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Original Contribution

Assessment of Environmental Hazards to Public Health in Temperate Urban Argentina

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Abstract: Human health risk in urban areas depends on multiple environmental features. We performed a year-round survey in a highly urbanized district located in temperate Argentina (General San Martín, Buenos Aires) to establish baseline information about environmental hazards associated with health risks. Sampling was stratified into low and high hazardous zones according to estimated indexes previously developed for the area for four hazards: drinking water and air pollution, and mosquito and rodent infestation. Water from wells showed lower concentrations of aluminum, manganese and iron, and higher values of arsenic than tap samples, with the latter showing records above the maximum permitted for arsenic, aluminum and chromium. Benzene concentration in air was higher in summer than in winter, and in areas close to dumps and landfills, gas stations, high traffic pathways and industries with respect to low hazard areas. Adult mosquito collections were more abundant in high hazardous areas, three species from the genus *Culex* dominated the captures and the proportion of individuals from each species was variable seasonally and spatially. Rodent activity was recorded inside and outside dwellings, and its observed values did not differ between low and high hazardous areas. In the comparison between field data and estimated hazard maps, high accuracy was obtained for air pollution maps, intermediate accuracy for water pollution and mosquito infestation, and poor accuracy for rodent infestation. How to improve field surveys and estimated maps are both discussed, highlighting the need for dynamic feedback between GIS-based models and environmental monitoring.

Keywords: Water pollution, Air pollution, Mosquito infestation, Rodent infestation, Urban district, Human health risk

Introduction and Purpose

Two-thirds of the global population are expected to live in cities by 2050 (Jensen and Wu 2018). In developing countries, this leads to unplanned urbanization associated

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with overcrowding, poor sanitation, inadequate waste disposal, insufficient access to safe drinking water and exposure to etiologic agents of infectious diseases (Moore et al. 2003). These problems compromise the quality of life standards of the population by altering the physical and biological environment, affecting air and water quality and increasing the occurrence of zoonoses (McGranahan et al. 2001). Identifying priority areas is an essential step in developing management strategies, and risk maps based on models, after proper field validation, are a valuable tool in decision making (Elliott and Wartenberg 2004).

Access to safe drinking water is essential for public health (Hrudey et al. 2006). Water obtained precariously through perforations or informal connections to the water supply network may be contaminated by the inadequate disposal of liquid effluents and garbage (Cabral 2010). Some metals usually found in water are essential for human health but may result in severe health problems when ingested in high amounts, whereas others (e.g., arsenic, cadmium, lead and mercury) can be toxic even at low concentrations (WHO 2011). Water-borne diseases (including diarrhea, cholera, infectious hepatitis and arsenicosis, WHO 2011) occur worldwide but are particularly widespread in developing countries, where access to safe drinking water is not always guaranteed.

Air pollution also represents a major environmental hazard to human health, particularly with respect to cancer, and respiratory and cardiovascular affections (WHO 2016). In developing countries, *ca.* 40% of such diseases are linked to vehicular and industrial emissions, solid fuel smoke and passive exposure to tobacco smoke (Maiztegui and Delucchi 2010). Volatile organic compounds (VOCs) are a recognized group of air pollutants and precursors of secondary pollutants (Hubbell et al. 2005). They are emitted outdoors mainly by vehicular traffic, industries, dumps and landfills, and indoors by certain building materials, furnishing and paints (Lyu et al. 2020). Aromatic VOCs, in particular benzene, have been highlighted as harmful for human health (IARC Working Group 2018).

Zoonoses are diseases transmitted to humans either by direct contact with infected secretions and excretions of animal hosts or mediated by (often arthropod) vectors. The spatiotemporal dynamics of zoonotic diseases is driven by a complex interaction among environmental, ecological and social factors (WHO 2014). Anthropophilic mosquitoes such as *Aedes aegypti* (vector of dengue, chikungunya, Zika and yellow fever viruses) and *Culex* spp. (vectors of West Nile virus and St. Louis encephalitis viruses; Weaver et al. 2018) have colonized urban areas due to the use of human-made habitats (e.g., artificial containers and sewage systems) for their immatures (Honnen and Monaghan 2017). Rodents, the main urban vertebrate pests, are reservoirs of bacteria and viruses of public health importance belonging to genera such as *Leptospira*, *Salmonella*, *Yersinia*, *Streptobacillus* and *Orthohantavirus* (Meerburg et al. 2009).

Human health risks are driven by environmental hazards in combination with socio-demographic factors that determine which populations are more vulnerable to them (Lindley et al. 2006). In this context, a hazard is defined as any exposure, either simple (a specific physical, chemical or biological agent) or complex, capable of causing an adverse health effect (Saracci 2017). Vulnerability designates the degree to which a population is susceptible to, or unable to cope with, adverse effects caused by a given hazard (Brooks 2003). Hazards and vulnerability can be integrated to obtain quantitative risk maps, which are a valuable tool to understand complex spatial problems, communicate results and plan management actions (Klimešová and Brožová 2012).

Recently, Morandeira et al. (2019) assessed human health risk in a highly urban district in temperate Argentina by creating a map that combined four hazard indexes (water and air pollution, and mosquito and rodent infestation) and a vulnerability index. According to this map, over 83% of the population of the district (around 345,000 inhabitants) was exposed to relatively high levels of at least one environmental hazard, and *ca.* 30,000 people were exposed to relatively high levels of all hazards. Furthermore, the most hazardous areas were located where the most vulnerable populations lived, increasing health risk. In this context, the aim of the present study was to obtain baseline information of water and air pollution, mosquito and rodent infestation levels in the previously studied district (General San Martín, Buenos Aires). Also, we aimed to evaluate these formerly produced geographic hazard indexes by assessing their association with field sampled hazard indicators and disease reports.

Methods

Study Site

General San Martín District (GSM) is located in Buenos Aires Province, in temperate-humid Argentina (central coordinates: 34°34′S 58°33′W). Average temperatures range between 8.6 and 16.4°C in winter and between 19.7 and 29.3°C in summer (CABA 2020). The district covers 56.3 km^2, houses 414,196 inhabitants (INDEC 2010) and is highly urbanized, with commercial and industrial (metallurgical, chemical, petrochemical and textile) activities distributed within a broad residential matrix. Most (92%) of the households have access to the public water net inside their premise, and around 78% of them are connected to the sewage system (AySA 2019). GSM has been pointed out as the third riskiest district for child health in Argentina (Maiztegui and Delucchi 2010) and is among the top four districts in Buenos Aires Province regarding environmental concerns (Velázquez and Celemín 2013).

Background

We used hazard, vulnerability and risk maps presented in Morandeira et al. (2019) as inputs for this study. Briefly, the authors estimated environmental risk to human health by combining self-generated hazard and vulnerability indexes in a Geographic Information System. Equations including multiple environmental variables were built for each hazard (water and air pollution, and mosquito and rodent infestation, see Table S1) using census tract as the minimum spatial resolution, and were displayed on maps. Intermediate calculations, as well as the final indexes, were scaled between 0 (lowest hazard/vulnerability/risk) and 1 (highest hazard/vulnerability/risk); therefore, these indexes should only be used for comparative purposes within the extent of the study area. A regionalization of the combined four hazards was produced by categorizing each hazard index in relatively low and high levels by using Jenks' Natural Breaks thresholds (Fig. 1).

