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Mapping distance-decay of cardiorespiratory disease risk related to neighborhood environments

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ABSTRACT

Neighborhood characteristics affect an individual's quality of life. Although several studies have examined the relationship between neighborhood environments and human health, we are unaware of studies that have examined the distance-decay of this effect and then presented the risk results spatially. Our study is unique in that is explores the health effects in a less developed country compared to most studies that have focused on developed countries. The objective of our study is to quantify the distance-decay cardiorespiratory diseases risk related to 28 neighborhood aspects in the Federal District, Brazil and present this information spatially through risk maps of the region. Toward this end, we used a quantile regression model to estimate risk and GIS modeling techniques to create risk maps. Our analysis produced the following findings: i) a 2500 m increase in highway length was associated with a 46% increase in cardiorespiratory diseases; ii) 46,000 light vehicles in circulation (considering a buffer of $\leq$500 m from residences) was associated with 6 hospital admissions (95% CI: 2.6, 14.6) per cardiorespiratory diseases; iii) 74,000 m^2 of commercial areas (buffer $\leq$1700 m) was associated with 12 hospital admissions (95% CI: 2.2, 20.8); iv) 1 km^2 increase in green areas intra urban was associated with less two hospital admissions, and; vi) those who live $\leq$500 m from the nearest point of wildfire are more likely to have cardiorespiratory diseases that those living $>$500 m. Our findings suggest that the approach used in this study can be an option to improve the public health policies.

1. Introduction

Neighborhood characteristics, which include the built environment, socioeconomic conditions and environmental factors affect an individual's quality of life. Studies have identified predictive relationships between these factors, social behaviors and human health (Sampson et al., 2002; Yen and Syme 1999; Pauleit and Duhme 2000; Baldauf et al., 2013). The prevalence of tobacco consumption has been shown to be positively correlated to the concentration of convenience stores within a neighborhood (Chuang et al., 2005). Neighborhoods with few parks and a low perceived safety were correlated to increased obesity rates in children (Wall et al., 2012). The design of the neighborhoods can both support and reduce the amount of physical activity by residents, particularly their walking and cycling rates (Sallis et al., 2012; Lee et al., 2007; Brian et al., 2012). The neighborhood built environment includes associations to mental illness (Villanueva et al., 2013) cardiovascular diseases (Chum and Patricia, 2015), noise and air pollution exposure (Adams and Kanaroglou, 2016; Weber et al., 2014) and body mass index (James et al., 2014).

The large body of research connecting the neighborhood environment with quality of life has supported the need for public and private-sector policies to promote healthier communities. Policies that improve the physical, social and service environments of neighborhoods (CBHA, 2015; Diez-Roux, 2007). The impact goes beyond quality of life, Nowak and Heisler (2010) demonstrate that the presence of green spaces in U.S neighborhoods provide a $500 million savings per year to the economy because the green spaces are responsible for air pollution removal, which is one of the main causes of cardiorespiratory disease (Mortimer et al., 2012;

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Buonanno et al., 2013; Valdés et al., 2012). Additionally, Wang et al. (2005) reported that every dollar invested in building bike and pedestrian trails reduces $3 dollars in medical costs.

Although several studies have examined the relationship between neighborhood environments and human health, we are unaware of studies that have examined the distance-decay of this effect and then presented the risk results spatially. Our study is unique in that is explores the health effects in a less developed country compared to most studies that have focused on developed countries. Specifically in Brazil, an example of country in development, to our knowledge there are no studies that have assessed the relationship between neighborhoods environments and health. The objective of our study is to quantify the distance-decay cardiorespiratory diseases risk related to 28 neighborhood aspects in the Federal District, Brazil and present this information spatially through risk maps of the region.

2. Materials and methods

2.1. Study design and overview

We conducted a cross-sectional study to examine the effects of neighborhood environment on hospital admissions for cardiorespiratory diseases. We examined the Federal District (FD) in Brazil, which is located in central Brazil at 15° 47′ 02″ S and 47° 49′ 09″W, the region has an area of 5802 km^2 and a population of 2.5 million. The health data were provided from the Brazilian National Health Database (Datasus, 2013) and included the residential addresses of individuals (all ages) admitted to FD hospitals between 2008 and 2013 for cardiorespiratory illness.

To preserve patient privacy the health data were provided at the *lote* address level. In the FD the address system is composed of five gradations, which include, from coarse to fine: i) administrative region - coarse, ii) sector, iii) street, iv) conjunct, and v) *lote* - fine. Only 560 of the 7307 hospital admissions were provided at the *lote* level, which occurred in 65 different *lote* areas. The sample size (N=7307) represents a subset with address information. In Table 1, we present the number of admissions and the number of different regions where an admission occurred by address level. Appendix 1 shows a map to provide context (spatial extent and scale) for each spatial unit of the FD address system.

The method used to link the health data to address blocks has previously been used by our research group (Réquia et al., 2015a, 2015b). In short, we used an address matching process directly with the blocks. There was no loss during the geolocation procedure.

2.2. Predictor variables

We generated 28 predictor variables that were used in the GIS processing and statistical analysis to explore their effects on hospital emissions for cardiorespiratory diseases. These variables were grouped into six categories: i) transportation - 6 variables, ii) land use - 10 variables, iii) air pollution inventory - 6 variables, iv) meteorological and terrain - 3 variables, v) demographic and economic - 2 variables, and vi) Natural Issues - 1 variable.

The transportation attributes consisted of the length of highways, the length of the streets and avenues, vehicle counts (light vehicles, heavy vehicles and motorcycles) and the number of bus terminals. The roads network and bus terminals data were provided by the Brazil Secretary of State for Habitation (Sedhab, 2012). The vehicle count data were obtained from three sources: the Transit Department of the FD (Detran, 2009), the Route Department (DER, 2010), and the report on Urban Transport of the FD - PDTU (GDF, 2008). The temporal scale of the vehicle count data is daily average (Monday to Friday). Vehicle count data were assigned in the GIS to the corresponding road link (233 traffic roads). These 233 roads (approximately 615 km) do not represent the total road segments in the FD. It represent the roads linked to the vehicle count data provided. We present in Appendix 2 a map with the 233 traffic roads considered in our analysis.

Table 1
Health data structure.

Address level	Number of unique address blocks (geographic polygons)	Number of hospital admissions in all address blocks
1 – AR	0	0
2- Sector	37	1286
3- Street	361	3090
4- Conjunct	1084	2371
5- *Lote*	65	560
TOTAL	1547	7307

"AR: Administrative Region; TOTAL: aggregation".

The land use categories included industrial, commercial, urban, exposed soil, civil construction, and natural environment (water and green area). These areas were identified using the database provided by Sedhab (2012).

