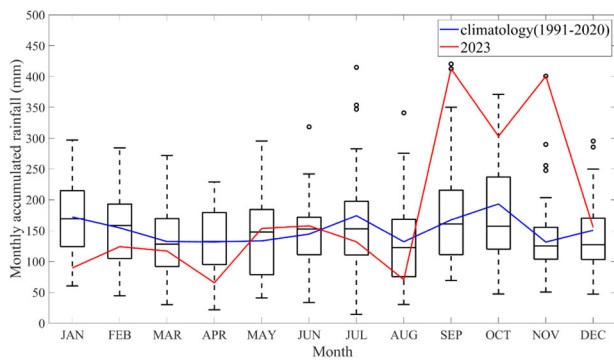


Fig. 1 | Monthly Precipitation boxplot from 1981 to 2023 for Taquari-Antas basin.

passed, the state's Civil Defense confirmed new casualties and missing persons.

The majority of extreme rain events that occur in the State of Rio Grande do Sul (RS) and result in floods directly affecting the population are caused by meteorological systems on a synoptic and sub-synoptic scale that act in a large part of the Southern Region of Brazil during the whole year. Among these systems, we have: cold fronts^{5,6} baroclinic troughs⁷, Upper-Level Cyclonic Vortices⁸ and extratropical and subtropical cyclones^{9–13}. The state of RS is characterized by having the highest frequency of occurrence of severe storms among the states in the southern region of Brazil, including tornadoes^{14,15}, and on many occasions they end up causing extreme precipitation events. One of the main factors that contribute to the development of these storms is the presence of the Low Level Jet (LLJ), mainly in the spring and winter period^{16–19}.

Teixeira and Satyamurty indicated²⁰ how the main conceptual model associated with the occurrence of precipitation extremes in the region is related to four relevant characteristics; (i) the intensification of a trough in the middle troposphere in the east of the Pacific Ocean that approaches the continent three days before the occurrence of the EEC, (ii) the presence of a low-pressure system centered in the north of Argentina one day before the occurrence of the event extreme, (iii) the development of LLJ from the northern quadrant over Paraguay 2 days before the occurrence of extreme precipitation, and (iv) a strong convergence of moisture flow over the southern region one day before the extreme rain.

Conditions of extreme precipitation in Southern Brazil increase during the positive phase of the El Niño–Southern Oscillation (ENSO), known as El Niño, as documented by numerous studies^{21,22}. This influence is more accentuated from November to February, but significant relationship between El Niño and abundant rainfall in South Brazil is observed at different seasons²³. The warming of the Pacific Ocean Sea surface waters causes a response from the atmosphere in the form of Rossby waves trains that propagate from the Niño region toward the Southeastern South America, strengthening the upper-level Subtropical Jet over South Brazil^{24,25}, and favoring the occurrence of more intense troughs. At lower levels, the frequency and intensity of the LLJ is increased during El Niño phases^{26,27}, transporting more moisture and causing more instability over South Brazil.

September 2023 marked the rainiest month in Porto Alegre in 107 years (until this month), according to the National Institute of Meteorology (INMET). The monthly accumulated rainfall in Porto Alegre already reached 413.8 mm. According to INMET, this is the highest monthly volume since 1916, when the historical record series began. The previous record was in May 1941, with a precipitation volume of 405.5 mm. The other months with the highest accumulations are, respectively, June 1944 (403.6 mm), April 1941 (386.6 mm), and June 1982 (365.6 mm). According to measurements from the conventional meteorological station, the days with the highest rainfall in the month were, in order, September 4 (with 60 mm), September 14 (58.4 mm), and September 13 (56.3 mm).

Mapping flood risk is a critical component of disaster management and urban planning, particularly in regions prone to flooding due to factors like

extreme rainfall, river overflow, or coastal inundation. Flood risk mapping involves assessing the likelihood of flooding and its potential impacts, which can help inform decisions related to land use, infrastructure development, and emergency preparedness. Flood risk mapping typically combines various data sources and modeling techniques to estimate flood probability and vulnerability. Remote sensing and geospatial data, including digital elevation models (DEMs), land use and land cover data, and hydrological information, are often integrated to create comprehensive flood risk maps. Moreover, historical flood records are valuable for identifying high-risk areas and understanding past events²⁸.

Flood modeling is an essential component of flood risk assessment and management, particularly in the face of increasing climate-related extreme events. A variety of modeling approaches have been developed and employed to simulate and predict flood dynamics. In this comparative discussion, we delve into the key methods commonly used in flood modeling and evaluate their relative strengths and weaknesses. One widely used method is hydrodynamic modeling, such as the HEC-RAS and MIKE Flood models. These models operate on the principles of fluid dynamics, considering the interplay between river flow, topography, and structures to predict flood extents and depths. They are known for their accurate representation of flow dynamics, making them suitable for riverine and coastal floods, and their adaptability to complex scenarios. However, they are data-intensive and computationally demanding²⁹. As pointed out by ref. 30, the choice of flood modeling method should be influenced by the specific objectives, data availability, computational resources, and the scale of the study. Our study will focus on the HEC-RAS, which involves simulating the flow of water through channels, rivers, and other water bodies to predict potential flooding.

The study aims to assess weather event severity, particularly focusing on September 4th, 2023, and its intense, localized precipitation which raises concerns about hydrological impacts such as flash floods. Additionally, the study examines trends in heavy precipitation events, aligning with broader climate change concerns.

Results

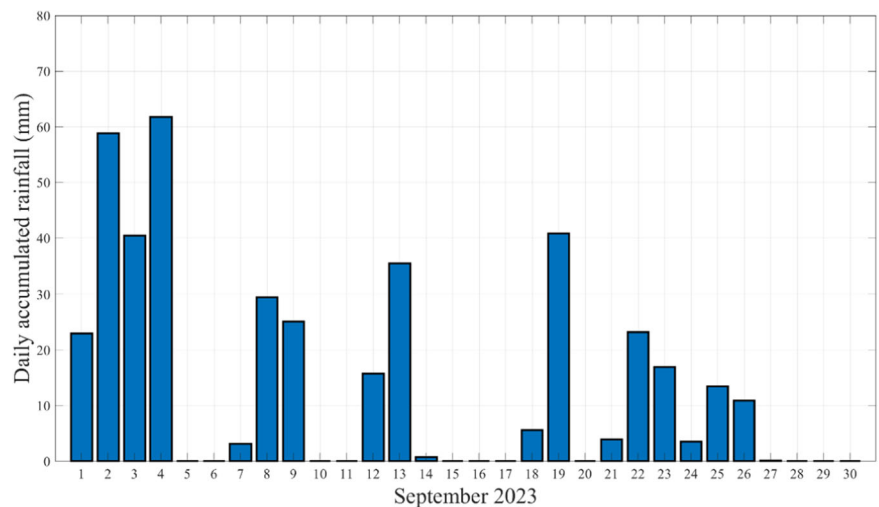
Rainfall analyses

The area experiences evenly distributed precipitation throughout the year, as shown in Fig. 1. While there is not a distinct monthly pattern, the greatest cumulative rainfall is recorded in October (193.3 mm) and September (167.5 mm). Conversely, the lowest cumulative rainfall is observed in November (131.6 mm) and March (132.4 mm). In September 2023, the accumulated rainfall reached 412.4 mm, which is the second-highest value in the entire dataset (a positive anomaly of 244.83 mm). It is noteworthy that during the period of this study, the planet was under the influence of an El Niño event. According to the Climate Prediction Center, the 3-month mean Oceanic Niño Index (September–October–November/2023) was +1.6, and the monthly Southern Oscillation Index was −1.3 in September 2023, indicating a strong El Niño event and a robust coupling with the atmosphere. This is consistent with previous studies indicating that spring is the season when occurs the strongest linking between El Niño and the atmosphere³¹ and the more relevant anomaly signal in the eastern RS³². The highest value of the studied dataset in September was recorded in 2009, with 420.22 mm, also during an El Niño event.

The analysis of daily accumulated precipitation for September 2023 (Fig. 2) reveals that on September 4th, the daily accumulated rainfall in the Bacia Taquari Antas region was 61.82 mm. While this is a significant amount, it does not represent the highest 24-h rainfall within the region for the period of 1981–2023. There were 34 instances with higher accumulated rainfall values, with three of them occurring in September. Throughout the entire dataset, there were two events with more than 100 mm of precipitation in 24 h, one of which occurred in September, specifically on September 13, 1988, with 144.39 mm.

In addition, there were four days with accumulated precipitation exceeding 80 mm, as shown in Fig. 3. Within the first five days of September, there was a total of 184.11 mm of rainfall, making it the second-highest value

Fig. 2 | Daily Precipitation for September 2023 for Taquari-Antas basin.



for this period (the record for the monthly maximum consecutive 5-day precipitation is 212.42 mm on July 5th to 9th, 2020). This amount also exceeds the climatological values for September, which are 175.42 mm for the period 1981–2010 and 167.53 mm for the period 1991–2020.

To investigate subdaily precipitation on September 4th, 2023, we analyzed the maximum accumulated precipitation over 1 h, 3 h, 6 h, and 12 h. Among the observed stations, three recorded precipitation values in 1 h ranging from 20 mm to 40 mm (Fig. 3a). In the 3-h analysis, these values increased to as much as 60 mm (Fig. 3b). The accumulated precipitation over 6 h showed values around 100 mm (Fig. 3c). Notably, the maximum precipitation within the 12-h period in the Taquari Antas basin (as delimited in the area) reached significant values, exceeding 140 mm, which is nearly equivalent to the climatological monthly average for the entire month (Fig. 3d).

