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RESEARCH ARTICLE

A city-level analysis of $PM_{2.5}$ pollution, climate and COVID-19 early spread in Spain

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Abstract

Purpose The COVID-19 outbreak has escalated into the worse pandemic of the present century. The fast spread of the new SARS-CoV-2 coronavirus has caused devastating health and economic crises all over the world, with Spain being one of the worst affected countries in terms of confirmed COVID-19 cases and deaths per inhabitant. In this situation, the Spanish Government declared the lockdown of the country.

Methods The variations of air pollution in terms of fine particulate matter ($PM_{2.5}$) levels in seven representative cities of Spain are analyzed here considering the effect of meteorology during the national lockdown. The possible associations of $PM_{2.5}$ pollution and climate with COVID-19 accumulated cases were also analyzed.

Results While the epidemic curve was flattened, the results of the analysis show that the 4-week Spanish lockdown significantly reduced the $PM_{2.5}$ levels in only one city despite the drastically reduced human activity. Furthermore, no associations between either $PM_{2.5}$ exposure or environmental conditions and COVID-19 transmission were found during the early spread of the pandemic.

Conclusions A longer period applying human activity restrictions is necessary in order to achieve significant reductions of $PM_{2.5}$ levels in all the analyzed cities. No effect of $PM_{2.5}$ pollution or weather on COVID-19 incidence was found for these pollutant levels and period of time.

Keywords COVID-19 spread · SARS-CoV-2 · $PM_{2.5}$ pollution · Climate · Lockdown

Introduction

Due to the growing COVID-19 pandemic, the government of Spain declared a lockdown on March 14, 2020. Extraordinary control policies were executed in an effort to reduce the COVID-19 transmission. At the beginning of the lockdown, from March 15 to March 29, 2020, named here as *minor lockdown*, people were recommended to work from home, and other measures such as travel restrictions, isolation, and quarantine of patients, cancellation of private and public events, online education, closing of restaurants, bars and pubs, or the prohibition of public congregations, were imposed. During those two weeks, only essential products could be sold in supermarkets and drugstores, and only a small amount of activities were allowed. During the last two weeks of the lockdown, from March 30 to April 12, 2020, named here as *major lockdown*, the Spanish Government imposed more severe restrictions due to the national emergency caused by the collapse of the health system. This situation forced people to stay at home (except for very limited purposes) and only essential work such as healthcare and social care sectors, police and armed forces, water and electricity supply was allowed. Besides, important industrial activities such as construction were forbidden. These unprecedented measures gave positive results and flattened the epidemic curve after a month of lockdown [1]. The impact of particulate matter (PM) on health is well-known

