



Deposited via The University of York.

White Rose Research Online URL for this paper:

<https://eprints.whiterose.ac.uk/id/eprint/204641/>

Version: Accepted Version

Article:

Lome Hurtado, Alejandro, Touza, Julia M., White, Piran Crawford Limond et al. (2024) 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. *Environmental Management*. pp. 657-667. ISSN: 0364-152X

<https://doi.org/10.1007/s00267-023-01905-x>

Reuse

This article is distributed under the terms of the Creative Commons Attribution (CC BY) licence. This licence allows you to distribute, remix, tweak, and build upon the work, even commercially, as long as you credit the authors for the original work. More information and the full terms of the licence here:

<https://creativecommons.org/licenses/>

Takedown

If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.

1
2 **When space and time matter in environmental injustice:**
3 **A Bayesian analysis of the association between socio-**
4 **economic disadvantage and air pollution in Greater**
5 **Mexico City.**

6
7
8
9
10 Alejandro Lome-Hurtado*, Julia Touza^a, Piran C. L. White ^a, Colin J. McClean^a

11
12 *Facultad de Ciencias Económicas y Empresariales, Universidad Panamericana,
13 Guadalajara; Mexico.

14
15 ^aDepartment of Environment and Geography & York Environmental Sustainability
16 Institute, University of York, Wentworth Way, University of York, York, YO10 5NG,
17 United Kingdom

18
19
20 *Author*

21 *Corresponding author*

22 to Alejandro Lome-Hurtado, email: alexlome@up.edu.mx ; alejandro.lomehu@gmail.com.

23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42

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

46

47 **Abstract**

48 Environmental injustice refers to the unequal burden of pollutants on groups with lower
49 socioeconomic status. An increasing number of studies have identified associations between
50 high levels of pollution and socioeconomic disadvantage. However, few studies have
51 controlled adequately for spatio-temporal variations in pollution. This study uses a Bayesian
52 approach to explore the association between socioeconomic disadvantage and pollution in
53 Mexico City Metropolitan Area. We quantify the association of socioeconomic disadvantage
54 with PM₁₀ and ozone and evaluate the impact of accounting for spatio-temporal structure of
55 the pollution data. We find a significant positive association between socio-economic
56 disadvantage and pollution for levels of PM₁₀, but not ozone. The inclusion of the spatio-
57 temporal element in the modelling results in improved weaker estimates of this association
58 but this does not alter results substantially. These findings confirm the robustness of previous
59 studies that found signs of environmental injustice where spatio-temporal variations have not
60 been explicitly considered, confirming that targeted policies to reduce pollution in socio-
61 economically disadvantaged areas are required.

62

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

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

65

66

67

68 1. Introduction

69

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

79

80 In this paper we focus on air pollution as a severe threat to public health. Air pollution causes
81 respiratory and cardiovascular disease, and mental ill-health, and has been established as a
82 major modern mortality risk. Air pollution caused over 4.2 million premature deaths
83 worldwide in 2016 and it is also estimated that fine particulate matter in polluted air causes
84 7 million deaths every year (World Health Organization, n.d.). The World Bank estimated a
85 loss of US\$225 billion, in terms of labour income, due to deaths caused by air pollution
86 (Bank, 2016). The health impacts are not evenly distributed across the population;
87 communities with low socioeconomic status are at greater risk of chronic disease due to their
88 disproportional exposure to air pollution (Schweitzer and Valenzuela, 2004; Niessen *et al.*,
89 2018).

90

91 There is extensive work that illustrates social inequalities in the exposure to air pollution, and
92 that greater exposure is experienced by people with low socioeconomic status or non-white
93 background. Su *et al.* (2010) showed the inverse association between NO₂ concentration and
94 socioeconomic status indicators (income) by census tracts in Vancouver and Seattle. Padilla
95 *et al.* (2014) showed that deprived census blocks in two French metropolitan areas, Lille and
96 Marseille, were the most exposed to NO₂. In middle-income countries with developing
97 economics, evidence of environmental injustice is growing (Hajat *et al.*, 2015). Kopas *et al.*
98 (2020) showed that poor, low-caste communities in India were more exposed to emissions
99 from coal power plants than their wealthier, high-caste counterparts. Lome-Hurtado *et al.*
100 (2020) demonstrated unequal exposure of the elderly and children to air pollution in Mexico
101 City. Chakraborti and Voorheis (2021) showed that low-income areas in Mexico experience
102 a disproportional burden of air pollution, with a decline in socioeconomic status within the
103 investigated municipalities being associated to an 1% annual increase in air pollution levels.

104

105 The challenge of addressing the causes and consequences of air pollution is receiving
106 increasing attention. Air pollution can be caused by different sources such as industrial
107 activity, urbanization, traffic pollution, and institutional and natural sources that lead to
108 pollution concentrations that are often clustered temporally and spatially (Kampa and
109 Castanas, 2008; Diarra and Marchand, 2011; Landrigan *et al.*, 2018; Manisalidis *et al.*, 2020).
110 The problem of air pollution can be exacerbated by institutional drivers, such as an inefficient
111 judicial system (inefficiency of law enforcement) that may not be applied correctly in relation
112 to environmental quality policies (Lomborg and Pope, 2003; Diarra and Marchand, 2011) in
113 certain areas. Some policy instruments, such as low emissions zones, target traffic emissions
114 reductions in certain locations within a city. Alternatively, there may be restrictions on

115 vehicle movements, such as the program “Hoy no circula” in Mexico City, where vehicles
116 do not circulate in certain geographical areas on specific days (Ambiente, n.d.). Factors
117 associated with urbanization, such as the improvement or deterioration of road infrastructure,
118 may cause fewer or higher traffic jams in specific municipalities, or there may be
119 manifestations or demonstrations which change the travel patterns across the city (Carrier *et*
120 *al.*, 2014; Arceo *et al.*, 2016). Some environmental contributory factors to air pollution, such
121 as wildfires, also exhibit a spatio-temporal pattern, being more common in specific areas and
122 at certain times of the year (Cobelo *et al.*, 2023).

123
124 These spatio-temporal characteristics of air pollution concentrations have important
125 implications when understanding the relationship between air pollution and socioeconomic
126 status. Ignoring the spatial dependence of factors that contribute to pollution clusters (i.e.,
127 locations close to each other exhibit more similar pollution levels than those further apart)
128 may generate spatial autocorrelation problems in models of air pollution. In particular, if
129 residuals display spatial autocorrelation, the independence and identically distributed
130 assumption of many models is violated, and this causes standard errors to be artificially low,
131 leading to coefficients that may appear significant when they are not (i.e., inflates type I
132 errors) (Anselin, 2002; Dormann *et al.*, 2007). There have been different efforts to capture
133 this inherently spatial nature of air pollution when isolating the effect of socioeconomic
134 background on the exposure to this health risk. For instance, Sun *et al.* (2010) and Padilla *et*
135 *al.* (2014) used generalized additive models (GAMs) to remove spatial autocorrelation. More
136 recently, Verbeek and Hinck (2022) used a geographically weighted regression that allows
137 for spatial variation in parameter estimates revealing thus localized patterns on the
138 relationship between air pollution and socio-economic indicators, and therefore reveal where
139 such association is more pronounced within urban areas. This technique is exemplified when
140 evaluating the effect of low emissions zones in London and Brussels. Other authors, such as
141 Chakraborti and Voorheis (2021) focus on temporal patterns using a fixed-effects panel data
142 model that controls for time-invariant factors across locations. Here, we propose the use of
143 a Bayesian approach, to account for the spatio-temporal structure in the pollution data in an
144 attempt to avoid modelling errors caused by spatial and serial autocorrelation. Lome-Hurtado
145 *et al.* (2021) used this approach to capture the health determinants of child mortality risk with
146 a space-time structure such as physical activity and diet; and Li *et al.* (2014) used it to control
147 for the space-time patterns associated with household burglary.

