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The Use of Macro-Level Safety Performance Functions for Province-Wide Road Safety Management

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Abstract: Safety Performance Functions (SPFs) play a key role in identifying hotspots. Most SPFs were built at the micro-level, such as for road intersections or segments. On the other hand, in case of regional transportation planning, it may be useful to estimate SPFs at the macro-level (e.g., counties, cities, or towns) to determine ad hoc intervention prioritizations. Hence, the final aim of this study is to develop a predictive framework, supported by macro-level SPFs, to estimate crash frequencies, and consequently possible priority areas for interventions. At a province-wide level. The applicability of macro-level SPFs is investigated and tested thanks to the database retrieved in the context of a province-wide Sustainable Urban Mobility Plan (Bari, Italy). Starting from this database, the macro-areas of analysis were carved out by clustering cities and towns into census macro-zones, highlighting the potential need for safety interventions, according to different safety performance indicators (fatal + injury, fatal, pedestrian and bicycle crashes) and using basic predictors divided into geographic variables and road network-related factors. Safety performance indicators were differentiated into rural and urban, thus obtaining a set of 4 × 2 dependent variables. Then they were linked to the dependent variables by means of Negative Binomial (NB) count data models. The results show different trends for the urban and rural contexts. In the urban environment, where crashes are more frequent but less severe according to the available dataset, the increase in both population and area width leads to increasing crashes, while the increase in both road length and mean elevation are generally related to a decrease in crash occurrence. In the rural environment, the increase in population density, which was not considered in the urban context, strongly influences crash occurrence, especially leading to an increase in pedestrian and bicyclist fatal + injury crashes. The increase in the rural network length (excluding freeways) is generally related to a greater number of crashes as well. The application of this framework aims to reveal useful implications for planners and administrators who must select areas of intervention for safety purposes. Two examples of practical applications of this framework, related to safety-based infrastructural planning, are provided in this study.

Keywords: macro-level safety analysis; safety performance functions; regional variables; road crashes

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1. Introduction

The use of Safety Performance Functions (SPFs) is critical for different applications, such as predicting crash frequencies for new road segments or intersections, comparing different project alternatives and ranking them according to benefit–cost analyses, and determining the safety potential of a road site in the context of an enhancement project [1]. For this reason, they have been widely used in road safety studies and analysis in order to determine the most dangerous road sites and to predict the expected crash reduction after the implementation of given countermeasures.

The SPFs are specific for a family of road sites, and they are calibrated for segments or intersections, making a distinction between different categories of segments and intersections (e.g., divided/undivided segments, signalized/unsignalized intersections).

This is since different geometric characteristics imply different parameters which may be influential in predicting crashes.

The reliability of SPFs in predicting crashes and their wide use, has led researchers to try extending their applicability not only to single segments and intersections, but also to some larger areas [2–4]. Under this view, the idea of considering "macro-level SPFs" starts by aggregating areas with comparable characteristics and allows us to make predictions for them. This approach is justified by an important aspect of macro-level SPFs, i.e., their potential practical use, related to the type of application. For example, they may be useful for highlighting zones where the crash frequency is higher than average. If this concept is extended to counties, provinces, or regions, they may be used to highlight areas which may potentially benefit from road safety improvements, if some funds should be allocated to different local administrations. In the case of regional transport plans, they may be useful for identifying counties, cities, or towns where interventions should be prioritized with respect to other contexts [5].

In this study, this latter aspect is particularly investigated. In fact, starting from the available dataset for the sustainable mobility plan, a province-based SPF was developed with the aim of highlighting areas with potential for safety improvements, considering both urban and rural road networks. Hence, the main objective of this study is developing a predictive framework for crash frequencies at a province-wide level by using, as the aggregation variable, the macro-zones limit of census, to define the areas of interest, and discussing its potential practical applicability.

Related Work

In recent years, the concept of SPFs was not limited to specific road segments or intersections, but it was also taken to a higher level considering macro-level SPFs. In these macro-level SPFs, safety performances refer to wide areas, such as census blocks [6], traffic analysis zones, TAZs or districts [7–12], city wards [13], cities, counties [3], regions, and states.

Choosing the level of spatial aggregation is not straightforward, since it may depend on data availability, the intended use of results, and local factors. For example, Montella et al. [4] argued that the use of TAZs may not lead to a homogeneous representation of a city (Naples, Italy, in this specific case), with several small zones for which zero crashes were recorded. This problem is generally present in very large cities in which TAZs may coincide with blocks or even single buildings. Moreover, TAZs are often delimited by urban arterials, on which crashes may cluster, generating border effects which should be taken into account while modelling data. More refined techniques, such as the Bayesian Poisson–lognormal models [14] are, for example, able to explicitly account for spatial correlations among TAZs, performing better than traditional models.

Moreover, a typical problem of SPFs is their transferability in different contexts, especially when these functions are transferred to other regions. For example, Farid et al. [15] assessed the transferability of SPFs across different states of the United States; Intini et al. [16] assessed the transferability of American SPFs to two European countries. In both cases, it was noted how a simple calibration process may be improved by considering other influential variables or more refined procedures. While the transferability issue is still generally scarcely studied for macro-level SPFs, an attempt at investigating the international transferability of macro-level SPFs between the United States and Italy was made [2]. They concluded that some similarities can be noted between US counties and Italian provinces, but also several differences. Hence, choosing the appropriate spatial aggregation is also driven by geographic factors.

In these macro-level studies, the variables predicting crashes are aggregated as well, and related to the entire transport system and mobility phenomenon rather than site-specific, also including socio-economic factors. In the previously cited studies, some of the most frequently considered variables are total population or population divided into age or gender classes (demographics is generally used in other types of safety studies such as those based on self-reported behaviors, see e.g., [17,18], rather than for crash predictions), population density, vehicle miles travelled, modal split, total number of trips (generated or attracted by the zones), some measures of traffic speed and congestion. Supply-related variables are also used, such as the length of road network or the number of bus stops served per hour [4], the pavement conditions [9,19], and the density of different urban road types [6,7]. Other socio-economic variables such as income, unemployment rate [7,20], private car and driving license ownership, number of registered vehicles [11], instruction level [3,6], and number of hotels/motels [9,10] were considered as well. In the study by Wang et al. [12] focused on pedestrian crashes, the number, type, and distance between intersections and the prevalent land use were considered.

As previously indicated, in most previous studies, the elementary unit of analysis ranges from narrow/very narrow (such as census blocks or TAZs) to very wide (regions and countries, especially in studies focused on transferability or geographic variations of safety outcomes within a country), whereas in this study, an intermediate dimension is explored, by considering census macro-zones within a province, and focusing on potentially transferrable models based on easily retrievable geographic and road network-related variables. This choice may have possible practical implications, as discussed in the following.

2. Methods

The level of spatial aggregation used is defined as follows. The information collected for each area are further described, followed by the presentation of the statistical methods used for modelling purposes.

2.1. Data Description

The data collection is articulated in two different steps. The first one is related to the definition of the macro-areas used for the study, carved out from the Metropolitan City (Province) of Bari. The zones have been aggregated and then, for each zone, the crashes that had occurred were recorded. The second step concerns the choice of the safety performance indicators to be used as dependent variables in the modelling stage, based on the available data. For this aim, the crashes were differentiated by severity and involved users and then classified as urban or rural.

