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When space and time matter in environmental injustice: A Bayesian analysis of the association between socio-economic disadvantage and air pollution in Greater Mexico City.

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Abstract

Environmental injustice refers to the unequal burden of pollutants on groups with lower socioeconomic status. An increasing number of studies have identified associations between high levels of pollution and socioeconomic disadvantage. However, few studies have controlled adequately for spatio-temporal variations in pollution. This study uses a Bayesian approach to explore the association between socioeconomic disadvantage and pollution in Mexico City Metropolitan Area. We quantify the association of socioeconomic disadvantage with PM_{10} and ozone and evaluate the impact of accounting for spatio-temporal structure of the pollution data. We find a significant positive association between socio-economic disadvantage and pollution for levels of PM_{10}, but not ozone. The inclusion of the spatio-temporal element in the modelling results in improved weaker estimates of this association but this does not alter results substantially. These findings confirm the robustness of previous studies that found signs of environmental injustice where spatio-temporal variations have not been explicitly considered, confirming that targeted policies to reduce pollution in socio-economically disadvantaged areas are required.

Keywords: space-time patterns, vulnerability, inequities, random effects, Mexico.

JEL codes: O13, Q53, I32, C11, and C23

1. Introduction

Environmental injustice refers to the disproportionate exposure of people in socially disadvantaged groups, such as those with lower socioeconomic status or those experiencing discrimination based on their race/ethnicity to environmental hazards. These include air, soil, and water pollution (Landrigan *et al.*, 2018; Moreno-Jimenez *et al.,* 2016), which are often associated with proximity to power stations and hazardous waste sites (Funderburg and Laurian, 2015). These disadvantaged communities also have limited access to green spaces (Wolch *et al.,* 2014) and public infrastructure (Carvalho and Carvalho, 2021), and face a higher risk of morbidity and mortality due to COVID-19 (Aschner *et al*., 2021). All these factors make them more vulnerable to the adverse health impacts of air pollution.

In this paper we focus on air pollution as a severe threat to public health. Air pollution causes respiratory and cardiovascular disease, and mental ill-health, and has been established as a major modern mortality risk. Air pollution caused over 4.2 million premature deaths worldwide in 2016 and it is also estimated that fine particulate matter in polluted air causes 7 million deaths every year (World Health Organization, n.d.). The World Bank estimated a loss of US$225 billion, in terms of labour income, due to deaths caused by air pollution (Bank, 2016). The health impacts are not evenly distributed across the population; communities with low socioeconomic status are at greater risk of chronic disease due to their disproportional exposure to air pollution (Schweitzer and Valenzuela, 2004; Niessen *et al.*, 2018).

There is extensive work that illustrates social inequalities in the exposure to air pollution, and that greater exposure is experienced by people with low socioeconomic status or non-white background. Su et al. (2010) showed the inverse association between NO_2 concentration and socioeconomic status indicators (income) by census tracts in Vancouver and Seattle. Padilla *et al.* (2014) showed that deprived census blocks in two French metropolitan areas, Lille and Marseille, were the most exposed to NO_2. In middle-income countries with developing economics, evidence of environmental injustice is growing (Hajat *et al.,* 2015). Kopas et al. (2020) showed that poor, low-caste communities in India were more exposed to emissions from coal power plants than their wealthier, high-caste counterparts. Lome-Hurtado *et al.* (2020) demonstrated unequal exposure of the elderly and children to air pollution in Mexico City. Chakraborti and Voorheis (2021) showed that low-income areas in Mexico experience a disproportional burden of air pollution, with a decline in socioeconomic status within the investigated municipalities being associated to an 1% annual increase in air pollution levels.

The challenge of addressing the causes and consequences of air pollution is receiving increasing attention. Air pollution can be caused by different sources such as industrial activity, urbanization, traffic pollution, and institutional and natural sources that lead to pollution concentrations that are often clustered temporally and spatially (Kampa and Castanas, 2008; Diarra and Marchand, 2011; Landrigan *et al.*, 2018; Manisalidis *et al.*, 2020). The problem of air pollution can be exacerbated by institutional drivers, such as an inefficient judicial system (inefficiency of law enforcement) that may not be applied correctly in relation to environmental quality policies (Lomborg and Pope, 2003; Diarra and Marchand, 2011) in certain areas. Some policy instruments, such as low emissions zones, target traffic emissions reductions in certain locations within a city. Alternatively, there may be restrictions on vehicle movements, such as the program “Hoy no circula” in Mexico City, where vehicles do not circulate in certain geographical areas on specific days (Ambiente, n.d.). Factors associated with urbanization, such as the improvement or deterioration of road infrastructure, may cause fewer or higher traffic jams in specific municipalities, or there may be manifestations or demonstrations which change the travel patterns across the city (Carrier *et al.*, 2014; Arceo *et al.,* 2016). Some environmental contributory factors to air pollution, such as wildfires, also exhibit a spatio-temporal pattern, being more common in specific areas and at certain times of the year (Cobelo *et al.*, 2023).

These spatio-temporal characteristics of air pollution concentrations have important implications when understanding the relationship between air pollution and socioeconomic status. Ignoring the spatial dependence of factors that contribute to pollution clusters (i.e., locations close to each other exhibit more similar pollution levels than those further apart) may generate spatial autocorrelation problems in models of of air pollution. In particular, if residuals display spatial autocorrelation, the independence and identically distributed assumption of many models is violated, and this causes standard errors to be artificially low, leading to coefficients that may appear significant when they are not (i.e., inflates type I errors) (Anselin, 2002; Dormann et al., 2007). There have been different efforts to capture this inherently spatial nature of air pollution when isolating the effect of socioeconomic background on the exposure to this health risk. For instance, Sun *et al*. (2010) and Padilla *et al.* (2014) used generalized additive models (GAMs) to remove spatial autocorrelation. More recently, Verbeek and Hinck (2022) used a geographically weighted regression that allows for spatial variation in parameter estimates revealing thus localized patterns on the relationship between air pollution and socio-economic indicators, and therefore reveal where such association is more pronounced within urban areas. This technique is exemplified when evaluating the effect of low emissions zones in London and Brussels. Other authors, such as Chakraborti and Voorheis (2021) focus on temporal patterns using a fixed-effects panel data model that controls for time-invariant factors across locations. Here, we propose the use of a Bayesian approach, to account for the spatio-temporal structure in the pollution data in an attempt to avoid modelling errors caused by spatial and serial autocorrelation. Lome-Hurtado *et al.* (2021) used this approach to capture the health determinants of child mortality risk with a space-time structure such as physical activity and diet; and Li *et al.* (2014) used it to control for the space-time patterns associated with household burglary.

This paper applies a Bayesian approach to examine the associations of low socioeconomic status and air pollution (PM_{10} and ozone) exposure in Mexico City Metropolitan Area (MCMA). It investigates the importance of controlling for potential factors with simultaneous space-time patterns. Following Lome-Hurtado *et al.* (2021) and Li *et al.* (2014), our model estimates pollution exposure at temporal (monthly) and spatial (municipality) scales. Moreover, we acknowledge that the direction of causality between the economic and social disadvantage and the exposure to the pollutants could be in either direction (Chakraborti and Voorheis 2021). The level of air pollution is likely to affect where people with low socioeconomic status live, in cheaper and often in more polluted areas. However, income may affect pollution through greater production levels in areas of low socioeconomic status.

The high levels of income inequality, population density, and air pollution in the MCMA, the largest urban agglomeration in Mexico (Paquette, 2015; México, 2020) makes it a suitable case study area. The MCMA is classified as the third-largest metropolis in the world and has the lowest per capita GDP in the Organization for Economic Cooperation and Development (OECD) forum of countries (Paquette, 2015). This area consists of 16 municipalities within Mexico City and 59 in the State of Mexico[1]. In Mexico City, PM_{10} and ozone concentrations have reached levels above the threshold established by the World Health Organization (15 $\mu g/m^3$ annual mean and 45 $\mu g/m^3$ 24-hour mean for PM_{10}; and 100 $\mu g/m^3$ 8-hour daily maximum and 60 $\mu g/m^3$ 8-hour mean peak season for ozone) (Organization, 2006). In 2010 there were 20,500 deaths due to the air pollution, with particulate matter being in the top ten of the riskiest health factors of mortality in Mexico (IHME, 2014). Arceo et al. (2016) estimated that 1 μg/m3 increase of in 24-h PM_{10} in Mexico City results in an additional 0.24 deaths per 100,000 births.

