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Analysis and description of crimes in Mexico City using point pattern analysis within networks

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ABSTRACT
Mexico City has one of the largest urban areas in the world. Because of its large population and other social factors, it has a high incidence of crime, which was raising serious concerns in the inhabitants and the authorities as well. We analyse the spatial distribution of crime incidence in Mexico City between January 2018 and December 2019. The results focus the location of high-risk areas for different kind of crimes and permit to detect those streets where crime rate is higher than the average rate. In this study, we consider the data as a realization of spatial point processes. Our analysis shows the existence of clusters with high crime incidence running east-west across the central part of the urban area.

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Crime Distribution; Mexico city; Spatial point processes; Street networks

I. Introduction

Taking more than 9 million inhabitants, according to the 2020 census count (INEGI, 2020 (INEGI 2020)), Mexico City is one of the largest cities in the world. Located in a former lake basin, its metropolitan area also includes several municipalities in the neighbouring states of Mexico and Hidalgo (see Figure 1). Despite being the main economic centre of the country, welfare is not well distributed, and most of the inhabitants of the metropolitan area live in marginated areas. Poverty, unemployment and other social factors contribute to an apparently high incidence of crimes which apparently occur at random in the city (Jímenez, 2003 (Jiménez 2003); Vilalta and Muggah, 2016 (Vilalta and Muggah 2016)). However, the number of crimes per 100,000 inhabitants is much smaller than in other smaller cities in the country, such as Ciudad Juarez or Tijuana.

Wortley and Mazerolle (2008) (Wortley and Mazerolle 2016) consider that crimes are associated with the social, geographical and economic environment, and the crime rates will show variation in time and space at different scales. This approach to analysis of criminal activities is known in the literature as environmental criminology (Sánchez-Salinas, 2014 (Sáncez-Salinas 2014) and other works, like Ranson et al. 2019 (Ranson, Amio, and Baumer 2019) or Vandeviver and Steenbeek, 2019 (Vandeviver and Steenbeek 2019)).

In Mexico, the scarcity of reliable information about crime incidence influences the perception of peoples about insecurity, making people feel unsafe. This is also influenced by lack of trust in the justice system, which makes people to avoid reporting even they have been victims of a crime. According to W. Pansters and B.H. Castíllo (2007) (Pansters and Castíllo 2007), about 75% of crimes occurring in the Mexico City are not denounced to the authorities. This is particularly true for crimes such as violent robbery and rape, where the proportion of non-denounced incidents is high. These two crime types represent more than 82% of the crimes committed in the city (W. Pansters and B.H. Castíllo (2007) (Pansters and Castíllo 2007)).

Despite citizens perception of crime incidence, clusters of criminal events may be the result of different causes and factors, and it is strongly necessary to analyse those factors which have a high influence in the occurrence of different crime types in distinct spatial locations of the city. Unlike other spatial phenomena, crimes in urban areas occur along street networks, even if they occur inside buildings or houses. We consider this started hypothesis because buildings and houses are spread along streets and avenues (Kim, 2018 (Kim 2018) and Bright et al. 2019 (Bright, Koskien, and Malm 2019)).

Assuming that crimes are random events occurring at point locations in space and time, a sensible way to

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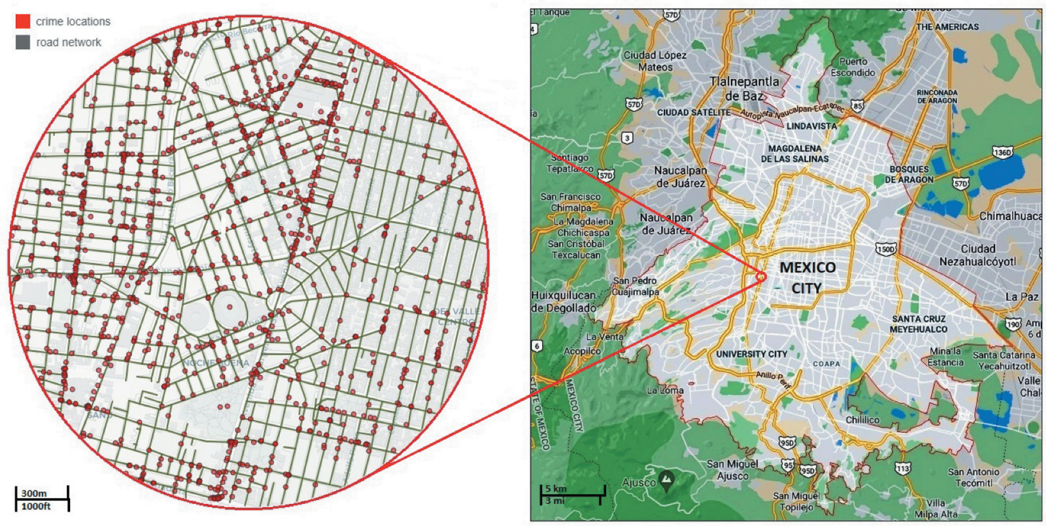

Figure 1. Street network and boundary of Mexico City.

study their incidence and gain insight about factors associated with such incidence is by making the analysis in the context of spatial point processes. Point processes are a powerful statistical tool used to analyse random events that occur at point locations, such as crimes, earthquakes and forest fires, among many others. The most common models are those where the locations are given in two dimensions. Univariate point processes include only the location of events, while point processes with marks (or marked point processes) include additional information about each event. Point pattern analysis can be used to answer a variety of questions (Cressie, 1993 (Cressie 1993); Diggle, 2003 (Diggle 2003); Illian et al., 2008 (Illian et al. 2008)).

The scientific context of such questions depends on the area of application, but goals can be classified into three broad groups. First, one might be interested in whether the spatial pattern for the observed data is grouped, distributed regularly or completely at random. A second goal relates to the relationship between different types of events in a marked process or process with marks (variables measured only at fire locations, such as size of area burned, cause of fire or year of occurrence). The third goal is to estimate the intensity or number of events per unit area.

In this work we analyse three types of crimes reported in Mexico City during two years (2018 and 2019). Using several techniques developed for the analysis of spatial point patterns, our analysis will focus on crimes against peoples integrity (rape and homicide) and violent robbery. Crime patterns may be explained by the spatial distribution of social and economic factors associated with crime incidence. Interest is usually on the detection of trends and patterns in the intensity of events. Studies also point to the interaction of risk factors, the multiplicative effect when several risk factors are present, and how certain protective factors may work to offset risk factors (Wang, Lee, and Williams, 2019 (Wang, Lee, and Williams 2019)). Unlike other studies where the point pattern observed is considered a realization of a spatial point process in the Euclidean space and are useful to identify areas of high crime incidence at the neighbourhood level, our approach based on linear networks considers the observed pattern as a realization of a point process in a linear network space. This allows identification of high crime incidence at street block level.

