Spatiotemporal Trends of Extreme Precipitation in Caraguatatuba (SE Brazil) from CHIRPS Data (1981–2024) Using GEE and Climate Indices

Yasmim Carvalho Guimarães[1], Andrés Velastegui-Montoya[2], Gabriela Alves Carreiro [1], Luana Albertani Pampuch Bortolozo [1,3], Enner Alcântara [1,3]

[1]Graduate Program in Natural Disasters, (Unesp/CEMADEN), São José dos Campos, Brazil
yasmim.guimaraes@unesp.br, g.carreiro@unesp.br;
[2]Faculty of Engineering in Earth Sciences, ESPOL Polytechnic University, Guayaquil, Ecuador– dvelaste@espol.edu.ec;
[3]Institute of Science and Technology, Environmental Eng. Dept., Unesp, São José dos Campos, Brazil
luana.pampuch@unesp.br, enner.alcantara@unesp.br

Keywords: Precipitation patterns, Coastal city, Extreme weather events, Climate indices, Temporal trends.

Abstract

Climate change has intensified the variability and frequency of extreme events, particularly affecting vulnerable coastal urban areas. In Caraguatatuba, located on the north coast of São Paulo, the impacts are exacerbated by social inequalities and inadequate infrastructure. However, detailed analyses of climate indices in the region are still scarce. This study analyzes precipitation patterns in Caraguatatuba, calculating climate indices to identify trends and support risk mitigation. CHIRPS daily precipitation data at 0.05° spatial resolution were processed using Google Earth Engine and R to compute the ETCCDI indices PRCPTOT, CDD, CWD, R95p, R99p, Rx1day, and Rx5day. Statistical tests were applied to detect significant trends. The results indicate an increase in consecutive dry periods (CDD, $p=0.0065$) and at the intensity of daily extreme rainfall (Rx1day, $p=0.0044$) in the southwestern area, while other indices did not show significant trends. These findings highlight the city's increasing climate vulnerability and the urgent need for adaptation strategies. By offering a replicable framework based on open-access remote sensing and cloud platforms, this study supports policy development to enhance urban resilience and monitoring climate-related disasters in coastal cities.

1. introduction

Global climate patterns are undergoing significant and ongoing changes, resulting increased climate variability and more frequent extreme events, such as floods and droughts (IPCC, 2023, Visconti and Young, 2024). These phenomena pose significant global challenges, significantly affecting human health, generating socioeconomic repercussions and environmental damage (WHO, 2021, Bell et al., 2018). The risks are intensified in urban areas due to vulnerabilities and compounded by local factors, such as geomorphological features and climate patterns (Birkmann et al., 2016, Wannewitz et al., 2024). In this context, the study of climate indices provides insights into local conditions, offering essential information for analyzing risks related to extreme events, as seen in seasonal studies and the tendency toward wetter conditions (Zhang et al., 2011, Alexander et al., 2006).

Research has demonstrated the potential of these indices to reveal meaningful patterns in climate. In China, for example, research on precipitation trends revealed increases in total rainfall and a growing persistence of extreme precipitation events, suggesting particularly severe conditions in autumn and summer (Gan et al., 2022). In Turkey, droughts were analyzed using intensity-duration-frequency curves based on precipitation deficits rather than relying solely on the Standardized Precipitation Index, showing that droughts with a 2-year return period were significantly less severe than those with more extended return periods (Cavus and Aksoy, 2020). In Brazil, a study of six annual precipitation indices from 1950 to 1999 found that intense rainfall has become more concentrated over fewer days, revealing positive trends in CDD and R20mm indices and a negative trend in Rx5day (Dufek and Ambrizzi, 2008).

The increasing frequency of climate anomalies adds pressure on disaster management systems, particularly in urban and coastal regions, which are often the first to experience the impacts and must continuously adapt (Meerow, 2017). Coastal cities like Caraguatatuba, located in São Paulo, illustrate these challenges. The municipality has a history of extreme rainfall, notably the March 1967 disaster, when over 600 mm of rain in two days, combined with a storm surge, caused over 400 deaths and the largest recorded landslide in the country's history (7.6 million m^3) (Pezzoli et al., 2013, Cabral et al., 2023, Arasaki et al., 2012). More recently, in February 2023, the northern coast of São Paulo was once again severely affected by extreme rainfall, which triggered hundreds of landslides, resulting in 46 deaths and affecting thousands of people (Bonini et al., 2025).

