Municipal climate vulnerability in Western Paraná (2012–2024): a multivariate approach to territorial planning

Vulnerabilidade climática municipal no oeste do Paraná (2012–2024): uma abordagem multivariada para o planejamento territorial

Rafael Venturin Piacentini [1]

Irene Carniatto de Oliveira [2]

[1] Master's Degree in Energy Engineering in Agriculture, Researcher, Centro de Ciências Exatas e Tecnologias, Universidade Estadual do Oeste do Paraná, Cascavel, PR, Brazil
E-mail: labhea.rafaelventurin@gmail.com

[2] PhD in Forest Engineering, Professor, Centro de Ciências Biológicas e da Saúde, Universidade Estadual do Oeste do Paraná, Cascavel, PR, Brazil
E-mail: irenecarniatto@gmail.com

doi:10.18472/SustDeb.v16n3.2025.58151

Received: 07/05/2025
Accepted: 25/11/2025

ARTICLE- DOSSIER

ABSTRACT
This study investigates the occurrence of extreme weather events in municipalities of the Western mesoregion of Paraná, Brazil, between 2012 and 2024, using records from the State Civil Defence database. The adopted methodology involved multivariate statistical analysis using Principal Component Analysis (PCA), applied to data categorised into five event types: flash floods, flooding, heavy rainfall, gales, and hail. The results revealed distinct spatial patterns of municipal vulnerability, allowing the identification of groups of municipalities more prone to specific types of events. The proposed approach contributes to territorial planning and the formulation of public policies aimed at risk management and climate change adaptation.

Keywords: Regional development. Sustainable development. Urban and regional management. Regional infrastructure. Regional policies.

RESUMO
Este estudo investiga a ocorrência de eventos climáticos extremos nos municípios da mesorregião oeste paranaense entre 2012 e 2024 com base nos registros do banco de dados da Defesa Civil do estado do Paraná. A metodologia adotada envolveu a análise estatística multivariada por meio da Análise de Componentes Principais (PCA), aplicada a dados categorizados em cinco tipos de eventos: enxurradas, alagamentos, chuvas intensas, vendavais e granizo. Os resultados revelam padrões espaciais distintos de vulnerabilidade municipal, permitindo identificar grupos de municípios com maior propensão a determinados tipos de eventos. A abordagem proposta contribui para o planejamento territorial e para a formulação de políticas públicas voltadas à gestão de riscos e à adaptação às mudanças climáticas.

Palavras-chave: *Desenvolvimento regional. Desenvolvimento sustentável. Gestão urbana e regional. Infraestrutura regional. Políticas regionais.*

1 INTRODUCTION

In recent decades, the intensification of extreme weather events has highlighted the risks associated with climate change, particularly in territories with high socio-environmental vulnerability. Recent reports indicate an increase in the frequency and intensity of phenomena such as droughts, floods, and windstorms, which calls for more precise territorial analyses (IPCC, 2021). In Brazil, studies show that these events are not evenly distributed, occurring more frequently in certain regions, such as the South, thus requiring specific approaches at the municipal scale (Cunha Ferreira; Kemenes, 2023; Marengo *et al.*, 2023).

Despite advances in scientific production, a methodological gap persists in the integrated application of multivariate statistical tools and spatialisation of territories. Many studies are limited to case analyses or broad-scale assessments, hindering the identification of local patterns (Ferreira *et al.*, 2021; Santos; Bernardino, 2022). Well-structured quantitative research generates testable data that can inform evidence-based public policies (Creswell; Creswell, 2018). Techniques such as factor analysis, clustering, and composite indicators are essential to capture socio-environmental complexity without compromising objectivity (Hair *et al.*, 2019). In the field of climate adaptation, the use of quantitative methods has been central to risk, exposure, and sensitivity assessments at multiple territorial scales (Füssel, 2010; Hallegatte *et al.*, 2016; Hinkel; Bisaro, 2015, 2016; Preston *et al.*, 2011).

Environmental disasters also reflect anthropogenic causes, such as improper land use, unplanned urbanisation, and intensive agro-industrial practices, which intensify socio-spatial vulnerability (Freitas *et al.*, 2021). These events disrupt the ecological and social dynamics of territories, often exacerbated by weak public policies (Silva; Oliveira, 2019).

Climate changes have amplified such disasters, increasing the frequency of heatwaves, intense rainfall, and prolonged droughts (IPCC, 2021). Understanding these phenomena requires regionally focused studies that reveal the interactions between local factors and global dynamics (Pereira *et al.*, 2022). In Brazil, policies such as the National Policy on Climate Change Adaptation (PNPDEC) and the National Plan for Adaptation (PNA) outline mitigation and adaptation guidelines, but their effectiveness depends on subnational governments' technical and financial capacity (MMA, 2016). From this perspective, territorial diagnostics and the use of tools such as PCA and cluster analysis are strategic for supporting public decision-making and empirically mapping local vulnerabilities.

In this study, the concept of climate vulnerability is understood in the classical sense proposed by Adger (2006) and reinforced by the IPCC (2021), as the degree to which a system is susceptible to, or unable to cope with, the adverse effects of climate variability and change. It is a composite construct comprising three interrelated components: exposure, sensitivity, and adaptive capacity (Füssel, 2010; Preston *et al.*, 2011). *Exposure* refers specifically to the magnitude and frequency of climate-related hazards to which a municipality is subject, such as extreme rainfall or drought. *Sensitivity* describes the extent to which the local population, economy and infrastructure are affected when exposed to these hazards. *Adaptive capacity* represents the ability of institutions, communities and infrastructure to anticipate, cope with and recover from adverse events. It is important to stress that exposure is not synonymous with vulnerability; it is only one of its dimensions. Confusing these concepts can lead to analytical errors and an underestimation of the role of socioeconomic and institutional factors in determining climate impacts.

In this context, analysing municipalities in Western Paraná using multivariate statistical techniques contributes to understanding the relationship between socio-environmental vulnerability and extreme events. The literature shows that environmental disasters are associated with failures in territorial governance, socioeconomic vulnerabilities, and land use changes. Therefore, this research seeks to answer the following question: How can the municipalities of Paraná be grouped by the frequency of extreme climate events from 2012 to 2024? The general objective is to classify the municipalities of Western Paraná according to these criteria.

The scientific relevance of this study lies in the articulation between multivariate statistics and geotechnologies in climate studies (Oliveira *et al.*, 2020; Rodrigues *et al.*, 2023). From an applied perspective, the results guide public managers in planning prevention and response policies for natural disasters, prioritising the most exposed municipalities.

Data from Ciped/Simepar were used, covering 956 extreme events recorded between 2012 and 2024 across 50 municipalities. The variables were processed using Exploratory Factor Analysis (EFA) and Principal Component Analysis (PCA) to identify relevant components. Subsequently, the k-means clustering method was applied to form five clusters, and the results were spatialised using GIS tools in QGIS software.

The results revealed five distinct groupings based on event frequency and type, offering a territorial typology useful for climate risk management. The integration of statistical and geographic methods proved effective in supporting public policies aimed at climate resilience.

2 METHODOLOGY

This study falls within a positivist approach, with a quantitative nature and a descriptive and exploratory design, according to Gil's (2008) classification. The investigation aims to describe patterns and explore relationships among variables associated with the occurrence of extreme weather events.

The study area comprises the 50 municipalities of the Western Mesoregion of Paraná, as shown in Figure 1, according to the classification of the Brazilian Institute of Geography and Statistics (IBGE). This region is characterised by high agricultural production, significant urbanisation, and frequent extreme weather events, including windstorms, flash floods, droughts, and hail.

