Understanding the Influence of Weather on Traffic Incidents in Spain

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ABSTRACT

Analyzing the impact of weather conditions on traffic incidents is relevant for assessing the vulnerability of road networks. While previous research has examined specific factors, a holistic framework regarding traffic incident protection remains necessary. This study applies an integrated multi-dimensional approach to evaluate precipitation effects in Gipuzkoa, Spain (2021–2024). Specifically, regression models are employed to quantify the relationship between precipitation and the occurrence, frequency, and severity of traffic incidents. Regression results quantify the observed patterns and indicate that precipitation conditions play a critical role in shaping road safety outcomes. Particularly, wet conditions increase the odds of incident occurrence by 70%, raise the number of incidents by 25%, and elevate the likelihood of severe outcomes by 24%. Crucially, when incidents coincide with registered flood events, the odds of a severe outcome more than double the normal scenario, identifying active disasters as a significant risk amplifier. Furthermore, the study shows that factors such as geography and the season amplify the overall risk chain of road incidents. These findings support the development of weather-responsive traffic management strategies.

Keywords

Weather conditions, Traffic Incidents, Logistic regression, Poisson regression, Climate change.

INTRODUCTION

Climate change has become one of the most prominent challenges facing modern transportation systems, contributing to an estimated USD 15 billion in annual physical damages from weather-related events such as intensifying storms, seasonal flooding, and abnormal precipitation patterns (UNEP-FI, 2024; IPCC, 2023). Beyond their destructive impact on infrastructure, climate change–driven hazards generate cascading effects (EEA, 2024; Li et al., 2023; Liang et al., 2021; Tang et al., 2024) that significantly increase both the likelihood, frequency, and severity of road incidents altering road friction, limit visibility, and disrupt driver behavior, collectively amplifying traffic risk (Liang et al., 2021; Mills et al., 2019). Therefore, understanding how the weather influences everyday traffic incidents is essential not only for road safety but also for ensuring the resilience of our transportation infrastructure.

Traditional safety research focuses on road accidents (Zou et al., 2021; Najafi Moghaddam Gilani et al., 2021; Tang et al., 2024; Liu et al., 2025). However, adverse weather not only triggers accidents; it also causes a wide range of disruptions that compromise the integrity of the transport network

Previous research has examined the relationship between weather and traffic (especially accidents), yet the literature remains notably fragmented regarding the conceptualization and measurement of this relationship (e.g., Lobo et al., 2019). This fragmentation is evident in the divergence of research paths: one path focuses on disruptions to driver perception and behavior (Liang et al., 2021; Tang et al., 2024); a second evaluates environmental conditions and climate indicators in isolation (Pechatnova et al., 2019; Shiau et al., 2023); and a third, emerging path concentrates on the resilience of specific critical infrastructures (Mo et al., 2024).

Methodologically, the common approaches to evaluate the traffic risks will be mentioned in the background section, which range from classical statistical models to advanced machine learning (ML) and deep learning (DL) frameworks, including lagged models, data mining, and quasi-experimental designs. Despite these contributions, certain gaps persist in the literature, primarily concerning data consistency and the adopted methodologies. While occurrence, frequency, and severity are interrelated, most research examines them in isolation, often overlooking how extreme events such as flooding shift these risk dynamics. This fragmented approach fails to capture the comprehensive risk chain from initial exposure to outcome incidents within a granular timeline. Moreover, a significant geographical bias toward Central Europe and Asia leaves regions with unique climatic profiles, such as Gipuzkoa, under-researched. This study addresses these gaps by establishing a localized methodological framework for Gipuzkoa, a region whose geographic and climatic particularity have been largely ignored in a literature dominated by cases from Central Europe and Asia. By utilizing high-resolution temporal data aggregated in 6-hour intervals, this research examines three distinct outcomes of the risk chain (occurrence, frequency, and severity). Consequently, this study seeks to answer the following research questions:

- RQ1: Does the precipitation increase the likelihood of occurrence of a traffic incident?
- RQ2: How does the precipitation raise the frequency of traffic incidents?
- RQ3: How does the precipitation exacerbate the severity of traffic incidents, and how does it change with flood presence?
- RQ4: How do additional factors (such as geography and seasonality, among others) influence these three dimensions in the specific context of Gipuzkoa?

Addressing these research questions, this research contributes to both academic literature and practical crisis management by enhancing the vulnerability assessment of road networks under extreme climatic events and offering a localized framework for emergency response planning in the region during heavy rainfall.

LITERATURE REVIEW

Research into the intersection between meteorological hazards and road safety has traditionally evolved along distinct methodological paths, often isolating one dimension of risk while omitting others. This section synthesizes the literature according to evaluation frameworks to address the relationship between precipitation and traffic safety.

Incident occurrence analysis

Research examining incident occurrence primarily utilizes binary outcome models to determine how weather conditions influence the probability of accidents. While logistic regression remains a foundational approach for identifying the odds of an event, as seen in studies by Jalilian et al. (2019) regarding environmental causes, recent studies like Mo et al. (2024) have evolved toward dynamic short-term crash analysis. Spatial dimensions are also central; Ye et al. (2023) identified location-specific precipitation effects with weather interactions, demonstrating that specific weather-infrastructure interactions create concentrated accident-prone areas where risk occurrence is highest.

To address the limitations of traditional regression, particularly the rare event nature of accidents, researchers are increasingly adopting quasi-experimental and machine learning (ML) frameworks to quantify uncertainty and handle class imbalance. Tafazzol et al. (2025) and Mills et al. (2019) utilized matched-pair analyses to isolate the relative risk of occurrence during storms, finding that rainfall and winter precipitation can increase crash likelihood by up to 38% and 137%, respectively. Simultaneously, advanced computational approaches have demonstrated superior predictive performance; Schlögl (2020) implemented a balanced bagging approach with Random Forest and XGBoost to handle imbalanced data, identifying real-time humidity and wind speed as critical discriminatory predictors of occurrence.

