Daily and Latent Lagged Effects of Rainfall on Pedestrian–Vehicle Collisions

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ABSTRACT

Walking safety has been a primary concern for researchers and authorities, who have developed numerous studies concerning the interaction between pedestrians and vehicles. Nevertheless, few studies have focused on the impacts of weather conditions on pedestrian–vehicle collisions. This research aims at improving knowledge on this subject by investigating the impact of daily precipitation and the lagged effects associated with past accumulated precipitation. Using the city of Porto, Portugal, as a case study, an incremental approach consisting of three models, one Poisson and two negative binomial, was developed to explore the relation between weather conditions and the occurrence of pedestrian–vehicle collisions. The first model accounts exclusively for meteorological variables, providing an insight into the trends of crash frequency under the effects of temperature and precipitation. Then, variables for road classification and land use were introduced in the second and third models, respectively, to account for the diversity of the urban environment. These variables act as proxies for the level of exposure associated with different types of urban space, allowing for a more in-depth understanding of the impacts caused by meteorological conditions. The modeling results show that the number of pedestrian–vehicle collisions tends to increase on rainy days, following the general trend observed in the literature for other types of crashes. Regarding the lagged effects, the results show that the number of pedestrian–vehicle collisions is likely to decrease after a wet week but increases after a wet month.

1. Introduction

Walking is an integral part of human activity. Although it offers immense health and environmental benefits, walking involves a significant trade-off, as pedestrians, and particularly elderly people, bear the highest burden of traffic injuries. For instance, according to Pucher and Dijkstra (2003), pedestrians are 23 times as likely to suffer fatal injuries as car occupants in the United States (140 vs 6 deaths per billion kilometers). The European Road Safety Observatory (2017) reports that pedestrians represent both the highest percentage of nonfatal road crash casualties admitted to hospital and the longest average hospital stay. In addition, at the European level, the elderly fatality rate is well above average and quickly rises above the age of 70.

In Portugal, pedestrian safety deserves special attention because between 2006 and 2015 the percentage of pedestrian fatalities of all road fatalities increased from 16% to 25%. In 2015, this percentage was higher than the average of the European Union (21%). In addition, the rate of pedestrian fatalities observed in Portugal in 2015 was also higher than the European average (14 vs 11 deaths per million inhabitants) (European Road Safety Observatory 2017).

Several studies focused on pedestrians were conducted with diverse objectives, such as evaluating risk factors affecting the frequency and severity of pedestrian victims

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(Jacobsen 2003; Mujalli et al. 2019), analyzing the interaction between vehicles and pedestrians when crossing a street (Holland and Hill 2007; Granié et al. 2014), or estimating pedestrian traffic volume (Molino et al. 2009). Despite these efforts, the factors contributing to the occurrence and severity of road crashes involving pedestrians are still not sufficiently explored. As other road users, pedestrians present a large variability in relation to their individual characteristics and mobility patterns. However, the available information about them is usually scarce and inconsistent, which makes it harder to analyze and represent their behavior.

Theofilatos and Yannis (2014) noted that there are very few studies specifically devoted to the effects of meteorological conditions on crashes involving vulnerable road users, namely power two-wheelers, cyclists, and pedestrians. This is in contrast to the numerous studies that address the weather effects on the frequency and/or severity of other types of crashes or that simply do not discriminate those effects between different road users (Edwards 1998; Brijs et al. 2008; Bergel-Hayat et al. 2013; Black and Mote 2015; Black et al. 2017; Lobo et al. 2019).

A study conducted by Aultman-Hall et al. (2009) is among those that analyzed the impacts of adverse weather on pedestrian behavior. Focusing on the observation of pedestrian traffic in downtown Montpelier, Vermont, the authors found that precipitation reduces the average hourly pedestrian volume by approximately 13%. The same study shows that a combination of diverse meteorological variables, such as temperature, relative humidity, and precipitation accounts for 30% of the variance measured in hourly pedestrian volumes. Regarding the investigation of weather impacts on pedestrian safety, most studies have analyzed these effects together with those produced by other factors, such as pedestrian, vehicle, road, and traffic characteristics. Categorical variables have generally been used to represent different types of weather: clear, cloudy, fog, dust, wind, rain, storm, or snow. Lee and Abdel-Aty (2005) used an ordered probit model to estimate the likelihood of five pedestrian injury severity levels (no injury, possible injury, nonincapacitating evident injury, incapacitating evident injury, and fatal injury). The authors considered, among other effects, the impact of clear versus adverse weather in Florida, having found that adverse weather increases injury severity due to the higher crash impacts caused by the decrease in both drivers' and pedestrians' sight and the increase in reaction times and braking distances. Kim et al. (2008) found an opposite effect on pedestrian fatalities (−35%) in North Carolina, using multinomial logit and heteroskedastic logit models. No significant results were determined for nonfatal injuries. Li and Fernie (2010) observed that when pedestrians crossed a signalized intersection in Toronto, Ontario, Canada, in cold weather (<10°C), the compliance rate was reduced by a factor of 2 relative to the observed rate in warm temperatures (>10° and <25°C). In addition, the compliance dropped to a value as low as 3% during snowy conditions. More recently, Li et al. (2017) and Mujalli et al. (2019) used data mining techniques to identify factors affecting pedestrian injury severity, including meteorological conditions. Using open data from the United Kingdom (STATS19 database), Li et al. (2017) applied classification, regression tree, and random forest models to analyze slight and serious injuries and fatalities among pedestrians. The meteorological conditions were classified as rain, snow, mist, and fog, as reported by police officers. In the end, the study identified various significant severity predictors, distinguishing their impact by two categories of weather conditions: good and adverse weather. However, the study does not quantify the impacts of meteorological variables. Mujalli et al. (2019) extracted rules from Bayesian networks to study the main factors associated with the severity of pedestrian–vehicle collisions in Jordan. The weather was classified as clear, rain, and other. The authors found that the latter category, which includes snow, storm, wind, fog, and dust, is the only one that is represented in significant rules, that is, with a confidence of at least 50%, for the occurrence of fatal or serious injuries. Zhai et al. (2019) also investigated the risk factors affecting the severity of pedestrian injuries but used a mixed logit modeling approach. Despite the availability of meteorological data at 1-min intervals for Hong Kong, only two binary variables (temperature above 30°C and the presence of rain) were found to be significant for the likelihood of severe injury and fatal crashes. Additionally, the authors analyzed the interaction between these two factors and risky driving/walking behaviors, concluding that the effects of driver inattention and reckless crossing on crash severity increase in hot weather or on rainy days. However, the likelihood of severe injury or fatal crashes under rainfall decreases when the footpath is overcrowded.