Despite this context, there remains a lack of studies applying climate indices from the Expert Team on Climate Change Detection and Indices (ETCCDI) in Brazilian coastal areas, which would provide standardised metrics for tracking climate extremes over time. To address this gap, the present study analyze precipitation patterns in Caraguatatuba using a set of ETCCDI indices. It aims to identify trends and seasonal behaviours, assess the municipality's exposure to extreme rainfall events, and provide scientific evidence to support decision-making. By integrating open-access climate data and a replicable structure, this work contributes to the development of resilient urban planning and disaster risk reduction strategies in coastal areas.

2. Materials and Methods

2.1 Study Area

Caraguatatuba is located in the southeastern region of Brazil, within the state of São Paulo, surrounded by Natividade da

Serra, Paraibuna, Salesópolis, São Sebastião and Ubatuba (Fig.1). At geographic coordinates 23°37'13" S latitude and 45°24'47" W longitude and an altitude of 2 m above sea level (Geografos, 2025), it forms part of São Paulo's Northern Coast. With a total area of 485,95 km^2, Caraguatatuba encompasses both urban and rural zones, with the urban area predominantly located along the coastline, where its infrastructure and population are concentrated. Additionally, the municipality includes a portion of the Parque Estadual da Serra do Mar, which covers its entire green area.

Figure 1. Geographical location of Caraguatatuba.

The city has undergone substantial demographic changes over the decades. Between 1970 and 1980, its population increased by 124% (from 15,073 to 33,802 residents), a period marked by a significant shift from rural to urban settlement patterns. This transformation highlights Caraguatatuba's growing role as an urban centre, driven by both population growth and the development of its tourism sector (Gigliotti and Santos, 2013). As of 2024, the population of Caraguatatuba was estimated to be 141,084 people (World Population Review, 2025).

The rainfall pattern in Caraguatatuba is shaped by its latitude, the humidity from the ocean, and the presence of the Serra do Mar Mountain range. These factors contribute to precipitation through orographic effects, where the mountains force moist air upwards, leading to rainfall. Additionally, the region's climate is influenced by the movement of frontal systems, which is altered by these topographical and atmospheric conditions. These dynamics are typical of coastal areas with mountainous terrain, resulting in seasonal rainfall variability and extreme weather events (Santos and Galvani, 2014).

Due to its high vulnerability to extreme weather events, Caraguatatuba's geographical location and topographical features, such as its coastal position and the influence of the Serra do Mar, amplify the impacts of intense rainfall and prolonged droughts (Bukvic et al., 2020).

2.2 Methodological Proposal

The methodology for this study focused on climate analysis using Google Earth Engine (GEE) and R, an open-source programming language and statistical computing environment widely used for data analysis, visualization, and spatial statistics. Initially, the area of interest was defined and, an appropriate precipitation dataset, the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), was selected due to its excellent temporal (daily) and spatial (0.05° grid) resolution (Climate Hazards Center, 2025). A custom function was developed in Google Earth Engine to process annual precipitation data from January 1981 to December 2024.

Subsequently, various precipitation indices were calculated in the R environment, including total precipitation (PRCPTOT), consecutive wet days (CWD), consecutive dry days (CDD), maximum 1-day (Rx1day) and 5-day (Rx5day) precipitation, as well as extreme precipitation indicators R95p and R99p. The definitions of these indices are presented in Table 1, while their respective formulas are detailed in Table 2. In these equations, P_i denotes the daily precipitation on day i; n is the total number of days; P_{95} and P_{99} represent the 95th and 99th percentiles of daily precipitation over a reference period; k indicates the start of a wet or dry sequence, with m representing its duration in consecutive days; and j corresponds to the starting day of a 5-day accumulation period (WMO, 2025, Climdex Project, 2023).

Climate Index	Definition
PRCPTOT	Total annual precipitation from days with at least 1 mm of rain ($P_i \geq 1$ mm).
R95p	Total annual precipitation from days when daily rainfall exceeds the 95th percentile ($P_i > P_{95}$).
R99p	Total annual precipitation from days when daily rainfall exceeds the 99th percentile ($P_i > P_{99}$).
CWD	Maximum number of consecutive days with at least 1 mm of precipitation.
CDD	Maximum number of consecutive days with less than 1 mm of precipitation.
Rx1day	Maximum daily precipitation amount in the year.
Rx5day	Maximum total precipitation over five consecutive days.