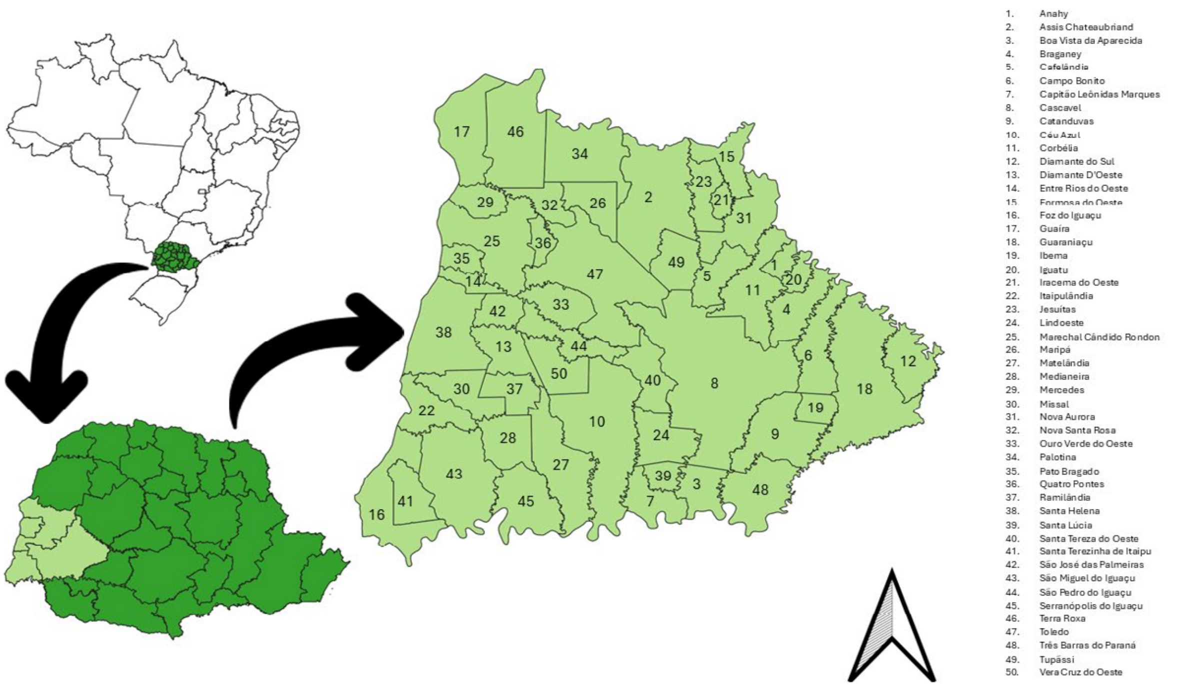

Figure 1 – Location of the study area

Source: Authors' elaboration (2025)

Data were collected in March 2025 from the Disaster Information System of Paraná (SISDC-PR). The temporal scope adopted spans from 2012 to 2024, with the enactment of Law No. 12.608, dated

April 10, 2012, serving as the theoretical framework, which established the National Policy for Civil Protection and Defence. Records of 30 types of extreme weather events were analysed. Raw data were extracted from the Civil Defence of the State of Paraná's disaster registry database for the period from 2012 to 2024, totalling 956 events recorded in the region.

Initially, data entries were standardised by removing duplicate records and correcting geographic and temporal inconsistencies. Subsequently, the data were organised into a matrix, with municipalities as rows and event types as columns, accounting for the annual frequency of each event in each municipality. Standardisation was performed using the following equation, based on the 2022 Demographic Census:

$$X = F \times (a / N) \quad (1)$$

Where:
X = Risk classification for the event;
F = Event frequency;
a = Total number of people affected (including fatalities);
N = Municipal population according to the 2022 Census.

Statistical analysis was performed using Jamovi software, version 2.6.44. Initially, descriptive statistics were applied to identify general patterns of occurrence and variability. Subsequently, Principal Component Analysis (PCA) with varimax rotation was employed to reduce dimensionality and identify underlying factors. The KMO index (0.500) and Bartlett's test of sphericity ($p < 0.001$) indicated the adequacy of the matrix for PCA.

Subsequently, hierarchical clustering analysis was conducted to identify similarities among variables. Based on this analysis, non-hierarchical clustering using the K-means method was applied, with the optimal number of groups determined using the Gap statistic.

Finally, the clustering results were translated into a thematic map using QGIS software, version 3.34.12. For this purpose, the official shapefile of municipalities provided by IBGE was used, enabling the spatial representation of the identified groups and facilitating the visualisation of vulnerabilities at the territorial scale.

3 RESULTS AND DISCUSSION

The standardised data analysis revealed a wide variation in the relative intensity of adverse events across the municipalities of the Western Mesoregion of Paraná, accounting for population size and enabling more equitable comparisons between localities. The total frequency of events showed a higher incidence in Foz do Iguaçu and Cascavel, in contrast to lower records observed in municipalities such as Anahy and Iguaçu. This heterogeneity reflects differences in institutional capacity and population density, underscoring the need for public policies tailored to local specificities (Hinkel; Bisaro, 2016; Preston *et al.*, 2011).

The highest standardised impact values were recorded in Cascavel, Toledo, Foz do Iguaçu, and Marechal Cândido Rondon, all with means exceeding 10,000, which indicated high frequency and intensity proportional to population. Particularly, Cascavel presented a mean of 16,510.05 and a high standard deviation (19,607.48), with elevated skewness (8.53) and kurtosis (28.77), suggesting the occurrence of sporadic, severe extreme events. In contrast, municipalities such as Boa Vista da Aparecida and Jesuítas showed low values, which may indicate either lower exposure or potential under- reporting of events (Gall; Borden; Cutter, 2009).

Windstorms led in average impact (181.29) and total sum (9,064.43), with high skewness (5.42) and kurtosis (30.61), followed by flash floods and hydrometeorological events. Geological and technological events were rare, while viral infectious diseases showed sporadic yet significant impacts, as indicated by their high kurtosis values (42.44). These characteristics justify the use of Spearman's correlation, which is more robust to skewed distributions and outliers (Ghasemi; Zahediasl, 2012; Mukaka, 2012).

The concentration of impacts in larger municipalities such as Cascavel and Foz do Iguaçu is associated with population density and urban complexity—factors that increase disaster vulnerability (Adger, 2006; Cutter *et al.*, 2003). In Cascavel, initiatives such as risk area mapping and educational campaigns are part of the Municipal Risk Management Programme, whereas Foz do Iguaçu has implemented reforestation and flood control guidelines (Cascavel, 2023; Foz do Iguaçu, 2022), demonstrating the influence of technical capacity on vulnerability patterns.

The correlation matrix (Figure 2) identified territorial clusters with similar behaviours, related to geographic proximity, climate, and governance. These results reinforce the need for integrated territorial approaches encompassing climatic, social, and economic variables and indicate that localised interventions are essential to mitigate the impacts of extreme events.

