Infrastructure, Development, and Vulnerability: The Uneven Effects of Rainfall on Highway Safety in Brazil

Victor A. L. Brasileiro[1], Geymerson S. Ramos[2,1], Andre L. L. Aquino[1]

[1]Orion Lab., Instituto de Computação – Universidade Federal de Alagoas (UFAL)
CEP 57.072-900 – Maceió – AL – Brazil
[2]Inria, INSA Lyon – CITI, UR3720
69621 Villeurbanne – France

{victor.brasileiro,geymerson,alla}@orion.ufal.br

Abstract. *This study presents a nationwide assessment of the association between rainfall and crash occurrence on the Brazilian federal highway network across the 27 states. The alignment between these seasonal patterns is quantified using Spearman's correlation. The results reveal pronounced spatial variability in both the direction and magnitude of the rainfall–crash relationship. Significant negative correlations are concentrated in the North, whereas significant positive correlations are observed mainly in the Southeast and in Paraíba. A Fisher-z regression shows a positive, statistically significant association between state GDP and the strength of the correlations, indicating that more economically developed states in Brazil are more sensitive to weather-related impacts on highway safety.*

1. Introduction

Road safety management depends not only on long-term structural interventions but also on timely operational decisions, such as when and where to intensify enforcement, communication, and emergency readiness. Weather is one of the context variables that can change driving conditions and mobility routines, and rainfall is particularly relevant because it can affect visibility, surface friction, and travel behavior [Becker et al. 2022]. For public policy, the practical question is not whether rainfall matters in general, but how its association with crash occurrence varies across territories and seasons in ways that can support actionable planning.

Brazil offers a challenging setting for this problem. The federal highway system spans regions with distinct rainfall regimes and socio-territorial configurations, from areas where heavy rainfall can constrain circulation to contexts where traffic remains intense under adverse conditions. In such a heterogeneous environment, a uniform assumption that "rain increases crashes" may lead to poorly targeted calendars and inefficient allocation of operational resources [Zhang et al. 2024]. It is important to identify state-specific association profiles and translate them into planning cues compatible with how road and highway safety agencies operate, especially in Low-Middle-Income Countries (LMICs), where evidence gaps in road and highway safety interventions remain substantial [Goel et al. 2024].

In this study, we aim to identify and profile the locations where crash occurrence is more strongly associated with seasonal rainfall patterns. Our work addresses this challenge by integrating administrative crash records from Brazil's Federal Highway Police

(*Polícia Rodoviária Federal*, PRF) with meteorological observations from the National Institute of Meteorology (*Instituto Nacional de Meteorologia*, INMET) for the 2008–2025 period. While previous work has examined rainfall–crash associations in specific Brazilian highway segments [Guideli et al. 2021], a systematic state-level analysis across the federal network remains lacking. Our contribution includes a methodology for assessing the extent to which seasonal rainfall patterns are associated with the temporal distribution of crashes at the national level. By using this information, policymakers can proportionally take action to improve urban infrastructure and road/highway safety.

The remainder of this work is organized as follows: in Section 2, we discuss related work; in Section 3, we present the datasets; and in Section 4, we discuss the methodology. The results are presented and discussed in Section 5. Finally, we set out the conclusions in Section 6.

2. Related Work

The literature on road analysis and improvement is vast and constantly evolving. Contributions cover optimized infrastructure, traffic control, road safety, and the influence of variables such as climate, wealth, and human behavior. According to Goel et al. [Goel et al. 2024], only a small fraction of this body of work focuses on LMICs, such as Brazil, that are rapidly expanding their road and highway infrastructure and experiencing significant changes in traffic patterns.

In the context of our work, which analyzes the influence of rainfall on the number of highway crashes, Zou et al. [Zou et al. 2024] investigate the effects of weather factors on road traffic casualties using provincial-level data from China covering the period 2006–2021. The results reveal that precipitation is negatively associated with casualties in the short run (consistent with exposure reduction) and positively associated over longer horizons. Furthermore, the study incorporates socioeconomic variables, such as GDP per capita and health investment. It shows that territorial heterogeneity in the weather-crash relationship cannot be explained by meteorological factors alone.

Zhang et al. [Zhang et al. 2024] investigate the factors influencing road traffic accidents across 31 provinces in China using data from 2009 to 2021. The authors apply geographically weighted regression (GWR) to demonstrate that the effects of variables such as highway mileage, population, and GDP per capita vary significantly across regions, underscoring the inadequacy of uniform road safety approaches. The study shows that provinces with higher motorization and road infrastructure tend to experience more accidents, while better economic conditions may mitigate this effect.

