



Article Urban Road Crashes and Weather Conditions: Untangling the Effects

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Abstract: Most previous studies show that inclement weather increases the risk of road users being involved in a traffic crash. However, some authors have demonstrated a little or even an opposite effect, observed both on crash frequency and severity. In urban roads, where a greater number of conflict points and heavier traffic represent a higher exposure to risk, the potential increase of crash risk caused by adverse weather deserves a special attention. This study investigates the impact of meteorological conditions on the frequency of road crashes in urban environment, using the city of Porto, Portugal as a case study. The weather effects were analyzed for different types of crashes: single-vehicle, multi-vehicle, property-damage-only, and injury crashes. The methodology is based on negative binomial and Poisson models with random parameters, considering the influence of daily precipitation and mean temperature, as well as the lagged effects of the precipitation accumulated during the previous month. The results show that rainy days are more prone to the occurrence of road crashes, although the past precipitation may attenuate such effect. Temperatures below 10 °C are associated with higher crash frequencies, complying with the impacts of precipitation in the context of the Portuguese climate characteristics.

Keywords: vehicle crashes; property-damage-only crashes; injury crashes; urban environment; weather; lagged effects

1. Introduction

In the last decades, many developed countries have experienced a consistent decrease in the number of road crashes and victims. However, there is still a great deal of room for improvement in the developing countries, where the rapid increase of urban population and car ownership puts an additional pressure on road safety targets [1]. The goals are quite ambitious: the World Health Organization defines the objective of halving road deaths and injuries worldwide by 2020; the European Commission goes even further with its "Vision Zero" strategy, adding to the previous objective the elimination of road fatalities caused by human error by 2050 [2]. In this sense, public authorities and researchers have been focused for many years on the study of incident/accident causation as a means to prevent road crashes. The development of automated driving is currently regarded as a centerpiece of the plans to reduce road crashes and injuries. Therefore, the quest for knowledge on the factors affecting road safety will continue at least until a full automation of road transport is implemented, providing crucial inputs to the development of technology and safety regulations.

The impact of meteorological conditions on road safety is no exception to this collective effort, having been the object of numerous studies in the past [3]. Different approaches have been used to

highlight the contribution of weather conditions to road crashes with respect to the geographic region, type of road, type of crash, crash severity, and time scale.

Fixing the time scale is particularly relevant to the objectives of each study [4–6]. The identification of regional patterns and cross-country comparisons are typically performed on a monthly or yearly time basis. When the evaluation of pre-crash conditions under adverse weather is the objective, the time scale is reduced, at least, to a daily basis. In turn, the spatial scope of each study has been reported as a major factor affecting the relation between weather and road safety. Contradictory effects of meteorological variables on crash frequency and severity have been reported in the existing literature [3,4,7], stressing the need for further research, especially in regions where the relation between weather conditions and road crashes was not previously assessed.

This research consists in the first effort to analyze the weather effects on road crash frequency in Portugal, using the city of Porto as a case study. Porto is located in the Northern Region of Portugal and has the particularity of belonging to one of the sunniest countries and, at the same time, one of the wettest regions in Europe [8]. To accomplish this objective, four negative binomial and Poisson models were developed to investigate the impact of meteorological conditions on four crash types: single-vehicle, multi-vehicle, property-damage-only, and injury crashes. The meteorological variables were selected to characterize the weather conditions on the crash day and the accumulated precipitation during the previous 30 days. Binary variables representing the road category and weekend days were used to account for spatial and temporal variations of exposure, overcoming the lack of traffic data. Because the objective is to evaluate the global impact of rainfall on urban road crashes, this research does not deal with the potential endogeneity between precipitation and exposure. The impact of rainfall intrinsically aggregates the impacts of risk and exposure [9], which should not be dissociated from each other for the purpose of crash frequency analysis.

Therefore, this paper contributes to the knowledge on the relation between meteorological conditions and road safety by focusing on an unstudied area and by evaluating current and lagged weather effects on the frequency of four different types of crash. The methods and results presented in this study may be used to improve daily alerts on traffic safety, particularly by incorporating the effects of current and past weather conditions at the city scale.

The remainder of this paper is structured as follows. Section 2 provides a literature overview on previous studies focusing on the relation between weather and crash frequency. The data description in Section 3 presents the meteorological and crash datasets used in this research. Section 4 details the random parameters negative binomial and Poisson models. Then, the paper proceeds with the model estimation in Section 5, and the discussion of the obtained results in Section 6, using different assessment scenarios. The study's main conclusions are summarized in Section 7. Finally, Section 8 presents the main limitations of the present analysis and applied methods, providing guidance for future research.

2. Literature Review

Meteorological conditions are widely referenced as a major factor affecting transport operations. In general, the performance of all transport modes decreases under adverse weather, as the systems become more exposed to the risk of congestion, delays, and crashes. Some literature has focused on the impact of adverse and extreme weather on diverse transport modes in the context of climate change [10,11]. However, the weather effects on road transport have received a special attention, given that this mode accounts for the highest share of fatalities, injuries, and property damages.