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[2–4] in terms of its effects on morbidity and mortality. Two sizes of particulate matter are used to analyze air quality; fine particulate matter or $PM_{2.5}$, with a diameter of 2.5 µm or less, and coarse particles or $PM_{10,}$ with a diameter of 10 µm or less. However, the former is more worrying because their small size allows them to penetrate deeper into the human respiratory system via inhalation, which can potentially promote respiratory diseases [5, 6] such as COVID-19. Thus, it is of note that citizens exposed to a high concentration of $PM_{2.5}$ are more prone to developing chronic respiratory diseases favorable to infective agents [7]. Long-term exposure to these small particles can produce a chronic inflammatory stimulus, especially in unhealthy people [8]. In addition, short-term exposure to $PM_{2.5}$ particles may also increase susceptibility to infections [9]. Indeed, this type of pollution can harm human airways, promoting viral infections, and diminish the immune response [7, 10]. The World Health Organization's air quality guidelines recommend that $PM_{2.5}$ concentration should not exceed a 10 µg/m^3 annual mean and 25 µg/m^3 24-hour mean [11]. Due to combustion processes, road traffic is the main emission source of atmospheric $PM_{2.5}$ [12]. Other sources of $PM_{2.5}$ in urban environments include Sahara dust events [13], shipping [14], secondary inorganic aerosol or biomass burnin [15], combustion processes in thermal power stations and other industrial sectors, the transport of anthropogenic aerosols from central Europe to Mediterranean areas, and certain agricultural activities [16]. Spain, which still consumes a considerable amount of fossil fuels, is quite near to the Sahara desert and has approximately 47 million inhabitants. The Mediterranean zone has been identified as a crossroads of air masses with many kinds of aerosols caused by many anthropogenic and natural sources, such as the resuspension of dust from Africa, the production of sea salt, industrial and urban aerosols, fires, and smoke from Eastern Europe [17]. We have recently demonstrated that the Spanish lockdown did not decrease air pollution (NO_2, CO, SO_2, and PM_{10}) considering meteorological factors on the pollutants' levels [18]. Furthermore, the O_3 levels were generally increased during this period. In the current paper, we focus on the variations of air pollution in terms of fine particulate matter, wich could be associated with the COVID-19 spread [7], in several representative Spanish cities during the lockdown using $PM_{2.5}$ pollution and COVID-19 data. Meteorological parameters, which significantly affect air pollution [19, 20] have also been taken into account. Several studies in the same research line have shown evidence of significant reductions of severe $PM_{2.5}$ pollution during COVID-19 lockdowns in other countries, such as India [21] and Malaysia [22]. However, an increase of 20.5% for $PM_{2.5}$ during first month of SARS-CoV-2 outbreak was reported in Tehran [23]. In China, which probably applied one of the strictest lockdown measures, the fine particulate matter in the atmosphere was not significantly reduced either during the COVID-19 lockdown [24]. On the other hand, some studies have reported positive association between COVID-19 daily new cases and $PM_{2.5}$ levels in the Netherlands [25], in Milan [26] and in China [27]. However, additional research is needed to test the exploratory associations found between $PM_{2.5}$ pollution and COVID-19 prevalence so far [28]. In this paper, we investigate the impact of environmental data and $PM_{2.5}$ level on the COVID-19 outbreak, modelling $PM_{2.5}$ level and COVID-19 spread.

Data

$PM_{2.5}$ pollution

Seven major Spanish cities were considered in this study (see Fig. 1). Table 1 shows the information of each selected city with populations (on January 1, 2019) that vary from 97,260 to 3,266,126 inhabitants [29]. $PM_{2.5}$ pollution data was obtained from official web pages: Bilbao [30]; Madrid [31]; San Sebastián [30]; Santiago [32]; Valladolid [33]; Vigo [32] and Vitoria [30]. This pollution data was obtained from the traffic station of each city (see Table 1) whose levels were mainly determined by traffic emissions [34]. Every day, $PM_{2.5}$ (in µg/m^3) were collected from each station from March 4 to April 14, 2019, and from March 2 to April 12, 2020, using the sampling method defined by the current Directive 2015/1480 [35] instead of the previous [36], following the gravimetric method of determining $PM_{2.5}$ mass fraction in suspended particulate matter [37]. The measurements are commonly performed with active samplers operating at 2.3 m^3/h over a sampling period of 24 h. The range of application of this European Standard is from 1 µg/m^3 (detection method limit) up to approximately

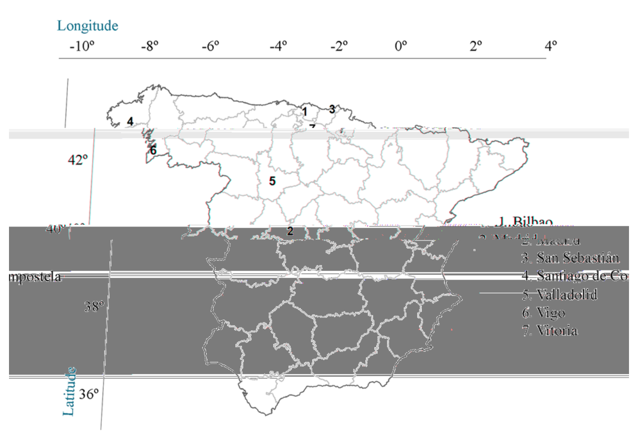

Fig. 1 Map of Spain with the eight cities considered for the $PM_{2.5}$ pollution analysis. Location coordinates are those of the pollution station. The provincial borders are shown in grey