The manuscript is organized as follows: Section II describes the data set used on this study to analyse crime incidence in Mexico City. In Section III we describe the statistical methodology used for this analysis and we provide the details needed to clarify the used methods. Section IV presents the results and discussion with their implications in terms of models fitting and correlations between crime types. Finally, Section V presents the conclusions.

II. Data

The region of interest in our study is Mexico City, defined by the point of coordinates (19.184421; −99.395371) at South-West and the North-East point of coordinates (19.600561; −98.935618). The city had been the capital of the Aztec empire, in the colonial era became the capital of New Spain and now is the capital of the United Mexican States. This area owns a surface over 1.485 square kilometres in the Valley of Mexico, a large valley in the high plateaus in the centre of Mexico, at an altitude of 2.250 m.

Figure 1 shows the boundary of the urban area of Mexico City (right side), as well as one street map location zoom level (left side) that allows us to perceive in detail the complexity of the city's street network and the large numbers of criminal incidence. The streets of sample region conforms to a complex network of streets and avenues ranging from highways with up to 8 lanes to narrow streets that only allow pedestrian traffic. The street maps for Mexico City define a series of line segments and vertices at the intersections and consists on 229 224 vertices and 277,194 segments.

Due to the nature of the criminal activity, these occur either at points along those streets or at homes that can be assigned to a point on a threshold buffer zone for the street or avenue, which justifies the spatial analysis based on spatial point processes projected on the street network coordinate system.

However, since in point processes analysis the object of interest is the intensity function, defined as the average of events per unit area, the sub-denounce rate would only affect the magnitude, but not its shape, so descriptive inferences are valid. Based on the above discussion, the results obtained in Section IV can be considered as scaled version of the intensity function obtained if all crimes were reported and prosecuted.

The data used in this work correspond to homicide, violent robbery and rape, reported in Mexico City for which an investigation file was opened. This implies that the events analysed are only the events that were denounced or for which the attorney's office of Mexico City considered there were enough elements for a prosecution. It is then expected that the incidence in real terms to be greater than the one reported here. Crimes on these categories have a strong effect in society, and as a result, the government imposed a new protocol in police action since January 2018. This significant step ahead, taken in the fight against criminality, allows police officers to geo-reference any criminal incidence reported and assisted by them. As a result a database which includes the street map, the spatial and temporal coordinates of the crimes and another specific information was created.

Thereby, the databases are stored in the public domain of the Attorney General of Mexico City. All the denounced crimes with an investigation file between January 2018 and December 2019 are free to download. In this database, the total number of crimes considered for this study and prosecuted for 2018 was 53,890, while for January-December 2019 the total crimes prosecuted was 44,344. The variables included in our study are: the geographical position in which the crime occurred, type of crime and year of occurrence.

Based on above data, we propose to identify some pattern of crime incidence and spatial association between crime types from past case summaries and give support to police officer to identify different crime patterns and even to predict criminal activities. The results could be used in intelligent crime analysis and guidance the decision makers to increase the numbers of law enforcement personnel in some areas where the prediction shows a high risk of crimes.

III. Statistical methodology

Statistical data analysis comprised the use of exploratory and inferential techniques to gain insight about the spatial variation of crime incidence in the study area. Exploratory techniques included plots of the different variables from database and maps with counts of the number of crimes by street segments, used to gain insight about the presence of clustering of events and spatial variability patterns of the different crime types considered in this work. The patterns observed in such plots were tested through the computation of test statistics for clustering and uniformity. We also tested for spatial interactions of different crime types using spatial point processes methods.

A. Spatial Point Processes

Spatial point process analysis is based on the assumption of the existence of a random mechanism from which a point configuration X is chosen from a probability space. The probabilistic context thus allows to speak of things such as the probability that the number of crimes in a given area B is less than a fixed number k, $P[N_X(B) < k]$ or about the average number of crimes in that neighbourhood, $E[N_X(B)]$. In mathematical terms B is an arbitrary set inside a study area W, also known as the spatial window (in our case the urban area boundary of Mexico City). $N(B)$ denotes the number of points or events inside a set of measure B. Depending on the geometric space used, this set may be street segment of longitude equal to B linear units or a circle of radius r with area equal to B. Usually, the main objective is the estimation of the intensity function, defined as:

$$\lambda(s) = \lim_{|ds| \to 0} \left\{ \frac{E[N(ds)]}{(ds)} \right\} \tag{1}$$

where s is a point inside W and ds is an infinitesimal circle centred in s.

The intensity function may be interpreted as a rate of the number of events (crimes) per street unit length.

A quick estimator of the intensity function is the density estimator:

$$\lambda(s) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{s - s_i}{h}\right) \quad (2)$$

where K is a kernel function, n is the number of events in W and h is a parameter known as the band width which controls the amount of smoothing in the estimator of $\lambda(s)$. Thus, the intensity function can be considered an indicator of the risk to becoming a crime victim in a given location s.

Another useful quantity for analysis of point patterns is Ripley's K-function (Ripley, 1976 (Ripley 1976) and Ripley, 1977 (Ripley 1977)):

$$\lambda K(r) = E[N(X \cap b(u, r))], \quad (3)$$

where r, denotes the distance between points in the pattern under analysis.

The K-function measures the average number of points inside a disc of radius r centred in a point event $\boldsymbol{u}$. If points in the pattern $\boldsymbol{X}$ are scattered completely at random inside W, then $K(r) = \pi r^2$. Departures from this value indicate non-random spread which may be clustered (above) or repulsive (below). When two or more point patterns are analysed, it is also useful to compute the K-cross function, $K_{i,j}(r)$, defined as the expected number of type-j points within a distance shorter than r from an arbitrary type-i point, standardized by the density of the point pattern X_j.

$$K_{ij}(r) = \frac{E\left[\sum_j I(||x^{(i)} - x^{(j)}||) < r\right]}{\lambda_j}, \quad (4)$$

when points of X_i do not interact with points of X_j, $K_{ij}(r) = \pi r^2$, and this implies that the two patterns are independent.