148
149 This paper applies a Bayesian approach to examine the associations of low socioeconomic
150 status and air pollution (PM₁₀ and ozone) exposure in Mexico City Metropolitan Area
151 (MCMA). It investigates the importance of controlling for potential factors with
152 simultaneous space-time patterns. Following Lome-Hurtado *et al.* (2021) and Li *et al.* (2014),
153 our model estimates pollution exposure at temporal (monthly) and spatial (municipality)
154 scales. Moreover, we acknowledge that the direction of causality between the economic and
155 social disadvantage and the exposure to the pollutants could be in either direction
156 (Chakraborti and Voorheis 2021). The level of air pollution is likely to affect where people
157 with low socioeconomic status live, in cheaper and often in more polluted areas. However,
158 income may affect pollution through greater production levels in areas of low socioeconomic
159 status.

160

161 The high levels of income inequality, population density, and air pollution in the MCMA,
162 the largest urban agglomeration in Mexico (Paquette, 2015; México, 2020) makes it a
163 suitable case study area. The MCMA is classified as the third-largest metropolis in the world
164 and has the lowest per capita GDP in the Organization for Economic Cooperation and
165 Development (OECD) forum of countries (Paquette, 2015). This area consists of 16
166 municipalities within Mexico City and 59 in the State of Mexico¹. In Mexico City, PM₁₀ and
167 ozone concentrations have reached levels above the threshold established by the World
168 Health Organization (15 µg/m³ annual mean and 45 µg/m³ 24-hour mean for PM₁₀; and 100
169 µg/m³ 8-hour daily maximum and 60 µg/m³ 8-hour mean peak season for ozone)
170 (Organization, 2006). In 2010 there were 20,500 deaths due to the air pollution, with
171 particulate matter being in the top ten of the riskiest health factors of mortality in Mexico
172 (IHME, 2014). Arceo et al. (2016) estimated that 1 µg/m³ increase of in 24-h PM₁₀ in Mexico
173 City results in an additional 0.24 deaths per 100,000 births.

174

175

176 2. Data and Methods

177

177 2.1 Data

178

179

180

181

182

183

184

185

186

187

188

189

190

191

192

193

194

195

196

197

198

199

200

201

202

203

204

All variables were developed for each municipality in the study region. Monthly pollution data allow for the control of temporal variation within a year. PM₁₀ 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 PM₁₀ 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 PM₁₀ 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.

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

212

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

217

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

226

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

234

235 2.2 Statistical Analysis

236

237 Following these studies, the pollution data are modelled as:

238

$$239 \quad y_{imt} = \alpha + \beta_1 \times disadvantage\ index_{i,t'} + \beta_2 \times temperature_{imt} + \beta_3 \times \\ 240 \quad humidity_{imt} + \beta_4 \times pop\ density_i + \beta_5 \times roads_i + \beta_6 \times industries_{it} + (s_i + u_i) + \\ 241 \quad v_t + st_i t^* + \varepsilon_{it} \quad (1)$$

242

243 Where y_{imt} represents either PM₁₀ or ozone in the municipality i , in a specific month m
 244 over the year t . Thus, we model PM10 and ozone separately. This study assumes a normal
 245 distribution, for both pollutants $y_{imt} \sim Normal(covariates, \varepsilon_{it})$. Following Chakraborti
 246 and Voorheis (2021), to consider the relationship between pollution and low socioeconomic
 247 conditions, we assigned the 2010 disadvantage index values to the 2012-2015 pollution data
 248 and the 2015 disadvantage index values to the 2016-2019 pollution data. The
 249 $disadvantage\ index_{i,t'}$ represents the disadvantage of the municipality i for the previous
 250 census year, represented as t' . The 2010 socio-economic disadvantage index was assumed to

251 relate to pollution released in the 2012 to 2015 period, while the 2015 socio-economic
 252 disadvantage index was used to explain the pollutants released from 2016 to 2019. A positive
 253 sign on this variable would imply that an increase in the disadvantage index relates to an
 254 increase in air pollution exposure on average for the study period. The *temperature* and
 255 *humidity* variables are the average levels of these variables in each municipality i in month
 256 m over the year t . The *pop density* variable is the population density in the municipality i
 257 for either the year, t , 2010 or 2015 using similar reasoning to our disadvantage index; *roads*
 258 represents the number of roads in the municipality i ; and *industries* is the number of
 259 industries (machinery and equipment) in the municipality i .

260
 261 The term, $(s_i + u_i)$, denotes the spatial component for each municipality, i , that controls the
 262 overall spatial structure of the data. This spatial component uses the Besag, York, and Mollié
 263 (BYM) model (Besag, York, and Mollié, 1991). The s_i term captures the spatial structure
 264 and u_i the spatial unstructured of the data over time. An intrinsic conditional autoregressive
 265 Gaussian distribution (ICAR) to the priors for the spatial structure (s_i) was used following
 266 Li *et al.* (2014). The spatial structure component may capture the level of clustering and
 267 demonstrate that nearby municipalities may have similar levels of air pollution. Therefore,
 268 a spatial adjacency matrix W of size $N \times N$ (where N is the number of municipalities) was
 269 used in the spatial structure of s_i to model the level of the neighborhood of the municipalities
 270 in the ICAR model. The matrix off-diagonal values may have two values: either $w_{ij}=1$ (when
 271 the municipality i and municipality j share a common boundary) or $w_{ij}=0$ (if municipality i
 272 and municipality j do not share a common boundary), giving that $(i \neq j)$. Therefore, two
 273 municipalities are neighbors when their random effects are correlated; otherwise, such
 274 municipalities are conditionally independent. The spatial unstructured term, u_i , captures the
 275 remaining potential spatial variability that does not present a spatial pattern. This
 276 unstructured term captures the part of the overall spatial variability that does not display a
 277 spatial pattern (a clustering structure). The term, u_i , follows a normal distribution $u_i \sim N(0,$
 278 $\sigma^2_u)$, where u_i was allocated a prior distribution of Gamma, a highly non-informative
 279 distribution (Kelsall and Wakefield, 1999), on the precisions of s_i , u_i , and v_t .

280
 281 The term v_t captures the potential serial correlation in the data (the overall time trend). The
 282 term $st_i t^*$ captures the potential local spatio-temporal variations (space-time factors) of the
 283 contaminant in specific municipalities in a given year which may be caused by certain
 284 changes in its institutional, urban, and natural risk drivers (outlined in the introduction).
 285 Therefore, this space-time term, $st_i t^*$, assesses a linear departure of a municipality's time
 286 trend from the overall time trend. In this sense, a local trend (in terms of pollution) of each
 287 municipality is captured by the new term. This term is also modelled using the BYM prior
 288 model. Nearby municipalities may have more similar pollution trends than other
 289 municipalities which are farther apart. A prior distribution of Gamma was allocated to these
 290 new terms. Noninformative priors $N(0, 0.001)$ were assigned to the six regression
 291 coefficients, β 's, and the intercept in each model; the normal distribution has a mean of zero
 292 and a large variance due to the absence of genuine prior expectations. Finally, the error
 293 term (ε_{it}) captures the variability that is not explained by the other terms in equation 1, which
 294 follows a normal distribution: $\varepsilon_{it} \sim (0, \sigma^2_\varepsilon)$.

295

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

309
 310

311 3. Results

312 3.1 Descriptive analysis

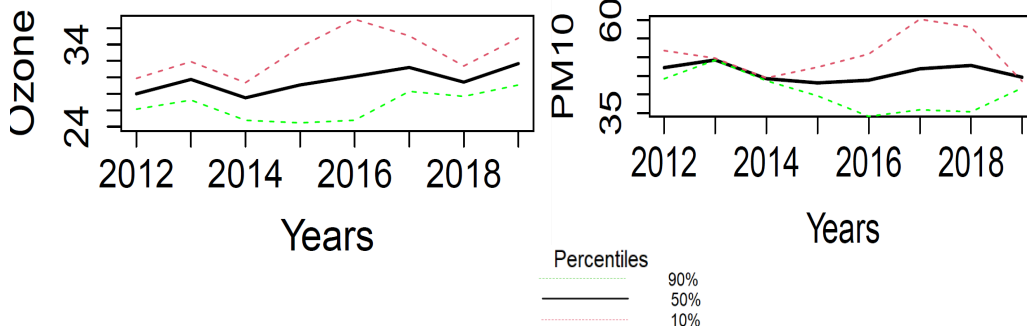
313 The descriptive statistics of the data used in the analysis are shown in Table 1a and 1b, at the
 314 municipality level in the MCMA from 2012 to 2019. The period saw a slight reduction for
 315 PM_{10} while there was a slight increase of ozone (see Figure 1). Note that PM_{10} and ozone
 316 concentrations have reached levels above the threshold. In the period of study, 2012-2019,
 317 the annual average concentration of PM_{10} was 45.92 $\mu\text{g}/\text{m}^3$. Meanwhile, for ozone such
 318 average was 29.6 ppm. These values are so higher than the threshold established by the World
 319 Health Organization (20 $\mu\text{g}/\text{m}^3$ annual average and 100 $\mu\text{g}/\text{m}^3$ 8-hour mean for PM_{10} and
 320 ozone, respectively).