Graham and Glaister (2003) and Mitra et al. (2007) are among the very few studies using quantitative variables to represent the effects of precipitation. Both of them use average measures of annual rainfall. However, contradictory results were found: whereas the former authors estimated that a 10% increase in annual precipitation is associated with a 3.9% increase in pedestrian casualties in the United Kingdom, the latter found that the same increase in precipitation reduces pedestrian–vehicle collisions at intersections by a staggering 65% in Tucson, Arizona (reduction of 15% in the total number of crashes). These differences may be explained by the frequency of rainfall events in both regions. In the United Kingdom, drivers are very used to rainfall, and thus they may not properly evaluate the increased risks of driving under adverse weather. In Tucson, however, rainfall is rare, which raises issues about the stability of the statistical finding and, by extension, the reasons accounting for it. This is confirmed in a subsequent study by Mitra and Washington (2012) using the same data but focused on all types of crashes that occurred in intersections. In the latter study, the authors noted that Tucson has an average of about 30 cm of accumulated precipitation per year and that the rainy season occurs during summer, when many people leave the city. Therefore, the rain effect in Tucson may be confounded with other exposure metrics and should not be generalized to other regions. In turn, Martensen et al. (2016) found that daily accumulated precipitation did not affect the overall number of victims of road crashes. When road users are analyzed separately, the authors found that the number of victims traveling in passenger cars increased with daily precipitation, while victims using bicycles and motorbikes decreased; no effect was found on pedestrian victims.

In relation to studies considering all types of crashes, analyzing meteorological impacts mainly focused on precipitation effects. Good literature reviews on this subject provided by Xu et al. (2013) and by Theofilatos and Yannis (2014) show that most studies associate precipitation with an increased risk of crash. Nevertheless, some studies have revealed contrasting conclusions. Eisenberg (2004) obtained different impacts on the crash counts of the 48 contiguous states of the United States, in terms of sign and/or magnitude, produced by daily rainfall, monthly rainfall, and monthly snowfall. Bergel-Hayat et al. (2013) found a decrease in total crash frequency under rainfall in Athens, Greece, and in compliance with the abovementioned study by Mitra et al. (2007), attribute the results to an overcompensation of crash risk considering uncommon weather events. Black et al. (2017) also showed evidence of different driving behavior patterns under bad weather. On the one hand, the authors concluded that rainfall increases the relative risk of crashes more than the relative risk of injuries, whereby no effects were observed on fatalities, which denotes a certain tendency of drivers to counteract the adverse meteorological conditions. On the other hand, regions with more days of rainfall per year do not necessarily have a smaller relative crash risk that may be attributed to the familiarity of drivers with such conditions. Therefore, the diversity of the road environment and the climatic characteristics of each study area seem to produce different regional patterns that may affect both crash risk and exposure to risk. First, cultural differences reveal different driving behaviors to tackle the degradation of visibility and tire–road friction under adverse weather. Second, precipitation may differently affect traffic volume and the choice of transport mode from one region to another. Elvik's laws of accident causation (Elvik 2006) described that a short-term change in driving behavior is expected when exposure to hazardous conditions increases. Eisenberg (2004) and Lobo et al. (2019) also observed this fact when accounting for the lagged effects of precipitation. Eisenberg (2004) found that the impacts of rainfall on crash frequency is much smaller on rainy days occurring no more than 3 days after the last precipitation than on rainy days occurring after a dry spell of more than 20 days. In particular, the rainfall impacts after a 20-day dry spell increase by a factor of 2 for nonfatal crashes and by a factor of 3 for fatal crashes. This fact was attributed to the short-term effects of pavement cleaning and adapting driving behavior to counteract adverse meteorological conditions that tend to be diluted in the long term, as more days pass without raining. In a study aimed at analyzing the weather effects on different types of crashes not involving pedestrians (single-vehicle, multivehicle, property-damage-only, and injury crashes), Lobo et al. (2019) concluded that the crash risk increases on rainy days but this may be counteracted by the amount of precipitation observed during the previous month. Besides that a rise in precipitation on the previous days increases the probability of the pavement being clean, the fact that this effect was only observed for single-vehicle crashes and for injury crashes (it is statistically insignificant for the remaining analyzed crash types) indicates the existence of a behavioral adaptation to adverse weather, as single-vehicle and injury crashes are typically associated with higher speeds.

Given that the climatology of each region and the road users' behavior and adjustment to changing meteorological conditions assume a crucial role in the relation between weather and road safety, it is difficult to extrapolate the results obtained for a specific region to another region with different climatology and walking/driving culture. This fact clearly shows the need for new research aimed at delivering tailored instruments to prevent road crashes and improve safety in different regions.