2. Data and Methods

2.1 Data

All variables were developed for each municipality in the study region. Monthly pollution data allow for the control of temporal variation within a year. PM_{10} and ozone data were obtained from the Automatic Air Quality Monitoring Network of Mexico City (RAMA, n.d.) in a period spanning from 2012 to 2019. Following previous studies, the 24hr means for PM_{10} and ozone (from 10am to 6pm) were each averaged into monthly mean concentrations, based on the measuring stations which had at least 75% of the information in each year (Romieu *et al.*, 2012; Lome-Hurtado *et al.,* 2019). In total the data for 331 stations were used (120 and 211 stations for PM_{10} and ozone, respectively). A universal kriging algorithm was applied to assign an interpolated pollutant value, from the measuring stations, to each municipality. Kriging has previous been used for similar interpolations (Su *et al.*, 2011; Lome-Hurtado *et al.,* 2019; Gao *et al.*, 2021). Note that the pixel size of the raster was of 1.20 x1.20 meters (cell size), and when the municipality boundary intersected several raster pixels we took the mean. An advantage of kriging is the production of standard errors which quantify the degree of uncertainty of the spatial prediction. Larger standard errors typically exist in areas with fewer measuring stations. Municipalities with boundaries beyond 16 km of a measuring station (from the centroid of the municipality) were removed from the analysis, following similar criteria as in previous studies (Arceo et al., 2016; Lopez-Feldman et al., 2021). Note that beyond this distance, we identified larger standard errors (due to fewer measuring stations), this problem is often acknowledged in the literature (Künzli et al., 2005, Lome-Hurtado et al., 2019). This resulted in the inclusion of 48 municipalities out of the 75 total which comprise the MCMA (Greater Mexico City). This includes all 16 municipalities within central Mexico City and 32 of the municipalities beyond its boundaries in the MCMA. These municipalities account for just over 92% of the population living in the MCMA.

A set of socioeconomic, climatic and demographic covariates were assembled. Economic and social disadvantage indices for 2010 and 2015 were obtained from the Mexican National Council for the Evaluation of Social Development Policy (CONEVAL, n.d.).These social

[1] An additional municipality was excluded from this analysis, belonging to the State of Hidalgo.

gap indices measure four components of socioeconomic disadvantage: education, health, basic services, and quality and space in housing. municipalities with higher values are more socioeconomically disadvantaged compared with those with lower values. For 2010 index values vary from -1.83 to -0.10. For 2015 index values vary from -1.6 to -0.32; as an additional robustness test, we also use the alternative CONAPO index in the analysis (CONAPO, n. d.). The CONAPO index also measures the level of marginalization (related to socioeconomic and demographic conditions) or level of poverty as the CONEVAL index.

Population density also may be related to socioeconomic conditions and is also a contributing factor to air pollution production (Hajat *et al.*, 2013). Population density data for the analysis were developed based on the Population and Housing Census for 2010 and 2015 (INEGI, n.d. d., n.d. c).

Previous studies on exposure to air pollution have also identified automobile traffic and industry processes as its principal sources (Querol et al., 2008; Carrier et al., 2014). A variable to capture the number of roads was obtained from official infrastructure maps (INEGI, n. d. b) for the 2011 year. This represents the number of major and large roads, including avenues, extensions, circuits, peripherals, road axles, passages, and viaducts. An industry variable was developed from the 2009 and 2014 Economic Census (INEGI, n. d. a). This variable contains the amount of machinery and equipment of the manufacturing industries.

Temperature and relative humidity are often associated with air pollution in previous studies (Arceo *et al.,* 2016). Monthly average temperature and relative humidity interpolated values were used in our analysis after obtained the data from the 331 sites of the Automatic Air Quality Monitoring Network of Mexico City (RAMA, n.d.) from 2012 to 2019 and using the same kriging technique used for the pollution values. Correlation between variables was assessed in order to avoid problems associated with collinearity, ad all correlations were below 0.55. Note that all the mentioned variables are at the municipality level.

2.2 Statistical Analysis

Following these studies, the pollution data are modelled as:

$$y_{imt} = \alpha + \beta_1 \times disadvantage\ index_{i,t'} + \beta_2 \times temperature_{imt} + \beta_3 \times humidity_{imt} + \beta_4 \times pop\ density_i + \beta_5 \times roads_i + \beta_6 \times industries_{it} + (s_i + u_i) + v_t + st_i\, \mathrm{t}^* + \varepsilon_{it} \quad (1)$$

Where y_{imt} represents either PM_{10} or ozone in the municipality i, in a specific month m over the year t. Thus, we model PM10 and ozone separately. This study assumes a normal distribution, for both pollutants $y_{imt} \sim Normal\ (covariates, \varepsilon_{it})$. Following Chakraborti and Voorheis (2021), to consider the relationship between pollution and low socioeconomic conditions, we assigned the 2010 disadvantage index values to the 2012-2015 pollution data and the 2015 disadvantage index values to the 2016-2019 pollution data. The $disadvantage\ index_{i,t'}$ represents the disadvantage of the municipality i for the previous census year, represented as t'. The 2010 socio-economic disadvantage index was assumed to relate to pollution released in the 2012 to 2015 period, while the 2015 socio-economic disadvantage index was used to explain the pollutants released from 2016 to 2019. A positive sign on this variable would imply that an increase in the disadvantage index relates to an increase in air pollution exposure on average for the study period. The $temperature$ and $humidity$ variables are the average levels of these variables in each municipality i in month m over the year t. The $pop\ density$ variable is the population density in the municipality i for either the year, t, 2010 or 2015 using similar reasoning to our disadvantage index; $roads$ represents the number of roads in the municipality i; and $industries$ is the number of industries (machinery and equipment) in the municipality i.

The term, $(s_i + u_i)$, denotes the spatial component for each municipality, i, that controls the overall spatial structure of the data. This spatial component uses the Besag, York, and Mollié (BYM) model (Besag, York, and Mollié, 1991).The s_i term captures the spatial structure and u_i the spatial unstructured of the data over time. An intrinsic conditional autoregressive Gaussian distribution (ICAR) to the priors for the spatial structure (s_i) was used following Li *et al.* (2014). The spatial structure component may capture the level of clustering and demonstrate that nearby municipalities may have similar levels of air pollution. Therefore, a spatial adjacency matrix W of size *N x N (where N is the number of municipalities)* was used in the spatial structure of s_i to model the level of the neighborhood of the municipalities in the ICAR model. The matrix off-diagonal values may have two values: either *wij=1 (*when the municipality *i* and municipality *j* share a common boundary*)* or *wij=0* (if municipality *i* and municipality *j* do not share a common boundary)*,* giving that $(i \neq j)$. Therefore, two municipalities are neighbors when their random effects are correlated; otherwise, such municipalities are conditionally independent. The spatial unstructured term, u_i, captures the remaining potential spatial variability that does not present a spatial pattern. This unstructured term captures the part of the overall spatial variability that does not display a spatial pattern (a clustering structure). The term, u_i, follows a normal distribution $u_i \sim N(0, \sigma^2 u)$, where u_i was allocated a prior distribution of Gamma, a highly non-informative distribution (Kelsall and Wakefield, 1999), on the precisions of s_i, u_i, and v_t.

The term v_t captures the potential serial correlation in the data (the overall time trend). The term $st_i\ t^*$ captures the potential local spatio-temporal variations (space-time factors) of the contaminant in specific municipalities in a given year which may be caused by certain changes in its institutional, urban, and natural risk drivers (outlined in the introduction). Therefore, this space-time term, $st_i\ t^*$, assesses a linear departure of a municipality's time trend from the overall time trend. In this sense, a local trend (in terms of pollution) of each municipality is captured by the new term. This term is also modelled using the BYM prior model. Nearby municipalities may have more similar pollution trends than other municipalities which are farther apart. A prior distribution of Gamma was allocated to these new terms. Noninformative priors N (0, 0.001) were assigned to the six regression coefficients, β´s, and the intercept in each model; the normal distribution has a mean of zero and a large variance due to the absence of genuine prior expectations. Finally, the error term (ε_{it}) captures the variability that is not explained by the other terms in equation 1, which follows a normal distribution: $\varepsilon_{it} \sim (0, \sigma^2_{\varepsilon})$.