Table 1. Precipitation index definitions.

Commonly used tests for identifying climate trends include the Mann-Kendall test, Sen's slope estimator, and linear regression (Güçlü, 2018). Linear regression was used in 48% of the literature-reviewed cases, while the Mann-Kendall test accounted for 39% (Silva et al., 2013). Although the Mann-Kendall test is widely adopted for its non-parametric nature, it is less sensitive than parametric methods, such as linear regression, particularly when dealing with small sample sizes or subtle trends. Linear regression not only identifies the direction and magnitude of trends but also provides statistical significance and confidence intervals, assuming normality and homoscedasticity. Therefore, due to its higher sensitivity and ability

Climate Index	Formula	Unit
PRCPTOT	$\text{PRCPTOT} = \sum_{i=1}^{n} P_i$	mm
R95p	$\text{R95p} = \sum_{i \in \{P_i > P_{95}\}} P_i$	mm
R99p	$\text{R99p} = \sum_{i \in \{P_i > P_{99}\}} P_i$	mm
CWD	$\text{CWD} = \max\left(\sum_{i=k}^{k+m} 1\right)$	days
CDD	$\text{CDD} = \max\left(\sum_{i=k}^{k+m} 1\right)$	days
Rx1day	$\text{Rx1day} = \max(P_i)$	mm
Rx5day	$\text{Rx5day} = \max\left(\sum_{i=j}^{j+4} P_i\right)$	mm

Table 2. Climate indices, their formulas and units.

to quantify trend intensity, linear regression was chosen as a method in the present study. A significance level of α = 0.05 was used.

To enable spatial visualization of the climate indices, zonal statistics were applied using QGIS (version 3.22.5) for the years 1985 and 2024. Zonal statistics are a powerful tool that integrates spatial and statistical data, enabling the computation of metrics such as mean, maximum, minimum, and standard deviation within each defined region. This approach provides valuable insights into spatial patterns and variability, supporting scientific analysis and practical applications (Saldanha et al., 2024).

3. Results and Discussions

The trends observed in the precipitation indices for the Caraguatatuba region are discussed in this section. The results are evaluated for each climate index calculated, allowing the identification of seasonal patterns, the impact of extreme weather events, and long-term variability in rainfall.

For the analyzed period, the PRCPTOT index (Fig. 2) ranges between 1200 mm and 2200 mm, peaking at 2215 mm in 1983, with notable values in 2009 (2089 mm) and 2023 (1831 mm). These results align with previous studies, which report average values of around 2000 mm in the Ilha Grande Bay region (Luiz-Silva and Oscar-Júnior, 2022). A slight decreasing trend in total annual precipitation is observed. However, there is a weak or nonexistent linear relationship between precipitation and year (p-value of 0.9938).

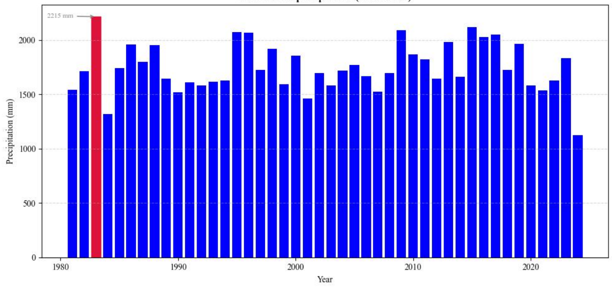

Figure 2. Annual total precipitation of Caraguatatuba.

The index also reflects extreme rainfall events, such as February 19, 2023, when over 600 mm fell in 24 hours, causing severe flooding and landslides in several coastal cities, including Caraguatatuba (Union, 2023). It also reflects the intense rainfall on January 9, 2009, which caused severe flooding in Caraguatatuba, particularly in the neighbourhoods of Massaguaçu and the city centre, as well as another event in December 2009 that affected areas such as Morro do Algodão and Jardim Primavera (Bortoletto, 2016).