The air pollution category included vehicular emissions along the 233 traffic routes within the FD. This inventory was previously calculated by our research group and more information can be found in Réquia et al. (2015a, 2015b). We used a bottom-up method to estimate emissions for road segments, which were represented by the vectors. In order to create a surface to represent the vehicular emissions for the entire FD area, we used the Inverse Distance Weighting (IDW) interpolation method. CO_2 was the pollutant with the highest emissions, at more than 30 million tons. On average, approximately 130,000 tons of CO_2 are emitted per year among the 233 routes. Conversely, CH_4 exhibited the lowest emissions, approximately 4000 tons.

The meteorological and terrain category included temperature, humidity, and slope – relief. The temperature and humidity data were obtained from Environmental Institute of Brasilia (Ibram, 2013), and the slope – relief data were obtained from Sedhab (2012). We the IDW interpolation method to model a surface with the values of temperature and humidity.

The demographic and economic category included population and income. These data were obtained from the census tracts of the FD (IBGE, 2012). Natural issues included wildfire locations, which were provided by the National Institute of Spatial Research of Brazil (Inpe, 2013).

Table 2 presents a summary of all 28 attribute datasets that were explored in this study.

2.3. GIS techniques for estimating predictor variables

First, we defined 15 buffers around each of 1547 address blocks (Table 1). The buffers were specified using a logarithmic scale, as suggested by some air pollution monitoring studies (Su et al., 2009; Liu et al., 2009). The buffer sizes (meters) include 50, 500, 870, 1140, 1350, 1540, 1700, 840, 1,960, 2080, 2180, 2280, 2370, 2450, and 2520.

Subsequently, we used GIS techniques to estimate each predictor variable inside each buffer. This process was performed for all 1547 address blocks. For example, in the hypothetical address block “A” there is 1292 and 120,290 m of street and avenue within the 50 and 1350 m buffers, respectively (Fig. 1). All GIS calculations were performed in ESRI's ArcGIS, version 10.3.

Table 2
Summary of attribute datasets.

Category	Variables	Unit	Variable definition
Transportation	Highways	m	Major roads which were mostly interstate
	Streets and avenues	m	Roads in an urban context
	Light vehicles	Vehicles	Passenger vehicles
	Heavy vehicles	Vehicles	Bus and trucks
	Motorcycles	Numbers	Vehicles with two in-line wheels
	Bus terminals	Coordinates	Location points. Large bus stations (outbound, inbound)
Land use	Industry areas	m^2	Area of land designated for industrial use
	Commercial areas	m^2	Area of land designated for commercial use
	Urbanization areas	m^2	Area of land designated for new urban area (under construction)
	Exposed soil	m^2	Degraded areas (no vegetation, no urban structures)
	Construction areas	m^2	Individual sites (private or public) under construction
	Green areas intra urban	m^2	Green areas along the streets
	Parks	m^2	Public green areas in neighborhoods designated for recreation (sport facilities)
	Forest	m^2	Large green area designated for conservation
	Lakes	m^2	Lakes in area
	Rivers	m	Rivers in area
Air pollution inventory	Particulate matter (PM)	tons	Tons of PM emissions in the area
	Carbon monoxide (CO)	tons	Tons of CO emissions in the area
	Methane (CH_4)	tons	Tons of CH_4 emissions in the area
	Nitrogen oxides (NO_x)	tons	Tons of NO_x emissions in the area
	Hydrocarbons (NMHC)	tons	Tons of non-methane hydrocarbons emissions in the area
	Carbon dioxide (CO_2)	Tons	Tons of CO_2 emissions in the area
Meteorological and terrain	Temperature	°C	Temperature
	Relative Humidity	%	Relative Humidity
	Slope - relief	Unit	Altitude measured: very low (1), low (2), median (3), high (4), and very high (5)
Demographic and economic	Population	Number	Population in area
	Income	R$	Total income per month, per population and per census tract (Brazilian currency)
Natural Issues	Wildfire	Coordinates	Location points of wildfire

2.4. Statistical analysis

In our study, the response variable was the rate of hospital admissions per capita in each of the 1547 address blocks. To account for the variation in geographic area due to the varying address units, the population data were estimated for each health data polygon based on the overlapping proportion of the area (area of the census tracts and area of the health data). This process resulted in 20 health data blocks with a less than one individual, which were removed from the analysis. The analysis was conducted with 1527 address blocks that included 7269 hospital admissions.

We performed Quantile regression to evaluate how the quantiles of the response variable change with the variation in the predictor variable. This is different from Ordinary Least Squares (OLS) regression, which assesses how the mean response variable changes in accordance to the predictor variable. Studies that report findings based on conditional means of the response variable may be miss effects of the predictors (Reich et al., 2011; Koenker and Hallock 2001; Bind et al., 2015). The quantile regression is described as follows:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_k x_{ki} + e_i \tag{1}$$

Where y_i is the response variable for the *ith* quantile; $\beta_0 + \beta_1,\ldots+\beta_k$ are the coefficients associated with the *ith* quantile; $x_{1i}, x_{2i},\ldots, x_{ki}$ are the predictor variables for the *ith* quantile; and e_i is the residual error.

We estimated the risk of cardiorespiratory diseases related to neighborhood environment, using the quantile regression coefficient (β) for each buffer size. Also we calculated the risk considering the effect from single predictor variables (total of 28 predictors). In order to create a multivariate model we tried to control with other variables, such income, population, green areas intra urban, transportation and land use, but we did not find any significant associations. Eq. (2) describes the estimated risk.

$$Risk_{kij} = \beta_{kij} \times IQR_{kj} \tag{2}$$

where *k* is the predictor variable; *i* represents the quantile *ith*, which we used 0.05, 0.10, 0.25, 0.75, 0.90 and 0.95; *j* is the buffer size; and IQR is the interquartile range. This is a scaling factor, which is equal to the difference between the 75th and 25th percentile. The Eq. (3) describes the IQR.

$$IQR_{kj} = 75^{th} Percentile_{k,j} - 25^{th} Percentile_{k,j} \tag{3}$$

The risk estimated were expressed as a hospital admission increase with an IQR increase in each predictor variable. We considered results to be significant in all analyses with a p-value ≤ 0.05 and reported the corresponding 95% of Confidence Interval (CI). Statistical analysis were conducted with R software, version 2.10.1.

2.5. Sensitivity analysis

We conducted a sensitivity analysis to examine the robustness of the primary results. We divided the address blocks based on the level of population and income (high/low values). For the low values we considered the values below the quantile 0.25, whereas for the high values we considered the values greater than quantile 0.75. As a result, we generated four sub groups: i) high population and high income, ii) low population and high income, iii) low income and high population, and iv) low population and low income.

Finally, we applied the statistical method described above for each sub group of population and income.