For September 4th, 2023, one station recorded values between 200 mm and 250 mm in the 24-h precipitation category (Fig. 3e). Moreover, for the entire month of September, nearly all stations observed accumulated precipitation exceeding 400 mm, more than twice the expected amount for the month (Fig. 3f).

The trend analyses for the 12-climate precipitation show that only two index present statistical significance on changes: Rx5day a positive trend (increase of 61.35 mm between 1981 and 2023) and R25 a positive trend (increase of 7.82 days between 1981 and 2023) (Figs. 4 and 5). The results show an increase in days with accumulation greater than 25 mm and greater accumulation in a period of 5 days. Although the other indices do not show a significant trend, it is possible to observe an increase in total precipitation, consecutive wet days, and the number of days with accumulations above 10 mm, 20 mm, 30 mm, and 50 mm, as well as in the single-day accumulation, in addition to a decrease in consecutive dry days.

The spatial trend analysis was conducted for the indices R5x5day and R25 to investigate the spatial distribution of changes for the two indices that show significance within the region (mean). It is noteworthy that almost all regions exhibit significance in changes, with the most significant changes observed in the central-east portion (Fig. 6).

Flood model validation and risk map

The Nash-Sutcliffe Efficiency (NSE) validation score was 0.99 (with $R^2 = 0.99$) (Fig. 7). The NSE is a widely used statistic to assess the performance of hydrological or environmental models by comparing simulated values with observed data. In this case, an NSE value of 0.99 indicates that the model's predictions closely align with the observed data, capturing a significant portion of the variability in the system being studied. An NSE score of 0.99 implies that the model captures around 99% of the variance present in the observed data. The higher the NSE value, the better the model's performance in replicating the observed behavior. This validation

score suggests that the model, in the context of the specific study or application, is providing reasonably accurate predictions.

Figure 8 depicts the simulation of the flood extent for the period from September 2 to 5, 2023. From September 2 to 4, there was approximately 665.75 mm of rainfall. On September 5, the rain ceased. The figure illustrates the progression of the flood extent in the Taquari-Antas basin and highlights the census sectors, cities declared in a state of calamity, cities where flood-related fatalities occurred, and buildings. The flood extent on September 2 covered an area of 495.69 km², reaching its peak on September 4 at 1848.17 km². On September 5, the flood extent began to recede, covering 1521.11 km².

Table 1 displays the extent of the flood area, the amount of rainfall, the area of the census sector affected by the flood, the area of cities declared in a state of calamity affected by the flood, the area of cities where people lost their lives due to the flood, the area of buildings affected by the flood and built-up areas or the period from September 2 to 5, 2023. These data are crucial for assessing the impact of the floods, including the extent of the affected area, the damage to buildings and infrastructure, as well as the human impact, including areas where tragedies such as fatalities occurred. The analysis of this data is essential for planning disaster prevention and response measures, as well as for evaluating the long-term effects of the floods in the affected region.

Cross-referencing the flood extent on September 4, 2023, with the municipalities declared in a state of calamity, we find that the municipality with the smallest affected area was Nova Alvorada, and the one with the largest affected area was Venâncio Aires (Fig. 9). Nova Alvorada has a population of 3163 inhabitants (population density of 21.25 inhabitants per km²) and an urbanized area of 1.11 km². Venâncio Aires has 63,763 inhabitants (population density of 89 inhabitants per km²) and an urbanized area of 25.21 km².

When intersecting the flooded area on September 4, 2023, with the cities where fatalities were recorded, we find that the city of Cruzeiro do Sul had the largest flooded area, followed by the city of Estrela, and the city with the smallest affected area was Passo Fundo (Fig. 10). Cruzeiro do Sul has a population of 11,600 inhabitants and a built-up area of 8.42 km². Estrela is a city with 32,183 inhabitants and a built-up area of 15.38 km². Passo Fundo has 206,215 inhabitants and a built-up area of 59.51 km².

The land use and land cover (LULC) class with the largest flooded area was farming, followed by the forest class, and the class with the smallest flooded area was wetland, followed by the urban area class (Fig. 11).

Figure 9 highlights the flooded areas within cities that have been officially declared as being in a state of calamity. It focuses on the affected areas in locations where the situation has reached a critical level, leading to official declarations of calamity. The main purpose is to provide a visual representation of the extent of flooding in these specific areas. In Fig. 10 the

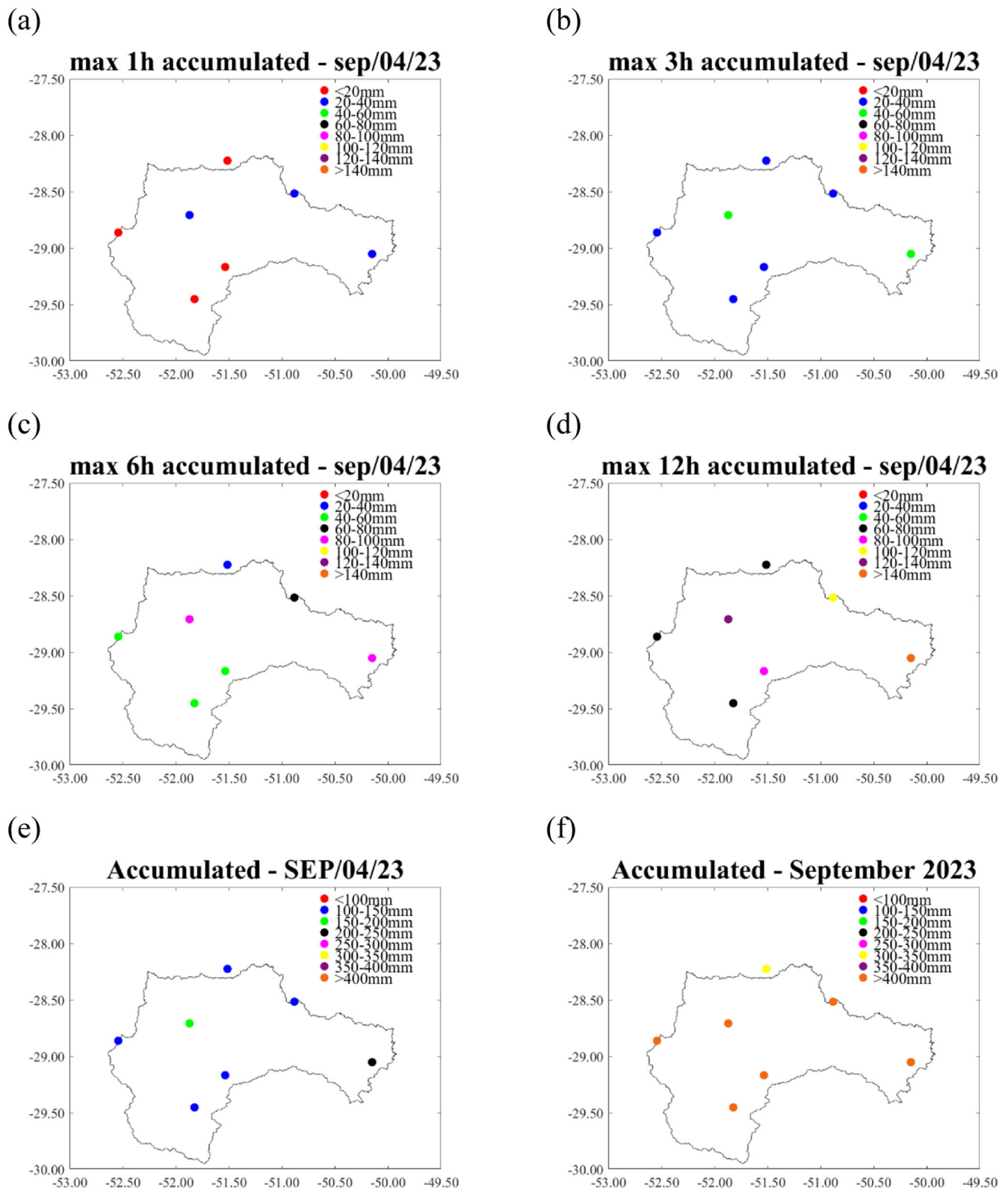


Fig. 3 | September 2023 precipitation data in the Taquari-Antas Basin. a Maximum accumulated rainfall for 1h; **b** maximum accumulated rainfall for 3h; **c** maximum accumulated rainfall for 6h; **d** maximum accumulated rainfall for 12h; **e** accumulated for September, 4th, 2023; **f** accumulated for September, 2023.

flooded areas within cities where fatalities have occurred due to flooding are shown. It emphasizes the regions where human lives have been lost as a direct result of the flooding. The purpose is to visually highlight the spatial relationship between the flooded areas and occurrences of deaths. Fig. 11 presents a more detailed analysis of the flooded areas, classified according to

different Land Use and Land Cover (LULC) classes. Instead of focusing solely on affected urban areas, this figure categorizes the flooded areas based on various types of land cover, such as urban, agricultural, forested, etc. This allows for a more nuanced understanding of the impacts of flooding on different types of land cover.