2.1.1. Spatial Aggregation in the Context of a Province-Wide Sustainable Urban Mobility Plan

Sustainable Urban Mobility Plans (SUMPs) are recently introduced by the European Union as urban mobility plans, which emphasize measures for enhancing and promoting sustainable mobility, whilst reducing vehicular traffic and emissions [21]. Based on a study by Kiba-Janiak and Witkowski [22], the most frequently introduced measures in the SUMPs of European capital cities are access restrictions for passenger and freight transport (implying both spatial and time restrictions). Within the SUMPs, different targets are set for the whole mobility system, including road safety targets whose main aim is to reduce the crash occurrence, especially for Vulnerable Road Users (VRUs).

In Italy, the drafting of the SUMPs is not strictly limited to a specific city; it could be developed by large cities and by groups of cities, including provinces (considering provinces as an agglomerate of urban settlements), with a view to optimize transport and mobility working simultaneously on different cities that are seen as a unique system and not as separate entities. The starting point for the applicability of macro-level SPFs is the availability of a crash dataset; in this case, it is the same dataset achieved in the context of the development of a province-wide SUMP (for the Metropolitan City of Bari MCB, Italy).

In detail, the MCB province (see Figure 1) is 3862 km^2 wide and it has a population of about 1.2 million inhabitants. About 25% of total inhabitants (0.3 million) live in the main city (Bari). Another three densely populated cities, with a population between 50,000 and 70,000 inhabitants, are Altamura, Molfetta, and Bitonto. Most of the other towns in the MCB province are significantly less populated.

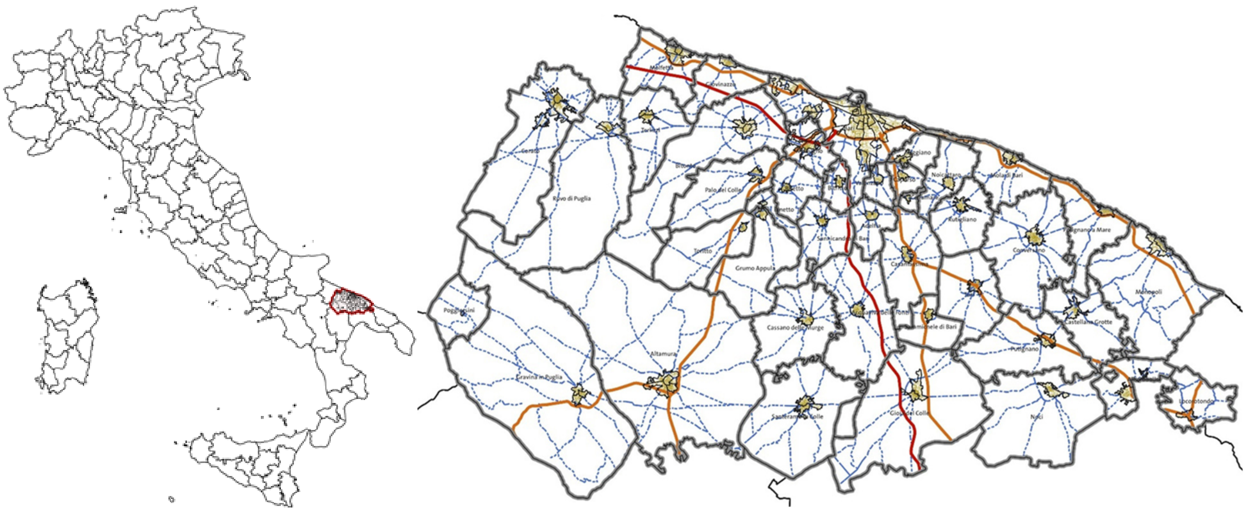


Figure 1. Identification of the Metropolitan City of Bari in Italy (on the left) and delimitation of the 41 areas belonging to the cities/towns in the province (on the right), by highlighting the road network (freeways in red, highways in orange, secondary/minor rural roads represented by blue dotted lines, urban roads in yellow).

According to the Italian National Institute of Statistics (ISTAT), Italian cities and towns are divided into census zones [23]. Moreover, census zones are further aggregated into "macro" census zones of greater dimensions (and more inhabitants). In detail, most small towns in the province are aggregated into a single census macro-zone; medium- and large-sized towns are aggregated into two or more census macro-zones (a rural zone surrounding the urban area and one, or more, census macro-zones covering the urban area); cities are aggregated into several census macro-zones.

This study uses the census macro-zones as the unit of spatial aggregation for the macro SPF, which are a trade-off between census zones and large areas such as towns/cities or counties. Hence, in this case, the macro SPF development is aimed at highlighting which areas may evidently need safety interventions, at a reasonable level of detail. In fact, in this way, small road networks belonging to census macro-zones are highlighted as areas requiring safety interventions, which may be planned and prioritized at the provincial level, by overcoming the previously mentioned issues of using census zones and the potentially dispersive information provided by a model developed using large areas (e.g., towns or counties) as the unit of aggregation.

Moreover, the definition of census macro-zones is useful as well, making a distinction between safety performances of urban road networks and safety performances of rural road networks, since, as previously indicated, most rural areas are separated by the urban census macro-zones, apart from the case of small towns (represented by single zones). This issue related to small towns was overcome by separating urban and rural safety performances, thanks to an artificially recreated urban macro-zone. It was obtained by using boundaries of urban agglomerates as the zone limit. Following this procedure, each town/city in the province is divided into a rural zone and one or more urban macro-zones. This led to an urban dataset composed of 81 macro-zones and a rural dataset composed of 43 macro-zones (see Figure 2).

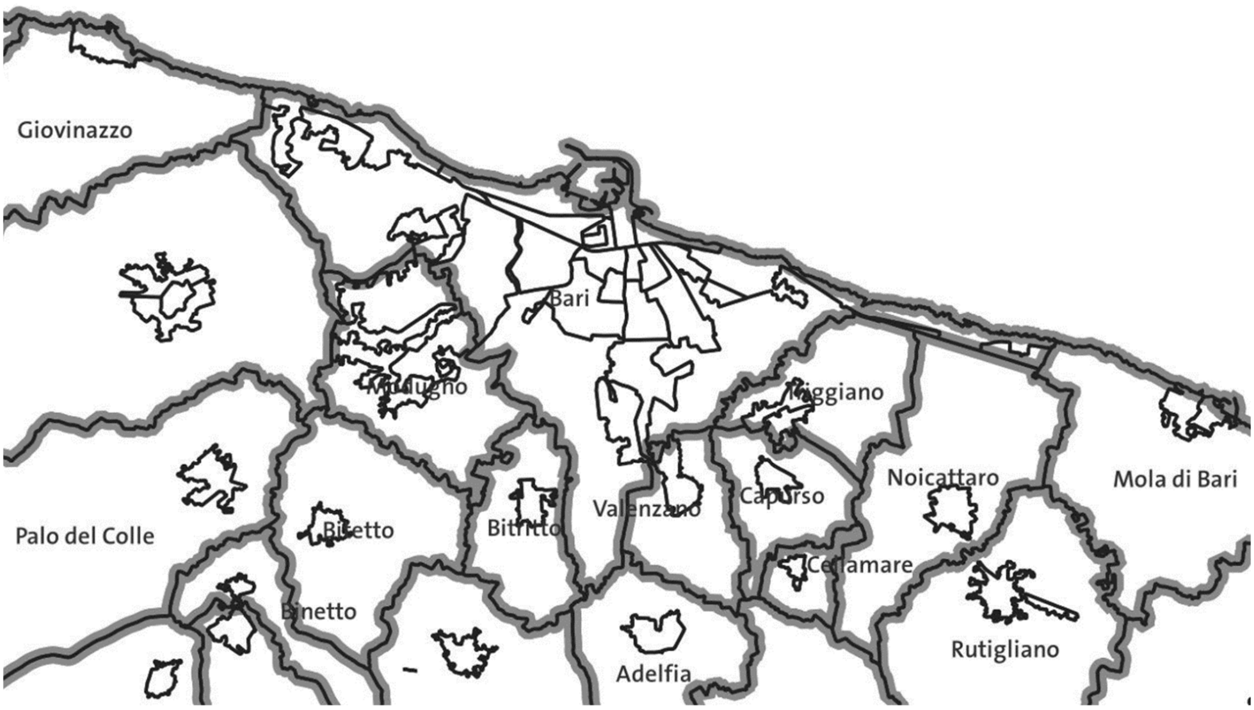


Figure 2. Example of disaggregation of each town/city area into macro-zones (town/city area boundaries are in dark grey, while the delimitation of macro-zones is represented by thin black lines, urban areas of major towns/cities are divided into more macro-zones).