Despite these advances, a critical gap remains in temporal granularity. While weather clearly increases incident probability, daily or weekly scales often create a "smoothing effect" that masks hourly risks. Our study addresses this by adopting a 6-hour analysis window; this sub-daily scale allows for a precise alignment with emergency response shifts, a practical necessity highlighted by Kolísková & Neubauer (2025). Furthermore, although machine learning offers high accuracy, logistic regression is preferred here for its superior interpretability. It allows for a robust estimation of odds ratios and a clear quantification of environmental risk factors, maintaining consistency with established road safety research.

Incident frequency analysis

In relation to incident frequency research, Poisson regression remains a foundational method for linking meteorological variables to incident counts. Kolísková and Neubauer (2025) and Shiau et al. (2023) demonstrate its utility, noting that factors like heavy precipitation and extreme heat significantly affect total accident numbers. This is further supported by Lio et al. (2019) and Pechatnova et al. (2019), who highlight that variables such as wind speed and humidity act as critical risk enhancers for aggregate counts across different geographic scales. Another key finding is that the impacts of weather on road safety are rarely immediate. Nazif-Muñoz et al. (2021), Liang et al. (2021), and Li et al. (2024) emphasize the role of lagged and non-linear effects, where past meteorological conditions from previous hours or even days, exert a delayed influence on current frequency. For instance, the impact of extreme thermal stress can persist and accumulate for up to 14 days, a complex relation that disproportionately affects safety in both temperate and tropical climates (Li et al., 2023).

Climate-specific and geographic contexts further refine these relationships. The data-driven approach by Hsu, C. -K. (2024) revealed that traditional seasonal categories may not apply in tropical climates, and that adverse weather conditions including heavy rainfall, sub-optimal temperatures, and strong wind contributed to increased frequency especially during congested weekday traffic; this is confirmed by Shiau et al. (2023) research, which found that a decrease in the Diurnal Temperature Range (DTR) can increase long-term accidents by 17.1%. In Northern European contexts, MacLachlan et al. (2023) identified that zero-crossing temperatures (fluctuating around 0°C) significantly peak risks due to icing conditions. Furthermore, the type of terrain plays a role in magnifying risk; Wen et al. (2019) and Zhang et al. (2025) utilized spatial-temporal models to show that mountainous terrain and wind-slope synergies drastically intensify the danger posed by precipitation, leading to higher incident rates compared to standard road geometries.

When data exhibits overdispersion or excess zeros, negative binomial regression is preferred over Poisson. Studies by Lobo et al. (2019) and Zou et al. (2021) demonstrate that these models better capture "threshold effects," where incident frequency accelerates disproportionately once weather reaches extreme levels. While these aggregate models quantify the total societal burden, they often overlook real-time binary precursors or injury levels—a gap that necessitates integrating occurrence and severity-focused perspectives (Tang et al., 2024; Filapek et al., 2025). To address this, the present study focuses specifically on active incident periods (n>=1), evaluating the behavior of environmental risk factors only when an event occurs. This approach allows for a granular analysis of incident dynamics, shifting the focus from total counts to the specific conditions of the event.

Incident severity analysis

Research on incident severity typically utilizes ordered or multinomial logistic regression to determine how weather conditions intensify the magnitude of an accident. Studies such as those by Li et al. (2024) and He et al. (2023) highlight that both extreme heat and precipitation are consistently linked to higher mortality and injury rates. This relationship is particularly evident in low and middle-income regions, where infrastructure limitations often fail to mitigate the increased physical risks posed by extreme weather situations. Similarly, Najafi Moghaddam Gilani et al. (2021) and Jeong et al. (2022) demonstrate the high predictive power of Artificial Neural Networks (ANN) and logit models in metropolitan environments, achieving classification accuracies up to 98.9% for injury levels.

Another key dimension of severity analysis is the interaction between weather, human behavior, and geography. Zhai et al. (2019) utilized high-resolution weather data to demonstrate that meteorological conditions influence severity both directly, through reduced visibility and vehicle control, and indirectly, by triggering risky behaviors; Liu et al. (2022) confirmed this by a similar analysis using Bayesian networks. For instance, jaywalking and reckless driving tend to increase during rainy or hot conditions, suggesting that weather acts as a catalyst for behavioral adaptations that further escalate accident severity. Global climate shifts further exacerbate this influence; Nazif-Munoz et al. (2021) proved that "warm nights" are significantly associated with higher traffic fatalities by 31% relative risk in diverse urban contexts, likely due to driver fatigue. Liu et al. (2025) introduced the use of Association Rule Mining (Apriori) to characterize the relative risk of major accidents, revealing strong influence correlations between weather patterns and collision forms that aid in forecasting casualties with high precision.

Furthermore, geographic and infrastructure variations play a significant role, as shown by Omranian et al. (2018) and Lio et al. (2019), who found that wind speed and sunshine duration are strong predictors of severe injuries in high-density urban districts. Severity often increases more sharply on rural roads or specific urban districts where infrastructure is less resilient to adverse weather.

Finally, multi-outcome studies underscore that severity is a dynamic risk. Mills et al. (2019) noted that non-injury collisions can increase by 137% during winter storms, with risk levels typically peaking at the onset of the weather event. This is contextualized by the findings of Tafazzol et al. (2025), whose 16-year analysis revealed a paradoxical relationship: while rainfall increases the probability of an accident by 38%, it is simultaneously associated with a reduction in average severity due to speed compensation and increased driver caution.