2.6. GIS modeling for constructing risk maps

Risk maps for the FD were created using two data inputs

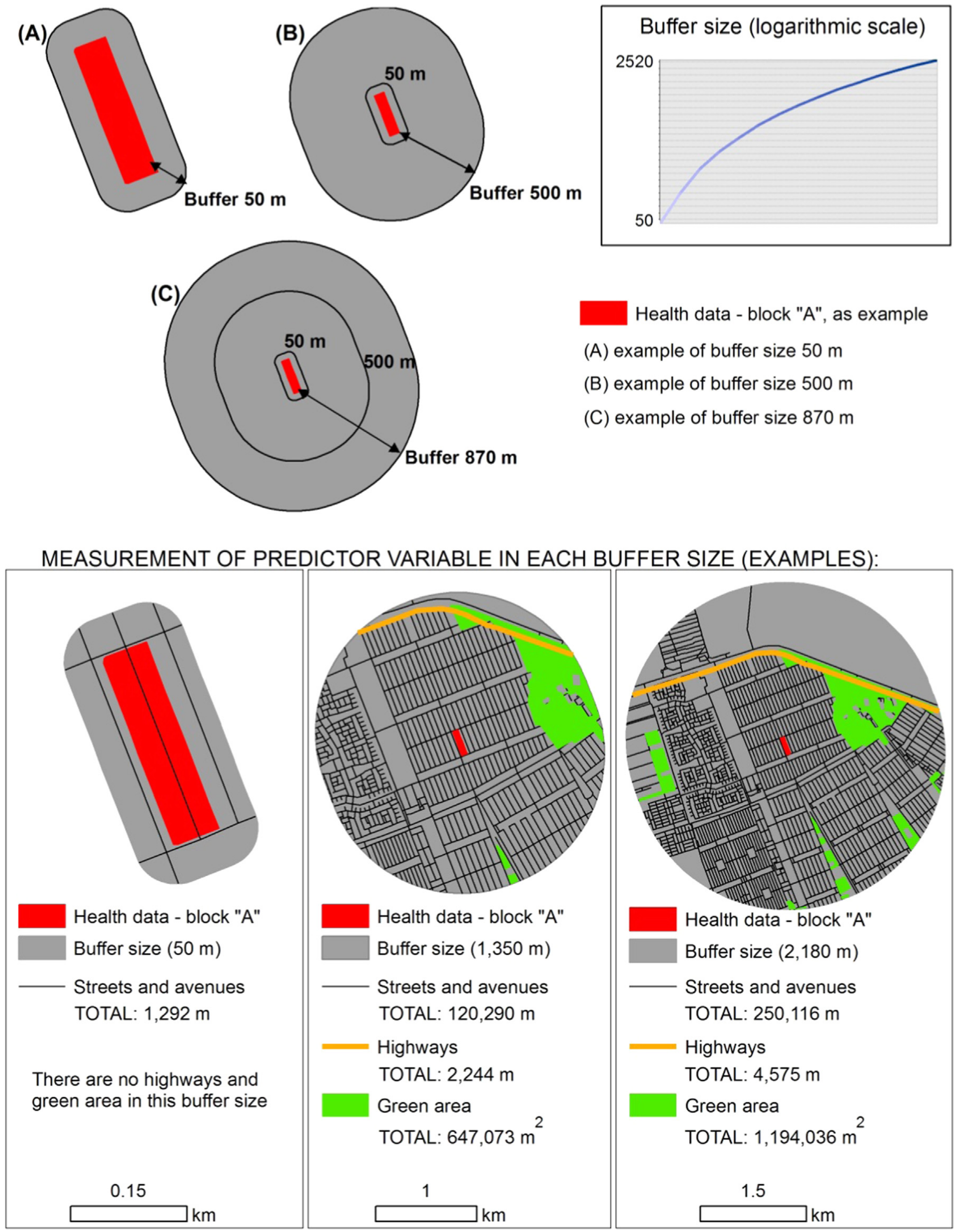

Fig. 1. Estimation of predictor variables within the different buffers.

including the estimated risk from the quantile regression analysis and the complete address geodatabase for FD region (streets as address level), which was provided by Sedhab (2012). The maps were developed for the significant predictor variables from the quantile regression analysis. The statistically significantly predictor variables were calculated for each of the address locations (6158 streets), for each of the 15 buffers 50–2520 m) using the same GIS techniques described in Section 2.2.

To allow comparison between risk variables and assess the total risk, we created one risk map per predictor variable and we calculated the total risk in a single map based on the sum of the risks from all buffers (Eq. (4)):

$$RM_{z,k,i} = \frac{Q_{z,k,j=1} \times Risk_{k,i,j=1}}{IQR_{k,j=1}} + \frac{Q_{z,k,j=2} \times Risk_{k,i,j=2}}{IQR_{k,j=2}} + \ldots + \frac{Q_{z,k,j=n} \times Risk_{k,i,j=n}}{IQR_{k,j=n}} \quad (4)$$

where *RM* is the risk map; *z* is a specific polygon, which means a specific street (total of 6158); k is the predictor variable; i represents the *ith* quantile; Q is the amount of the predictor variable k on the polygon z, for the buffer size j ($j=1$ for 50 m buffer, $j=2$ for 500 m buffer, $j=3$ *for* 870 m buffer, …, j=15 for 2520 m buffer); *Risk* is the estimated risk calculate using Eq. (2); and *IQR* is the interquartile range calculated using Eq. (3).

3. Results

3.1. Population descriptive statistics

We studied 7269 hospital admissions from 1527 address blocks. The average number of the hospital admissions per address block is 4.76 (0.017 per person), with a standard deviation equal to 21.71 (0.928 considering the rate). There is only one hospital admissions in each of the lower percentiles, 5th, 10th, and 25th. In the higher percentiles, 75th, 90th, and 95th, there are two, four, and nine hospital admissions, respectively.

3.2. Distance-decay of cardiorespiratory diseases risk

Using the quantile regression approach no statistically significant results occurred for the 0.05, 0.10, 0.25 and 0.75 quantiles. Quantiles 0.90 and 0.95 were statistically significant and will be the focus of the results and discussion. Thirteen variables had a zero confidence interval, indicating they did not affect the response variable, which included bus terminals, urban land area, construction area, parks, forests, lakes, PM, CH_4, NMHC, CO_2, temperature, humidity and population. We suspect the methodology may have influence the negligible effects observed for the air pollution, meteorological and population variables. For example, maybe the GIS technique used for measurement of air pollution inventory variables and meteorological variables (IDW interpolation) is inadequate at capturing the true spatial variation because of a limited number of points for interpolation. The population data, probably does not vary significantly in the number of people among the buffer sizes, which could lead to its insignificance.

Commercial land use was the only attribute that was statistically significant at all buffer sizes, which indicates that its commercial lands have a very large spatial effect. Highways were also significant in all but one buffer size (50 m), which is likely due to zoning rules that would limit housing near major highways.

Some variables presented IQR values equal to zero for the smallest buffers (e.g., for highways, buffer=50 m; industry areas, buffer 50–1700 m; exposed soil, buffer 50–1140 m), which means that there is no impact of these variables at these distances. (Table 3).