321

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

323

324



335 The values for temperature and relative humidity were relatively stable from 15.7°C to
 336 17.3°C and from 53.1% to 53.6%, respectively during the period. The economic and social
 337 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..

338 respectively. Even though Mexico is the world's 11th largest economy in terms of GDP
 339 measured at purchasing power parity (OCDE, 2017), such index illustrates that the income
 340 and social inequality remains high compared with other OECD countries. The population
 341 density had means of 4,005 people/km² and 4,169 people/km² in 2010 and 2015, respectively.
 342 Note that for other populated Latin cities such numbers were 3,026/km² (2023) and 7,528/km²
 343 (2022) for Santiago, Chile and Sao Paulo, Brazil (City Population, n.d.). The industrial
 344 variable (machinery and equipment) presented means of 2,646 and 3,423 in 2009 and 2014,
 345 respectively. The MCMA is in the top of the most industrialized areas in Mexico. In 2019,
 346 there were in total 8,629 economic units (Commercial and Industrial machinery and
 347 equipment, except automotive and electronic, repair, and maintenance), the State of Mexico
 348 occupied the first place with 1,780; followed for Jalisco (1,505), and Mexico City (1,207)
 349 (Data Mexico, n.d.). Lastly, the variable of number of roads (include big roads with high
 350 density of cars such as avenue, peripheral, viaduct, circuit, and road axis) had a mean of 764
 351 in the 2011 year. It is important to mention the standard deviations of the industrial and road
 352 variables were much higher than their mean. This illustrates the high concentration of the
 353 industries and roads in certain municipalities.
 354

355 **Table 1a. Descriptive statistics of PM₁₀, ozone pollutants¹, temperature, and relative**
 356 **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)	-----

357 ¹Monthly average in each year

358

359 **Table 1b. Descriptive statistics of social, economic, and**
 360 **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) 362 363
	2011 mean (sd)	
Number of roads	764.5 (1269)	

367

368 Spatial patterns exist in the datasets that might lead to problems of spatially autocorrelated
369 errors. The Global Moran Index of the pollution data for each year, from 2012 to 2019,
370 showed positive spatial autocorrelation, with mean values of 0.32 and 0.3 ($p < 0.0001$),
371 These results mean that there were some municipality clusters with similar PM₁₀ and ozone
372 records. Likewise, the Global Moran Index of the economic and social disadvantage index
373 had a mean of 0.31 and 0.35 for 2010 and 2015 years, respectively; there was also a certain
374 level of clustering. Lastly, the Autocorrelation Function (ACF) was used to measure the
375 presence of potential serial correlation; their mean values were 0.37 and 0.3 (lagged 1 year
376 for each municipality) across all the municipalities. This showed evidence of serial
377 correlation; that is, a certain level of association of the pollutants' records over time.

378

379

3.2 Socio-economic disadvantage index and pollution burden

380

381

382

383

384

385

386

387

388

389

390

391

392

393

394

395

396

397

Temperature has a significant positive relationship with PM₁₀, 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 PM₁₀ in the models.

Table 2a. Posterior means relating to different potential risk factors affecting PM₁₀, 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

398
399
400
401
402
403

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 PM₁₀, 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 PM₁₀ 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 (PM₁₀). This relationship was not significant for ozone. Note that much PM₁₀ 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 PM₁₀ 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 PM₁₀ illustrate the importance of accounting for spatial and time drivers of PM₁₀ 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-

452 temporal drivers of air pollution, omitted in traditional regression analysis. Despite the
453 inclusion of a range of climatic, demographic, and social control variables, one may still be
454 concerned that there are other factors driving pollution concentration variability in the study
455 period affecting the model coefficient of the disadvantage index. Such sources may vary
456 across space and time (as noted in the introduction). Our results show that with a one-unit
457 increase in the index, there may an increase of PM₁₀ concentrations by 1.1 ug/m³. It is also
458 notable that relative humidity ceases to show significant association as spatio-temporal
459 pattern is considered in the modelling.

460

461 These findings confirm the robustness of previous studies that found signs of environmental
462 injustice where spatio-temporal variations have not been explicitly considered, confirming
463 that targeted policies to reduce pollution in socio-economically disadvantaged areas are
464 required. Overall, the inclusion of a spatio-temporal element in the modelling results in
465 improved estimates of effect sizes, but does not substantially alter the findings, when spatio-
466 temporal variations have not been explicitly considered. Our results therefore show the
467 importance of decreasing the level of PM₁₀ in socio-economically disadvantaged areas. Our
468 findings are also consistent with previous spatial econometric environmental injustice studies
469 (Havard et al., 2009; Li *et al.*, 2018; Verbeek, 2019), which also show that accounting for
470 the spatial structure of the data resulted in a lower coefficient relating to socio-economic
471 disadvantaged status. We complement this literature by showing that controlling for air
472 pollution drivers that vary over time and space simultaneously further reduces the value of
473 this coefficient. Nevertheless, the overall findings of the present study (positive and
474 significant association of disadvantage status and PM₁₀) are in line with the recent study of
475 Chakraborti and Voorheis (2021), who demonstrated there is as a clear case of environmental
476 justice in Mexico.

477

478 The relevance of the space-time drivers of PM₁₀ show in this study can be related to factors
479 such as wildfires, structural fires, construction of new road infrastructure (paved and unpaved
480 roads), and burning waste in the open air, which are common in the MCMA according to the
481 Ministry of Environment in Mexico City (México, 2016). In 2016, the Ministry reported
482 2,162 ug/m³ of PM₁₀ emissions by open burning of urban waste, which represented 5.7% of
483 the total emissions. The construction sector (edification and demolition) was responsible for
484 2,305 ug/m³ and 978 ug/m³ of PM₁₀ (2.5% of the total) emissions in 2014 and 2016,
485 respectively. The forest fires generated 43.5 ug/m³ and 109.4 ug/m³ of PM₁₀ (2.8% of the
486 total) emissions in 2014 and 2016, respectively. The paved and unpaved roads were
487 responsible for 14,427.8 ug/m³ and 14,092.91 ug/m³ of PM₁₀ (3.7% of the total) emissions in
488 2014 and 2016, respectively. Other risk factors which show spatial and time patterns are
489 environmental regulations, judicial inefficiency, and demonstrations. The Mexican
490 government, through its air quality management program (PROAIRE), aims to apply
491 environmental regulations to reduce air pollution, specifically PM₁₀. This program has been
492 implemented since early 1989 and 1995, respectively (Metropolitana, 1994; SEMARNAT,
493 2017). The government has developed air pollution management strategies, but their
494 implementation has given different results depending on the areas and only a few
495 municipalities have managed to reach the air pollution targets (de San, 2019). Therefore,
496 spatially-targeted policies need to be implemented to reduce space-time drivers such as
497 wildfires, structural fires, and burning waste in the open air. Some of them were caused by
498 the hand of man e.g. 95% of the main scenarios being bonfires and poorly extinguished

499 cigarette butts, the abandonment of land, and the preparation of grazing areas with fire
500 (Semarnat, 2017). Similarly, such implement targeted emission programmes are needed to
501 mitigate air pollution specially in poorer areas-municipalities through new regulations
502 (Nguyen and Marshall, 2018) and health benefits. For instance, the spatial distribution of air
503 pollution is associated with the industrial distribution, which is concentrated in the north and
504 east Mexico City. Industrial emissions mainly affect the most economic and social
505 disadvantaged groups, who live near the production plants due to low rents and land prices
506 in those areas. Therefore, policies which tackle industry re-allocation or/and re-allocation of
507 such vulnerable groups are necessarily to reduce environmental injustice; especially in the
508 north of our study area where according our economic and social index, there are more
509 economic and social disadvantage conditions. In addition, some health programmes should
510 be created for poor people with high exposure to air pollution.