The R95p index (Fig. 3) ranges from 0 to 600 mm, with notable peaks in 2017 (468.91 mm), 2020 (331.74 mm), and between 2009 and 2011. A decreasing trend is observed, indicating a statistical relationship between R95p and year (p-value = 0.0159). Similarly, R99p (Fig. 3) varies between 0 mm and 300 mm, with a maximum of 288.14 mm in 2005, followed by peaks near 150 mm in 2017, 2020, and 2024. Despite gaps due to years without values above the 99th percentile, the index shows a significant downward trend. The p-value (0.0271) suggests a significant trend in the change of R99p over time.

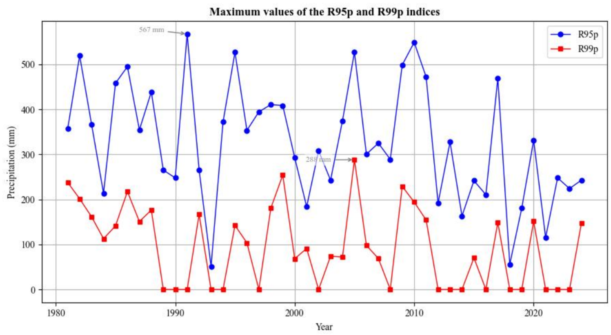

Figure 3. Total annual precipitation from days when daily rainfall exceeds the 95th Percentile and the 99th Percentile.

This value aligns with the event on March 15, 2017, when a heavy storm hit São Paulo’s northern coast, causing significant flooding in Caraguatatuba (Nova Imprensa, 2017). The storm resulted in damage and left at least three families homeless, highlighting the city’s vulnerability to intense rainfall events. This index can also reflect the events mentioned in the PRCPTOT section, specifically those recorded in 2009 when Caraguatatuba experienced significant flooding in January.

The consecutive Wet Days (CWD) index helps identify extended periods of continuous rainfall, which are often associated with increased flood risks and soil saturation. In contrast, the Consecutive Dry Days (CDD) index highlights prolonged dry spells commonly linked to drought conditions and water scarcity issues.

In this work, the CWD index (Fig. 4) ranges from 5 to 20 days, showing a decreasing pattern from 19 days in 1981 to 11 days in 2023. These values are consistent with ranges observed in other regions like the Médio Paraíba do Sul, Dois Rios basin, and the central-western portion of Macaé basin (11–14 days) (Luiz-Silva and Oscar-Júnior, 2022). However, the p-value of 0.187 indicates that there is no significant linear trend over time.

As for CDD index (Fig. 4) there is an increasing trend, ranging from 10 to 40 days: it rose from 29 days in 1981 to 39 in 2017 and 38 in 2022, aligning with climatological values along the coast (20–32 days) (Luiz-Silva and Oscar-Júnior, 2022). The p-value of 0.0065 indicates a statistically significant increase over time, with high confidence (1% significance level), meaning it

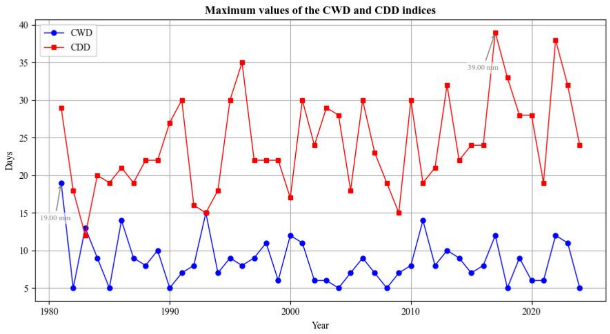

Figure 4. Consecutive wet days and consecutive dry days.

is highly unlikely that the observed effect of the year on CDD occurred by chance.

The Rx1day index highlights extreme daily precipitation events, offering insights into the potential risks of heavy rainfall and its associated impacts. Meanwhile, the Rx5day index captures intense precipitation accumulated over consecutive days, often related to flooding and broader hydrological hazards.

For the period under review, the Rx1day index (Fig.5) shows a decreasing trend, ranging from 50 mm to 150 mm, with peaks in 1985 (141.31 mm), 2005 (112.67 mm), and 2010 (115.33 mm). The p-value of 0.00441 indicates statistically significant evidence that the year variable has an effect on the variable Rx1day. The Rx5day index (Fig.5) also shows a downward trend, with peaks in 1985 (shared with Rx1day) with 211.35 mm, 1995 (208.42 mm), 1996 (205.01 mm), and 2017 (192.73 mm). However, the p-value of 0.509 suggests no statistically significant evidence that the year variable has an impact on the dependent variable Rx5day.