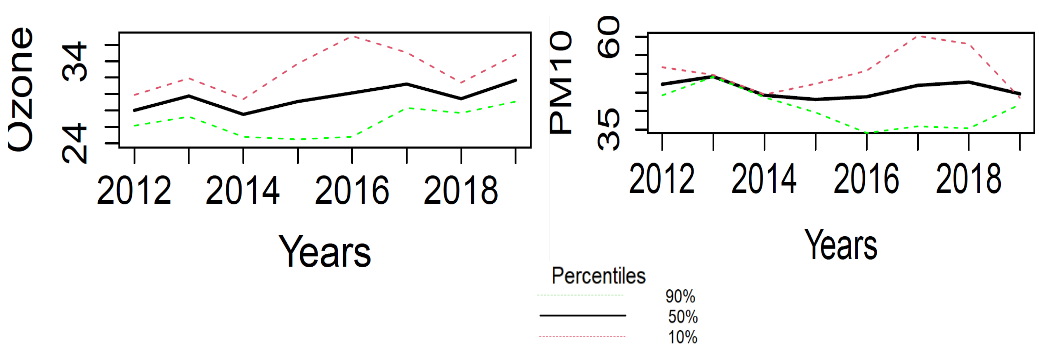
Three models were executed for each pollutant: model 1 includes the covariates and the time term, v_t; model 2 includes the terms of model 1 plus the spatial component, $(s_i + u_i)$; and model 3 includes the previous model terms plus the spatial-time term st_i t* to assess the importance of controlling for the space-time structure of the air pollution data to isolate the effect of marginalization on PM_{10}. the analysis of the panel using fixed effects is also performed to provide a comparison to the Bayesian approach. Parameter estimation was implemented in R and WinBUGS (a software for fitting Bayesian models, Spielgelhalter *et al.,* 1999; R Core Team , 2020). The models all reached convergence when between 40,000 to 10000 MCMC chains were used, with different initial values for each model (see supporting material for model run details)[2]. To choose the best Bayesian model, the deviance information criterion (DIC criterion) was used (Spiegelhalter et al., 2002). The DIC criterion is a statistical tool that assesses the balance of the model complexity with the fit to the data. Models with smaller DIC values are preferred.

3. Results

3.1 Descriptive analysis

The descriptive statistics of the data used in the analysis are shown in Table 1a and 1b, at the municipality level in the MCMA from 2012 to 2019. The period saw a slight reduction for PM_{10} while there was a slight increase of ozone (see Figure 1). Note that PM_{10} and ozone concentrations have reached levels above the threshold. In the period of study, 2012-2019, the annual average concentration of PM_{10} was 45.92 ug/m3. Meanwhile, for ozone such average was 29.6 ppm. These values are so higher than the threshold established by the World Health Organization (20 ug/m3 annual average and 100 ug/m3 8-hour mean for PM_{10} and ozone, respectively).

Figure 1. PM_{10} and ozone concentration values from 2012 to 2019.



The values for temperature and relative humidity were relatively stable from 15.7°C to 17.3°C and from 53.1% to 53.6%, respectively during the period. The economic and social disadvantage index presented mean values of -1.14 and -1.13 for 2010 and 2015 years,

[2] After having burned in the first 3,000 iterations, 37,000 were left for making inferences for model 1. Similarly, models 2 and 3 were run for 90,000 and 100,000 MCMC chains, and were left 70,000 and 85,000 for making inferences, respectively. To measure the convergence of the MCMC chains in each model, the history plots and the Gelman-Rubin diagnostic (Gelman and Rubin, 1992) were used. The first one was examined by visual inspection of the history plots, which is a common practice in Bayesian models. The values from the Gelman-Rubin diagnostic were obtained and they remained lower than 1.025 for every single model parameter, showing that the chains achieved convergence after the burn-in period..

respectively. Even though Mexico is the world's 11th largest economy in terms of GDP measured at purchasing power parity (OCDE, 2017), such index illustrates that the income and social inequality remains high compared with other OECD countries. The population density had means of 4,005 people/km^2 and 4,169 people/km^2 in 2010 and 2015, respectively. Note that for other populated Latin cities such numbers were 3,026/km² (2023) and 7,528/km² (2022) for Santiago, Chile and Sao Paulo, Brazil (City Population, n.d.). The industrial variable (machinery and equipment) presented means of 2,646 and 3,423 in 2009 and 2014, respectively. The MCMA is in the top of the most industrialized areas in Mexico. In 2019, there were in total 8,629 economic units (Commercial and Industrial machinery and equipment, except automotive and electronic, repair, and maintenance), the State of Mexico occupied the first place with 1,780; followed for Jalisco (1,505), and Mexico City (1,207) (Data Mexico, n.d.). Lastly, the variable of number of roads (include big roads with high density of cars such as avenue, peripheral, viaduct, circuit, and road axis) had a mean of 764 in the 2011 year. It is important to mention the standard deviations of the industrial and road variables were much higher than their mean. This illustrates the high concentration of the industries and roads in certain municipalities.

Table 1a. Descriptive statistics of PM_{10}, ozone pollutants[1], temperature, and relative humidity variables in the MCMA (short).

Variable description and name	2012 mean (sd)	2013 mean (sd)	2014 mean (sd)	2015 mean (sd)	2016 mean (sd)	2017 mean (sd)	2018 mean (sd)	2019 mean (sd)	Overall average 2012-2019
Particulate matter 10 (ug/m3)	47.18	49.25	44.23	43.09	43.82	46.88	47.77	44.61	45.92
	(13.32)	(15.61)	(12.72)	(9.83)	(14.13)	(15.46)	(12.94)	(15.74)	------
Ozone (ppm)	28	29.75	27.51	29.08	30.13	31.21	29.42	31.68	29.60
	(2.42)	(2.58)	(5.83)	(3.78)	(8.05)	(7.43)	(6.03)	(7.59)	------
Temperature (°C)	15.76	16.38	16.61	16.52	16.16	16.11	16.62	17.35	16.44
	(1.71)	(1.7)	(1.87)	(1.48)	(2.27)	(2.31)	(2.01)	(1.99)	------
Relative humidity (%)	53.12	53.58	56.91	61.92	58.81	55.45	57.69	53.60	56.39
	(9.36)	(13.32)	(10.61)	(8.11)	(10.65)	(11.03)	(9.24)	(10.51)	------

[1]Monthly average in each year

Table 1b. Descriptive statistics of social, economic, and demographic variables in the MCMA (short)

Variable name	**2010 mean (sd)**	**2015 mean (sd)**
Economic and social disadvantage index	-1.14 (0.4)	-1.13 (0.3)
Population density (people per km^2)	4005 (6402)	4169 (6526)
	2009 mean (sd)	**2014 mean (sd)**

Number of machinery and equipment	2646 (5409)	3423 (5409)
	2011 mean (sd)	
Number of roads	764.5 (1269)	

Spatial patterns exist in the datasets that might lead to problems of spatially autocorrelated errors. The Global Moran Index of the pollution data for each year, from 2012 to 2019, showed positive spatial autocorrelation, with mean values of 0.32 and 0.3 (p- < 0.0001) ,. These results mean that there were some municipality clusters with similar PM_{10} and ozone records. Likewise, the Global Moran Index of the economic and social disadvantage index had a mean of 0.31 and 0.35 for 2010 and 2015 years, respectively; there was also a certain level of clustering. Lastly, the Autocorrelation Function (ACF) was used to measure the presence of potential serial correlation; their mean values were 0.37 and 0.3 (lagged 1 year for each municipality) across all the municipalities. This showed evidence of serial correlation; that is, a certain level of association of the pollutants' records over time.

3.2 Socio-economic disadvantage index and pollution burden

The posterior means results of the disadvantage index and other risk factors associated with PM_{10} and ozone for each model are presented in Table 2a and 2b. The three models illustrate that the disadvantage index coefficient was significantly and positively associated with PM_{10} (with 95% CI). The disadvantage index coefficient from model 2, which controls for spatial structure, is lower, showing a weaker association, when compared with model 1. Model 3 accounts for spatial and temporal factors; its coefficient size for the disadvantage index falls slightly, relative to the previous model 2. This may mean that the disadvantage index coefficient was partially reflecting the effect of these spatio-temporal factors more generally on air pollution. The coefficient of this index in model 3 indicates that a one-unit increase in the disadvantage conditions is associated with an increase in the concentrations of PM_{10} by 1.1 ug/m^3. Meaning that the increase in presence in a municipality of socio-economic disadvantaged people, is associated with an increment in the level of air pollution (PM_{10}) exposure. The coefficient of the index using fixed effects was similar to model 1, but larger than the value of this coefficient in model 3.