Fieldwork

Fieldwork was designed to represent the three most widespread combinations of estimated hazards according to Morandeira et al. (2019): relatively low levels of all four hazards (15.4% of the study area), relatively high levels only of air pollution (31.2%) and relatively high levels of all four hazards (11.5%; Fig. 2). To achieve this, sites were selected in both low and high areas for each hazard sampled (Fig. 1). The location of sampling sites (private premises, community centers and public spaces) was selected to represent the heterogeneity of the region, according to access possibilities (see Supplementary Figure S2 for photographs of some of the sites). Sampling was conducted in four seasons as follows: June–August 2016 (winter), September–November 2016 (spring), December 2016–February 2017 (summer) and March–May 2017 (fall). Each of the studied hazards was sampled in at least two seasons and was characterized in the field by one or several variables listed in Table 1 (see Supplementary material S3 for a detailed description of the sampling methods).

Statistical Analyses

Sampled sites were geo-referenced in QGIS 3.4 (QGis Development Team 2019). The estimated hazard maps in Morandeira et al. (2019) were compared with field data by running generalized linear models (GLM) for each hazard, and a principal component analysis (PCA) with all hazards together; then, hazard and risk maps were compared with disease reports for the district. The three methodological approaches are summarized below:

Approach 1: Per Hazard GLM

Field measured values for each hazard (Table 1) were modeled as a function of the estimated hazard calculated for each of the sampled census tracts, the sampling season and their interaction (Eq. 1).

$$\text{Sampled\_variable}_{ij} \sim \text{estimated\_hazard}_i * \text{season} \qquad (1)$$

where i is the census tract and j is the season.

Modeling was performed in R software (R-Core-Team 2013) following a stepwise backward procedure (Zuur et al. 2009). Term selection was based on the Akaike Information Criterion (AIC, Akaike 1974), considering models with $\Delta AIC < 2$ as equivalent. After applying Eq. 1, environmental variables considered in the development of other hazard indexes (see Table S1) were entered in the selected model to check whether the explanatory power could be improved. Selected models were bootstrapped (1000 iterations) to detect very influential observations.

Water pollution was modeled using arsenic, chromium and aluminum concentrations as response variables; they were considered the most relevant variables as they presented heterogeneity within the district and values above the permitted maximum. Air pollution was modeled considering summer benzene concentration as response variable because all others (toluene, xylene and ethylbenzene concentrations) were highly correlated with it ($\rho > 0.89$), and winter records were very low and had very little variation among sites. For mosquito infestation we modeled

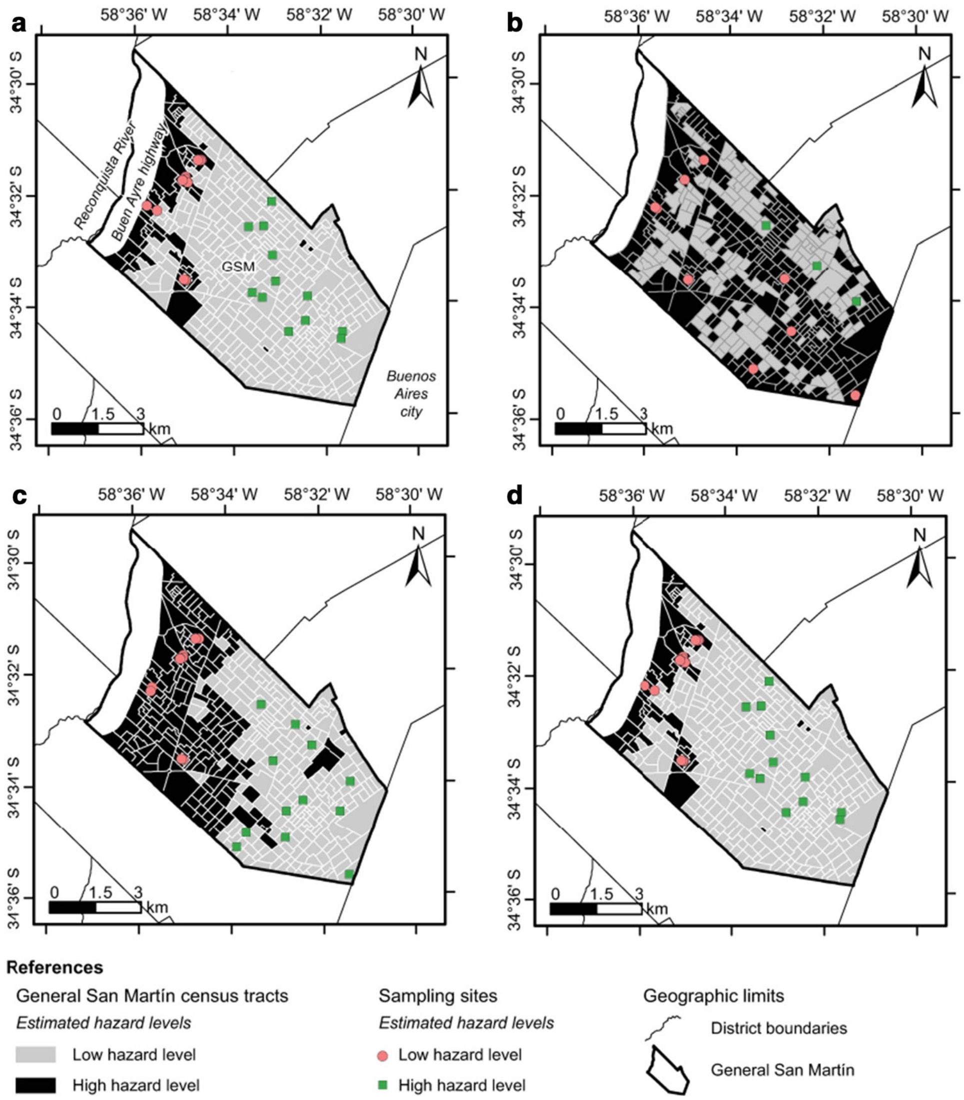

Fig. 1. Sampling sites on the estimated hazard maps of General San Martín (GSM, Buenos Aires Province, Argentina). **a** Water pollution; **b** air pollution; **c** mosquito infestation; **d** rodent infestation. Estimated hazard maps and relatively low/high hazard levels were obtained from Morandeira et al. (2019), with census tract as minimal sampling unit. The north–west area of GSM, between the Reconquista River and the Buen Ayre highway, is not populated and was not included in the study.

the sum of specimens of *Ae. aegypti* and *Cx. pipiens* averaged per trap per site, while for rodent infestation we modeled mean rodent activity (RA; Table 1).

Approach 2: Multi-Hazard PCA

To analyze the distribution patterns of the field measured values for each hazard among sampled sites, and to study the correspondence of estimated hazard maps with field samples, we performed a PCA based on the correlation matrix (Quinn and Keough 2002) using R software (R-Core-Team 2013). Because sampling of all four hazards was not always performed at the same sites, nearby sites were classified in nine groups, each with measures for all four hazards (Fig. 2), with the sole exception of group 1 (for which air was not sampled and the data registered for its neighboring group 2 was used). All sites in a group were close to each other (most were less than 0.5 km apart, and the maximum distance between two sites of the same group was 1.8 km) and all had the same classification of hazards (low levels of all four hazards, relatively high levels only of air pollution and relatively high levels of all four hazards). Each group was formed by three to six sites, except group 7 which had two sites and group 2 which had 11 sites.