Fig. 2 presents the risk calculated for each buffer size, in terms of IQR, quantiles and specific for each transportation category. For highways there is no risk in buffer <50 m, because the IQR is zero. Also, the risk at the quantile 0.95 was greater than at the quantile 0.90. The higher risks were found for the address blocks located 1140 m from the nearest highways; in a block with 3400 m of highways (at the buffer 1140 m) we found an increase of 15 admissions.

We also found higher risk for streets and avenues at the quantile 0.95. There is risk starting with the first buffer, 50 m (quantile 0.95; risk=3 hospital admissions; 95% CI: 0.6, 24.1), with IQR equal to 550 m. The higher risk is at the buffer 500 m (quantile 0.95; risk=6 hospital admissions; 95% CI: 1.4, 7.6), with IQR equal to 6550 m. The risk becomes zero at the buffer ≥ 1140 m, while the IQR continues to increase (Fig. 2).

For light vehicles, heavy vehicles and motorcycles there is no risk at buffer <50 m (IQR $=0$). For light vehicles, the higher risk is for distances ≤ 500 m (quantile 0.95; risk=6 hospital admissions; 95% CI: 2.6, 14.6), with IQR equal to 46,480 vehicles. The risk decreases between 870 and 2370 m (quantile 0.95; risk=4 hospital admissions; 95% CI: 1.8, 14.4) and for distances >2370 m the risk related to light vehicles is zero. For heavy vehicles the overall risk is smaller than for light vehicles. For the buffer between 1700 and 2080 m, the risk for heavy vehicles is equal to 1 patient (quantile 0.90; 95% CI: 0.2, 2.2) with the IQR equal to 9300 heavy vehicles. Finally, for motorcycles the higher risk is for buffer 870 m (quantile 0.95; risk=4 hospital admissions; 95% CI: 1.4, 9.7), IQR equal to 1800 motorcycles. For motorcycles the risk for buffer >870 m decreases to approximately 2 hospital admissions at the quantile 0.95 (Fig. 2).

The risk related to land use variables are presented by Fig. 3. For the industrial areas, there is no risk ≤ 2080 m. Between 50 and 1700 m the IQR for industry areas is zero; and between 1840 and 2080, even with IQR approximately equal to 6000 m^2, the risk is zero. So there is a very low risk only with the buffer >2080 m, and the higher risk is at the last buffer, 2520 m (quantile 0.90; risk=0.18 hospital admissions; 95% CI: 0.07, 0.55).

Considering commercial areas, we found significant risk for all of the buffers. The risk increases up to the buffer 1700 m, where is the highest risk (quantile 0.95; risk=12 hospital admissions; 95% CI: 2.2, 20.8), IQR equal to 74,000 m^2. Then the risk decreases to approximately 7 hospital admissions, at the quantile 0.95, while the IQR continues to increase (Fig. 3). For exposed soil, we observed an increasing effect of IQR change in cardiorespiratory risk between the distances 1350 to 2520 m. The higher risk is at the buffer 2450 m (quantile 0.95; risk=4 hospital admissions; 95% CI: 1.6, 16.4). The effect was the opposite when we considered the green areas intra urban. A decreasing risk was observed among all of the buffers, while the IQR increased with increasing buffer size. For rivers, there is significant risk only for 870–2280 m at the quantile 0.95; and 870–1700 m at the quantile 0.90 (Fig. 3).

For air pollution inventory variables presented risk only for short distances (<500 m). For income and slope were found unexpected results. We expected to find higher air pollution in areas with less income, and consequently, higher cardiorespiratory diseases (Lim et al., 2012; Branis and Linhartova, 2012). However, we found an increase risk between 870 and 1140 m, when in this same distance interval the IQR for income increased. Possibly here, the income does not present variation among the buffers sizes. We had the same problem with population data, as mentioned previously. Regarding to slope variable, the results showed a higher risk variation, while the IQR for slope was practically constant across all of the buffers. We suggest here that the slope variable is not a good predictor for cardiorespiratory risk in our study area. Probably it is because that most of urban area of the FD has a flat terrain. Therefore, the results for air pollution inventory, income and slope are presented on the Appendix 3.

Finally, for the wildfire variable, we found risk between 500–1540 m. The higher risk is at the 500 m (quantile 0.95; risk=4 hospital admissions; 95% CI: 3.0, 15.2). Then the risk decreases until the buffer 1700 m, when it becomes zero (Fig. 3).

The results obtained from sensitive analysis are presented in Figs. 4 and 5, which was conducted for the greatest risk quantile 0.95 (highways and green areas). The greatest risk for hospital admissions occurred where populations were highest. At the nearest distance of 50 m, only the high income and high population sub group presented a significant risk. Buffers larger than 500 m demonstrated that highways proximity produced a high risk for both high and low income sub-populations regardless if they were high or low income, see Fig. 4 for the distance decay for each sub population. Green areas decreased the hospital admission risk, the greatest impacts were noted in the low population density areas. The distance decay effects are presented in Fig. 5.

Table 3
Coefficient significantly different from zero in each buffer (95%CI does not contain the zero value).

Category	Variables	Q	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Transportation	Highways	0.90	*														
		0.95	*														
	Streets and avenues	0.90															
		0.95															
	Light vehicles	0.90	*														
		0.95	*														
	Heavy vehicles	0.90	*														
		0.95	*														
	Motorcycles	0.90	*														
		0.95	*														
	Bus terminals	0.90															
		0.95															
Land use	Industry areas	0.90	*	*	*	*	*	*	*								
		0.95	*	*	*	*	*	*	*								
	Commercial areas	0.90															
		0.95															
	Urbanization areas	0.90															
		0.95															
	Exposed soil	0.90	*	*	*	*											
		0.95	*	*	*	*											
	Construction areas	0.90															
		0.95															
	Green areas intra urban	0.90	*														
		0.95	*														
	Parks	0.90															
		0.95															
	Forest	0.90															
		0.95															
	Lakes	0.90															
		0.95															
	Rivers	0.90	*	*													
		0.95	*	*													
Air pollution inventory	PM	0.90															
		0.95															
	CO	0.90															
		0.95															
	CH_4	0.90															
		0.95															
	NO_x	0.90															
		0.95															
	NMHC	0.90															
		0.95															
	CO_2	0.90															
		0.95															
Meteorological and terrain	Temperature	0.90															
		0.95															
	Humidity	0.90															
		0.95															
	Slope - relief	0.90															
		0.95															
Demographic and economic	Population	0.90															
		0.95															
	Income	0.90															
		0.95															
Natural Issues	Wildfire	0.90	*														
		0.95	*														

Notes: Quantiles (Q); at the quantile 0.90, CI ≠0 and p-value ≤ 0.05 (light grey color); at the quantile 0.95, CI ≠0 and p-value ≤ 0.05 (dark grey color); CI contains zero (blank); Buffer 50 m (1); Buffer 500 m (2); Buffer 87 m (3); Buffer 1140 m (4); Buffer 1350 m (5); Buffer 1540 m (6); Buffer 1700 m (7); Buffer 1840 m (8); Buffer 1960 m (9); Buffer 2080 m (10); Buffer 2180 m (11); Buffer 2280 m (12); Buffer 2370 m (13); Buffer 2450 m (14); Buffer 2520 m (15); IQR equal to zero (*).