This study was conducted in the city of Porto, Portugal, mainly aiming to analyze the impacts of rainfall on the frequency of pedestrian–vehicle collisions, following on to the previous analysis by Lobo et al. (2019) about weather effects on the frequency of crashes not involving pedestrians. In comparison with previous studies focusing on pedestrian–vehicle collisions, using quantitative variables to represent daily and past-accumulated rainfall allows for a more reliable representation of the

TABLE 1. Monthly precipitation and temperature in Porto for the period 1971–2000 (source: Portuguese Institute for Sea and Atmosphere 2018).

Month	Mean monthly precipitation (mm)	Mean no. of days per month with precipitation ≥0.1 mm	Mean max daily temperature (°C)	Mean daily temperature (°C)	Mean min daily temperature (°C)
Jan	157.6	16.0	13.5	9.3	5.0
Feb	139.7	14.4	14.8	10.4	5.9
Mar	89.9	12.8	16.8	11.9	7.1
Apr	115.6	15.0	17.7	13.2	8.6
May	97.6	14.0	19.4	15.2	11.0
Jun	46.0	8.8	22.8	18.3	13.8
Jul	18.3	6.3	25.0	20.2	15.5
Aug	26.7	6.0	25.0	20.1	15.2
Sep	71.0	8.5	23.7	18.9	14.1
Oct	138.0	14.4	20.4	16.0	11.5
Nov	158.4	14.4	16.8	12.6	8.3
Dec	194.7	16.3	14.4	10.6	6.8

visibility and pavement conditions on the day of the crash and the behavioral adaption to long periods of rainfall, respectively. Since Porto is located at the northwest region of Portugal, corresponding to one of the wettest regions in Europe (Miranda et al. 2002; Tapia et al. 2015), this study area is an ideal location to examine the effects of the weather on pedestrian safety.

The proposed method consists of developing three models. Model 1 was developed considering the weather conditions on the day of the crash and the corresponding lagged effects. In addition to these effects, models 2 and 3 test different proxy variables, related with the road hierarchy and land use, respectively, to account for the spatial variability of the exposure to crash risk, in an alternative procedure to conduct a matched pair analysis, as used in previous research (Andrey et al. 2003; Black et al. 2017). This approach allows one to evaluate the relevance of exposure for the elasticity of the weather variables in relation to the frequency of pedestrian–vehicle collisions. The stability of the results returned by the developed models denotes that both types of spatial proxies capture the effects of exposure consistently and allow for a reliable interpretation of the weather effects.

2. Data description

a. Meteorological data

Portugal is well known for its temperate climate with an intra-annual variability that goes from a dry and hot summer to a humid and cold winter (State Meteorological Agency of Spain and Institute of Meteorology of Portugal 2011). However, strong differences occur between northern and southern regions, and between coastal and inland regions (Geographical Institute of Portugal 2018), showing an important interannual variability in temperature (Soares et al. 2012) but also in precipitation (Trigo and Câmara 2000), which ranges from around 400 to more than 2200 mm per year. The country's northwest coast, where Porto is located, is one of the highest precipitation regions in continental Europe (Miranda et al. 2002; Tapia et al. 2015), although minimum temperatures are high enough to make snowfall a very rare occurrence. Table 1 shows Porto's climate characterization in terms of precipitation and temperature.

In this study, precipitation and temperature data were obtained for the period between January 2001 and December 2005 from two meteorological stations: Serra do Pilar, located near the city center at an elevation of 90 m, and Porto Airport, located in the city's surroundings at an elevation of 63 m. The elevation of the study area varies between 0 m (sea level) and 140 m. The Serra do Pilar station belongs to the Geophysics Institute of the University of Porto and provides the daily accumulated precipitation data for this analysis. From these data, the accumulated precipitation was calculated throughout the previous 7 and 30 days, named respectively, for the sake of simplicity, weekly and monthly precipitation. Not a single snowfall event occurred during the observation period. Because no temperature data were available for the Serra do Pilar station, 10-min temperature measurements were retrieved from the Porto Airport station (Portuguese Institute for Sea and Atmosphere 2018). The daily mean temperature T was estimated from the average between the maximum and minimum measured values. Then, this variable was assigned to different categories to comply with a nonlinear variation of crash frequency with temperatures found in previous research (Brijs et al. 2008; Lobo et al. 2019). Considering that T varies between 3.6° and 30.4°C in the period under analysis, category thresholds were defined at 10° and 20°C, establishing three temperature categories: $T < 10°C$, $10° \leq T < 20°C$, and $T \geq 20°C$. Assuming the intermediate category ($10° \leq T < 20°C$)

as a reference, two binary variables related to $T < 10°C$ and $T \geq 20°C$ were generated to represent the effects of lower and higher values of T, respectively.