120 μg/m^3. Table 2 provides a city-level statistical summary of the $PM_{2.5}$ levels in each of the periods considered for the analysis, where the normal period includes both the period comprised from March 4 to April 14, 2019, and the period from March 2 to March 14, 2020, just before the minor lockdown started.

Meteorological data

The Application Programming Interface of the OpenData platform of the State Meteorological Agency was used to download the meteorological data necessary for this analysis. Eight meteorological stations were selected for the meteorological variables considered in this study: temperature, precipitation, wind velocity, min and max atmospheric pressure, and sunlight time, that is, number of hours with a solar irradiance over 120 W/m^2. The minimum pressure was discarded for the analysis because of the high correlation (very close to 1) between maximum and minimum pressure values. Table 3 provides a statistical summary of the meteorological variables considered corresponding to the entire period under study (including the normal, minor, and major lockdown periods).

COVID-19 data

COVID-19 data was also downloaded from multiple local and regional webpages: Bilbao [38], Madrid [39], San Sebastián [38], Santiago de Compostela [40], Valladolid [41], Vigo [40], and Vitoria [38]. Data was collected for the period comprised from March 18 to April 12, 2020, and

Table 1 Spanish city, province (PROV), population (POP, on January 1, 2019), and longitude (LO) and latitude (LA) of the air quality stations (QS) selected for the study

SPANISH CITY	PROV	POP	QS	LO	LA
Bilbao	Biscay	346,843	Europa	-2.9024	43.2549
Madrid – capital city	Madrid	3,266,126	Escuelas Aguirre	-3.6823	40.4217
San Sebastián	Gipuzkoa	187,415	Avenida Tolosa	-2.0109	43.3094
Santiago de Compostela	A Coruña	97,260	S. Caetano	-8.5311	42.8878
Valladolid	Valladolid	298,412	La Rubia II	-4.7406	41.6300
Vigo	Pontevedra	295,364	Coia	-8.7421	42.8548
Vitoria	Álava	251,774	Avenida Gasteiz	-2.6807	42.8548

Table 2 City-level statistical summary of $PM_{2.5}$ levels in terms of mean value, 1st quartile (1st Q), and 3rd quartile (3rd Q) at each of the different periods (normal, minor and major lockdown) considered for the analysis

Spanish city	Normal period			Minor lockdown			Major lockdown		
	Mean	1st Q	3rd Q	Mean	1st Q	3rd Q	Mean	1st Q	3rd Q
Bilbao	9.13	6.00	12.50	13.93	11.00	17.00	8.14	6.25	9.75
Madrid	11.51	6.00	14.00	6.60	4.50	8.50	7.00	5.00	9.00
San Sebastián	8.95	6.00	11.00	13.17	10.75	15.50	8.64	7.00	10.00
Santiago de Compostela	12.64	8.20	17.00	15.18	13.00	18.00	9.01	7.23	9.85
Valladolid	11.30	6.50	15.00	11.40	8.50	13.00	6.14	5.00	7.00
Vigo	9.11	6.45	12.00	11.93	9.20	13.50	6.21	5.00	6.78
Vitoria	7.33	4.25	10.00	10.87	9.00	13.50	6.36	4.50	7.00

Table 3 Summary of the meteorological variables (temperature (T), Precipitation (PR), Wind speed (WS), sunlight hours (SH) and maximum pressure (MP)) considered for the study in terms of mean value, 1st quartile (1st Q), and 3rd quartile (3rd Q) during the entire study period