Precipitation has consistently been identified as the most relevant meteorological condition affecting road crashes, with simultaneous effects on the visibility, vision, and tire-road friction. Consequently, it is the most important weather parameter in road safety studies [3,12]. Different variables have been used to investigate the effects of precipitation with respect to its type (rain or snow) and time scale.

Most studies in this field have shown that the occurrence of precipitation increases the total crash frequency; good literature reviews are provided by Theofilatos and Yannis [3] and by Xu et al. [13]. Low-level data aggregation studies consider crash and precipitation variables on a daily or shorter time scale. The precipitation accumulated during a short period is considered representative of the pre-crash situations observed during the same period, allowing inferring about the role that adverse weather conditions, such as reduced visibility and slippery road, play on the increase of crash frequency. Eisenberg [4], Brijs et al. [5], Keay and Simmonds [14], and Black et al. [15] are among the numerous authors that found a strong positive correlation between daily precipitation and crash frequency. These studies were developed in distinct geographic contexts, such as The Netherlands [5], Australia [14], and the US [4,15]. In turn, Malin et al. [16] and Norros et al. [17] are among the few studies using an hourly time scale and categorical precipitation variables. Malin et al. [16] analyzed the entire main road network in Finland, including motorways, multi-lane roads, and two-lane roads. The results showed that the relative accident risk is higher for snowfall in relation to sleet or rain. For the same type of precipitation, the crash risk increases with the precipitation intensity. The authors also found that motorways are the road type with the highest crash risk under rainfall or snowfall, contrasting with the lowest risk observed under good weather conditions. Norros et al. [17] used data from Helsinki's Ring-road I to conclude that heavy rain increases crash risk by 190%, while moderate to heavy snow may increases risk from 470 to 740%. The study by Jaroszweski and McNamara [12] used a three-hour time scale and obtained contradictory results from four models developed for two UK cities. In Manchester, the models showed a consistent positive correlation between rainfall and crash frequency. In London, one model returned a positive correlation, while the other showed a slightly negative correlation. The results were attributed to the differences between both cities' urban morphology and travel behavior, as well as to the use of different meteorological data sources.

In some low-level data aggregation studies, additional precipitation variables related to larger time periods are included to represent lagged effects, i.e., the impacts of past precipitation on the crash frequency observed on a daily or shorter period. Eisenberg [4] and Keay and Simmonds [14] analyzed different periods since the last precipitation and concluded that the crash risk in the first day of rainfall increases with the duration of the preceding dry spell. The researchers attributed this effect to the build-up of oil and grime accumulated on the pavement and to the readjustment of driving behavior to wet conditions. Similarly, Levine et al. [18] found that the crash risk in Hawaii is higher in the first day of rainfall. Brijs et al. [5] did not find evidence of lagged effects of precipitation.

Studies considering highly aggregated data are usually developed to highlight the seasonal variation of road crashes, with some authors also performing a cross-region comparison [4,19,20]. This approach tends to confirm the positive correlations between monthly- and yearly-accumulated precipitation and total crash frequency. Exceptions to this general trend are the studies by Bergel-Hayat et al. [6] and by Yannis and Karlaftis [21], which found a decrease of crashes under rainfall in the region of Athens, Greece. The authors speculated that, being rainfall an unusual event in Athens, drivers may become overly cautious and drive slower to compensate for the rain effects.

The impact of precipitation on crash severity is not so clear. While some authors noted that severe crashes increase under wet conditions [22–24], others found a contradictory or doubtful effect. Black et al. [15] obtained an increased risk of injury under rainfall, but the fatality risk did not change significantly in relation to good weather. Eisenberg [4] and Fridstrøm et al. [19] denoted that rainfall and snowfall may produce either positive or negative effects on fatal and injury crash frequency, depending on the quantity of accumulated precipitation and the region under analysis. Martensen et al. [9] found an increase in the number of victims in 4-wheeled vehicles under rainfall, but a decrease in two-wheeled vehicles. The authors attributed these results to a plausible decrease in the number of trips on 2-wheeled vehicles under rainfall, accompanied by an increase in the number of car trips. Antoniou et al. [25] suggested that the reduction in the number of injury crashes observed in Athens during the winter might be explained by the reduction of mobility under adverse weather.

In addition to precipitation, other meteorological conditions have been analyzed in the literature, such as the air temperature, sunlight, and wind speed. Overall, these parameters represent a much smaller and/or doubtful influence on road crashes than rainfall or snowfall. The air temperature has shown a predominantly negative correlation with crash frequency [5,17,24,26], although some studies had found an opposite effect [6,21]. Daily temperatures corresponding to extreme deviations from the seasonal standards were associated to higher crash frequencies by Brijs et al. [5] and by Malyshkina et al. [27]. Norros et al. [17], and Fridstrøm et al. [19] found a negative correlation between daylight duration and road crashes, but Brijs et al. [5] points toward an opposite effect. The latter study also demonstrates that sun dazzle during the winter may be a factor of increased risk, and that wind speed is only significant for heavy storms and/or heavy vehicles.

In the end, two major insights can be extracted from the literature. First, the weather variables that are not related with precipitation have a highly inconsistent effect on road crashes, suggesting that they may modify crash conditions, but are not a root cause of crash occurrence [26]. Second, regional climatology and driving behavior play an important role on the type and magnitude of the weather effects [6,21], highlighting the need for new research in non-studied areas.