We computed the K and the K-cross functions to the data for rape, homicide and violent robbery to test whether there is clustering, repulsion and interaction among the different crime types. The sample versions for the K-function is given by:

$$K_{ij}(r) = \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{\omega_{ij} I(d_{ij} \leq r)}{\lambda(s_i)\lambda(s_j)}, \quad (5)$$

where ω_{ij} is an edge correction factor (Diggle, 2013 (Diggle 2003)) and $\lambda(s)$ is the intensity function evaluated at the data points. An analogous expression exists for the K-cross function.

Tests of CSR and point pattern independence for the three crime types were constructed using these two functions and Monte Carlos simulation under the null hypothesis of complete spatial randomness (CSR) and independence between crime types. Departures of the empirical K- or K-cross functions above the πr^2 line are indicative of clustering and non-independence among the crime types respectively (Moller and Waagepetersen, 2004 (Moller and P 2004); Baddeley and Turner, 2005 (Badley and Turner 2005)).

B. Spatial point processes in street networks

The modelling process described in the previous section considers the points processes are defined at every point inside the study area W. However, crimes usually occur in the city streets or inside buildings aligned along a network of streets in the urban area. Modelling crime data using a network approach requires some modifications of the theoretical context, mainly the topology in terms of distances. The clustering analysis and correlation in a network, for example, requires a measure of distance along paths in the network. Common practice is to measure Euclidean distance between events defined as the length of the shortest path between two points in the city. However, this may be inappropriate when analysing crime data on a linear network of city streets (Okabe and Sugihara, 2012 (Okabe and Sugihara 2012)).

A linear network may be defined as the union $L = \cup_{i=1}^{N} l_i$ of many line segments in the plane, all of them of the form $l_i = [u_i, v_i] = \{w : w = t_{ui} + (1t)v_i, 0 \leq t \leq 1\}$, where $u_i, v_i \in \mathbb{R}^{\not\vDash}$ are the endpoints of l_i. We may assume that for $i \neq j$, the intersection of l_i and l_j is either empty, or is one of the endpoints of l_i or l_j.

A path between locations $\boldsymbol{u}$ and u' in L is a sequence $v_0, v_1, \ldots, v_m, v_{m+1}$ of the points in the network, with $v_0 = u$ and $v_{m+1} = u'$, so that $[v_i, v_{i+1}]$ is a subset of L for each $i = 0, \ldots, m$. The length of this path is:

$$\sum_{i=0}^{m} = \| v_i - v_{i+1} \|, \quad (6)$$

where $\| \cdot \|$ denotes Euclidean distance.

The shortest-path distance $\delta SP(u, u')$ between u and u' is the minimum of the lengths of all paths between u and u'. If there are no such paths, then $\delta SP(u, u') = \infty$, which implies the network is not connected.

IV. Results

Exploratory data analysis provided information about marginal correlations and possible non-spatial grouping of observations in the database. Such groups may indicate the presence of subpopulation and geographic zonation of crime occurrences in Mexico City.

The total number of occurrences for the three types of crime considered in this work was more or less similar

Table 1. Numbers of crimes reported in Mexico City for two years.

TYPE OF CRIME	2018		2019	
	Incidence	Inc./month	Incidence	Inc./month
HOMICIDE	1301	108.42	1302	108.50
VIOLENT ROBBERY	51544	4295.33	41963	3496.92
RAPE	1045	87.08	1079	89.92
TOTAL	53890	4490.83	44344	3695.33

for 2018 and 2019, with only slight differences due to the random nature of crime occurrences (Table 1). The monthly incidence for each crime type shows some variations from 2018 to 2019 as follows: monthly averages from 2018 to 2019 decreased with 18.59% for violent robbery, the rape increase with 3.25%, while the homicide crimes increased with one case. The overall incidence crimes for the three crime types in terms of number of events per month showed a decrease of 17.71% from 2018 to 2019 in the number of investigation folders.

However it is difficult to tell if the decrease was due to a higher number of police interventions or to a decrease in the number of denounces. Only homicides are prosecuted without denounce, so in this case, the increase in the number of events is linked to an increase in the number of events.

A. Spatial distribution of crime incidence

Figure 2 depicts the spatial patterns of incidents of reported rape offences with investigation files for the years 2018 (left) and 2019 (right). For this crime the pattern of occurrences is very similar in both years. There seem to be small clusters of rape events in the Historic Center and surrounding areas. For the rest of the city the pattern seems to be completely random, as some small clusters are to be expected given the high number of events in the study area. Note the existence of aligned points in some areas of the city, which suggests the existence of streets or avenues where this type of crime was committed repeatedly. The absence of events in the southern part of the city, in the lower part of the map, is due to the fact that it is a rural area, where the population density is comparatively low compared to the rest of the urban area.

Figure 3 shows the location of the homicides that occurred in Mexico City during the years 2018 (left) and 2019 (right). The maps show that the incidence of homicides shows the same pattern for 2018 and 2019, although the number of events has grown in 2019 and thus the size of homicide clusters has increased. The maps show the existence of areas with high incidence of homicides in the zone known as "Historic Center", which comprises the oldest part of the city as well as other high murder incidence zones in the north most part of the city, in the southwest and in the southeast parts of the city. Those areas have been described as

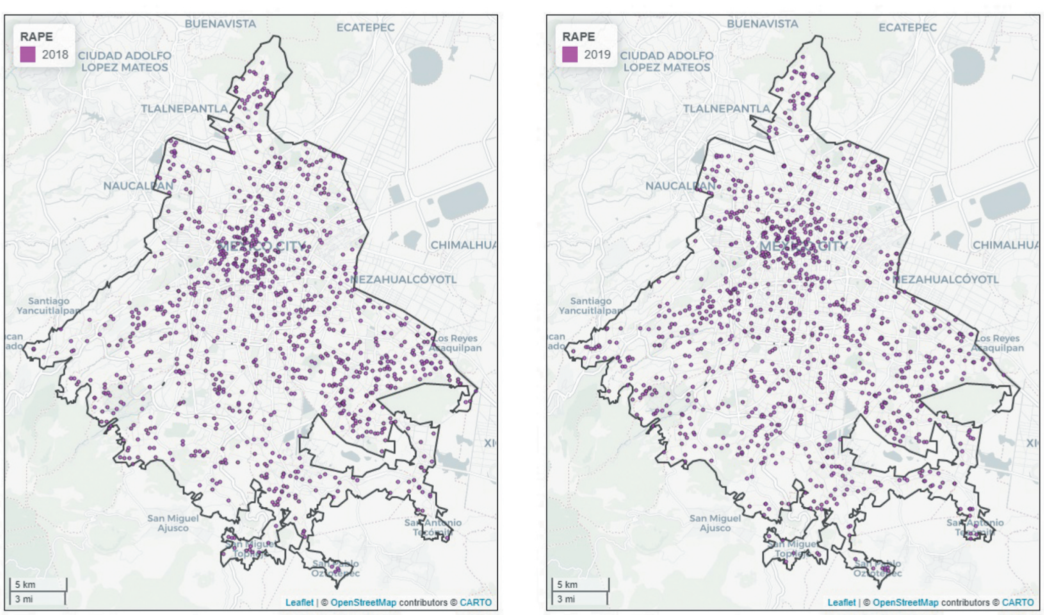

Figure 2. Reported rape for 2018 and 2019.