Spanish city	T (°C)			PR(mm)			WS (km/h)			SH (h)			MP (hPa)		
	Mean	1st Q	3rd Q	Mean	1st Q	3rd Q	Mean	1st Q	3rd Q	Mean	1st Q	3rd Q	Mean	1st Q	3rd Q
Bilbao	12.2	10.2	14.2	3.1	0.0	3.1	3.5	2.2	3.9	4.5	0.9	7.6	1017.1	1012.6	1022.7
Madrid	11.3	9.7	13.2	1.4	0.0	0.5	3.3	1.9	4.2	7.1	3.4	11.0	952.8	949.2	957.8
San Sebastián	11.2	9.3	13.0	3.92	0.0	5.1	4.5	2.8	5.3	5.3	1.4	9.0	990.7	986.3	996.2
Santiago de Compostela	10.3	8.4	12.5	4.2	0.00	3.4	2.9	1.9	3.6	5.9	2.4	10.4	978.5	974.2	983.3
Valladolid	10.9	7.9	11.6	1.2	0.0	1.2	2.2	1.4	2.8	7.3	4.3	10.6	935.9	932.0	941.1
Vigo	11.9	10.0	13.5	5.2	0.0	3.9	3.5	2.8	3.9	6.8	2.7	10.6	990.9	986.3	995.4
Vitoria	8.6	6.6	10.4	1.4	0.0	1.0	3.6	2.5	4.2	6.2	3.0	9.8	961.7	957.6	966.9

corresponded to the number of accumulated COVID-19 cases in each city.

Methods

R programming language

The R programming language [42] was used for the statistical analysis with several R packages: *effects* [43], *ggplot2* [44], *INLA* [45, 46], *lubridate* [47], *RCurl* [48], sjPlot [49] and *XML* [50].

Modeling $PM_{2.5}$ levels

In order to discriminate between the effects of meteorology and lockdown, the meteorological variables (temperature, precipitation, wind velocity, sunlight time, or atmospheric pressure), which modify pollutant levels [51], were considered in the statistical model. Weekend days were also considered because of their reduced pollutant levels as a result of less road traffic. Thus, the daily $PM_{2.5}$ pollutant levels of the seven cities were fitted through a statistical model considering meteorological variables, weekend days, and lockdown periods of time. The $PM_{2.5}$ pollutant levels for a city i on date t were modeled by Eq. (1), including quadratic terms capable of capturing non-linear relationships between the meteorological variables and the $PM_{2.5}$ level.

$$\begin{aligned}(\mathrm{PM}_{2.5})_{\mathrm{it}} = \alpha + \beta_{11}\ \mathrm{Temperature}_{\mathrm{it}} + \beta_{12}\ \mathrm{Temperature}^2_{it} + \beta_{21}\ \mathrm{Rain}_{\mathrm{it}} + \beta_{22}\\ \mathrm{Rain}^2_{it} + \beta_{31}\ \mathrm{Wind}_{\mathrm{it}} + \beta_{32}\ \mathrm{Wind}^2_{it} + \beta_{41}\ \mathrm{Sunlight}_{\mathrm{it}} + \beta_{42}\ \mathrm{Sunlight}^2_{it} + \beta_{51}\\ \mathrm{Max_pressure}_{it} + \beta_{52}\ \mathrm{Max_pressure}^2_{it} + \gamma\ \mathrm{Weekend}_t + \rho_i\ \mathrm{City}_i + (\delta_1 +\\ \delta_{1i})\mathrm{Minor_lockdown}_t + \left(\delta_2 + \delta_{2i}\right)\ \mathrm{Major_lockdown}_t\end{aligned} \tag{1}$$