2.1.2. Safety Performance Indicators and Predictor Variables

As mentioned above, the Safety Performance Functions (SPFs) require the use of safety performance indicators, which are used as dependent variables in the modelling stage. The selected safety performance indicators (see Table 1) are the following:

- fatal + injury (FI) crash frequency (crashes/year);
- fatal (F) crash frequency (crashes/year);
- pedestrian crash frequency (crashes/year);
- bicyclist crash frequency (crashes/year).

Table 1. Safety performance indicators for the MCB province.

Safety Performance Indicator	Total (Rural + Urban) (Crashes/Year)	Rural (Crashes/Year)	Urban (Crashes/Year)
Total crash frequency	3418.6	1112.4	2306.2
Fatal crash frequency	51.0	34.4	16.6
Pedestrian crash frequency	399.2	14.6	384.6
Bicyclist crash frequency	171.0	26.2	144.8

These four main indicators were further differentiated into rural crashes and urban crashes, thus obtaining a set of eight (4×2) dependent variables. All these crash-related indicators were calculated based on the ASSET (Puglia Regional Agency)–ISTAT (Italian National Institute of Statistics) database. This database contains the exact location, thanks to the geographic coordinates of crashes that have occurred and been recorded in the province, for the 5-year observation period 2015–2019. It should be pointed out that this dataset includes fatal + injury (FI) crashes only. Hence, the pedestrian and bicyclist crash frequencies should be intended as the frequency of FI crashes in which at least one pedestrian and one bicyclist was involved.

The modeling stage also requires the definition of independent variables. Based on previous research, a wide list of potential independent variables could be used for modelling. However, in this study, the aim is to develop a methodological framework to highlight safety issues at the planning level, potentially transferrable to other contexts and thus also based on simple variables to be collected, in order to be practically applied. Moreover, the number of census macro-zones in a province is evidently limited and then the use of an excessive number of predictors may lead to possible overfitting issues. Hence, the choice of predictors was limited to those variables which can be easily retrieved from main local database to foster applicability and transferability, divided into geographic variables and road network variables (see Table 2). Those variables are collected for each identified macro-zone in the province. The selection of potential predictors in safety analyses is always related to their possible relationships with crash occurrence and severity, and, in case of macro-level SPFs, they might represent wide areas.. The final purpose of estimating a province-based SPF implies relying on geographic variables which may have an impact on the driver behavior and safety perception, but also selecting road network-related variables, which may have a direct impact on crash frequency.

Table 2. Dependent variables considered.

Variable Type	Independent Variable	Source	Rural Environment				Urban Environment			
			Mean	St. dev.	Max.	Min.	Mean	St. dev.	Max.	Min.
Geographic	Population (inhabitants)	ISTAT	7945.1	6760.3	19,340.0	196.0	14,446.6	3804.4	22,661.0	1418.0
	Total area (m^2)	GIS	$85.4{\cdot}10^6$	$88.3{\cdot}10^6$	$419.7{\cdot}10^6$	$5.4{\cdot}10^6$	$1.9{\cdot}10^6$	$1.3{\cdot}10^6$	$7.9{\cdot}10^6$	$0.2{\cdot}10^6$
	Density (inhabitants/m^2)	ISTAT/GIS	0.3	0.4	2.1	0.0	10.1	5.5	35.4	2.2
	Mean elevation (m)	ISTAT	199.3	144.2	489.0	5.0	162.3	161.0	489.0	5.0
Road network	Secondary network length (m)	OSM/GIS	$38.8{\cdot}10^3$	$34.7{\cdot}10^3$	$163.2{\cdot}10^3$	$1.3{\cdot}10^3$	$1.0{\cdot}10^3$	$1.5{\cdot}10^3$	$9.1{\cdot}10^3$	0.0
	Primary network length (m)	OSM/GIS	$5.2{\cdot}10^3$	$6.6{\cdot}10^3$	$29.7{\cdot}10^3$	0.0	$0.3{\cdot}10^3$	$0.8{\cdot}10^3$	$4.3{\cdot}10^3$	0.0
	Freeway network length (m)	OSM/GIS	$1.6{\cdot}10^3$	$3.7{\cdot}10^3$	$15.6{\cdot}10^3$	0.0				
	Urban network length (m)	OSM/GIS					$30.2{\cdot}10^3$	$13.8{\cdot}10^3$	$74.2{\cdot}10^3$	$4.3{\cdot}10^3$

Notes: ISTAT data refer to the year 2019. OSM means Open Street Map, used as a reference for the road layouts; their length is after calculated in a GIS environment.

The geographic variables considered are the following (see also [24]):

- population,
- population density,
- area width,
- mean elevation of the area above sea level (see, e.g., [25]).

Population and area variables can be considered as surrogate risk exposure variables, since the increase in population may lead to an increase in road users and, then, in car traffic, cyclist, and pedestrian volumes; the increase in density can also be related to higher volumes and possible congestion in the area. The increase in the area width can be potentially indirectly related to the increase in road users on the network too. In fact, a larger area means a greater number of kilometers to be covered by users, hence greater exposure. Moreover, elevation is considered, since it may affect the driving behavior (lower speeds and more cautious attitude) and be related to a greater complexity in road geometry, which may be strictly connected to safety issues [26,27], especially in the rural environment (i.e., for higher elevations).

The variables related to the road network are length of the secondary road network (i.e., in this case, mainly roads managed by the province), length of the primary road net-work (i.e., in this case, roads managed at a national level), length of the freeway road net-work, and length of the urban road network. The length of the road network is clearly a surrogate risk exposure variable as well, as previously explained. To differentiate the possible impact of different categories of roads, the separated effect of different types of road networks is considered here, since the exposure to the total road network could have already been considered through the effect of area and population. In fact, the exposure to risk on a freeway network segment could be completely different than the exposure on a secondary network segment.

The length of the road network was considered (such as in previous safety studies, e.g., [24,28] rather than the percentage of road network falling under a given category with respect to the entire road network, for two different reasons (however, assuming that the two variables are mathematically related). The first reason is related to the practical implications of the framework; in fact, finding out the length of a road is easier and faster, thanks to GIS-based applications. Moreover, road agencies may already have stored official information about length of different road segments divided by categories and municipalities. The second reason is related to possible errors in estimating these data, since the length is an absolute value, while the percentage is relative. Hence, relying on the percentage would imply considering all the roads belonging to the network in the calculation, even those without any traffic or too short to be considered significant (which are usually not recorded in any official database of road agencies). Hence, not considering those roads could possibly lead to altering the percentage calculation. This issue is negligible when considering the length of the investigated roads instead.