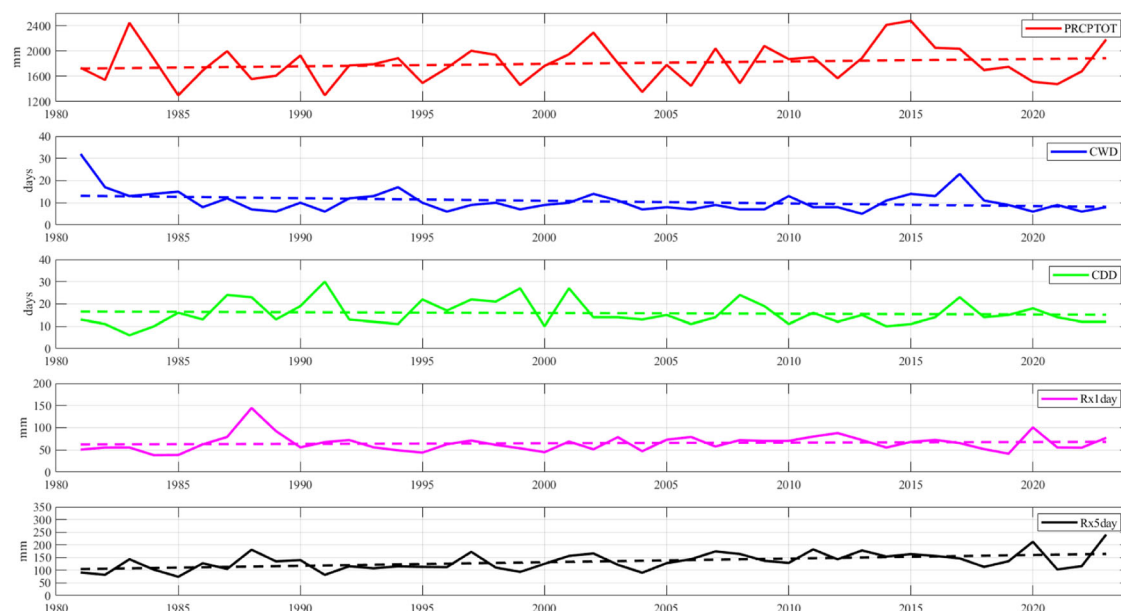


Fig. 4 | Climate precipitation index considering 1981–2022 period for Taquari-Antas basin.

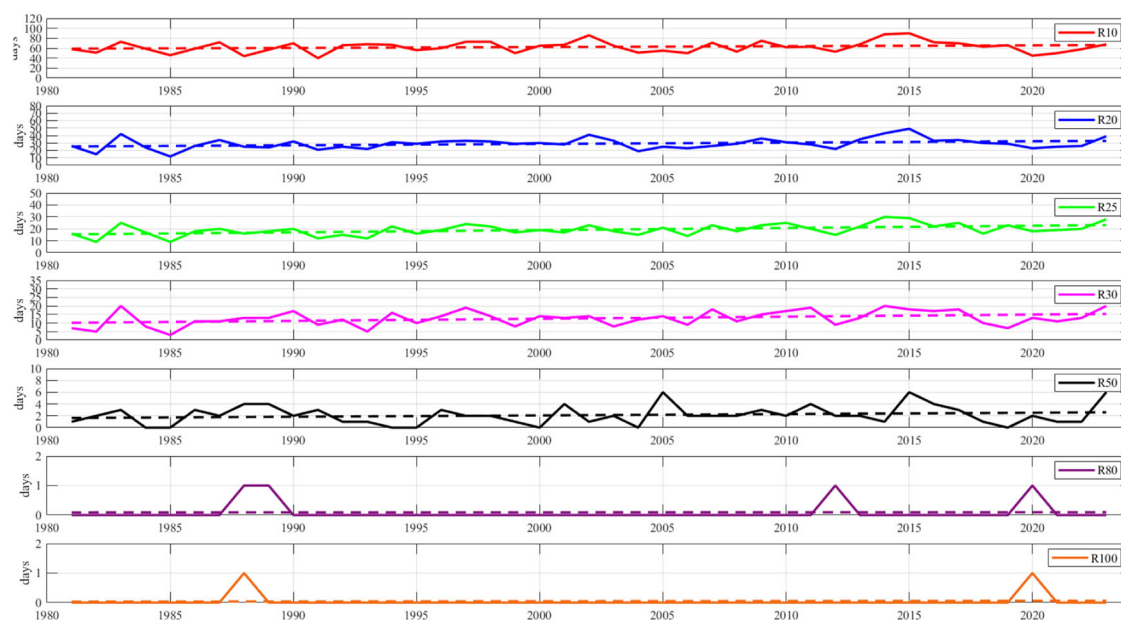


Fig. 5 | Climate precipitation index considering 1981–2022 period for Taquari-Antas basin.

O flood risk map shows that the class with the highest risk area was classified as extreme risk with 1090.17 km², followed by the high-risk class with an area of 317.31 km² (Fig. 12). The class classified as low risk occupied the smallest area, with 124.15 km². The extreme risk class, when intersected with building information, was the class with the largest area occupied by constructions, covering 0.90 km², while the smallest area occupied by constructions was concentrated in two classes, low and medium risk, with 0.07 km². The city with the largest area classified as being in an extreme flood risk zone was Cruzeiro do Sul, with an area of 61.58 km², followed by the city of Estrela with an area of 61.39 km².

In the state of Rio Grande do Sul, the declaration of a state of calamity in cities due to rains follows a procedure established by state authorities. Typically, this declaration is made by the state governor or competent bodies such as the State Civil Defense, in response to natural disasters such as floods caused by heavy rains. The process may involve an assessment of the severity of the damages caused by the rains in a particular city or region. This

assessment considers factors such as the number of people affected, material damage to properties, affected infrastructure, among other impacts. Once the severity of the situation is confirmed and justifies the need for emergency assistance from the state, the declaration of a state of calamity is formalized. This may include the allocation of additional financial and logistical resources to help respond to the damages caused by the rains and assist affected communities. It is important to emphasize that the declaration of a state of public calamity is a legal instrument that facilitates the mobilization of resources and the taking of emergency measures to deal with natural disasters. This declaration is made based on objective criteria and aims primarily to expedite assistance to affected areas and ensure the protection of the population in emergency situations.

One of the main influencing parameters of floods, included in geomorphological mapping, is slope, as it allows estimating the flow velocity of water³³. According³⁴, slopes between 0% and 5% are the ones that most influence flood-prone areas, as they represent floodplains and river terraces.

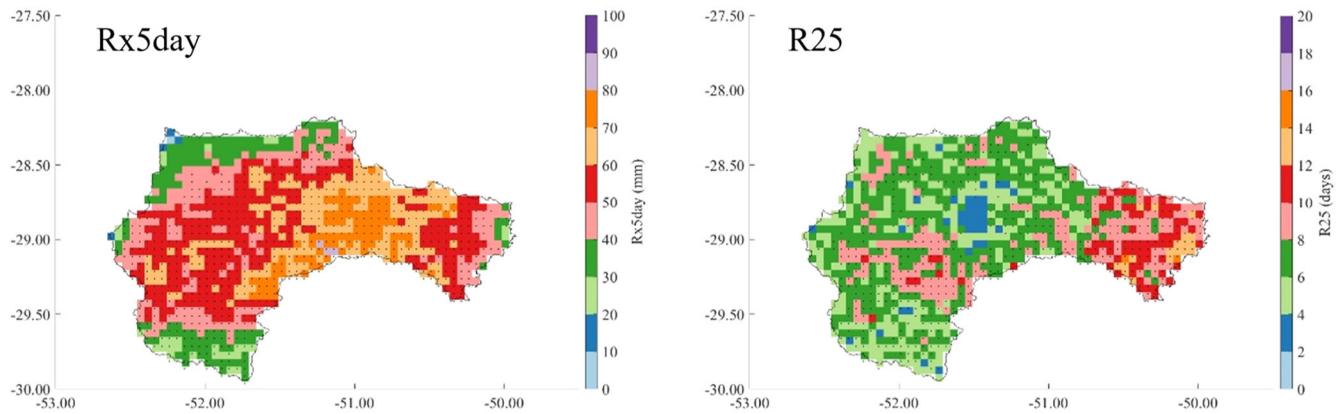


Fig. 6 | Spatial trend analysis for Rx5day and R25.

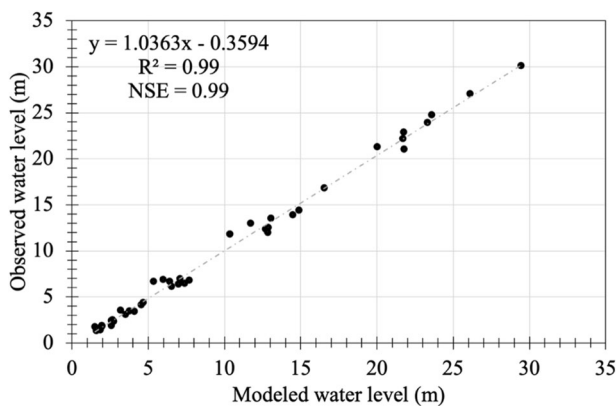


Fig. 7 | Flood model validation using water level data.