In this regression model, α is the global intercept of the model, β_{kj} (k = 1, 2, 3, 4, 5 and j = 1, 2) quantifies the corresponding meteorological covariate effect (in quadratic form, or not) on the $(PM_{2.5})_{it}$ values, γ quantifies weekend days effect on the $(PM_{2.5})_{it}$ values, ρ_i represents the city-specific effect at no lockdown $PM_{2.5}$ levels, δ_1 and δ_2 indicate the overall *lockdown* effect (*minor* and *major*, respectively) on $(PM_{2.5})_{it}$ levels, and δ_{1i} and δ_{2i} indicate the city-specific effect (*minor* and *major*, respectively) on the $(PM_{2.5})_{it}$ level. Bank holidays were computed as weekend days. Therefore, this model estimates the variations of $PM_{2.5}$ pollution levels because of lockdown while simultaneously accounting for week-day and meteorological effects.

Modeling COVID-19 spread

The association between COVID-19 spread and the $PM_{2.5}$ levels and environment was also studied for all the cities included in the study. Hence, the number of accumulated COVID-19 cases in each city was modelled in terms of each of the environmental covariates available (temperature, rain, wind velocity, sunlight time, maximum atmospheric pressure, and $PM_{2.5}$ level) through a Poisson model. Thus, the accumulated COVID-19 cases on date t, y_t, was modelled as follows:

$$\begin{aligned} y_t &= \mathrm{Po}(\mu_t)\\ \log(\mu_t) &= \alpha + \beta x_t + \delta_t \end{aligned} \tag{2}$$

where α is the global intercept of the model, x_t represents the environmental covariate, β refers to the coefficient that measures the magnitude of the effect of x_t on $\log(\mu_t)$, and δ_t is a temporally-structured effect for day t to control for serial correlation, which was defined by a first-order random walk. Lagged covariate effects were considered in the model by replacing the term x_t by x_{t-7}, and x_{t-14}, which allows assessing the possible effect of the environmental conditions on the previous two weeks on the total number of cases reported on date t. The model described by Eq. (2) was fitted using the Integrated Nested Laplace Approximation (INLA) method [45, 46].

Results and discussion

Global effects

A stepwise algorithm was applied to the regression model represented by Eq. (1) to find the subset of the variables providing the best model in terms of the Akaike information criterion. The overall variables included in this model and the coefficients associated with each one are shown in Table 4.

First, it is worth noting that the two precipitation-related variables were discarded, suggesting the absence of an association between precipitation and $PM_{2.5}$ values, and also that the maximum pressure and weekend days have a positive association with $PM_{2.5}$ levels, while wind velocity has a negative relationship with the particulate matter levels. The model also suggests that temperature and the number of sunlight hours have a quadratic relationship with $PM_{2.5}$ levels, which makes interpretation more challenging. Nevertheless, for the range of values attained by temperature and number of sunlight hours during the period under study, the coefficients estimated for the linear and quadratic

Table 4 Global effects estimated between variables and fine particulate matter with Eq. (1)

	Estimate	*p*-value
(Intercept) (α)	-88.5323	0.0014
Temperature (β_{11})	0.8601	0.0096
Temperature^2 (β_{12})	-0.0297	0.0425
Wind speed (β_{31})	-0.6965	0.0000
Sunlight hours (β_{41})	-0.2959	0.0789
Sunlight hours^2 (β_{42})	0.0525	0.0001
Max Pressure (β_{51})	0.0920	0.0008
Weekend day (γ)	0.8316	0.0205
Minor lockdown day (δ_1)	4.6398	0.0001
Major lockdown day (δ_2)	-1.2126	0.3487

The estimated model coefficients are shown toguether with the associated *p*-values

forms of these two variables indicate that higher values of these two variables are associated with higher $PM_{2.5}$ levels. The results obtained mostly agree with other studies in the literature. Thus, regarding the positive association of $PM_{2.5}$ with temperature and sunlight hours, dry sunny weather frequently leads to prevent the vertical dispersion of pollutants due to thermal inversion [52] and increases their concentration, generating significant smog episodes. Indeed, sunny weather also favors photochemical reactions [24, 53] while dry conditions prolong aerosols and atmospheric loadings [17]. The increase of wind speed can also decrease $PM_{2.5}$ levels [54, 55], while lower wind speeds can promote a reduction of particulate matter in the air because of an significant increase of deposition [53]. The rise of atmospheric pressure seems to positively affect PM formation [56].