The Research Gap: The Need for Integration

The collective findings from incident occurrence, frequency, and severity research confirm that integrating these dimensions into a single framework is essential to avoid skewed safety assessments. While these stages are intrinsically linked, current literature remains siloed, often analyzing them in isolation and focusing exclusively on road-specific accidents rather than on a broader category of road incidents. This split approach creates a significant knowledge gap not only in the European Atlantic context, but also in understanding the complete integrated risk chain of road incidents. Furthermore, there is a lack of integration between meteorological risk data and crisis management indicators, such as flood cover claims; this omission limits our understanding of how an extreme weather event may affect the road network in a crisis. By integrating a 6-hour occurrence analysis with incident frequency, severity, and flood coincidence data, this research fills this geographic gap, moving toward a holistic evaluative framework for improving the emergency management of the transportation infrastructure.

DATA MANAGEMENT: COLLECTION AND PREPROCESSING

This study focuses on a province from the Basque Country, with an average annual rainfall ranging from 1,200 mm to over 2,000 mm (Basque Government, 2023), more precisely on the province of Gipuzkoa, a region characterized by mountainous topography and an oceanic climate with high annual rainfall frequencies (Basque Government, N.D.). The combination of high traffic density, heavy freight transport along this key route connecting Spain and France, and frequent adverse weather conditions makes this road network particularly suitable for analyzing critical infrastructure resilience. For this analysis, a dataset was generated covering a four-year period (2021–2024) that contains 1,461 unique days, integrating meteorological records and road incident reports across the road networks of Gipuzkoa's 88 municipalities.

Weather data was obtained from the AEMET (state meteorological agency) OpenData platform via the Datosclima (2024) repository, using records from 14 meteorological stations distributed throughout the province and interpolated with the haversine equation to get weather data from the nearest one for each station covering a set of places in the province. The initial dataset consisted of 30,259 records, containing 13 variables, including daily temperature (minimum, average, and maximum), wind speed, and precipitation. To capture sub-daily variations, precipitation data were processed into 6-hour accumulation intervals (the standard granular temporal resolution provided by the source). The dataset was transformed, resulting in 18,636 specific time-block observations. In this study, precipitation was established as the primary exposure variable and categorized as Wet Conditions (precipitation > 0 mm) or Dry Conditions (precipitation = 0 mm).

Simultaneously, traffic incident data were obtained from Open Data Euskadi, the public data repository of the Basque Government. The raw dataset included 79,673 records featuring geographical coordinates, timestamps, incident causes, and severity levels. In this study, incident severity is inferred from its impact on road traffic status, categorized by incidence levels (e.g., yellow, red, black). This approach assumes that observed reductions in road capacity serve as a direct indicator of the event's magnitude. To ensure data quality, the records from Open Data Euskadi were compared against the annual reports of Trafikoa (Traffic Executive of the Basque Government). Such a comparison revealed that the incident records contain operational records not present in the formal accident database, and vice versa. Despite these discrepancies, this study prioritizes the Open Data Euskadi dataset for its incident-focused approach. Unlike accident-specific databases, which are often restricted by legal reporting criteria, this dataset captures a broader spectrum of road status—including minor disruptions that significantly impact infrastructure resilience. Furthermore, the accident-specific database contains extensive variables related to legal proceedings that fall outside the scope of this analysis, such as the number of victims, injuries, deaths, the number of people involved, and the type, traffic light priorities, and road signs, among others. The preprocessing phase focused on selecting unexpected traffic events; therefore, records classified as 'Road Works' were excluded from the primary incident analysis but retained as a contextual control variable. The cleaning process also involved correcting spatial coordinates and handling missing values to ensure a robust merge with the meteorological data.

To analyze the impact of weather on specific incidents and specific temporality, both datasets were aggregated into the same 6-hour blocks (00:00, 06:00, 12:00, 18:00) to serve as a primary exposure proxy, and assigning the nearest-neighbor spatial meteorological station information. The integration resulted in a final balanced dataset of 18,636 observations, capturing both seasonal variations and sub-daily shifts in weather patterns. This 6-hour temporal resolution represents the highest consistent data granularity available for this study. This resolution was selected to align with standard emergency response shifts and to prevent the 'smoothing effect' of daily aggregates, thereby ensuring that frequency and severity coefficients remain interpretable over the timing peaks relative to specific meteorological transitions. The primary variables selected for the analysis include:

- **Temporal identifiers:** Date, year, season, and time block (6-hour interval).
- **Spatial identifiers:** Meteorological station location, Municipality.

- **Traffic characteristics:** Incident Type, Cause, Road Name, Incidence Level (Severity), Presence of Road Works.
- **Exposure variable:** Binary precipitation status (Wet vs. Dry conditions).

The variables integrated into this study are summarized in ***Table 1***, which provides a detailed breakdown of their types and specific meanings.

Variable Category	Variable Name	Variable Type	Variable Value	Variable Meaning
Meteorological	Precipitation	Discrete	Wet, Dry	Binary precipitation value
Geographical	AEMET_Station	Discrete	Aretxabaleta … Zumarraga	Aretxabaleta … Zumarraga
Time	Date	Discrete	2024-01-1 … 2024-12-31	2024-01-1 … 2024-12-31
	Hour Block	Discrete	00-06 … 18-24	From 0 to 6 a.m. … From 18 to 24 p.m.
	Season	Discrete	Summer … Winter	Seasons of the year
	Day Type	Discrete	Weekday; Weekend	Type of day in the week
Road and incidents	Key	Discrete	215663 … 273990	Incident identificator
	Level Severity	Discrete	White Yellow Red Black	Incident severity is estimated based on road traffic flow, labeled as: White: Normal flow Yellow: Slow flow Red: Very slow flow Black: Stopped, not flow
	Road	Discrete	A AP GI N	Road type of the incident ocurred, where: A = Highway AP = Toll highway GI = Regional road
	Road Works	Discrete	With works; without works	Presence of road works