511

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

528

529

530 **5. Conclusion**

531 This study has provided further evidence of the existence of environmental injustice in the
532 MCMA, highlighting the importance of controlling for the space-time drivers in order to
533 obtain more accurate estimates of the association between socio-economic disadvantage and
534 exposure to PM₁₀. These results can inform public and social programmes which aim to
535 reduce inequalities in exposure to air pollution, by directing efforts to reduce the spatial and
536 temporal drivers of PM₁₀, shown to be significant in this study. This may be better achieved
537 by strategies that are spatially and temporally heterogeneous and target areas with lower SES,
538 which experience the highest level of air pollution. The effectiveness of these efforts will be
539 enhanced through better collaboration and coordination between decision-makers addressing
540 air pollution inequalities and injustice in Mexico City (de San, 2019).

541

542

543 **5. References**

544 Agency, C. E. P. (2011) 'Carl Moyer Program Guidelines' [internet]. Available at:

- 545 https://ww2.arb.ca.gov/sites/default/files/2020-06/2017_cmpgl.pdf (Accessed: 1 February
546 2021)
- 547 Ambiente, S. del M. (no date) 'Hoy no circula, n.d. ' [intenet]. Available at:
548 <https://www.sedema.cdmx.gob.mx/programas/programa/hoy-no-circula> (Accessed: 1
549 February 2021).
- 550 Anselin, L. *et al.* (1996) 'Simple diagnostic tests for spatial dependence', *Regional science*
551 *and urban economics*. Elsevier, 26(1), pp. 77–104.
- 552 Anselin, L. (2002) 'Under the hood issues in the specification and interpretation of spatial
553 regression models', *Agricultural economics*. Wiley Online Library, 27(3), pp. 247–267.
- 554 Arceo, E., Hanna, R. and Oliva, P. (2016) 'Does the effect of pollution on infant mortality
555 differ between developing and developed countries? Evidence from Mexico City', *The*
556 *Economic Journal*. Oxford University Press Oxford, UK, 126(591), pp. 257–280.
- 557 Arora, S. and Cason, T. N. (1999) 'Do community characteristics influence environmental
558 outcomes? Evidence from the toxics release inventory', *Southern Economic Journal*.
559 JSTOR, pp. 691–716.
- 560 Aschner, M., Paoliello, M. M., Tsatsakis, A., Bowman, A. B., Dorea, J. G., Hartung, T., ...
561 & Barbosa Jr, F. (2021). Social injustice in environmental health: A call for fortitude.
562 *Environmental research*, 194, 110675.
- 563 Bank, T. W. (2016) 'The cost of air pollution: strengthening the economic case for action',
564 *Washington: World Bank Group*.
- 565 Besag, J., York, J. and Mollié, A. (1991) 'Bayesian image restoration, with two
566 applications in spatial statistics', *Annals of the institute of statistical mathematics*. Springer,
567 43(1), pp. 1–20.
- 568 Buheji, M. *et al.* (2020) 'The extent of covid-19 pandemic socio-economic impact on
569 global poverty. a global integrative multidisciplinary review', *American Journal of*
570 *Economics*, 10(4), pp. 213–224.
- 571 Carrier, M. *et al.* (2014) 'The application of three methods to measure the statistical
572 association between different social groups and the concentration of air pollutants in
573 Montreal: A case of environmental equity', *Transportation Research Part D: Transport*
574 *and Environment*. Elsevier, 30, pp. 38–52.
- 575 Carvalho, C., & de Carvalho Cabral, D. (2021). Beyond the Favelas: An Analysis of
576 Intraurban Poverty Patterns in Brazil. *The Professional Geographer*, 73(2), 269–281.
- 577 Chakraborti, L. and Voorheis, J. (2021) 'Are poorer Mexicans exposed to worse air quality?
578 Long-term Evidence from Satellite Imaging Data', *Long-Term Evidence from Satellite*
579 *Imaging Data (January 04, 2021)*. Available at SSRN: <https://ssrn.com/abstract=3764819> or
580 <http://dx.doi.org/10.2139/ssrn.3764819>
- 581 Cobelo, I., Castelhana, F. J., Borge, R., Roig, H. L., Adams, M., Amini, H., ... & Réquia, W.
582 J. (2023). The impact of wildfires on air pollution and health across land use categories in
583 Brazil over a 16-year period. *Environmental Research*, 224, 115522.
- 584 City Population (no date) 'City Population', [intenet]. Available at:
585 <https://www.citypopulation.de/> (Accessed: 31 July 2023).
- 586 COMEAP (2018) 'The effects of long-term exposure to ambient air pollution on
587 cardiovascular morbidity: Mechanistic evidence' [intenet]. Available at:
588 [https://assets.publishing.service.gov.uk/
589 government/uploads/system/uploads/attachment_data/file/749657/COMEAP_CV_Mechanisms_Report.pdf](https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/749657/COMEAP_CV_Mechanisms_Report.pdf) (Accessed: 1 February 2021).
- 590 CONAPO (no date), 'Índices de Marginación', [intenet]. Available at:

- 592 http://www.conapo.gob.mx/es/CONAPO/Indices_de_Marginacion_Publicaciones,
593 (Accessed: 31 July 2023)
- 594 CONEVAL (n.d.) Medición de la pobreza.
595 [https://www.coneval.org.mx/Medicion/IRS/Paginas/Que-es-el-indice-de-rezago-](https://www.coneval.org.mx/Medicion/IRS/Paginas/Que-es-el-indice-de-rezago-social.aspx)
596 [social.aspx](https://www.coneval.org.mx/Medicion/IRS/Paginas/Que-es-el-indice-de-rezago-social.aspx).
- 597 Data Mexico (no date) 'Data Mexico', [internet]. Available at:
598 [https://www.economia.gob.mx/datamexico/en/profile/industry/commercial-and-industrial-](https://www.economia.gob.mx/datamexico/en/profile/industry/commercial-and-industrial-machinery-and-equipment-except-automotive-and-electronic-repair-and-maintenance?yearEconomicCensus=option1)
599 [machinery-and-equipment-except-automotive-and-electronic-repair-and-](https://www.economia.gob.mx/datamexico/en/profile/industry/commercial-and-industrial-machinery-and-equipment-except-automotive-and-electronic-repair-and-maintenance?yearEconomicCensus=option1)
600 [maintenance?yearEconomicCensus=option1](https://www.economia.gob.mx/datamexico/en/profile/industry/commercial-and-industrial-machinery-and-equipment-except-automotive-and-electronic-repair-and-maintenance?yearEconomicCensus=option1) (Accessed: 31 July 2023)
- 601 Debbage, N. (2019). Multiscalar spatial analysis of urban flood risk and environmental
602 justice in the Charlanta megaregion, USA. *Anthropocene*, 28, 100226.
- 603 Diarra, G. and Marchand, S. (2011) 'Environmental compliance, corruption and
604 governance: theory and evidence on forest stock in developing countries'. *Etudes et*
605 *Documents, CERDI* (E2011.01).
- 606 Dormann, C. *et al.* (2007) 'Methods to account for spatial autocorrelation in the analysis of
607 species distributional data: a review', *Ecography*. Wiley Online Library, 30(5), pp. 609–
608 628.
- 609 Duarte, A.L., Schneider, I.L., Artaxo, P. and Oliveira, M.L., 2022. Spatiotemporal
610 assessment of particulate matter (PM10 and PM2. 5) and ozone in a Caribbean urban
611 coastal city. *Geoscience Frontiers*, 13(1), p.101168
- 612 Fecht, D. *et al.* (2015) 'Associations between air pollution and socioeconomic
613 characteristics, ethnicity and age profile of neighbourhoods in England and the
614 Netherlands', *Environmental pollution*. Elsevier, 198, pp. 201–210.
- 615 Flanagan, E. *et al.* (2019) 'Connecting Air Pollution Exposure to Socioeconomic Status: A
616 Cross-Sectional Study on Environmental Injustice among Pregnant Women in Scania,
617 Sweden', *International journal of environmental research and public health*.
618 Multidisciplinary Digital Publishing Institute, 16(24), p. 5116.
- 619 Funderburg, R., & Laurian, L. (2015). Bolstering environmental (in) justice claims with a
620 quasi-experimental research design. *Land Use Policy*, 49, 511-526.
- 621 Gao, H. *et al.* (2021) 'The impact of long-and short-term exposure to different ambient air
622 pollutantson cognitive function in China', *Environment International*. Elsevier, 151, p.
623 106416.
- 624 Gelman, A. and Rubin, D. B. (1992) 'Inference from iterative simulation using multiple
625 sequences', *Statistical science*. Institute of Mathematical Statistics, 7(4), pp. 457–472.
- 626 Germani, A. R., Morone, P., & Testa, G. (2014). Environmental justice and air pollution: A
627 case study on Italian provinces. *Ecological Economics*, 106, 69-82.
- 628 Gravante, T. (2018) 'Movilizaciones y eventos de protesta en México, un análisis
629 comparado', *Desacatos*. Centro de Investigaciones y Estudios Superiores en Antropología
630 Social, (57), pp. 208–211.
- 631 Hajat, A. *et al.* (2013) 'Air pollution and individual and neighborhood socioeconomic
632 status: evidence from the Multi-Ethnic Study of Atherosclerosis (MESA)', *Environmental*
633 *health perspectives*. National Institute of Environmental Health Sciences, 121(11–12), pp.
634 1325–1333.
- 635 Havard, S. *et al.* (2009) 'Traffic-related air pollution and socioeconomic status: a spatial
636 autocorrelation study to assess environmental equity on a small-area scale', *Epidemiology*.
637 JSTOR, pp. 223–230.
- 638 IHME (Institute for Health Metric and Evaluation). 2014. Global Burden of Disease.