While all the geographic variables are considered as predictors of road crashes, either in the urban or in the rural environment, road network variables are considered as predictors of road crashes in the urban or rural case. In fact, the secondary and primary network lengths are predictors of both urban and rural crashes, since secondary and primary roads can also enter urban areas. On the other hand, the freeway network length is a predictor of rural crashes only (freeways do not enter urban areas) and the urban network length is clearly only a predictor of urban crashes.

2.2. Statistical Methods

Safety performance indicators were linked to the selected dependent variables by means of Negative Binomial (NB) count data models, which can account for the phenomenon of crash data over-dispersion [29]. NB models have already been used for developing macro-level SPFs in previous research [2,4,11].

NB models were estimated in the R environment [30]. The model structure used is reported in the following equation:

$$SPI = e^{\sum_{i=1}^{n} \beta_0 + \beta_i \ X_i} \tag{1}$$

where:

SPI = safety performance indicator (Table 1);
$\beta_{0,1,n}$ = coefficient estimates;
X_i = dependent variables (Table 2).

Preliminary models were firstly estimated by considering all the dependent variables together in predicting the safety performance indicators listed in Table 1: fatal (F), injury (I), pedestrian, and bicyclist crash frequencies for both urban and rural environment. The indicator related to injury crashes was not considered as an independent variable, since it almost coincides with the fatal + injury crash indicator (fatal crashes account for less than 3% of FI crashes). Hence, eight preliminary models were obtained in the first instance.

Afterward, stepwise regression algorithms, together with model comparisons based on likelihood ratio tests, were used to select the optimal combination of variables in terms of model fit. In particular, the Akaike Information Criterion (AIC) was used as a baseline metric for the stepwise regression. The Nagelkerke R^2 was used as a goodness-of-fit measure. The final selected models were compared to the corresponding null and full models through likelihood ratio tests. The chosen level of significance for all statistical tests was set to $p = 0.05$.

3. Results

The models obtained from the statistical analyses are reported as follows, divided into models for the rural and for the urban environment.

3.1. Models for the Rural Environment

The selected models obtained for the rural environment are reported in the next Table 3.

Table 3. Models estimated for the rural environment.

Independent Variables	Coefficient Estimates (Standard Errors in Parenthesis)			
	Total (F + I) Crashes	Fatal Crashes	Pedestrian (F + I) Crashes	Bicyclist (F + I) Crashes
(Intercept)	2.980 $(9.145\cdot10^{-2})$	$-5.309\cdot10^{-1}$ $(1.579\cdot10^{-1})$	-1.456 $(3.424\cdot10^{-1})$	$-6.764\cdot10^{-1}$ $(1.957\cdot10^{-1})$
Population density	-	-	$8.741\cdot10^{-1}$ $(3.219\cdot10^{-1})$	$4.760\cdot10^{-1}$ $(2.141\cdot10^{-1})$
Mean elevation	$-2.492\cdot10^{-3}$ $(3.949\cdot10^{-4})$	$-1.681\cdot10^{-3}$ $(7.111\cdot10^{-4})$	$-3.985\cdot10^{-3}$ $(1.238\cdot10^{-3})$	$-3.339\cdot10^{-3}$ $(7.973\cdot10^{-4})$
Length of the secondary road network	$8.963\cdot10^{-6}$ $(1.872\cdot10^{-6})$	$1.376\cdot10^{-5}$ $(2.428\cdot10^{-6})$	-	$1.492\cdot10^{-5}$ $(2.835\cdot10^{-6})$
Length of the primary road network	$4.832\cdot10^{-5}$ $(8.926\cdot10^{-6})$	-	$9.222\cdot10^{-5}$ $(2.402\cdot10^{-5})$	-
Goodness of fit measures				
Nagelkerke R^2	0.494	0.151	0.212	0.162
Mean square error (MSE)	231.61	0.25	0.28	0.18

Note: all coefficient estimates associated to the independent variables are statistically significant at the 5% level.

It is possible to note that the mean elevation is included in all models developed for the rural environment presented in Table 3. In particular, an increase in the mean elevation consistently leads to a decrease in all the types of investigated F + I crashes. On the other hand, an increase in the length of the secondary network consistently leads to an increase in all types of investigated F + I crashes (other than pedestrian crashes). The length of the primary network is related to an increase in F + I crashes and in pedestrian F + I crashes. Population density is influential on both pedestrian and bicyclist F + I crashes: more densely populated areas exhibit more pedestrian and bicyclist crashes.

3.2. Models for the Urban Environment

The selected models obtained for the urban environment are reported in the next table (Table 4).

In this case, area, population, and the length of the urban road network are included in all models developed for the urban environment. The relationship between area, population, and crashes is consistent for all crash types: the increase in both area and population leads to an increase in all the F + I crash types considered. Conversely, the increase in the length of the urban road network is related to a decrease in all the F + I crash types considered. The increase in the length of the secondary road network is related to a decrease in all crash types considered as well, other than urban fatal crashes, for which it is irrelevant. The increase in elevation leads to a decrease in all types of F + I crash other than fatal crashes.

Table 4. Models estimated for the urban environment.

Independent Variables	Coefficient Estimates (Standard Errors in Parenthesis)			
	Total (F + I) Crashes	**Fatal Crashes**	**Pedestrian (F + I) Crashes**	**Bicyclist (F + I) Crashes**
(Intercept)	1.823 ($1.350{\cdot}10^{-1}$)	-2.596 ($5.450{\cdot}10^{-1}$)	$3.657{\cdot}10^{-1}$ ($2.008{\cdot}10^{-1}$)	$-7.611{\cdot}10^{-1}$ ($2.563{\cdot}10^{-1}$)
Area	$3.421{\cdot}10^{-7}$ ($3.839{\cdot}10^{-8}$)	$4.403{\cdot}10^{-7}$ ($1.23{\cdot}10^{-7}$)	$2.264{\cdot}10^{-7}$ ($5.484{\cdot}10^{-8}$)	$1.858{\cdot}10^{-7}$ ($6.127{\cdot}10^{-8}$)
Population	$1.267{\cdot}10^{-4}$ ($1.029{\cdot}10^{-5}$)	$8.142{\cdot}10^{-5}$ ($4.039{\cdot}10^{-5}$)	$1.360{\cdot}10^{-4}$ ($1.527{\cdot}10^{-5}$)	$1.268{\cdot}10^{-4}$ ($1.925{\cdot}10^{-5}$)
Mean elevation	$-2.273{\cdot}10^{-3}$ ($2.093{\cdot}10^{-4}$)	-	$-1.441{\cdot}10^{-3}$ ($3.043{\cdot}10^{-4}$)	$-2.521{\cdot}10^{-3}$ ($4.002{\cdot}10^{-4}$)
Length of the urban road network	$-2.123{\cdot}10^{-5}$ ($3.925{\cdot}10^{-6}$)	$-3.625{\cdot}10^{-5}$ ($1.500{\cdot}10^{-5}$)	$-3.194{\cdot}10^{-5}$ ($5.718{\cdot}10^{-6}$)	$-1.599{\cdot}10^{-5}$ ($6.680{\cdot}10^{-6}$)
Length of the secondary road network	$-1.459{\cdot}10^{-4}$ ($2.221{\cdot}10^{-5}$)	-	$-1.544{\cdot}10^{-4}$ ($3.440{\cdot}10^{-5}$)	$-1.571{\cdot}10^{-4}$ ($4.323{\cdot}10^{-5}$)
Goodness of fit measures				
Nagelkerke R^2	0.714	0.059	0.361	0.345
Mean square error (MSE)	564.13	0.05	22.69	2.28

Note: all coefficient estimates associated to the independent variables are statistically significant at the 5% level.

