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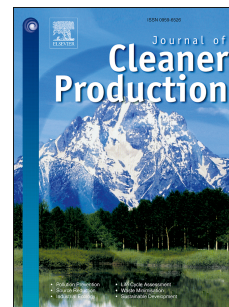
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Traffic-induced atmospheric pollution during the COVID-19 lockdown: Dispersion modeling based on traffic flow monitoring in Turin, Italy

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20 Europe, and also its high density of vehicular emissions. A Lagrangian approach is applied to
21 illustrate and analyze the effect of imposing full lockdown restrictions on the reduction of traffic-
22 induced air pollution in the city. To do this, the real-time traffic flow during the lockdown period
23 is recorded, and by utilizing CALPUFF version 7, the dispersion of PM_{2.5}, Total Suspended
24 Particulate (TSP), Benzo(a)pyrene (BaP), NO_x, and Black Carbon (BC) emitted from all
25 circulating vehicles during and before the lockdown period are compared. Results indicate that the
26 concentration of pollutants generated by road traffic sources (including passenger cars, busses,
27 heavy-duty vehicles, light-duty vehicles, mopeds, and motorcycles) reduced at least 70% (for
28 PM_{2.5}) up to 88.1% (for BaP) during the studied period. Concentration maps show that the
29 concentration reduction varied in different areas of the town, mainly due to the characteristics and
30 strength of the emission sources and the geophysical features of the area.

31 **Keywords:** Air quality, Dispersion Modeling, Emission, Pandemic, Transportation, Urban
32 planning.

33 1. Introduction

34 The novel coronavirus-caused infectious disease 2019 (COVID-19), which was announced as
35 a pandemic by the World Health Organization (WHO) on March 11, 2020 (WHO, 2020) has made
36 a shock to the world and is turning into the largest threat to the public health worldwide in the 21st
37 century (Chakraborty and Maity, 2020). To control the disease outbreak and flattening the
38 epidemic curve, many regions have been imposing a partial or full lockdown in the highly infected
39 areas. Although the lockdown restrictions were established to save public health by reducing the
40 transmission of the virus, changes in the air and water quality in some areas (Ambade et al., 2021;

41 Muhammad et al., 2020; Saadat et al., 2020; Sharifi and Khavarian-Garmsir, 2020) have attracted
42 the attention towards the environmental impacts of the pandemic lockdowns globally. In this
43 regard, numerous research has been conducted on the changes in the air quality during the
44 lockdown period in different countries across the globe, from China in the East (Griffith et al.,
45 2020; Huang et al., 2020) to the United States in the West (Naeger and Murphy, 2020; Zangari et
46 al., 2020), and some large areas such as western Europe (Menut et al., 2020). Besides, several
47 pieces of research studied the potential link between the improvements in the air quality as a result
48 of mitigating COVID-19 measures and the health benefits. These studies mainly concluded lower
49 air pollution-related mortality due to less exposure to air pollution during this period (Gupta et al.,
50 2020; Liu et al., 2021; Son et al., 2020). All these studies highlight the importance of air pollution
51 control strategies to protect human health whether air pollutants increase the infection rate of
52 COVID-19 or not (Cazzolla Gatti et al., 2020; Collivignarelli et al., 2021a; Dettori et al., 2020).

53 Air pollution, with its impacts both at the local and global scales, has caused many challenges
54 and problems all around the world over the years (Izquierdo et al., 2020; Sivarethinamohan et al.,
55 2020) such that concerns about this issue have been reflected in the 2030 Agenda for Sustainable
56 Development adopted by the United Nations General Assembly (UN, 2015). The WHO has labeled
57 air pollution as the major environmental threat to health (WHO, 2016) and has estimated that
58 around 90% of the world population do not breathe the air complying with its Air Quality
59 Guideline (WHO, 2005). Exposure to air pollutants leads to three million deaths per year (WHO,
60 2016), out of which 600,000 deaths happen among children less than five years of age (WHO,
61 2017). Such negative health impacts impose substantial economic costs to the societies (Chen and
62 Chen, 2021; Stewart et al., 2017) and affect both humans and ecosystems (Panepinto et al., 2014).
63 Therefore, in order to take steps towards clean air transitions, air quality action plans have been

64 considered as blueprints to achieve certain air quality objectives (Gross et al., 2019) by many
65 countries all around the world, such as Spain (Izquierdo et al., 2020), China (Cai et al., 2017), the
66 United Kingdom and the United States (Gross et al., 2019).

67 Air quality analysis and modeling in urban areas involve an inherent complexity (Pinto et al.,
68 2020) due to the existence of a high number of air pollutant emission sources, the meteorological
69 conditions of the region affecting the dispersion of the pollutants (Shen et al., 2021) and the
70 chemical transformations of pollutants into secondary aerosols (EPA, 2015). However, air
71 pollution dispersion models provide useful means to support decision-making in air quality control
72 (Holnicki et al., 2016; Ravina et al., 2019) through estimating the concentration of pollutants in
73 the atmosphere (Khan and Hassan, 2020). These deterministic mathematical models mostly follow
74 Gaussian, Eulerian, or Lagrangian approaches (Liu et al., 2019), the Gaussian being a steady-state
75 model and the two others being time-dependent (Khan and Hassan, 2020).