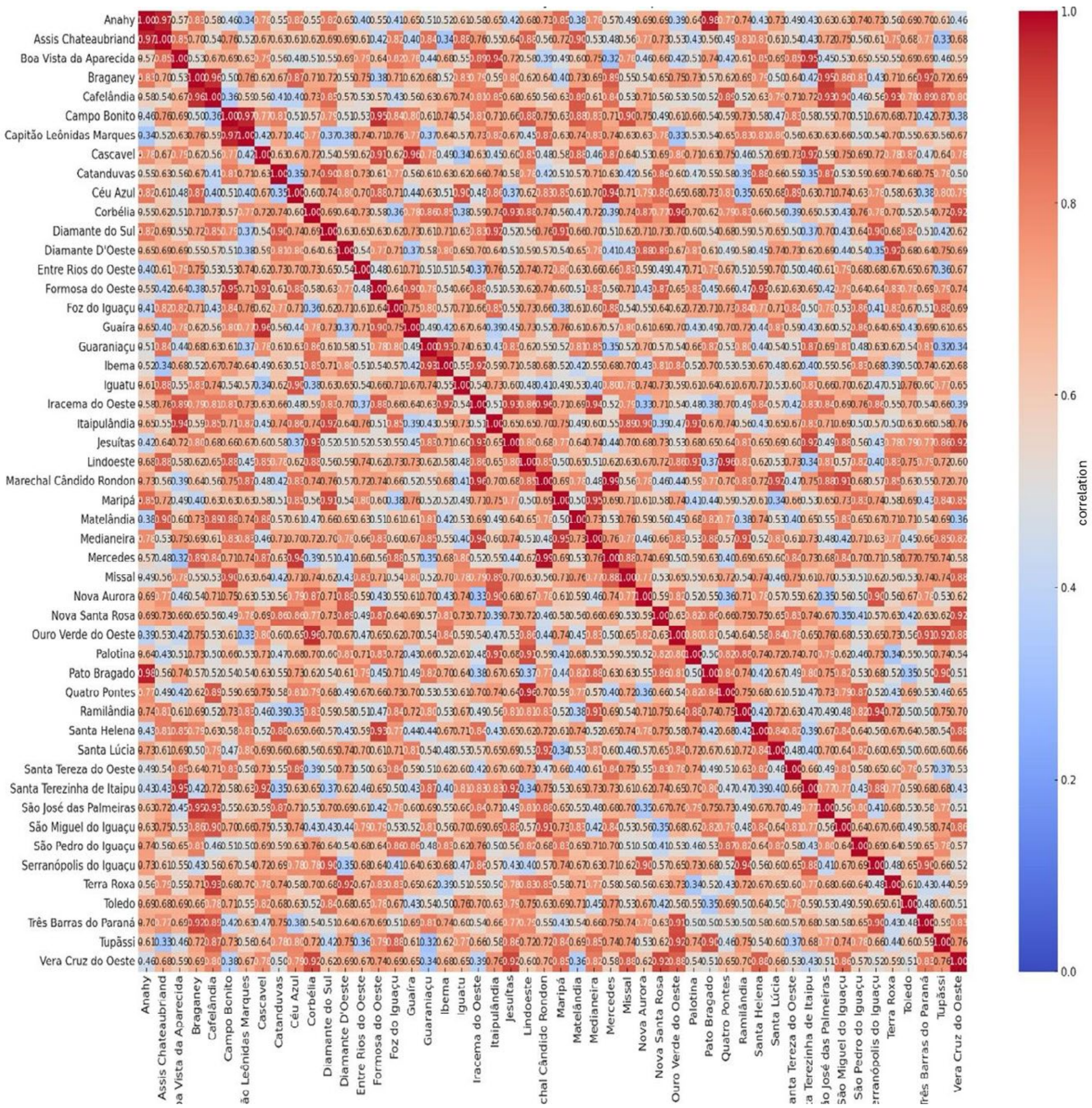

Figure 2 – Correlation matrix

Source: Authors' elaboration (2025)

Among the most relevant clusters, municipalities with correlation coefficients close to 1 stood out, indicating a strong similarity in the records. These patterns may reflect common environmental and structural conditions, such as rivers, topography, and climate, highlighting the importance of coordinated regional strategies. On the other hand, low or negative correlations reveal distinct profiles of incidence and impact, suggesting lower exposure or variations in monitoring capacity, infrastructure, and socioeconomic conditions.

Among the most evident clusters, pairs of municipalities with correlation coefficients above 0.90 also stood out, such as Assis Chateaubriand and Anahy, or Quatro Pontes and Nova Santa Rosa, located in territories with similar spatial and productive configurations. These correlations suggest common patterns of exposure or event recording, indicating that coordinated risk management strategies between neighbouring municipalities could be more effective.

Moreover, strong correlations were identified even between geographically distant municipalities, such as Santa Helena and Assis Chateaubriand, suggesting greater structural and institutional similarities than mere physical proximity. This finding reinforces the importance of regional strategies, both at the micro-regional scale and through inter-municipal cooperation networks for climate change adaptation. Recent experiences in Brazil corroborate this need. Saito *et al.* (2021), for example, highlight the potential of inter-municipal public consortia as instruments to overcome technical and institutional weaknesses in climate risk management, even though they face political-party challenges and local management issues. In the Metropolitan Region of Recife, inter-municipal coordination for climate resilience has been strengthened with support from UNDRR and ICLEI, and joint actions have been promoted for monitoring, risk assessment, and the implementation of low-cost solutions (UNDRR, 2023).

The analysis of correlations among municipalities is essential for understanding spatial dynamics and for guiding territorial planning, thereby enabling integrated risk management strategies. Meanwhile, the correlation matrix of climatic events (Figure 3) revealed patterns of linear association: positive values indicated simultaneity, negative values pointed to inverse relationships, and coefficients close to zero suggested independence among the phenomena.

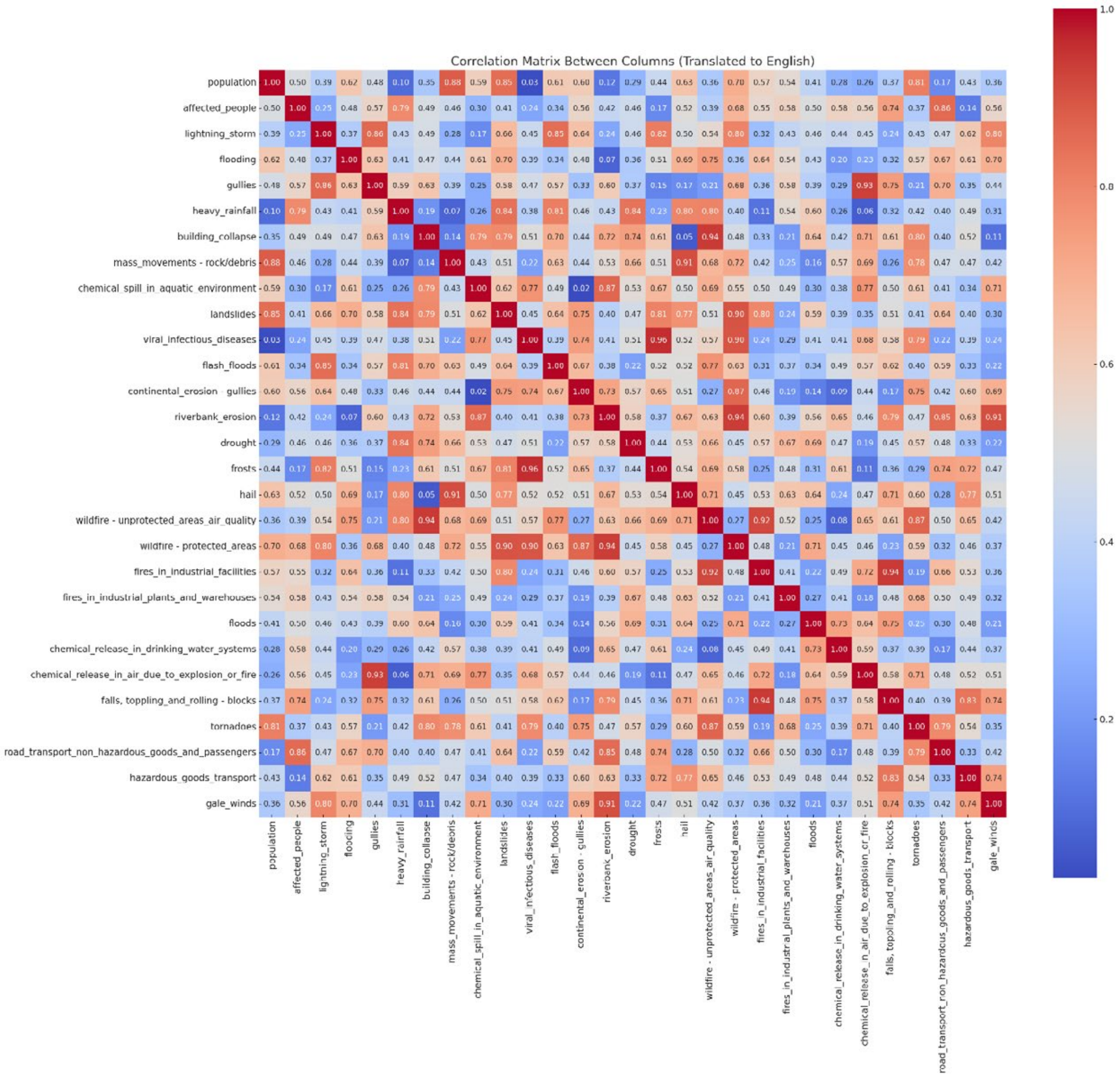

Figure 3 – Correlation Matrix for Extreme Events

Source: Authors' elaboration (2025)

Among the main findings, a strong positive correlation is observed among heavy rains, flooding, and inundation, suggesting that these events often coexist, especially in urban areas with inadequate drainage infrastructure. This result is consistent with studies linking failures in stormwater drainage to higher incidences of flooding and inundation (Brazil, 2012; Tucci, 2008). Furthermore, moderate to high correlations are evident among windstorms, tree or structure falls, and lightning storms, reinforcing the hypothesis that these severe atmospheric phenomena occur sequentially or simultaneously during extreme weather conditions (Silva Dias *et al.*, 2013).

Another relevant pattern is the moderate correlation between forest and urban fires, suggesting a possible relationship between prolonged dry periods and increased fire incidence across different environments. In contrast, events such as frosts show negative correlation with fires, which can be explained by the divergence of climatic conditions required for their occurrence – while fires are associated with dry and hot periods, frosts occur under cold temperatures and high humidity (Machado *et al.*, 2020).

Additionally, some events show low correlations with others, such as the release of chemicals and transport of hazardous materials. These events, primarily anthropogenic in origin, occur despite climatic conditions, justifying their weak association with the other phenomena analysed.