The seasonal dimension of traffic crashes is explored by Harirforoush et al. [Harirforoush et al. 2019], who examine how different weather conditions across seasons affect crash frequency and severity in urban contexts. The authors demonstrate that the temporal distribution of crashes exhibits distinct seasonal patterns, with peaks associated with adverse meteorological conditions such as rain and snow. The study combines spatial and temporal analysis to identify high-risk areas and periods, providing inputs for planning preventive interventions.

In the Brazilian context, Mantovani et al. [Mantovani et al. 2025] use open data from the Federal Highway Police to develop analyses and models to reduce crashes and deaths on federal highways. The authors apply data mining techniques to identify key factors associated with crash risk, providing inputs for data-driven decisions in public health and road safety policy.

Guideli et al. [Guideli et al. 2021] analyze the relationship between field-measured precipitation and crash frequency on the BR-376/PR, a Brazilian mountainous highway, between 2014 and 2018. Using local rain gauge data and crash records, the authors apply negative binomial regression and demonstrate that rainfall intensity significantly increases crash risk on this mountainous segment. The study also identifies distinct critical seasons for rainfall influence, alerting to the possible need for differentiated road safety policies across periods.

To contribute to the urban development of road and highway infrastructure in Brazil, we conduct a nationwide study using highway data and intelligent safety policies. We incorporate insights from state-of-the-art research, such as the seasonal crash patterns identified by Harirforoush et al. [Harirforoush et al. 2019], to show that, although Brazil is improving its highway and traffic infrastructure in most developed states, it still needs to invest proportionally in policies that keep pace with this growth and mitigate the impacts of factors such as rainfall.

3. Datasets

To support our analysis, we use the highway crash occurrence records from [PRF 2025], and data from the meteorological measurements from the Brazilian National Institute of Meteorology (INMET) [INMET 2025]. Both datasets cover the period from 2008 to 2025. The climatic data contains hourly precipitation measurements recorded throughout the years. For the state-level time-series analyses adopted in this paper, precipitation was summarized by median monthly precipitation.

Previous studies have demonstrated the analytical potential of the PRF crash database [Costa et al. 2014]. The PRF is the federal law enforcement agency responsible for policing and documenting incidents on Brazil's federal highways. The dataset used in this study comprises approximately 2.02 million crash records for the 2008–2025 period. Each entry corresponds to a crash occurrence and provides structured information that enables temporal and territorial aggregation. Temporal fields were standardized to extract year and calendar month, location identifiers were checked, and only records with valid, non-duplicated temporal and territorial information were used.

In broad terms, the records include: (a) temporal information (date, time, and day of week); (b) territorial and spatial localization (federal unit, municipality, highway reference such as BR and kilometer, and georeferenced coordinates); (c) crash characterization (e.g., cause and type of crash, and categorical severity); and (d) outcome counts describing involved people/vehicles and injury severity (including fatalities and injuries). The aggregation of this detailed, information-rich dataset enables us to examine local and national trends at different temporal granularities. Figure 1 presents the total number of crashes per year in Brazil from 2008 to 2025. After peaking in 2011, this number has declined since 2013.

This sustained reduction in total crashes after the early 2010s can be explained by a combination of concurrent interventions, including the intensification of impaired-driving law enforcement following the 2012 "New Lei Seca" (Law 12,760/2012), which has been repeatedly associated with reductions in severe outcomes [Guimarães and da Silva 2019].

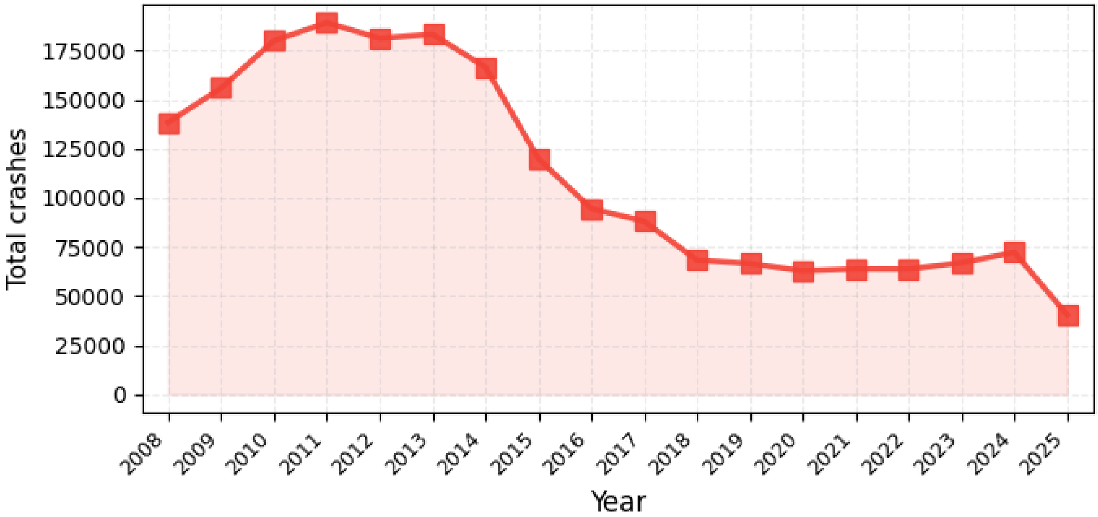

Figure 1. Total number of road crashes per year on Brazil's federal highway system (2008–2025).