3. Meteorological and Crash Data

Portugal is located in the West coast of the Iberian Peninsula and is characterized by a temperate climate with a dry season and a hot summer [28]. Strong differences arise between north-south and coastal-inland Portugal [29], showing an important inter-annual variability in temperature, but also in precipitation, which ranges from about 400 to over 2200 mm/year [30,31]. Porto is located at one of the wettest regions in continental Europe [8]. The city's characterization in terms of precipitation and temperature is presented in Figure 1.



Figure 1. Monthly precipitation and temperature in Porto for the period 1971–2000 [32].

In this study, precipitation and temperature data were obtained for the period under analysis, ranging from January 2001 to October 2005. The daily precipitation (D), corresponding to the precipitation height (in mm) accumulated during each calendar day, was retrieved from the meteorological station of the Geophysics Institute of the University of Porto, located at Serra do Pilar, near the city center. The monthly precipitation represents the lagged effects of this meteorological phenomenon, and was obtained for each day by summing the daily precipitation values observed in the previous 30 days. However, this variable is not considered in the developed models. Instead,

an interaction term given by the multiplication between daily and monthly precipitations (DM) was created for modelling purposes to nullify the lagged effects on days without rain.

The mean daily temperature (T) was calculated through the mean value between the minimum and maximum observed ten-minute air temperature values, retrieved from the meteorological station located at Porto Airport, in the city's surroundings [32]. Since a non-linear variation of crash frequency with air temperature has been reported in previous studies [5,27], two binary variables, T10 and T20, were created for modelling purposes. T10 is set to one if T is smaller than 10 °C, and to zero otherwise; T20 is set to one if T is equal to or greater than 20 °C, and to zero otherwise. In this sense, T10 and T20 represent the effects of a lower or a higher value of T, respectively, in relation to the interval between 10 and 20 °C, considered as the category of reference. The thresholds used to define the three temperature categories (T < 10 °C, 10 °C ≤ T < 20 °C, and T ≥ 20 °C) were defined taking into account that the minimum and maximum values of T obtained for the period under analysis were of 3.6 and 30.4 °C, respectively. In the end, four meteorological factors were used as explanatory variables in the developed models: D, DM, T10, and T20.

Crash data was retrieved from the official Portuguese Police database. This database contains all the crashes recorded by the police in the city of Porto between January 2001 and October 2005. A total of 25,736 single- and multi-vehicle crashes were reported during this period, excluding pedestrian-vehicle crashes, which are not considered in this study. Available data includes the date and location of each crash, the number of vehicles involved, and if there were victims or not. Based on this information, the original database was disaggregated in two different ways: (i) single-vehicle crashes versus multi-vehicle crashes, and (ii) property-damage-only crashes versus injury crashes. In the end, four datasets representing different crash types were used for model estimations.

The crash date and location allowed deriving the number of crashes of each type observed per day and road category. Each one of the four modelling datasets is a panel data with four observations per day; the dependent variable represents the crash counts observed per day in each category's entire network. The four road categories established by Porto's master plan were used to capture the spatial variation of traffic, aiming to overcome the lack of traffic data. In this sense, four explanatory binary variables were introduced in the models to set the road category and act as proxies for risk exposure: arterial (ART), principal distributor (PD), local distributor (LD), and local access (LA); in each observation, only the proxy variable of the corresponding road category is set to one, with the others being set to zero. An additional binary variable for weekends (WEND), set to one on weekend days and to zero otherwise, was introduced to capture the temporal variation of traffic volume. Other calendar effects (e.g., day of the week, month of the year, and season) were tested using additional binary variables. For simplicity, these effects were not included in the final models, since no relevant variations have been detected on the coefficients of the weather variables.

Table 1 shows the crash counts for each road category by crash type during the period under consideration. Common descriptive statistics are presented in Table 2.

Road Category	Single-Vehicle Crashes	Multi-Vehicle Crashes	Property-Damage-Only Crashes	Injury Crashes
Arterial	461 (15.6%)	3658 (16.0%)	3574 (15.8%)	545 (17.6%)
Principal distributor	821 (27.9%)	7305 (32.1%)	7342 (32.4%)	784 (25.3%)
Local distributor	758 (25.7%)	4816 (21.1%)	4404 (19.5%)	1170 (37.7%)
Local access	907 (30.8%)	7010 (30.8%)	7314 (32.3%)	603 (19.4%)
Total	2947	22,789	22,634	3102

Table 1. Absolute and relative frequency of crash occurrence by road category and crash type.

Variable	Mean	Standard Deviation	Minimum	Maximum
Number of crashes per day				
Single-vehicle	1.7	1.5	0.0	10.0
Multi-vehicle	13.2	5.5	1.0	34.0
Property-damage-only	13.1	5.4	1.0	35.0
Injury	1.8	1.4	0.0	8.0
Precipitation (mm)				
Daily	3.2	8.3	0.0	80.9
Monthly	97.5	98.3	0.0	567.2
Daily mean temperature (°C)	14.9	4.4	3.6	30.4

 Table 2. Variable description.