The analysis of the correlation matrix between climate events plays a crucial role in formulating public policies for disaster management. Identifying significant relationships among different kinds of occurrences enables the development of integrated prevention and response strategies that consider patterns of simultaneity and interdependence among the events analysed. Moreover, the results of this analysis provide support to apply more advanced statistical techniques, such as Principal Component Analysis (PCA), allowing a more in-depth approach to identify latent patterns of variability among climate events already recorded in the studied municipalities.

Data adequacy to apply Principal Component Analysis (PCA) was evaluated by the Kaiser-Meyer-Olkin (KMO) index and Bartlett's Test of Sphericity. The obtained KMO value was 0.500, which reached the minimum acceptable threshold for performing PCA. It suggested that the variables have moderate correlations with each other. Additionally, Bartlett's Test of Sphericity showed a p-value of 0.0001, rejecting the null hypothesis that the correlation matrix is an identity matrix. The results, shown in Table 1, confirm the existence of significant correlations among the variables, justify the statistical use of PCA to reduce data dimensionality and identify latent patterns of variability among the events analysed.

Table 1 – Principal Component Analysis for Extreme Events after Standardisation

Event	*Component*		
	1	*2*	*Singularity*
Floods	**0.99131**	0.10012	0.00729
Flash floods	**0.93652**	**0.33534**	0.01047
Urban flooding	**0.93541**	**0.35074**	0.00200
Infectious and viral diseases	**0.92878**	**0.34550**	0.01799
Hail	**0.87430**	**0.48021**	0.00499
Chemical spillage in lacustrine, riverine, marine and aquifer environments	**0.84161**	**0.53398**	0.00655
Road transport of passengers and non-hazardous cargo	**0.83993**	**0.53617**	0.00704
Heavy rainfall	**0.83270**	**0.51543**	0.04094
Gale	**0.82673**	**0.56147**	0.00127
Drought	**0.70955**	**0.68288**	0.03022
Fires in industrial plants, districts, parks and warehouses	-0.05590	0.00588	0.99684
Landslides	-0.05567	0.01767	0.99659
Wildfires in unprotected areas affecting air quality	-0.05324	0.05191	0.99447
Tornadoes	-0.03306	0.01693	0.99862
Fire in residential clusters	-0.12512	**0.97603**	0.03171
Release of chemicals into drinking water systems	-0.12117	**0.97395**	0.03673
Release of chemicals into the atmosphere due to explosion or fire	-0.12417	**0.96966**	0.04435
Lightning storm	-0.12358	**0.85800**	0.24856
Road transport of hazardous materials	**0.53123**	**0.83980**	0.01253
Collapse of affected buildings	**0.61940**	**0.77245**	0.01967
Affected	**0.63135**	**0.76610**	0.01449
Frost	-0.03255	-0.07715	0.99299
Wildfires in parks, environmental protection areas and national, state or municipal permanent preservation areas	-0.03386	-0.07564	0.99313

Event	Component		
	1	2	Singularity
Mass movements/ rock or dedris flow	-0.02145	-0.03658	0.99820
Falls, toppling and roll - blocks	-0.02145	-0.03658	0.99820
Gullies, gully erosion	-0.01893	-0.03541	0.99839
Guillies	-0.01123	-0.03147	0.99888
Riverbank erosion	-0.00864	-0.02716	0.99919

Source: Authors' elaboration (2025)

Principal Component Analysis (PCA) was applied to reduce the dimensionality of climate and environmental event data, while preserving information variability. The adequacy was confirmed by the KMO index (0.500) and Bartlett's Sphericity Test ($p < 0.001$), indicating significant correlations among variables and justifying the application of the technique.

Two principal components were extracted using the Kaiser-Guttman criterion (eigenvalues > 1) and Monte Carlo Parallel Analysis. The first, "Extreme Hydrometeorological Events," showed high factor loadings for floods (0.991), runoff (0.936), flooding (0.935), heavy rains (0.832), and strong winds (0.826), indicating severe precipitation-related events. The second, "Anthropogenic and Severe Atmospheric Disasters," highlighted residential-area fires (0.976), chemical releases into water (0.973), and building collapse (0.772), reflecting urban and technological risks.

The uniqueness analysis indicated that the extracted components well represent floods (0.007) and flooding (0.002), whereas events such as frost (0.992) and gully erosion (0.998) are less representative and require a specific approach due to their distinct dynamics.

These findings provide relevant insights for public policy. Municipalities affected by events from CP1 should prioritise drainage infrastructure and climate adaptation measures (Santos; Almeida, 2021; Silva *et al.*, 2020), while those affected by CP2 require actions such as industrial monitoring, regulation of hazardous cargo transport, and training (Oliveira; Pereira, 2019). Given the high uniqueness of events, as suggested by Costa *et al.* (2022), it is also essential for more effective, specific management. The Exploratory Factor Analysis (Table 2) reinforces these results by highlighting two main axes of variability, which guide the formulation of differentiated public policies to prevent and mitigate climate and technological risks.

Table 2 – Factor Loadings by Climate Event

Event	Factor		
	1	2	Singularity
Floods	**105.280**	**-0.3738**	0.00352
Flash floods	**102.869**	-0.1077	0.00104
Urban flooding	**102.722**	-0.1231	0.01053
Infectious and viral diseases	**102.015**	-0.1092	0.01861
Hail	**0.98302**	0.0441	0.00400
Chemical spillage in lacustrine, riverine, marine and aquifer environments	**0.95506**	0.1119	0.00697
Road transport of passengers and non-hazardous cargo	**0.95366**	0.1145	0.00757
Gale	**0.94419**	0.1444	4.34e-4
Heavy rainfall	**0.94017**	0.0989	0.04688
Drought	**0.83786**	**0.3130**	0.03237
Collapse of affected buildings	**0.75377**	**0.4434**	0.02148
Road transport of hazardous materials	**0.67212**	**0.5507**	0.00829

Event	Factor		
	1	2	Singularity
Wildfires in parks, environmental protection areas and national, state or municipal permanent preservation areas	-0.04684	-0.0429	0.99468
Frost	-0.04667	-0.0436	0.99462
Fires in industrial plants, districts, parks and warehouses	-0.04413	0.0139	0.99825
Landslides	-0.04146	0.0248	0.99832
Tornadoes	-0.03037	0.0177	0.99911
Falls, toppling and roll - blocks	-0.02707	-0.0201	0.99851
Mass movements/ rock or dedris flow	-0.02707	-0.0201	0.99851
Gullies, gully erosion	-0.02477	-0.0191	0.99872
Fire in residential clusters	0.00590	**0.9861**	0.02380
Release of chemicals into drinking water systems	0.00859	**0.9803**	0.03351
Release of chemicals into the atmosphere due to explosion or fire	0.00661	**0.9766**	0.04199
Lightning storm	0.01982	**0.8023**	0.34572
Wildfires in unprotected areas affecting air quality	-0.03030	0.0466	0.99781
Guillies	-0.01742	-0.0189	0.99913
Riverbank erosion	-0.01454	-0.0171	0.99934

Source: Authors' elaboration (2025).

The determination of the optimal number of clusters in the K-means method was carried out using the Gap statistic, as proposed by Tibshirani *et al.* (2001). The Gap Statistic graph compares the observed intra-cluster dispersion with the expected dispersion in a random distribution. The ideal number of clusters is the point at which the Gap value reaches a plateau with an acceptable standard error, and additional gains become insignificant. Based on this analysis, the optimal number of clusters was determined to be five, as the Gap statistic reached a plateau at this point.

The clustering into five groups revealed distinct patterns of risk and vulnerability among the analysed events. The merger hierarchy identified similarities among events, enabling the definition of specific strategies for disaster mitigation and response. Clusters 2 and 3 have concentrated most of the analysed records, while each one of Clusters 1, 4, and 5 included only one municipality, possibly indicating unique characteristics.

Cluster 2, composed of 43 municipalities, has concentrated the majority of the records (294), suggesting predominant event patterns. Cluster 3, with 106 records and 4 municipalities, represents a second, though smaller, significant group. Clusters 1, 4, and 5 contain a single municipality each: Cascavel, Guaraniaçu, and Foz do Iguaçu, respectively, reflecting distinct patterns. The sum of intra-cluster values (972) demonstrates that segmentation has captured some relevant differences among the groups.