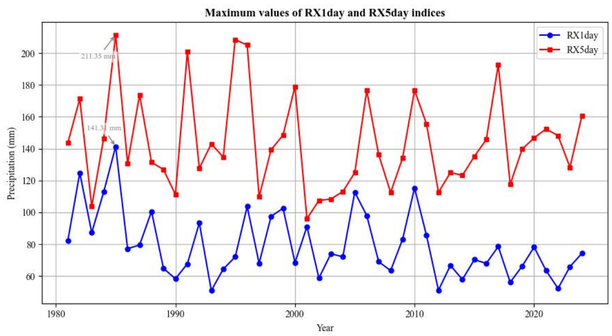

Figure 5. Maximum 1-day and 5-day precipitation total.

The results of both indexes may reflect events such as those on March 24, 2005, when intense rainfall caused floods and landslides in Caraguatatuba, impacting areas like Morro do Algodão, Porto Novo, Barranco Alto, Travessão, Perequê Mirim, Pegorelli, and Rodovia dos Tamoios (km 77). Similarly, the subsequent heavy rainfall on April 6, 2005, led to additional flooding in Massaguaçu, Getuba, Rio do Ouro, and Casa Branca, highlighting the concentration of extreme rainfall events during that period and their alignment with the high values captured by the Rx1day index (Bortoletto, 2016).

3.1 Linear Regression

Table 3 provides the climate indices, their corresponding p-values from the linear regression analysis, and the assessment of statistical significance.

Climate Index	P-value	Statistical Significance
PRCPTOT	0.9938	Not statistically significant
R95p	0.0159	Statistically significant
R99p	0.0271	Statistically significant
CWD	0.187	Not statistically significant
CDD	0.0064	Statistically significant
Rx1day	0.0044	Statistically significant
Rx5day	0.509	Not statistically significant

Table 3. Climate Index and Statistical Significance.

The indices R95p ($p = 0.0159$), R99p ($p = 0.0271$), CDD ($p = 0.0064$) and Rx1day ($p = 0.0044$) showed statistically significant trends over the analyzed period, indicating notable changes in both the intensity and frequency of extreme precipitation and dry events in Caraguatatuba.

3.2 Residuals Analysis

Linear regression assumptions were evaluated using Q-Q plots, which confirmed the normality of residuals. The Breusch-Pagan test indicated no significant heteroscedasticity for most indices, except for Rx1day ($p=0.02993$) and weak evidence for Rx5day ($p=0.07832$). The Durbin-Watson test showed no autocorrelation in the residuals (values between 1.5 and 2.5). Overall, the models are adequate, except for Rx1day, which requires caution due to heteroscedasticity.

3.3 Zonal Statistics

The zonal statistics analysis of the climate indices revealed significant spatial and temporal variations across the municipality of Caraguatatuba. It is essential to note that this analysis is only comparative as it does not account for year-by-year changes.

For Rx1day and Rx5day indices (Fig.6a and Fig.6b) a noticeable reduction is observed in the northeastern areas of the municipality, which includes forested regions and coastal neighbourhoods such as Portal da Fazendinha, Massaguaçu, Mococa, Costa Verde, and Tabatinga. Conversely, the western and southwestern regions, primarily classified as forest formations, showed an opposite trend, suggesting an increase in rainfall on isolated days or concentrated over a few days in these locations.

Regarding PRCPTOT (Fig.6c), a slight reduction is observed in the entire area, although precipitation remains relatively high. Coastal neighbourhoods in the eastern part of the municipality, such as Jardim Capricórnio, Jardim Bela Vista, Jardim Casa Branca, Martim de Sá, and Cidade Jardim, are the most affected.

The analysis of CWD and CDD (Fig.6d and Fig.6e) reveals contrasting dynamics. The number of consecutive rainy days remained relatively stable overall, with slight decreases in the southern area and increases in the northeast. This indicates that short, consecutive rainfall events still occur, which may contribute to the occurrence of floods and landslides, particularly in urban and hilly areas. On the other hand, the CDD index indicates a significant increase in the duration of dry periods, particularly in the southwestern portion of the municipality. This increase enhances susceptibility to drought, affects vegetation, and raises the risk of wildfires.