- 639 [http://www.healthdata.org/research-article/global-burden-severe-periodontitis-1990-2010-](http://www.healthdata.org/research-article/global-burden-severe-periodontitis-1990-2010-systematic-review-and-meta-regression)
640 [systematic-review-and-meta-regression](http://www.healthdata.org/research-article/global-burden-severe-periodontitis-1990-2010-systematic-review-and-meta-regression) (Accessed on 29 March 2018).
- 641 INEGI (no date a) 'Economic Census 2009 and 2014', [internet]. Available
642 at:<https://www.inegi.org.mx/programas/ce/2009/>;
643 <https://www.inegi.org.mx/programas/ce/2014/> (Accessed: 1 February 2021)
- 644 INEGI (no date b) 'Espacio y datos de México', [internet]. Available at
645 <https://www.inegi.org.mx/app/mapa/espacioydatos/default.aspx> (Accessed: 1 February
646 2021)
- 647 INEGI (no date c) 'Population and Housing Census 2010', [internet]. Available at:
648 <https://www.inegi.org.mx/programas/ccpv/2010/> (Accessed: 1 February 2021)
- 649 INEGI (no date d) 'Population and Housing Census 2015', Available at:
650 <https://www.inegi.org.mx/programas/intercensal/2015/>(Accessed: 1 February 2021)
- 651 Kampa, M. and Castanas, E. (2008) 'Human health effects of air pollution', *Environmental*
652 *pollution*. Elsevier, 151(2), pp. 362–367.
- 653 Kelsall, J. E. and Wakefield, J. C. (1999) 'Discussion of "Bayesian models for spatially
654 correlated disease and exposure data", by Best et al', *Bayesian statistics*. Oxford University
655 Press Oxford, 6, p. 151.
- 656 Kingham, S., Pearce, J., & Zawar-Reza, P. (2007). Driven to injustice? Environmental
657 justice and vehicle pollution in Christchurch, New Zealand. *Transportation Research Part*
658 *D: Transport and Environment*, 12(4), 254-263.
- 659 Künzli N, Jerrett M, Mack WJ et al (2005) Ambient air pollution and atherosclerosis in Los
660 Angeles. *Environ Health Persp* 113(2):201
- 661 Landrigan, P. J. *et al.* (2018) 'The Lancet Commission on pollution and health', *The lancet*.
662 Elsevier, 391(10119), pp. 462–512.
- 663 Li, G. *et al.* (2014) 'Space–time variability in burglary risk: a Bayesian spatio-temporal
664 modelling approach', *Spatial Statistics*. Elsevier, 9, pp. 180–191.
- 665 Li, V. O. K. *et al.* (2018) 'Air pollution and environmental injustice: Are the socially
666 deprived exposed to more PM_{2.5} pollution in Hong Kong?', *Environmental science &*
667 *policy*. Elsevier, 80, pp. 53–61.
- 668 Lomborg, B. and Pope, C. (2003) 'The global environment: Improving or deteriorating?',
669 in *John F. Kennedy, Jr. Forum at the* <http://ajae.oxfordjournals.org>.
- 670 Lome-Hurtado, A., Lartigue-Mendoza, J. and Trujillo, J. C. (2021) 'Modelling local
671 patterns of child mortality risk: a Bayesian Spatio-temporal analysis', *BMC Public Health*,
672 21(1), p. 29.
- 673 Lome-Hurtado, A., Touza, J. and White, P. C. L. (2019) 'Environmental Injustice in
674 Mexico City: A Spatial Quantile Approach', *Exposure and Health*. Springer, pp. 1–15.
- 675 López-Feldman, A., Heres, D., & Marquez-Padilla, F. (2021). Air pollution exposure and
676 COVID-19: a look at mortality in Mexico City using individual-level data. *Science of the*
677 *Total Environment*, 756, 143929.
- 678 Maldonado A., Collins T., Grineski S., Chakraborty J. Exposure to Flood Hazards in Miami
679 and Houston: Are Hispanic Immigrants at Greater Risk than Other Social Groups? *Int. J.*
680 *Environ. Res. Public Health*. 2016;13:775.
- 681 Manisalidis, I. *et al.* (2020) 'Environmental and health impacts of air pollution: a review',
682 *Frontiers in public health*. Frontiers Media SA, 8.
- 683 Metropolitana, C. A. (1994) 'La Contaminación Atmosférica en el Valle de México.
684 Acciones para su control 1988–1994'. *Comisión Ambiental Metropolitana México*.
- 685 México, S. del M. A. de la C. de (2016) 'Inventario de Emisiones de la Ciudad de México

- 686 2016'. *Dirección General de Calidad del Aire, Dirección de Monitoreo de Calidad del*
687 *Aire*.
- 688 México, S. del M. A. de la C. de (2020) 'Calidad del aire en la Ciudad de México, Informe
689 2018', *Dirección General de Calidad del Aire, Dirección de Monitoreo de Calidad del*
690 *Aire*.
- 691 Moreno-Jimenez, A., Cañada-Torrecilla, R., Vidal-Domínguez, M. J., Palacios-Garcia, A.,
692 & Martinez-Suarez, P. (2016). Assessing environmental justice through potential exposure
693 to air pollution: A socio-spatial analysis in Madrid and Barcelona, Spain. *Geoforum*, 69,
694 117-131.
- 695 Nel, A. (2005). Air pollution-related illness: effects of particles. *Science*, 308(5723), 804-
696 806.
- 697 Nguyen NP, Marshall JD (2018) Impact, efficiency, inequality, and injustice of urban air
698 pollution: variability by emission location. *Environ Res Lett* 13(2):024002
- 699 Niessen, L. W. *et al.* (2018) 'Tackling socioeconomic inequalities and non-communicable
700 diseases in low-income and middle-income countries under the Sustainable Development
701 agenda', *The Lancet*. Elsevier, 391(10134), pp. 2036–2046.
- 702 Nogales, R. *et al.* (2020) 'Multidimensional poverty and COVID-19 risk factors: A rapid
703 overview of interlinked deprivations across 5.7 billion people'. *University of Oxford*.
- 704 Organization, W. H. (2006) 'Air quality guidelines: global update 2005: particulate matter,
705 ozone, nitrogen dioxide, and sulfur dioxide'. *World Health Organization*.
- 706 Padilla, C. M. *et al.* (2014) 'Air quality and social deprivation in four French metropolitan
707 areas—A localized spatio-temporal environmental inequality analysis', *Environmental*
708 *research*. Elsevier, 134, pp. 315–324.
- 709 Paquette, C. (2015) 'OECD Territorial Reviews: Valle de México, Mexico'. *Editions de*
710 *l'OCDE*.
- 711 Pope III, C. A. *et al.* (2011) 'Lung cancer and cardiovascular disease mortality associated
712 with ambient air pollution and cigarette smoke: shape of the exposure–response
713 relationships', *Environmental health perspectives*. National Institute of Environmental
714 Health Sciences, 119(11), pp. 1616–1621.
- 715 Qin, Y. *et al.* (2017) 'Air quality, health, and climate implications of China's synthetic
716 natural gas development', *Proceedings of the National Academy of Sciences*. National Acad
717 Sciences, 114(19), pp. 4887–4892.
- 718 Querol, X. *et al.* (2008) 'PM speciation and sources in Mexico during the MILAGRO-2006
719 Campaign', *Atmospheric Chemistry and Physics*. Copernicus GmbH, 8(1), pp. 111–128.
- 720 RAMA (no date) 'Automatic Air Quality Monitoring Network of Mexico City', [internet].
721 Available at: <http://www.aire.cdmx.gob.mx/default.php?opc=%27aKBh%27> (Accessed: 1
722 February 2021)
- 723 R Core Team (2020). R: A language and environment for statistical
724 computing. R Foundation for Statistical Computing, Vienna,
725 Austria. URL <https://www.R-project.org/>.
- 726 Romieu, I. *et al.* (2012) 'Multicity study of air pollution and mortality in Latin America
727 (the ESCALA study)', *Res Rep Health Eff Inst*, 171, pp. 5–86.
- 728 de San, J. A. S. R. (2019) 'Management of air pollution in Mexico', *Management of*
729 *Environmental Quality: An International Journal*. Emerald Publishing Limited.
- 730 Schweitzer, L. and Valenzuela Jr, A. (2004) 'Environmental injustice and transportation:
731 the claims and the evidence', *Journal of planning literature*. Sage Publications, 18(4), pp.
732 383–398.