4. Discussion

In this section, the results in terms of influential factors on crash frequency are discussed in light of previous research. Afterward, some practical implications of this approach are described.

4.1. *Influential Factors on Crash Frequency*

The influential factors on rural and urban crash frequency (at the macro-zone level) are summarized in the next table (Table 5), according to the models presented in Tables 3 and 4. It is possible to note that all predictors are included in at least one model for estimating crash frequencies, except the freeway network length, which is not influential.

Table 5. Summary of the influential factors on crash frequency (+ = crash frequency increases as the predictor increases, − = crash frequency decreases as the predictor increases).

Variable Type	Predictors	Rural				Urban			
		F + I	**F**	**Ped. (F + I)**	**Bic. (F + I)**	**F + I**	**F**	**Ped. (F + I)**	**Bic. (F + I)**
Geographic	Population					+	+	+	+
	Total area					+	+	+	+
	Population density			+	+				
	Mean elevation	−	−	−	−	−		−	−
Road network	Urban road network length					−	−	−	−
	Secondary road network length	+	+		+	−		−	−
	Primary road network length	+		+					
	Freeway road network length								

As far as the geographic predictors are concerned, the increase in both population and total area of the macro-zones are consistently related to an increase in all the urban crash frequencies. This could be explained by the fact that, as expected, as the area and the population increase, the number of road users increases. Hence, these variables can be considered proxies of risk exposure measures (i.e., traffic, cycling, and pedestrian volumes). Population was found to be a consistent predictor of crashes in other studies as well, such as [2], which considers total, bicyclist, and pedestrian crashes at both at the country level in the United States and the province level in Italy, or that by Wang et al. [12] concerning pedestrian crashes. Moreover, other studies have found that the effect of population may depend on age classes: Montella et al. [4] and Saha et al. [6] have found that crash frequency can increase for both young (less than 25 years) and old (more than 65 years). Area variables are less frequently used, by preferring population, density or infrastructure-based exposure variables. For instance, Wei and Lovegrove [31] include areal zones as independent variables to predict bicyclist crashes at the TAZ aggregation level, but area predictors were not included in the final models (while cycling network lengths were selected). However, area width emerges in this study (based on census macro-zones) as an important exposure variable to be considered in the urban environment, together with population: urban crashes increase with both macro-zone area and population, while they are evidently not dependent on population density in this case.

However, it is worth noting that in the rural environment, area and population are not included in the predictors. In fact, in the rural case, population is low and scarcely variable among the rural macro-zones, and the area width does not seem relevant if information about the road network length is omitted. On the other hand, population density emerges as influential for predicting rural pedestrian and bicycle crashes. This can be clearly explained by the fact that, in the rural environment, cycling and pedestrian volumes are notably low, other than in the case of higher population density (e.g., presence in the rural macro-zone of very small villages far from the main town/city), which can be considered as a risk exposure measure for bicyclist and pedestrian crashes in the rural environment. The decrease in region population density was often related to higher mortality rates after traffic crashes in previous research [32,33]. However, in this case, where urban and rural areas were separated, this overall effect was not identified, other than the case of pedestrian and bicyclists, for which an opposite tendency was noted, as previously explained.

Mean elevation can be instead consistently highlighted as a predictor of crashes in both the urban and rural environments. In particular, the higher the elevation, the lower are all types of considered crash frequencies (with the only exception of fatal urban crashes). There are few studies in previous research which specifically assess the influence of terrain elevation. Choi et al. [34] identify the terrain factor as an important variable to consider while investigating major rural road crashes, flat terrain resulting in being significantly safer than mountainous terrain. In this study, a single province is investigated, with a mean elevation varying between about sea level and almost 500 m (thus not including "mountainous" terrains) and, as can be noted from Figure 1, most large urban areas are concentrated along the coastal strip. Thus, in the rural environment, the inverse elevation–crashes relationship could be explained by road infrastructures (mostly secondary roads, in opposition to [34], which are more adherent to the ground, e.g., with steeper grades and shorter curvature radii, with drivers being more prudent on them, see also [35]). In the urban environment, the interpretation related to the geometric design can be less relevant, while it is possible that the effect of elevation may be a proxy for other variables not controlled in this study (e.g., different driving populations in small rural towns with higher elevations than large coastal towns). In any case, elevation emerges as an aspect to be considered in further detail in future studies.

As far as the road network predictors are concerned, there is a clear difference between the urban and the rural environment. In the rural environment, as the secondary and primary road network length increase, crashes generally increase. Hence, in the rural environment, these lengths work as risk exposure measures, as expected. However, some important differences must be noted: while both secondary and primary network lengths predict F + I rural crashes, the secondary length is a predictor of fatal and bicyclist crashes and the primary length is a predictor of pedestrian crashes. Generally, on rural roads, the pedestrian and bicyclist volumes are very low. Hence, this specific result highlights that the few pedestrians are particularly endangered on primary roads (i.e., generally roads managed by the main national road agency, which have higher road standards and which are often divided, multi-lane roads, in agreement with [36], who, however, take into account the densely populated New York City area) and the few cyclists on secondary roads (i.e., generally roads managed by the province, which have lower road standards and are mostly two-way, two-lane roads). This was expected, since the low volume of rural bicyclists can be concentrated on secondary roads and the possible conflicts with pedestrians are surely more critical on primary than on secondary roads. At the same time, fatal crashes seem unaffected by the primary network length, but rather dependent on the secondary network length, thus leading to the argument that fatal crashes may be clustered on secondary roads, as expected. Moreover, the freeway network is uninfluential for predicting crashes at this aggregation level, given its limited extension in the investigated province and its relatively low crash rate with respect to other road types (see e.g., [37]).

In the urban environment, crash frequencies generally decrease with the urban and secondary network lengths, but they are not influenced by the primary network length (as expected, since the exposure to primary roads which cross the urban environment is clearly limited). The inverse relationship between urban crash frequencies and network length could seem counterintuitive. In the urban environment, it was already noted how population and area width act as risk exposure measures. Hence, it can be argued that area and population being equal, as the road network increases (i.e., as the road network "density", computed in respect to the area), urban crash frequencies decrease. More dense urban road networks may in fact imply short road segments, relatively low speeds, and congested flows with respect to less dense networks. This agrees with results from Marshall and Garrick [38], who argue that the risk of fatal or severe crashes may increase as the street network density (or intersection density) decreases, based on the analysis of Californian cities. Similar results were found by Guerra et al. [39], but with specific regard to population density, which in this study was found to be an insignificant predictor in the urban environment. It is worth noting that the secondary (urban) network length does not predict fatal crashes, possibly because the risk exposure to secondary roads in the urban environment is limited and the role of secondary roads is not a determinant for the occurrence of fatal crashes.

