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SPATIAL DISTRIBUTION OF SERIOUS TRAFFIC ACCIDENTS AND ITS PERSISTENCE OVER TIME IN MILAN

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1. Introduction

Over the last decades, the road safety issue has drawn worldwide attention. Traffic accidents (hereafter TA) involve great costs both at an economic and at a human level and are a major cause of premature mortality, overly affecting young people. To tackle this problem, the EU created a Community Road Accident database meant to monitor TA, and in 2001 set for its member states the target of halving in ten years the number of TA victims, meeting, however, with only partial success. The United Nations, in turn, in 2015 incorporated road safety into its Sustainable Development Goals, aiming to halve the number of global victims from TA by 2030. Italy, too, paid attention to the TA issue at both the national and regional level. Istat (Italian National Statistical Office) took care of updating, together with Automobile Club d'Italia, its TA recording framework, and developed new TA indicators (Broccoli and Bruzzone, 2019).

According to the literature, TA causes can be divided into a few categories, as from the Haddon Matrix of accident factors: a) reckless driving (non-compliance with the minimum safe distance, speeding, using a mobile phone while driving etc.: Gariazzo *et al*., 2018), b) driver's poor conditions (drugs and alcohol abuse, tiredness, old age: Rolison *et al*., 2018), c) vehicle poor conditions (faulty braking etc.: Moodley and Allopi 2008), and, last, d) flaws in the road infrastructure (Demasi *et al*., 2018, Ishtiaque, 2013).

Often, TA are the consequence of more than one factor: e.g., the driver's poor conditions affect driving behaviour, causing a breach of the traffic rules (Ishtiaque, 2013); the road infrastructure flaws, when tackled without an increased caution, multiply the TA probabilities (Wang *et al*., 2009).

In an urban setting, where crossroads and intersections are plentiful, the non-compliance with the right of way – either intentional or due to inattention – is the primary cause of TA (Reason *et al*., 1990). Speeding is a further leading cause of serious TA. Proof of this is that traffic congestion – which affects the vehicle speed – mitigates the TA seriousness. However, congestion does not reduce the total number of TA significantly either in the urban setting or on high-speed roads

(Noland and Quddus, 2005). Since most of TA in the urban setting occur during rush hour, speed plays a less momentous role in urban TA.

Apart from the road infrastructure, all other TA factors are contingent, and they can be ascribed to a random combination of events. The TA physical context, and therefore the road infrastructure, represents the non-contingent component: it does not forgive reckless driving or poor conditions of both driver and vehicle. This non-random nature of the infrastructure goes beyond the effects of differences such as those between high- and low-traffic areas or few- and many-intersections zones.

This study intends to analyse the road infrastructure role in TA occurring in an urban setting. We hypothesise that the TA spatial distribution is highly differentiated and that such a distribution persists over time, owing to the infrastructure stability. Therefore, we intend not only to ascertain the presence of blackspots, namely places where TA cluster, but especially to verify their over-time persistence.

Several studies having been carried out using geographic information systems (GIS) to identify spatial models underlying TA in towns and cities (Erdogan, 2009). These studies are based on partitions of the territory by zones (administrative subdivisions, geometric grids: Le *et al*., 2020) or by features (crossroads, intersections, road segments and tunnels: Erdogan *et al*., 2008; Wang *et al*., 2009). A suitable combination of partition criteria and blackspot identification methods contributes to better results. Indeed, the territory partition represents a crucial problem for any spatial analysis of TA (Ghadi and Török, 2018).