Table 1: Variable types and meaning

RESEARCH METHODOLOGY

This study aims to evaluate the relationship between precipitation and traffic incidents by aligning the previously described spatio-temporal dataset with the four research questions. This framework follows the risk chain of a traffic event, moving from the initial possibility of an occurrence of an incident to its outcome (Frequency + Severity of the incident). While the use of 6-hour temporal blocks was dictated by the maximum granularity of the AEMET records, this resolution serves as a strategic choice for this framework. It allows the analysis to move beyond daily averages and capture how sub-daily shifts in precipitation influence road safety during different operational windows. To provide a comprehensive assessment of risk in Gipuzkoa, the study addresses three outcome variables described below:

Incident occurrence (does precipitation increase the likelihood of an incident occurring?): defined as a binary indicator denoting whether at least one incident was recorded in a block. The analysis of this outcome aims to determine whether the transition from dry to wet conditions serves as a cause that alters the baseline safety of the road network.

$$\text{incident occurrece}=\begin{cases}1 \text{ if block has 1 incident}\\0 \text{ if block has 0 incidents}\end{cases}$$

Incident frequency (does precipitation increase the frequency of incidents?): measured as the total number of incidents observed per block among those where an occurrence was recorded. This allows us to assess if precipitation acts as a "multiplier," increasing the total count of incidents within a high-exposure window.

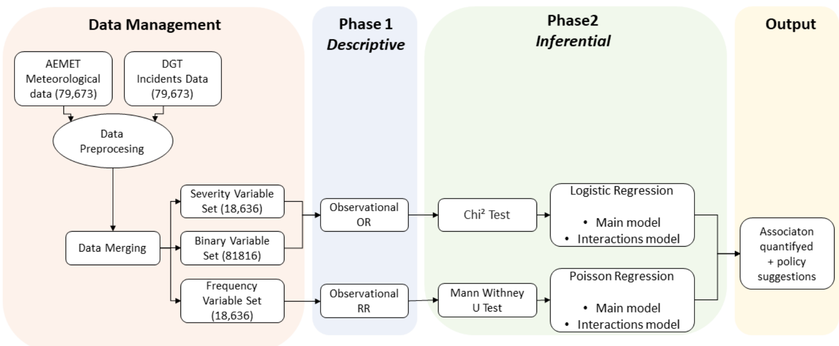
$$\text{incident frequency} = \text{number of incidents in a temporal block}$$

Incident severity (does precipitation increase the likelihood of high-severity outcomes?): established as a binary classification differentiating severe incidents (red or black levels) from non-severe incidents (yellow or white levels). This investigates the intensity of the risk, identifying if adverse weather specifically increases the likelihood of more dangerous or fatal incidents.

$$\text{incident severity}=\begin{cases}1 \text{ if incident level is red or black}\\0 \text{ if incident level is white or yellow}\end{cases}$$

This research follows a two-phased framework that integrates descriptive analysis and inferential modeling. First, the descriptive phase characterizes incident patterns through observational rates, providing a baseline assessment of the study area. Building upon these observations, the study moves to an inferential analysis to evaluate the independence, patterns, and proportional effects of precipitation across all outcome variables in greater depth. This allows understanding the data, enabling the identification of critical factors and informed decision-making to mitigate risks effectively in Gipuzkoa's province. The framework aligns as illustrated in Figure 1.

Figure 1. Methodological Framework



Descriptive analysis

In this phase, descriptive metrics were computed to quantify the baseline association between precipitation and traffic incidents. To ensure an unbiased estimation, the total meteorological exposure (N = 81,816 time blocks) was used as the denominator for occurrence rates, since for severity, the full incident dataset is used (N = 18,636 time blocks). For the analysis of incident frequency and severity, the data were filtered to include only those time blocks where at least one incident was recorded, allowing a focused assessment of event characteristics magnitude. Throughout this process, descriptive statistics—including mean, median, variance, and standard deviation—were examined to assess the overall data distribution and identify variability across all outcome variables.

Given that traffic incidents are relatively rare events, the odds ratio (OR) was used to measure the effect of precipitation on binary outcomes. The OR compares the odds of an incident occurring or being severe during wet conditions against the odds in dry conditions, as is shown:

$$\text{OR}=\frac{\frac{P(\text{risk}|\text{wet})}{P(\text{no risk}|\text{wet})}}{\frac{P(\text{risk}|\text{dry})}{P(\text{no risk}|\text{dry})}}$$

where the term "risk" is used as a general descriptor for the specific type of binary outcome variable being evaluated; depending on the model, this refers either to the probability of an incident occurring or to incident severity.

For the incident frequency (which is a count variable rather than binary), the rate ratio (RR) was employed instead of the OR. The RR compares the incident rate under precipitation exposure relative to the rate in unexposed conditions.

$$\mathrm{RR} = \frac{\mathrm{Risk(wet)}}{\mathrm{Risk(dry)}}$$

Inferential analysis

To statistically validate the patterns observed in the descriptive phase, a two-step inferential approach was implemented. First, bivariate tests were conducted to evaluate the independence between precipitation and the outcome variables. The Chi-square test was employed for categorical variables (occurrence and severity) to assess the significance of the association with weather conditions. For the count variable (frequency), the Mann-Whitney U test was utilized, as it is a robust non-parametric alternative for comparing groups when data do not follow a normal distribution or normality is not met.

Subsequently, generalized linear models (GLMs) were estimated to quantify the relationships and identify key risk factors. Following the established literature, two specific modeling techniques were employed: first, logistic regression was applied to the variables incident occurrence and severity to model the likelihood of these binary outcomes happening, and second, Negative binomial regression was applied to the variable Incident Frequency to model the expected rate of incidents per temporal registers.