4.2. Practical Implications

The SPFs have been widely used by practitioners, given their capability of finding hotspots and determining the potential reduction in crashes in a quantitative way. There are several practical implications, such as implementing ad hoc strategies for pedestrians [40], or modifying the layout of an intersection [41]. The use of macro-level SPFs extends the importance of this practice from the identification of specific segment/intersection hotspots to hotspot areas at a higher level. At the planning stage in a wide area (e.g., province, region, state), where the granularity of the safety analyses cannot be obtained at the level of the single segment or intersection, this aspect becomes crucial because it may help practitioners, administrations, and so forth, to be aware of the areas in which road networks may be prioritized for safety interventions and to allocate money effectively and in a timely manner. Thus, the use of public funds to make safety interventions, as well as the time window to decide which sites require interventions before than others, could be optimized by analyzing the specific targeted area. Afterward, according to safety performance targets, specific plan and policy objectives can be different, i.e., prioritizing the reduction of fatal crashes and/or the reduction of crashes to vulnerable road users in the urban environment. The latter targets are typical of SUMPs [21]. In the case of a province-wide SUMP, interventions may be differentiated according to the different urban or rural environments, and then specific targets can be evaluated. Two examples of uses of the developed models are provided below to show their practical implications in different cases.

In this sense, the developed models are here applied to the same dataset referring to the MCB (Metropolitan City of Bari), to show how they can potentially be used to highlight hotspot areas, with respect to each of the considered crash frequencies (fatal + injury, fatal, pedestrian, bicyclist) in both the urban and rural environment. Hotspot areas can be identified through different possible techniques and by using different possible safety performance indicators (crude or particularly refined). In this example, made to immediately show practical implications, the predicted crash frequency obtained by each model is compared to observed data for each of the *i*-esim census macro-zone ("*i*" in the Equation (2)) and percentage residuals $r(\%)$ are computed accordingly:

$$r(\%).i = \left(\frac{N_{obs} - N_{pred}}{N_{pred}}\right).i * 100 \quad (2)$$

where:

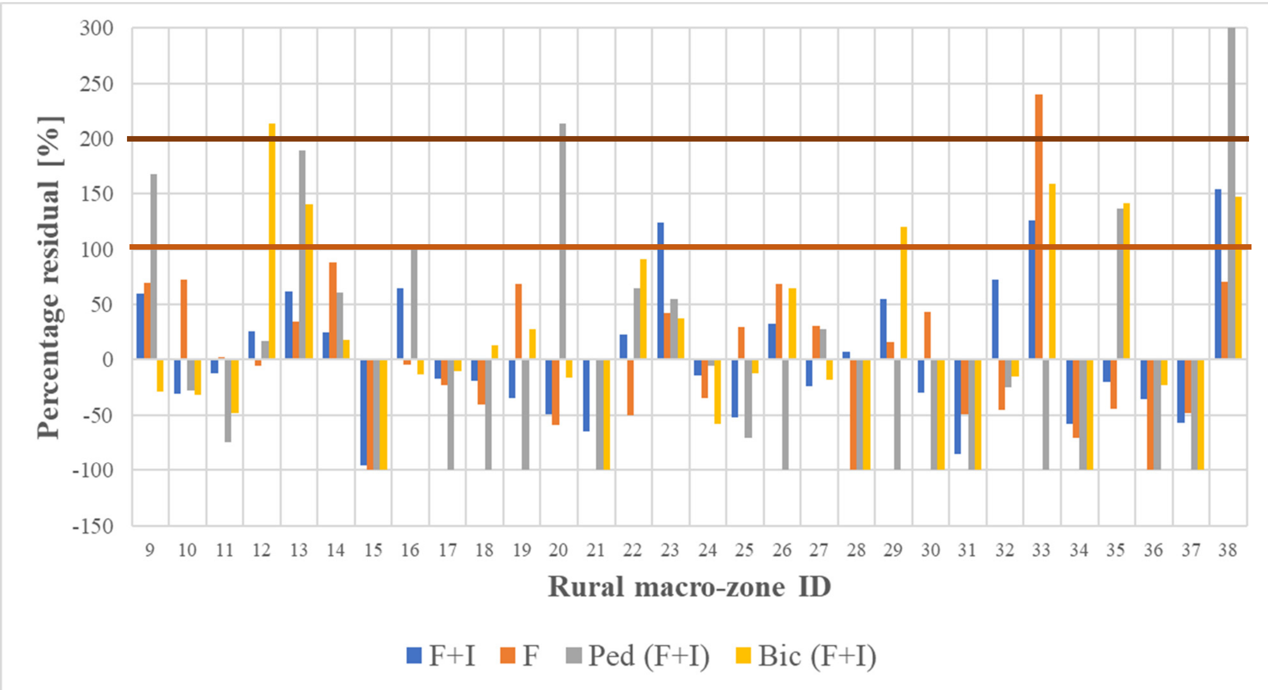
- N_{obs} is the annual average observed crash frequency;
- N_{pred} is the annual average predicted crash frequency.

Percentages are calculated considering the predicted crash frequency as a reference, since using observed frequencies may have led to instances in which the denominator is equal to zero. In this case, the percentage residual indicator shows how much the model prediction is exceeded (negatively or positively) by the actual observed value. Aiming at highlighting crash hotspot areas, different thresholds can be set (also according to objectives and policies). For instance, it could be decided to plan interventions in areas which exceed the +100% or the +200% percentage residual, which means that the observed value is more than two or three-times the predicted value, respectively, as demonstrated in the following figure (Figure 3).

The analysis of the previous figures is useful to show how it is possible to easily identify the zones which need area-wide safety interventions, since they exceed the chosen safety performance indicator based on the developed models. Moreover, different safety interventions can be planned, depending on which specific indicator is exceeded, i.e., that related to fatal + injury, fatal, pedestrian, or bicycle crashes. Clearly, if the latter two indicators are exceeded, policies and infrastructures for vulnerable road users should be prioritized.

Another example of the practical use of safety performance functions developed at a zonal level is that reported by the authors in [42]. In this instance, it is considered the case that a network of hospitals should be managed at the regional level for improving accessibility and safety of the road networks in the hospital areas, both for existing hospitals and in the case of new hospitals to be built. In order to identify which areas surrounding the several existing hospitals that were considered should be targeted for safety interventions, a similar approach was used, based on macro-relationships between crash frequencies and simple geographic variables which can be easily retrieved. In fact, at the planning level, macro-indicators should be necessarily used to compare different areas in terms of traffic safety, rather than considering single specific segments and intersections for safety interventions (see, e.g., [41]).

In the above-defined case, the unit of aggregation is the area (mostly urban) around the hospital, defined by the 3-min isochrone limit (i.e., from each point within the area boundary, the hospital can be reached within 3 min, considering peak hours of a working day). Hence, the relationship between the population in this area and the observed crashes in the same area can be derived, together with different possible prediction interval ranges. In fact, it was shown in this study and in previous research that the area population is a reliable aggregate predictor of traffic crashes at the urban level. Those areas close to the hospitals which exceed a given percentile of the prediction interval can be highlighted for policies and interventions dedicated to improving their safety conditions. Clearly, also in this case, the threshold definition may vary according to local factors and the specific study objectives.