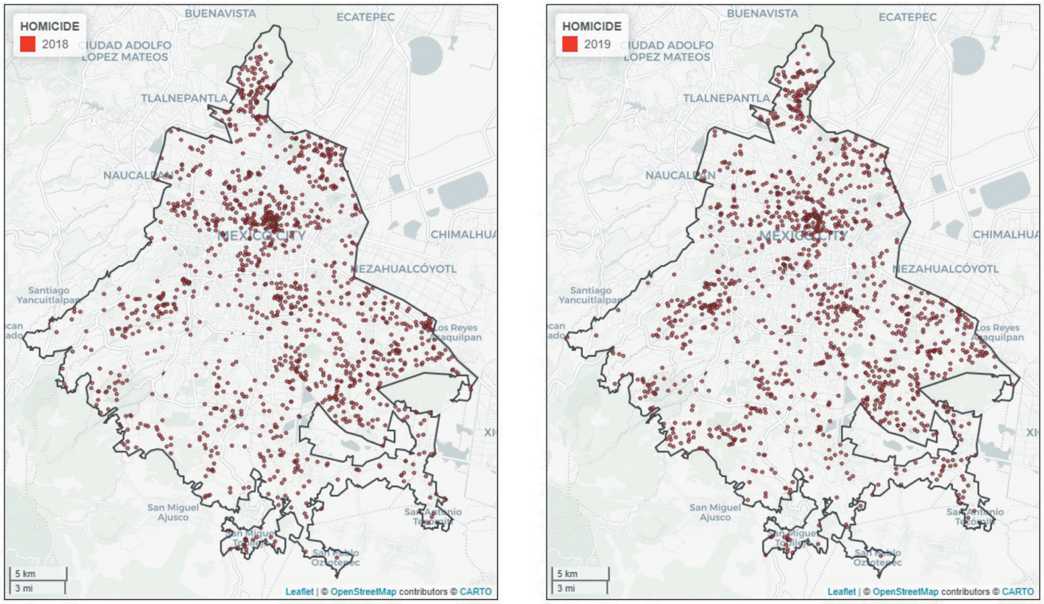

Figure 3. Homicides in Mexico City.

areas where drug selling gangs operate and most of the homicides are the results of fights and revenge acts among criminal groups.

In Figure 4 we present the incidence of violent robberies in the urban area. On the left side we display the violent robberies for the entire year 2018, while on the right side there are the same crimes but for 2019. As we can deduce, violent robberies are evenly spread in most part of Mexico City. The number of incidents was higher for 2018, but the spatial pattern does not show any notorious change. Basically, there is no place where a crime of this type shows lower incidence and this in part explains why about 37% of the population over 25 years has been the victim of a robbery at least once in their life. We can easily observe the different scale intensity due to the high number of violent robberies that occurred in the same area.

The below figures of this section plot the intensity functions (Kernel) for crimes studied in this article along with the spatial coordinates of points where these

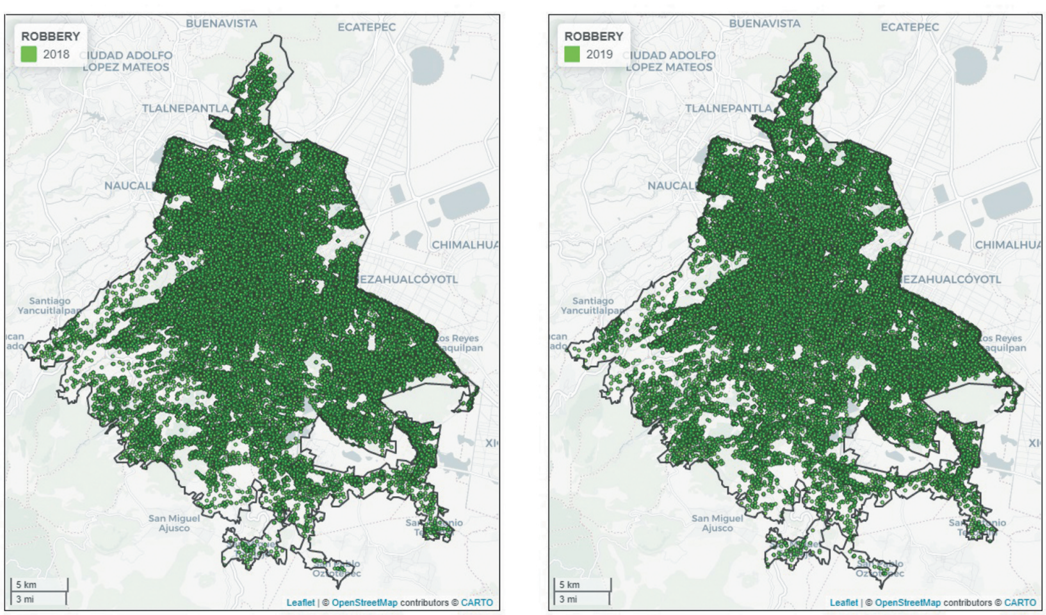

Figure 4. Violent robberies in Mexico City.

crimes took place. To maintain the consistency of the article, we kept the colours as in the previous figures with which we represented each crime and year, as following: 2018 and 2019, magenta for rape, red and green for homicide and violent robberies respectively.

Figure 5 shows a non-parametric estimate of the intensity function (Kernel) for rape offences, considering that the specific process that generated them is defined in the Euclidean plane. The colour scale is in terms of number of sexual offences per square kilometre. The estimated intensity function shows the presence of a high incidence of sexual attacks, mainly north of the Historic Center (Barrios de La Lagunilla, Tepito and Colonia Guerrero) and in the La Merced area, southeast of the Zocalo. Another peak of importance occurs in the eastern part of the City, apparently in the municipalities of Iztapalapa and Iztacalco. The presence of three clusters aligned in a southwest direction with respect to the clusters described in the Historic Downtown area of the city is striking. These clusters occur in the area of Chapultepec, first, second and third sections.