- 733 SEMARNAT (2017) ‘Estrategia Nacional de Calidad del Aire’. *Secretaría de Medio*
 734 *Ambiente y Recursos Naturales*. Available at:
 735 <https://www.gob.mx/semarnat/documentos/calidad-del-aire-98085>. (Accessed: 1 February
 736 2021).
- 737 Spiegelhalter, D. J. *et al.* (2002) ‘Bayesian measures of model complexity and fit’, *Journal*
 738 *of the royal statistical society: Series b (statistical methodology)*. Wiley Online Library,
 739 64(4), pp. 583–639.
- 740 Su, J. G. *et al.* (2011) ‘Does exposure to air pollution in urban parks have socioeconomic,
 741 racial or ethnic gradients?’, *Environmental Research*. Elsevier, 111(3), pp. 319–328.
- 742 Venkatapuram S and Marmot M (2009). Epidemiology and social justice in light of social
 743 determinants of health research. *Bioethics* 23, 79–89.
- 744 Verbeek, T. (2019) ‘Unequal residential exposure to air pollution and noise: a geospatial
 745 environmental justice analysis for Ghent, Belgium’, *SSM-population health*. Elsevier, 7, p.
 746 100340.
- 747 Verbeek, T., & Hincks, S. (2022). The ‘just’ management of urban air pollution? A
 748 geospatial analysis of low emission zones in Brussels and London. *Applied Geography*,
 749 140, 102642.
- 750 Wan, Z., Wang, L., Chen, J., & Sperling, D. (2021). Ship scrappage records reveal
 751 disturbing environmental injustice. *Marine Policy*, 130, 104542.
- 752 Wolch J.R., Byrne J., Newell J.P. Urban green space, public health, and environmental
 753 justice: The challenge of making cities ‘just green enough’ *Landsc. Urban*
 754 *Plan.* 2014;125:234–244.
- 755 World Health Organization (no date) ‘9 out of 10 people worldwide breathe polluted air,
 756 but more countries are taking action’ [internet]. Available at:
 757 [https://www.who.int/news/item/02-05-2018-9-out-of-10-people-worldwide-breathe-](https://www.who.int/news/item/02-05-2018-9-out-of-10-people-worldwide-breathe-polluted-air-but-more-countries-are-taking-action)
 758 [polluted-air-but-more-countries-are-taking-action](https://www.who.int/news/item/02-05-2018-9-out-of-10-people-worldwide-breathe-polluted-air-but-more-countries-are-taking-action) (Accessed: 1 February 2021).
- 759 World Health Organization (2006) ‘Air quality guidelines for particulate matter, ozone,
 760 nitrogen dioxide and sulfur dioxide. Global update 2005. Summary of risk assessment’
 761 [internet]. Available at: [https://www.who.int/phe/health_topics/outdoorair_aqg/en/index](https://www.who.int/phe/health_topics/outdoorair_aqg/en/index.html)
 762 [.html](https://www.who.int/phe/health_topics/outdoorair_aqg/en/index.html) (Accessed: 1 February 2021)
- 763 Wu, J. and Pu, Y. (2020) ‘Air pollution, general government public-health expenditures and
 764 income inequality: Empirical analysis based on the spatial Durbin model’, *PLoS one*. Public
 765 Library of Science San Francisco, CA USA, 15(10), p. e0240053.

766

767 DECLARATIONS**768 Competing interests**

769 The authors declare that they have no competing interests.

770 Funding

771 No funding required.

772 Availability of data and material773 The obtained raw datasets during the current study are available in the cited references in
 774 the data section.**775 Ethics approval and consent to participate**

776 Not applicable

777 Consent for publication

778 Not applicable

779

780

APPENDIX

Table A1a. Posterior means relating to different potential risk factors affecting PM₁₀, 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

781
782
783
784
785
786
787

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

788
789
790
791
792
793

Table A2a. Yearly posterior means relating to different potential risk factors affecting PM₁₀, 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.

794
795

796
797

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

798
799
800
801
802

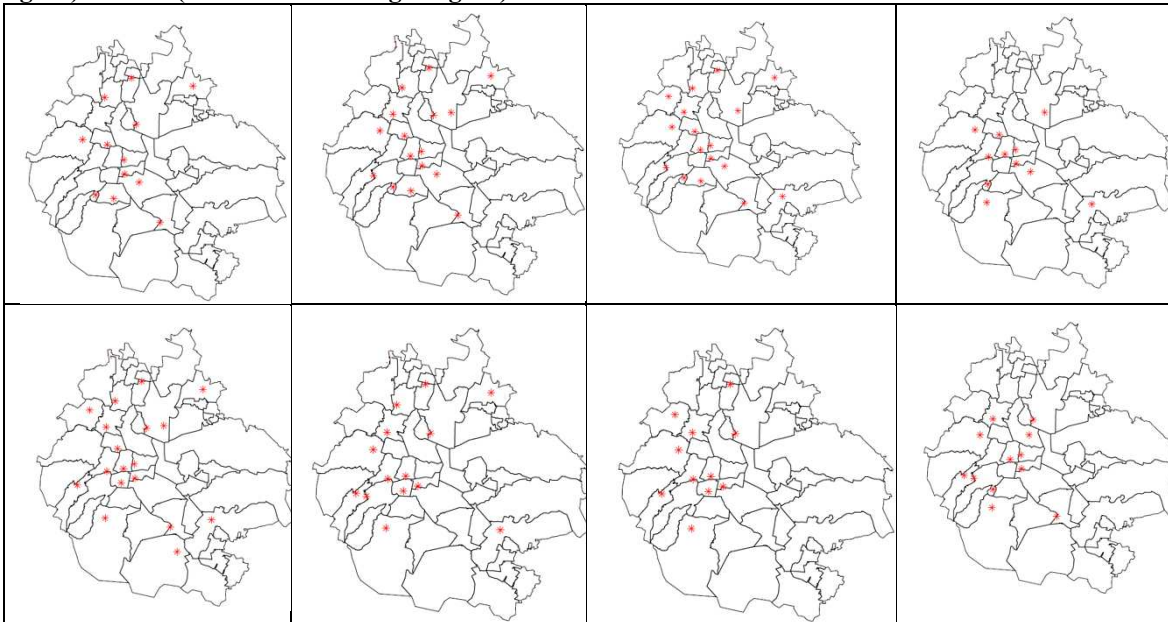
Table A3. Monthly log posterior means relating to different potential risk factors affecting PM₁₀ and ozone, with 95% credible intervals displayed in the brackets, for Model 3 (space+space-time interactions).