In the end, five explanatory meteorological variables were considered for modeling purposes: daily, weekly and monthly precipitation, and binary variables for $T < 10°C$ and for $T \geq 20°C$. The description of the meteorological variables is summarized in Table 2.

b. Crash data

Crash data were retrieved from the official Portuguese Police database, containing information about all the crashes recorded by the police in the city of Porto. During the 5-yr period under consideration, around 28 000 crashes of all types were recorded, including approximately 23 000 property-damage-only crashes and 5000 injury crashes. From the total amount of recorded crashes, 1819 involved pedestrians, which in turn were selected for this study. The available information from the police database includes the location of each crash.

c. Proxies for risk exposure

To account for the level of exposure to risk, and given the unavailability of vehicle and pedestrian traffic data, different proxy variables for exposure were considered. These proxies are associated with the urban space where the crashes have occurred. Similarly to the previous study for vehicle crashes in Porto (Lobo et al. 2019), the road type was included in model 2 as a proxy for risk exposure, considering that it represents the diversity of the road's functional and geometric characteristics, and is associated with traffic volume patterns. However, because the present study focuses on pedestrians, a different proxy is tested in model 3, related to the predominant land use in the area. The land use characterizes the main human activities surrounding the road environment, which may be associated with different levels of pedestrian and vehicular traffic generation. The crash location allowed us to classify the road type and predominant land use according to the city's master plan. In Porto, roads are classified into four types: arterial, principal distributor, local distributor, and local access (Fig. 1). In terms of land use, the city is divided into five zones: high-density residential, low-density residential, industrial, services, and historical center (Fig. 2). The size and crash distribution associated with each road type and land use are presented in Table 3.

Model 1 is modeled after a time series dataset, in which the dependent variable is the number of pedestrian–vehicle collisions per day observed in the entire city. This number ranged between zero and six during the analyzed period, with an average of one crash per day. Then, the time series dataset used in model 1 is transformed into two panel datasets for models 2 and 3, using the road type and land-use variables, respectively, to standardize the dependent variable. In the dataset of model 2, the pedestrian–vehicle collisions observed per day in the whole city were separated according to the four road types. The spatial unit of observation is the road network in each category, originating four observations per day. In the dataset of model 3, the crash counts were distributed by the five categories of land use. In this case, the spatial unit of observation is the road network in each land-use zone, originating five observations per day. If one road crosses different zones with different land uses, it is assigned to the zone that represents the largest share of its length. As a result, models 2 and 3 use different datasets that are 4 and 5 times as large as the dataset of model 1, respectively. Furthermore, the dependent variables of models 2 and 3 are constructed to account for the size variations between different types of road or land use. In model 2, the dependent variable represents the number of crashes per day divided by the total length of the corresponding road type (in hundreds of kilometers). In model 3, the dependent variable is the number of crashes per day divided by the total area of the corresponding type of land use (in tens of square kilometers). Four explanatory binary variables in model 2 and five in model 3 were used to set the road type and the land use; each variable was set to one if it represented the road type (model 2) or the land use (model 3) associated with each observation, and to zero otherwise. The combination of road type and land use in a single model was not pursued because it would have implied using an excessive number of binary variables compared with the variables representing the meteorological impacts under investigation. In the three models, an additional binary variable for holidays and weekend days, set to one in these cases and to zero otherwise, was included to represent the variation of exposure in relation to working days.

TABLE 2. General description of the meteorological variables.

	Mean	Std dev	Min	Max
Daily precipitation (mm)	3.2	8.3	0.0	80.9
Daily mean temperature (°C)	14.8	4.4	3.6	30.4
Weekly precipitation (mm)	22.8	33.7	0.0	279.0
Monthly precipitation (mm)	99.2	97.2	0.0	567.2

3. Methodological approach

The available data do not allow for a detailed characterization of the aspects of pedestrian and driver exposure, behavioral adjustment (risk compensation), and hazardous conditions (e.g., visibility and road surface friction). Instead, these aspects are indirectly addressed

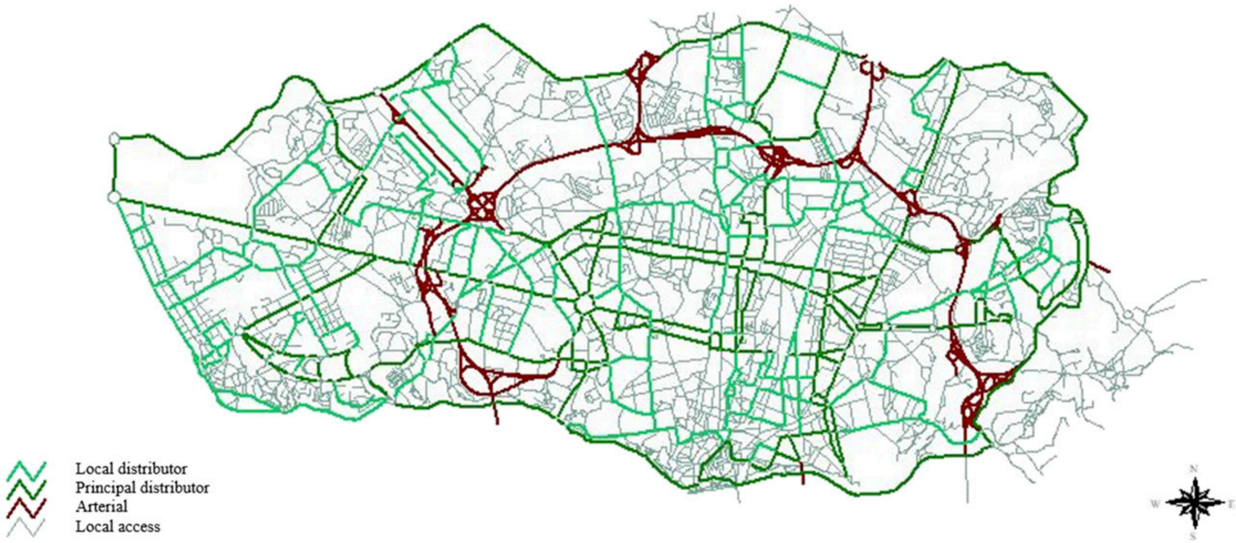

FIG. 1. Road classification in Porto.

through the use of the collected weather data and the road type and land-use proxies. Considering the available data, this study uses a traditional modeling framework. The method consists of estimating three models using Poisson or negative binomial regressions.