The estimate of the non-parametric intensity (Kernel) function for the homicides is shown in Figure 6. Clusters can be seen in various areas of the city, which have been

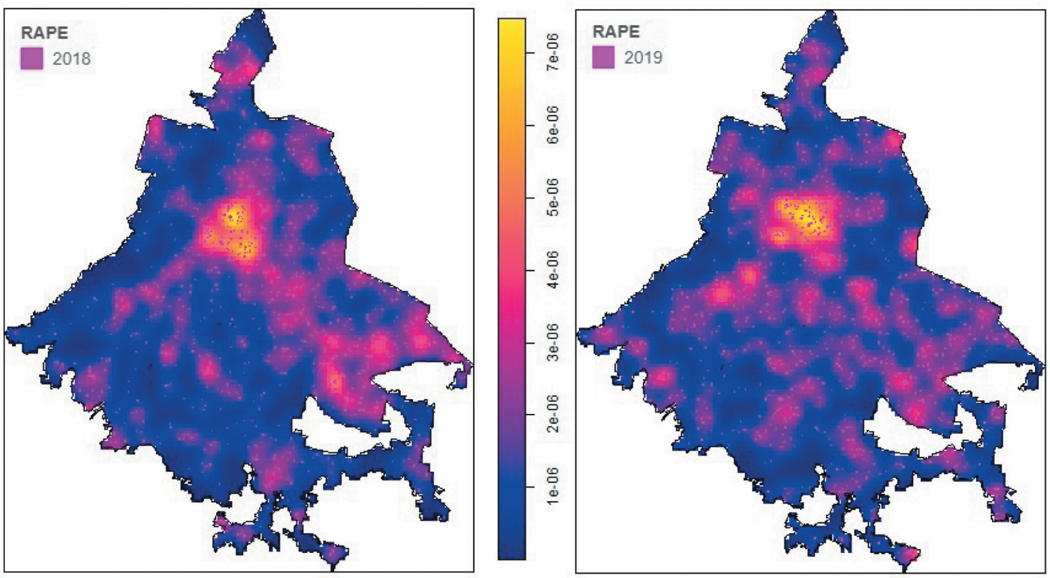

Figure 5. Intensity function for rape offences.

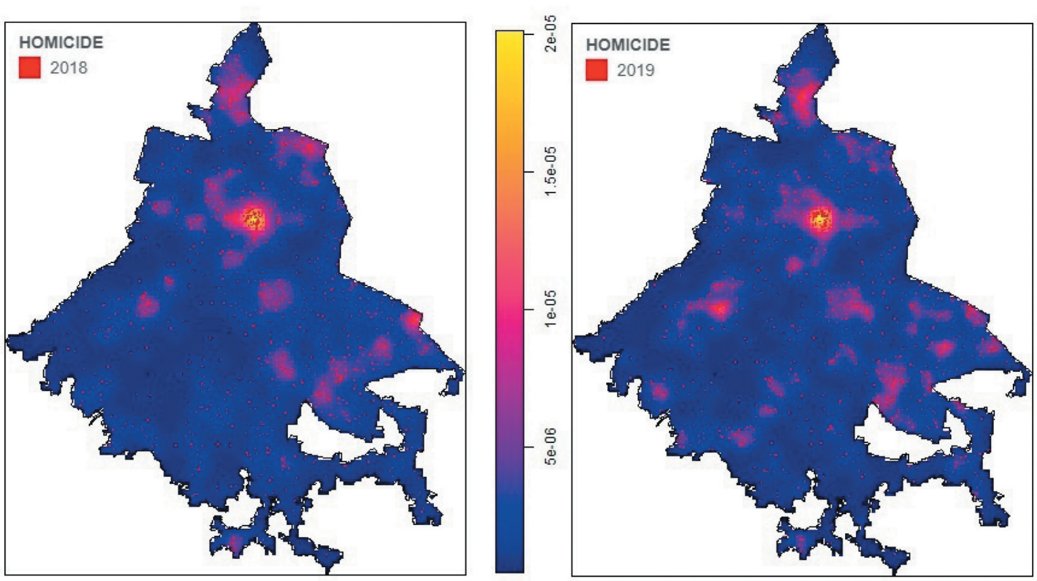

Figure 6. Kernel density estimation for homicides.

considered violent neighbourhoods for several years, including the area known as Tepito, north of the historic centre, as well as in several neighbourhoods in the municipalities of Iztapalapa and Iztacalco in the east, and Gustavo A. Madero in the northern part of the city. It is not clear whether those conglomerates are associated with the high presence of drug trafficking activities and poverty in those areas so formal statistical models for this crime type are needed. The peaks in the estimates of the intensity function make clear that intentional homicides do not occur at random in the urban area of Mexico City.

The intensity function estimate for violent robberies in Figure 7 shows that although occurrence of this type of crime is spread all over the urban area, there are wide areas where the density of robberies is very high. Those high-density zones are located in parts of the city with high economic activity (restaurants, convenience stores, banks, offices, etc.) as well as zones with industries and poor neighbourhoods. The pattern of this crime type is preserved from 2018 to 2019, despite the fact that for the last year the numbers of occurrence are reduced. This suggests that people who perpetrate this crime type have a pattern that does not change over time and that could be associated with social and economic factors that remain constant in the urban area.

B. Spatial association between crime types

The possible spatial association between the three different crime types considered in this work was assessed using the *K*-cross function. As mentioned previously, this function measures, for a given crime type *A* and distant *r*, the number of events of another crime type *B* inside a circle of radius *r* centred at an event of type *A*. If crimes of type *A* and *B* occur independent of each other, the *K*-cross function should follow the parabola πr^2.

In Figure 8 we plot in solid line the empirical *K*-cross function between crimes for 2018 with distance less than 600 metres, as well as the Monte Carlo 95% confidence for the null hypothesis of spatial independence. The dotted lines correspond to the edge corrected theoretical values for *K*-cross.

The top line of the figure above display from left to right the *K*-cross function between rape and homicides, homicides and robberies as well between robberies and rape, which were occurred in 2018. The charts from the other line corresponds to the same occurrences but for 2019. The plots show strong departures from the spatial independence hypothesis, with all the empirical values above the confidence band. This implies that given that a rape has occurred at some location, one should expect also occurrence of homicides in the neighbouring areas.