In Fig. 13, it can be observed that the predominant extreme flood risk is in slope classes of 0 to 3%, covering an area of ~435.25 km² (representing 53.33% of its area) and 3–8%, covering an area of ~414.83 km² (representing 57.64% of its area). Together, these classes correspond to 83.24% of the total slope area (out of the 1844.57 km² study area), which represents 1535.59 km². There is a trend of increasing representation of risk areas with the increasing representation of flat and gently undulating areas (slope between 0 and 8%). It is directly related to the infiltration capacity of precipitation, which, in turn, is influenced by the relief, rock properties, and characteristics of surface formations: more permeable materials favor underground water flow, while less permeable materials favor surface runoff and its organization into denser drainage networks.

Discussion

The presented analysis offers insights into the precipitation dynamics of the Bacia Taquari-Antas basin. This analysis focuses particularly on September 2023, when in its first days, a low pressure expanded from the continent toward the Atlantic Ocean, directly impacting Rio Grande do Sul and forming an extratropical cyclone. The findings, spanning monthly, daily, and subdaily scales, along with trend analyses, provide a comprehensive understanding of the precipitation patterns and potential implications for the local climate. Besides, it shows the potential impacts of a common synoptic situation, the central South America low-pressure expansion and extratropical cyclone formation over Rio Grande do Sul during spring^{2,4}.

The even distribution of precipitation throughout the year aligns with the expected characteristics of certain climate types. The concentration of the greatest cumulative rainfall in October and September may be influenced by regional climate drivers. The anomalous precipitation in September 2023, the second highest in the dataset, suggests potential variability that warrants further investigation. The analysis of daily precipitation

highlights the significance of September 4th, 2023, with a substantial accumulation of rainfall. The comparison with historical data indicates that while notable, this event was not the most extreme in the dataset. The identification of instances with higher 24-h rainfall, including historical events in September, underscores the importance of considering long-term trends in assessing the severity of current weather events.

The subdaily analysis on September 4th, 2023, reveals intense precipitation over short durations, particularly in the 12-h period. The observed values exceeding 140 mm in this period, coupled with stations recording 200–250 mm, raise concerns about the intensity and localized nature of the rainfall. Such extreme subdaily precipitation events may have significant implications for local hydrology, including the potential for flash floods and soil erosion.

The identified positive trends in Rx5day and R25 indices suggest an increase in both the intensity and frequency of heavy precipitation events over the analyzed period. The rise in the maximum 5-day precipitation and the number of days with precipitation exceeding 25 mm may indicate a shift towards more extreme and sustained precipitation events. These trends align with broader concerns related to climate change, emphasizing the need for adaptive measures in water resource management and infrastructure planning.

Of the over 100 cities affected by the flooding, the majority were concentrated amongst those in the Taquari Valley region. In Muçum, more than half of the residences were destroyed. Thousands of people were left homeless and had to be accommodated in the homes of relatives or in shelters provided by the local municipalities. Floods resulting from extreme rainfall events have emerged as a critical concern in the field of hydrology and disaster management. The increasing frequency and intensity of extreme rainfall events, often linked to climate change, pose substantial risks to communities and infrastructure. These events can result in devastating consequences, including loss of life, damage to property, and disruption of essential services. In response to this growing threat, there has been a surge in research focused on the modeling and prediction of flood occurrences arising from extreme precipitation. Such modeling not only aids in understanding the complex interplay of meteorological, hydrological, and geographical factors but also enables the development of effective strategies for flood risk assessment and mitigation³⁵.

The study employs a simulation model, as depicted in Fig. 8, to analyze the flood extent during the period from September 2 to 5, 2023. It is essential to elucidate the methodology and data sources used in the simulation. A transparent description of the hydrological model, its parameters, and the input data, particularly rainfall data, is critical for the reproducibility of the study. Citations to relevant modeling frameworks or hydrological tools, as well as the source of rainfall data, would enhance the scientific rigor of the analysis.

Figure 8 illustrates the temporal evolution of the flood extent, indicating a peak on September 4 at 1848.17 km². Understanding the dynamics of flood

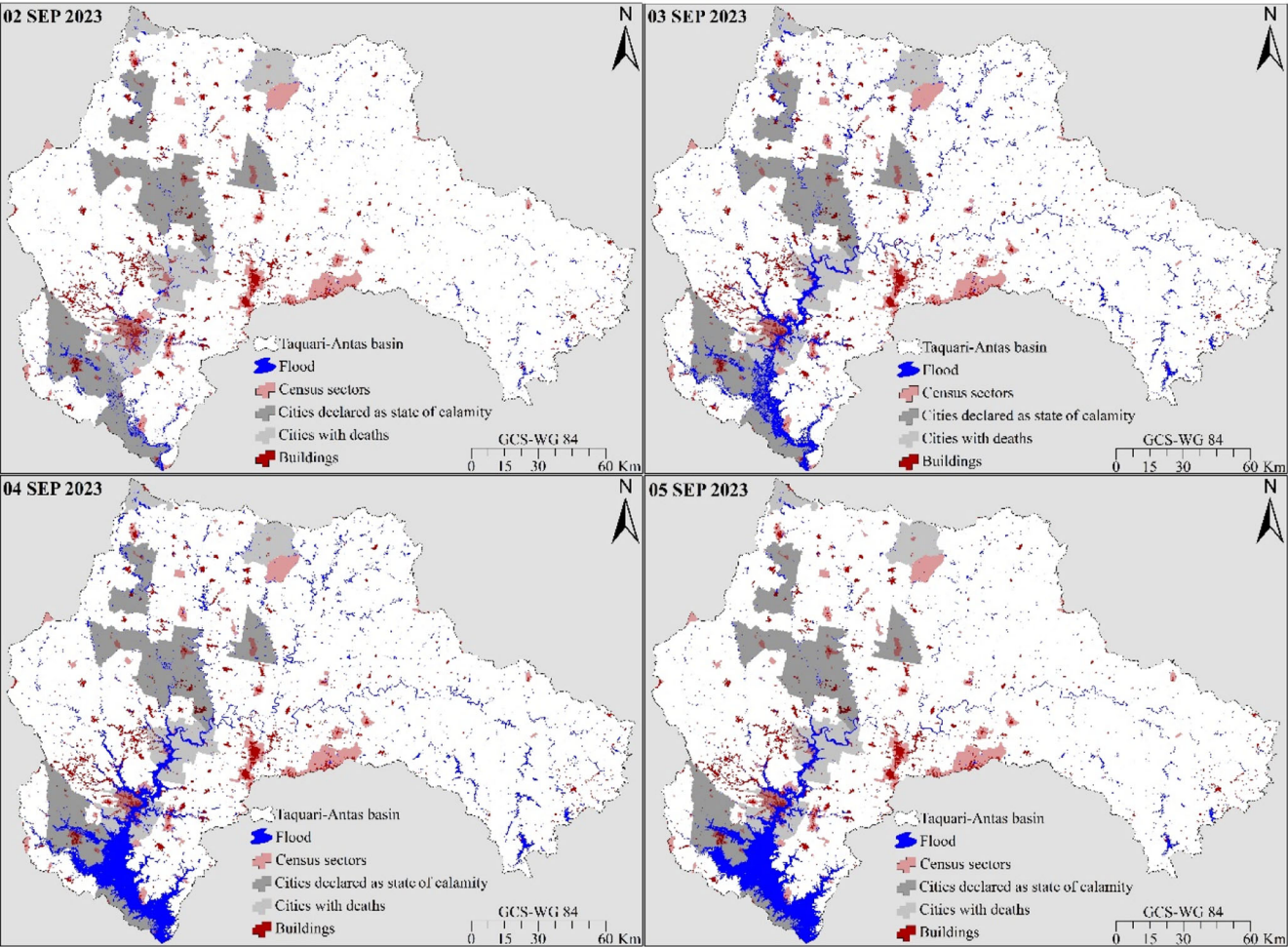


Fig. 8 | Simulated progression of flood extent in the Taquari-Antas basin.

progression and recession is crucial for flood forecasting and management. The cessation of rainfall on September 5 and the subsequent decrease in the flood extent provide valuable insights for disaster response planning, emphasizing the importance of timely and accurate weather forecasts.

Table 1 comprehensively presents data on flood impact, including affected areas, rainfall amounts, and impacts on census sectors, cities, and

Table 1 | Flood area in square kilometers, the amount of rainfall in millimeters, the area of the census sector affected by the flood in square kilometers, the area of cities declared in a state of calamity affected by the flood in square kilometers, the area of cities where people lost their lives due to the flood in square kilometers, and the area of buildings affected by the flood in square kilometers for the period from September 2 to 5, 2023

Classes	Time			
	02 Sep 23	03 Sep 23	04 Sep 23	05 Sep 23
Flood (km ²)	495.69	1361.61	1848.17	1521.11
Rainfall/day (mm)	243.47	168.39	253.89	0.00
Census sectors (km ²)	30.9	115.48	144.39	132.93
Cities declared as state of calamity (km ²)	88.21	249.67	424.28	438.79
Cities with deaths (km ²)	47.89	208.73	268.85	244.64
Buildings (km ²)	0.25	0.97	1.25	1.01
Urban area (km ²)	2.94	20.83	32.29	30.19

buildings. This information is vital for assessing the severity of the flooding event. The inclusion of various parameters, such as the areas of cities in a state of calamity and locations with fatalities, facilitates a nuanced understanding of the diverse impacts on both the built environment and human populations.