Temperature has a significant positive relationship with PM_{10}, and relative humidity becomes no significant when the model accounts for spatio-temporal structure. In general, population density, roads, and industry variables had no association with PM_{10} in the models.

Table 2a. Posterior means relating to different potential risk factors affecting PM_{10}, with 95% credible intervals displayed in the brackets.

Variable	Panel data model with fixed approach[1]	Model 1 (simple) Posterior estimates (credible intervals)	Model 2 (space) Posterior estimates (credible intervals)	Model 3 (space + space-time interactions) Posterior estimates (credible intervals)

Intercept	-------	47.01 (46.5, 47.5)	47.01 (46.5, 47.5)	47.01 (46.52, 47.68)
Socioeconomic disadvantage index	**2.42** (1.06))**	**1.98 (1.45, 2.05)**	**1.2 (0.35, 1.9)**	**1.1 (0.37, 1.9)**
Temperature	**-2.05** (0.062)**	**3.04 (2.53, 3.64)**	**1.98 (1.63, 2.74)**	**1.89 (1.75, 2.69)**
Relative humidity	**-1.05** (0.013)**	**0.23 (0.05, 0.42)**	0.07 (-0.09, 0.24)	-0.008 (-0.2, 0.15)
Population density	0.0005 (0.0005)	0.05 (-0.02, 0.11)	0.04 (-0.03, 0.11)	0.02 (-0.02, 0.1)
Number of roads	------	0.08 (-0.2, 0.32)	0.13 (-0.16, 0.38)	0.05 (-0.29, 0.23)
Number of machinery and equipment	**-0.0005** (0.0001)**	0.021 (-0.09, 0.11)	-0.01 (-0.13, 0.11)	0.01 (-0.12, 0.1)
DIC value	See note 1	2180	2160.7	2088

Note: The spatial and spatio-temporal terms are not included since each municipality has a value, but most of them were significant (94% and 91% of the total of values for model 2 and model 3, respectively) at 95% CI.
[1] Adj. R-Squared: 0.66 and F-statistic with p-value: < 2.22e-16. The model includes the municipality fixed effects and yearly controls.
* $p<0.05$; ** $p<0.01$

In the case of ozone, the three Bayesian models illustrate that the disadvantage index estimate was not significantly related. Temperature is once again significantly related.

Table 2b. Posterior means relating to different potential risk factors affecting ozone, with 95% credible intervals displayed in the brackets.

Variable	Panel data model with fixed approach[1]	Model 1 (simple) Posterior estimates (credible intervals)	Model 2 (space) Posterior estimates (credible intervals)	Model 3 (space+space-time interactions) Posterior estimates (credible intervals)
Intercept	-------	47.01 (46.5, 47.5)	47.01 (46.5, 47.5)	47.01 (46.52, 47.68)
Socioeconomic disadvantage index	0.4 (0.51)	0.32 (-0.2, 0.85)	0.3 (-0.23, 0.86)	0.28 (-0.3, 0.89)
Temperature	**1.17** (0.029)**	**2.05 (1.96, 3.51)**	**1.04 (0.73, 1.94)**	**1.01 (0.75, 2.0)**
Relative humidity	**-0.13** (0.0063)**	**0.17 (0.09, 0.35)**	0.05 (-0.06, 0.2)	-0.004 (-0.1, 0.91)
Population density	-0.0003 (0.00023)	-0.07 (-0.05, 0.98)	-0.06 (-0.04, 0.91)	-0.01 (-0.03, 0.1)
Number of roads	------	0.007 (-0.01, 0.042)	0.017 (-0.06, 0.04)	0.003 (-0.02, 0.02)
Number of machinery and equipment	-0.0001 (0.0000705)	0.001 (-0.08, 0.01)	-0.002 (-0.013, 0.021)	0.001 (-0.01, 0.01)
DIC value	See note 1.	2190	2170.3	2098

Note: The spatial and spatial-temporal terms are not included due to that each municipality has a value, but most of them were significant (90% and 85% of the total of values for model 2 and model 3, respectively) at 95% CI.

[1] Adj. R-Squared: 0.61 and F-statistic with p-value: < 2.22e-16. The model includes the municipality fixed effects and yearly controls.

* p<0.05; ** p<0.01

Model 3, controlling for space and space-time patterns, was the best fit according to the DIC criterion (for both pollutants); the DIC values were lower when compared with model 2 and model 1. Hence, the outcomes of model 3 were consistent in producing the best robust estimates in the association between the disadvantage index and air pollution. As an additional robustness test, we executed the models with the CONAPO index; see Tables 1Aa and 1Ab in the Appendix section. For the case of PM_{10}, the coefficients of the socio-disadvantage index were significant and similar to the previous results with 1.49 and 1.02 values for the panel data with fixed effects and for model 3 (with space and time interactions), respectively. Such values were lower but consistent compared with the CONEVAL index. For the case of ozone, the values of the coefficients for the index were 0.15 and 0.33 for the panel data with fixed effects and for model 3, respectively. These coefficients were also similar to the CONEVAL index results and not significant. For the rest of the covariates, results were also similar to those obtained with the CONEVAL index. Finally, we have provided the annual outcomes of the models in the Appendix (Tables 2a and 2b), which also are consistent with the main results shown here.

4. Discussion

The analysis provides evidence of environmental injustice in the distribution of PM_{10} across the MCMA, controlling for the space-time drivers using a Bayesian approach. To the best of our knowledge, this is the first work in environmental injustice in Mexico that analyses the space-time potential factors of air pollution. We found a positive association between low socioeconomic status and air pollution (PM_{10}). This relationship was not significant for ozone. Note that much PM_{10} pollution is emitted directly from specific sources, and tends to be found relatively close to these sources, travelling up to 50 km (Nel A., 2005). These sources include industrial plants, construction sites, wildfires, urban areas with high levels of wood burning for domestic fuel, and heavily-used roads with tire and brake wear from road traffic. While ozone is not emitted directly, it is produced in the troposphere from precursor gases which come from both anthropogenic sources (manufacturing, energy transformation, road transport) as well as natural ones (vegetation especially forests). Formation is thus often a more regional process, and more directly linked to weather conditions, sunlight, and wind speeds and directions at larger scales (Duarte, *et al.,* 2022). Therefore, spatio-temporal differences operating over small spatial scale (neighbourhoods etc.) are likely to be more important for PM_{10} than ozone. Unsurprisingly, ozone was positively related to temperature, which is likely to be dependent on sunlight.

The findings of this study in relation to PM_{10} illustrate the importance of accounting for spatial and time drivers of PM_{10} to better understand the association between this pollutant and socio-economic disadvantage. When a spatial-time term was introduced in the regression model, the coefficient size for the disadvantage index fell slightly, indicating a weaker effect, relative to the previous models (without such a space-time term). This seems to indicate that the coefficient for this disadvantage index could partially reflect the effect of such spatial-temporal drivers of air pollution, omitted in traditional regression analysis. Despite the inclusion of a range of climatic, demographic, and social control variables, one may still be concerned that there are other factors driving pollution concentration variability in the study period affecting the model coefficient of the disadvantage index. Such sources may vary across space and time (as noted in the introduction). Our results show that with a one-unit increase in the index, there may an increase of PM_{10} concentrations by 1.1 ug/m^3. It is also notable that relative humidity ceases to show significant association as spatio-temporal pattern is considered in the modelling.

These findings confirm the robustness of previous studies that found signs of environmental injustice where spatio-temporal variations have not been explicitly considered, confirming that targeted policies to reduce pollution in socio-economically disadvantaged areas are required. Overall, the inclusion of a spatio-temporal element in the modelling results in improved estimates of effect sizes, but does not substantially alter the findings, when spatio-temporal variations have not been explicitly considered. Our results therefore show the importance of decreasing the level of PM_{10} in socio-economically disadvantaged areas. Our findings are also consistent with previous spatial econometric environmental injustice studies (Havard et al., 2009; Li *et al.*, 2018; Verbeek, 2019), which also show that accounting for the spatial structure of the data resulted in a lower coefficient relating to socio-economic disadvantaged status. We complement this literature by showing that controlling for air pollution drivers that vary over time and space simultaneously further reduces the value of this coefficient. Nevertheless, the overall findings of the present study (positive and significant association of disadvantage status and PM_{10}) are in line with the recent study of Chakraborti and Voorheis (2021), who demonstrated there is as a clear case of environmental justice in Mexico.