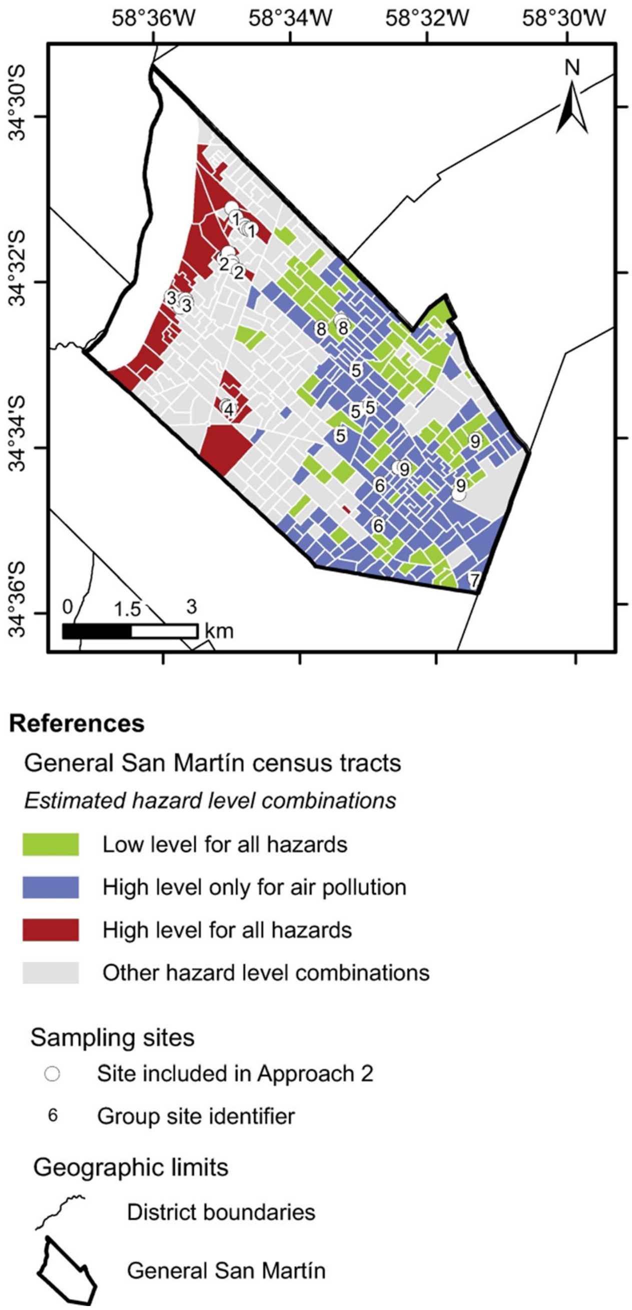

Fig. 2. Group of sites on the map of General San Martín District showing the estimated combinations of hazard levels, derived from high and low levels for each hazard (see Fig. 1). Sites included in the methodological Approach 2 (multi-hazard PCA), along with their group identifier, are shown.

Groups 1–4 present high level of all hazards, groups 5–7 have high level only of air pollution, and groups 8–9 have low level of all hazards. Sampled values for each hazard per group of sites were used to run the multi-hazard PCA. For water pollution, a water-PCA with all water variables which presented variability among groups of sites (conductivity, total dissolved solids, nitrates, aluminum, arsenic, chromium, manganese and selenium) was previously computed to reduce the number of variables that describe water pollution, and the resulting first two principal components were included as explanatory variables in the multi-hazard PCA. As in the first approach, air pollution was represented by summer benzene concentrations, while mosquito and rodent infestations were represented by the same variables but averaged for all sampled seasons.

Approach 3: Health Data and Risk Map

Data on disease cases in GSM during 2016 and 2017 discriminated by neighborhood were provided by the Ministry of Health of Buenos Aires Province. Using bibliography, we selected all diseases for which a given hazard is considered a causal factor; we then classified these diseases into four groups, according to their associated hazard. We manually georeferenced each case using data on the neighborhood and a layer (provided by the Municipality of San Martín) in which the district is divided into 56 localities. Median estimated risk indexes (one for each hazard) were obtained for each locality based on the values for each census tract (Morandeira et al. 2019) and compared with the number of disease cases associated with each hazard using standard Spearman correlations. To overcome a high number of zeros and a large dispersion in the data, correlations were run considering the subset of localities with > 10 cases per hazard, and also with log-transformed number of cases. We also estimated the proportion of cases per locality relative to the total number of cases per hazard so that all hazards added to 1, and then, we summed them up and scaled them between 0 and 1. Lastly, the population proportion at each locality (respect to the population of the entire district) was subtracted to the proportion of cases for each hazard. A positive value in a given locality therefore indicates more cases than expected according to its population if the number of affected people were homogeneously distributed throughout the district (therefore, we would expect a higher hazard index value in such locality), whereas a negative value indicates the opposite.

Results

Water Pollution

All dwellings located in low hazard areas were connected to the water network, whereas in high hazard areas samples of

Table 1. Summary of Field Work Performed for Each Hazard; the Number of Sites and the Variables Recorded, Along with a Brief Description of the Sampling Methods and Laboratory Processing are Provided (Details are Provided in Supplementary Material S3).

Hazard	Number of sampled sites	Sampled variables	Sampling methods and laboratory processing
Water pollution	26 in winter, 27 in summer	Source (tap or well)	Registered in situ
		Temperature	Measured in situ with portable multi-parametric analyzer
		pH	Measured in situ with portable multi-parametric analyzer
		Conductivity	Measured in situ with portable multi-parametric analyzer
		Total dissolved solids	Measured in situ with portable multi-parametric analyzer
		Nitrates concentration	Reactive kits
		Nitrites concentration	Reactive kits
		Total organic carbon	TOC-L Analyzer Jenck
		Concentration of metals (aluminum, arsenic, cadmium, chromium, cobalt, copper, iron, lead, manganese, mercury, nickel, selenium, silver and zinc)	Inductively Coupled Plasma Mass Spectrometer (ICP-MS) with collision cell
		Presence of coliforms	Monitors and m-ENDO medium
		Presence of pseudomonas	Monitors and m-CETRIMIDA medium
Air pollution	10 in winter, 10 in summer	Benzene, toluene, ethylbenzene and xylenes concentrations	Passive monitoring devices placed in pairs, and gas chromatography with flame-ionization detection
Mosquito infestation	20 in spring and summer, 16 in fall	Number of males and females of each species	Light traps for adults placed in pairs in exteriors
Rodent infestation	24 in summer, 21 in fall	Rodent activity (RA)	Rodent bait stations ($\approx$ 160 per season) placed in and outside dwellings, and in public spaces

both tap and well water were collected. Recorded values of physical and chemical variables are provided in Table 2, disaggregated by hazard level, season and water origin, along with standard ranges accepted by the Argentine Food Code (AFC 2019).

Regarding physical parameters, temperature records in summer tap samples were higher in high hazard areas than in low hazard areas. Also in summer tap samples, some pH values below the permitted range were registered both at low and high hazard areas (Table 2). Conductivity was higher in well than in tap samples, and presented values indicative of water with corrosive properties. Total dissolved solids values were also higher in well than in tap water; although all records were below the permitted maximum, water palatability is considered good at concentrations < 600 mg L^{-1} (WHO 2011).

Nitrate and nitrite concentrations could only be measured for summer samples due to budget restrictions; all measurements were below the established maximum. The recorded nitrate values showed a tendency to higher values in well than in tap water, whereas nitrite concentration was very low in both types of samples (Table 2). Total organic carbon (TOC) values in tap water samples frequently presented values higher than the 2 mg L^{-1} threshold proposed for groundwater (Chapman and Kimstach 1996).

Regarding metal analyses, values above the permitted maximum were recorded for arsenic and chromium in well samples and for aluminum in tap samples, whereas manganese values in tap samples were close to the maximum

Table 2. Water Pollution. Mean (and Range) Values of Physical and Chemical Variables for Water Samples Taken in Low and High Hazard Areas, According to Season and Sample Origin -Tap or Well- (the Number of Samples Analyzed is Informed Between Brackets).