To ensure a meaningful interpretation of the model coefficients, specific reference categories were established for each independent variable. These baselines provide a stable point of comparison to measure the relative change in risk comparing categories. Both occurrence and frequency of the regression models act in function of the following reference categories for each variable:

- Precipitation: Dry conditions serve as the reference to isolate the specific impact of rain.
- Temporal Factors: The year 2021 was chosen as the temporal baseline. For sub-daily variations (typically the lowest traffic volume), the 00:00–06:00 block was used, and Summer was selected as the seasonal reference due to its historically lower rainfall.
- Day Type: Weekends were established as the reference to compare against the higher-intensity traffic patterns of workdays.
- Geography: The San Sebastián Airport station was selected as the geographic reference due to its historically lower presence monitored.
- For the severity model, Motorways (A) and the presence of road works (without works) were also included as baselines.

Going in depth for the model specifications, the analysis employed two specifications for each outcome. The first model included only main effects, while the second introduced two-way interaction terms between precipitation presence and all control variables (Time, Day Type, Season, Year, and Meteorological Station) to assess how the effect of rain is modulated by contextual conditions.

The baseline specification for the occurrence and frequency logistic regression models included only main effects and is expressed as:

$$\mathrm{logit(P)}=\ln\left(\frac{\mathrm{P}}{\text{1-P}}\right) = \beta_0 + \sum_{i=1}^{n} \beta_i X_i$$

Where P is the probability of the event, β_0 is the intercept, and β_i represents the effect change in log-odds for each predictor, X_i, relative to its reference category of the variable i, and n is the total number of predictor variables included in the model. To evaluate the modulating effects, the interaction model was represented as follows:

$$\mathrm{logit(P)}= \ln\left(\frac{\mathrm{P}}{\text{1-P}}\right) = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=2}^{n} \beta_{ij}\left(X_i \cdot X_j\right)$$

where the j index is defined specifically as the primary variable of interest (precipitation), and i represents the set of contextual variables as before. Here, the parameter interpretations are maintained, with the addition of $\beta_{ij}\left(X_i \cdot X_j\right)$ to show how the effect of precipitation changes depending on the value of each contextual variable.

For the frequency model, dispersion measures were analyzed only for blocks with at least one incident in order to focus on incident magnitude and avoid zero-inflation bias in the count data. The Median Absolute Deviation (MAD) was 0, and the Index of Dispersion (variance/mean) was 0.897, indicating no evidence of overdispersion in the number of incidents. These statistics justify the use of the second GLM of the Poisson regression model to analyze incident frequency in blocks with at least one incident, instead of a negative binomial regression. All variable definitions in the Poisson model with and without interactions follow the same logic as in the logistic regression, except that it uses a log function to model the mean expected count (λ). The baseline Poisson GLM model was defined as:

$$\ln(\lambda) = \beta_0 + \sum_{i=1}^{n} \beta_i X_i$$

Since the interactions GLM model was defined as:

$$\ln(\lambda) = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=2}^{n} \beta_{ij}\left(X_i \cdot X_j\right)$$

Both have the same variable/index interpretation as in the last model.

The model performance was evaluated to confirm the suitability of the model through convergence diagnostics and log-likelihood comparisons. Goodness-of-fit model was evaluated employing the likelihood ratio test (LRT), Akaike information criterion (AIC), and pseudo R^2 (Cox & Snell and McFadden). For all models, the final effect was quantified by exponentiating the coefficients, e^{β}, to produce ORs for binary outcomes and RR for frequency, allowing for a direct comparison of incident rates between wet and dry conditions.

RESULTS AND DISCUSSIONS

This section presents findings following the two-phase analytical framework: first, characterizing incident patterns through descriptive analysis divided into the three research questions defined above, followed by inferential modeling to examine precipitation's effect on incident occurrence, frequency, and severity.

Descriptive results

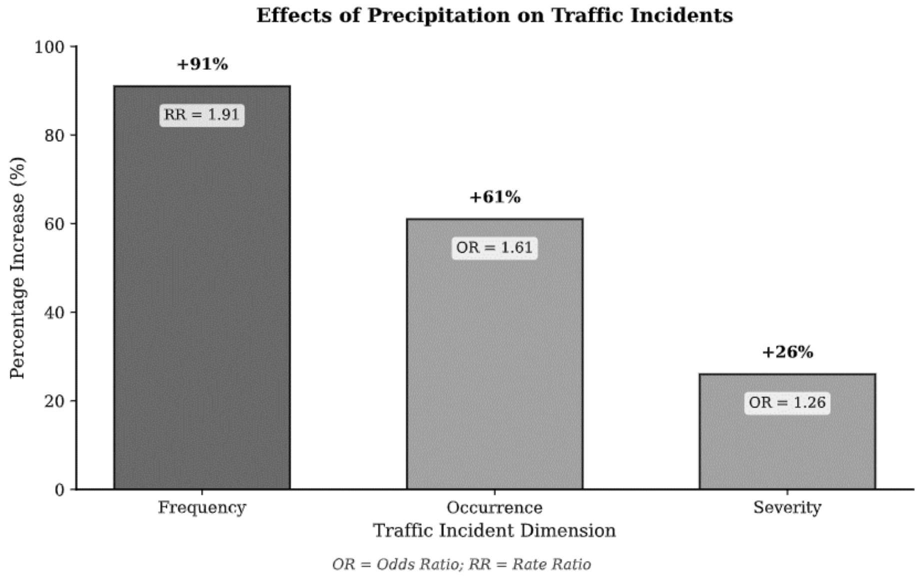
The following results are organized to address RQ1–RQ3 sequentially, examining observational precipitation's effect on occurrence, frequency, and severity, respectively (***Figure 2***). RQ4 is addressed transversally across all three dimensions, as these factors emerged as significant modifiers within each model rather than constituting an independent analytical layer over the case study. In summary, the descriptive analysis revealed that precipitation demonstrates a clear observational association across all dimensions (Figure 2).