76 Dispersion models have been widely used for modeling the concentration of air pollutants in
77 various case studies. In research conducted by Kesarkar et al. (2007), AERMOD, which is a
78 steady-state Gaussian model, was utilized to model the dispersion of PM₁₀ in Pune, India.
79 Modeling the dispersion of PM₁₀ was also conducted by Brusca et al. (2016) for the city of Turin,
80 Italy, which is also the case study in the present research, by applying a 3D Computational Fluid
81 Dynamics (CFD), coupling Eulerian and Lagrangian approaches. Omidi Khaniabadi et al. (2018)
82 used the Gaussian SCREEN3 model and a Gaussian plume model to investigate the dispersion of
83 fine particles including PM₁₀, PM_{2.5}, and PM_{1.0} related to a cement plant in Iran. Abdul-Wahab et
84 al. (2017) considered a cement plant in Oman and used CALPUFF, as an advanced non-steady-
85 state Lagrangian puff model, to model the dispersion of CO₂ emission. Moreover, Ravina et al.

86 (2018) used CALPUFF as a part of an integrated dispersion and externalities model to estimate
87 the delta-concentration maps for NO_x , $\text{PM}_{2.5}$, and PM_{10} and calculate the health damage costs for
88 the district heating system in the city of Turin. Selection among CALPUFF, SPRAY (which is a
89 Lagrangian particle model), and AERMOD for modeling the pollutant dispersion is possible in the
90 extended version of this integrated model (Ravina et al., 2020b).

91 Air pollution in urban areas is mainly linked with vehicular trips (Guttikunda et al., 2019; Pinto
92 et al., 2020; Xiang et al., 2020). Therefore, the travel of various types of vehicles with different
93 ages and fuel types on urban roads and streets adds more complication to the inherent complexity
94 of the air quality modeling. However, air pollution dispersion models have also been used in the
95 literature with a focus on traffic-induced air pollution. For instance, in the Tehran Metropolitan in
96 Iran, which is struggling with air pollution as a major problem, Shahbazi et al. (2017) studied the
97 impact of the traffic emission reduction plans on the concentration of CO and NO_x in the city by
98 using Comprehensive Air Quality Model with Extensions (CAMx) that is an Eulerian
99 photochemical model. Also, Shahbazi and Hosseini (2020) used CAMx to investigate the
100 concentration of CO, NO_2 , O_3 , $\text{PM}_{2.5}$, SO_2 , and Black Carbon (BC) in Tehran in a highly polluted
101 period in December 2017. Furthermore, considering the high level of traffic-related pollution in
102 the metropolitan area of Madrid, Spain, and the Air Quality and Climate Change Plan launched by
103 the city council to tackle air pollution issues, Izquierdo et al. (2020) used an Eulerian chemical-
104 transport model called Community Multiscale Air Quality (CMAQ) to evaluate the outcome of
105 implementing this plan regarding the concentration levels of $\text{PM}_{2.5}$, NO_2 and O_3 in the city. In
106 another research, Borge et al. (2018) also used CMAQ to assess the traffic-related NO_2 emissions
107 based on a short-term action plan in the city of Madrid. Applying CALPUFF, Abdul-Wahab and

108 Fadlallah (2014) and Charabi et al. (2018) studied the concentration of CO, NO_x, and CO₂
109 resulting from traffic in two different areas in Oman.

110 The lockdowns imposed by the governments to control the spread of COVID-19 highly
111 impacted the transportation sector in all countries (Gualtieri et al., 2020; Ranjbari et al., 2021), and
112 therefore, rather significant improvements in the air quality in this period have been reported in
113 many areas (Chen et al., 2021; Gautam, 2020; Wang et al., 2020; Xiang et al., 2020). However, Le
114 et al. (2020) highlighted the unexpected air pollution in northern China during the COVID-19
115 lockdown period, which happened despite up to 90% reduction of certain emissions from various
116 sources in this period. Improvements in the air quality have also been observed in Italy (Deserti et
117 al., 2020a, 2020b), with an average of 48-60% reduction in road traffic leading to a significant
118 reduction in NO₂ levels (Gualtieri et al., 2020). Collivignarelli et al. (2021b) studied the impact of
119 the pandemic on the concentration of NO₂ in three megacities of London, Milan, and Paris,
120 highlighting the role of traffic restrictions on the reduction of NO₂ concentration in these cities.