4. Rainfall–Crash Association and Correlation Analysis

Our study integrates crash records and meteorological data to examine the association between rainfall patterns and crash occurrence across 27 Brazilian states. Considering that the number of crashes and the volume of precipitation exhibit seasonal patterns over the same period across different years [Harirforoush et al. 2019], each state is represented by two time series. The first consists of the monthly aggregation of crashes recorded between 2008 and 2025. The second corresponds to the median monthly precipitation over the same period, which characterizes the seasonal rainfall cycle.

By computing rainfall–crash Spearman correlation [Myers and Sirois 2014], we assess the extent to which the seasonal pattern of rainfall is associated with the temporal distribution of crashes in each state. Spearman's correlation was adopted because it is robust to non-normality, non-linearity, and the presence of outliers, which are common characteristics of aggregated road safety time-series data.

4.1. Crash Time Series

The crash time series is computed from PRF records [PRF 2025]. For each Brazilian state s, we identify the crashes x that occurred in calendar month $m \in \{1, \ldots, 12\}$ and year $a \in \mathcal{A} = \{2008, \ldots, 2025\}$, and compute the total number of crashes $C_{s,m,a}$ for month m of year a. Each crash contributes equally to the count, regardless of its severity or the number of vehicles involved. To obtain the seasonal profile, the monthly counts were summed across all available years, yielding one value per calendar month:

$$\hat{C}_{s,m} = \sum_{a \in \mathcal{A}} C_{s,m,a} \qquad m = 1, \ldots, 12 \tag{1}$$

The summation preserves the cumulative volume of crashes, so that months with consistently higher occurrence across several years produce larger aggregate values. The result is a 12-point vector $\hat{\mathbf{C}}_s = (\hat{C}_{s,1}, \ldots, \hat{C}_{s,12})$ that captures the characteristic seasonal shape of crash occurrence for each state. Figure 2 illustrates this profile for the state of Amapá.

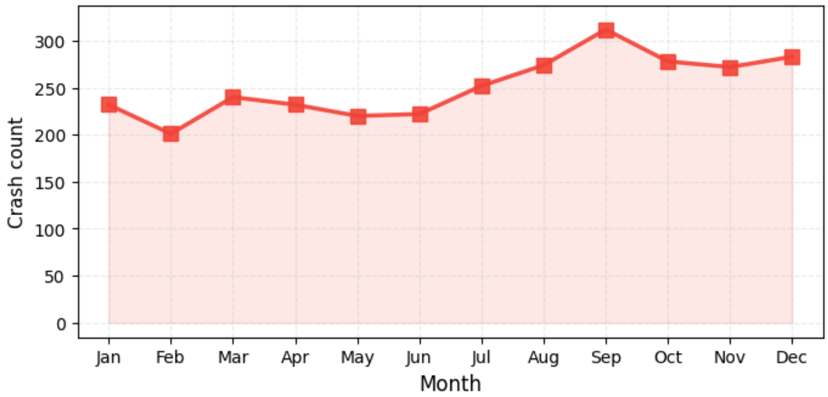

Figure 2. Total crashes per calendar month summed across 2008–2025 for Amapá (AP).

The time series exhibits an increasing trend, with January and February concentrating fewer crashes than the months at the end of the year, a period associated with increased commercial activity, school holidays, and festive travel, which tend to elevate traffic exposure and, consequently, the number of recorded crashes.

4.2. Rainfall Time Series

We use the data provided by [INMET 2025] to compute the rainfall time series. Considering $R_{s,m,a}$ as the total rainfall (in mm) recorded at the state s, in month m of year a, we construct the seasonal profile of the monthly values by computing the median $\tilde{R}_{s,m}$ across years. The median was chosen instead of the arithmetic mean for robustness: precipitation distributions are typically right-skewed, and isolated extreme events (e.g., atypical storms) in a single year could distort the mean, whereas the median remains representative of the typical rainfall for that calendar month. The result is a 12-point vector $\tilde{\mathbf{R}}_s = (\tilde{R}_{s,1}, \ldots, \tilde{R}_{s,12})$ that captures the characteristic seasonal rainfall regime of different states in Brazil.