	Low hazard		High hazard				
	Winter	Summer	Winter		Summer		Maximum or range allowed
Variable (unit)	Tap (9)	Tap (8)	Tap (12)	Well (5)	Tap (16)	Well (3)	
Temperature (°C)	12.4 (11.0–13.3)	29.0^{a} (27.0–32.1)	12.7 (10.5–14.6)	15.8 (12.6–18.9)	25.5^{b} (20.7–30.0)	28.5^{a,b} (27.4–30.0)	No regulation
pH	7.5 (7.3–7.6)	6.3 (**5.2**–7.4)	7.3 (7.0–7.6)	7.6 (7.4–7.9)	6.5 (**4.9**–7.8)	7.1 (6.9–7.3)	6.5–8.5
Conductivity (μS cm^{-1})	415^{a} (386–458)	361^{a} (182–449)	414^{a} (378–439)	1291^{b} (1253–1330)	380^{a} (220–787)	899^{b} (581–1330)	No regulation
TDS (mg L^{-1})	201^{a} (187–222)	232^{a} (109–294)	199^{a} (182–218)	638^{b} (619–658)	241^{a} (134–474)	553^{b} (336–849)	1500
Nitrates (mg L^{-1})	nd	1.1 (0.6–1.7)	nd	nd	1.3 (0.3–1.9)	8.5 (7.2–9.7)	45
Nitrites (mg L^{-1})	nd	0.008 (0.004–0.012)	nd	nd	0.006 (0.002–0.009)	0.010 (0.007–0.012)	0.1
TOC (mg L^{-1})	2.9^{a} (2.1–3.9)	1.4 (0.8–2.7)	2.9^{a} (0.3–5.0)	1.3^{b} (0.7–1.6)	1.5 (0.5–3.2)	0.2 (0.0–0.4)	No regulation
Aluminum (μg L^{-1})	62^{a} (22–152)	41 (31–55)	97^{a} (23–**473**)	0.1^{b} (0.1–0.1)	48 (27–181)	34 (31–37)	200
Arsenic (μg L^{-1})	1.6^{a} (1.3–1.9)	1.4^{a} (1.0–1.6)	1.9^{a} (1.5–2.6)	**13.8**^{b} (8.1–**17.0**)	1.6^{a} (1.4–1.9)	**16.8**^{b} (**15.1–19.7**)	10
Cadmium (μg L^{-1})	BDL	BDL	BDL	BDL	0.2 (BDL-0.2)	BDL	5
Chromium (μg L^{-1})	2.3 (0.6–4.5)	2.6 (0.2–5.2)	4.1 (0.6–5.0)	18.9 (1.2–50.0)	4.7 (2.9–5.7)	38.7 (4.5–**63.0**)	50
Cobalt (μg L^{-1})	0.3^{a} (0.3–0.4)	0.7 (BDL–0.7)	0.4^{a,b} (0.3–0.6)	0.5^{b} (0.3–1.1)	0.5 (BDL–0.7)	0.4 (0.3–0.5)	No regulation
Copper (μg L^{-1})	15.7 (0.4–74.0)	12.1 (0.5–52.4)	51.8 (0.2–531.0)	3.7 (1.2–6.1)	2.6 (0.5–27.8)	7.7 (1.6–18.8)	1000
Iron (μg L^{-1})	24.2 (7.5–63.0)	24.8^{a} (6.1–87.1)	44.5 (2.1–193.0)	9.6 (1.2–29.0)	31.8^{a} (4.3–286.0)	1.3^{b} (0.8–1.9)	300
Lead (μg L^{-1})	12.2 (0.2–97.0)	1.4 (0.2–4.1)	4.5 (0.2–47.0)	0.5 (0.3–1.0)	0.4 (0.2–1.9)	0.4 (0.3–0.5)	50
Manganese (μg L^{-1})	14.6^{a} (4.9–45.0)	9.0 (4.6–15.2)	21.6^{a} (3.2–98.0)	0.2^{b} (BDL–0.4)	10.2 (2.4–57.3)	0.5 (BDL–0.8)	100
Mercury (μg L^{-1})	BDL	BDL	BDL	BDL	BDL	BDL	1
Nickel (μg L^{-1})	0.6^{a} (0.4–1.1)	1.5 (0.6–3.9)	0.8^{a} (0.3–2.7)	1.3^{b} (0.9–2.0)	1.5 (0.7–3.6)	1.7 (1.2–2.2)	20
Selenium (μg L^{-1})	0.7^{a} (0.1–0.9)	1.3^{a} (1.2–1.4)	0.8^{a} (BDL–1.1)	1.4^{b} (1.1–1.5)	1.3^{a} (1.2–1.5)	1.8^{b} (1.8–1.8)	10
Silver (μg L^{-1})	0.6^{a} (0.5–0.7)	BDL	0.6^{a,b} (0.5–0.8)	0.7^{b} (0.6–0.8)	BDL	0.7 (0.6–0.8)	50
Zinc (μg L^{-1})	13.9 (1.1–48.0)	18.2 (BDL–38.7)	34.9 (0.8–269.0)	9.5 (3.5–14.0)	7.2 (BDL–54.7)	4.4 (0.6–11.4)	5000

TDS Total dissolved solids; *TOC* Total organic carbon.

Note that all households sampled in the low hazard area were connected to the water network. Some recorded values were below the detection limit (BDL); mean values were calculated from only those values above the detection limit. Maximum values or range as established by the Argentinean Food Code (AFC 2019); values in bold indicate recorded values above the maximum or below the minimum allowed. nd means no data. Superscript letters indicate significant differences among water sources at each hazard level in the same season (e.g., low hazard-winter-tap, high hazard-winter-tap, high hazard-winter-well) ($p < 0.05$, Wilcoxon tests). Method detection limits: 0.01 μg L^{-1} for cadmium, 0.05 μg L^{-1} for mercury, and 0.1 μg L^{-1} for cobalt, manganese, selenium, silver and zinc.

(Table 2). In either one or both seasons, well samples were characterized by higher values of arsenic and lower concentrations of aluminum, iron, manganese, nickel and selenium than tap samples. The recorded values of cadmium, cobalt, copper, lead, mercury, silver and zinc were below the maximum allowed and presented no differences between water sources (Table 2).

Microbiological studies were negative in all samples, indicating that water was not contaminated with animal or human feces.

Air Pollution

Summer concentrations of the four species analyzed (benzene, toluene, ethylbenzene and xylenes, hereafter BTEX) were higher than those obtained in winter, when concentrations were sometimes below the detection limits of the technique. In summer, mean concentration values of the four pollutants in low hazard areas were lower than in areas associated with a main source of emissions (Table 3), being these differences statistically significant in the case of benzene and toluene records.

The BTX/E ratios obtained for each nearby source type in winter and summer highlighted the following aspects: (1) in winter, toluene appears to be the dominant species compared to benzene and xylenes, a situation that is completely reversed in summer; (2) BTX/E ratios in winter in areas influenced by dumps and landfills were similar to those in gas stations, but different to the ones registered in areas influenced by industries; (3) in summer, these ratios showed a very similar pattern for dumps and landfills, gas stations and high traffic pathways, slightly different for industries and markedly different for low hazard areas (Fig. 3).