It is noteworthy that both spatial smoothing techniques, such as the Kernel Density Estimation (KDE) and clusterisation techniques, such as the Getis-Ord Gi*, meant to calculate and plot TA dispersal, constitute planar methods. In contrast, the TA distribution does not have a two-dimensional nature. Indeed, an analysis aiming to identify places characterised by a *relatively high TA incidence* should consider additional information, such as traffic fluxes, congestions, and vehicles speed. To bypass this planar methods limitation, it is possible to adopt some expedient. In particular, it is possible to divide thoroughfares into segments and to calculate TA per segment (Bíl *et al.,* 2013). By doing this, one can normalise additional TA factors such as traffic flows – which are expected to be constant along the thoroughfare – and the average speed, which at times can be measured. Unfortunately, these expedients are not available in urban settings, owing to the intricacy of the road network. In urban settings, however, it is possible to identify places characterised by an *absolutely high TA incidence*. Such identification has an intrinsic utility as to interventions and policies meant to reduce TA incidence.

The specific issue of the persistence of TA spatial distribution patterns – the present study subject – has received little attention in current literature. Indeed, the persistence of TA distribution patterns has been mainly analysed as to *time* (Kingham *et al.,* 2011; Duarte Monedero *et al*., 2021) – also in order to boost the data reliability – rather than as to *space*. A few studies have analysed the persistence of TA distribution patterns in terms of both space and time, but as a secondary issue (Cheng *et al*., 2018). Therefore, the persistence of TA spatial distribution patterns has not been satisfactorily tested with statistical tools.

2. Data and methods

Our dataset (from Istat 2021, Section *Incidenti Stradali*: http://dati.istat.it/) comprises accidents with casualties in Milan (the Italian city with the highest density of TA) in the five time-series waves from 2015 to 2019. Accidents georeferentiation was obtained from the TA street addresses by means of an experimental elaboration of geocoding (Cimbelli and Caterino, 2016). We divided the municipality territory (181.7 square km) into administrative and geometric zones and counted the TA number in those zones. We used QGIS, and OpenStreetMap (OSM) as background.

When dividing the territory, we moved from relatively larger units to smaller ones. In particular, from 88 administrative units (*Nuclei Identità Locale*, i.e., Local Identity Nuclei, hereafter NIL) with an average surface of 2.06 square km, and from a specially-made geometric grid of 88 squares (each with the same surface of the average NIL), to a second, specially-made grid comprising 5568 hexagons circumscribing 200-metre circles, and equivalent to a 34,641 square metres area.

The shift from administrative units to geometric grids was motivated by the fact that specially-made polygon grids, as opposed to administrative units, are of equal size and *do not* respond to administrative purposes. Since the present study goal is to test the hypotheses of a substantial difference in TA between the territorial units, and of the over-time persistence of this difference, geometric grids are better suited to the task. Their very construction would exclude the possibility that the abovementioned differential derives from the unequal size of the territorial units or from the administrative reasons behind a certain type of territorial partition (for instance, a partition into high- and low-urbanised sections etc.).

The shift from larger to smaller units, in turn, is motivated by the fact that it is advisable to check whether the differential in TA and its over-time persistence are the results of short-range TA blackspots, rather than spurious outcomes ascribable to average values of larger territorial units (Hashimoto *et al.,* 2016).

The comparison between the territorial units was carried out by calculating the TA number in each unit, the differential in TA between units, and the over-time consistency of the TA spatial distribution. As for the grid of smaller, and therefore more numerous, polygons (N = 5568), the comparison was conducted by means of a hotspot analysis Getis-Ord Gi* (Getis and Ord, 1992), which in turn used as weights a Queen's case contiguity matrix. The z scores obtained through this analysis were then used to verify the difference in scores between the units and the over-time persistence of the spatial distribution of such scores.

In order to measure the over-time consistency of the TA spatial distribution, we made recourse to the Cronbach Alpha coefficient (Cronbach, 1951), and we calculated it for all three territorial partitions of the Milan municipality considered in this study, namely the NIL, the grid of squares and the grid of hexagons (1):

$$Cronbach\ \alpha_{[0,\ 1]} = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma^2 x}\right) \quad (1)$$

where k is the number of items (here, the 2015 to 2019 waves of TA counts – or of hotspot z scores – in the territorial units); $\sigma^2{}_i$ is the variance of TA of the *i-th* wave; $\sigma^2{}_x$ is the variance of the sum of all the waves counts for each observation unit.