Figure 3 illustrates this profile for the state of Amapá. The resulting rainfall time series exhibits a precipitation pattern consistent with the state's climatological regime. Located in the Amazon region, Amapá has a well-defined rainy season, typically from January to June, with peak precipitation between March and May, and a relatively drier period in the second half of the year. In Figure 3, precipitation is higher in February and March, gradually decreasing in the subsequent months and reaching a minimum in October.

4.3. Spearman's rank-correlation

Using the time series that represent the characteristic seasonal patterns of rainfall ($\tilde{\mathbf{R}}_s$) and crashes ($\hat{\mathbf{C}}_s$), the rainfall–crash association is quantified independently for each state

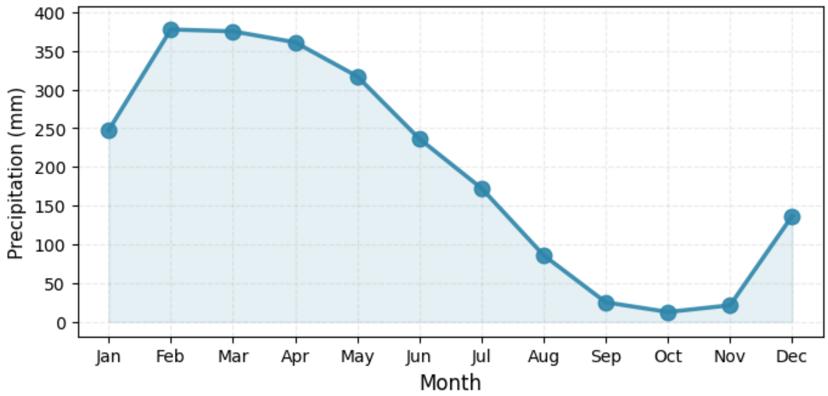

Figure 3. Median monthly accumulated precipitation across 2008–2025 for Amapá (AP).

through Spearman's rank-correlation coefficient ρ, defined in Equation (2). This metric measures the strength and direction of the monotonic relationship between the two variables, namely $\tilde{\mathbf{R}}_s$ and $\hat{\mathbf{C}}_s$.

Spearman's ρ is defined as the Pearson correlation computed on the ranks of each variable rather than on the raw values, making it naturally robust to non-linearity, outliers, and distributional assumptions and properties that are desirable given the right-skewed nature of precipitation data and the discrete character of crash counts. Unlike a purely linear metric, it captures consistent increases or decreases in the data, regardless of the underlying functional form.

Given n paired observations, each variable is first converted into ranks. Let $R(x_i)$ and $R(y_i)$ denote the ranks of the i-th observation. Spearman's correlation can then be computed as the Pearson correlation between the ranked variables:

$$\rho = \frac{\sum_{i=1}^{n} \left(R(x_i) - \overline{R_x}\right) \left(R(y_i) - \overline{R_y}\right)}{\sqrt{\sum_{i=1}^{n} \left(R(x_i) - \overline{R_x}\right)^2 \sum_{i=1}^{n} \left(R(y_i) - \overline{R_y}\right)^2}} \tag{2}$$

When there are no tied ranks, the coefficient can be computed using the simplified expression:

$$\rho = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n(n^2 - 1)}, \tag{3}$$

where $d_i = R(x_i) - R(y_i)$ is the difference between the ranks of each pair of observations and n is the total number of observations. The value of ρ ranges from -1 to 1, where values close to 1 indicate a strong positive monotonic relationship, values close to -1 indicate a strong negative monotonic relationship, and values near zero indicate little or no monotonic association.

In this context, the test evaluates whether periods with higher precipitation are consistently associated with higher or lower numbers of crashes. The corresponding null hypothesis states that there is no monotonic relationship between the two time series ($\rho = 0$). In contrast, the alternative hypothesis indicates the presence of a positive or negative monotonic association ($\rho \neq 0$).

As a further step, one can assess the relationship between state-level ρ values and other covariates, such as gross domestic product, by fitting an Ordinary Least Squares (OLS) model to the Fisher z-transformed correlation coefficients [Silver and Dunlap 1987]. Since raw Spearman's ρ is bounded in $[-1, 1]$ and exhibits a non-normal sampling distribution, the Fisher transformation $z = arctanh(\rho)$ is required to map ρ to a real line and obtain an approximately normal variable with variance that is independent of the magnitude of the correlation. The regression is then defined as

$$z_s = \beta_0 + \beta_1 x_s + \varepsilon_s, \tag{4}$$

where x_s represents the corresponding value of the explanatory variable, β_0 is the intercept, β_1 captures the association between x_s and z_s, and ε_s is an idiosyncratic error term. The index s identifies the states in the sample.