First, to analyze the trends of pedestrian–vehicle collisions under different weather conditions, the total number of crash occurrences per day, regardless of their location, was regressed against the meteorological variables using a Poisson regression (model 1). The Poisson distribution is frequently used on crash frequency analysis, as the number of crashes per unit of time is a nonnegative integer. One requirement of the Poisson distribution is that the mean of the count process is equal to the variance. When the variance is significantly higher than the mean, the data are considered to be overdispersed; in such cases, a negative binomial approach is recommended (Sawalha and Sayed 2001; Caliendo et al. 2007; Couto and Ferreira 2011). In this study, tests for overdispersion were used to select the most appropriate model for each dataset, as suggested by Cameron and Trivedi (1990). The results obtained

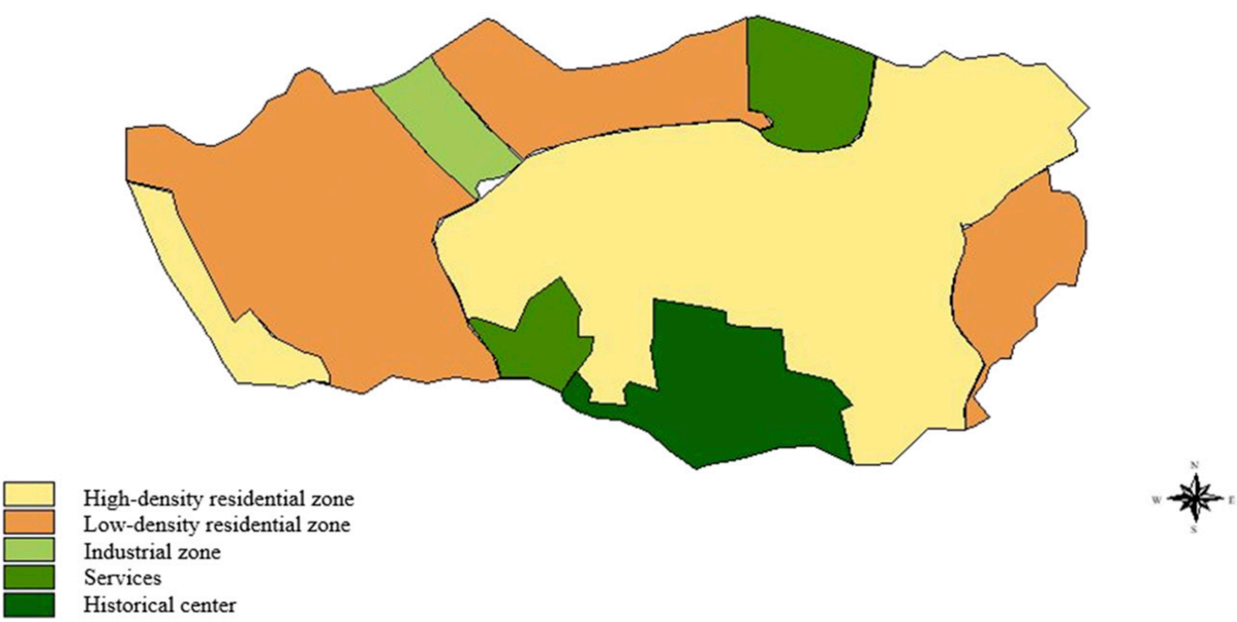

FIG. 2. Land-use zones in Porto.

TABLE 3. Distribution of pedestrian–vehicle collisions by type of road and land use (2001–05).

	Length (km)	Area (km^2)	Absolute (relative) crash frequency
Road classification			
Arterial	36.4	—	29 (1.6%)
Principal distributor	78.1	—	709 (39.0%)
Local distributor	81.7	—	559 (30.7%)
Local access	361.9	—	522 (28.7%)
Total	558.1	—	1819 (100%)
Land-use classification			
High-density residential	—	17.2	759 (41.7%)
Low-density residential	—	13.3	511 (28.1%)
Industrial	—	1.1	26 (1.4%)
Services	—	2.5	83 (4.6%)
Historical	—	3.1	440 (24.2%)
Total	—	37.2	1819 (100%)

for model 1's dataset favor the Poisson distribution in relation to the negative binomial distribution; the null hypothesis of the variance of the dependent variable being equal to the mean was not rejected because the test statistics are lower than the critical value from the χ^2 table for 1 degree of freedom (3.84).

The Poisson regression 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 (Greene 2007). The Poisson probability of the outcome $Y = y_i$ can be expressed by

$$\text{Prob}(Y = y_i|x_i) = e^{-\lambda_i}\lambda_i^{y_i}/y_i!. \tag{1}$$

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

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

where $\boldsymbol{\beta}$ is a vector of coefficients of the explanatory variables.

In the second stage, the two panel datasets resulting from the separation of daily crash counts by road type and by land use, described in the previous section, were used to estimate models 2 and 3, respectively. In these cases, the tests for overdispersion (Cameron and Trivedi 1990) favor the negative binomial distribution, as the test statistics are greater than 3.84. The negative binomial model deals with overdispersed crash data through an error term that is added to the Poisson formulation. Then, the parameter λ_i becomes

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

where ε_i is a gamma-distributed error term with mean equal to 1 and variance α. The error term allows the variance to differ from the mean, since $\text{Var}\{Y\} = \lambda_\iota + \alpha\lambda_i^2$. The probability density function of the negative binomial model can be defined as

$$\text{Prob}(Y = y_i|X_i) = \Gamma(\theta + y_i)/[\Gamma(\theta)\Gamma(y_i + 1)]u_i^\theta(1 - u_i)^{y_i}, \tag{4}$$

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.