Figures 9 and 10 further break down the impact at the municipality level, detailing affected areas and fatalities. The comparison of municipalities in a state of calamity and those with recorded fatalities, along with demographic and geographical characteristics, offers valuable insights. Citation of the sources of municipality data, GIS tools used, and any demographic databases consulted would strengthen the reliability of the municipality-level analysis. Fig. 11 categorizes flooded areas based on LULC classes, indicating the prevalence of flooding in farming and forested areas. The scientific discussion should delve into the implications of land use patterns on flood dynamics, considering factors such as soil characteristics and land management practices. Citing the sources of LULC data and the methodology employed for classification is critical for the scientific robustness of this analysis.

The discussion rightly emphasizes the importance of the presented data for disaster management and long-term impact evaluation. This aligns with established scientific literature on disaster risk reduction and climate change adaptation. Citations to relevant studies on disaster planning, risk assessment, and the socio-economic impacts of floods would contextualize the findings within the broader scientific discourse.

Studies on Taquari-Antas floods in Rio Grande do Sul, Brazil, have focused on understanding flood vulnerability, coping strategies, and exposure indicators through participatory approaches such as Delphi surveys^{36,37}.

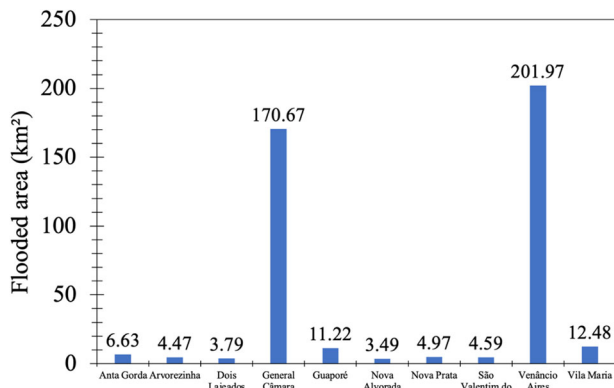


Fig. 9 | Flooded area in cities declared as state of calamity.

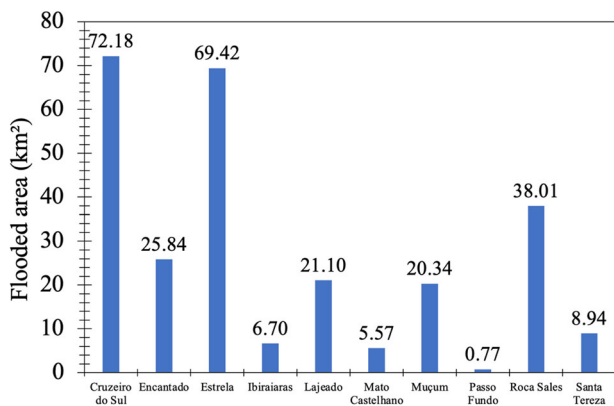


Fig. 10 | Flooded area in cities with deaths.

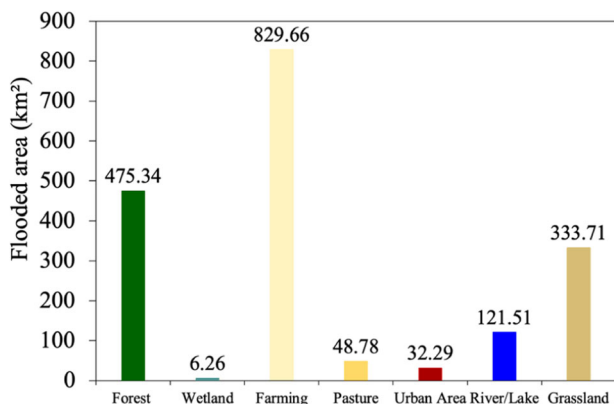


Fig. 11 | Flooded area by LULC classes.

These studies involve collaboration among experts, policymakers, and practitioners to develop flood vulnerability indexes tailored to the region's context. The research emphasizes the importance of consensus-building among stakeholders to effectively address flood impacts and enhance resilience in the basin. Tognoli et al. analyzed³⁸ a dataset from Encantado's pluviometric station in southern Brazil spans 78 years (1943–2020), including rainfall records ($n = 36,466$) and data on Taquari River levels during 44 flood events since 1941. Notably, three major floods occurred post-2001, with the most severe reaching a record level on July 8th, 2020. Human settlement in flood-prone areas has increased rapidly, with 34% of flood events occurring between 2011–2020, primarily from July to October.

The dataset provides valuable insights for developing predictive models and assessing correlations between floods, extreme events, and climate change.

Flooding is a pervasive natural hazard with profound impacts on communities, infrastructure, and ecosystems. Assessing flood risk is essential for informed decision-making, disaster preparedness, and sustainable land use planning. This comprehensive overview delves into the key components of flood risk assessment, drawing insights from established literature and methodologies. Understanding the hydrological and meteorological factors contributing to floods is fundamental. Precipitation patterns, land use changes, and soil characteristics influence runoff and river discharge. Advanced hydrological models, such as the Soil and Water Assessment Tool or Hydrologic Engineering Center-Hydrologic Modeling System, can simulate watershed responses to rainfall events³⁹. Topographic features play a crucial role in flood dynamics. DEMs aid in delineating flood-prone areas. Combining topographic data with land use information, derived from satellite imagery or land cover databases, enhances the accuracy of flood risk assessments. Geographic Information System (GIS) tools facilitate spatial analyses to identify vulnerable zones⁴⁰.

Hydraulic modeling assesses how floodwaters propagate through river channels and inundate floodplains. Models like HEC-RAS (River Analysis System) and MIKE Flood incorporate hydraulic principles to simulate flood scenarios. These models consider factors such as channel geometry, riverbed characteristics, and floodplain roughness, providing detailed insights into flood extents⁴¹. The impact of flooding extends beyond physical damage to encompass socioeconomic vulnerabilities. Population density, infrastructure density, and economic value within flood-prone areas contribute to overall risk. Social vulnerability indices, demographic data, and economic valuations assist in quantifying the human and economic dimensions of flood risk⁴².

Climate change introduces additional uncertainties to flood risk assessments. Altered precipitation patterns, sea-level rise, and changes in extreme weather events necessitate dynamic modeling approaches. Coupling hydrological models with climate projections allows for the incorporation of future climate scenarios into flood risk assessments⁴³. Incorporating community perspectives is essential for a holistic understanding of flood risk. Stakeholder engagement, community workshops, and surveys help identify local knowledge, perceptions, and historical experiences. Community involvement enhances the effectiveness of risk communication and the development of resilience strategies⁴⁴.

The presented flood risk map provides a spatial representation of varying risk levels in a specific region. The findings reveal critical information about the distribution of flood risk, particularly in terms of area classification and the intersection with urban structures. This discussion delves into the significance of these results in the context of urban vulnerability to flooding, drawing insights from established literature on flood risk assessment and urban resilience. The map categorizes the study area into different risk classes, with extreme risk covering the largest area (1090.17 km²), followed by high risk (317.31 km²) and low risk (124.15 km²). The spatial variation in flood risk underscores the heterogeneous nature of vulnerability within the region. Such variations can be attributed to topographical features, land use patterns, and hydrological characteristics, as highlighted by previous research on flood risk mapping⁴⁵.

An intriguing aspect of the analysis involves the intersection of extreme risk areas with building information. The extreme risk class exhibited the largest area occupied by constructions (0.90 km²). This finding accentuates the potential for significant impact on built infrastructure in high-risk zones. The concentration of the smallest area occupied by constructions in low and medium-risk classes (0.07 km²) suggests a relatively lower exposure of buildings in these areas. This aligns with studies emphasizing the importance of considering building vulnerability in flood risk assessments⁴⁶.

The city-level analysis identifies Cruzeiro do Sul and Estrela as having the largest areas classified as being in an extreme flood risk zone (61.58 km² and 61.39 km², respectively). These results underscore the urban vulnerability to flooding, emphasizing the need for targeted mitigation and

Fig. 12 | Flood risk map classification and census sectors, cities declared as state of calamity, cities with deaths and the location of buildings.