5. Results

Figure 4 shows the spatial distribution of the state-level association between precipitation and the number of crashes on the Brazilian federal highway system. For each state, we report Spearman's ρ, computed from the time series representing the annual pattern in the number of crashes and the time series representing the annual precipitation pattern. In states shown in red ($\rho < 0$), months with higher precipitation tend to coincide with fewer crashes. In states shown in blue ($\rho > 0$), higher-precipitation months tend to coincide with more crashes. The strength of the association is given by $|\rho| \in [0, 1]$, with values close to 0 indicating a weak or no monotonic relationship and values close to 1 indicating a strong monotonic relationship between rainfall and the number of crashes.

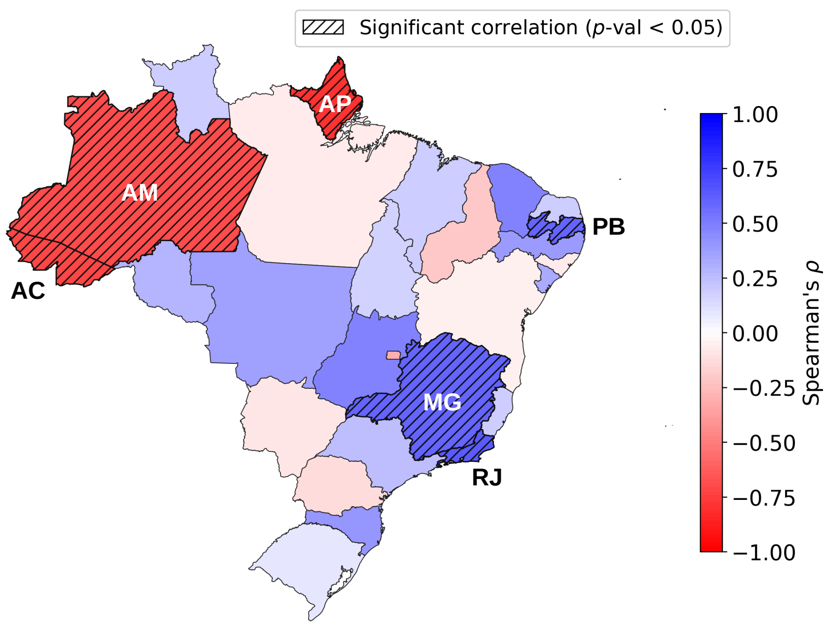

Figure 4. Spatial distribution of state-level Spearman correlation between rainfall and crash counts on Brazil's federal highway system.

Brazil has continental dimensions and substantial socioeconomic heterogeneity across states. The map of Spearman's ρ shows spatial variation in both the direction and the magnitude of the association between rainfall and the number of crashes. Of the 27 states, 10 have negative correlations, and 17 have positive correlations. Statistically significant correlations (p-value < 0.05) are indicated by hatched areas. Three states show significant negative associations: AP (Amapá, $\rho = -0.80$), AC (Acre, $\rho = -0.72$), and AM (Amazonas, $\rho = -0.70$). Therefore, months with higher precipitation tend to coincide with fewer crashes. In contrast, three states show significant positive associations: RJ (Rio de Janeiro, $\rho = 0.64$), MG (Minas Gerais, $\rho = 0.61$), and PB (Paraíba, $\rho = 0.59$). In these regions, higher-precipitation months tend to coincide with more crashes.

In states where correlation values are low ($\rho \approx 0$), the trends representing rainfall and crashes suggest no consistent joint pattern. Increases or decreases in precipitation are not consistently accompanied by corresponding increases or decreases in crash counts. São Paulo, one of the most economically developed states, presents a low and non-significant Spearman correlation ($\rho = 0.23$). By observing the normalized time series representing the typical annual patterns of crash counts and rainfall in Figure 5, we can see that precipitation is highest between January and March, decreases toward mid-year, and starts increasing again after August, while crash counts are higher at the beginning and end of the year. The crash curve is less stable during the dry months, which weakens the overall association.

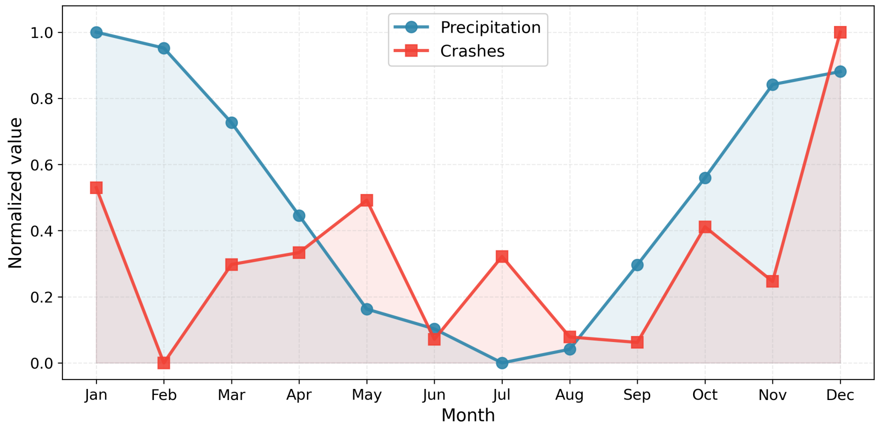

Figure 5. Representative seasonal rainfall–crash profiles for São Paulo (SP).