Coefficients of determination

Table 5 shows the coefficients of determination (R^2) for each model using $PM_{2.5}$ data with Eq. (1).

From this analysis, it follows that the $PM_{2.5}$ levels seem to be quite dependent on meteorological factors while the inclusion of city-level and lockdown effects is fundamental to improve R^2 values.

Table 5 Coefficients of determination (R^2) for each model using $PM_{2.5}$ data with Eq. (1)

Model	R^2
Meteorological	0.2853
Meteorological + Weekend	0.2921
Meteorological + Weekend + City	0.3476
Meteorological + Weekend + City * Lockdown	0.4486

Marginal city-specific effect for the $PM_{2.5}$ pollutant

The minor lockdown led to overall increases in $PM_{2.5}$ levels in the cities considered (see results of Table 4). Nevertheless, the full analysis of the proposed model requires the consideration of the city-specific coefficients omitted in Table 4. In fact, the global city-specific effects and the global period (*no lockdown*, *minor* or *major lockdown*) effects were employed for the estimation of the city-specific marginal effects of the $PM_{2.5}$ levels. The city-specific effects of the city-period interactions were also considered in this analysis. These results show the $PM_{2.5}$ variations due to the COVID-19 lockdown in each city. Figure 2 shows these city-specific marginal effects with the 95% confidence intervals estimated with the Eq. (1) for the $PM_{2.5}$ pollution levels during minor lockdown, major lockdown, and no lockdown.

The point estimates represented in this figure show the adjusted effect of the combination of city and period under study on $PM_{2.5}$ pollution levels. The differences between $PM_{2.5}$ concentrations during the normal period, minor, and major lockdown were not significantly different in many of the cities. However, there was a rising trend in the minor lockdown $PM_{2.5}$ levels in some cities considering meteorological and week-day effects, especially in Bilbao and San Sebastián. Considering that relative humidity was not included in the linear regression, these results may simply be an artifact due to high relative humidity episodes that can improve the aqueous-phase oxidation of pollutants such as SO_2 and $PM_{2.5}$ levels [24]. Both are coastal cities in the north of Spain, where higher humidity is usual and are more likely to receive atmospheric particles from shipping and

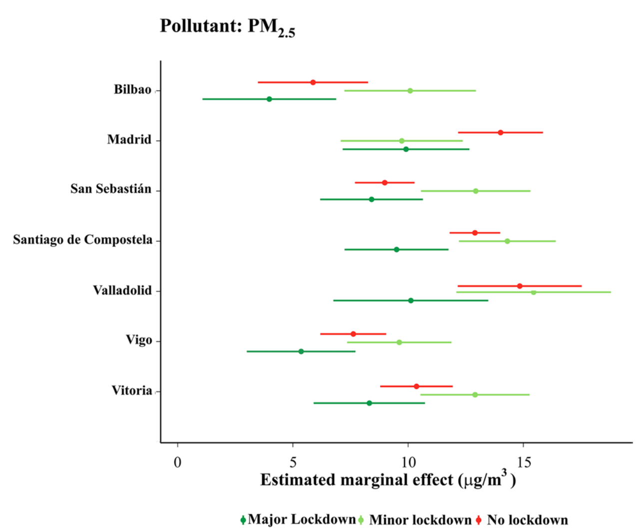

Fig. 2 City-specific marginal effects estimated for the $PM_{2.5}$ pollution levels during minor lockdown, major lockdown, and no lockdown periods. Marginal effects are statistically significant different when there is not overlapping of the confidence intervals