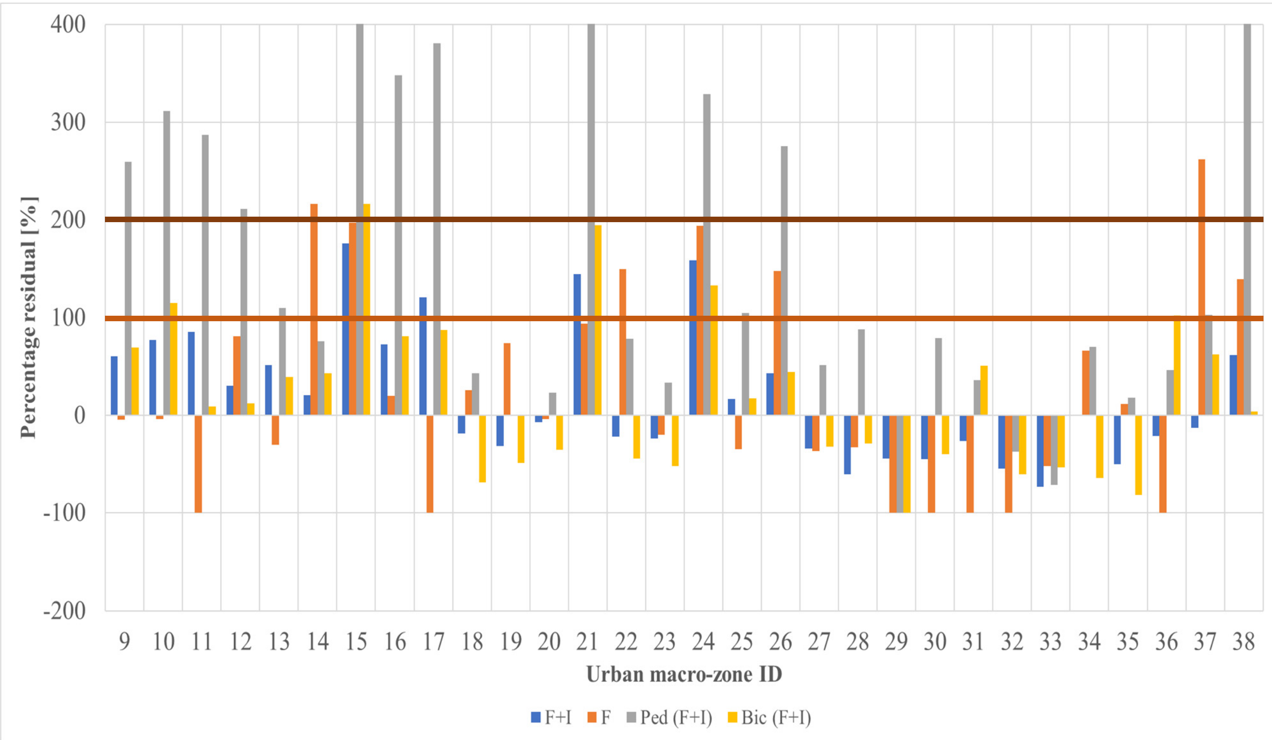


Figure 3. Identification of rural and urban macro-zones highlighted for safety interventions (considering two possible percentage residual thresholds in this example: +100% and +200%; note that the y-axis is truncated to 300% and 400% and that only 30 macro-zones are displayed in both cases for graphical reasons).

5. Conclusions

This study investigated the influential factors on crash frequency for rural and urban environments at the census macro-zone spatial aggregation level within a province. The safety performance indicators used as dependent variables in the modeling stage are fatal + injury (F + I) crash frequency, fatal (F) crash frequency, pedestrian (Ped, F + I) crash frequency, and bicyclist (Bic, F + I) crash frequency. Eight easily retrievable independent variables were considered, grouped in two categories: geographic and road network variables. Safety performance indicators were linked to the dependent variables by means of Negative Binomial (NB) count data models, which can account for the phenomenon of crash data over-dispersion. The eight models obtained from the regression were divided into rural and urban models.

This study confirms that the crash-related factors have varying effects depending on the environment in which crashes occur. In particular:

- the increase in population and area width can be related to an increase in each of the considered urban traffic crash types, while the same variables were not selected for rural models, in which the increase in population density is instead related to an increase in bicycle and pedestrian fatal + injury crashes.
- The mean elevation of the macro-zones is consistently related to a decrease in traffic crashes in both the urban and rural environment, possibly hiding other factors not considered in this study.
- The increase in the network length is generally related to an increase in rural crashes and a decrease in urban crashes (with some exceptions in which it is irrelevant), which was explained according to previous research and by considering the simultaneous effect of the other predictors. The freeway network length seems irrelevant for predicting crashes at this aggregation level.

It was shown how such models may help in identifying areas (in this example case macro-zones) in which urban/rural crash frequencies are higher than the predicted mean for given conditions, in order to highlight areas with high potential for safety improvements. Those areas could be targeted for specific infrastructural interventions and/or transport policies, to improve the overall safety level, possibly with specific regard to some road users (i.e., the general driving population or some categories of users, such as vulnerable road users). Those practical implications were treated in this study, by showing some possible examples of applications.

Given the importance of the topic in cases of transport planning, which involves the prioritization of safety interventions according to specific objectives, such as in the case of mobility plans, the usefulness of similar studies is evident. Clearly, the database and variables should be enlarged and models which can be easily transferrable to other contexts should be improved, in order to help practitioners and decision makers to target specific areas in which safety improvements are more greatly needed.