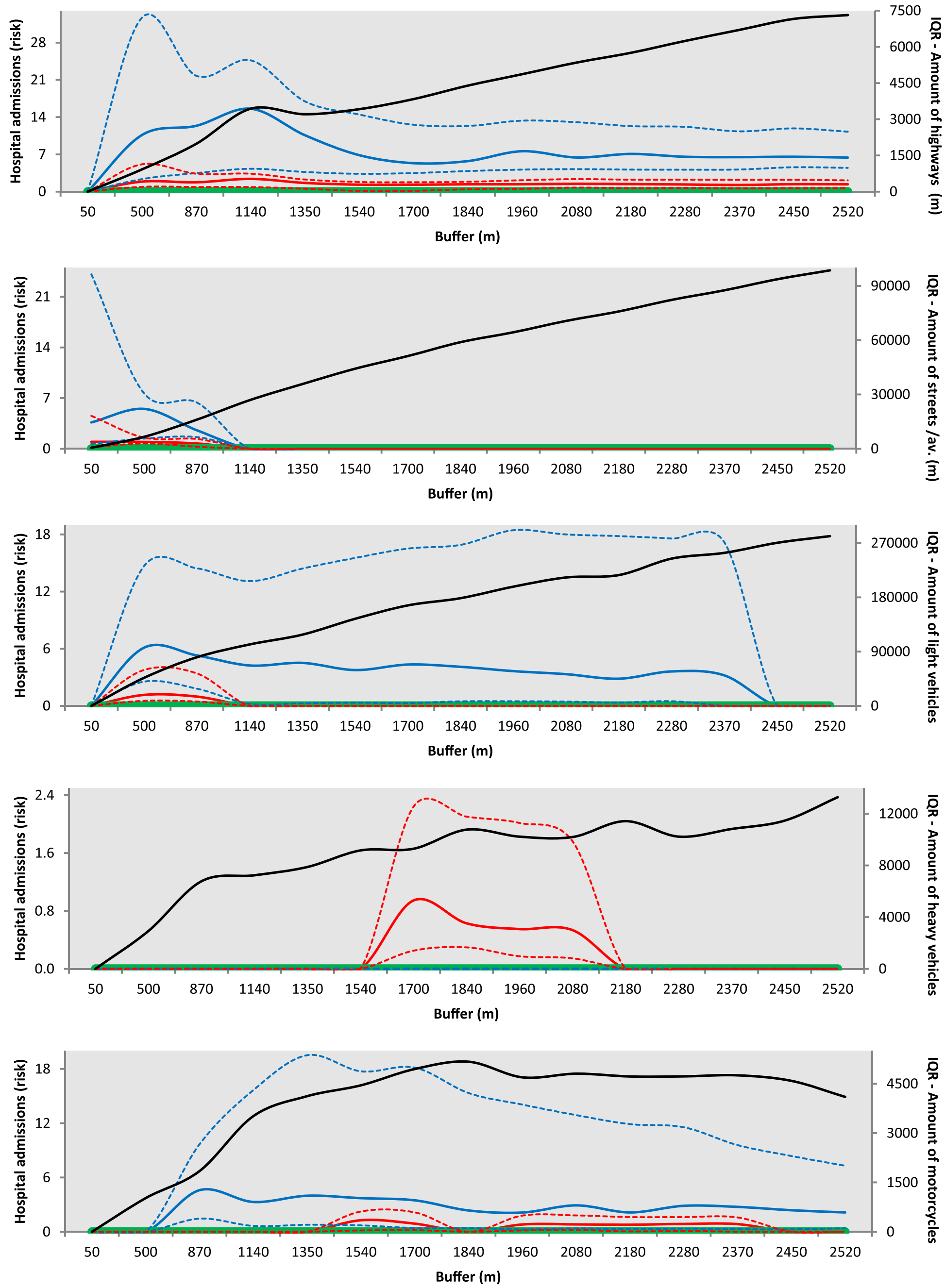

Fig. 2. Risk and distance decay – Category: transportation. Notes: blue solid line (hospital admissions – risk – coefficients at the quantile 0.95); red solid line (hospital admissions – risk – coefficients at the quantile 0.90); green solid line (hospital admissions – risk – coefficients at the quantiles 0.05; 0.10; 0.25; 0.75); blue dash line (hospital admissions – risk – 95% CI of coefficients at the quantile 0.95); red dash line (hospital admissions – risk – 95% CI of coefficients at the quantile 0.90); black solid line (IQR - amount of predictor variable). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.3. Risk map

We plot the spatial variation of health risk separately for quantile 0.90 (Fig. 6) and quantile 0.95 (Fig. 7). Income, slope, inventory of CO and inventory of NO_x were excluded from risk mapping because their results were unexpected.

4. Discussion and conclusion

Significant health risk occurred for 15 of the neighborhood attributes that we calculated in this study. From those 15, nine of the variables did not present a significant risk for the smaller buffers (typically ≤ 500 m). Our findings indicate that to predict the neighborhood influence on cardiorespiratory diseases that the neighborhood must be assessed beyond the very local level of the residence. Seven of the attributes were significant up to a distance of 2520 m, which included the influence of highways, the number of motorcycles, industrial and commercial land use, the amount of exposed soil, natural areas and income.

Living close to a highway presents a host of potential benefits such as accessibility; however, the proximity can also lead to negative health effects form noise and air pollution. Brugge et al. (2013) identified that cardiorespiratory disease risk increased for people who live within 50 m from highways by 49% (95% CI: 6%) and for those who live between 10 and 50 m was 41% (95% CI: 6%).