A detailed analysis of those clusters, Table 3, may provide additional insights. For example, if Cluster 2 mainly encompasses hydrological events and Cluster 3 focuses on atmospheric events, this differentiation could guide specific public policies. Thus, the segmentation contributes to planning more effective preventive and response actions, promoting climate resilience and risk management.

Table 3 – Means for clusters from the k-means test after standardisation

Extreme Event	*1*	*2*	*3*	*4*	*5*
Affected	**4.667**	**-0.203**	-0.151	-0.235	4.882
Lightning storm	**5.596**	-0.100	-0.217	-0.217	-0.217
Urban flooding	**1.619**	-0.174	-0.154	-0.196	6.690
Guilles	**-0.141**	0.023	-0.141	-0.141	-0.141
Heavy rainfall	**2.854**	-0.193	-0.099	-0.190	6.015
Building collapses	**4.791**	-0.197	-0.228	-0.228	4.813
Mass movement – rock/debris flow	**-0.141**	-0.141	-0.141	6.930	-0.141
Chemical spillage in lacustrine, riverine, marine and aquifer environments	**2.972**	-0.189	-0.207	-0.207	6.177
Landslides	**-0.308**	-0.090	0.723	1.604	-0.308
Infectious and viral diseases	**1.501**	**-0.171**	-0.150	-0.202	6.664
Flash floods	**1.479**	**-0.168**	-0.166	-0.227	6.638
Continental erosion – guillies, gully erosion	**-0.141**	**0.023**	-0.141	-0.141	-0.141
Riverbank erosion	-0.141	0.023	-0.141	-0.141	-0.141
Drought	3.915	-0.204	-0.044	-0.325	5.362
Frost	-0.291	-0.072	0.994	-0.291	-0.291
Hail	2.497	-0.189	-0.124	-0.213	6.357
Wildfires in unprotected areas affecting air quality	-0.254	-0.153	1.838	-0.254	-0.254
Wildfires in parks, environmental protection areas and national, state or municipal permanent preservation areas	-0.292	-0.175	2.102	-0.292	-0.292
Fires in residential clusters	6.836	-0.163	0.126	-0.163	-0.163
Fires in industrial plants, districts, parks and warehouses	-0.266	-0.229	2.660	-0.266	-0.266
Floods	-0.162	**-0.138**	-0.162	-0.162	6.908
Release of chemicals into drinking water systems	6.811	**-0.135**	-0.166	-0.166	-0.166
Release of chemicals into the atmosphere due to explosion or fire	6.815	**-0.135**	-0.169	-0.169	-0.169
Falls, toppling and rolls – blocks	-0.141	**-0.141**	-0.141	6.930	-0.141
Tornadoes	-0.239	-0.011	0.301	-0.239	-0.239
Road transport of passengers and non-hazardous	2.976	-0.195	-0.139	-0.205	6.184
Road transport of hazardous materials	5.359	-0.207	-0.123	-0.215	4.263
Gale	3.111	-0.193	-0.165	-0.234	6.085

Source: Authors' elaboration (2025)

Cluster analysis was performed using the K-means clustering method and revealed distinct vulnerability profiles of municipalities with respect to extreme events. The segmentation into five clusters allowed us to identify specific patterns that help us understand the predominant risk factors in each group.

Cluster 1: Characterised by climatic events typical of rural areas, such as drought, windstorms, and hail, with occasional records of flash floods. The low incidence of urban events, such as flooding and viral infectious diseases, suggests lower urbanisation and greater exposure to atmospheric phenomena.

Cluster 2: Includes municipalities highly vulnerable to hydrometeorological events, such as flooding, flash floods, windstorms, and hail, in addition to viral infectious diseases. These municipalities, generally more urbanised, require urban planning and robust mitigation strategies.

Cluster 3: Groups municipalities with the highest indices of windstorms, flooding, and hail represent critical scenarios. This group should be prioritised in public policies aimed at prevention and emergency response.

Cluster 4: The largest group identified showed moderate averages of the analysed events, with a focus on drought, windstorms, and hail. These municipalities appeared to be more resilient or to experience fewer recurring extreme events.

Cluster 5: has a mixed profile, with high incidence of windstorms, flooding, hail, and drought, in addition to viral infectious diseases. The combination of climatic and urban events points to the need for integrated urban and environmental adaptation actions.

Thus, cluster spatial analysis, illustrated in the thematic map of Figure 4, highlights the territorial distribution of vulnerability and resilience patterns in the Western mesoregion of Paraná. This approach enables the identification of regional risk concentrations and supports the implementation of more effective strategies for disaster risk management and mitigation.

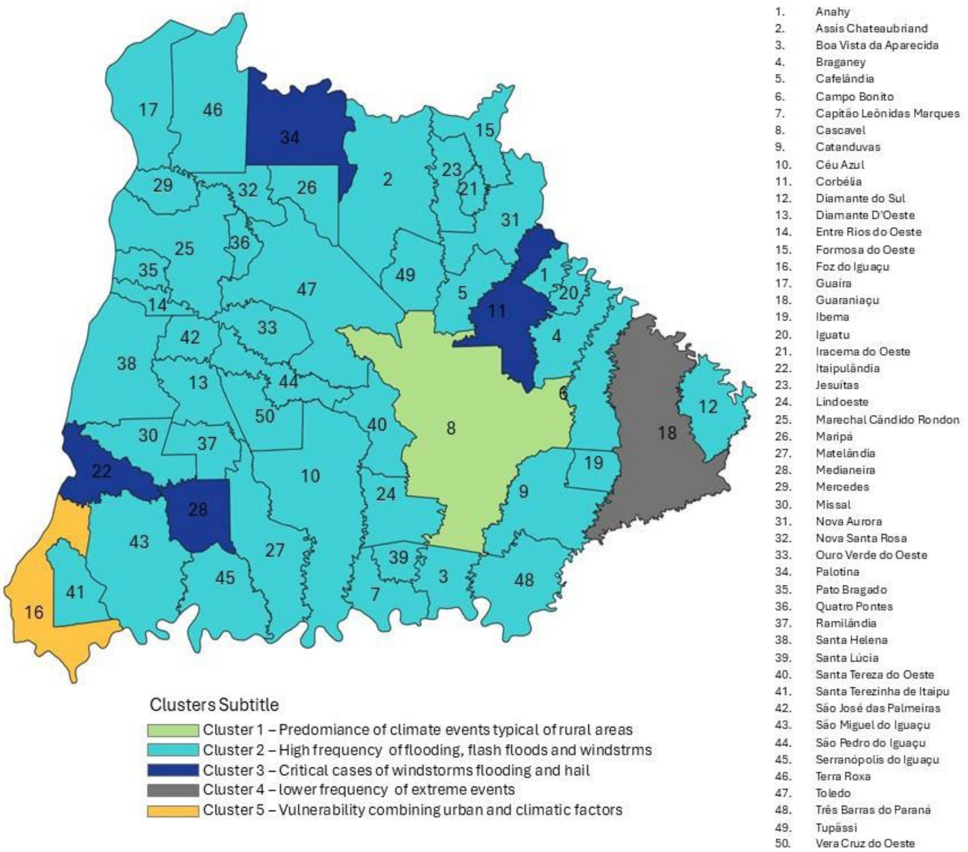

Figure 4 – Thematic map clustering the municipalities

Source: Authors' elaboration (2025)

Figure 4 shows the spatial distribution of the clusters identified by K-means clustering analysis, segmenting the municipalities from the studied region into five distinct groups based on vulnerability indicators to extreme events. Each cluster reflects territorial patterns of risk and resilience, to allow understanding of regional dynamics.

Cluster 1 (green): Composed mainly of rural municipalities, characterised by events such as droughts and windstorms, with a low incidence of flooding and viral infectious diseases.

Cluster 2 (cyan blue): Encompasses most municipalities and reflects high urban vulnerability, with high frequency of floods, flash floods, and windstorms.

Cluster 3 (dark blue): Represents the most critical scenarios, showing the highest rates of windstorms, floods, and hailstorms, and should be prioritised for risk mitigation actions.

Cluster 4 (grey): Includes municipalities with a lower frequency of extreme events, suggesting greater resilience or less exposure to disasters.

Cluster 5 (yellow): Displays a mixed profile, combining urban and climatic vulnerabilities, which requires differentiated risk management strategies.

Clusters' spatialisation highlights regional vulnerability patterns and supports the formulation of public policies to prevent and adapt the population to extreme climate events. Thus, to complement this analysis, the line chart of means by cluster (Figure 6) allows comparison of the average frequency of adverse events per group. Lines indicate the most relevant events in each cluster, providing a clear view of the factors that influenced their formation.