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References

1. AASHTO (American Association of State Highway and Transportation Officials). *Highway Safety Manual*, 1st ed.; AASHTO: Washington, DC, USA, 2010.
2. Lee, J.; Abdel-Aty, M.M.; De Blasiis, R.; Wang, X.; Mattei, I. Mattei International transferability of macro-level safety performance functions: A case study of the United States and Italy. *Transp. Saf. Environ.* **2019**, *1*, 68–78. [CrossRef]
3. Lee, J.; Abdel-Aty, Q.M. Cai Intersection crash prediction modeling with macro-level data from various geographic units. *Accid. Anal. Prev.* **2017**, *102*, 213–226. [CrossRef] [PubMed]
4. Montella, A.; Marzano, V.; Mauriello, F.; Vitillo, R.; Fasanelli, R.; Pernetti, M.; Galante, F. Development of macro-level safety performance functions in the city of Naples. *Sustainability* **2019**, *11*, 1871. [CrossRef]
5. Demasi, F.; Loprencipe, G.; Moretti, L. Road safety analysis of urban roads: Case study of an Italian municipality. *Safety* **2018**, *4*, 58. [CrossRef]
6. Saha, D.; Alluri, P.; Gan, A.; Wu, W. Spatial analysis of macro-level bicycle crashes using the class of conditional autoregressive models. *Accid. Anal. Prev.* **2018**, *118*, 166–177. [CrossRef] [PubMed]
7. Cai, Q.; Abdel-Aty, M.; Lee, J. Macro-level vulnerable road users crash analysis: A Bayesian joint modeling approach of frequency and proportion. *Accid. Anal. Prev.* **2017**, *107*, 11–19. [CrossRef] [PubMed]
8. Cai, Q.; Abdel-Aty, M.; Lee, J.; Eluru, N. Comparative analysis of zonal systems for macro-level crash modeling. *J. Saf. Res.* **2017**, *61*, 157–166. [CrossRef]
9. Lee, J.; Abdel-Aty, X.M. Jiang Development of zone system for macro-level traffic safety analysis. *J. Transp. Geogr.* **2014**, *38*, 13–21. [CrossRef]
10. Lee, J.; Abdel-Aty, X.M. Jiang Multivariate crash modeling for motor vehicle and non-motorized modes at the macroscopic level. *Accid. Anal. Prev.* **2015**, *78*, 146–154. [CrossRef]
11. Pirdavani, A.; Daniels, S.; van Vlierden, K.; Brijs, K.; Kochan, B. Socioeconomic and sociodemographic inequalities and their association with road traffic injuries. *J. Transp. Health* **2017**, *4*, 152–161. [CrossRef]
12. Wang, X.; Yang, J.; Lee, C.; Ji, Z.; You, S. Macro-level safety analysis of pedestrian crashes in Shanghai, China. *Accid. Anal. Prev.* **2016**, *96*, 12–21. [CrossRef]
13. Quddus, M.A. Modelling area-wide count outcomes with spatial correlation and heterogeneity: An analysis of London crash data. *Accid. Anal. Prev.* **2008**, *40*, 1486–1497. [CrossRef]
14. Siddiqui, C.; Abdel-Aty, M.; Choi, K. Macroscopic spatial analysis of pedestrian and bicycle crashes. *Accid. Anal. Prev.* **2012**, *45*, 382–391. [CrossRef]
15. Farid, A.; Abdel-Aty, M.; Lee, J.; Eluru, N.; Wang, J.H. Exploring the transferability of safety performance functions. *Accid. Anal. Prev.* **2016**, *94*, 143–152. [CrossRef]
16. Intini, P.; Berloco, N.; Binetti, R.; Fonzone, A.; Ranieri, V.; Colonna, P. Transferred versus local Safety Performance Functions: A geographical analysis considering two European case studies. *Saf. Sci.* **2019**, *120*, 906–921. [CrossRef]
17. Hasanat-E-Rabbi, S.; Hamim, O.F.; Debnath, M.; Hoque, M.S.; McIlroy, R.C.; Plant, K.L.; Stanton, N.A. Exploring the Relationships between Demographics, Road Safety Attitudes, and Self-Reported Pedestrian Behaviours in Bangladesh. *Sustainability* **2021**, *13*, 10640. [CrossRef]
18. Intini, P.; Berloco, N.; Colonna, P.; De Gennaro, D.; Ranieri, V.; Ryeng, E. Self-reported route familiarity and road safety negative outcomes: First results from a transnational survey-based study. *Transp. Res. Procedia* **2020**, *45*, 46–53. [CrossRef]
19. Lee, J.; Nam, M.B. Abdel-Aty Effects of pavement surface conditions on traffic crash severity. *J. Transp. Eng.* **2015**, *141*, 04015020. [CrossRef]
20. Lee, J.; Abdel-Aty, M.; Shah, I. Evaluation of surrogate measures for pedestrian trips at intersections and crash modeling. *Accid. Anal. Prev.* **2019**, *130*, 91–98. [CrossRef]
21. Wefering, F.; Rupprecht, S.; Bührmann, S.; Böhler-Baedeker, S. Guidelines. In *Developing and Implementing a Sustainable Urban Mobility Plan*; European Platform on Sustainable Urban Mobility Plans; European Commission: Brussels, Belgium, 2014.
22. Kiba-Janiak, M.; Witowski, J. Sustainable urban mobility plans: How do they work? *Sustainability* **2019**, *11*, 4605. [CrossRef]
23. ISTAT. Istituto Nazionale di Statistica. Available online: https://www.istat.it/it/archivio/104317 (accessed on 12 April 2022).
24. Jones, A.P.; Haynes, R.; Kennedy, V.; Harvey, I.M.; Jewell, T.; Lea, D. Geographical variations in mortality and morbidity from road traffic accidents in England and Wales. *Health Place* **2008**, *14*, 519–535. [CrossRef] [PubMed]
25. Azimian, A.; Pyrialakou, V.D.; Lavrenz, S.; Wen, S. Exploring the effects of area-level factors on traffic crash frequency by severity using multivariate space-time models. *Anal. Methods Accid. Res.* **2021**, *31*, 100163. [CrossRef]
26. Intini, P.; Berloco, N.; Colonna, P.; Ottersland Granås, S.; Olaussen Ryeng, E. Influence of road geometric design consistency on familiar and unfamiliar drivers' performances: Crash-based analysis. *Transp. Res. Rec.* **2019**, *2673*, 489–500. [CrossRef]
27. Intini, P.; Berloco, N.; Ranieri, V.; Colonna, P. Geometric and operational features of horizontal curves with specific regard to skidding proneness. *Infrastructures* **2019**, *5*, 3. [CrossRef]
28. Osama, A.; Sayed, T. Evaluating the impact of bike network indicators on cyclist safety using macro-level collision prediction models. *Accid. Anal. Prev.* **2016**, *97*, 28–37. [CrossRef] [PubMed]
29. Lord, D.; Mannering, F. The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives. *Transp. Res. Part A Policy Pract.* **2010**, *44*, 291–305. [CrossRef]

30. Venables, W.N.; Ripley, B.D. Exploratory multivariate analysis. In *Modern Applied Statistics with S*; Springer: New York, NY, USA, 2002.
31. Wei, F.; Lovegrove, G. An empirical tool to evaluate the safety of cyclists: Community based, macro-level collision prediction models using negative binomial regression. *Accid. Anal. Prev.* **2013**, *61*, 129–137. [CrossRef] [PubMed]
32. Clark, D.E. Effect of population density on mortality after motor vehicle collisions. *Accid. Anal. Prev.* **2003**, *35*, 965–971. [CrossRef]
33. Gedeborg, R.; Thiblin, I.; Byberg, L.; Melhus, H.; Lindbäck, J.; Michaelsson, K. Population density and mortality among individuals in motor vehicle crashes. *Inj. Prev.* **2010**, *16*, 302–308. [CrossRef]
34. Choi, J.; Kim, S.; Heo, T.Y.; Lee, J. Safety effects of highway terrain types in vehicle crash model of major rural roads. *KSCE J. Civ. Eng.* **2011**, *15*, 405–412. [CrossRef]
35. Haynes, R.; Jones, A.; Kennedy, V.; Harvey, I.; Jewell, T. District variations in road curvature in England and Wales and their association with road-traffic crashes. *Environ. Plan. A* **2007**, *39*, 1222–1237. [CrossRef]
36. Ukkusuri, S.; Miranda-Moreno, L.F.; Ramadurai, G.; Isa-Tavarez, J. The role of built environment on pedestrian crash frequency. *Saf. Sci.* **2012**, *50*, 1141–1151. [CrossRef]
37. Elvik, R. Why some road safety problems are more difficult to solve than others. *Accid. Anal. Prev.* **2010**, *42*, 1089–1096. [CrossRef]
38. Marshall, W.E.; Garrick, N.W. Street network types and road safety: A study of 24 California cities. *Urban Des. Int.* **2010**, *15*, 133–147. [CrossRef]
39. Guerra, E.; Dong, X.; Kondo, M. Do denser neighborhoods have safer streets? population density and traffic safety in the Philadelphia Region. *J. Plan. Educ. Res.* **2019**, 0739456X19845043. [CrossRef]
40. Thomas, L.; Lan, B.; Sanders, R.L.; Frackelton, A.; Gardner, S.; Hintze, M. Changing the future?: Development and application of pedestrian safety performance functions to prioritize locations in Seattle, Washington. *Transp. Res. Rec.* **2017**, *2659*, 212–223. [CrossRef]
41. Colonna, P.; Intini, P.; Berloco, N.; Fedele, V.; Masi, G.; Ranieri, V. An integrated design framework for safety interventions on existing urban roads—Development and case study application. *Safety* **2019**, *5*, 13. [CrossRef]
42. Ranieri, V.; Berloco, N.; Intini, P.; Ottomanelli, M. Methods for road infrastructure planning in areas close to hospitals at the regional level. Paper presented at the AIIT TIS 2022 International Conference, Rome, Italy, 15–16 September 2022.