Additionally, increases in CDD were also observed in some urbanised neighbourhoods in the northeast, including Tabatinga, Costa Verde, Mococa and Tamandua Island. This situation is

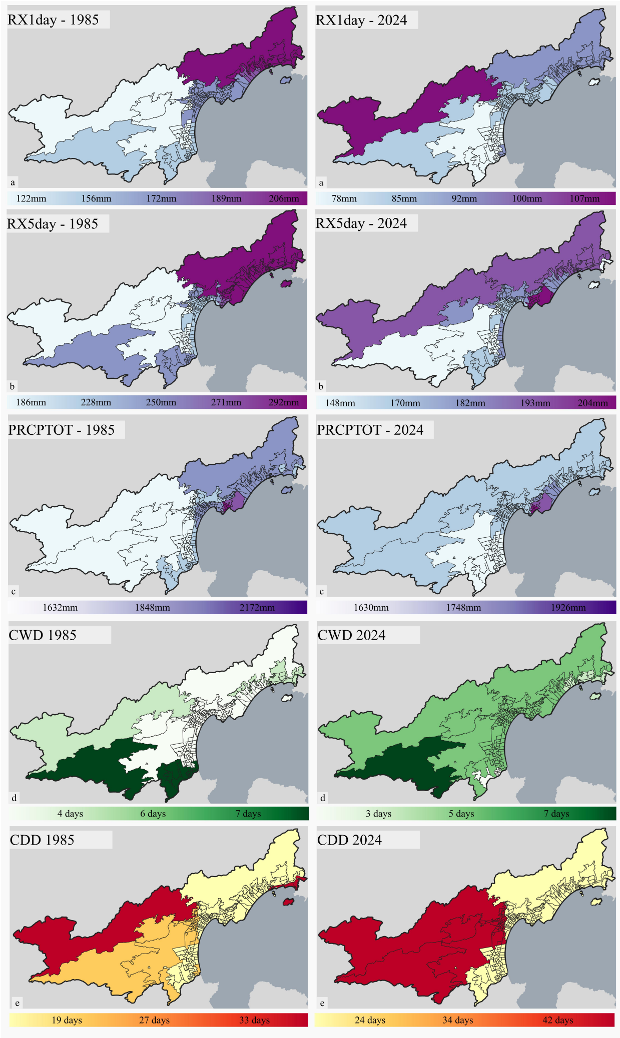

Figure 6. Zonal statistics analysis for the years 1985 and 2024: a)Rx1day b)Rx5day c)PRCPTOT d)CWD e)CDD.

particularly concerning, as prolonged dry periods followed by intense rainfall can lead to higher risks of rapid flooding, soil degradation, and mass movements.

Concerning R95p and R99p (Figure7), there is a clear pattern of reduction in the magnitude of extreme rainfall events across the entire territory. This reduction indicates a decrease in the frequency or intensity of heavy rainfall events over much of the urban area and the southern part of the municipality. However higher intensities persist in the hillside areas to the west-southwest and northeast.

3.4 Limitations of the Analysis

The study’s findings are subject to limitations inherent to remote sensing data and the Google Earth Engine platform. Specifically, the CHIRPS precipitation dataset, while widely used, may underestimate extreme rainfall peaks in regions with complex topography. This limitation can affect the accuracy of event detection and trend interpretation. Moreover, relying on linear regression models simplifies the analysis and may overlook important nonlinear climatic dynamics, such as those associated with ENSO variability or land-use change. These factors could introduce additional uncertainties not captured in the current approach.

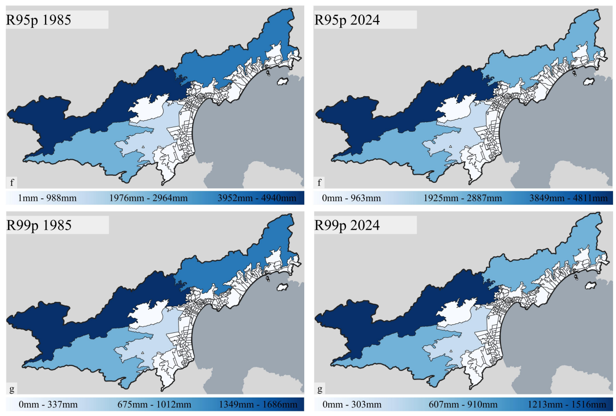

Figure 7. Zonal statistics analysis for R95p and R99p for the years 1985 and 2024.