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)	803
			804
			805

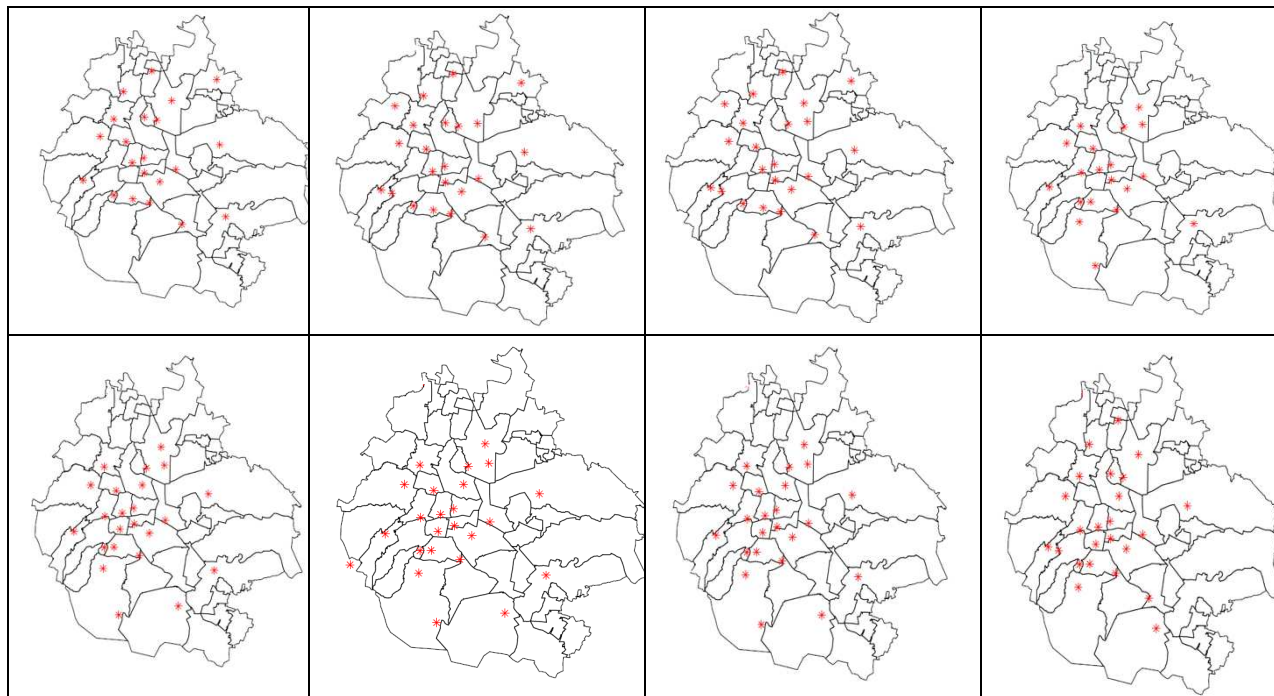
806
807
808

Figure A1.a. PM₁₀ monitoring stations across Greater Mexico City (short) from 2012 (first row and left figure) to 2019 (second row and right figure).



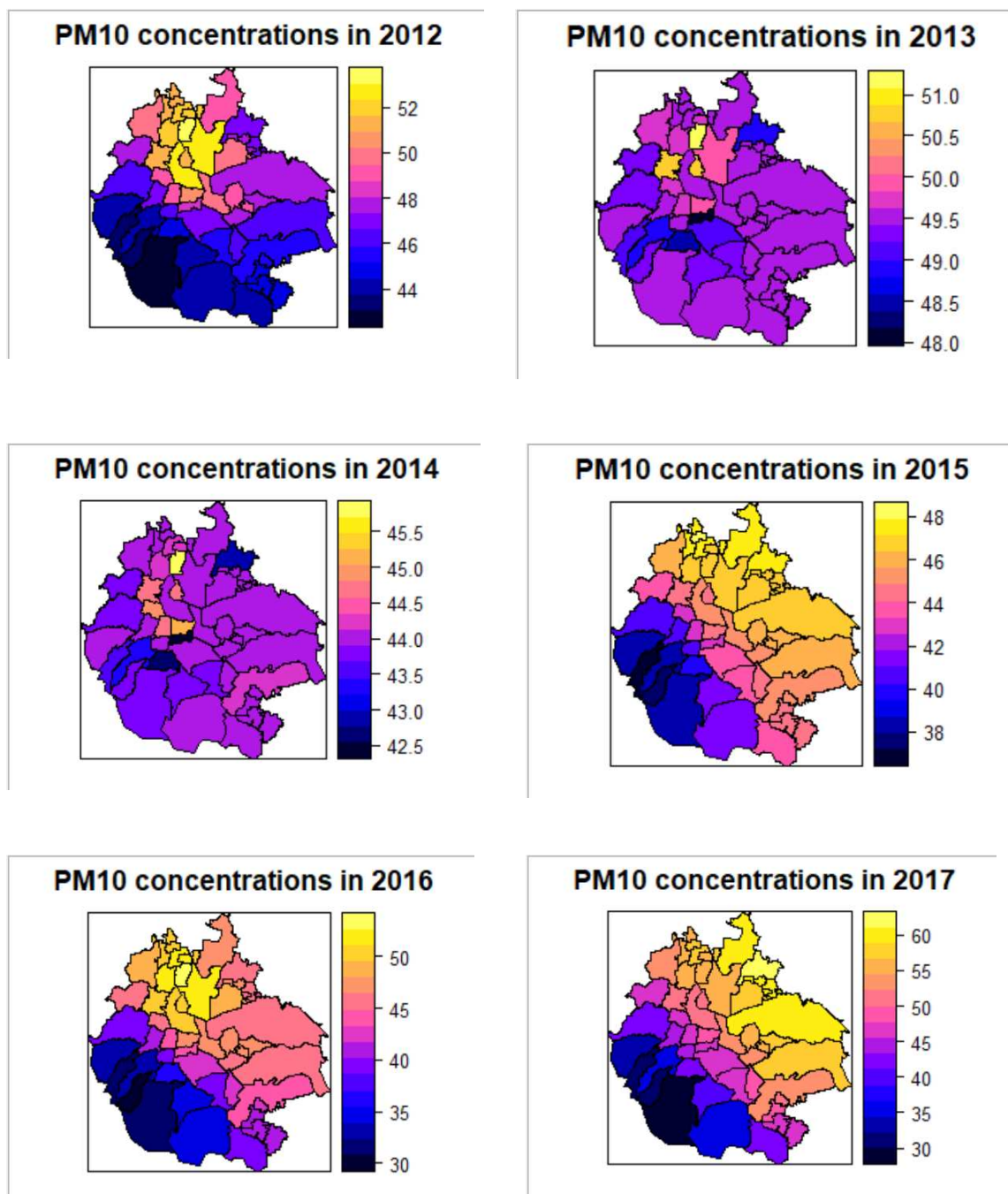
809
810
811
812

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).