Considering the typical annual patterns of crash counts and rainfall in states with statistically significant correlations, Figures 6 and 7 represent Amapá and Minas Gerais, respectively. In the first state ($\rho < 0$), the number of crashes increases over the year, with fewer occurrences in January and February and higher volumes in the later months. In contrast, rainfall is concentrated between January and March and decreases toward the end of the year. For Minas Gerais ($\rho > 0$), months with higher precipitation tend to coincide with higher numbers of crashes. The number of crashes is higher between January and March, decreases until mid-year, and increases again from September to December. Precipitation follows a similar seasonal pattern.

Brazil is divided into 5 grand regions: North, South, Southeast, Northeast, and Central-West. Interestingly, the states with significant negative associations are located in the North. In contrast, the Southeast region includes two of the three states with significant positive associations, namely Rio de Janeiro and Minas Gerais. Paraíba is located in

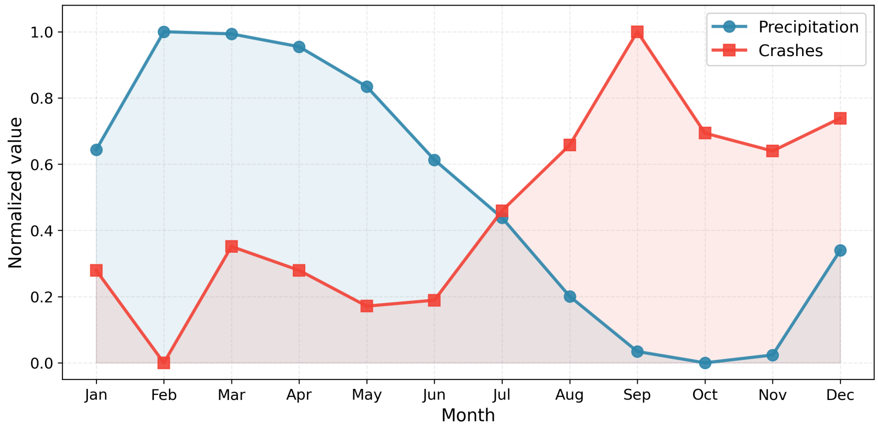

Figure 6. Representative seasonal rainfall–crash profiles for Amapá (AP).

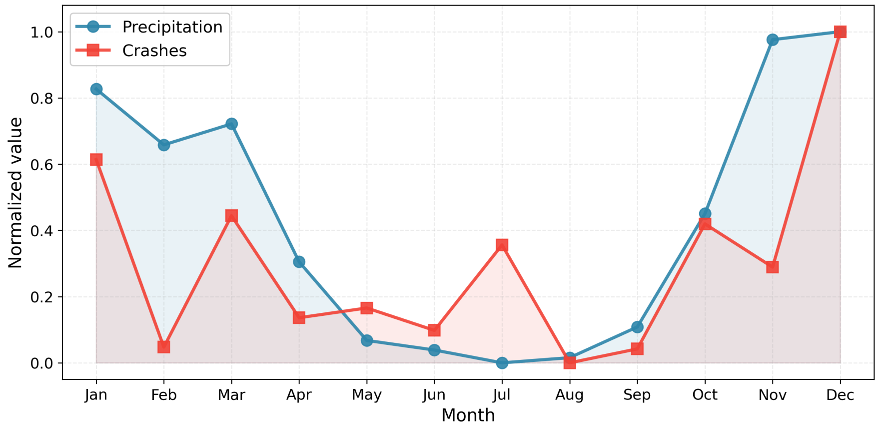

Figure 7. Representative seasonal rainfall–crash profiles for Minas Gerais (MG).

the Northeast. This spatial pattern may reflect regional differences in traffic demand, infrastructure, and rainfall regimes.

In the North, months with higher precipitation may coincide with reduced mobility, as the road network has a higher proportion of segments with limited trafficability (e.g., BR-319 and BR-163) during the rainy season, which can restrict vehicle circulation and reduce traffic exposure. In contrast, in the Southeast, the traffic density, urbanization, and fleet size are substantially higher. Rainfall events may occur under saturated road networks, reduced visibility, and lower pavement friction, conditions that tend to coincide with higher crash rates.