4. Conclusions

This study evaluated seven extreme precipitation indices for the region of Caraguatatuba over 44 years (1981–2024). The regression analysis results highlight the intricate nature of temporal relationships for different climate indices. Overall, the analysis of the annual total precipitation (PRCPTOT) showed no significant linear trend over time, as indicated by the high p-value. In contrast, indices such as R95p, R99p, CDD, and Rx1day exhibit statistically significant trends, indicating noticeable temporal changes. Specifically, the CDD index shows a strong positive trend. This may reflect a shift toward more prolonged dry spells in the region, which could affect local water resources and ecosystem stability.

Zonal statistics for 1985 and 2024 reveal a decrease in the intensity of extreme rainfall events in the northeastern area, while the southwestern region exhibits the opposite trend. Additionally, the duration of dry periods increases significantly in the forested southwestern areas and some northeastern neighbourhoods, raising concerns about drought, vegetation stress, wildfires, and the subsequent risk of flooding.

Future research could enhance the analysis by incorporating additional climate variables, such as temperature or relative humidity, to more accurately capture complex temporal patterns. Additionally, employing non-linear models, such as polynomial regression or machine learning algorithms, could help detect intricate, non-linear relationships.

References

Alexander, L. V., Zhang, X., Peterson, T. C., Caesar, J., Gleason, B., Klein Tank, A. M. G., Haylock, M., et al., 2006. Global observed changes in daily climate extremes of temperature and precipitation. *Journal of Geophysical Research: Atmospheres*, 111(D5), D05109.

Arasaki, E., Alfredini, P., Pezzoli, A., Rosso, M., 2012. Coastal area prone to extreme flood and erosion events induced by climate changes: study case of Juqueriquere River Bar Navigation, Caraguatatuba (Sao Paulo State), Brazil. *International Journal on Marine Navigation and Safety of Sea Transportation*, 6(4), 509–514.

Bell, J. E., Brown, C. L., Conlon, K., Herring, S., Kunkel, K. E., Lawrimore, J., 2018. Changes in extreme events and the potential impacts on human health. *Journal of the Air & Waste Management Association*, 68(4), 265–287. https://doi.org/10.1080/10962247.2017.1401017.

Birkmann, J., Welle, T., Solecki, W., Lwasa, S., Garschagen, M., 2016. Boost resilience of small and mid-sized cities. *Nature*, 537, 605–608.

Bonini, J., Martins, T., Sugiyama, M. et al., 2025. Landslide inventory of the 2023 Serra do Mar disaster (Brazil). *Discover Geoscience*, 3, 40. https://doi.org/10.1007/s44288-025-00153-2.

Bortoletto, K., 2016. Study of Social and Environmental Vulnerabilities in Areas at Risk of Natural Disasters in the Municipality of Caraguatatuba, SP. Doctoral dissertation, Institute of Geosciences and Exact Sciences, Rio Claro Campus, Rio Claro – SP. Submitted in partial fulfillment of the requirements for the degree of Doctor of Geography.

Bukvic, A., Rohat, G., Apotsos, A., de Sherbinin, A., 2020. A Systematic Review of Coastal Vulnerability Mapping. *Sustainability*, 12(7), 2822. https://doi.org/10.3390/su12072822.

Cabral, V., Reis, F., Veloso, V. et al., 2023. The consequences of debris flows in Brazil: a historical analysis based on recorded events in the last 100 years. *Landslides*, 20, 511–529. https://doi.org/10.1007/s10346-022-01984-7.

Cavus, Y., Aksoy, H., 2020. Critical drought severity/intensity-duration-frequency curves based on precipitation deficit. *Journal of Hydrology*, 584, 124312. www.sciencedirect.com/science/article/pii/S0022169419310479.

Climate Hazards Center, 2025. Chirps: Climate hazards group infrared precipitation with station data.

Climdex Project, 2023. Climdex project: Climate extremes indices. https://www.climdex.org/indices.html. Accessed: 2024-11-13.

Dufek, A. S., Ambrizzi, T., 2008. Precipitation variability in São Paulo State, Brazil. *Theoretical and Applied Climatology*, 93(3), 167–178. https://doi.org/10.1007/s00704-007-0348-7.