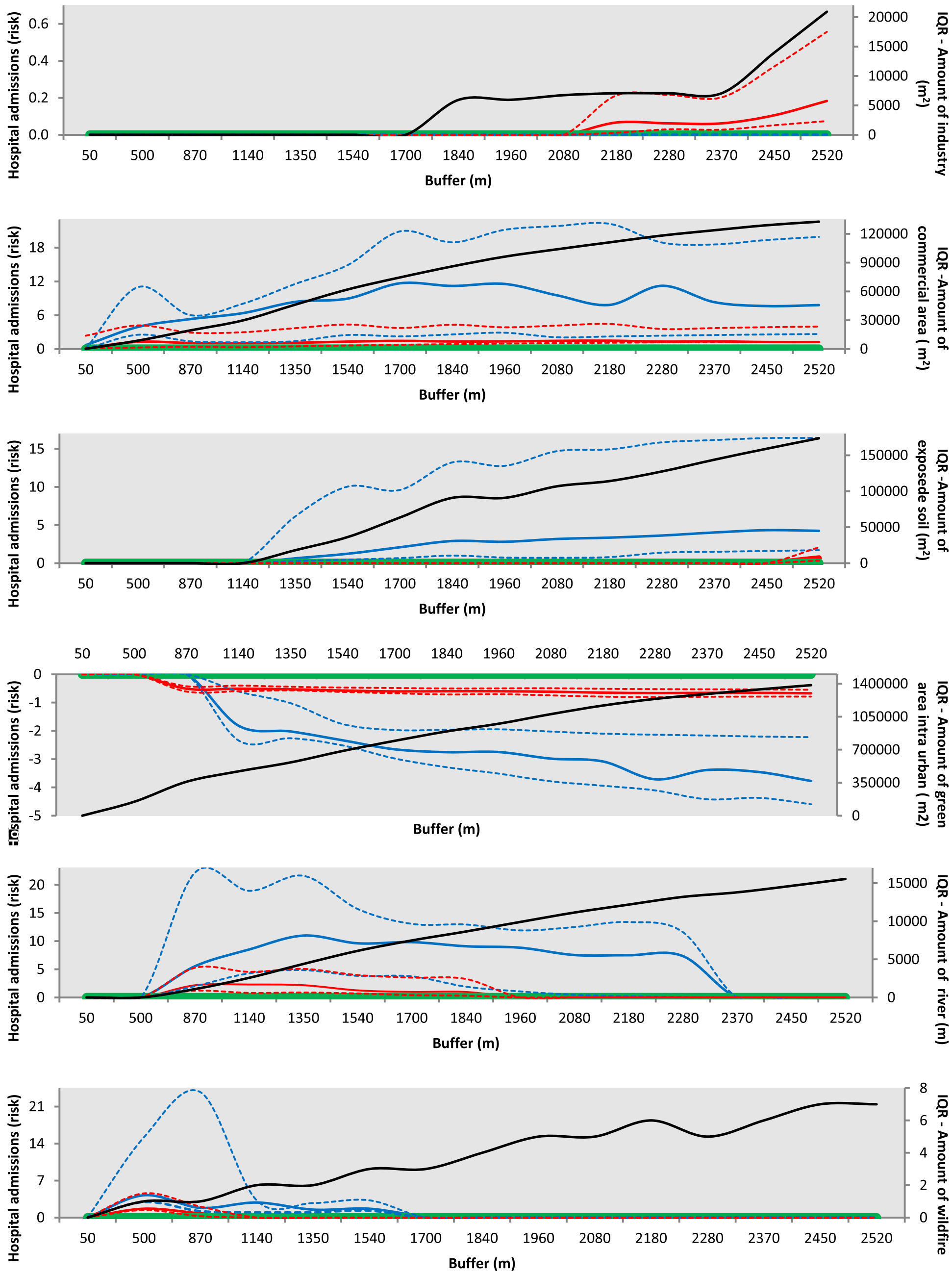

Fig. 3. Risk and distance decay – Category: land use and Natural Issues (wildfire). Notes: blue solid line (hospital admissions – risk – coefficients at the quantile 0.95); red solid line (hospital admissions – risk – coefficients at the quantile 0.90); green solid line (hospital admissions – risk – coefficients at the quantiles 0.05; 0.10; 0.25; 0.75); blue dash line (hospital admissions – risk – 95% CI of coefficients at the quantile 0.95); red dash line (hospital admissions – risk – 95% CI of coefficients at the quantile 0.90); black solid line (IQR - amount of predictor variable). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Our findings agree that the proximity to a highway increases the risk of cardiorespiratory disease. For example, a 2500 m increase in highways (buffer 500–1140 m) was associated with a 46% increase in cardiorespiratory diseases (quantile 0.95). The effect from streets and avenues occurs more locally with the maximum significant distance of 870 m. The highest risk occurred for the buffer 500 m (quantile 0.95), buffers that are much smaller likely have little variation because all residences are located adjacent to a street. A 6000 m increase in streets and avenues (buffer 50–500 m) was associated with a 51% increase in hospital admissions per cardiorespiratory diseases (quantile 0.95).

The risk from heavy duty vehicles may not have localized effects because of the proximity between the operating locations of heavy duty vehicles and the location of residences. Williams et al. (2009) identified that most heavy duty vehicle routes are far away from residences, which do not translate to adverse health effects. Heavy duty vehicle risk was significant for buffers between 1540 m and 2180 m, which is consistent with the notion that their routes occur at fair distances from residences. The risk for motorcycles and light duty vehicles occurs at much closer distances and the strength of this risk decreases as buffer sizes are increased. These findings of traffic effects and adverse health outcomes are in agreement with other studies such as Williams et al. (2009) in Seattle, Washington – US, where women living within 150 m of arterial roads had 21% (95% CI: 15.6%; 23.5%) lower NK cytotoxicity (immune function) than women who live more than 150 m from arterial roads.

Our findings for the risk from industrial areas has the same

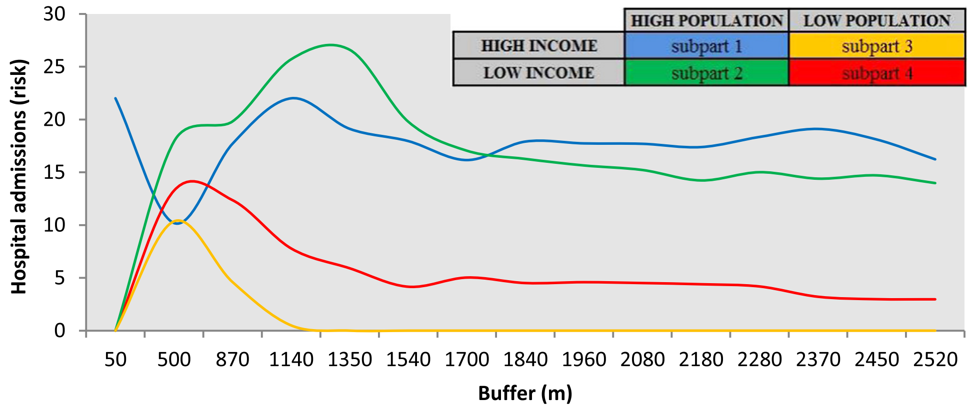

Fig. 4. Sensitive analysis – hospital admissions risk for highways (quantile 0.95).