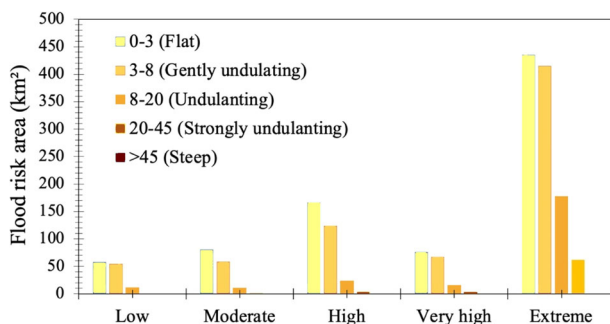
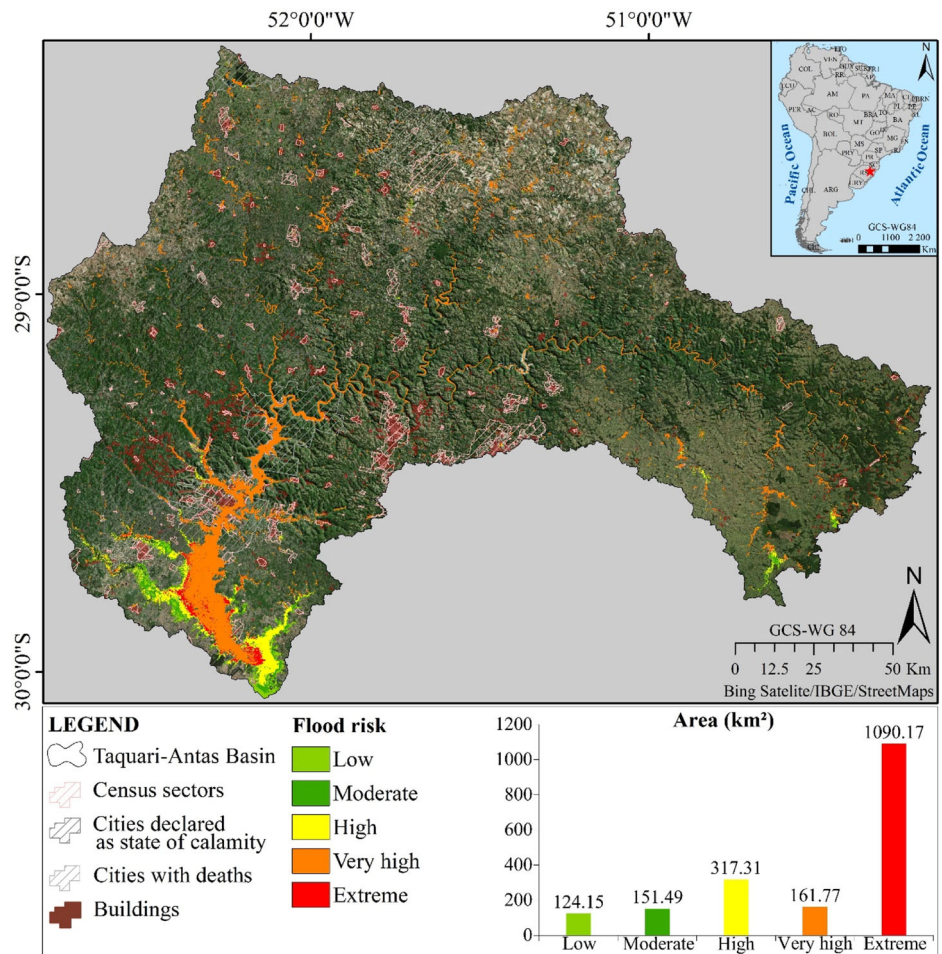


Fig. 13 | Flood risk class versus slope for the study area.

adaptation strategies. Urban areas often exhibit increased vulnerability due to factors such as high population density, impervious surfaces, and limited green spaces⁴⁷.

The insights from the flood risk map carry significant implications for urban planning and resilience measures. Cities identified with large areas in extreme risk zones may require heightened infrastructure resilience, early warning systems, and community preparedness initiatives. The integration of flood risk data into urban planning frameworks is crucial for developing sustainable and resilient cities⁴⁸. While the presented findings offer valuable insights, it is essential to acknowledge potential limitations. The accuracy of the flood risk map relies on the quality of input data, modeling methodologies, and assumptions made during the analysis. Transparent documentation of these aspects is crucial for the reproducibility and reliability of the results.

The catastrophic flooding and extreme rainfall events that occurred in Rio Grande do Sul in September 2023 can be attributed to a complex interplay of meteorological, hydrological, and geographical factors influenced by climate change. The increasing frequency and intensity of extreme rainfall events in the region suggest a changing climate pattern that poses substantial risks to communities and infrastructure. Properly mapped flood risk information can aid in decision-making for urban planning, emergency response, and climate adaptation strategies. It also contributes to raising public awareness and enhancing resilience to flood events. Through an in-depth analysis of this climatic disaster, we aim to uncover the specific mechanisms and contributing factors that led to this unprecedented event. This research will not only enhance our understanding of the dynamics of extreme precipitation but also contribute to the development of more effective strategies for flood risk assessment and mitigation in the future.

In conclusion, the multifaceted analysis of precipitation dynamics in the Bacia Taquari Antas region for September 2023 has provided comprehensive insights into the complex nature of rainfall patterns and their potential implications for local climate dynamics. The key findings, spanning monthly, daily, and subdaily scales, along with trend analyses, contribute significantly to understanding both the normal climate variability and the anomalous precipitation observed in September 2023.

Methods

Study area

The Taquari River Basin is in the northeastern region of the state of Rio Grande do Sul, in the southern region of Brazil and covers an approximate area of 26,500 km² (Fig. 14). Its boundaries are the Pelotas River Basin to the north, the Jacuí River Basin to the west and south, and the Caí and Sinos River Basins, along with small coastal basins, to the east. It drains an area of

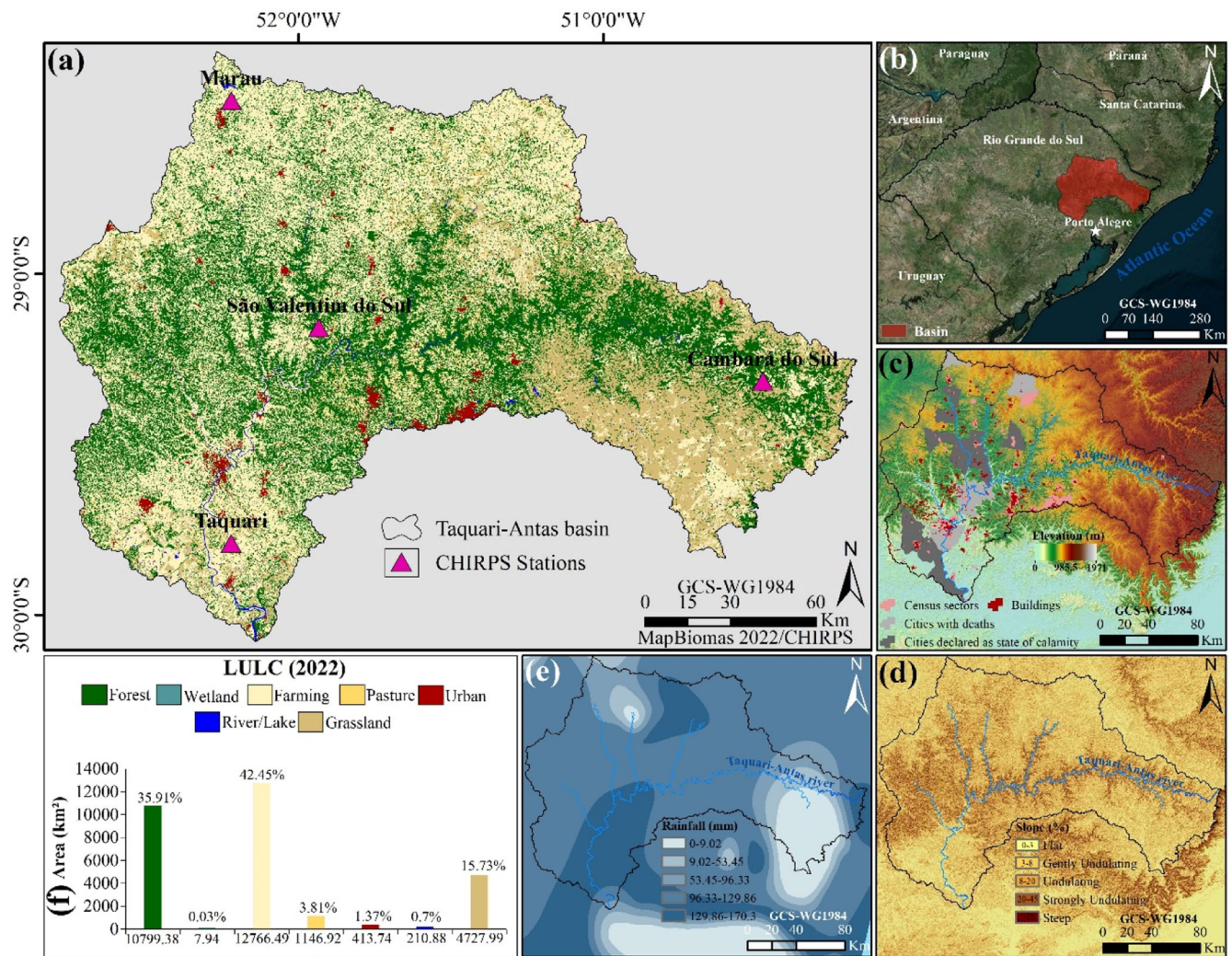


Fig. 14 | Location of Taquari-Antas basin in Rio Grande do Sul State, Brazil. **a** Location of Taquari-Antas basin in Rio Grande do Sul State, Brazil; **b** location of Taquari-Antas basin; **c** Digital Elevation Model (MDE) for the study area; **d** slope, **e** rainfall (mm); and **f** land use and land cover (LULC) in Km².

approximately 26,428 km², which corresponds to about 9% of the state of Rio Grande do Sul's territory. This hydrographic basin is one of the most important in the state and plays a significant role in providing water and supporting agriculture and industry in the region. The Taquari River is the main watercourse in the basin, formed by the confluence of the Forqueta and Jacuí rivers, and it runs through an extensive area of the state, flowing into the Jacuí River, which, in turn, empties into Guaíba Lake. The basin covers a considerable geographic area and features a wide variety of ecosystems, ranging from plain areas to more mountainous zones, creating a diverse landscape. This region is essential for the economy and the environment of the state of Rio Grande do Sul, contributing to agricultural and livestock production, hydroelectric power generation, and the supply of water to local populations. Additionally, the Taquari River Basin plays a crucial role in conserving the region's biodiversity.