Addressing the first research question (RQ1) on incident occurrence, between 2021 and 2024, a total of 18,636 valid traffic incidents for this study were recorded in Gipuzkoa across 81,816 exposure registers; the data confirms that traffic incidents are relatively rare events, occurring in only 15.7% of the analyzed temporal blocks. While the general meteorological conditions were skewed toward dry weather (72.3% of the registers), a striking 42.3% of all incidents occurred during precipitation presence. This disproportion suggests that rain presence increases incident risk significantly beyond what would be expected based on exposure time alone.

When looking at incident occurrence, the probability of an incident in dry conditions was 13.9%, which rose to 20.6% during rain. This is interpreted as an odds ratio (OR) of 1.61, meaning the odds of an incident happening are 61% higher when it rains (wet conditions).

Turning to RQ2, which examines incident frequency, the impact on the observational distribution was more pronounced. Although most blocks (74.2%) reported only a single incident, average frequency increased significantly under wet conditions significantly increased average frequency, with 17.4% of blocks recording two incidents and others reaching up to 27. The observed RR reveals a 91% increase in the incident rate during rain. This suggests that precipitation-related incidents are prone to cascading effects, where a single hazard triggers a cluster of events. This phenomenon aligns with the EEA (2024) assessment, which claims that climate-related disruptions to critical infrastructure can lead to system-wide challenges rather than remaining isolated. In this context, the high frequency recorded in specific blocks (up to 27 incidents) reflects a loss of systemic resilience, where environmental stressors may facilitate a chain of secondary collisions or network-wide failures.

Figure 2. Observational effects of precipitation on traffic incidents



With respect to RQ3 on incident severity, these incidents showed a clear upward observational trend. Severe outcomes (classified as red or black levels) represented 6.6% of the total dataset. However, when there are wet conditions, the proportion of severe incidents rises to 7.4%, compared to 6.0% in dry weather. This resulted in an OR of 1.26, indicating that the odds of an incident resulting in a high-severity outcome are 26% higher during precipitation.

Inferential results

Before applying the regression models, independence tests were conducted to ensure the validity of our approach and the foundation of the contextual regression factors for the analysis. The Chi-square tests (for occurrence and severity) and the Mann-Whitney U test (for frequency) all returned highly significant results (P-Val <0.05). These tests provided enough statistical evidence to reject the null hypothesis, confirming that precipitation is not just a random factor but is significantly associated with changing incident patterns in Gipuzkoa.

The GLMs were estimated to isolate the effect of precipitation from other factors like location and time. In all cases, all models converged correctly with significant log-likelihood ratio (LLR) tests (P-Val <0.05). The models that included interaction terms performed better than the simple main-effects models, showing lower AIC and higher Pseudo-R^2 values, as presented in Table 2.

Table 2. Models' performance

Model Outcome	Specification	Log-Likelihood	AIC	Pseudo-R^2 (CS)
Occurrence	Main Effects	-31.540	63.130	0,095
	Interaction	-31.470	63.037	0,096
Frequency	Main Effects	-17.114	34.279	0,072
	Interaction	-17.016	34.128	0,086
Severity	Main Effects	-3.600	7.259	0,094
	Interaction	-3.506	7.123	0,103

To determine the most robust framework for predicting traffic risk, a comparative analysis was performed between the Main Effects Models and the Interaction Models across three dimensions: Occurrence, Frequency, and Severity.

In all three modeling scenarios, the inclusion of two-way interactions with precipitation resulted in a superior statistical fit. As shown in the comparative metrics, the Interaction Models consistently outperformed the base specifications, yielding lower Akaike Information Criterion (AIC) values and higher Log-Likelihood scores. However, the substantive gain in explanatory power varies; while the improvement is marginal for Occurrence, it becomes more prominent for Frequency and particularly substantial for the Severity dimension.

The transition from Main Effects to Interaction models revealed a critical shift in how variables contribute to risk (see ***Table 3*** in the Appendix section):

- With respect to incident occurrence (RQ1), in the baseline model, almost all factors (Year, Precipitation, Hour, Station) were statistically significant except for Season. However, in the Interaction model, significance shifted toward Year, Season, and Precipitation. This suggests that the "Season" effect, which seemed irrelevant initially, manifests through its interaction with rainfall, although the overall model fit remains largely similar to the main-effects version.
- Regarding incident frequency (RQ2), the model showed the most dramatic improvement in Pseudo-R^2 (increasing from 0.072 to 0.086). Interestingly, while the main effects model had many significant predictors, the interaction model concentrated significance in Year and Season. This indicates that the frequency of incidents is highly sensitive to how rainfall interacts with specific temporal contexts.
- With respect to incident severity (RQ3), a notable shift occurred; while Precipitation was a primary driver in the main effects model (OR = 1.24), its significance as a standalone variable diminished in the interaction model, being replaced by Year, Weekday, Road Type, and Season. This implies that rain's impact on severity is strictly dependent on the infrastructure (Road Type). It is important to note that while the interaction model offers a superior fit, the main-effects model may provide a more robust basis for generalization. Given the lower frequency of severe incidents in certain interaction categories, the main-effects specification avoids potential over-fitting, ensuring that the findings remain statistically stable across the entire dataset. Additionally, a complementary model incorporating flood coincidence revealed a further escalation of severity risk (OR = 2.18), as detailed in the following section.

Deepening of the pattern's characterization: contextual factors across RQ1–RQ4

Beyond the direct effect of precipitation, the models reveal geographic and temporal patterns that modulate risk across all dimensions (RQ4). ***Table 3*** presents the quantification of significant control and contextual variables; those failing to reach significance in at least one dimension were excluded. This section provides a localized guide for interpreting these quantification results within the risk chain.