The relevance of the space-time drivers of PM_{10} show in this study can be related to factors such as wildfires, structural fires, construction of new road infrastructure (paved and unpaved roads), and burning waste in the open air, which are common in the MCMA according to the Ministry of Environment in Mexico City (México, 2016). In 2016, the Ministry reported 2,162 ug/m^3 of PM_{10} emissions by open burning of urban waste, which represented 5.7% of the total emissions. The construction sector (edification and demolition) was responsible for 2,305 ug/m^3 and 978 ug/m^3 of PM_{10} (2.5% of the total) emissions in 2014 and 2016, respectively. The forest fires generated 43.5 ug/m3 and 109.4 ug/m^3 of PM_{10} (2.8% of the total) emissions in 2014 and 2016, respectively. The paved and unpaved roads were responsible for 14,427.8 ug/m^3 and 14,092.91 ug/m^3 of PM_{10} (3.7% of the total) emissions in 2014 and 2016, respectively. Other risk factors which show spatial and time patterns are environmental regulations, judicial inefficiency, and demonstrations. The Mexican government, through its air quality management program (PROAIRE), aims to apply environmental regulations to reduce air pollution, specifically PM_{10}. This program has been implemented since early 1989 and 1995, respectively (Metropolitana, 1994; SEMARNAT, 2017). The government has developed air pollution management strategies, but their implementation has given different results depending on the areas and only a few municipalities have managed to reach the air pollution targets (de San, 2019). Therefore, spatially-targeted policies need to be implemented to reduce space-time drivers such as wildfires, structural fires, and burning waste in the open air. Some of them were caused by the hand of man e.g. 95% of the main scenarios being bonfires and poorly extinguished cigarette butts, the abandonment of land, and the preparation of grazing areas with fire (Semarnat, 2017). Similarly, such implement targeted emission programmes are needed to mitigate air pollution specially in poorer areas-municipalities through new regulations (Nguyen and Marshall, 2018) and health benefits. For instance, the spatial distribution of air pollution is associated with the industrial distribution, which is concentrated in the north and east Mexico City. Industrial emissions mainly affect the most economic and social disadvantaged groups, who live near the production plants due to low rents and land prices in those areas. Therefore, policies which tackle industry re-allocation or/and re-allocation of such vulnerable groups are necessarily to reduce environmental injustice; especially in the north of our study area where according our economic and social index, there are more economic and social disadvantage conditions. In addition, some health programmes should be created for poor people with high exposure to air pollution.

On another note, our findings should be interpreted with some caution due to several methodological and data limitations. Mexico City, as the capital of Mexico, is considered the most important city in terms of political and economic aspects; some drivers of pollution, as those mentioned above, could take place in certain municipalities and in specific days, and our controlling for these events, or other daily drivers variation of air pollution would have required daily analysis with more fine spatial and temporal resolution, not available for this study. The use of data at the municipality level may also potentially mask important variations within municipalities, and may result in less accurate estimation of the coefficients. To obtain more reliable results, a smaller scale of the geographical area may be required. In addition, the area of study was limited to 48 municipalities (of a total of 75). The practice of removing municipalities has been used in previous studies (Arceo *et al.,* 2016; Lopez-Feldman et al., 2021) due to the availability of having few and concentrated monitoring pollution stations in certain areas; this study follows the same criterion. Note that the means and standard deviations of the disadvantage indices, over the period studied, were similar in the included and not included areas, meaning that both areas are similar in terms of disadvantage.

5. Conclusion

This study has provided further evidence of the existence of environmental injustice in the MCMA, highlighting the importance of controlling for the space-time drivers in order to obtain more accurate estimates of the association between socio-economic disadvantage and exposure to PM_{10}. These results can inform public and social programmes which aim to reduce inequalities in exposure to air pollution, by directing efforts to reduce the spatial and temporal drivers of PM_{10}, shown to be significant in this study. This may be better achieved by strategies that are spatially and temporally heterogeneous and target areas with lower SES, which experience the highest level of air pollution. The effectiveness of these efforts will be enhanced through better collaboration and coordination between decision-makers addressing air pollution inequalities and injustice in Mexico City (de San, 2019).

5. References

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Competing interests

The authors declare that they have no competing interests.

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Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

APPENDIX

Table A1a. Posterior means relating to different potential risk factors affecting PM_{10}, with 95% credible intervals displayed in the brackets, using CONAPO index.

Variable	Panel data model with fixed approach[1]	Model 1 (simple) Posterior estimates (credible intervals)	Model 2(space) Posterior estimates (credible intervals)	Model 3 (space+space-time interactions) Posterior estimates (credible intervals)
Intercept	-------	47.01 (46.5, 47.5)	47.01 (46.5, 47.5)	49.78 (45.75,53.84)
Dep_Ind (Marginalization index)	1.49 (22.8)	**1.98 (1.45, 2.05)**	**1.2 (0.35, 1.9)**	**1.02 (0.07,1.98)**
Temp (Temperature)	-0.41 (0.35)	3.04 (2.53, 3.64)	1.98 (1.63, 2.74)	2.18 (1.47,2.89)
Re_hum (Relative humidity)	-0.29 (0.07) ***	0.23 (0.05, 0.42)	0.07 (-0.09, 0.24)	-0.03 (-0.29,0.24)
Pop density (Population density)	0.001 (0.001)	0.05 (-0.02, 0.11)	0.04 (-0.03, 0.11)	0.04 (-0.08,0.16)
Roads (Number of roads)	------	0.08 (-0.2, 0.32)	0.13 (-0.16, 0.38)	0.002 (-0.5,0.49)
Industries (Number of machinery and equipment)	-0.0002 (0.0003)	0.021 (-0.09, 0.11)	-0.01 (-0.13, 0.11)	0.02 (-0.14,0.16)
DIC value	See note 1.	2180	2160.7	2088

Note: The spatial and spatial-temporal terms are not included due to that each municipality has a value, but most of them were significant (94% and 91% of the total of values for model 2 and model 3, respectively) at 95% CI.

[1] Adj. R-Squared: 0.66 and F-statistic with p-value: < 2.22e-16. The model includes the municipality fixed effects and yearly controls.

* p<0.05; ** p<0.01, *** p<0.001

Table A1b. Posterior means relating to different potential risk factors affecting ozone, with 95% credible intervals displayed in the brackets, using CONAPO index.

Variable	Panel data model with fixed approach[1]	Model 1 (simple) Posterior estimates (credible intervals)	Model 2(space) Posterior estimates (credible intervals)	Model 3 (space+space-time interactions) Posterior estimates (credible intervals)
Intercept	-------	47.01 (46.5, 47.5)	47.01 (46.5, 47.5)	30.78(28.83,32.75)
Dep_Ind (Marginalization index)	**0.15(0.92)**	**0.32 (-0.2, 0.85)**	**0.3 (-0.23, 0.86)**	**0.33(-0.13,0.8)**

Temp (Temperature)	-0.23(0.16)	2.05 (1.96, 3.51)	1.04 (0.73, 1.94)	-0.83(-1.15,-0.51)
Re_hum (Relative humidity)	0.004(0.031)	0.17 (0.09, 0.35)	0.05 (-0.06, 0.2)	0.25(0.13,0.38)
Pop density (Population density)	0.001(0.00043) **	-0.07 (-0.05, 0.98)	-0.06 (-0.04, 0.91)	-0.01(-0.07,0.05)
Roads (Number of roads)	------	0.007 (-0.01, 0.042)	0.017 (-0.06, 0.04)	0.01(-0.23,0.24)
Industries (Number of machinery and equipment)	0.0004(0.00013) ***	0.001 (-0.08, 0.01)	-0.002 (-0.013, 0.021)	-0.05(-0.12,0.03)
DIC value	See note 1.	2190	2170.3	2098

Note: The spatial and spatial-temporal terms are not included due to that each municipality has a value, but most of them were significant (90% and 85% of the total of values for model 2 and model 3, respectively) at 95% CI.
[1] Adj. R-Squared: 0.61 and F-statistic with p-value: < 2.22e-16. The model includes the municipality fixed effects and yearly controls.
* p<0.05; ** p<0.01, *** p<0.001

Table A2a. Yearly posterior means relating to different potential risk factors affecting PM_{10}, with 95% credible intervals displayed in the brackets.