4. Methodological Approach

The number of crashes per day, as a non-negative integer, is usually modelled using count regression techniques. Poisson and negative binomial models are commonly used to represent count data. While the former imposes that the mean equals the variance, the latter is usually preferred when data is overdispersed, i.e., when the variance is significantly higher than the mean. Past studies have tested different models to deal with the overdispersion typically affecting road crash data [22,33–35]. In this study, tests for overdispersion were used to verify the hypothesis of the variance being equal to the mean (null hypothesis) for each one of the four crash modelling datasets, as suggested by Cameron and Trivedi [36]. The results allowed selecting the most appropriate model for each dataset.

The Poisson model specifies that each observation y_i is drawn from a Poisson distribution with parameter λ_i , related to a vector of explanatory variables X_i , and can be expressed as follows:

$$\operatorname{Prob}(Y = y_i | X_i) = \frac{e^{-\lambda_i} \cdot \lambda_i^{y_i}}{y_i!}.$$
(1)

The parameter λ_i represents the expected number of crashes for observation i ($\lambda_i = E{Y}$). The log-linear function used to link λ_i with X_i is given by:

$$\lambda_i = e^{\beta X_i},\tag{2}$$

where β is a vector of coefficients of the explanatory variables.

To deal with overdispersed crash data, the negative binomial model adds an error term to the Poisson model, such as the parameter λ_i becomes:

$$\lambda_i = e^{\beta X_i + \varepsilon_i},\tag{3}$$

where ε_i is a gamma-distributed error term with mean equal to one and variance α . The error term allows the variance to differ from the mean, since $Var{Y} = \lambda_i + \alpha$. λ_i^2 . The probability density function of the negative binomial model can be defined as:

$$\operatorname{Prob}(Y = y_i | X_i) = \frac{\Gamma(\theta + y_i)}{\Gamma(\theta) \cdot \Gamma(y_i + 1)} \cdot u_i^{\theta} \cdot (1 - u_i)^{y_i}, \tag{4}$$

where $\Gamma(.)$ is a gamma function, $\theta = 1/\alpha$, α is the dispersion parameter, and $u_i = \theta/(\theta + \lambda_i)$. When α is equal to zero, $\theta \to \infty$, and the negative binomial distribution reverts to the Poisson distribution.

Since all the road category variables are included in the model, no intercept is considered. Given the macroscopic nature of the road functional classification, these variables may incorporate an array of unobserved heterogeneous factors that vary across observations of the same road category. To deal with this heterogeneity, a random parameters approach was followed [37,38], such as:

$$\beta_i = \beta + \omega_i,\tag{5}$$

where ω_i is a normally distributed term with mean equal to zero and variance σ^2 affecting the coefficients of road category variables ($\omega_i = 0$ for the remaining variables). The parameter λ_i in the Poisson and negative binomial models is respectively reformulated by the following expressions:

$$\lambda_i | \omega_i = e^{\beta_i X_i}, \tag{6}$$

$$\lambda_i | \omega_i = e^{\beta_i X_i + \varepsilon_i},\tag{7}$$

Model estimations were performed through a simulated maximum likelihood method developed by Greene [39], using econometric software Limdep 9.0.

5. Model Estimation

The overdispersion tests revealed that the null hypothesis of the variance being equal to the mean was rejected for all models except the one for injury crashes, because the resulting values in this case are lower than the critical value from the χ^2 table for one degree of freedom (3.84). Therefore, the models for single-vehicle, multi-vehicle, and property-damage-only crashes were estimated using a negative binomial regression, while the model for injury crashes was estimated through a Poisson regression. Modelling results are presented in Table 3.

Variable	Single-Vehicle Multi-Veh Crash Model Crash Model		Property-Damage-Only Crash Model	Injury Crash Model	
-	Coefficient (σ)	Coefficient (σ)	Coefficient (σ)	Coefficient (σ)	
ART	-1.494 *	0.750 *	0.722 *	-1.221 *	
	(0.367 *)	(0.324 *)	(0.309 *)	(0.247 *)	
PD	-0.847 *	1.484 *	1.478 *	-0.867 *	
		(0.180 *)	(0.182 *)	(0.290 *)	
LD	-1.056 *	1.075 *	0.971 *	-0.468 *	
	(0.516 *)	(0.098 *)	(0.132 *)	(0.284 *)	
LA	-0.745 *	1.457 *	1.489 *	-1.133 *	
		(0.054 *)	(0.037 *)	(0.301 *)	
WEND	0.113 *	-0.398 *	-0.372 *	-	
D	0.021 *	0.010 *	0.011 *	0.012 *	
DM	-4.7×10^{-5} *	-	-	-4.6×10^{-5} *	
T10	0.114 **	0.091 *	0.092 *	0.130 *	
T20	-	-0.088 *	-0.076 *	-	
α	5.653 *	20.582 *	19.821 *	-	
	Single-Vehicle Crash Model	Multi-Vehicle Crash Model	Property-Damage-Only Crash Model	Injury Crash Model	
Number of observations	6,912	6,912	6,912	6,912	
Overdispersion test $[g(\lambda_i) = \lambda_i]$	5.344	8.615	8.699	2.304	
Overdispersion test $[g(\lambda_i) = \lambda_i^2]$	5.411	8.285	8.372	2.452	
Log likelihood	-5,858	-14,065	-13,997	-5,968	
AIC	11,738	28,155	28,021	11,958	

Table 3	Modelling	results.
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Note: σ : Standard deviation of parameter distribution; α : Dispersion parameter for negative binomial models; * Significant at the 1% level; ** Significant at the 5% level.