These results reinforce the need to have sustainable public policies for each group of municipalities. While Cluster 3 requires emergency interventions to mitigate the effects of recurring disasters, Cluster 4 could be the focus of studies on factors contributing to its resilience. The observed patterns corroborate previous studies indicating that urban density and poor infrastructure are critical factors in greater vulnerability to extreme events in areas such as those represented by Cluster 2 (Smith *et al.*, 2020).

Clusters' spatialisation not only identifies priority areas for mitigation but also suggests the importance of integrating urban and rural planning strategies, especially in Clusters 5 and 2. Given the projected increase in the frequency and intensity of extreme climate events due to climate change, the results presented underscore the importance of regional adaptation strategies, particularly in highly vulnerable clusters.

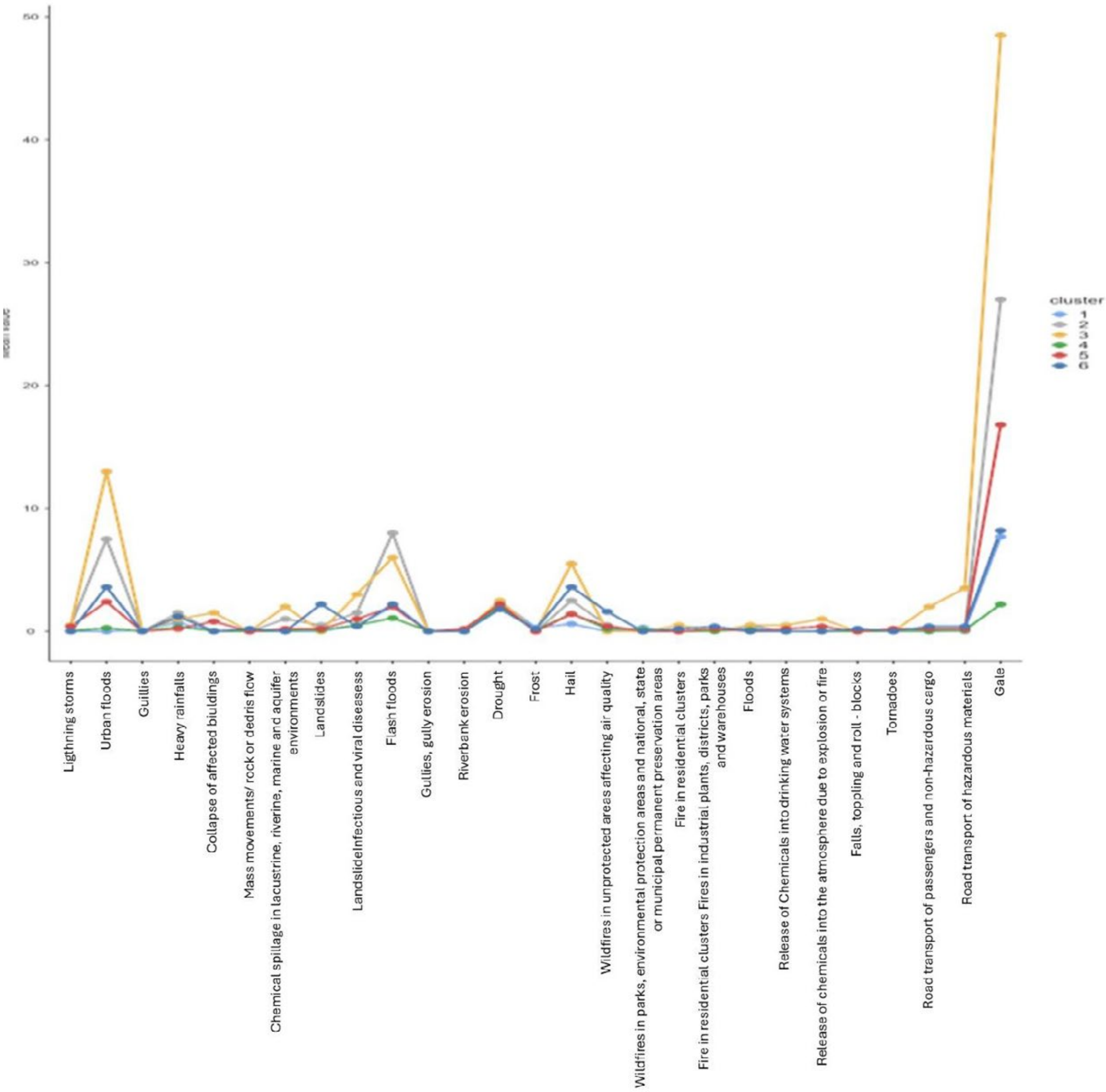

Figure 5 – Means across clusters

Source: Authors' elaboration (2025)

Figure 5 shows that Clusters 2 and 3 show sharp peaks in specific variables, particularly in cases of flooding, flash floods, hailstorms, and windstorms, confirming their high exposure to intense hydrometeorological events. These patterns may be related to higher population density, accelerated urbanisation, and a lack of adaptive infrastructure - common characteristics of vulnerable regions.

Cluster 3, in particular, stands out due to a significant spike in windstorm variable, with an average close to 50, which drastically differentiates it from the other groups. This answer reinforces how difficult the situation is in these municipalities, making them a priority for integrated risk mitigation and climate adaptation actions, such as strengthening urban infrastructure and establishing early warning systems.

In contrast, Cluster 4, which represents the largest group, shows a more stable line near the horizontal axis and indicates a range of low to moderate exposure to adverse events. This profile may reflect geographical features, lower population density, or greater resilience, suggesting that these municipalities experience fewer extreme climate impacts and require fewer emergency investments. However, ongoing preventive strategies may be important to keep this promising scenario.

Subsequently, the cluster scatter plot (Figure 6) provides a visual perspective of the spatial distribution of the groups, allowing for dealing with possible territorial factors associated with the patterns of event occurrences.

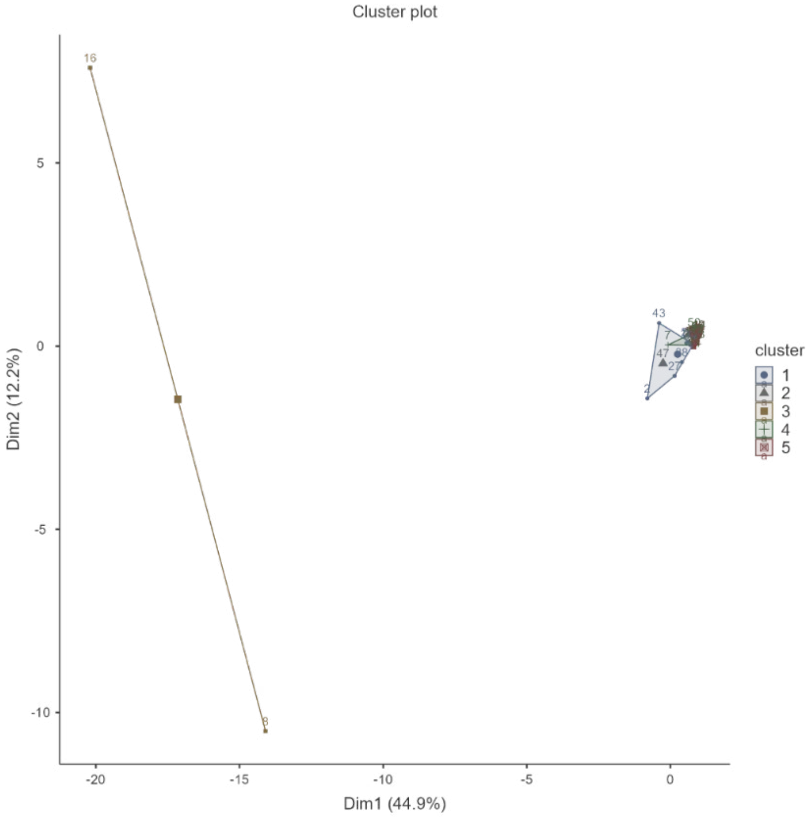

Figure 6 – Scatter and Clustering of Standardised Data by Clusters

Source: Authors' elaboration (2025)

The cluster scatter plot shows the distribution of municipalities in a two-dimensional space, based on the main components that explain data variability. Dimensions Dim1 (44.9%) and Dim2 (12.2%) capture a significant portion of the variance, allowing visualisation of the formed groupings and identification of important patterns.