Gan, R., Li, D., Chen, C., Yang, F., Ma, X., 2022. Impacts of climate change on extreme precipitation in the upstream of Chushandian Reservoir, China. *Hydrology Research*, 53(3), 504-518. https://doi.org/10.2166/nh.2022.135.

Geografos, 2025. Caraguatatuba, São Paulo. https://www.geografos.com.br/cidades-sao-paulo/caraguatatuba.php. Accessed: 2024-11-12.

Gigliotti, C., Santos, M., 2013. A Expansão Urbana de Caraguatatuba (1950-2010): Uma Análise das Transformações Sócio Espaciais. *Caminhos de Geografia*, 14(46), 150–159. www.seer.ufu.br/index.php/caminhosdegeografia/ISSN1678-6343.

Güçlü, Y., 2018. Multiple Sen-innovative trend analyses and partial Mann-Kendall test. *Journal of Hydrology*, 566, 685–704.

IPCC, 2023. *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. IPCC, Geneva. Accessed: 2025-05-05.

Luiz-Silva, W., Oscar-Júnior, A. C., 2022. Climate extremes related with rainfall in the State of Rio de Janeiro, Brazil: a review of climatological characteristics and recorded trends. *Natural Hazards*, 114, 713–732. https://doi.org/10.1007/s11069-022-05409-5.

Meerow, S., 2017. Double exposure, infrastructure planning, and urban climate resilience in coastal megacities: A case study of Manila. *Environment and Planning A: Economy and Space*, 49(11), 2649–2672.

Nova Imprensa, 2017. Chuva forte deixa Caraguatatuba debaixo d’água. https://novaimprensa.com/2017/03/chuva-forte-deixa-caraguatatuba-debaixo.html. Accessed: 2024-11-21.

Pezzoli, A., Sakai, R., Cartacho, D., Arasaki, E., Alfredini, P., De Souza, W., 2013. Extreme Events Assessment Methodology Coupling Debris Flow, Flooding and Tidal Levels in the Coastal Floodplain of the São Paulo North Coast (Brazil). *International Journal of Geosciences*, 4.

Saldanha, R., Akbarinia, R., Pedroso, M. et al., 2024. Zonal statistics datasets of climate indicators for Brazilian municipalities. *Environmental Data Science*, 3, e2.

Santos, D. D., Galvani, E., 2014. Distribuição sazonal e horária das precipitações em Caraguatatuba-SP e a ocorrência de eventos extremos nos anos de 2007 a 2011. *Ciência e Natura*, 36(2), 214–229. https://doi.org/10.5902/2179460X11891.

Silva, L. P., Santos, P. R. A., Ribeiro, G. M. S., Medeiros, S. E. L., Silva, W. K. M., Abrahão, R., 2013. Métodos estatísticos para detectar tendências em dados climáticos históricos: revisão bibliográfica. *Cadernos de Ciência Tecnologia*. www.embrapa.br/cct.

Union, E. G., 2023. The 2023 carnival disaster in são paulo: an all-time record for rainfall in brazil. https://blogs.egu.eu/divisions/nh/2023/05/22/the-2023-carnival-disaster-in-sao-paulo-an-all-time-record-for-rainfall-in-brazil/. Accessed: 2024-11-21.

Visconti, G., Young, K., 2024. The effect of different extreme weather events on attitudes toward climate change. *PLOS ONE*, 19(5), 1-10. https://doi.org/10.1371/journal.pone.0300967.

Wannewitz, M., Ajibade, I., Mach, K. J., Magnan, A., et al., 2024. Progress and gaps in climate change adaptation in coastal cities across the globe. *Nature Cities*, 1(9), 610–619. https://doi.org/10.1038/s44284-024-00106-9.

WHO, 2021. Climate change and health. https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health. Accessed: 2025-05-05.

WMO, 2025. World Meteorological Organization - Climate. https://public.wmo.int/en/our-mandate/climate. Accessed: 2024-11-12.

World Population Review, 2025. Caraguatatuba, brazil. https://worldpopulationreview.com/cities/brazil/caraguatatuba. Accessed: 2024-11-12.

Zhang, X., Alexander, L., Hegerl, G., Jones, P., Tank, A. K., Peterson, T. C., Trewin, B., Zwiers, F. W., 2011. Indices for monitoring changes in extremes based on daily temperature and precipitation data. *Wiley Interdisciplinary Reviews: Climate Change*, 2(6), 851–870.