The variables associated with daily precipitation and mean temperature below 10 °C show positive correlations with crash frequency, represented by coefficients that are reasonably stable across the four models. The effect of a mean daily temperature higher than 20 °C is statistically significant only for multi-vehicle and property-damage-only crashes, with a negative correlation. The lagged effects of

monthly precipitation are only statistically significant for single-vehicle and injury crashes, denoting a negative impact on frequency.

As previously mentioned, the remaining variables were introduced with the sole purpose of being a proxy for risk exposure, taking advantage of easily accessible data to overcome the lack of traffic counts. Since the focus of this research is to analyze the influence of weather conditions, and that an in-depth analysis of risk exposure would require the detailing of its main drivers, the results obtained for the proxy variables are not discussed. Therefore, the following section highlights the relevance of the analyzed meteorological effects on the frequency of each crash type.

6. Discussion of Results

Table 3 demonstrates that the impact of weather conditions on road crash frequency results from the combination of different meteorological factors that, individually, may produce either positive or negative impacts, especially if lagged effects are considered. To provide a better insight on these impacts, based on the coefficients shown in Table 3, the percent variation measuring the responsiveness of crash frequency to the variation of each meteorological factor was computed for the following scenarios:

- S1: The daily precipitation doubles, while the monthly precipitation is maintained at the sample mean and the daily mean temperature lies between 10 and 20 °C;
- S2: The daily precipitation doubles in the first day of rainfall after a dry spell greater than one month, i.e., the monthly precipitation is null, and the daily mean temperature lies between 10 and 20 °C;
- S3: The monthly precipitation doubles, while the daily precipitation is maintained at the sample mean and the daily mean temperature lies between 10 and 20 °C;
- S4: The daily mean temperature is lower than 10 °C, while daily and monthly precipitations are maintained at the sample mean;
- S5: The daily mean temperature is equal to or higher than 20 °C, while daily and monthly precipitations are maintained at the sample mean.

Table 4. Estimated percent variations of crash counts in different scenarios.

Scenario	Single-Vehicle Crashes	Multi-Vehicle Crashes	Property-Damage-Only Crashes	Injury Crashes
S1	4.5%	3.3%	3.7%	1.5%
S2	7.2%	3.3%	3.7%	4.0%
S 3	-2.3%	_	-	-2.3%
S4	12.1%	9.6%	9.6%	13.9%
S 5	_	-8.4%	-7.3%	_

The results for each scenario are presented in Table 4.

The occurrence of precipitation and temperature values below 10 °C are the most relevant meteorological factors affecting road crashes in Porto, increasing the number of crashes, regardless their classification (Table 3). Considering the results of most previous studies [3,13], the interpretation of the daily precipitation effect is straightforward; in rainy days, the deterioration of visibility and tire-road friction leads to the occurrence of more crashes. From Table 4, it is possible to conclude that the impact of doubling the daily precipitation is generically higher in the first day of rainfall after a long dry spell (S2) than in a day following a month with average precipitation (S1), specifically 7.2% versus 4.5% for single-vehicle crashes, and 4.0% versus 1.5% for injury crashes. The results obtained for Porto are aligned with the findings obtained by Eisenberg [4], Keay and Simmonds [14] and Levine et al. [18] across different regions of the globe. In the case of multi-vehicle and property-damage-only crashes, the respective impacts of 3.3% and 3.7% do not vary between S1 and S2, because the frequency

of these crashes do not depend on lagged effects, in accordance with the results shown in Table 3. This fact further highlights the relevance of visibility loss and wet pavement to the occurrence of collisions between vehicles.

The lagged effects of precipitation are, according to Eisenberg [4] and Keay and Simmonds [14], essentially associated with two main factors: oil and grime accumulated on the pavement and driving behavior. When rainfall starts, the build-up of oil and grime on the road surface and a non-immediate readjustment of driving behavior to hazardous weather conditions increase the crash risk beyond the impacts of the reduced visibility and wet pavement associated with a rainy day. If the rainfall period proceeds, the crash risk starts to fall at some point in time, because the pavement becomes completely cleaned and drivers get used to counteract the inclement weather effects by adopting more careful driving practices, such as reducing speed and paying more attention to their surroundings. The moment at which the crash risk reverts its growing trend is very difficult to determine, because it depends on the quantity of oil and grime accumulated during the previous dry spell, as well as on the driving culture and behavior.

In this study, the interaction term DM was considered to represent the lagged effects of precipitation. Given that the impacts of daily precipitation on crash frequency always have a positive sign (Table 3), the sign of DM coefficients may be attributed to the influence of monthly precipitation. When statistically significant, the effect of DM counteracts the increase of crash frequency attributed to the daily precipitation. Therefore, the increase of the precipitation during the previous month seems to capture the reversing trend of the crash risk associated with the lagged effects described above. In fact, it is reasonable to assume that, after a rainy month, the pavement is completely cleaned from oil, and that drivers already had enough time to readjust their behavior to compensate for the adverse meteorological conditions. In Table 4, it is possible to observe that the expected reduction of crash frequency in Porto caused by doubling DM, while maintaining constant the daily precipitation (S3), is of 2.3% both for single-vehicle and injury crashes. The relevance of DM for the decrease of single-vehicle and injury crashes are typically associated with the practice of higher speeds.