Mosquito Infestation

The total number of collected specimens increased from the beginning till the end of the sampling season, whereas species richness was also maximum in the fall (Table 4). The general abundance pattern was driven by mosquitos of the genus *Culex*, which dominated all captures (92–95% of the individuals collected). More specimens were collected in high hazard areas than in low hazard areas during the summer and fall, whereas no such pattern was observed in spring (Table 4). During spring, very few mosquitoes were collected in the relatively high hazard sampling locations. In contrast, many specimens were collected in the relatively low hazard locations, in gardens with high vegetation coverage and shade, whereas few mosquitoes were collected in small patios. Within *Culex* sp., more *Cx. pipiens* were detected in the high hazard areas and more *Cx. apicinus* in the low hazard areas (Table 4). In summer there was a significant increase in the number of collected specimens in the high hazard sampling points, mainly from the genus *Culex; Cx. apicinus* disappeared and practically all specimens captured were identified as *Cx. pipiens*. Finally, during the fall many specimens of *Cx. pipiens* were collected in high hazard areas, whereas in the low hazard sampling sites the other species of the genus prevailed. *Aedes aegypti* was collected in small numbers, as well as *Ae. albifasciatus, Cx. bidens/interfor*, *Cx. chidesteri*, *Cx. dolosus, Cx. eduardoi*, *Cx. lahillei* and *Psorophora varinervis*.

Rodent Infestation

Signs of rodent activity, which included incisor marks in the paraffin block and hairs stuck in the tape, were found inside and outside dwellings both in high and low hazard areas. Although rodent activity appeared to be higher in the high hazard area in both seasons, these differences were not significant presumably due to its high variability (Table 4). In summer, two dead rats (*Rattus sp.*) were found in a park and a street located in the low hazard area, but no rodent activity was recorded in bait traps placed in those sites. Similarly, during the fall a live rat, along with signs of rodent activity and burrows, was observed in a low-income neighborhood located in the high hazard area.

Approach 1: Per Hazard GLM

Water pollution. Arsenic and chromium concentrations were positively associated with the estimated water hazard index, which explained 39.8 and 22.3% of the variation in the data, respectively. In these two models no seasonal effects were verified, and including population density raised explanatory power to 48.1 and 37.2%, respectively (Table 5). Aluminum concentration was not significantly associated with any of the proposed variables. The water source (well or tap) on its own explained a high percentage of variability in the concentration of arsenic (95.2%), intermediate for chromium (55.7%) and low for aluminum (17.9%).

Air pollution. Benzene concentration recorded at each of the 20 sampled sites was modeled as a function of the season and the estimated air hazard index at each of the

Table 3. Air Pollution. Mean (and Range) Benzene, Toluene, Ethylbenzene and Xylenes Concentrations (in μg m^{-3}) in Low and High Hazard Areas, Disaggregated by Nearby Main Source of Emission (Number of Species Between Parentheses) and Season.

Variable	Low hazard (6)		High hazard							
			Dumps and landfills (6)		Gas stations (2)		High traffic pathways (4)		Industries (2)	
	Winter	Summer	Winter	Summer	Winter	Summer	Winter	Summer	Winter	Summer
Benzene	BDL	4.4* (1.4–7.6)	1.2 (BDL–1.6)	13.9* (8.1–21.6)	1.1 (1.1–1.2)	19.6 (18.7–20.6)	BDL	14.2 (7.9–16.7)	BDL	15.7 (12.8–18.7)
Toluene	2.1* (1.6–2.5)	3.8 (1.6–5.3)	4.1* (3–5.2)	8.9 (4.5–14.6)	4.0 (3.9–4.1)	12.5 (12.5–12.5)	2.0 (1.4–2.8)	8.8 (4.1–11.5)	1.9 (1.7–2.2)	10.4 (6.2–14.6)
Ethylbenzene	BDL	8.9 (6.5–12.2)	1.1 (BDL–1.1)	12.7 (6–27.4)	1.2 (1.1–1.2)	17.8 (17.3–18.3)	BDL	12.8 (6.4–16.3)	2.1 (BDL–2.1)	16.0 (9.6–22.4)
Xylenes	BDL	14.2 (9.7–21.0)	3.2 (BDL–3.5)	19.0 (10.5–38)	3.5 (3.4–3.5)	25.6 (24.9–26.2)	BDL	19.1 (10.8–23.6)	BDL	33.4 (23.6–43.3)

Some recorded values were below the detection limit (BDL); mean values were calculated from only those values above the detection limit.
*Significant differences among main source of emission for the same season ($p < 0.05$, Wilcoxon tests).
Method detection limits: 0.98, 1.04, 1.02 and 2.62 μg m^{-3} for benzene, toluene, ethylbenzene and xylenes, respectively.

census tracts where the sampling sites were located. The resulting model without interaction explained almost 88% of the variation (Table 5). Field measured benzene was higher in summer than in winter and was positively associated with the air hazard index (Fig. 4). Including human population density in the model raised explanation power to 92% (Table 5).

Mosquito infestation. The number of specimens of container mosquitoes (*Ae. aegypti* + *Cx. pipiens*) was associated with the estimated hazard index and the season without interaction and explained 52.1% of the variation in the data (Table 5). No variables from other hazards were significantly correlated.

Rodent infestation. The obtained model explained only 17.7% of the variation in rodent activity, and the season was not significant. Also, the pattern of the residuals was quite inadequate, suggesting that the model could be unreliable. The inclusion of variables from other hazards did not improve the results.

Approach 2: Multi-hazard PCA

The first two axes of the water-PCA explained together 92.1% (PC1 = 73.6% and PC2 = 18.5%) of the variance. The PC1 was strongly associated with conductivity, total dissolved solids, nitrates, arsenic, chromium and selenium, while the PC2 was mainly associated with aluminum and manganese (Table S4).

The first two axes of the multi-hazard PCA explained together 80.5% (PC1 = 47.9% and PC2 = 32.6%) of the variance. The PC1 mainly described the general environmental conditions, including all four hazards, while the PC2 discriminated among hazards (Fig. 5, Table S5). Groups of sites 1, 2 and 3 (with high estimated levels for all hazards) were consistently ordered along negative values of PC1, and quite away from zero along PC2, indicating relatively poor environmental conditions (i.e., high values of all hazards). Group 3 displayed the highest values of water pollution (Water-PC2) and rodent infestation, while groups 1 and 2 presented lower values of these two variables, but higher values of air and water pollution (Water-PC1), showing high consistency with the estimated hazard levels. The remaining groups showed positive values for PC1 and values close to zero for PC2, indicating relatively good environmental conditions (i.e., low values of all hazards). In relation to the estimated hazard levels, the obtained results are highly consistent for groups 8 and 9 (predicted as low hazard level); intermediately consistent

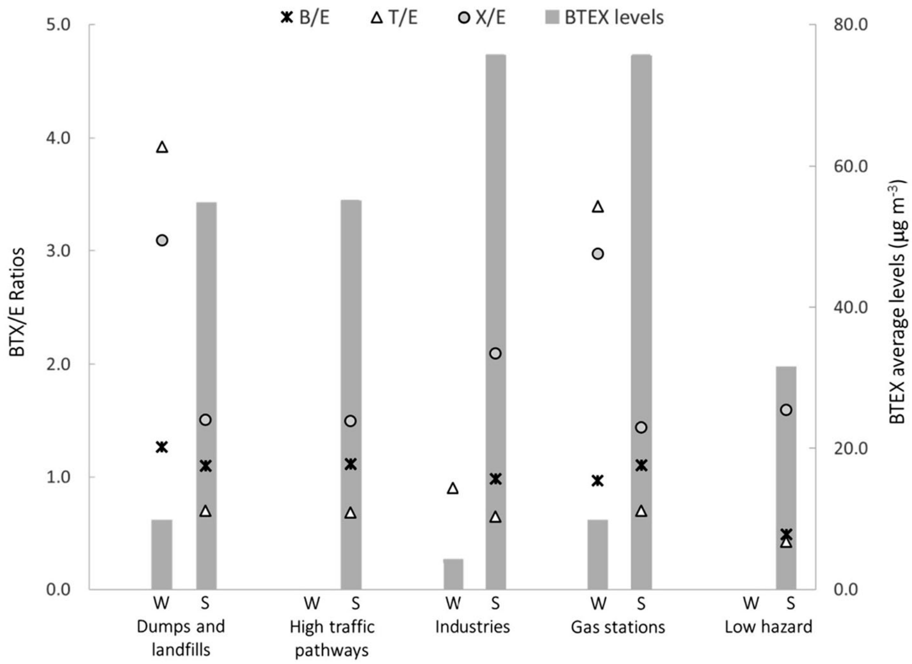

Fig. 3. Mean BTEX (B: benzene, T: toluene, E: ethylbenzene and X: xylenes) total levels (in μg m^{-3}) and BTX/E ratios (B/E, T/E and X/E), disaggregated by nearby main source of emission and season (W: winter, S: summer).

for groups 5, 6 and 7 (predicted as low level for all hazards except for air pollution); and not consistent for group 4 (predicted as high hazard level).