Variable	Panel data model with fixed approach[1]	Model 1 (simple) Posterior estimates (credible intervals)	Model 2(space) Posterior estimates (credible intervals)	Model 3 (space+space-time interactions) Posterior estimates (credible intervals)
Intercept		46.11 (45.7, 46.5)	46.11 (45.5, 46.7)	46.11 (45.52, 46.68)
Dep_Ind (Marginalization index)	1.84(2.05)	**1.85 (1.35, 1.85)**	**1.1 (0.29, 1.88)**	**1.08 (0.27, 1.87)**
Temp (Temperature)	-0.41(0.35)	3.84 (3.13, 3.84)	2.44 (1.73, 3.14)	2.17 (1.45, 2.89)
Re_hum (Relative humidity)	-0.29(0.07) ***	0.34 (0.06, 0.62)	0.09 (-0.17, 0.36)	-0.009 (-0.27, 0.25)
Pop density (Population density)	0.001(0.001)	0.06 (-0.02, 0.16)	0.05 (-0.05, 0.17)	0.03 (-0.07, 0.15)
Roads (Number of roads)		0.09 (-0.32, 0.52)	0.11 (-0.36, 0.58)	0.07 (-0.39, 0.53)
Industries (Number of machinery and equipment)	-0.0002(0.0003)	0.02 (-0.08, 0.14)	-0.01 (-0-15, 0.12)	0.01 (-0.12, 0.16)
DIC value		2179.9	2164.7	2089.3

Note: The spatial and spatial-temporal terms are not included due to that each municipality has a value, but most of them were significant (94% and 91% of the total of values for model 2 and model 3, respectively) at 95% CI.

Table A2b. Yearly posterior means relating to different potential risk factors affecting ozone, with 95% credible intervals displayed in the brackets.

Variable	Panel data model with fixed approach[1]	Model 1 (simple) Posterior estimates (credible intervals)	Model 2(space) Posterior estimates (credible intervals)	Model 3 (space+space-time interactions) Posterior estimates (credible intervals)
Intercept		46.11 (45.7, 46.5)	46.11 (45.5, 46.7)	30.44(29.31,31.56)
Dep_Ind (Marginalization index)	-0.91(0.824)	**1.85 (1.35, 1.85)**	**1.1 (0.29, 1.88)**	**0.25(0,0.5)**
Temp (Temperature)	-0.26(0.07) ***	3.84 (3.13, 3.84)	2.44 (1.73, 3.14)	-0.27(-0.42,-0.13)
Re_hum (Relative humidity)	0.004(0.02)	0.34 (0.06, 0.62)	0.09 (-0.17, 0.36)	0.19(0.11,0.27)
Pop density (Population density)	0.0006(0.0004)	0.06 (-0.02, 0.16)	0.05 (-0.05, 0.17)	-0.02(-0.05,0.02)
Roads (Number of roads)		0.09 (-0.32, 0.52)	0.11 (-0.36, 0.58)	0.02(-0.19,0.23)
Industries (Number of machinery and equipment)	0.0007(0.0001) ***	0.02 (-0.08, 0.14)	-0.01 (-0-15, 0.12)	-0.08(-0.15,-0.01)
DIC value		2179.9	2164.7	2089.3

Table A3. Monthly log posterior means relating to different potential risk factors affecting PM_{10} and ozone, with 95% credible intervals displayed in the brackets, for Model 3 (space+space-time interactions).

Variable	PM10	OZONE
Dep_Ind (Marginalization index)	**0.040 (0.03, 0.10)**	**0.005 (-0.025,0.035)**
Temp (Temperature)	0.042 (0.024,0.061)	0.006 (0.0032, 0.0088)
Re_hum (Relative humidity)	-0.002 (-0.009,0.003)	-0.0061 (-0.011, -0.0010)
Pop density (Population density)	0.039 (-0.031, 0.118)	-0.026 (-0.055, 0.005)
Roads (Number of roads)	0.015 (-0.49, 0.56)	0.379 (0.27, 0.98)

Industries (Number of machinery and equipment)	0.015 (-0.006, 0.032)	0.245 (-0.013, 0.57)

Figure A1.a. PM_{10} monitoring stations across Greater Mexico City (short) from 2012 (first row and left figure) to 2019 (second row and right figure).

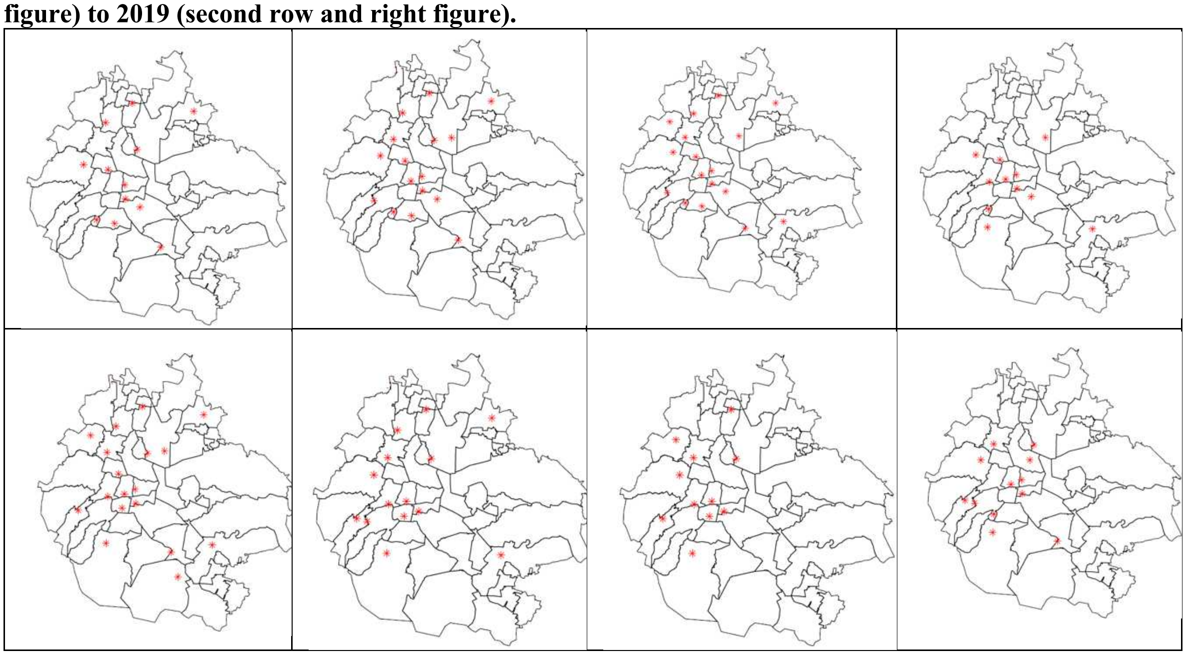


Figure A1.b. Ozone monitoring stations across Greater Mexico City (short) from 2012 (first row and left figure) to 2019 (second row and right figure).