Given that holidays and weekends, the road type, and the land use are represented by macroscopic binary variables, these variables may incorporate an array of unobserved heterogeneous factors that may vary across observations of the same category. To deal with this heterogeneity, a random parameter approach was followed (Shankar et al. 1998; Lord and Mannering 2010), such as

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

where ω_i is a normally distributed term with mean equal to 0 and variance σ^2. The term ω_i affects only the coefficients of the holiday or weekend variable (all models), the road type variable (model 2), and the land-use variable (model 3), as well as the intercept of model 1. Because all of the road type or the land-use variables are included in models 2 and 3, respectively, these models do not include an intercept term.

Therefore, in the random parameter Poisson and negative binomial models, λ_i is reformulated as shown by Eqs. (6) and (7), respectively:

$$\lambda_i|\omega_i = e^{\beta_i X_i} \quad \text{and} \tag{6}$$

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

Model estimations were performed through a simulated maximum likelihood method developed by Greene (2007), using econometric software Limdep 9.0. In the end, the three models were compared considering the perspective of the rainfall impacts on pedestrian–vehicle collisions.

4. Results and discussion

The results from the estimation of model 1 (meteorological variables only), model 2 (meteorological and road type variables), and model 3 (meteorological and land-use variables) are presented in Table 4. From these results, the elasticities of the statistically significant meteorological variables at the 5% level were calculated (Table 5).

TABLE 4. Modeling results. Note that σ = scale parameters for distributions of random parameters and α = dispersion parameter for negative binomial models. After the first five rows, all numbers given are coefficient values, with the significance (P) value in parentheses.

	Model 1	Model 2	Model 3
No. of observations	1789	7156	8945
Overdispersion test $[g(\lambda_i) = \lambda_i]$	1.266	6.578	7.635
Overdispersion test $[g(\lambda_i) = \lambda_i^2]$	1.037	3.256	4.664
Log likelihood	−2321	−3408	−5191
Akaike information criterion	4660	6848	10 413
		Coef (P value)	
Intercept	0.087 (0.036)	—	—
σ	0.176 (0.000)	—	—
Weekend	−0.709 (0.000)	−0.851 (0.000)	−0.779 (0.000)
σ	0.237 (0.000)	0.423 (0.000)	0.325 (0.000)
Road classification			
Arterial	—	−8.286 (0.000)	—
σ	—	3.767 (0.000)	—
Principal distributor	—	−0.864 (0.000)	—
σ	—	0.598 (0.000)	—
Local distributor	—	−1.081 (0.000)	—
σ	—	0.227 (0.000)	—
Local access	—	−3.257 (0.000)	—
σ	—	0.311 (0.014)	—
Land-use classification			
High-density residential	—	—	−0.944 (0.000)
σ	—	—	—
Low-density residential	—	—	−1.261 (0.000)
σ	—	—	—
Industrial	—	—	−11.689 (0.000)
σ	—	—	6.633 (0.000)
Services	—	—	−8.802 (0.000)
σ	—	—	5.361 (0.000)
Historical	—	—	−2.165 (0.000)
σ	—	—	2.467 (0.000)
Meteorological effects			
Daily precipitation	6.2×10^{-3} (0.038)	9.2×10^{-3} (0.007)	6.0×10^{-3} (0.007)
Daily mean temperature <10°C	0.038 (0.554)	0.036 (0.653)	0.012 (0.836)
Daily mean temperature ≥20°C	0.029 (0.719)	0.084 (0.408)	−0.013 (0.869)
Weekly precipitation	-1.4×10^{-3} (0.135)	-7.9×10^{-4} (0.456)	-1.7×10^{-3} (0.020)
Monthly precipitation	8.1×10^{-4} (0.008)	7.5×10^{-4} (0.041)	8.8×10^{-4} (0.000)
α	—	1.941 (0.000)	12.148 (0.001)

From a general perspective, and despite the fact that model 1 does not account for exposure effects, the results are very consistent across the three models, especially with respect to the impacts of the meteorological conditions during the day of the crash. The three models show a positive correlation between daily precipitation and pedestrian–vehicle collisions, whereas the temperature variables do not produce statistically significant effects. For example, on a day with 1 cm of accumulated precipitation, pedestrian–vehicle collisions in Porto are expected to increase between 6% (models 1 and 3) and 10% (model 2). For a 5-cm rainfall (heavy rain), the crash frequency may rise between 35% (models 1 and 3) and 58% (model 2). Considering the elasticities at the sample mean, the results in Table 5 indicate that the doubling of the mean daily precipitation is associated with an increase of 2%–3% in pedestrian–vehicle collisions, ceteris paribus.

In contrast, Martensen et al. (2016) found no effect of daily precipitation on pedestrian–vehicle collisions in Belgium. However, the authors observed a positive correlation between air temperature and the frequency of this type of crashes, attributing this effect to an increased exposure associated with good weather conditions, under which walking is a more attractive activity. Nevertheless, the impacts estimated in this study for daily precipitation are in line with the results of the most

TABLE 5. Estimated percent variations in pedestrian–vehicle collisions associated with doubling the mean rainfall values.