The mean daily temperature seems to have a negative correlation with crash frequency, in line with the results obtained by Brijs et al. [5], El-Basyouny and Kwon [24] and Andreescu and Frost [26]. Specifically, the temperature ranges sitting below and above the category of reference (10 $^{\circ}C \leq T <$ 20 °C) are respectively associated with an increase or a decrease of crash frequency. According to Table 4, when the mean daily temperature decreases from the category of reference to a value below 10 °C, maintaining constant the precipitation variables (S4), single-vehicle crashes increase by 12.1%, multi-vehicle and property-damage-only crashes increase by 9.6%, and injury crashes increase by 13.9%. While these results suggest a higher crash risk for lower temperature values, it should be noted that such effect is hardly associated with snowfall or roadway icing. These events are extremely rare in Porto, since winter seasons are predominantly wet, and a minimum mean daily temperature of 3.6 °C has been observed during the five years considered in this study. In turn, when the mean daily temperature climbs above 20 °C (S5), only multi-vehicle and property-damage-only crashes are affected, experiencing a decrease of 8.4% and 7.3%, respectively, in relation to the category of reference. As multi-vehicle and property-damage-only crashes represent the great majority of crash occurrences in Porto, higher temperatures do not seem to produce a relevant impact on more specific crash situations, represented by single-vehicle and injury crashes. From the results of this study, and in compliance with the findings by Andreescu and Frost [26], it is possible to infer that the temperature may represent seasonal meteorological effects beyond rainfall that are generically associated with the occurrence of the majority of road crashes, but acts more as a modifier of crash conditions than as a root cause. In this sense, S4 and S5 provide an idea about the variation of crash frequency attributed to seasonal meteorological factors beyond rainfall.

7. Conclusions

The impacts of inclement weather on the occurrence of road crashes has been studied by researchers for a long time, demonstrating clear evidence of a cause-effect relationship between both phenomena. However, that relationship is affected by regional climate and driving behavior patterns, with some authors reporting contradictory effects produced by identical meteorological factors.

This research introduces a novel perspective on the study of meteorological impacts on crash frequency by analyzing different types of urban road crashes, focusing on the number of vehicles involved and on the existence of victims. Additionally, this analysis is the first contribution to the subject developed in Portugal, highlighting the regional patterns of a previously unstudied area. In this sense, the influence of weather conditions on the crash counts registered in the city of Porto were evaluated, dividing the police crash database, in a first stage, between single-vehicle and multi-vehicle crashes and, in a second stage, between property-damage-only and injury crashes. Subsequently, four negative binomial or Poisson regression models were estimated to analyze the effects of diverse meteorological factors, including the daily precipitation and mean temperature, and the precipitation accumulated during the previous week and month.

The results demonstrate that the daily precipitation and mean temperature below 10 °C present a positive correlation with the number of daily crashes. These results are consistent across the four developed models. The impact of temperatures above 20 °C is only statistically significant for multi-vehicle and property-damage-only crashes, presenting a negative correlation. In turn, the precipitation during the previous month is negatively correlated with single-vehicle and injury crashes. These results support the following main conclusions:

- An increase of daily precipitation, associated with a loss of visibility and wet pavement, increases the overall crash counts. The impacts are higher on the first day of rainfall;
- The impacts of daily precipitation tend to be counteracted by the lagged effects of past precipitation
 observed in the long term, presumably because of the pavement cleaning from oil and grime and
 the readjustment of driving behavior to adverse meteorological conditions;
- Lower temperatures are associated with an increase of crash frequency. Higher temperatures
 are related with a decrease in the number of crashes, but this effect may not be significant for
 less frequent crash types. The temperature reflects seasonal weather effects, but may hardly be
 described as a root cause of road crashes;
- The observed meteorological impacts on crash frequency in Porto are in line with the impacts found in other regions of the globe, confirming the general tendency to associate precipitation and winter months with an increase of crash counts [3,13].

From a broader perspective, this work belongs to a set of studies focused on the meteorological impacts on road safety, helping to understand one of the main issues contributing to crash occurrence. The results of such studies provide relevant inputs to the development of advanced driver-assistance systems, being crucial to the safety and acceptance of fully-automated vehicles. New driving technology is required to continuously monitor driving conditions, including weather-related parameters, such as visibility and tire-road friction, and to adequately intervene in every situation with the aim of protecting all road users.

Finally, in the actual context of climate change, the projections presented by the Intergovernmental Panel on Climate Change Fifth Assessment Report (AR5) depict, among others, a temperature increase, changes in the precipitation patterns, and an increase in the number and strength of extreme weather events related with rainfall and wind [40]. These changes, predicted all over the world, can vary from one region to another, reinforcing the need to continuously report and link the meteorological variables to several phenomena, of which road crashes are an example. Therefore, the examination of the impact of meteorological conditions on road crashes is of critical importance and should be continuously evaluated.