Cluster 1 (blue) forms a more compact group, indicating greater similarity among its municipalities. This characteristic may be associated with homogeneity in vulnerability indicators analysed, possibly reflecting a predominantly rural profile. On the other hand, Cluster 2 (yellow) is significantly separated from the others, with two municipalities standing out as particularly distant. This configuration suggests that these municipalities have extreme characteristics in some of the analysed variables, which may reflect very specific vulnerabilities or exceptional situations.

Clusters 3, 4, and 5 are located closer together and are slightly dispersed to show some heterogeneity within their groups. Nonetheless, their proximity indicates shared characteristics, which may make it easier to formulate integrated public policies for these municipalities, particularly regarding climate mitigation and adaptation.

This spatial analysis reinforces the conclusions drawn from the previous chart and highlights municipalities that require greater attention due to their specific vulnerabilities. PCA variability provides a detailed view of each component's contribution to the data's variability and supports interpretation of the results.

The arrangement of vectors in the Principal Component Analysis (PCA) variable plot reveals which events have the greatest impact on differentiating municipalities, allowing for more precise interpretation of the predominant risks in each cluster. This analysis is essential to develop public policies to mitigate and adapt municipalities to natural and environmental disasters, and to provide a solid foundation to make preventive actions and territorial management strategies.

Regarding hydrometeorological events such as windstorms, flash floods, and urban flooding, the adoption of Nature-Based Solutions (NBS) has shown positive results in urban contexts. For example, Curitiba's Master Plan integrates green infrastructure as a measure to increase urban resilience, to mitigate flooding, and to promote environmental sustainability (Curitiba, 2023). This kind of intervention can be applied to municipalities in Cluster 3 to prioritise areas with higher vulnerability.

For municipalities in Cluster 5, where hazardous chemical releases and lightning storms are more frequent, public policies inspired by Canada's chemical management framework may be adapted. Canada implements strict control measures, including detailed risk assessments and preventive regulations, which minimise exposure to dangerous substances (Government of Canada, 2020).

Additionally, areas that are prone to wildfires, such as municipalities in Cluster 2, may get some benefit from Integrated Fire Management (IFM), which combines controlled burning with educational and community engagement actions. Experiences conducted at the Serra Geral do Tocantins Ecological Station have demonstrated that IFM significantly reduces wildfire extent while promoting ecological and social benefits (OECO, 2022).

These public policies not only address the specific vulnerabilities of each cluster but also promote climate adaptation and strengthen territorial resilience. The adoption of integrated climate governance systems, based on Sustainable Development Goals (SDGs 13 and 11), can serve as a strategic axis to coordinate action among municipalities with different profiles and consequently maximise the impact of initiatives. Thus, this analysis provides valuable support to decision-makers and policymakers in prioritising actions based on evidence and successful practices in similar contexts.

4 FINAL CONSIDERATIONS

This research aimed to identify and analyse the occurrence of extreme weather events in Paraná municipalities. It used Exploratory Factor Analysis (EFA), Principal Component Analysis (PCA), and cluster grouping techniques. These methods allowed categorising five distinct groups of municipalities based on climatic and socio-environmental indicators, to provide a structured overview of vulnerability and the spatial patterns of these events.

The results revealed distinct territorial patterns: municipalities more exposed to heavy rainfall, prolonged droughts, and rising temperatures, and highlighted the importance of sustainable political actions to regional needs. Cluster analysis enabled the grouping of municipalities with similar characteristics, suggesting the need for public policies that address the specific vulnerabilities of each group. For instance, municipalities that are more exposed to windstorms and floods require investments in resilient infrastructure, while those more susceptible to wildfires demand robust monitoring and prevention strategies. Such actions are essential to mitigate climate impacts and strengthen territorial resilience, especially in a context of fast climate changes.

According to this analysis, reliance on incomplete historical time series and the absence of socioeconomic variables are among the constraints that limit a more comprehensive understanding of the social and economic dynamics associated with extreme events. Moreover, although the applied climatic data are robust, they did not consider variables such as average income, social vulnerability, or available infrastructure - factors that could enrich this research.

While the findings provide valuable inputs for public managers and territorial planning, it is important to emphasise that the limitations discussed here, such as the incomplete historical time series and the absence of socioeconomic variables, require attention when using this study as a direct management tool. The results should therefore be studied primarily as decision-support evidence, to be complemented by broader, more up-to-date local analyses before practical implementation.

For future studies, it is recommended to include social and economic indicators, such as the Municipal Human Development Index (MHDI) and population density, and to link references to climate data for a more holistic perspective. It is also suggested to expand the temporal scope to monitor trends and test the stability of groupings over time.

As a practical outcome, it would be relevant to implement a continuous monitoring system for extreme weather events, with regular updates. Such data could support the formulation of targeted public policies, such as municipal master plans for climate adaptation, investments in resilient infrastructure, and preventive actions aimed at the most vulnerable populations.

Lastly, this study aims to contribute to the field of environmental sciences by offering a replicable methodology for territorial analysis of extreme weather events. By highlighting patterns and trends, it provides essential support to public managers and policymakers in addressing the challenges posed by climate change, protecting communities, and promoting sustainable development.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

The authors declare that no generative AI or AI-assisted technologies were used in the creation, writing, or editing of this manuscript.

REFERENCES

ADGER, W. N. Vulnerability. **Global Environmental Change**, [s. l.], v. 16, n. 3, p. 268–281, 2006. Available in: https://doi.org/10.1016/j.gloenvcha.2006.02.006.

ALTUNKAYNAK, A.; KUMAR, M.; SINGH, V. P. **Correlation and Regression Analysis in Environmental Sciences**. Water Resources Publications, 2020.

BRASIL. Ministério das Cidades. Secretaria Nacional de Saneamento Ambiental. **Drenagem Urbana Sustentável**. Brasília: MCIDADES, 2012.

BRASIL. Ministério do Meio Ambiente. **Plano Nacional de Adaptação à Mudança do Clima** – Volume I: Estratégia Geral. Brasília: MMA, 2016. Available in: https://www.gov.br/mma. Accessed on: 3 maio 2025.

CASA CIVIL DO MUNICÍPIO DE CASCAVEL. **Plano Diretor de Desenvolvimento Urbano de Cascavel – PDDU**. Cascavel: Prefeitura Municipal, 2023. Available in: https://www.cascavel.pr.gov.br. Accessed on: 3 maio 2025.

CRESWELL, J. W.; CRESWELL, J. D. **Research Design**: qualitative, quantitative, and mixed methods approaches. 5. ed. Thousand Oaks: SAGE, 2018.

CUNHA FERREIRA, L. G.; KEMENES, A. A influência dos eventos climáticos extremos na climatologia da planície litorânea piauiense. **Revista Brasileira de Climatologia**, v. 32, n. 19, p. 634–657, 2023. Available in: https://doi.org/10.55761/abclima.v32i19.16349. Accessed on: 3 maio 2025. Portal de Periódicos UFGD

CURITIBA. **Plano Diretor de Curitiba**: soluções baseadas na natureza para drenagem urbana. Curitiba: Prefeitura Municipal, 2023. Available in: www.curitiba.pr.gov.br.

CUTTER, S. L. *et al.* Social vulnerability to environmental hazards. **Social Science Quarterly**, [s. l.], v. 84, n. 2, p. 242–261, 2003. Available in: https://doi.org/10.1111/1540-6237.8402002.

DA SILVA, G. A. M. *et al.* Detecção e atribuição das anomalias anuais dos índices de extremos de chuva e temperaturas máxima e mínima diárias sobre o litoral de São Paulo/Brasil. **Revista Brasileira de Geografia Física**, v. 14, n. 5, p. 3008–3043, 2021. Available in: https://doi.org/10.26848/rbgf.v14.5.p3008-3043. Accessed on: 3 maio 2025. Periódicos UFPE

FERREIRA, C. de C. M.; OLIVEIRA, T. A. de. Os eventos extremos em Juiz de Fora - MG: investigação a partir da técnica dos máximos de precipitação. **Revista de Geografia**, v. 38, n. 3, p. 281–304, 2021. Available in: https://periodicos.ufpe.br/revistas/revistageografia/article/view/249645. Accessed on: 4 maio 2025

FOZ DO IGUAÇU. **Plano Municipal de Mitigação e Adaptação às Mudanças Climáticas – PMMAC**. Foz do Iguaçu: Secretaria Municipal de Meio Ambiente, 2022. Available in: https://www.pmfi.pr.gov.br. Accessed on: 3 maio 2025.