Approach 3: Health Data and Risk Map

A total of 6799 disease cases were associated with one of each of the four hazards considered. Number and distribution of cases varied widely according to its associated causal factor, being those linked to water and air pollution

Table 4. Mosquito and Rodent Infestation. For Mosquitoes, Mean (and Range) Number of Specimens (Females and Males) Per Site, Collected Per Hazard Level and Sampling Season are Reported.

Variable	Low hazard			High hazard		
	Spring	Summer	Fall	Spring	Summer	Fall
Mosquitoes						
Females	2.0 (0–7)	1.2 (0–7)*	5.3 (0–66)*	1.6 (0–11)	9.1 (0–26)*	9.8 (0–38)*
Males	1.7 (0–5)	0.4 (0–2)*	3.0 (0–37)*	0.6 (0–3)	4.2 (0–27)*	11.6 (0–66) *
Species	5	4	8	4	4	4
No. *Aedes aegypti*	0	8	1	1	4	4
% *Culex apicinus*	0.20	0	0.10	0.77	0	0.02
% *Culex maxi*	0	0.01	0.41	0	0.001	0.01
% *Culex pipiens*	0.70	0.42	0.17	0.17	0.97	0.95
Rodents						
RA	nd	0.4 (0–4.8)	2.4 (0–8.3)	nd	5.1 (0–36.4)	7.7 (0–33.3)

Species, number (No.) of specimens of *Aedes aegypti* and proportion (%) of more abundant species are calculated based on the number of females (as males were not identified to species). For rodents, mean (and range) values of rodent activity (RA) per hazard level and sampling season are informed.
nd means no data.
*Significant difference between estimated low and high hazard levels for the same season and sex ($p < 0.05$, Wilcoxon tests).

Table 5. Generalized Linear Models for Each Environmental Hazard (Water and Air Pollution, Mosquito and Rodent Infestation)

Hazard	Response variable	Distribution error	Model	Explanatory variables	% Explained
Water pollution	Arsenic*	Negative binomial	Basic	Water index	39.8
			Improved	Human population	48.1
	Chromium*	Negative binomial	Basic	Water index	22.3
			Improved	Human population	37.2
Air pollution	Benzene**	Poisson	Basic	Air index + season	87.8
			Improved	Human population	92.0
Mosquito infestation	No. of specimens***	Negative binomial	Basic	Mosquito index + season	52.1
			Improved	–	
Rodent infestation	RA****	Quasipoisson	Basic	Rodent index	17.7
			Improved	–	

The response variable and the distribution errors used, the explanatory variables included, and the percentage of the variability in the data explained is informed considering only the corresponding hazard index and the season (basic model), and also considering the addition of other environmental variables to the basic model (improved model).
*In μg L^{-1}, rounded to integer; **in μg m^{-3}, rounded to integer; ****Ae. aegypti* and *Cx. pipiens* averaged per trap per site, rounded to integer; ****rounded to integer. RA is for rodent activity.

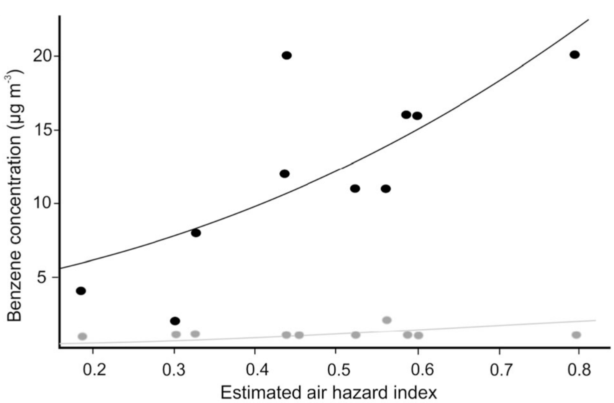

Fig. 4. Field recorded benzene concentration in winter (grey dots) and summer (black dots) as a function of the estimated air hazard index per sampling census tract calculated in Morandeira et al. (2019). Solid lines indicate the predictions of the generalized linear model considering the hazard index and the season as explanatory variables.

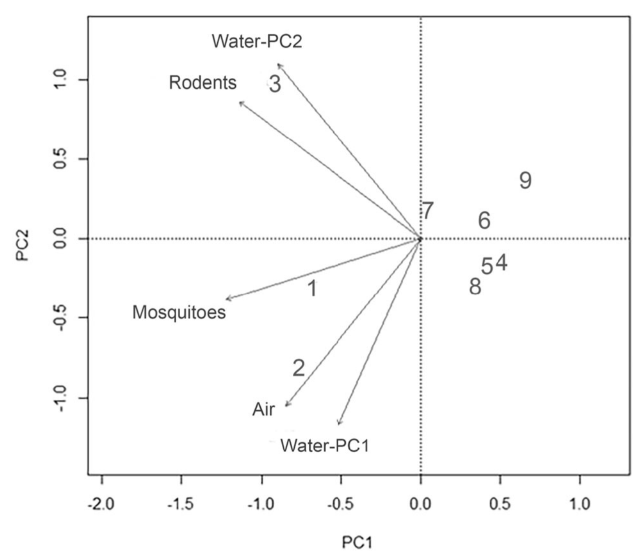

Fig. 5. Ordination of groups of sites produced by principal component analysis (scaling 1) based on water pollution (PC1 and PC2), air pollution (Air), mosquito infestation (Mosquitoes) and rodent infestation (Rodents). Numbers correspond to each of the nine groups of sites in Fig. 2.

the most numerous and broadly distributed (Table 6). The estimated risk per locality was not significantly correlated to the number of disease cases for any of the four hazards.

It is noteworthy that, although smaller in extension, the localities with higher population (Fig. 6a) and/or located in the most centric area were the ones with highest number of disease cases (Fig. 6b). In fact, over one-third of the total cases reported were concentrated in only one locality, and the same pattern was observed when subtracting the proportion of the population to the proportion of disease cases per locality (Fig. 6c). Several localities in the center and east of the district presented a higher proportion of disease cases than expected according to their population, whereas the estimated high-risk zone at the western fringe of the district was remarkably underrepresented.

Discussion

As risk is heterogeneous and multidimensional, the development of tools to assess exposure and organize mitigation actions is essential in any management strategy (Edjossan-Sossou et al. 2020). In Argentina, there have been few attempts to address the correspondence between estimated risk and field based data (see Castilla 2000 for example). GSM, a highly urban district in temperate Buenos Aires Province, has been highlighted regarding its high environmental risk to human health (Maiztegui and Delucchi 2010; Velázquez and Celemín 2013). In the present study, we reported baseline data for the district, and we contrasted previously generated hypotheses on the spatial arrangement of environmental hazards and risk. We first discuss field records obtained for each hazard, and we then refer to different approaches to compare the obtained values with hazard and risk maps for the area from Morandeira et al. (2019).