The present study used factor analysis (principal factor method) as a further measure of the over-time consistency of the TA spatial distribution. The first factor would produce the same loadings (with value = 1) for all the waves, provided their TA exhibit correlations equal to 1. Therefore, the loadings std dev. would be inversely proportional to the over-time persistence of the TA spatial distribution. We added to the loadings a factor analysis post-estimation, namely the Kaiser-Meyer-Olkin (KMO) statistic. KMO measures the adequacy, for each variable in the model and for the complete model, of the data used for the factor analysis (2):

$$\mathrm{KMO}_{[0,\ 1]} = \frac{\sum_{i\neq j} r_{i\,j}^2}{\sum_{i\neq j} r_{i\,j}^2 + \sum_{i\neq j} p_{i\,j}^2} \quad (2)$$

where r is the correlation between the variables i and j (here, the time-series waves of TA values – or of hotspot z scores – in the territorial units); and p is the partial correlation between the said variables.

The information provided by the KMO statistic is different from, and complementary to, the Alpha coefficient. While Alpha is a measure of the degree of closeness of the values for each observation unit over the various items, the KMO statistic is a summary of how small the partial correlations are relative to the original (zero-order) correlations between the items/variables. The partial correlation for each pair of variables is comprised of the correlation between those variables after partialling out the influence of all other variables. KMO, ultimately, is a measure of the proportion of variance among variables that might be ascribed to an underlying factor. In our case, we suppose that this factor is represented by an ecological component underlying the TA.

3. Results

Table 1 shows that the number of TA with casualties, of TA with pedestrian casualties, of deaths and casualties due to TA in the Milan municipality remained rather stable over time, with a clear declining trend as to the number of deaths only.

Figure 1 shows that, in the 88 administrative NIL of Milan, the TA distribution is clearly differentiated. The over-time consistency of the TA spatial distribution can be visually appraised by means of the correlation matrix shown in Figure 1. Table 2 adds further information. The std dev. of the TA in the observation units is high. The Alpha coefficient, close to 1 (0.997), proves that the TA spatial distribution is highly persistent over time. The std dev. of the factor loadings is fractional (0.002), and the KMO measure (0.929) proves that almost all the variance between variables might be ascribed to an underlying factor.

Table 1 – *Traffic accidents with casualties. Milan municipality: 2015 to 2019.*

TA/Victims	2015	2016	2017	2018	2019
TA with casualties	8,729	8,935	8,559	8,523	8,263
TA with pedestrian casualties	1,259	1,368	1,317	1,365	1,305
TA deaths	53	50	53	49	34
TA casualties	11,465	11,905	11,123	11,112	10,743

Source: Istat 2021 – Yearly Survey on Road Accidents resulting in death or injury.

Figure 1 – *Choropleth map of traffic accidents with casualties. Milan municipality: 2015 to 2019. Partition: 88 NIL.*