Similar conclusions can be drawn from the *K*-cross function between violent robberies and rape for the two years considered in this analysis, shown in the bottom line of the same figure. Given that a rape event has occurred at a given location, one should expect the occurrence of violent robberies in the neighbourhood. The spatial association between homicides and violent robberies for 2018 and 2019 showed a slightly different behaviour. For both years, the two crime types seem to be independent.

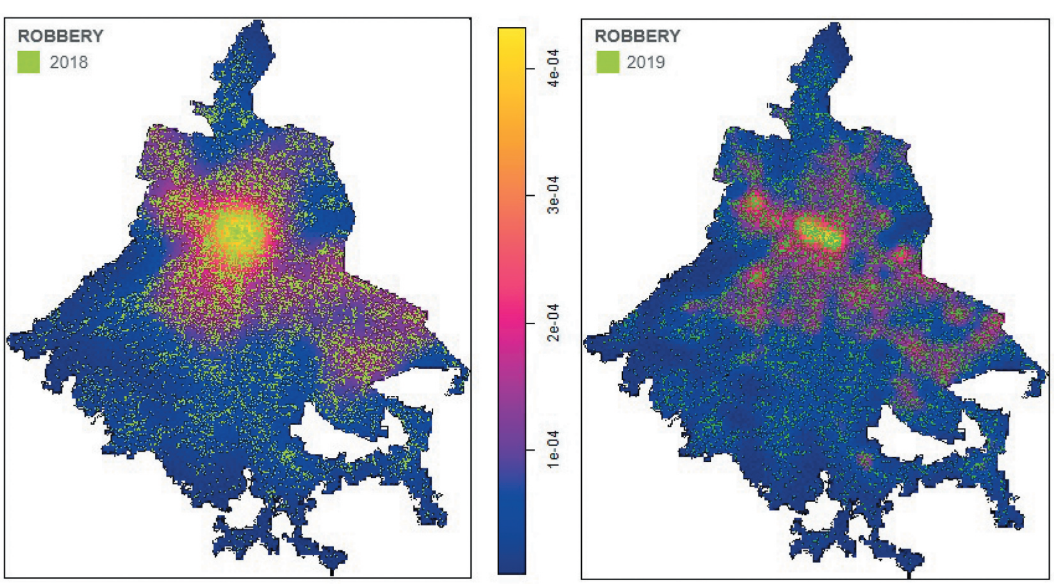

Figure 7. Intensity function for violent robberies.

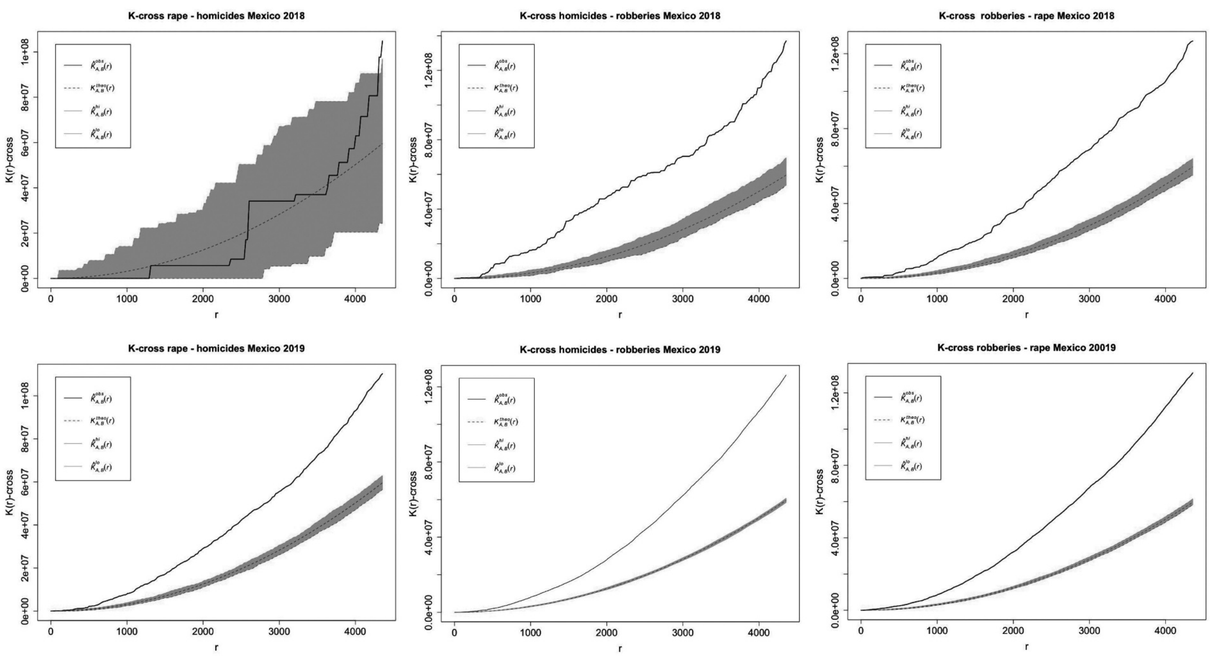

Figure 8. *K*-cross association function between different type of crimes and years in Mexico City.

C. Application on the street network

Given that the majority of the crimes that occurred in Mexico City occur in the urban area and that in the geo-referencing of the events, the police or the agents of the Public Prosecutor's Office associate the fact with a point on a road, the analysis of the criminal incidence in the city can be done considering the events as realizations of a point processes defined in a street network. The database used in this project includes the street map of the urban area of the city, so through an analysis and processing of the basic information we were able to associate the spatial coordinates of the crime events on the street map for Mexico City, projected on the same coordinate system.

The street network for Mexico City is defined by a large amount of line segments and the intersections of the same. Although it is not possible to appreciate patterns on this map due to the large number of points, the coincidence of points and roads can be seen in areas with low crime incidence.

The process to obtain non-parametric estimates for the intensity over the network for crimes requires the computation of distances between events. Unlike the Euclidean analysis of the previous section where distance is measured as the shortest path between two points, in a linear network distance is measured as the shortest path along streets.

The descriptive map of these distances is shown in Figure 9. It should be pointed out that this map contains the distances between the location points of the 97,473 crimes of the three observed types in the database. Once these distances have been computed, the next step is to calculate the kernel estimates for the intensity function along the street network.

The graphs below display just the kernel intensity function of registered crimes occurrence in 2018 and 2019 over streets network, but without the spatial coordinates of the incidence points. As in the previous intensity function graphs, maintaining the same scales in both maps 2018, 2019 respectively, should be considered while comparing.