Comparing the socioeconomic profiles of the North and Southeast regions (those with the largest numbers of states on opposite sides of Spearman's correlation), we observe that the states with statistically significant associations also lie at opposite ends of the economic spectrum. According to the IBGE report on Brazil's 2023 Gross Domestic Product (GDP), Rio de Janeiro (≈ R$ 1.17 trillion) and Minas Gerais (≈ R$ 0.97 trillion) rank second and third among the states with the highest GDP [IBGE 2023]. In contrast, Acre and Amapá are among the states with the lowest GDP, at approximately R$ 26.2 billion and R$ 28 billion, respectively. Figure 8 shows the scatter plot of state GDP versus Spearman's ρ. Because the x-axis values are highly skewed by large differences in GDP across states, a logarithmic scale was used.

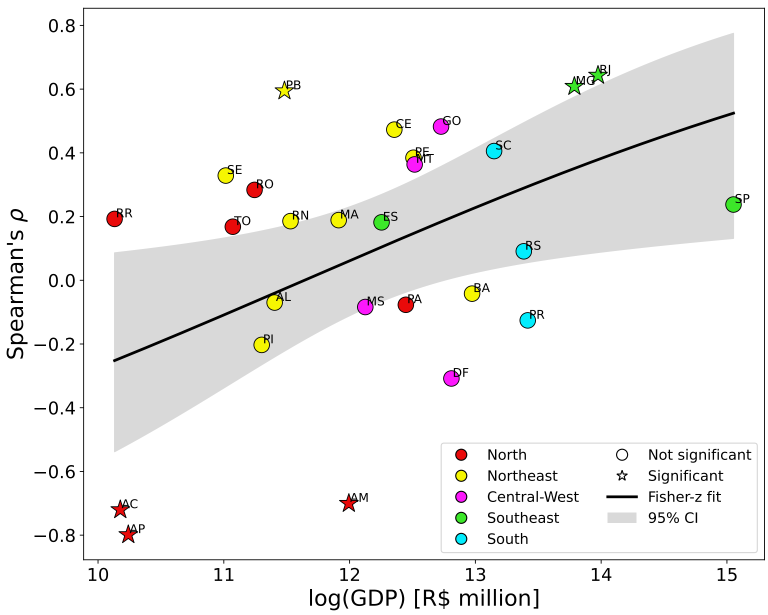

Figure 8. State-level Spearman correlation between rainfall and crash counts versus log(GDP) across Brazilian federal units.

To verify whether higher-GDP states show stronger associations between precipitation and traffic accidents, we applied a Fisher-z regression to state-specific correlation coefficients with log(GDP). The Fisher-z transformation allows correlations to be analysed with linear models and then back-transformed for interpretation. GDP was positively associated with the strength of the correlation ($\beta = 0.171$, SE = 0.071, p-value = 0.023, R^2 = 0.19). These findings indicate that the precipitation–crash relationship is substantially stronger in more economically developed states.

This result does not contradict the benefits of development. It reveals an important externality of mobility expansion that requires policy attention. Although higher-GDP states have historically concentrated investments in transport infrastructure and network expansion, they also show stronger rainfall–crash associations under adverse weather conditions. This behavior suggests that economic development and roadway modernization alone are insufficient to mitigate rainfall-associated safety risks when they are accompanied by rapid motorization, high traffic exposure, and complex urban dynamics.

In several of these states, accelerated urban growth has often occurred without adequate spatial and mobility planning, increasing impermeable surfaces, overloading drainage systems, and intensifying congestion under adverse weather conditions. These factors amplify operational risk during rainfall and help explain the positive rainfall–crash associations observed. From a policy perspective, this indicates that infrastructure quality must be complemented by integrated land-use planning, resilient drainage design, demand management, and adaptive traffic operations to reduce vulnerability to precipitation events.

The negative correlations identified in lower-GDP states suggest that different mobility patterns, lower traffic densities, or more cautious behavioral responses to rainfall may coincide with fewer crashes under adverse weather. Rather than being interpreted as a structural advantage, this should be seen as a window of opportunity for proactive planning. As these states undergo economic and urban expansion, the implementation of preventive policies, such as risk-sensitive highway design, weather-adapted enforcement strategies, and early integration of climate resilience into transport planning, will be essential to avoid reproducing the high-exposure model observed in more developed regions.

At the same time, higher-GDP states should aim to transition toward rainfall–crash relationships that resemble the negative patterns found in less motorized contexts, prioritizing systemic safety approaches that reduce exposure and enhance network robustness. Together, these differentiated yet complementary strategies underscore the need for development pathways that align economic growth, urban form, and climate-responsive road-safety management.