Regarding land use and land cover, LULC, (Fig. 14b), in the region of the headwaters of the Taquari-Antas River, in the Campos de Cima da Serra (grassy plains), extensive cattle ranching predominates. This landscape changes around the city of Antônio Prado, where small rural properties with intensive land use, primarily for livestock farming, become more common. As for agricultural use, the sub-basins of the Carreiro, Forqueta, and Antas rivers stand out in terms of cultivated areas, with corn and soybean crops being predominant. In addition to these crops, rice is cultivated in the flatter areas to the south of the basin. The forest vegetation is primarily Mixed Ombrophilous Forest, characterized by broad-leaved trees, with the

Araucaria being the main tree species. It develops alongside small shrubs and patches of vegetation. The continuity of this forest is interrupted by the presence of steppes, which are open grassland areas dominated by low-lying species. These areas may have different names based on their specific characteristics.

Datasets

The flowchart (Fig. 15) summarizes the data and methods used to map the flood risk. The study utilized DEMs and CHIRPS dataset for rainfall analysis. Climate indices were analyzed, and flood events were simulated using HEC-RAS 2D model. Model performance was evaluated using observed data, and flood risk was mapped using the FEMA method. Various statistical tests were conducted to understand time series characteristics, and land use data were incorporated for flood modeling. The study provides insights into disaster management and urban planning.

Digital elevation model

The study makes use of a diverse array of data sources, including DEM images obtained from the PALSAR L-Band sensor on the Advanced Land Observing Satellite (ALOS) as part of the Japan Aerospace Exploration Agency's (JAXA) mission (https://www.eorc.jaxa.jp/ALOS/en/index_e.htm). Additionally, the DEM is created using SRTM data available on the Alaska Satellite Facility (ASF) website (<https://asf.alaska.edu>), which has been resampled (up-sampled) to achieve a pixel size of 30 meters from its

original 12.5 meters and adjusted to orthometric altitude based on the EGM96 geoid model. It is also converted to geometrical altitude, which is measured with respect to the ellipsoid. Due to the high number of scenes required to cover the entire study area, these scenes will not be individually detailed in this context.

Rainfall data

For the analysis of rainfall, the study utilized the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset, as introduced by ref. 49. The CHIRPS dataset incorporates satellite imagery and in-situ station data and provides rainfall information at temporal scales ranging from daily to annual, with a spatial resolution of $0.05^\circ \times 0.05^\circ$. It covers the period from 1981 to September 2023 and is accessible at this link: <https://data.chc.ucsb.edu/products/CHIRPS-2.0/>. For the analysis of rainfall, the study utilized the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset⁴⁹. CHIRPS incorporates satellite imagery and in-situ

station data, providing rainfall information at temporal scales ranging from daily to annual, with a spatial resolution of $0.05^\circ \times 0.05^\circ$. It covers the period from 1981 to September 2023 and is accessible at this link: <https://data.chc.ucsb.edu/products/CHIRPS-2.0/>.

The CHIRPS dataset was selected to carry out these analyses because it performs well over the region of interest. For the month of September, regarding the Brazilian territory, CHIRPS presents the best of some statistics scores in the South states—e.g., determination coefficient is 0.99 and BIAS is 6.76⁵⁰. Besides^{51,52}, show that over Brazil and southern South America CHIRPS generally presents correlation higher and root mean square errors and standard deviations smaller than many other datasets when extreme precipitation is considered. Lastly, in a broader view, CHIRPS presents some metrics such as mean error and BIAS smaller in South America than in Europe, Africa and Australia⁵³.

A mean time series were performed to Bacia Taquari Antas on daily time scale from 1981 to September 2023. With this data we performed daily and monthly analyses and performed climatologies (based on 1991–2020 period). We also calculate 12 climate index defined by ETCCDI (Expert Team on Climate Change Detection and Indices^{54–57}) for the period 1981–2022 (Table 2). To Analyze changes on climate precipitation index, a trend analyses using the Mann-Kendall test^{58,59} was used with a confidence level of 95%. The Sen Curvature test⁶⁰ was used to estimate the magnitude of this trend.

To investigate sub-daily precipitation on September 2023, we used meteorological stations from INMET only for September 2023 data. There are 7 meteorological stations from INMET on region and precipitation data is measured at each 1 h (Fig. 16).

Given the large area of the basin under study, the study employed a Thiessen Diagram algorithm⁶¹ to determine which rainfall stations had the greatest influence on the accumulated rainfall (Fig. 17). This approach identified four key stations through the algorithm, located in the municipalities of Camará do Sul-RS, São Valentim do Sul-RS, Marau-RS, and Taquari-RS. Statistical analyses were applied to these time series to identify patterns and anomalies and to calibrate the 2D flood model.

To understand the characteristics of the time series, several statistical tests were conducted: 1. Augmented Dickey–Fuller (ADF) Test: This test was used to assess the seasonality of the data and verify the stability of the

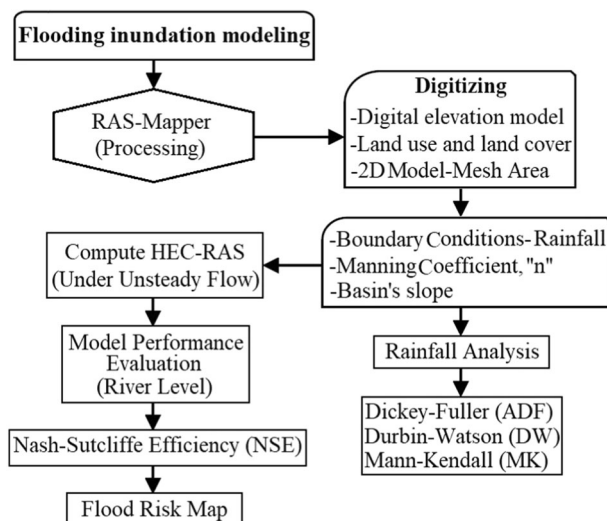


Fig. 15 | Flowchart of data and methods used in the study.

Table 2 | Climate precipitation extreme index defined by ETCCDI

Acronym	Index	Definition	Unit
PRCPTOT	Annual total precipitation in wet days	Let RR_{ij} be the daily precipitation amount on day i in period j . If l represents the number of days in j , then: $PRCPTOT_j = \sum_{i=1}^l RR_{ij}$	mm
Rx1day	Monthly maximum 1-day precipitation	Let RR_{ij} be the daily precipitation amount on day i in period j . The maximum 1-day value for period j are: $Rx1day_j = \max(RR_{ij})$	mm
Rx5day	Monthly maximum consecutive 5-day precipitation	Let RR_{kj} be the precipitation amount for the 5-day interval ending k , period j . Then maximum 5-day values for period j are: $Rx5day_j = \max(RR_{kj})$	mm
CDD	Maximum length of dry spell	maximum number of consecutive days with $RR < 1$ mm: Let RR_{ij} be the daily precipitation amount on day i in period j . Count the largest number of consecutive days where: $RR_{ij} < 1$ mm	days
CWD	Maximum length of wet spell	maximum number of consecutive days with $RR \geq 1$ mm: Let RR_{ij} be the daily precipitation amount on day i in period j . Count the largest number of consecutive days where: $RR_{ij} \geq 1$ mm	days
R10	Annual count of days when $PRCP \geq 10$ mm	the number of days where: $RR_{ij} \geq 10$ mm	days
R20	Annual count of days when $PRCP \geq 20$ mm	the number of days where: $RR_{ij} \geq 20$ mm	days
R25	Annual count of days when $PRCP \geq 25$ mm	the number of days where: $RR_{ij} \geq 25$ mm	days
R30	Annual count of days when $PRCP \geq 30$ mm	the number of days where: $RR_{ij} \geq 30$ mm	days
R50	Annual count of days when $PRCP \geq 50$ mm	the number of days where: $RR_{ij} \geq 50$ mm	days
R100	Annual count of days when $PRCP \geq 100$ mm	the number of days where: $RR_{ij} \geq 100$ mm	days

Station	Lat/Lon
837 - Soledade	-28.86/-52.54
882 -Teutonia	-29.45/-51.82
894- Serafina Correa	-28.70/-51.87
840 - Bento Gonçalves	-29.16/-51.53
844 -Lagoa Vermelha	-28.22/-51.51
880 - Vacaria	-28.51/-50.88
897 - Cambara do Sul	-29.05/-50.15

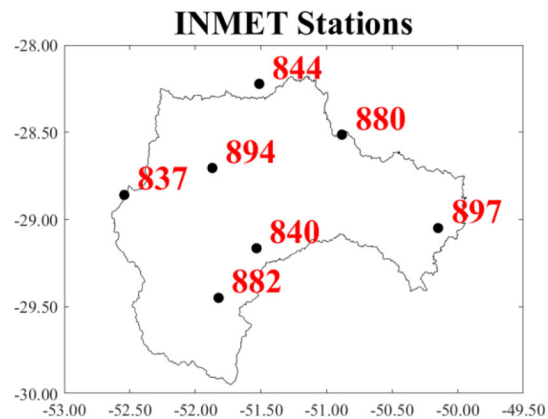
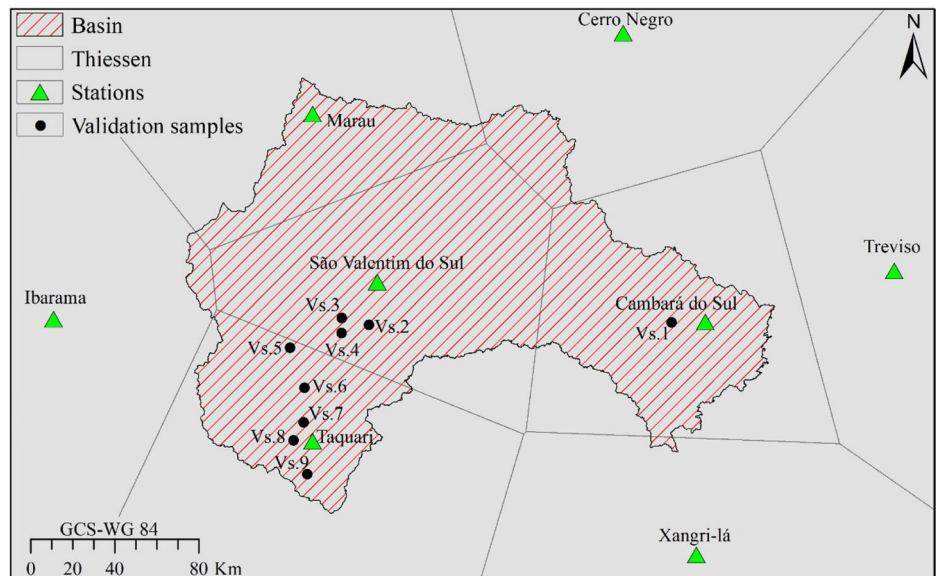


Fig. 16 | “Location of INMET Meteorological Stations used for sub-daily analysis in the Taquari-Antas Basin region during September 2023.”