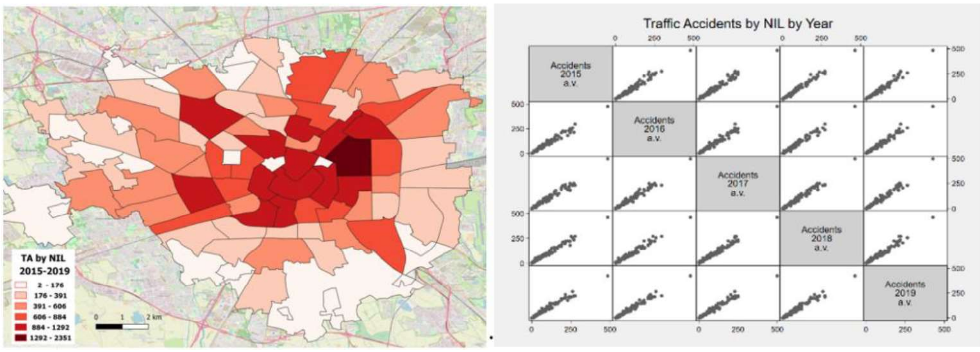

Figure 2 shows the TA distribution in the 88 square cells of the specially-made geometric grid covering the Milan territory. One can notice that in this case, too, the TA spatial distribution is uneven. Table 3 shows that the average std dev. of the TA over the five-year span is, in the case of the geometric grid, even higher than that for the NIL (Table 2). Concurrently, the Alpha coefficient for the 88 cells is higher than the NIL one. The loadings std dev. is slightly higher while the KMO measure is slightly lower. All in all, these findings prove that the differential in TA between the territorial units and the over-time consistency of the TA spatial distribution do not depend on the administrative nature of subdivisions such as the NIL.

Table 2 – *Traffic accidents with casualties. Milan municipality: 2015 to 2019. Partition: 88 NIL.*

Variables	Territ. Units	Mean	Std. Dev.	Alpha	Factor 1 loadings	KMO
TA with casualties 2015	88	98.56	85.66	0.9955	0.9931	0.9141
TA with casualties 2016	88	100.69	83.80	0.9958	0.9909	0.9372
TA with casualties 2017	88	96.39	82.95	0.9960	0.9894	0.9489
TA with casualties 2018	88	95.77	80.93	0.9956	0.9927	0.9118
TA with casualties 2019	88	93.16	76.34	0.9959	0.9899	0.9362
Av. val., (tot. Alpha), [std. dev.], {tot. KMO}	88	96.91	81.94	-0.9966	[0.0017]	{0.9294}

Figure 2 – *Choropleth map of traffic accidents with casualties, and correlation matrix. Milan municipality: 2015 to 2019. Partition: 88 squares.*

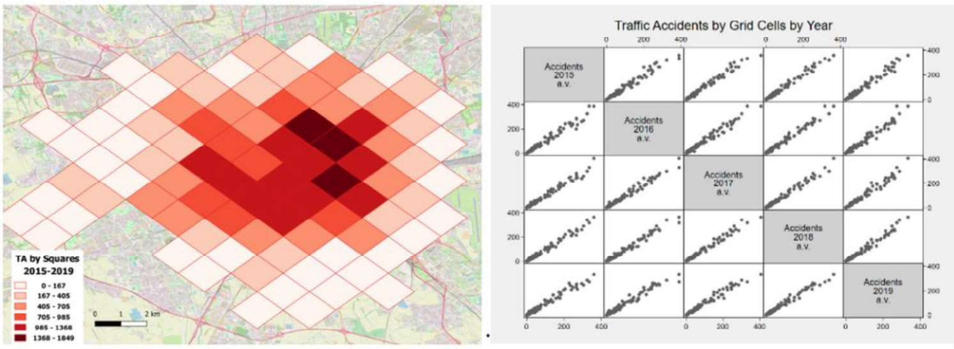

Table 4 tests the hypothesis that the differential in TA between territorial units is just the consequence of an uneven distribution of the road network extent over the same units. The results prove that – even when controlling for the road network extent – the differences between the territorial units remain vast (average std dev. 2.26 vs the five-year mean of 3.07). Concurrently, the Alpha coefficient changes only slightly (0.994), and the same occurs with the loadings std dev., while the KMO measure is even higher. The aforesaid hypothesis, therefore, should be rejected.

Table 5, in turn, intends to check whether the territorial units' differential in TA and the over-time consistency of the TA spatial distribution persist when selecting only a portion of the TA: that with pedestrian casualties. Table 5 shows that, even in the case of pedestrian casualties, the differences in the TA spatial distribution remain vast (with an average std dev. higher than the mean of the five-year period), while the consistency of the TA spatial distribution decreases fractionally (0.986). The loadings std dev. is higher than in the previous samples, but the KMO measure stays on values similar to the previous ones.