6. Conclusion

This study provided a nationwide evaluation of the association between seasonal precipitation and crash occurrence on Brazil's federal highways by combining long-term crash records (2008–2025) with meteorological data for all 27 states. Representing each state through monthly crash totals and median monthly rainfall allowed the identification of the alignment between their seasonal cycles using Spearman's correlation. The results revealed significant negative associations concentrated in the North and significant positive associations mainly in the Southeast and Paraíba, indicating that rainfall's effect on crashes depends on regional mobility dynamics rather than climate alone.

In lower-mobility contexts, the rainy season tends to reduce traffic exposure and coincide with fewer crashes, whereas in highly motorized and densely trafficked states, precipitation occurs under saturated conditions. The positive relationship between state GDP and the strength of the correlations indicates that more economically developed regions, despite better infrastructure, tend to show stronger rainfall–crash associations. This finding highlights an externality of mobility expansion: infrastructure growth and fleet increases have not always been matched by proportional investments in weather-resilient safety strategies, which is a key issue for the sustainable development of the transport system.

Incorporating weather-responsive speed management, resilient pavement and drainage design, improved signage visibility, and real-time meteorological information into traffic operations is essential, particularly in high-demand states, while ensuring safe trafficability remains a priority in regions where rainfall restricts circulation. Future studies should include direct measures of traffic exposure, infrastructure quality, and rainfall intensity to advance causal analyses and more targeted climate-resilient road-safety policies.

Acknowledgements

We thank the Alagoas State Research Support Foundation (FAPEAL) for the resources provided through call E:60030.0000000352/2021, and the Brazilian National Council for Scientific and Technological Development (CNPq) for financial support through project number 407515/2022-4.

References

Becker, N., Rust, H. W., and Ulbrich, U. (2022). Weather impacts on various types of road crashes: a quantitative analysis using generalized additive models. *European Transport Research Review*, 14(1):37.

Costa, J., Bernardini, F., Lima, T., and Viterbo, J. (2014). Uma análise da qualidade dos dados relativos aos boletins de ocorrências das rodovias federais brasileiras para o processo de mineração de dados. In *Anais do VI Workshop de Computação Aplicada em Governo Eletrônico*, pages 9–16, Porto Alegre, RS, Brasil. SBC.

Goel, R., Tiwari, G., Varghese, M., and Bhalla, K. (2024). Effectiveness of road safety interventions: An evidence and gap map. *Campbell Systematic Reviews*, 20(2):e1402.

Guideli, L. C., Cuenca, A. L. R., Silva, M. A., Passini, L. B., and Pinheiro, J. H. S. (2021). Road crashes and field rainfall data: mathematical modeling for the Brazilian mountainous highway BR-376/PR. *Transportes*, 29(3).

Guimarães, A. G. and da Silva, A. R. (2019). Impact of regulations to control alcohol consumption by drivers: an assessment of reduction in fatal traffic accident numbers in the federal district, brazil. *Accident Analysis & Prevention*, 127:110–117.

Harirforoush, H., Bellalite, L., and Bénié, G. B. (2019). Spatial and temporal analysis of seasonal traffic accidents. *American Journal of Traffic and Transportation Engineering*, 4(1):7–14.

IBGE (2023). Brasil PIB 2023. `https://www.ibge.gov.br/explica/pib.php`. Last accessed: February 26, 2026.

INMET (2025). Instituto Nacional de Meteorologia (INMET): Dados históricos de precipitação. `https://bdmep.inmet.gov.br/`. Last accessed: February 11, 2026.

Mantovani, D., Cardoso, D. S., and Leal, G. A. (2025). Reduction of traffic accidents and deaths in Brazil: A data-driven approach. In *Proceedings of the 2025 AIS SIGSAND Symposium*. AIS Electronic Library (AISeL).

Myers, L. and Sirois, M. J. (2014). Spearman correlation coefficients, differences between. *Wiley StatsRef: Statistics Reference Online*.

PRF (2025). Polícia Rodoviária Federal (PRF) — Dados Abertos PRF. `https://www.gov.br/prf/pt-br/acesso-a-informacao/dados-abertos/dados-abertos-da-prf`. Last accessed: February 11, 2026.

Silver, N. C. and Dunlap, W. P. (1987). Averaging correlation coefficients: should fisher's z transformation be used? *Journal of applied psychology*, 72(1):146.

Zhang, K., Wang, S., Song, C., Zhang, S., and Liu, X. (2024). Spatiotemporal heterogeneity analysis of provincial road traffic accidents and its influencing factors in China. *Sustainability*, 16(17):7348.

Zou, X., Sun, L., Lan, T., Fan, C., Liu, S., Zhao, H., and Qiu, J. (2024). The effects of weather factors on road traffic casualties: Analysis on provincial panel data of China from 2006 to 2021. *Heliyon*, 10(17):e36788.