8. Limitations and Future Research

Future research should address the main limitations of this study, particularly seeking for a better specification of risk exposure and for cross-region comparisons that allow for more representative insights. The evaluation of risk exposure may be a difficult task, especially if no traffic data is available, as it is the case of this study. In fact, risk exposure usually depends on a wide array of factors that are not always easy to quantify, including a complete characterization of the roadway infrastructure and surrounding environment (e.g., geometric parameters and roadside activities), and the knowledge of road users' decisions about everyday mobility (e.g., variations in modal choice and special events). Even if traffic data is available, some sort of aggregation is necessary to comply with the spatial and/or temporal units of the crash counts. The consideration of calendar effects (e.g., month of the year, day of the month, day of the week, and hour of the day) is also dependent on the selected time unit.

In turn, regional comparisons are strongly dependent on data availability. If comparable data is available for different regions, then the influence of diverse geographic, meteorological, and cultural patterns may be highlighted.

Finally, since pedestrians bear the highest burden of traffic injuries [41], it is important to investigate the contribution of the weather effects to pedestrian-vehicle collisions. Therefore, the authors plan to extend this research to this type of crashes in the near future.

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References

- 1. World Health Organization. *Global Status Report on Road Safety 2013: Supporting a Decade of Action;* World Health Organization: Geneva, Switzerland, 2013.
- 2. European Commission. *White Paper on Transport—Roadmap to a Single European Transport Area;* Publications Office of the European Union: Luxembourg, 2008.
- 3. Theofilatos, A.; Yannis, G. A review of the effect of traffic and weather characteristics on road safety. *Accid. Anal. Prev.* **2014**, *72*, 244–256. [CrossRef] [PubMed]
- 4. Eisenberg, D. The mixed effects of precipitation on traffic crashes. *Accid. Anal. Prev.* **2004**, *36*, 637–647. [CrossRef]
- 5. Brijs, T.; Karlis, D.; Wets, G. Studying the effect of weather conditions on daily crash counts using a discrete time-series model. *Accid. Anal. Prev.* **2008**, *40*, 1180–1190. [CrossRef] [PubMed]
- 6. Bergel-Hayat, R.; Debbarh, M.; Antoniou, C.; Yannis, G. Explaining the road accident risk: Weather effects. *Accid. Anal. Prev.* 2013, *60*, 456–465. [CrossRef] [PubMed]
- Edwards, J.B. The Relationship Between Road Accident Severity and Recorded Weather. J. Saf. Res. 1998, 29, 249–262. [CrossRef]
- Miranda, P.M.A.; Coelho, F.E.S.; Tomé, A.R.; Valente, M.A.; Carvalho, A.; Pires, C.; Pires, H.O.; Pires, V.C.; Ramalho, C. 20th Century Portuguese Climate and Climate Scenarios. In *Climate Change in Portugal: Scenarios, Impacts and Adaptation Measures*; Santos, F.D., Forbes, K., Moita, R., Eds.; Gradiva: Lisbon, Portugal, 2002; pp. 23–83.
- 9. Martensen, H.; Focant, N.; Diependaele, K. Let's Talk about the Weather—Interpretation of Short Term Changes in Road Accident Outcomes. *Transp. Res. Proc.* **2016**, *14*, 96–104. [CrossRef]