	Model 1	Model 2	Model 3
Daily precipitation	2.0%	3.0%	2.0%
Weekly precipitation	—	—	−3.9%
Monthly precipitation	8.4%	7.7%	9.1%

previous studies about other types of crashes (Xu et al. 2013; Theofilatos and Yannis 2014), which usually relate the poorer conditions of visibility and tire–road friction observed on rainy days with the increase in crash numbers. The elasticities obtained for daily precipitation in this study lie between the previously obtained values for nonpedestrian crashes in Porto (Lobo et al. 2019). The elasticities for nonpedestrian crashes vary from 1.5% to 4.5%, depending on the type of crash, which means that the increase in pedestrian–vehicle collisions caused by rainfall scales approximately with the same increase in other types of crashes. Considering the studies conducted in other regions, Levine et al. (1995) found that, on average, a 1-cm increase in daily precipitation increases the total crash frequency in Hawaii by 5%. Eisenberg (2004) and Black et al. (2017), using data from different sets of U.S. states, estimated that, for a precipitation between 1 and 2 cm, the crash frequency increases by around 25%. For higher values than 5 cm, the former study observed an increase of 35%, while the latter reported an increase of more than 50%. Therefore, under heavy rain, the increase in pedestrian–vehicle collisions in Porto is aligned with the increase in the total number of crashes occurred in other regions. However, given the variability that was verified for lower precipitation values (1–2 cm), the results found for Porto should not be extrapolated to other regions.

With regard to the lagged effects of rainfall, these are represented in this analysis by the weekly and monthly precipitations. Only model 3 shows evidence of a negative correlation between the precipitation accumulated during the previous week and the occurrence of pedestrian–vehicle collisions. The other models did not return statistically significant estimates for this variable. In turn, all the three models reveal that the monthly precipitation is positively correlated with this type of crash. Specifically, the elasticities at the sample mean show that when the monthly precipitation doubles, the crash frequency should increase between 8% and 9%. On the basis of the results from model 3, when the mean weekly precipitation doubles, pedestrian–vehicle collisions decrease by approximately 4%, ceteris paribus (Table 5).

In the previous study on nonpedestrian crashes conducted in Porto (Lobo et al. 2019), it was found that when the precipitation of the previous month doubles, the frequency of single-vehicle crashes and injury crashes decreases by around 2%. No effect was observed in relation to the weekly precipitation. In Chicago, Illinois, Changnon (1996) found that the increase in the total number of crashes and related injuries was higher on rainy days belonging to dry months than on rainy days in normal-to-wet months. Eisenberg (2004), in a nationwide analysis for the United States, and Keay and Simmonds (2006), in a study on Melbourne, Australia, analyzed different periods since the last precipitation and concluded that the crash risk on the first day of rainfall after a dry spell increased with the number of preceding days without rain. Nevertheless, Brijs et al. (2008) tested for the dry spell effects using data from three cities in the Netherlands without significant results. Thus, the positive correlation between monthly precipitation and pedestrian–vehicle collisions returned by the three models developed in the present analysis seems to differ from the increased crash risk of rainfall after long dry periods found by previous studies for other crash types. However, the results cannot be directly compared with previous research as, to the best of the authors' knowledge, there are no other studies investigating the lagged effects of precipitation on pedestrian–vehicle collisions in the literature.

The weekly and monthly precipitation representing the lagged effects in this study cannot be associated with poor conditions during the day of the crash. Therefore, these effects should be associated with other risk factors beyond daily precipitation, such as pavement cleaning and walking and driving behavior. A possible explanation for the obtained results can be related with risk compensation and exposure variation during the rainfall season; there might be an initial period of adaptation of road users to more hazardous conditions (Elvik 2006), accompanied by the fact that some people, especially inactive people, may avoid planning outdoor activities in the short term (Aultman-Hall et al. 2009). Such behaviors could explain the negative correlation that the weekly precipitation tends to have with daily pedestrian–vehicle collisions. After a long period of rain, road users may start to get used to adverse weather, underestimating its effects and adopting risky behaviors, such as accepting lower time gaps for crossing the road and practicing higher driving speeds. Additionally, the exposure to risk is also likely to increase, as more people cannot delay outdoor activities any longer. These considerations may explain the positive correlation between monthly precipitation and crash frequency.

Despite the focus of this analysis being placed on the meteorological impacts on pedestrian–vehicle collisions, the interpretation of the binary variables used to capture the exposure provide an additional insight on the occurrence of this type of crashes. Table 4 shows that the uncertainty of results stemming from the scale parameters for distributions of random parameters σ is limited in relation to the coefficients of the proxy variables. For instance, in model 2, all the coefficients estimated for the road type variables have a statistically significant random component, but in any case, σ is high enough to revert the sign of the average value. In model 3, the effect of the historical center is the only one that can revert its sign within the limits of $\boldsymbol{\beta} \pm \sigma$. This is probably associated with a greater heterogeneity of land use in this zone, where residential, commercial, and tourism activities share the same urban space. In opposition, the coefficients of high-density and low-density residential zones do not reveal statistically significant random components.

Therefore, based on the average coefficients, the results of model 2 indicate that principal and local distributors are more prone to the occurrence of crashes involving pedestrians, followed by local access roads and arterial roads. Principal and local distributors include Porto's main avenues and streets, which collect and distribute vehicular traffic between different zones of the city. In addition, these roads are frequently characterized by an important commercial activity, attracting large volumes of pedestrians. In turn, local access roads have smaller traffic volumes, and, in many cases, their geometry imposes the practice of lower speeds relative to distributors, which may explain the smaller crash risk. Naturally, arterial roads are even less prone to the occurrence of crashes involving pedestrians, as this category comprises motorways, where pedestrian traffic is prohibited by law. Nevertheless, a few pedestrian–vehicle collisions occur on these roads due to law violations committed by pedestrians.