sea salt, two of the main sources of the pollutant analyzed. On the other hand, the major lockdown period led to a general reduction in fine particulate matter, although only one statistically significant reduction was found in Santiago de Compostela, from 12.41±0.60 to 8.90±1.16 μg/m^3, in terms of marginal effects. This reduction of $PM_{2.5}$ particles must be related to the drastically reduced human activity during the Spanish lockdown [24]. However, the relationship between traffic and anthropogenic activity with particulate matter sources and particle size is not necessarily unequivocal [12], so that the variations shown may not always be as clear as might be expected. Nevertheless, the reduction of this fine particulate matter was not expected to be very high because these inhalable particles are emitted in large volumes and persist in the air for longer periods, which means they can spread easier [57]. In fact, these low reductions are in in good agreement with our previos study of variations in air quality in terms of PM_{10} levels during this period [18]. Since a significant part of this fine particulate matter is from natural sources, a reduction in emissions of human origin would need a much longer lockdown to avoid severe $PM_{2.5}$ pollution.

Association analysis of $PM_{2.5}$ pollution and weather patterns with COVID-19 spread

Figure 3 shows that the strict national lockdown imposed in Spain flattened the epidemic curve as expected by the Spanish authorities.

The relationship between $PM_{2.5}$ exposure or meteorological factors (data shown in Figs. S1-S6 in the Supplementary material) and COVID-19 data (Fig. 3) during the Spanish lockdown is shown in Fig. 4.

Thus, no association is observed between COVID-19 accumulated cases and $PM_{2.5}$ levels or climate patterns, contrary to what we could expect according to recent results on the effect of particulate matter levels [25–27] or climate conditions [58, 59]. Anyhow, it is still unclear the relationship between COVID-19 transmission and $PM_{2.5}$ exposure which is in need of further investigation and many controversial results have been reported about the effect of climate on the COVID-19 spread, partly as a consequence of the different statistical methodologies chosen [60]. We have used univariate Poisson models accounting for the presence of temporal autocorrelation in the data. The inclusion of such a temporal term allows capturing the epidemic growth and reduces the chances of obtaining spurious or artefactual associations, which can easily arise when correlation coefficients are computed. The fact that many published studies are strongly based on correlation coefficients, together with the existing uncertainty about COVID-19 data, are sufficient reasons for still being cautious about the association between COVID-19 and the environment or $PM_{2.5}$ pollution. Furthermore, the use of multivariate modelsthat allow accounting for several of the factors (environmental or non-environmental) that are possibly implicated in COVID-19 is highly advisable, although we discarded the use of these models in this case due to the length of the time series available.