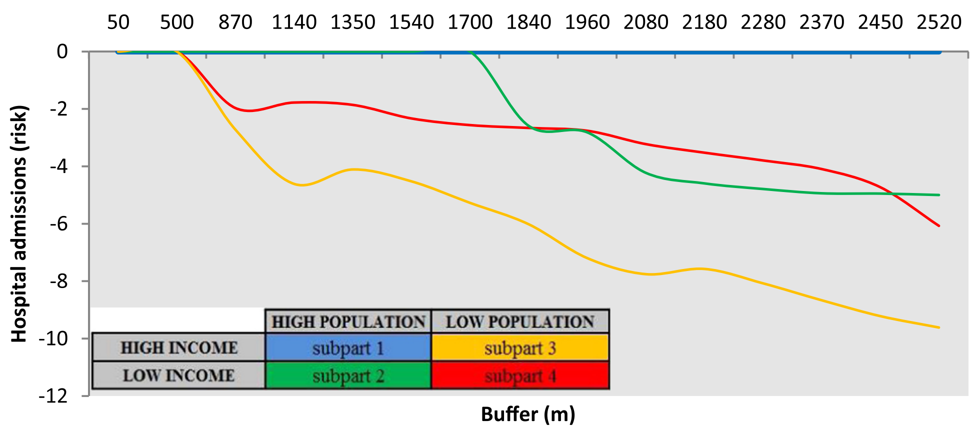

Fig. 5. Sensitive analysis – hospital admissions risk for green areas (quantile 0.95). Notes: there is no significant risk for high population and high income (subpart 1).

effect on health risk as the highways, such that, residences are not located near industrial regions because of land use policies implemented to limit the exposure. Increased risk occurs for buffers > 2080 m, the increase is small compared to other factors with the greatest risk only increasing by 0.18 hospital admissions (quantile 0.90; 95% CI: 0.07; 0.55). The FD has limited industrial land use within the region.

The FD has a very high concentration of commercial land use. We found significant risk for all commercial area buffers, with the highest risk for the 1700 m buffer (quantile 0.95; risk = 12 hospital admissions; 95% CI: 2.2; 20.8). For the commercial area, we estimated that the cardiorespiratory diseases risk with buffer 1700 m (quantile 0.95) is 197% higher, than for the buffer 500 m. Comparing the 1700 m buffer with the 2520 m buffer (largest buffer), the risk decreased to 49%. James et al. (2014) studied the effect of commercial areas in association with walking and Body Mass Index (BMI) and found a decreasing effect with larger buffer size as well. However, the authors observed the strongest effect of commercial area on BMI in the 400 m radial buffer, with a decrease out to the 1600 m buffer.

For exposed soil (Fig. 3), our findings showed an increasing risk beginning at 1140 m (quantile 0.95). Below 1140 m the risk is zero for all quantiles. It was observed that at the last buffer, 2520 m, the risk increased 572% (quantile 0.95). Probably the risk also exists for distances > 2520 m. We suggest that crustal particles (air pollutant from exposed soil) on the FD have high association with cardiorespiratory diseases. Other studies have found this association (Zanobetti and Schwartz, 2009; Laden et al., 2000). Also, as for previous studies (Rodriguez et al., 2013; Wallace et al., 2009), the meteorological conditions, such as wind direction and wind speed, can contribute to the possibility that the risk still exists at distances > 2520 m.

Our results showed that the vegetation intra urban has an important effect to minimize the cardiorespiratory risk (Fig. 3). A decreased risk was observed beginning at 1140 m. The findings suggest that a 1 km^2 increase in green areas intra urban (buffer 1140 to 2520 m) was associated with less 2 hospital admissions (quantile 0.95). Other studies have found the positive effect from green areas to improve health (Nardo et al., 2010; Zandbergen and Green, 2007). For instance, Nielsen and Hansen (2007) reported that who live in short distances from green areas are associated with less stress and a lower likelihood of obesity. Berg et al. (2010) showed that there is less occurrence of mental health for who live < 1 km from green spaces. Also, Villeneuve et al. (2012) reported that in Ontario, Canada, an increase in the IQR of green areas, using a 500 m buffer, was associated with reduced non-accidental mortality (RR = 0.95, 95% CI: 0.94; 0.96). For respiratory disease mortality, the authors found a relative risk equal to 0.91 (95% CI: 0.89; 0.93).

For water (rivers and lakes), we observed that the presence of rivers is positively associated with cardiorespiratory risk (Fig. 3). The results showed that there is an increase risk between 870 and 1350 m (quantile 0.95). Then the risk begins to decrease. A 3200 m increase in river (buffer 870–1350 m) was associated with 98% increase in cardiorespiratory risk (quantile 0.95). We suggest that in the FD around the rivers there is a higher population, consequently, a higher number of cars. No significant results were found for lakes. It was not possible compare this result with other studies. We did not find studies that considered water as variable to represent the neighborhood environment.

Considering the points of wildfire (Fig. 3), our findings showed a decreasing risk between 500 and 1540 m. Individuals who live ≤ 500 m from the nearest point of wildfire are more likely to have