With respect to the land use, the average coefficients obtained in model 3 show that pedestrian–vehicle collisions are more likely to occur at high-density residential zones, followed by low-density residential, the historical center, services, and industrial zones. Although the residential zones are classified after their prevailing land use, these zones in Porto are frequently characterized by mixed land use, featuring a more or less significant concentration of small shops and public services. Therefore, the higher crash risk at residential zones, and also in the historical center, is probably associated with a higher volume of pedestrians walking in these areas. The smaller crash risk in relation to the residential zones observed, on average, at the historical center may be associated with the former's narrow and cobbled streets that limit the practiced speeds. In turn, the two zones classified as services and the industrial zone predominantly consist of large infrastructures with their own parking lots. As these zones rely heavily on private transport, the volume of pedestrians is lower than in other zones of the city, which leads to the occurrence of less pedestrian–vehicle collisions.

Last, it is possible to observe that, as expected, fewer crashes occur on holidays and weekends, as pedestrian and vehicular traffic in cities is usually lower.

5. Conclusions

The variation of meteorological conditions is expected to produce mixed effects on both the crash risk and the exposure to risk. Additionally, meteorological conditions may affect the crash risk through the deterioration of road conditions and through lagged effects on road users' behavior. Based on these assumptions, the present study introduces a novel perspective on the impact of meteorological conditions on the frequency of pedestrian–vehicle collisions. Thus, three different models were used to analyze the effects of diverse meteorological variables. Among the selected variables, temperature was found to be statistically insignificant. Therefore, the analysis focused on the effects of rainfall, represented by daily, weekly, and monthly accumulated precipitation, whereby the latter two represented the lagged effects of this phenomenon. Additionally, binary variables defining the type of road, the land use, and the day of the week were included to represent the diversity of the urban environment and traffic conditions.

The results show that increasing daily precipitation leads to more pedestrian–vehicle collisions, in agreement with the findings from previous research for other types of crashes. Moreover, a higher precipitation volume during the previous 30 days also increases this type of crashes, revealing that wet-monthly periods are related to a higher risk of collisions involving pedestrians. A contradictory effect was found with respect to the precipitation accumulated during the previous seven days. The weekly precipitation and the monthly precipitation can be associated with the effects of rainfall on road users' behavior, potentially reflecting that they may, at the beginning of a wet period, adopt more cautious behaviors to counteract the increased risk posed by the adverse meteorological conditions. However, after a long period of rainfall, road users may start to underestimate those risks and assume nonsufficiently careful practices. Additionally, it is expected that pedestrian traffic decreases at the beginning of a wet period. However, if the rainfall period continues for a long time, at some point pedestrian traffic is expected to rise again, as people that initially avoided walking due to adverse weather cannot delay outside activities anymore due to personal needs. The results from the modeling procedure carried out in this study support the following three conclusions:

1) The increase in pedestrian–vehicle collisions during rainy days is in line with the variation of the numbers of all types of crashes observed in most previous studies.
2) Wet-weekly periods may decrease the frequency of pedestrian–vehicle collisions, probably due to

the mixed effects affecting both crash risk and exposure. The behavioral adaptation of road users and the potential reduction of pedestrian traffic volume may counteract, in the short term, the hazardous effects of precipitation.

3) Wet-monthly periods increase the risk of crashes involving pedestrians, contradicting previous findings for other types of crashes. This may be caused by the habituation of road users to hazardous conditions, reflecting a potential increase in pedestrian exposure and risky behaviors in the long term.

Previous studies focusing on pedestrian–vehicle collisions did not explore the relation between precipitation and crash risk. Therefore, the outcomes of this study cannot be directly compared to previous findings. The specific nature of meteorological impacts on pedestrian–vehicle collisions, as well as cross-country differences in terms of climatology and road users' culture and behavior may explain the finding of contradictory lagged effects of precipitation between this study and other studies for other types of crashes.

6. Limitations and future research

Despite the contributions to understand the relation between adverse weather and the risk of crashes involving pedestrians, the quantitative approach followed in this study presents some limitations that are mainly related to the available data. The weather and crash data come from different sources that overlap only for the years between 2001 and 2005. Therefore, changes in factors that affect pedestrian and driver exposure/vulnerability, such as distractions related with the use of technology and the availability of new driver assistance systems, have occurred since then, which may partially account for the variation in the proportion of pedestrian deaths in relation to the total road fatalities. In addition, this study considers weather and crash variables aggregated at a daily time scale and proxy variables for traffic exposure. Such variables are commonly used to analyze the weather effects on crash risk but are still insufficient to represent the exact weather and traffic conditions at the time of a crash.

In the actual context of climate change, the projections presented in the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change depict, among other effects, an increase in temperature, changes in precipitation patterns, and an increase in the number and strength of extreme weather events (Pachauri et al. 2014). These changes, predicted all over the world, can present variations in intensity and typology from one region to another, reinforcing the need to continuously report and link meteorological variables to several phenomena, of which road crashes are an example. Therefore, the evaluation of the impacts of weather conditions on road crashes is of critical importance and should be continuously addressed to ensure the safety of all road users.

Thus, further research focusing on pedestrian–vehicle collision risk should explore the relevance of the weather effects on crash risk across space and time, considering different contexts imposed by the surrounding environment and the evolution of climate, technology, and mobility patterns. To do this, the interaction between meteorological conditions, exposure, and technology or behavioral change must be addressed. In addition, regional and cross-country comparisons could be performed to highlight the diversity in geographic, meteorological, and cultural characteristics. Future research should also seek to improve the specification of precrash conditions, particularly if real-time weather and/or traffic data are available. The improvement of data quality is a key aspect to fully take advantage of the most advanced modeling techniques.

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