The logistic regression confirms that precipitation is a major trigger for road safety events, increasing the odds of an incident by 70% (OR = 1.70). This finding aligns with the relative risk magnitudes reported by Mills et al. (2019) and Tafazzol et al. (2025), who both observed a significant increase in the likelihood of incidents during intense precipitation. However, spatial heterogeneity remains the most dominant factor: stations like Ordizia (OR = 9.99) and Renteria (OR = 8.42) showed drastically higher baseline odds than the reference station. Temporal patterns reflect traffic exposure (Tang et al., 2024); daytime hours (06:00–18:00) exhibit nearly four times the odds (~3.5) compared to overnight periods. Day type (weekdays vs. weekends) and seasonal effects alone were not a significant driver for determining the occurrence of an incident.

For the frequency model, precipitation increases the number of incidents per time-block by 25% (IRR = 1.25). Unlike occurrence, temporal patterns play an important role as winter shows the highest frequency rate (IRR = 1.37) followed by autumn, suggesting that seasonal conditions contribute to incident accumulation; this accumulation aligns with Mills et al. (2019), who identified collision frequency peaks during the onset of winter. Spatially, the pattern partially mirrors occurrence, with Ordizia (IRR = 1.38) and Renteria (IRR = 1.35) showing the highest incident rates. Notably, several stations with significant occurrence odds, such as Elgoibar and Mutriku, among others, do not exhibit statistical significance regarding incident frequency. This divergence suggests that while these locations are more susceptible to incident initiation, these occurrences remain temporally dispersed rather than clustering within a single time-block.

Regarding severity, precipitation increases the odds of a severe outcome by 24% (OR = 1.24), but the model reveals a distinct risk profile. Location and seasonality emerge as dominant: winter incidents are nearly five times more likely to be severe than summer ones (OR = 4.71). Legazpia (OR = 22.51); this outlier reflects a localized concentration of high-severity incidents, identifying it as a particularly critical mountain corridor. Furthermore, daytime hours are associated with lower severity (OR = 0.38 for 12:00–18:00) compared to nighttime, consistent with visibility constraints identified by Najafi Moghaddam Gilani et al. (2021) and Ye et al. (2023).

To understand how risk factors behave during an active crisis, we integrated Spanish insurance compensation consortium data from Puime Pedra et at. (2025) into this severity framework. While a stratified interaction approach was limited and unstable by subgroup size (n = 384), incorporating flood coincidence in the severity regression revealed that flood events increase the odds of a severe incident (OR = 2.18). This effect holds when controlling all contextual variables, including precipitation, year, hour, season, road type, work road, and meteorological station. The direct effect of rainfall remained independently significant (OR = 1.18), suggesting floods partially mediate the relationship between precipitation and severity.

The interaction models prove that precipitation risk is not uniform; its impact is significantly amplified by specific geographic and temporal contexts, depending also on the outcome variable. For occurrence, coastal and mountainous areas like Mutriku (OR = 2.25) and Zumarraga (OR = 1.94) combined with highways (AP) show the highest sensitivity. Lastly, while "day type" was not significant as a main effect, its interaction with rain carries a specific severity risk; weekday rainfall increases severe outcome odds by 46% (OR = 1.46) due to the synergy between high-volume traffic and visibility constraints, as was seen in the literature.

Through this process of applying statistical analysis and methods, patterns and behavior of incidents were represented, and confirmed a consistent full risk chain, where precipitation increases the likelihood of an event (70%), the frequency of incidents (25%), and the severity of the outcome (24%). Beyond precipitation, the flood coincidence model identifies the most critical amplifier (OR = 2.18) when a crisis exists. These risks are most intense in mountainous regions and during winter months, and the past year 2023 showed a notable intensification of risk across all three dimensions. Temporal patterns remain relatively stable across precipitation conditions, suggesting systemic elevation of risk regardless of the time of day or week. This observation aligns with the findings of Tafazzol et al. (2025), who noted similar temporal consistency in their analysis of traffic accidents.

Strategic policy recommendations

This study's findings reveal a clear risk chain: adverse weather conditions trigger increased incident occurrence, which in turn elevates both frequency and severity, given that adverse weather conditions make this road network particularly suitable for analyzing critical infrastructure resilience. Based on this evidence, three levels of intervention are recommended for Gipuzkoa's road safety management:

1. Geographic prioritization: Authorities should deploy speed reduction measures specifically in "high-sensitivity" zones like Ordizia, Rentería, and Legazpia, where the interaction between rainfall and geography nearly overcomes the occurrence or severity odds. Given the meteorological heterogeneity that represents geographic-specific weather, warnings would be more effective in the specific areas, rather than general regional alerts.
2. Seasonal mitigation: Given the 37% increase in incident frequency during winter and its significant impact on severity, maintenance crews and emergency services should increase preemptive road treatments during the winter months. This is especially critical during weekday mornings, when the interaction between high-volume work-related traffic and rain amplifies the severity by 46%.
3. Infrastructure adaptation: The significantly lower severity rates on highways suggest that the safety design of these roads is robust and enough. Policy should focus on upgrading secondary roads where incident severity is highest, with better drainage and high-friction pavement to achieve a similar safety performance level of the highway network. Furthermore, the fact that flood events more than double the odds of severity underscores the urgent need for an integrated operational protocol. Such a framework should synchronize real-time hydrological alerts with traffic management systems to mitigate high-consequence outcomes during extreme weather.

By adopting these three levels of interventions, Gipuzkoa can transition from a reactive safety model to a proactive, resilient framework that specifically addresses the unique hazards posed by its meteorological and geographic landscape.

CONCLUSIONS

This study investigated the impact of precipitation on traffic incidents in Gipuzkoa province from 2021 to 2024, aiming four core research questions: whether precipitation increases the probability of an incident occurring, whether it raises the frequency of multiple events, whether it exacerbates their severity, and how additional factors (such as geography and seasonality) influence the occurrence, frequency, and severity of precipitation-related incidents. While most traditional research examines these outcomes in isolation, the framework developed here reveals how precipitation impacts the full incident profile of the risk chain through a two-phase approach. By first characterizing patterns through descriptive statistics and subsequently using inferential analysis to quantify these patterns through generalized linear models, the analysis demonstrated that precipitation consistently elevates risk across all three dimensions.