FREITAS, D. A.; FRAGELLI, T. B. M.; ALMEIDA, D. D. S. Desastres ambientais e vulnerabilidade socioespacial: uma análise da percepção dos moradores do bairro da Glória, em Joinville (SC). **Revista Brasileira de Estudos Urbanos e Regionais**, v. 23, 2021. Available in: https://rbeur.anpur.org.br. Accessed on: 3 maio 2025.

FÜSSEL, H. M. An updated assessment of the risks from climate change based on the IPCC's SRES. **Climatic Change**, v. 30, n. 3, p. 297–324, 2010.

GALL, M.; BORDEN, K. A.; CUTTER, S. L. When do losses count? Six fallacies of natural hazards loss data. **Bulletin of the American Meteorological Society**, [s. l.], v. 90, n. 6, p. 799–810, 2009. Available in: https://doi.org/10.1175/2008BAMS2721.1.

GHASEMI, A.; ZAHEDIASL, S. Normality tests for statistical analysis: a guide for non-statisticians. **International Journal of Endocrinology and Metabolism**, [s. l.], v. 10, n. 2, p. 486–489, 2012. Available in: https://doi.org/10.5812/ijem.3505.

GOVERNMENT OF CANADA. **Risk Assessment and Management of Chemicals**. Ottawa: Canada.ca, 2020. Available in: www.canada.ca.

HAIR, J. F. *et al.* **Multivariate Data Analysis**. 8. ed. Andover: Cengage, 2019.

HALLEGATTE, S. *et al.* **Shock Waves**: managing the impacts of climate change on poverty. Washington: World Bank, 2016.

HINKEL, J.; BISARO, A. A review and classification of analytical methods for climate change adaptation. **WIREs Climate Change**, v. 6, n. 2, p. 171–188, 2015. DOI: 10.1002/wcc.322.

HINKEL, J.; BISARO, A. Methodological choices in solution-oriented adaptation research: a diagnostic framework. **Regional Environmental Change**, v. 16, n. 1, p. 7–20, 2016. DOI: 10.1007/s10113-014-0682-0.

IPCC – Intergovernmental Panel on Climate Change. **Climate Change 2021**: the physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the IPCC. Cambridge University Press, 2021.

MACHADO, L. A. T. *et al.* Extreme Weather Events in Brazil: floods and droughts. **Frontiers in Climate**, v. 2, 2020. Available in: https://doi.org/10.3389/fclim.2020.583511.

ISSN-e 2179-9067

MARÉNGO, J. A. Mudanças climáticas e eventos climáticos extremos foram abordados em palestra pelo climatologista do Cemaden. **Centro Nacional de Monitoramento e Alertas de Desastres Naturais**, 2023. Available in: https://www.gov.br/cemaden/pt-br/assuntos/noticias-cemaden/mudancas-climaticas-e-eventos-climaticos-extremos-foram-abordados-em-palestra-pelo-climatologista-do-cemaden. Accessed on: 3 maio 2025.

MUKAKA, M. S. A guide to appropriate use of correlation coefficient in medical research. **Malawi Medical Journal**, [s. l.], v. 24, n. 3, p. 69–71, 2012. Available in: https://doi.org/10.4314/mmj.v24i3.

NASCIMENTO, J. M.; ALMEIDA, A. M.; COSTA, C. A. R. Risco e vulnerabilidade: desastres naturais e os desafios das políticas públicas no Brasil. **Revista Gestão – Sustentabilidade Ambiental**, v. 9, n. 1, p. 252–269, 2020.

O LIBERAL. **Eventos climáticos extremos se tornarão mais frequentes no Brasil, alertam especialistas**. 11 maio 2024. Available in: https://www.oliberal.com/mundo/eventos-climaticos-extremos-se-tornarao-mais-frequentes-no-brasil-alertam-especialistas-1.812598. Accessed on: 3 maio 2025.

OECO. **Mudança de paradigma**: quando o fogo vira ferramenta de combate à crise climática. OECO, 2022. Available in: www.oeco.org.br.

OLIVEIRA, T.; TAVARES, J.; SILVA, M. Análise dos eventos climáticos extremos e de suas causas climáticas para redução de riscos nas bacias hidrográficas Aguapeí e Peixe, São Paulo, Brasil. **Revista Brasileira de Meteorologia**, v. 35, n. 2, p. 123–135, 2020. Available in: https://www.scielo.br/j/rbmet/a/vqQTJrVVkqvqfcZjTKGVqWv/. Accessed on: 4 maio 2025.

PEREIRA, H. S.; LIMA, K. M.; ANDRADE, J. R. Mudanças climáticas e impactos regionais: desafios e estratégias para adaptação. **Revista Brasileira de Climatologia**, v. 30, p. 318–333, 2022.

PRESTON, B. L.; YUEN, E. J.; WESTAWAY, R. M. Putting vulnerability to climate change on the map: a review of approaches, benefits and risks. **Sustainability Science**, v. 6, n. 2, p. 177–202, 2011. DOI: 10.1007/s11625-011-0129-1.

RODRIGUES, L. dos S.; SANTOS, C. da S. dos; RITA, F. dos S.; LOPES, G. D.; MARQUES, R. F. de P. V.; ROSA, M. S. da. Análise de índices de extremos climáticos (SPI e SPEI) na região do Baixo Paraíba do Sul e Itabapoana. **Gestão Ambiental,** Campina Grande: EPTEC, 2023. 264f. Available in: https://www.researchgate.net/publication/376034798_ANALISE_DE_INDICES_DE_EXTREMOS_CLIMATICOS_SPI_E_SPEI_NA_REGIAO_BAIXO_PARAIBA_DO_SUL_E_ITABAPOANA. Accessed on: 4 maio 2025.

SAITO, S. M. R. *et al.* Fortalecendo os laços: a cooperação intermunicipal como estratégia de redução de riscos de desastres. **Urbe. Revista Brasileira de Gestão Urbana**, v. 13, 2021. Available in: https://www.scielo.br/j/urbe/a/LRZtytPMdKd7RXt8fwqH4JD/. Accessed on: 9 maio 2025.

SANTOS, E.; BERNARDINO, D. C. de S. Mudanças climáticas, eventos climáticos extremos e movimentos de massa no Brasil: uma revisão sistemática. **ResearchGate**, 2022. Available in: https://www.researchgate.net/publication/374857371_Mudancas_climaticas_eventos_climaticos_extremos_e_movimentos_de_massa_no_Brasil_Uma_revisao_sistematica. Accessed on: 4 maio 2025

SHARMA, S.; PANIGRAHI, P. K. **Correlation coefficient estimation under non-normal distributions**: a robust approach. Environmental Modelling; Software, v. 141, 2021.

SILVA DIAS, M. A. F. *et al.* A Review of the Influence of the Urban Environment on the Weather and Climate in the Metropolitan Area of São Paulo. **Urban Climate**, v. 6, p. 3-19, 2013.

SILVA, R. F.; OLIVEIRA, M. D. C. Desastres socioambientais e gestão do risco: uma análise crítica das políticas públicas no Brasil. **Revista Katálysis**, v. 22, n. 2, p. 298–308, 2019.

TIBSHIRANI, R.; WALTHER, G.; HASTIE, T. Estimating the number of clusters in a data set via the Gap statistic. **Journal of the Royal Statistical Society**: Series B (Statistical Methodology), v. 63, n. 2, p. 411-423, 2001.

TUCCI, C. E. M. **Gestão da drenagem urbana**. Brasília: Agência Nacional de Águas, 2008.

UNDRR. **Metropolitan Recife advances coordination of intermunicipal actions for disaster and climate resilience**. United Nations Office for Disaster Risk Reduction, 2023. Available in: https://mcr2030.undrr.org/news/metropolitan-recife-advances-coordination-intermunicipal-actions-disaster-and-climate. Accessed on: 9 maio 2025.

UNISINOS. **Brasil teve 12 eventos climáticos extremos em 2023**. Instituto Humanitas Unisinos, 2024. Available in: https://www.ihu.unisinos.br/639285. Accessed on: 3 maio 2025.

VIANA, V. Mais incêndios e menos desmatamento: o que acontece na Amazônia brasileira? **El País**, 27 out. 2024. Available in: https://elpais.com/america-futura/2024-10-27/mas-incendios-y-menos-deforestacion-que-pasa-en-la-amazonia-brasillena.html. Accessed on: 3 maio 2025

ISSN-e 2179-9067