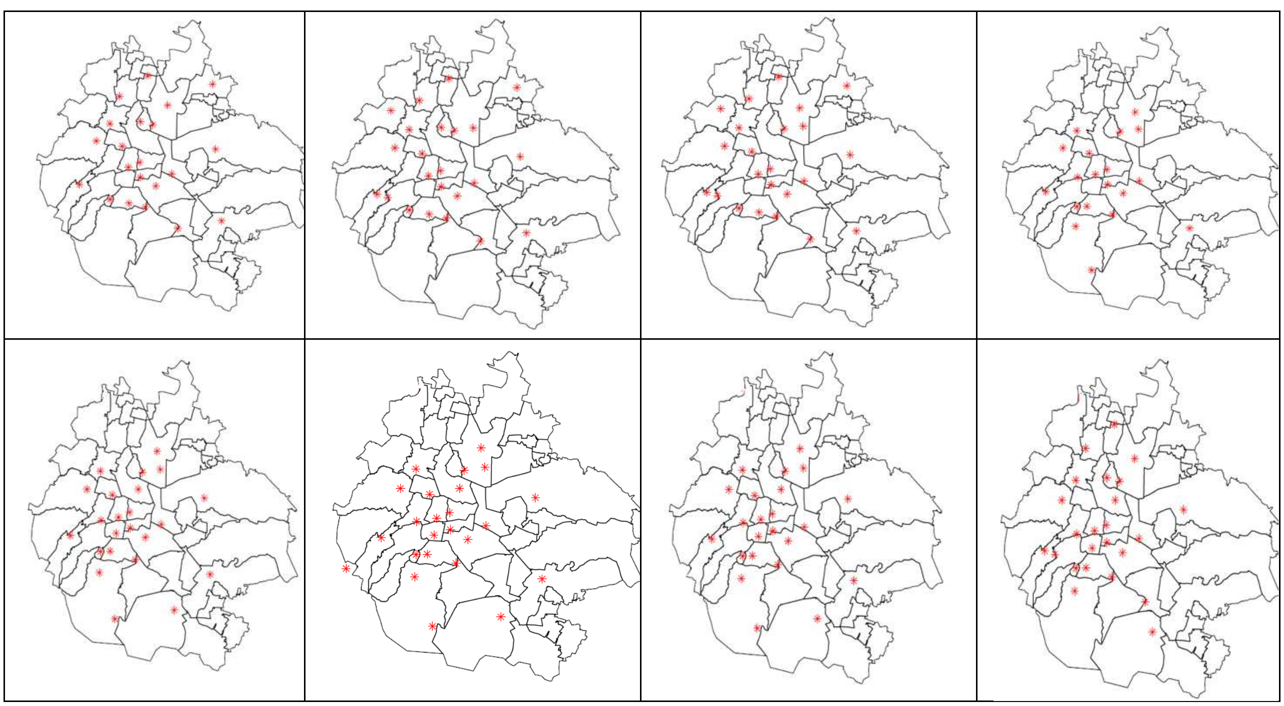
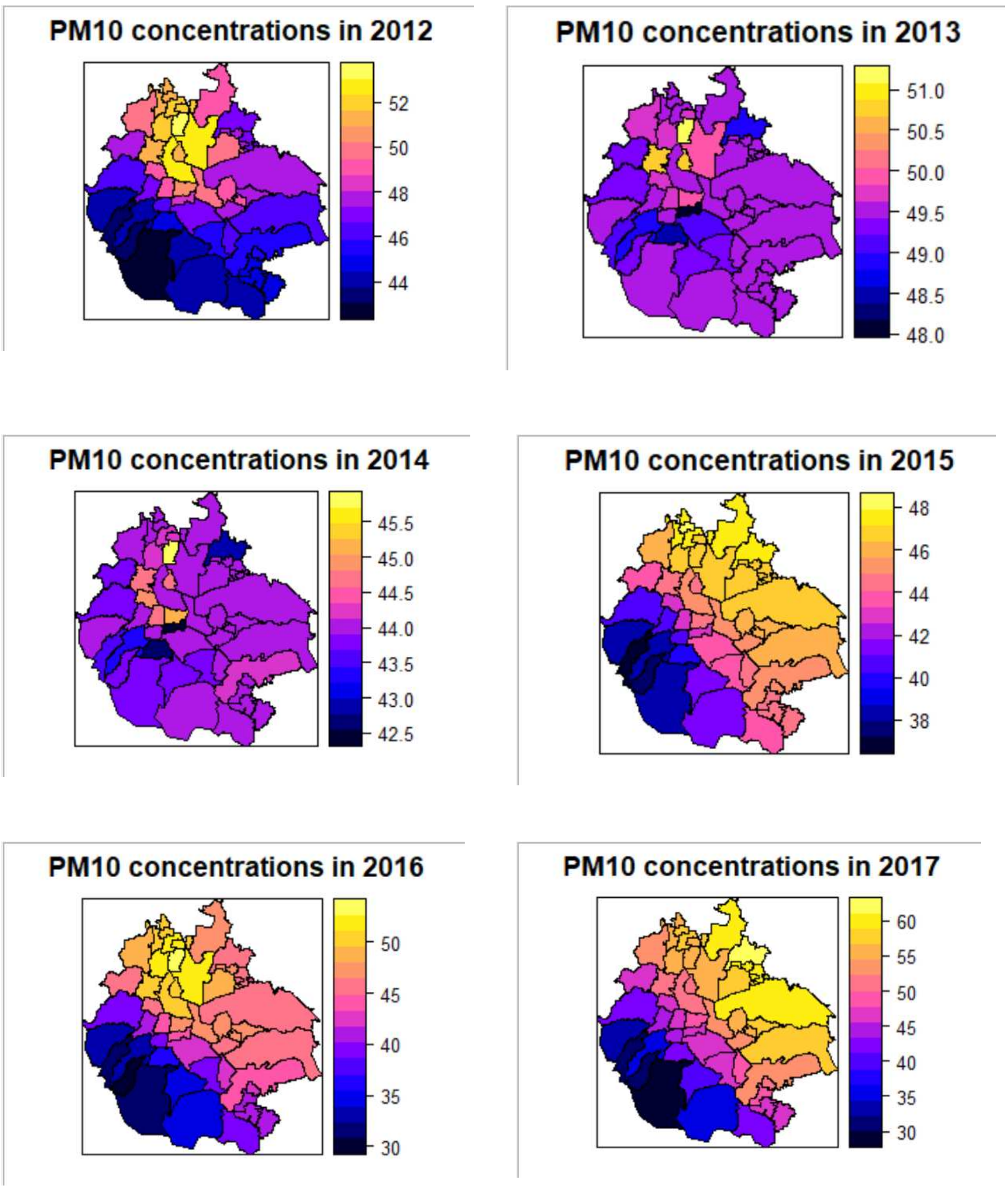


Fig. A2a. Spatial distribution of PM_{10} concentrations from 2012 to 2019 in mg/m3, in Greater Mexico City (short).



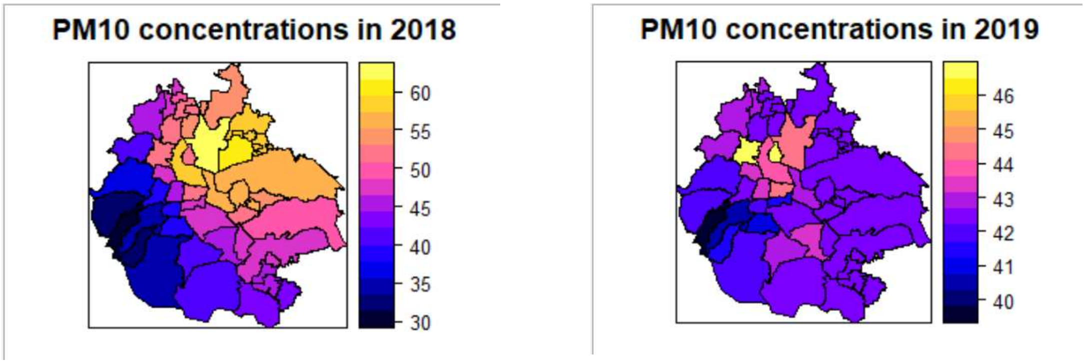
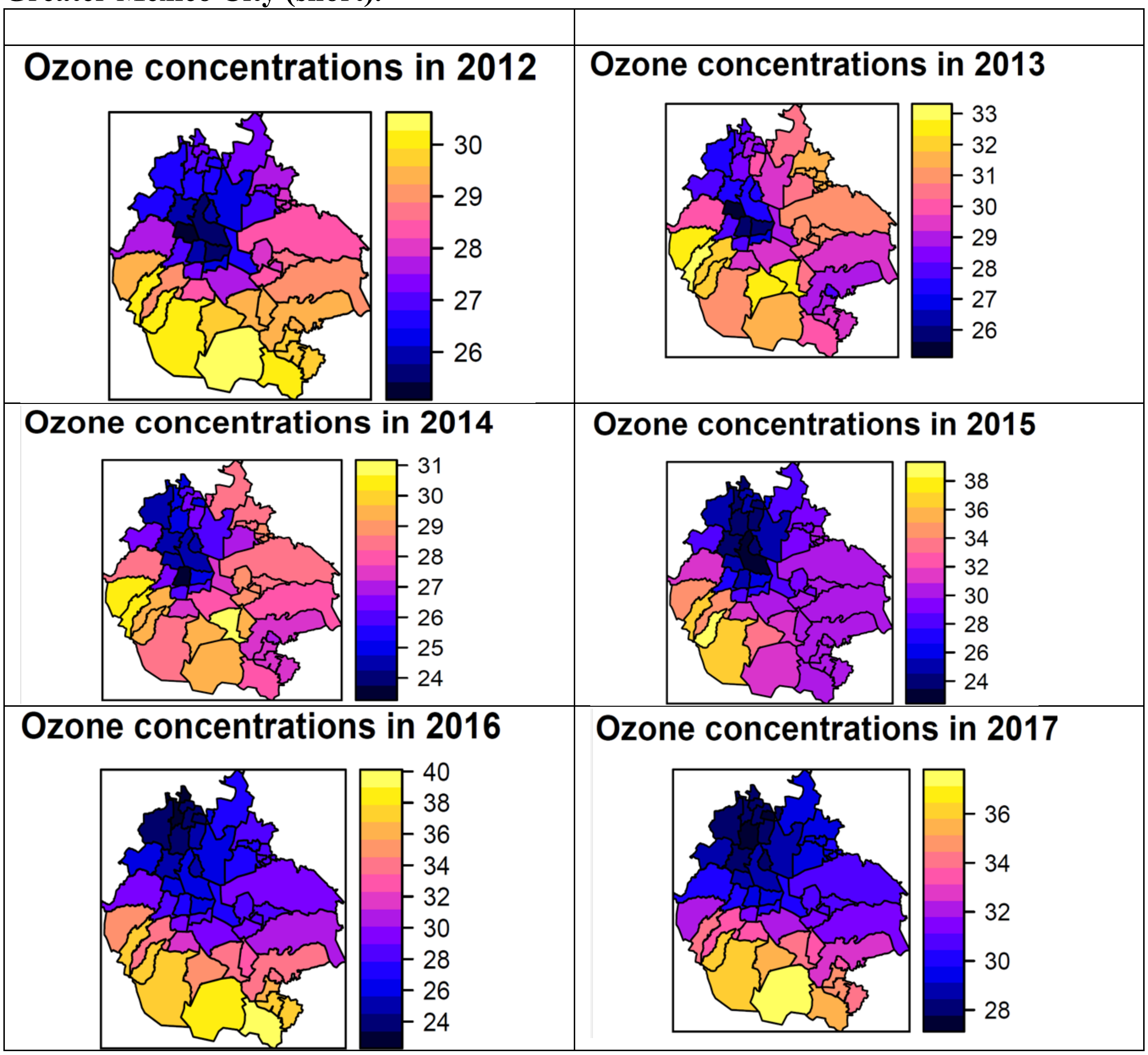