- Changnon, S.A. Effects of summer precipitation on urban transportation. *Clim. Chang.* 1996, 32, 481–494. [CrossRef]
- 11. Koetse, M.J.; Rietveld, P. The impact of climate change and weather on transport: An overview of empirical findings. *Transp. Res. D Transp. Environ.* **2009**, *14*, 205–221. [CrossRef]
- 12. Jaroszweski, D.; McNamara, T. The influence of rainfall on road accidents in urban areas: A weather radar approach. *Travel Behav. Soc.* 2014, *1*, 15–21. [CrossRef]
- 13. Xu, C.; Wang, W.; Liu, P. Identifying crash-prone traffic conditions under different weather on freeways. *J. Saf. Res.* **2013**, *46*, 135–144. [CrossRef]
- 14. Keay, K.; Simmonds, I. Road accidents and rainfall in a large Australian city. *Accid. Anal. Prev.* **2006**, *38*, 445–454. [CrossRef] [PubMed]
- 15. Black, A.W.; Villarini, G.; Mote, T.L. Effects of Rainfall on Vehicle Crashes in Six U.S. States. *Weather Clim. Soc.* **2017**, *9*, 53–70. [CrossRef]
- Malin, F.; Norros, I.; Innamaa, S. Accident risk of road and weather conditions on different road types. *Accid. Anal. Prev.* 2019, 122, 181–188. [CrossRef] [PubMed]
- 17. Norros, I.; Kuusela, P.; Innamaa, S.; Pilli-Sihvola, E.; Rajamäki, R. The Palm distribution of traffic conditions and its application to accident risk assessment. *Anal. Methods Accid. Res.* **2016**, *12*, 48–65. [CrossRef]
- Levine, N.; Kim, K.E.; Nitz, L.H. Daily fluctuations in Honolulu motor vehicle accidents. *Accid. Anal. Prev.* 1995, 27, 785–796. [CrossRef]
- 19. Fridstrøm, L.; Ifver, J.; Ingebrigtsen, S.; Kulmala, R.; Thomsen, L.K. Measuring the contribution of randomness, exposure, weather and daylight to the variation in road accidents. *Accid. Anal. Prev.* **1995**, *27*, 1–20. [CrossRef]
- Chang, L.Y.; Chen, W.C. Data mining of tree-based models to analyze freeway accident frequency. J. Saf. Res. 2005, 36, 365–375. [CrossRef]
- Yannis, G.; Karlaftis, M.G. Weather Effects on Daily Traffic Accidents and Fatalities: A Time Series Count Data Approach. In Proceedings of the Transportation Research Board 89th Annual Meeting Compendium of Papers, Washington, DC, USA, 10–14 January 2010.
- 22. Caliendo, C.; Guida, M.; Parisi, A. A crash-prediction model for multilane roads. *Accid. Anal. Prev.* 2007, 39, 657–670. [CrossRef]
- 23. Jung, S.; Qin, X.; Noyce, D.A. Rainfall effect on single-vehicle crash severities using polychotomous response models. *Accid. Anal. Prev.* **2010**, *42*, 213–224. [CrossRef]
- 24. El-Basyouny, K.; Kwon, D.W. Assessing Time and Weather Effects on Collision Frequency by Severity in Edmonton Using Multivariate Safety Performance Functions. In Proceedings of the Transportation Research Board 91st Annual Meeting Compendium of Papers, Washington, DC, USA, 22–26 January 2012.
- 25. Antoniou, C.; Yannis, G.; Katsohis, D. Impact of Meteorological Factors on the Number of Injury Accidents. In Proceedings of the 13th World Conference on Transport Research, Rio de Janeiro, Brazil, 15–18 July 2013.
- 26. Andreescu, M.P.; Frost, D.B. Weather and traffic accidents in Montreal, Canada. *Clim. Res.* **1998**, *9*, 225–230. [CrossRef]
- 27. Malyshkina, N.V.; Mannering, F.L.; Tarko, A.P. Markov switching negative binomial models: An application to vehicle accident frequencies. *Accid. Anal. Prev.* **2008**, *41*, 217–226. [CrossRef] [PubMed]
- 28. State Meteorological Agency of Spain and Institute of Meteorology of Portugal. *Iberian Climate Atlas—Air Temperature and Precipitation (1971-2000);* AEMET Documentation Unit: Madrid, Spain, 2011.
- 29. Atlas de Portugal. Available online: http://dev.igeo.pt/atlas/index1.html (accessed on 30 October 2018).
- 30. Trigo, R.M.; Câmara, C.C. Circulation weather types and their influence on the precipitation regime in Portugal. *Int. J. Clim.* **2000**, *20*, 1559–1581. [CrossRef]
- 31. Soares, P.M.M.; Cardoso, R.M.; Miranda, P.M.A.; Medeiros, J.; Belo-Pereira, M.; Espírito-Santo, F. WRF high resolution dynamical downscaling of ERA-Interim for Portugal. *Clim. Dynam.* **2012**, *39*, 2497–2522. [CrossRef]
- 32. Portuguese Institute for Sea and Atmosphere. Available online: http://www.ipma.pt/en (accessed on 30 October 2018).
- Lord, D.; Washington, S.P.; Ivan, J.M. Poisson, Poisson-gamma and zero-inflated regression models of motor vehicle crashes: Balancing statistical fit and theory. *Accid. Anal. Prev.* 2005, 37, 35–46. [CrossRef] [PubMed]
- 34. Anastasopoulos, P.C.; Mannering, F.L. A note on modeling vehicle accident frequencies with random-parameters count models. *Accid. Anal. Prev.* 2009, *41*, 153–159. [CrossRef]

- 35. Couto, A.; Ferreira, S. A note on modeling road accident frequency: A flexible elasticity model. *Accid. Anal. Prev.* **2011**, *43*, 2104–2111. [CrossRef]
- 36. Cameron, A.C.; Trivedi, P.K. Regression-based tests for overdispersion in the Poisson model. *J. Econom.* **1990**, 46, 347–364. [CrossRef]
- Shankar, V.; Albin, R.; Milton, J.; Mannering, F. Evaluating median cross-over likelihoods with clustered accident counts: An empirical inquiry using the random effects negative binomial model. *Transp. Res. Rec.* 1998, 1635, 44–48. [CrossRef]
- 38. Lord, D.; Mannering, F. The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives. *Transp. Res. A Pol.* **2010**, *44*, 291–305. [CrossRef]
- 39. Greene, W.H. *Limdep Version 9.0—Econometric Modelling Guide;* Econometric Software, Inc.: Plainview, NY, USA, 2007.
- 40. Intergovernmental Panel on Climate Change. *Climate Change* 2014: *Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change;* Intergovernmental Panel on Climate Change: Geneva, Switzerland, 2014.
- 41. European Commission. *Traffic Safety Basic Facts on Pedestrians* 2017; European Commission Directorate General for Transport: Brussels, Belgium, 2017.



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