Table 3 – *Traffic accidents with casualties. Milan municipality: 2015 to 2019. Partition: 88 squares.*

Variables	Territ. Units	Mean	Std. Dev.	Alpha	Factor 1 loadings	KMO
TA with casualties 2015	88	96.73	94.75	0.9964	0.9937	0.9213
TA with casualties 2016	88	98.41	95.79	0.9969	0.9903	0.9411
TA with casualties 2017	88	94.69	93.28	0.9965	0.9928	0.9351
TA with casualties 2018	88	93.86	90.93	0.9960	0.9965	0.8918
TA with casualties 2019	88	91.44	86.06	0.9968	0.9908	0.9495
Av. val., (tot. Alpha), [std. dev.], {tot. KMO}	88	95.03	92.16	(0.9972)	[0.0025]	{0.9272}

Table 4 – *Traffic accidents with casualties per kilometre of road. Milan municipality: 2015 to 2019. Partition: 88 squares.*

Variables	Terr. Units	Mean	Std. Dev.	Alpha	Factor 1 loadings	KMO
TA w. cas. per Km. 2015	88	3.12	2.34	0.9926	0.9882	0.9271
TA w. cas. per Km. 2016	88	3.18	2.36	0.9937	0.9805	0.9530
TA w. cas. per Km. 2017	88	3.05	2.27	0.9929	0.9860	0.9392
TA w. cas. per Km. 2018	88	3.05	2.20	0.9925	0.9896	0.9158
TA w. cas. per Km. 2019	88	2.98	2.11	0.9933	0.9835	0.9401
Av. val., (tot. Alpha), [std. dev.], {tot. KMO}	88	3.07	2.26	(0.9944)	[0.0037]	{0.9348}

Figure 3 and Table 6 check the over-time consistency of the TA spatial distribution when moving from larger to smaller territorial units (namely, the 5568 hexagons). The results show that the hotspot analysis z scores present vast differences in their spatial distribution (with an average std dev. much higher than the mean of the five years), an Alpha equal to 0.981, while both the loadings std dev. and the KMO measure hang around values not far from the previous ones.

Lastly, Table 7, based on the said hexagons, shows the over-time consistency of the z scores spatial distribution for those units regarded as real hotspots by the Getis-Ord Gi* procedure: namely, units exhibiting – in the first year of the time series – z scores with p value <0.10. By excluding units with low z scores, the sample shrank from 5568 to 203 units, generating, as expected, a fall in the std dev. when compared to the sample mean. However, Alpha remains high (0.892), and the variations registered by the loadings std dev. and by the KMO statistic are modest. These results suggest that the over-time consistency of the TA spatial distribution concerns the territorial units with higher TA incidence and not only the lower-incidence units.

Figure 3 – *Maps of hotspots of traffic accidents with casualties from Getis-Ord Gi*, and correlation matrix. Milan municipality: 2015 to 2019. Partition: 5568 hexagons. Yellow hexagons = 90% confidence level; orange hexagons = 95% c.l.; red hexagons = 99% c.l.*