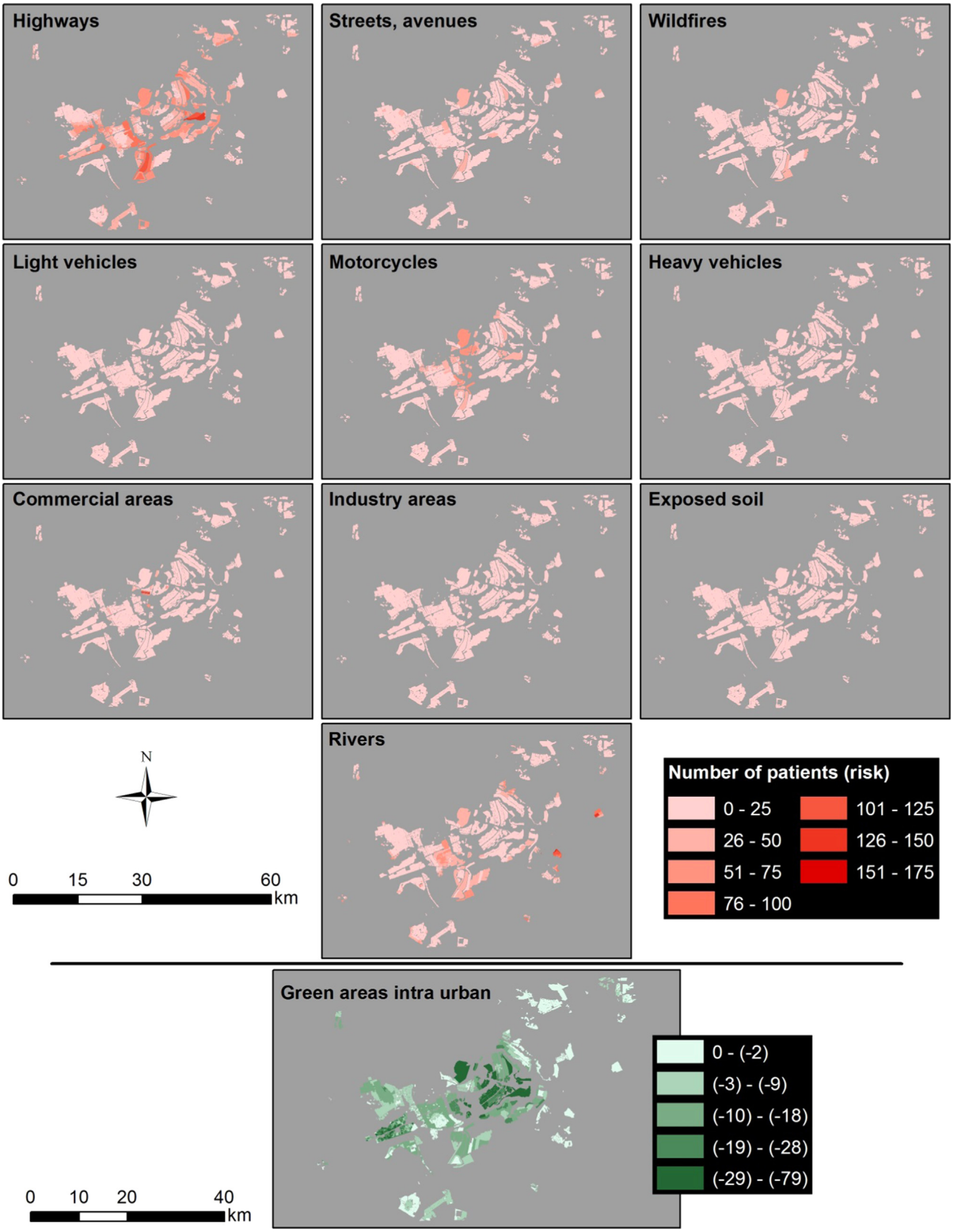

Fig. 6. Risk map, considering quantile 0.90.

cardiorespiratory diseases than those living > 500 m. The cause here is that the wildfire is related to air pollution emissions, for instance Particulate Matter (PM), Carbon Monoxide (CO), Black Carbon (BC). Several studies have found the effects from wildfires on human health (Williams et al., 2012; Youssouf et al., 2014; O'Neill et al., 2013). Johnston et al. (2014), for instance, show that the wildfire events in Sydney, Australia, were associated with increases in hospital attendances for respiratory conditions (OR 1.07,

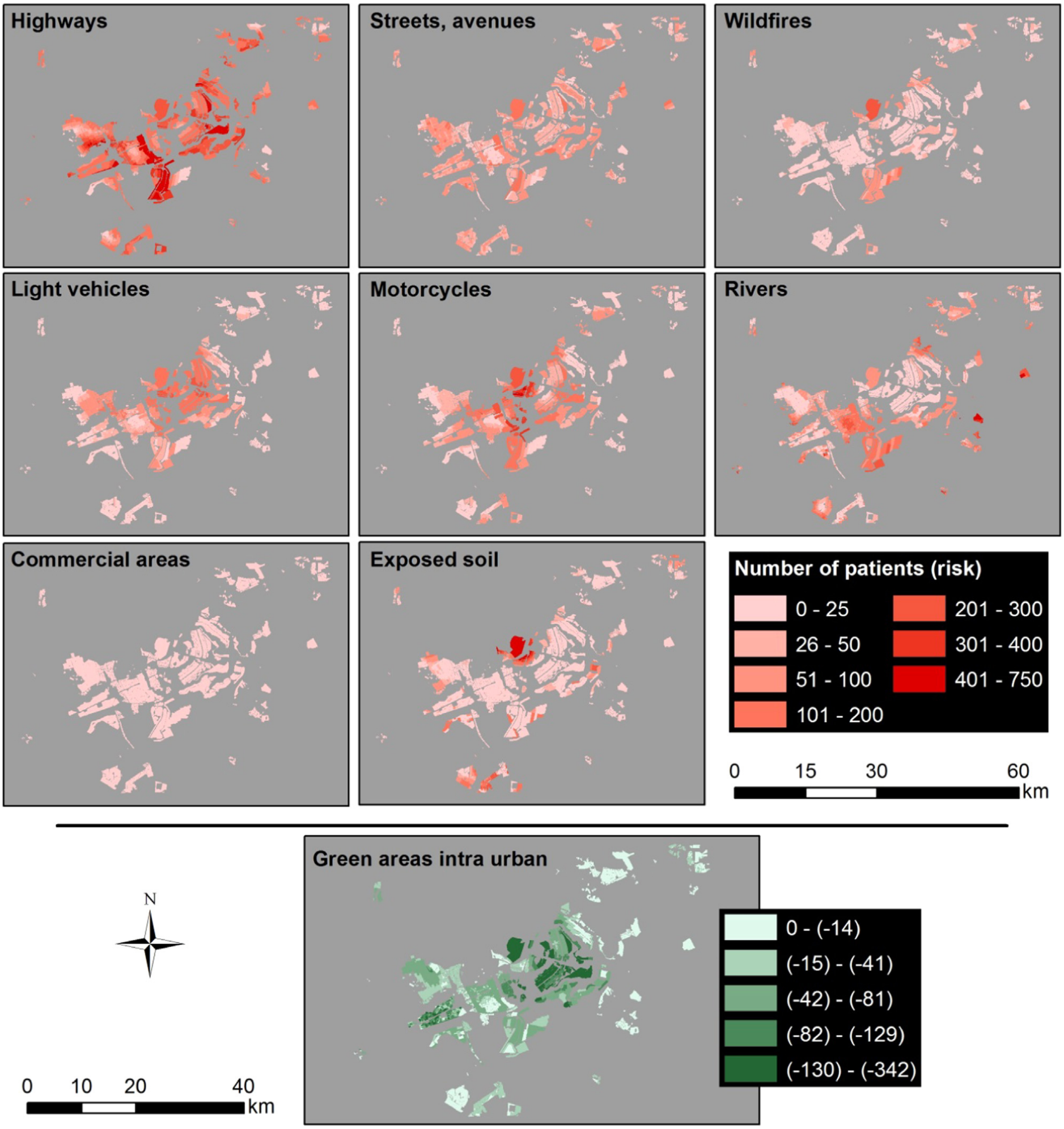

Fig. 7. Risk map, considering quantile 0.95.

95% CI: 1.04; 1.10).

Our study has some limitations. First, the variables light vehicles, heavy vehicles and motorcycles are only from 233 roads of the FD (mostly highways and big avenues). Probably if we had access to the data from all roads, we would find a higher effect from these variables to the hospital admissions. Second, the health data do not represent the real total number of hospital admission in the FD between 2008 and 2013. The health data used in this study represent a subset with address information. Finally, our results should be interpreted carefully as the association may be influenced by residual confounding of other variables, including socioeconomic, lifestyle, indoor contribution etc. Further research is needed to identify potential confounding role of other factors-related cardiorespiratory risk.

In conclusion, our findings suggest that predictor variables related with transportation, land use and wildfire can explain the occurrence of cardiorespiratory diseases. The risk map created can presents the spatial distribution of the risk, even for areas where we did not have access of health data. The spatial analysis of these variables, for instance the amount of each variable per buffer and the risk map, can be a potential tool to guide and enhance the public health policies in the FD.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.envres.2016.07.038.

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