Fig. A2b. Spatial distribution of Ozone concentrations from 2012 to 2019 in mg/m3, in Greater Mexico City (short).



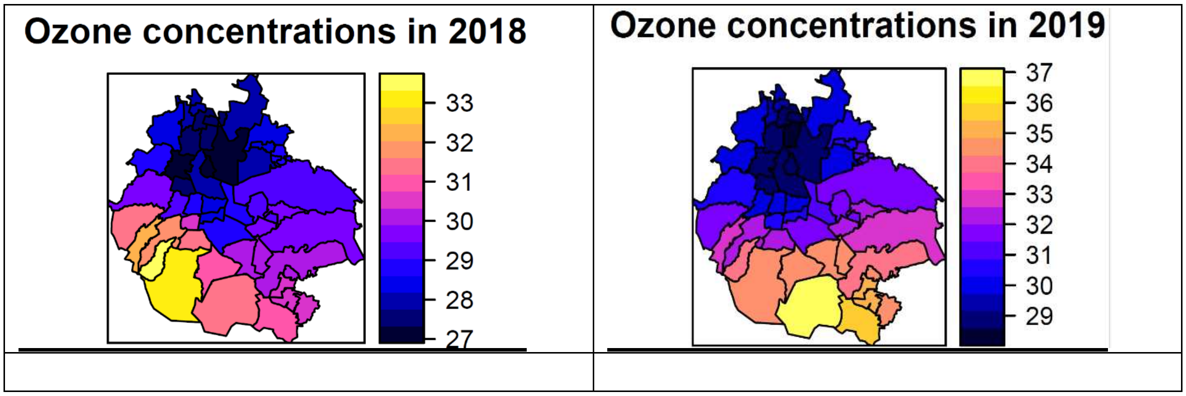
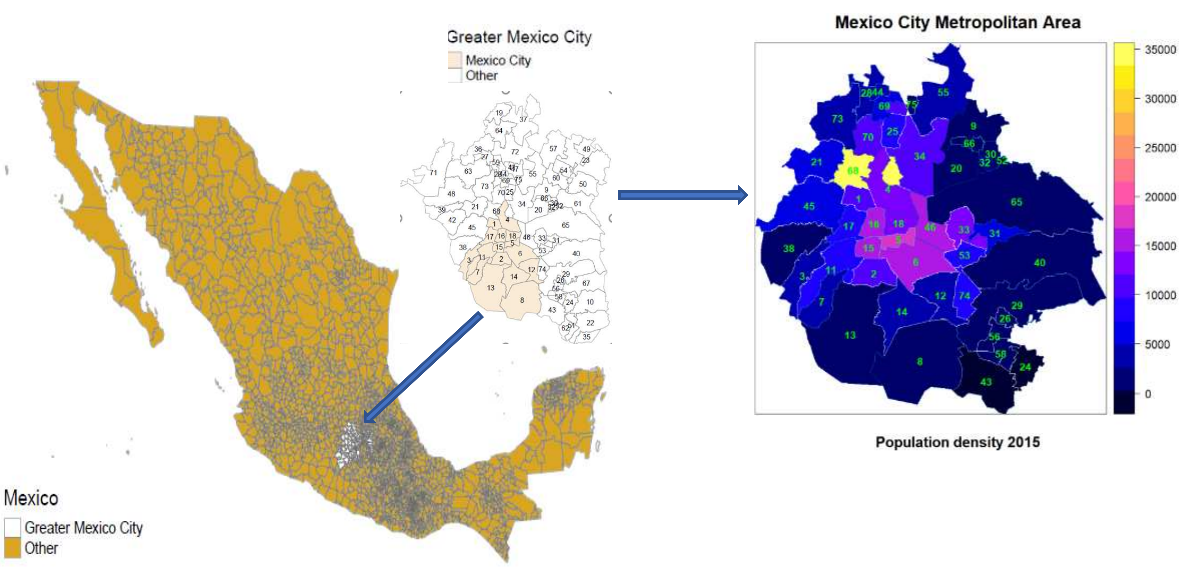


Figure A3. Mexico, Greater Mexico City, and MCMA.



Municipalities of Greater Mexico City: 1) Azcapotzalco, 2) Coyoacán, 3) Cuajimalpa de Morelos, 4) Gustavo A. Madero, 5) Iztacalco, 6) Iztapalapa, 7) La Magdalena Contreras, 8) Milpa Alta, 9) Acolmán, 10) Amecameca, 11) Alvaro Obregón, 12) Tláhuac, 13) Tlalpan, 14) Xochimilco, 15) Benito Juárez, 16) Cuauhtémoc, 17) Miguel Hidalgo, 18) Venustiano Carranza, 19) Apaxco, 20) Atenco, 21) Atizapán de Zaragoza, 22) Atlautla, 23) Axapusco, 24) Ayapango, 25) Coacalco de Berriozábal, 26) Cocotitlán, 27) Coyotepec, 28) Cuautitlán, 29) Chalco, 30) Chiautla, 31) Chicoloapan, 32)Chiconcuac,33) Chimalhuacán,34) Ecatepec de Morelos, 35) Ecatzingo, 36) Huehuetoca, 37) Hueypoxtla, 38) Huixquilucan, 39) Isidro Fabela, 40) Ixtapaluca, 41) Jaltenco, 42) Jilotzingo, 43) Juchitepec, 44) Melchor Ocampo, 45) Naucalpan de Juárez, 46) Nezahualcóyotl, 47) Nextlalpan, 48) Nicolas Romero, 49) Nopaltepec, 50) Otumba, 51) Ozumba, 52) Papalotla, 53) La Paz, 54) San Martín de las Pirámides, 55) Tecámac, 56) Temamatla, 57) Temascalapa, 58) Tenango del valle, 59) Teoloyucan, 60) Teotihuacan, 61) Tepetlaoxtoc, 62) Tepetlixpa, 63) Tepotzotlán, 64) Tequixquiac, 65) Texcoco, 66) Tezoyuca, 67) Tlalmanalco, 68) Tlalnepantla de Baz, 69) Tultepec, 70) Tultitlan, 71) Villa del Carbón, 72) Zumpango, 73) Cuautitlán Izcalli, 74) Valle de Chalco Solidaridad and 75) Tonanitla. Note: the 48 municipalities (MCMA) of this study are Mexico City and the following municipalities numbers:

9,20,21,24,25,26,28,29,30,31,32,33,34,38,40,43,44,45,46,52,53,55,56,58,65,66,68,69,70,73,74,75. Source: own elaboration with INEGI data and Lome-Hurtado *et al.,* 2021.