813

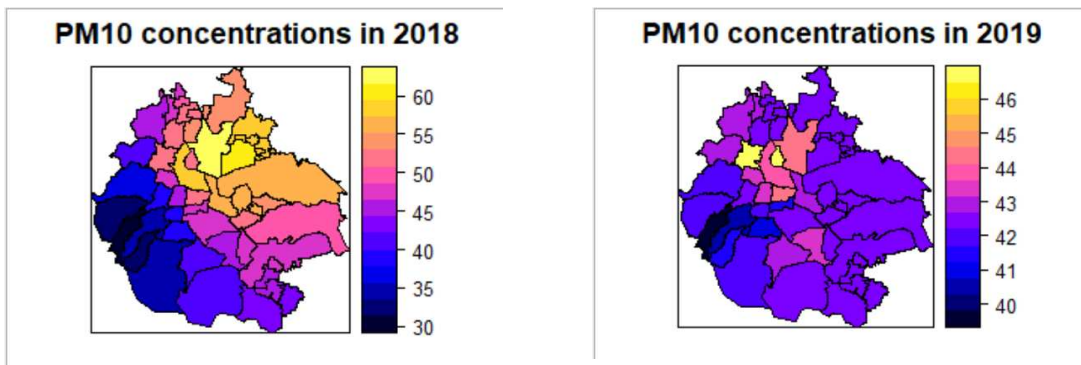
814 Fig. A2a. Spatial distribution of PM₁₀ concentrations from 2012 to 2019 in mg/m³, in
815 Greater Mexico City (short).
816



817

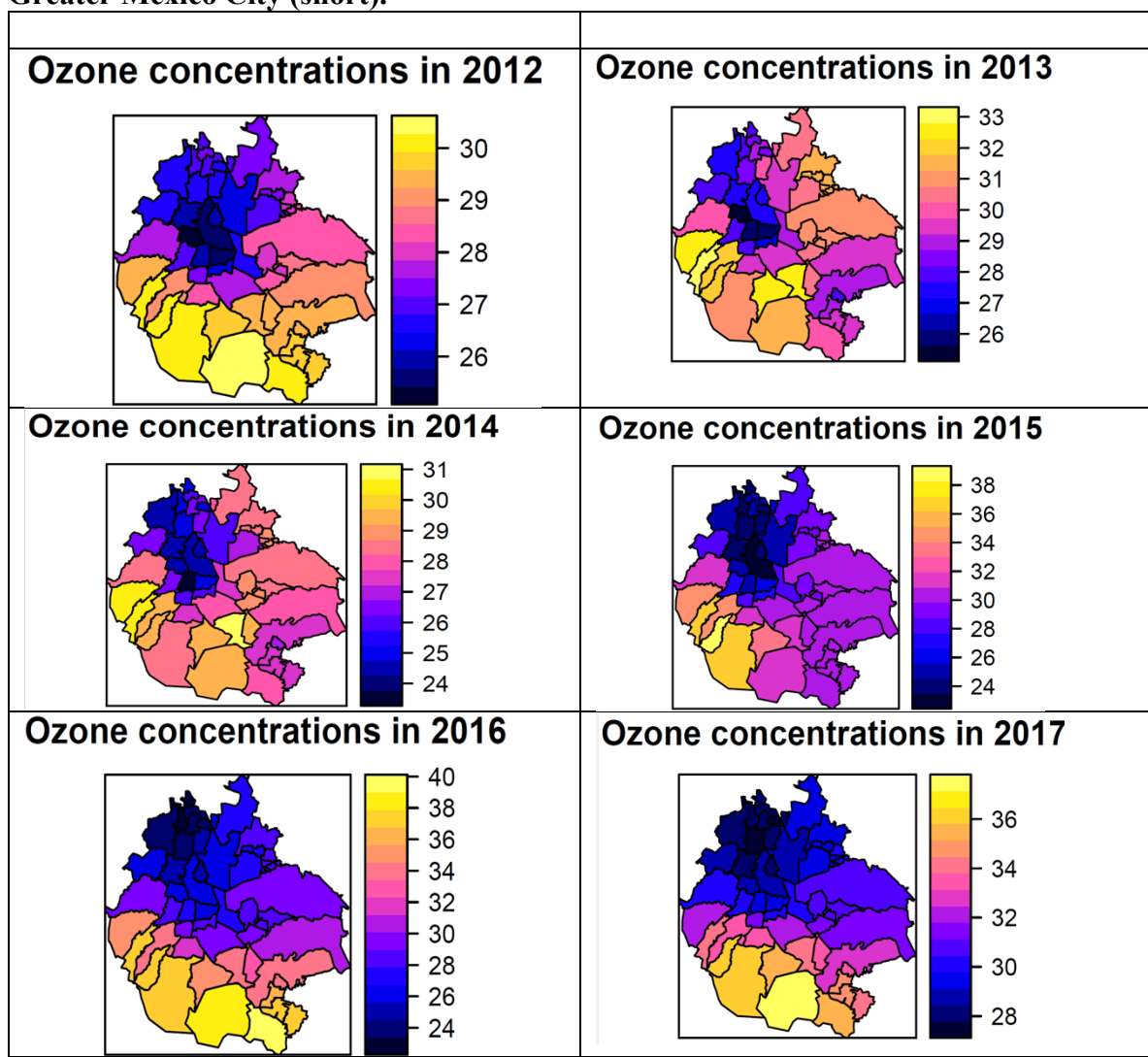
818

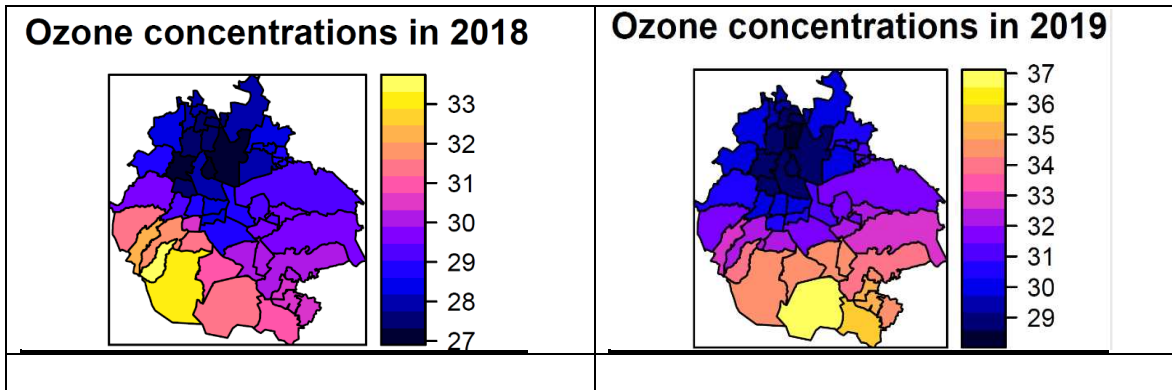
819



820
821
822

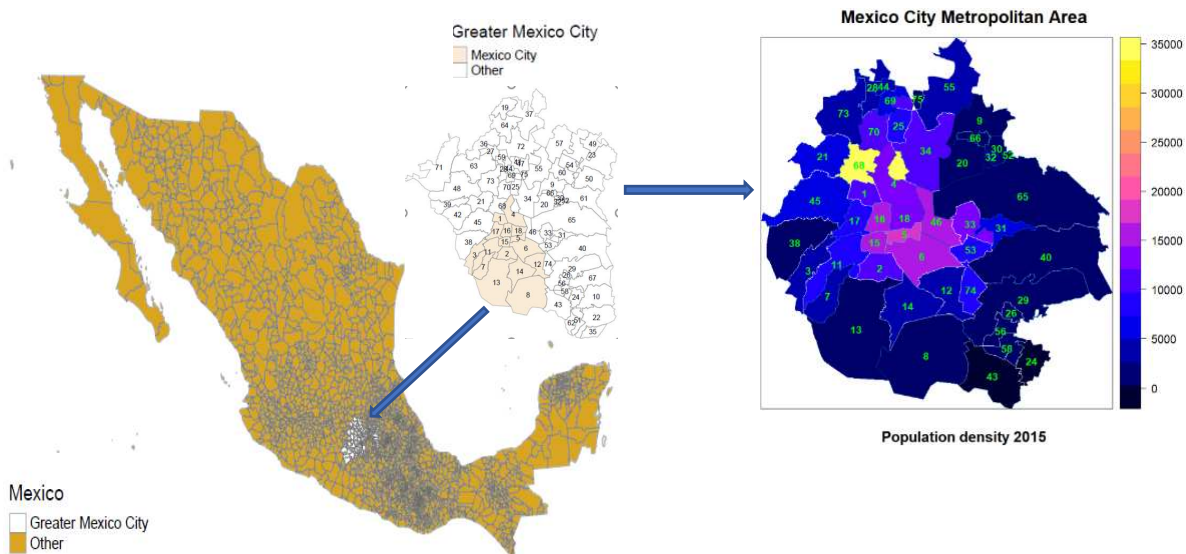
Fig. A2b. Spatial distribution of Ozone concentrations from 2012 to 2019 in mg/m³, in Greater Mexico City (short).





823
824
825
826
827
828
829
830
831
832

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



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

847 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:
848 own elaboration with INEGI data and Lome-Hurtado *et al.*, 2021.
849
850
851