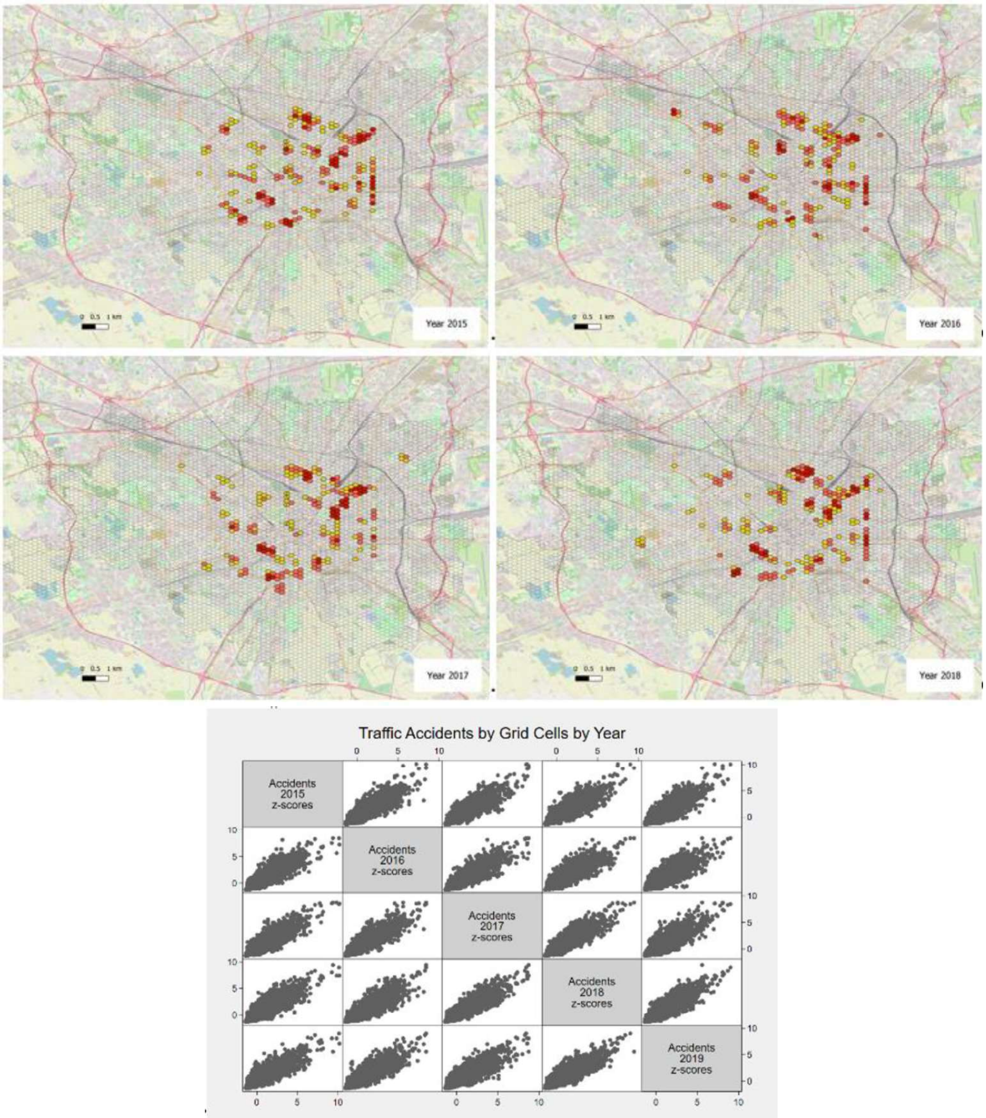

Table 5 – *Traffic accidents with pedestrian casualties. Milan municipality: 2015 to 2019. Partition: 88 squares.*

Variables	Terr. Units	Mean	Std. Dev.	Alpha	Factor 1 loadings	KMO
TA w. pedestrian cas. 2015	88	14.17	14.71	0.9834	0.9541	0.9472
TA w. pedestrian cas. 2016	88	15.30	16.05	0.9806	0.9744	0.9035
TA w. pedestrian cas. 2017	88	14.84	15.83	0.9813	0.9695	0.9146
TA w. pedestrian cas. 2018	88	15.30	15.92	0.9810	0.9713	0.9043
TA w. pedestrian cas. 2019	88	14.66	15.28	0.9839	0.9517	0.9280
Av. val., (tot. Alpha), [std. dev.], {tot. KMO}	88	14.85	15.56	(0.9856)	[0.0105]	{0.9190}

Table 6 – *Z scores of traffic accidents with casualties. Milan municipality: 2015 to 2019. Partition: 5568 hexagons.*

Variables	Terr. Units	Mean	Std. Dev.	Alpha	Factor 1 loadings	KMO
TA w. cas. (z scores) 2015	5568	−0.0012	0.685	0.9757	0.9516	0.9329
TA w. cas. (z scores) 2016	5568	−0.0011	0.677	0.9759	0.9510	0.9319
TA w. cas. (z scores) 2017	5568	−0.0019	0.682	0.9749	0.9578	0.9235
TA w. cas. (z scores) 2018	5568	−0.0009	0.682	0.9753	0.9546	0.9281
TA w. cas. (z scores) 2019	5568	−0.0019	0.662	0.9770	0.9427	0.9412
Av. val., (tot. Alpha), [std. dev.], {tot. KMO}	5568	−0.0014	0.678	(0.9805)	[0.0056]	{0.9315}