Fig. 17 | Thiessen Diagram for the study area, with rainfall stations and water level stations highlighted for model validation.



mean, standard deviation, and the presence of seasonality. The null hypothesis of the ADF test indicates that if the time series has a unit root, it is not stationary. If seasonality is present, the data is considered non-stationary. 2. Durbin–Watson (DW) Test: The DW test was employed to evaluate autocorrelation in non-lagged dependent variables and is suitable for small sample sizes. It provides values ranging from 0 to 4, with values close to 2 indicating no autocorrelation, values close to 0 suggesting positive autocorrelation, and values close to 4 implying negative autocorrelation. 3. Mann–Kendall Test: The Mann–Kendall test is a robust, sequential, and nonparametric method used to detect statistically significant time trends. The null hypothesis (H0) suggests there is no trend in the data, while the alternative hypothesis (HA) indicates the presence of a trend, which can be either increasing or decreasing.

To confirm time-series trends, the Theil–Sen Robust Linear Regression (TS) was utilized. This approach is non-parametric, median-based, and insensitive to outliers. It returns slope and intercept values, composing the classical regression line equation. The results of these statistical analyses were used to calibrate the flood model for September 4, 2023.

Land use and land cover and urban data

The study also utilized a Land Use and Land Cover (LULC) map from the MapBiomias project, specifically from the year 2022, collection 7. This map provides valuable information about the classification of land areas. You can access this data at https://mapbiomas.org/en?cama_set_language=en. Additionally, urban data, in shapefile format, were obtained from OpenStreetMap via <http://download.geofabrik.de>. These urban data layers were

Table 3 | Manning's n roughness values associated with different land covers for the low, medium, and high ranges

Description	Land cover	Manning's n
Forest	Forest formation	0.06
Non-Forest Natural	Wetland	0.04
	Grassland	
Farming	Pasture	0.04
	Agriculture	
	Soybean	
	Rice	
Non-vegetated area	Urban area	0.07
Water	River, Lake	0.035

used to delineate urban areas within the municipality. Census sector data, also in shapefile format, were employed to identify urban areas with high density and low density. These data were instrumental for both qualitative and quantitative analyses aimed at understanding the impacts of extreme rainfall events on flooding. The integration of these various data sources allowed for a comprehensive assessment of the effects of extreme rainfall events on floods, including the influence of land use, urban development, and density on the flood patterns in the studied area.

Flooding inundation modeling

The study involved simulating flood events that occurred on September 1, 2023, using HEC-RAS 2D model⁶² (Hydrologic Engineers Corps - River Analysis System). It is a cutting-edge tool for flood modeling that offers a two-dimensional approach to simulating flood dynamics. Unlike traditional one-dimensional models, HEC-RAS 2D takes into account both the vertical and horizontal dimensions of flood flows, providing a more accurate representation of flood extents and depths. By considering complex flow interactions, it enables engineers and researchers to assess flood risk, plan flood control measures, and make informed decisions regarding floodplain management. This advanced modeling approach is particularly valuable when dealing with areas prone to flooding, offering a more comprehensive understanding of flood behavior and aiding in the development of effective flood mitigation strategies.

HEC-RAS 2D is a widely used hydrodynamic modeling tool that has been employed in various regions worldwide^{63–65}. For the model calibration, daily rainfall data from 1981 to September 2023, sourced from CHIRPS, were analyzed using a box and whisker plot. This data helped fine-tune the model parameters. The HEC-RAS 2D model is based on solving one or two-dimensional Saint-Venant equations, which account for both steady and unsteady flow (dynamic) regimes.

In this study, the unsteady flow method was used, and the September 2023 flood event was modeled directly using precipitation data. Precipitation data were incorporated into the model on a daily basis. The rainiest day recorded in the basin during the flood, which considered all four seasons, was September 4th, with a total of 431.375 mm of rainfall. The input data required for the development of the 2D model included: 1. Topography of the basin, derived from the PALSAR DEM. 2. Mesh area and boundary conditions, which were defined through distributed rainfall data across the entire basin. 3. Output conditions, using the basin's slope. 4. Manning's coefficient, represented as " n ," which is a parameter used to describe surface roughness.

To assign specific values for Manning's " n " in the model, Land Classification layers were used. These layers helped identify parameter values for Manning's " n " (Table 3) based on the land use and land cover data from the year 2022, sourced from MapBiomass. While it is difficult to pinpoint the exact Manning's " n " values that best represent the study area's actual conditions, as these values lack independent physical bases, the range of values tested fell within the commonly used range in flood modeling literature⁶⁶.

Table 4 | Flood risk classifications scheme

Velocity × Depth (m ² /s)	Flood risk
<0.2	Low
0.2–0.5	Moderate
0.5–1.5	High
1.5–2.5	Very high
>2.5	Extreme

A graph was generated from the stratified classes, focusing on flood areas within the urban perimeter. This graph included data related to the areas of the flood patches. All datasets were then organized within the HEC-RAS/RAS MAPPER software to simulate the event. Subsequently, for the analysis of the results, a Geographic Information System (GIS) was employed. Geoprocessing techniques and digital cartography were integrated into the ArcGIS software, which is developed by ESRI (Environmental Systems Research Institute) in 2015. This GIS-based approach allowed for the visualization, analysis, and interpretation of the simulation results within a spatial context, providing valuable insights into the impact of the flood event on the urban area and its surroundings.

In this study, to validate and assess the results generated by the model, we used observed data from river levels, extracted from the fluvimetric station and data generated by the model. The flood model was validated using 9 water level station (01 to 05 September 2023) inside the Taquari-Antas basin (see Fig. 4 for location). We assessed the model quality using the Nash Sutcliffe efficiency⁶⁷ (NSE). The NSE consists of a normalized statistic that determines the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information"). NSE indicates how well the plot of observed versus simulated data fits the 1:1 line. It is defined as Eq. (1):

$$NSE = 1 - \frac{\sum_{t=1}^T (Q_0^t - Q_m^t)^2}{\sum_{t=1}^T (Q_0^t - \bar{Q}_0)^2} \quad (1)$$

where (Q_0) is the mean of observed discharges, and Q_m is modeled discharge. Q_0^t is observed discharge at time t .

The Nash–Sutcliffe efficiency is calculated as one minus the ratio of the error variance of the modeled time-series divided by the variance of the observed time-series. In the situation of a perfect model with an estimation error variance equal to zero, the resulting Nash–Sutcliffe Efficiency equals 1 ($NSE = 1$). Conversely, a model that produces an estimation error variance equal to the variance of the observed time series results in a Nash–Sutcliffe Efficiency of 0.0 ($NSE = 0$). $NSE = 0$ indicates that the model has the same predictive skill as the mean of the time-series in terms of the sum of the squared error. In the case of a modeled time series with an estimation error variance that is significantly larger than the variance of the observations, the NSE becomes negative. An efficiency less than zero ($NSE < 0$) occurs when the observed mean is a better predictor than the model. Values of the NSE nearer to 1, suggest a model with more predictive skill.

Flood risk mapping

To map the flood risk, we used the U.S. Federal Emergency Management Agency⁶⁸ method. In this method, the guide risk levels are divided into five discrete categories – low, moderate, high, very high and extreme (Table 4). This method was used⁶⁹ to produce a flood map and evaluated the flood risks in case of insufficient flow data in Turkey. The method uses the velocity and the flood depth from the 2D model HEC-RAS.

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José Mantovani: Conceptualization, Methodology, Formal Analysis, Data Curation, Writing—Original Draft. Enner Alcântara: Conceptualization, Methodology, Formal Analysis, Writing—Review & Editing. Luana A. Pampuch: Writing—Review & Editing. Edward Park: Writing—Review & Editing. Cheila Flávia Praga Baião: Writing—Review & Editing. Edward Park: Writing—Review & Editing. Maria de Souza Custódio: Writing - Review & Editing. Luiz Felipe Gozzo: Writing—Review & Editing. Cassiano Antonio Bortolozzo: Writing—Review & Editing.

Competing interests

The authors declare no competing interests.

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