Water Pollution

Although over 90% of GSM dwellings have access to tap water, certain areas—mainly located on the western border of the district—lack connection to the water network or have poor water and sewage infrastructure. Deficient connections through exposed hoses that can be easily punctured or broken could promote bacterial and chemical contamination. However, according to our results access to tap water defines the level of water risk independently of

Table 6. Number of Disease Cases and Affected Localities (Out of 56 Covering All General San Martin District) Associated with Each of the Considered Hazards (Water and Air Pollution, Mosquito and Rodent Infestation).

Hazard	Associated disease	2016		2017	
		Cases	Localities	Cases	Localities
Water pollution	Diarrhea and gastroenteritis	1368	24	1932	26
	Recurrent fevers	52	11	7	5
	Bacterial intestinal infections	4	2	0	0
	Intestinal infections (virus, others)	0	0	7	4
	Hepatitis A	0	0	2	2
	Cholera	0	0	0	0
	Salmonella	0	0	0	0
	Shigelosis	0	0	0	0
	Total	1424	25	1948	26
Air pollution	Asthma and status asthmaticus	1077	25	1249	28
	Anemias	277	19	336	23
	Spontaneous abortion	9	5	6	5
	Respiratory conditions due to other external factors	1	1	0	0
	Myeloid leukemia	0	0	2	1
	Allergic and vasomotor rhinitis	0	0	6	5
	Total	1364	28	1599	30
Mosquito infestation	Dengue	376	19	65	15
	Viral encephalitis	1	1	1	1
	Total	377	19	66	15
Rodent infestation	Rat-bite fever	6	4	14	7
	Viral hemorrhagic fevers (unspecified)	1	1	0	0
	Hemorrhagic fevers caused by Arenaviruses	0	0	0	0
	Other hemorrhagic fevers (including Hantavirus Pulmonary Syndrome)	0	0	0	0
	Tularemia	0	0	0	0
	Leptospirosis	0	0	0	0
	Total	7	5	14	7

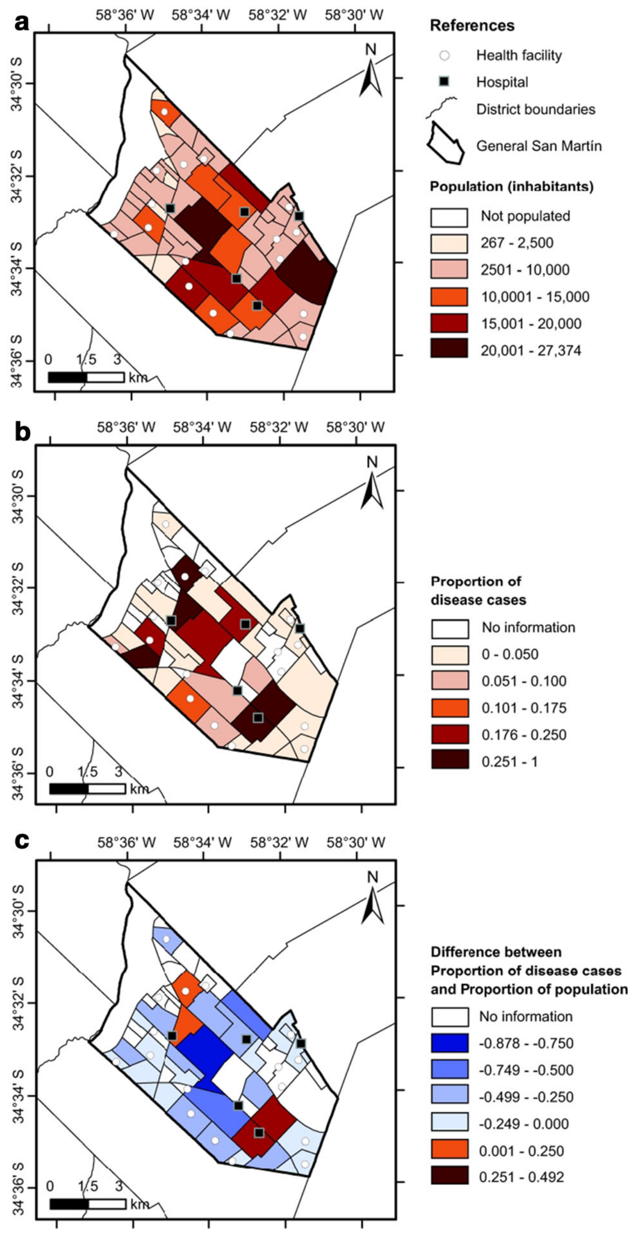

Fig. 6. Relation between population and reported disease cases in General San Martín localities ($N = 56$) for the 2016–2017 period. **a** Population; **b** proportion of cases per locality relative to the total number of cases per hazard, summed for the four hazards and scaled between 0 and 1. Note that several localities ($N = 22$) have no available information; **c** Difference between the proportion of disease cases as in (**b**) and the population proportion at each locality (respect to the population of the district, scaled between 0 and 1).

the quality of the connection. Well samples showed higher values of conductivity, total dissolved solids and arsenic than those from tap water. Groundwater quality has been recently the focus of multiple studies, being arsenic exposure one of the main concerns (Machado et al. 2019). The international arsenic guideline value for drinking water has been lowered from 50 to 10 μg L^{-1} (WHO 1993), and although this became law in Argentina in 2007, each province regulates the permissible concentration (Bundschuh et al. 2012). Buenos Aires Province maintains its maximum at 50 μg L^{-1}, otherwise there would be a several-fold increase in the number of people exposed to potentially harmful levels of this contaminant. Although the water source was considered when developing the estimated water hazard index (the proportion of dwellings of each census tract connected to the water network was indeed the primary variable, see Morandeira et al. 2019), including the dichotomical variable well vs. tap in the modeling markedly raised the percentage of explained variance in the data. This may be related to the difference in scale between the minimal sampling units of the GIS analysis (census tract) and the field surveys (dwelling) and might be improved by sampling a larger number of dwellings within a given census tract. Conductivity and total dissolved solids values in well water were in accordance with those reported by other investigations on the same aquifer and are related to naturally occurring hydrochemical and physical processes (Armengol et al. 2017). TOC concentrations above 2 mg L^{-1} in water bodies and groundwater are generally related to contamination due to municipal or industrial wastes (Chapman and Kimstach 1996). However, in the study area tap water receives special treatment before its distribution, and therefore, the recorded high TOC values may be related to natural organic matter or by-products of its decomposition. The presence of high concentrations of aluminum in some tap samples could be a particular event associated with an excessive use of flocculants in the water purification process, whereas the presence of iron and manganese could be a consequence of leaching from deposits in the pipes.