Observational results indicated that precipitation increased occurrence probability by 48%, incident frequency by 91%, and the probability of a severe outcome by 24%. These findings were further validated by regression models, which showed that precipitation increased the odds of an incident occurring by 70% and raised the incident rate by 25% when events happened, and made incidents 24% more likely to be severe. Apart from precipitation, other factors have also shown a strong influence on the occurrence, frequency, and severity of traffic incidents. Geographic location emerged as the strongest moderator in the study, with wet conditions significantly amplifying the baseline risk differences between meteorological stations such as Ordizia, Mutriku, Zumarraga, or Legazpia, relying on the outcome variable. Seasonal factors like winter and autumn notably intensified the impact of precipitation on both occurrence and frequency, while the year 2023 demonstrated an overall intensification of risk across all examined outcomes.

A particularly unexpected finding was that while precipitation effects remained relatively stable across the time of day, their interaction with weekdays significantly increased the severity risk. A central contribution of this research is the integration of flood coincidence data, which identified flooding as a critical risk amplifier that more than doubles the odds of a severe incident (OR = 2.18). Furthermore, the data showed that high-capacity highways maintained lower severity rates than secondary roads, even under adverse weather. By looking at all three dimensions together, this framework exposed patterns that previous studies would miss, suggesting that decision-makers should prioritize context-specific interventions, focusing on preventing initial incidents in high-risk geographic areas, and mitigating the increased frequency and severity of crashes during the winter months and active flood events.

LIMITATIONS AND FUTURE WORK

Despite these insights, the study faced several limitations that must be acknowledged. First, the absence of real-time traffic volume data (Average Daily Traffic) represents a primary constraint. While the study utilizes road incidence levels (e.g., yellow, red, black) as a proxy for severity, incorporating actual vehicle counts would allow for a more precise calculation of crash rates and exposure-adjusted risk.

Second, the binary classification of precipitation (Wet vs. Dry) is a simplification that limits the ability to capture specific effects of different rainfall intensities. This approach was adopted to facilitate model stability and provide a clear overview of the general impact of rain on the network. However, future studies could refine these results by incorporating quantitative intensity thresholds to better understand how different water volumes influence incident dynamics. Furthermore, while the 6-hour analysis window offers a significant advancement over daily aggregates, achieving precise meteorological matching at the exact moment of each incident remains a priority for future research. Such granular synchronization would eliminate the 'smoothing effect' and further refine the causal link between weather and road safety.

Finally, the spatial coverage of meteorological stations introduces a degree of uncertainty. Although 14 stations were used, municipalities located far from a recording site may experience variations in the "wet/dry" classification accuracy due to the complex orography of the Basque Country. Future research should expand this framework to other regions to test its generalizability and incorporate other weather variables, including temperature fluctuations, precipitation intensity, and compound weather events. Integrating these factors will be essential for developing a more robust, holistic understanding of road risk management in the face of global climate shifts.

These findings are intended to be used in the development of an accessibility index for critical infrastructures during extreme events, such as floods, by incorporating the impact of road incidents.

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APENDIX

Variable	Variable	OR Ocurrence	RR Frequency	OR Severity
Baseline	Precipitation: With rain	1,70	1,25	1,24
Temporal	Year: 2022	1,52	ns	1,94
	Year: 2023	1,32	1,13	0,57
	Year: 2024	1,25	ns	ns
	Hour Block: 06-12	3,55	1,12	0,61
	Hour Block: 12-18	3,95	1,11	0,38
	Hour Block: 18-24	2,26	ns	0,42
	Season: Autumn	ns	1,08	1,78
	Season: Spring	ns	1,05	2,06
	Season: Winter	ns	1,37	4,71
	Day Type: Weekday	1,37	1,05	ns
Spatial	Station: Aretxabaleta	5,78	1,24	6,79
	Station: Azpeitia	5,65	1,29	2,95
	Station: Beasain	1,43	ns	ns
	Station: Elgeta	4,65	1,34	3,45
	Station: Elgoibar	2,39	ns	ns
	Station: Irún	1,18	ns	4,09
	Station: Legazpia	2,28	1,16	22,51
	Station: Mutriku	1,51	ns	ns
	Station: Ordizia	9,99	1,38	2,58
	Station: Renteria	8,42	1,35	3,07
	Station: Segura-Lastala	5,17	1,13	ns
	Station: Zumaia	4,58	1,22	5,37
	Station: Zumarraga	1,52	ns	ns
	Road Type: AP (Toll Highway)	-	-	0,07
	Road Type: N (National)	-	-	0,30
Interactions	Rain × Year: 2022	ns	ns	0,59
	Rain × Year: 2023	1,26	1,23	1,65
	Rain × Season: Autumn	1,31	1,18	ns
	Rain × Season: Winter	1,27	1,44	0,54
	Rain × Station: Azpeitia	1,79	ns	ns
	Rain × Station: Elgoibar	1,51	ns	ns
	Rain × Station: Legazpia	1,48	ns	ns
	Rain × Station: Mutriku	2,25	ns	ns
	Rain × Station: Segura-Lastala	1,36	ns	ns
	Rain × Station: Zumaia	1,55	ns	ns
	Rain × Station: Zumarraga	1,94	ns	ns
	Road Type: AP (Toll Highway)	-	-	16,12
	Rain × Day Type: Weekday	-	-	1,46
Validation	Flood Coincidence (binary)	-	-	2,18

Table 3. Key Findings by Incident Outcome[1]

[1] Symbol "-" indicates that the value does not apply for that effect variable, while "ns" means that the variable was not significant within the model