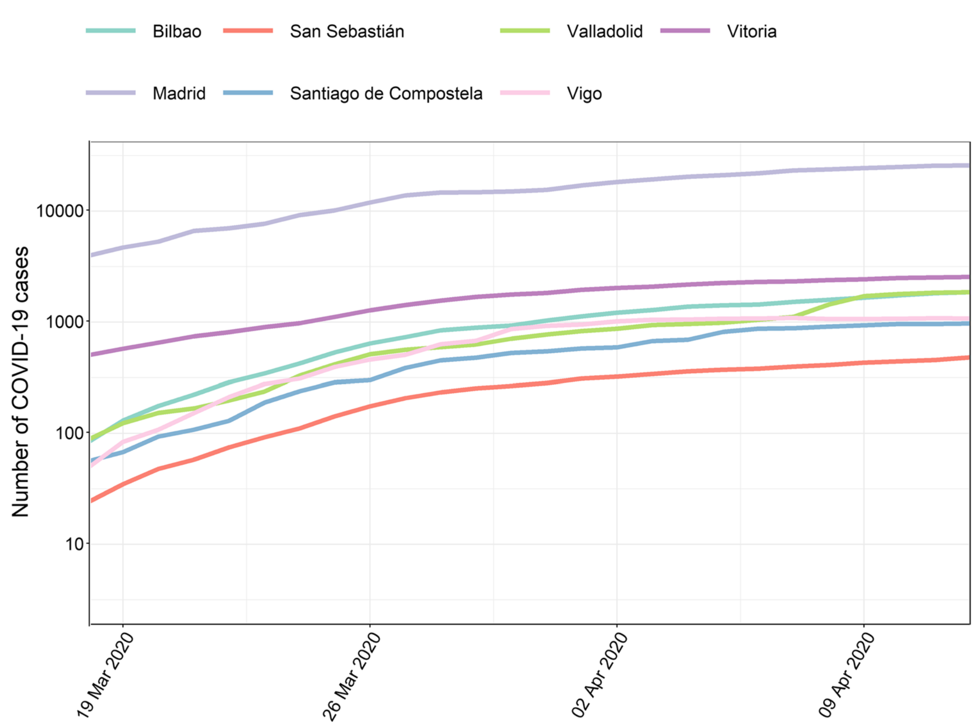

Fig. 3 COVID-19 data used for the association study with COVID-19 accumated cases for the seven cities considered in the study

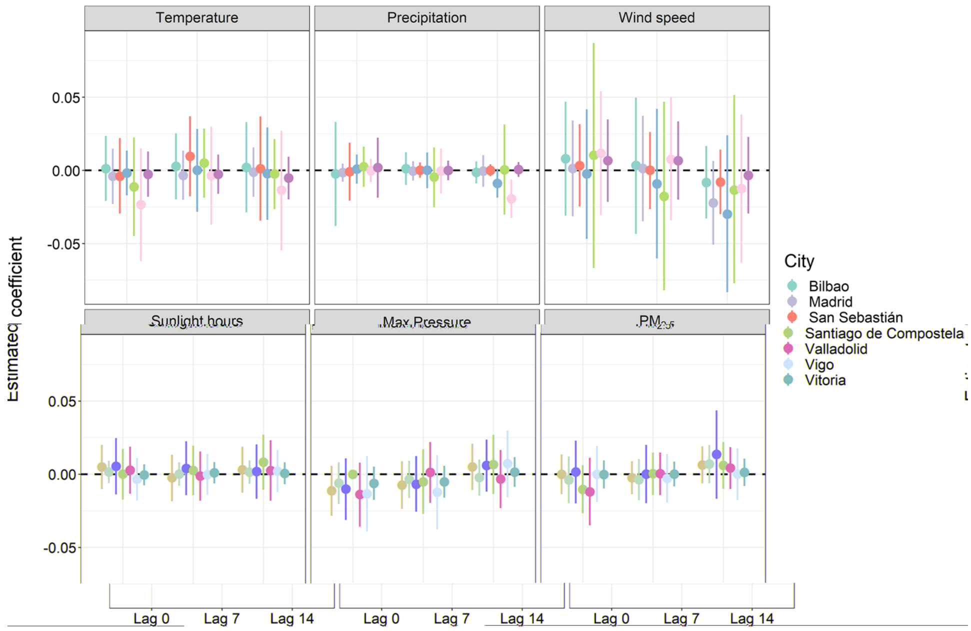

Fig. 4 Effects of each environmental covariate and $PM_{2.5}$ exposure on COVID-19 spread estimated for each city under study. Each dot represents the estimation of the coefficient (β parameter in Eq. (2)), whereas the segment corresponds to the 95% credible interval associated with the estimation

Conclusions

Air pollution was analyzed at the city-level through a regression model to determine the changes of $PM_{2.5}$ during the Spanish lockdown while accounting for the effect of some meteorological factors. While the 4-week national lockdown reduced the COVID-19 accumulated cases in Spain, the results of this study show a significant decrease of $PM_{2.5}$ pollution in only one city. Furthermore, no relationship between COVID-19 spread and $PM_{2.5}$ exposure or weather patterns was found during this period in Spain.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s40201-022-00786-2.

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Declarations

Conflict of interest Authors have no conflict of interests.

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