Air Pollution

Atmospheric concentrations of pollutants are strongly affected not only by emission processes but also by meteorological conditions. In this study, passive monitors were used as sampling methods, placed outdoors for four weeks at each sampling campaign. Although this is a simple and efficient method, it has some limitations in the temporal resolution of its results, being unsuitable for the study of short-term variations (Seethapathy et al. 2008). In the study area, seasonal variabilities of monthly mean values of variables such as speed and wind direction and atmospheric stability conditions are of minor influence, but temperature and mixed layer height have a more significant weight (Ulke and Mazzeo 1998). The latter, a key parameter related to the atmospheric capability to disperse pollutants and the domain in which dispersion takes place, is higher in summer than in winter facilitating the dispersion of pollutants in the atmosphere (Ulke and Mazzeo 1998). However, we obtained higher concentrations of the four BTEX species in summer and in all the sampling sites, which might indicate that the effect of temperature was more important than that of the height of the mixed layer. From this, we infer that (1) higher BTEX levels in summer than in winter might be associated with evaporative processes favored by higher temperatures, and (2) spatial and temporal differences observed in levels and interspecies ratios could be associated with dominant emission sources of each area, and with factors that interfere with emission processes or with photochemical degradation processes, such as temperature, solar radiation or distances from the emission sources to the sampling points. Moreover, we found similar patterns in interspecies ratios for dumps and landfills, gas stations and high traffic pathways in summer, which could be associated with similar dominant emission sources in these areas. Reported concentrations of benzene are within the range of values reported by other authors for different cities throughout the globe (Colman Lerner et al. 2014). According to the World Health Organization, the concentrations of airborne benzene associated with an excess lifetime risk of leukemia of 10–4 and 10–5 are 17 and 1.7 $\mu g\ m^{-3}$, respectively, and in Europe the benzene concentration for the protection of human health is limited to 5 $\mu g\ m^{-3}$ as an annual average (EU 2008; WHO 2000). In the higher hazard zones during the summer, we reported benzene levels between 8 and 22 $\mu g\ m^{-3}$, in the order of the values associated with an excess lifetime risk of leukemia of 1:10,000. Based on these results, a more comprehensive BTEX monitoring is encouraged.

Mosquito Infestation

As expected, more mosquitoes were collected in the higher hazard zone. During field sampling, a high heterogeneity was verified at a small scale in residential areas, and although the vegetated surfaces map used to calculate the theoretical hazard index was very detailed, such information was then summarized to the census tract minimal unit. Also, the commercial traps presented low range attraction (50–100 m) so sampling sites might not have been representative of the entire census tract where they were located. Within the genus *Culex*, there was a marked difference in species composition between relatively high and low hazard areas, seen mainly in the alternation of dominance among *Cx. pipiens*, *Cx. apicinus* and *Cx. maxi*. Even though the trap was proven effective (over 60 specimens were collected per trap/night), *Ae. aegypti* was barely detected. This species presents variable susceptibility to different types of traps (Kröckel et al. 2006), and the one used in this study seems to be inefficient to detect it, as autochthonous dengue transmission during the sampling period has been reported in the area. It is also worth mentioning that the mosquito hazard index was highly spatially heterogeneous; for instance, within the same locality some census tracts presented intermediate values whereas others presented the maximum values of the entire district.

Rodent Infestation

Our results do not support the predictions made by Morandeira et al. (2019), as no differences in rodent activity were found between high and low hazard areas. Moreover, when trying to validate the estimated map using field data, we were unable to fit an adequate model that explained a substantial proportion of the variation in rodent activity. These results could be due to the limited number of rodent bait stations, sample sites and sampling seasons of the current study that were probably not enough to accurately depict the associations between rodent infestation and environmental and demographic variables. In addition, the amount of food refuse available for commensal rodents due to improper garbage removal seen in slums and low-income neighborhoods could have reduced the attraction of the bait stations. This reduction in the effectivity of the technique to estimate abundance in some high hazard localities could mask the difference in rodent abundance between low and high hazard areas. The sighting of one live rat, together with several burrows, in the high hazard area also supports this idea, since rats are very rarely seen in broad day light at low abundances. Also, the findings of two death rats in sites where no rodent baits were active suggests an underestimation of rodent abundance. The use of bait stations has been reported as an adequate, cheap and user-friendly method to monitor rodent pests, particularly for studies performed in public urban spaces, where traps are more prone to be stolen, moved or harmed, and may pose a risk to non-target animals (Thomas 1999; Cavia et al. 2012). Though the use of bait stations is much less time-consuming than trapping as a method for rodent abundance estimation, it still demands a lot of work, particularly when attempting to cover a large area as the one studied here. Future studies should either intensify the sampling effort by increasing both the number of bait stations and sample sites, or try a less demanding estimation method of rodent infestation, such as reports of rodent sightings or systematic interviews and surveys.

Three different comparisons between empirical data and previously published estimated hazard and risk indexes were performed in this study. In the per hazard GLM approach, correspondence was high for air pollution, intermediate for water pollution and mosquito infestation, and poor for rodent infestation. Both for water and air pollution, the models significantly increased explanatory power when including human population density, suggesting that this variable should have been considered in the building of estimated hazard indexes, as was the case for mosquito and rodent infestation (Table S1). The loose association between indexes and field data for some hazards could also suggest that the proposed models may not adjust tightly to reality. In particular, biological populations have a high random component and are therefore harder to predict than physical and chemical variables. Another valuable feature of estimated and field comparisons is to identify sites with anomalous behaviors. For example, in summer there were two benzene records that departed widely from the expected pattern (Fig. 4) and deserve further studies regarding emission sources. Similarly, by means of the multi-hazard PCA we could observed that group 4, previously classified as high level for all hazards, behaved as a low hazard area. This group is immersed in a different landscape matrix than groups 1, 2 and 3 which are located within a continuous strip of high hazard zone in the western section of the district (Fig. 2), and deserves further study. Modeling was also valuable to identify sampling flaws; for instance, in the selection of air sampling sites, a gap at intermediate levels of estimated hazard (0.6–0.8) can be identified (Fig. 4), and both in air pollution and mosquito infestation levels no maximum hazard census tracts were included.

Finally, there are several issues to be addressed regarding the lack of association between the estimated risk index and disease case reports: (1) incomplete/unreliable disease reports: although the report of each case includes the information about the neighborhood, it is not clear whether it corresponds to the residence of the patience or to the health facility where he/her was diagnosed. In fact, most cases were reported in the district center or in nearby neighborhoods, where the main hospitals and health facilities are located; (2) connectivity: GSM is a relatively small district, and its center is distant no more than 15–20 min in public transportation from all its boundaries. It is also surrounded by highly urbanized districts and adjacent to Buenos Aires City, to which many residents travel every day to work or study. Therefore, they could have attended health care facilities, or even acquired the disease, outside the study area; (3) under report: the relatively high-risk area was most likely underrepresented in the reported cases of disease linked to all the hazards considered. This could be due to the reluctance of some dwellers of very poor neighborhoods to report their true address (to avoid stigmatization), or even to go to a health facility when ill (due to cultural or economic reasons).

In brief, this study highlights the need for dynamic feedback between GIS-based models and environmental monitoring. Estimations based on available environmental and socio-demographic information enable the design of fieldwork to maximize sampling efforts and prioritize more threatened areas. In turn, data obtained from field surveys aids in the improvement in future predictions based on geographic layers. Addressing the dialectic relation between GIS-based models and environmental monitoring would therefore significantly improve human-health risk assessments. Indeed, these two approaches applied synergically are valuable tools to detect heterogeneity in disease case reports and, probably, in access to public health services.

Conclusion

This study provided valuable baseline field data regarding four environmental hazards highly relevant to human health, namely water and air pollution, and mosquito and rodent infestation. Further sampling is encouraged to improve the results obtained, monitor changes and add new environmental hazards, such as electrical risk, building or structural problems, as well as those related to pet-transmitted diseases (mange, rabies and dermic diseases due to flea and tick bites), among others. It would also be interesting to consider other sampling variables not contemplated in the air pollution studies, as well as to perform analysis of surface waters, such as ditches and puddles, which may represent a hazard particularly to children, who sometimes use them for recreation in low-income neighborhoods. Empirically verified hazard and risk maps are valuable as dynamic monitoring tools, which can be updated as new data becomes available, and allow for the assessment of different prospective scenarios and the adjustment of action plans.

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