In Figure 10 we represent the density maps corresponding to rape offences over the street network for 2018 (left hand) and 2019 (right hand). According to these maps, in 2018 this kind of crime was concentrated in the centre and east part of the urban area.

For 2019, sexual attacks were concentrated around the same high-density zone of 2018, but spread south and northeast sides of it. It is noteworthy that, some peaks have been identified in the western boundaries of the city and others in the southeast in 2019. Nevertheless, the maps show that the geographic pattern for this crime has changed.

Figure 11 depicts the intensity maps for intentional homicides for the two years considered in the analysis. Homicides in 2018 are identified to spread along the high-density zone running east to west, with peaks in areas such as the city centre, and other poor neighbourhoods

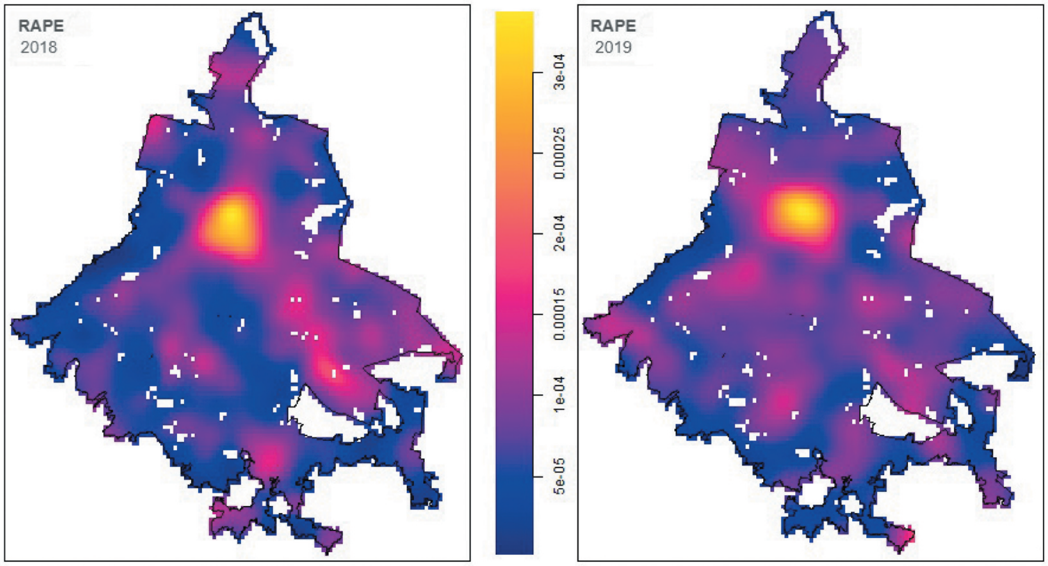

Figure 9. Spatial distribution of distances between crimes.

along that zone. The map for 2019 shows more dispersed clusters and they are spread over the study area.

Thus, the kernel estimate of the intensity function only has small peaks that could be analysed separately defining a small region of interest in such a way to only include the cluster on interest in the map.

We can observe in Figure 12 the intensity function over streets network of violent robberies that befell in 2018 (left-hand side) and 2019 (right-hand side). A similar pattern has been observed on rape offences but on a lower intensity scale. It seems that violent robberies are met close or around the high-density zone of rape activity described in Figure 10.

For dataset of 2018, the streets network of Mexico City downtown is completely covered by the highest intensity of violent robberies. While for 2019 the higher intensity keeps up in the same area, the pattern of violent robberies shows the intensity function has spread over a wider region of the city.

We remarked a significant scaling down of violent robberies in downtown city. Note that the values of the scale for the estimated intensity function for 2019 are about three quarters of the values for 2018. The significant decrease of intensity crimes cluster in the city centre could be explained by the police actions on this area.

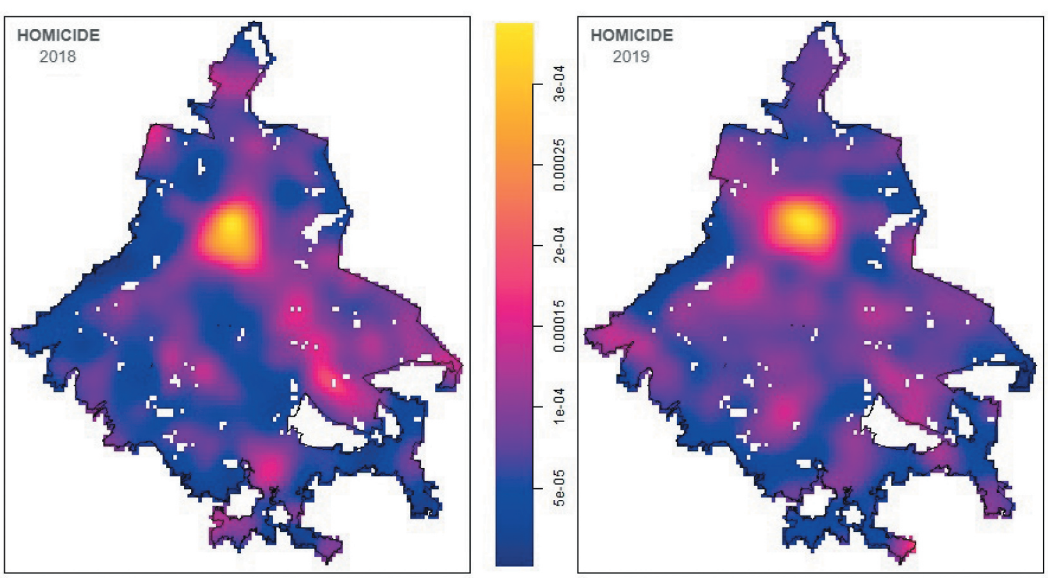

Figure 10. Network intensity function for rape in Mexico City.