Table 7 – *Z scores of traffic accidents with casualties (p <0.10). Milan municipality: 2015 to 2019. Partition: 203 out of 5568 hexagons.*

Variables	Terr. Units	Mean	Std. Dev.	Alpha	Factor 1 loadings	KMO
TA w. cas. (z scores) 2015	203	2.23	0.560	0.8751	0.7460	0.9068
TA w. cas. (z scores) 2016	203	1.86	0.672	0.8760	0.7430	0.9030
TA w. cas. (z scores) 2017	203	1.95	0.691	0.8629	0.8036	0.8812
TA w. cas. (z scores) 2018	203	1.95	0.757	0.8585	0.8253	0.8648
TA w. cas. (z scores) 2019	203	1.85	0.721	0.8690	0.7791	0.8841
Av. val., (tot. Alpha), [std. dev.], {tot. KMO}	203	1.97	0.680	(0.8919)	[0.0358]	{0.8867}

4. Conclusions

This study analysed the problem of traffic accidents in the context of large cities. We hypothesised that TA-intensive areas retain this characteristic over time. To test this hypothesis, we used data concerning TA with casualties that occurred over a five-year period in the Milan municipality. We divided the territory into three types of partition in order to check whether the hypothesis held no matter the partition. We found, in all three partitions, vast differences in their TA spatial distribution, even when controlling for the road network extent in the observation units. Moreover, we found a robust over-time persistence of the TA spatial distribution. In the case of TA with pedestrian casualties, the TA spatial distribution exhibited an over-time persistence similar to that of the generic case of TA with casualties. Further findings showed that the over-time persistence concerned the most TA-intensive territorial units, namely TA blackspots, and not only the TA-light units. The persistence of the TA spatial distribution was measured through multiple procedures: the Cronbach Alpha, the variance between the factor loadings, and the KMO statistic. Their results suggest that the high differential in TA spatial distribution and its persistence over time are not contingent and derive from tendentially stable features of the road infrastructure. All this allows the identification of areas in need of targeted interventions on the infrastructure, while optimising scarce resources in the perspective of a TA reduction in tune with national and supranational guidelines.

5. Limitations, and room for further research

This study analysed TA spatial distribution and its persistence by administrative units and various grid cells. Further territorial partitions could be profitably used: e.g., zones around road features such as intersections, crossways, and road segments. As for the methods, as well, more could be done. Our approach revolved around the over-time *internal consistency* of TA location data because we intended to investigate the persistence of traffic accidents in certain territorial units, rather than the accidents proximity or the impact of close-by zones on the accidents distribution. TA distribution, however, is suitable to spatial analyses using contiguity and distance matrices, kernel density estimations and random point process techniques, to mention just a few other geo-statistical approaches.

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SUMMARY

Spatial distribution of serious traffic accidents and its persistence over time

This study intended to analyse the spatial distribution of serious road accidents in large cities to test the hypothesis of its over-time persistence.

Yearly road accidents with casualties in the Milan municipality from 2015 to 2019 constituted this study data. In order to analyse the accidents spatial distribution, we divided the municipality territory according to three different partitions: one of 88 administrative units, two specially-made grids of respectively 88 squares and 5568 hexagons. We evaluated the over-time persistence of the TA spatial distribution through correlations, Cronbach Alpha, factor loadings and the KMO statistic applied to the accidents densities and Getis-Ord Gi* z scores of the units within the three territorial partitions.

Repeated evidence emerged of a high and persistent differential in accidents between the territorial units, suggesting the existence of an infrastructure non-contingent factor underlying road accidents.

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