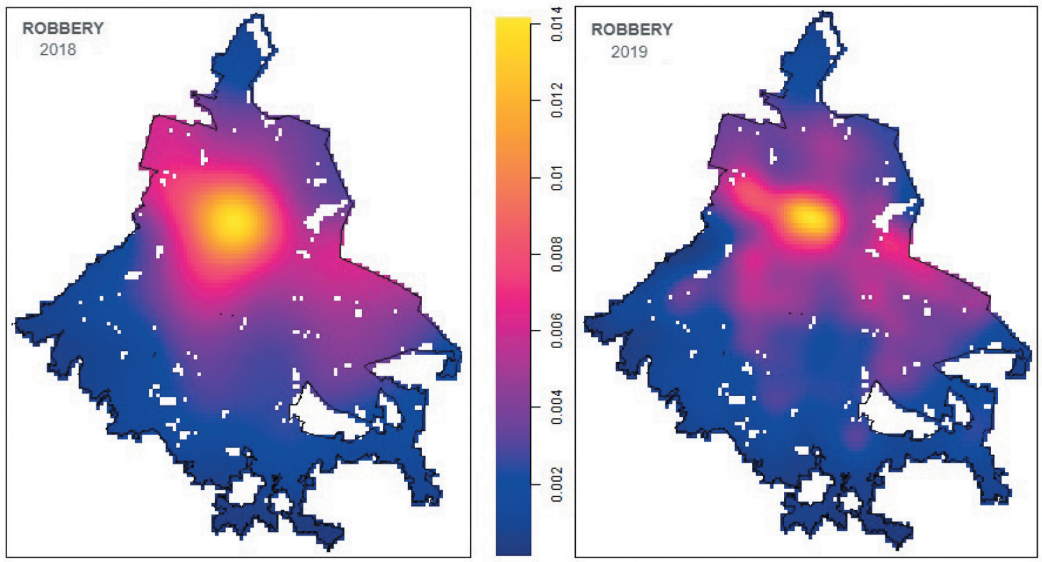

Figure 11. Homicides intensity function over street network for 2018 (left) and 2019 (right).

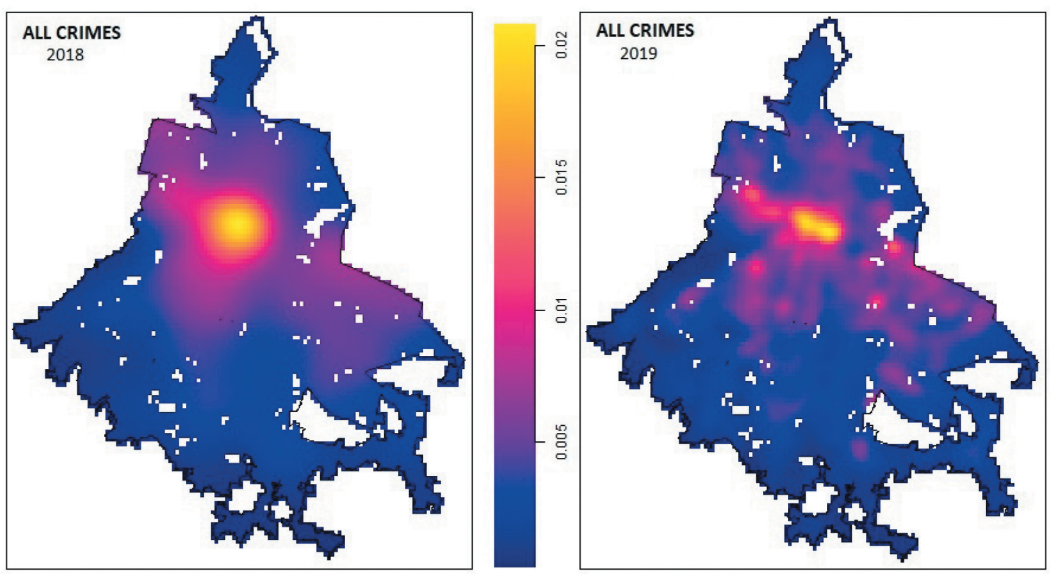

Figure 12. Violent robberies intensity function over network.

Figure 13 shows the kernel estimate of the intensity function over street network computed using the locations of all the crime types for the two years. This map gives an idea of where the areas with higher criminality in the urban area are, regardless of the crime type. The map shows that criminal incidents tend to occur around a high-intensity zone that runs east to west along the urban area. This zone covers parts of Mexico City that have a large history of criminal activity and where social factors contribute to the high incidence of crimes. The map also shows that crime activity spreads north and south of the high-intensity zone, mainly to areas where crimes like violent robbery are profitable for criminals.

Crime in Mexico City is a deep concern for the working population and for the government. Except for homicides that are prosecuted ex-officium, it is believed that a high proportion of other crimes and offences are not denounced either because of a lack of trust in the justice system or because of the fear the burden that following a denounce implies in Mexico.

The advantage of the analysis of crime incidence using spatial point patterns is that it permits to obtain good estimates of the actual pattern of crime incidence, despite the low number of denounces. The maps obtained in this way can be used to design strategies for crime prevention and combat. Using external information for social and economic variables, point pattern analysis can be used to screen out which factors influence crime incidence and if the effect of those variables shows geographic variation.

It is clear that although all governments claim that high numbers in crime rates are non-significant, the numbers in Table 1 contradict such statements. However, the amount of non-reported crimes makes difficult the evaluation of more reliable quantities such as the relative risk for each crime type, as these quantities require knowledge of the total number of crimes occurring in the city. Thus, spatial point processes are a powerful and useful tool for the analysis of criminality in geographic areas. It is also useful to detect hot spots and with appropriate modelling, and it can be used to predict future trends in crime incidence. Although modelling requires advanced training in statistics, analysis such as the one we have presented in this work can be done using standard statistical and geospatial tools.

V. Conclusions

Criminal incidence in Mexico City is high, and the population's perception of insecurity is that crimes may occur practically anywhere in the urban area. Our analysis has shown that for the three crime types considered in this study the spatial distribution is in a clustered pattern, concentrated in the area known as"Historic Center". A possible explanation is that crimes are more frequent in areas where the density of possible victims is higher:.

The use of point pattern analysis techniques allows detecting in a non-subjective way the areas of higher crime incidence. There are differences in the results obtained when kernel estimation of the intensity function is obtained using Euclidean distance and network distance. Those differences are explained by the stronger smoothing induced by the kernel based on Euclidean distance, as this approach assigns density to locations out of the street network.

The spatial analysis of crime incidence we have done on a linear network allows to identify street segments where the incidence is higher than in neighbouring street segments. This information is potentially useful for authorities as high incidence in some streets may be indicative of the existence of crime gangs operating in those street segments.

The $K-$cross analysis of the three crime types has shown that they are independent of each other, meaning that the intensity of a given crime type does not affect the incidence rate of the other two. This is an important result, as it suggests that the three crime types analysed may be related to different risk factors.

Despite slight changes in the spatial pattern of crime incidence in Mexico City, the overall number of crimes during 2018 and 2019 has not changed significantly. The areas with high crime incidence have not changed either, suggesting that the efforts of the current local authorities to fight crime have worked properly just in the case of violent robberies.

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