121 Although Xiang et al. (2020) showed that considering meteorological conditions plays a
122 significant role in concluding the impacts of the pandemic on the traffic-induced air pollution
123 levels within the cities, to the best of the authors' knowledge, no study has utilized air pollution
124 dispersion models to study the changes in the concentration of air pollutants during the COVID-
125 19 pandemic lockdown mainly focusing on the changes in urban transportation activities, yet. This
126 is while some pieces of research are available on the analysis of the impact of COVID-19
127 restrictions on the changes in the traffic-related air pollution considering meteorological conditions
128 from the lens of statistical analysis (Chen et al., 2021; Rossi et al., 2020; Xiang et al., 2020).
129 Furthermore, as stated by Gualtieri et al. (2020), most of the studies focusing on the implications

130 of COVID-19 lockdowns for the urban air quality lack quantification of the changes in road mobile
131 sources during the lockdown restrictions.

132 Therefore, to fill the existing gap, the present research aims at applying a Lagrangian approach
133 to illustrate and analyze the role of traffic in the city of Turin, Italy, on the air quality of the city
134 during the lockdown period. This is done by comparing the emission of NO₂, Benzo(a)pyrene
135 (BaP), PM_{2.5}, Total Suspended Particulate (TSP), and BC from all traffic mobile sources in the
136 city during normal days and the COVID-19 country lockdown period based on the real-time traffic
137 flow data recorded in this period. Since the first pandemic lockdown and mobility restrictions in
138 Italy led to 42% fewer daily trips (Cartenì et al., 2020), modeling the dispersion of traffic-induced
139 pollutants before and during the lockdown period can provide useful insight into the role of mostly
140 unnecessary traffic in polluting the atmosphere in this city.

141 The remainder of the paper is structured as follows. Section 2 introduces the study area and
142 provides an overview of the research method applied, and the data gathered. Sections 3 presents
143 the results and section 4 provides a discussion and analysis on the maps illustrating the
144 concentration of pollutants before and during the lockdown period. Finally, section 5 concludes
145 the key findings of the paper on the changes in the concentration of air pollutants during the
146 COVID-19 pandemic lockdown, which are attributed to the changes in vehicular transportation
147 activities.

148

149 2. Materials and Method

150 2.1. Description of the study area

151 This research considers the city of Turin as the study area for two main reasons: (1) its special
152 meteorological and geographic condition in Po Valley, which is one of the most polluted regions
153 in Europe both in summer and winter (Deserti et al., 2020a); and (2) its high density of vehicular
154 emissions, which is among the highest in Europe (Padoan et al., 2018).

155 Turin, the capital of the Piedmont region, is a highly industrialized city and densely populated
156 metropolitan area, enjoying a humid subtropical climate. Being known as one of the most
157 technological industrial centers in Europe, this city is located in the western end of the Po Valley,
158 one of the most polluted areas in Europe in the northern part of Italy (Bono et al., 2016; Deserti et
159 al., 2020a). The city suffers from the low dispersion of pollutants, since it is surrounded by the
160 Alps and hills in the North, West, and East, and the wind speed in this area is low. Therefore, the
161 air quality standards are not met in this city (Padoan et al., 2018), and the air quality of Turin is
162 put among the worst in Europe (Sicard et al., 2020).

163 Research shows that the individual particles of atmospheric PM in Turin are small enough to
164 enter the deep zones of the resident's lungs and cause serious health problems for them
165 (Malandrino et al., 2016). Road traffic is one of the most important sources of pollutant emissions
166 in Turin, owning the following share of the total concentration in the city: 40% of the PM₁₀, 30%
167 of the PM_{2.5}, and 75 - 77% of NO₂ (Padoan et al., 2018; Piedmont Region, 2018). The motorization
168 rate in Turin is around 615 per 1000 inhabitants (Kyoto-Club, 2019), leading to a high car density
169 in this city. Therefore, studying the role of traffic in the emission of air pollutants is of high
170 importance in this region.

171

172 2.2. Data

173 2.2.1. Traffic flow

174 The traffic flow data considered in the current research refers to two time periods before and
175 during the first COVID-19 lockdown in the city of Turin. The pre-lockdown flow data were taken
176 from the standard hourly mean flows for the year 2018 provided by 5T S.r.l., a company working
177 in the areas related to traffic management in Turin. For the full lockdown period, the real-time
178 traffic flow reported continuously by the real-time traffic monitoring of the 5T website
179 (http://opendata.5t.torino.it/get_fdt) was recorded from March 9th to May 18th, 2020, representing
180 the lockdown period. The recording was conducted with a frequency of 10 minutes and then, mean
181 hourly flow was calculated and used for the analysis. The real-time traffic monitoring network in
182 Turin is based on 31 traffic sensors, however, not all these sensors are properly transmitting data.
183 Therefore, in this study, the analysis is restricted to 15 monitoring points, which effectively report
184 data. Although this traffic monitoring network reports average vehicle speed in every road branch,
185 speed data were not employed in the present study, due to low accuracy. For both the pre-lockdown
186 and full lockdown periods, the available data reported total traffic flow, which was subsequently
187 disaggregated based on circulating vehicle categories.

188

189 2.2.2. Vehicle type share

190 44 categories of circulating motor vehicles were identified for Turin, considering the class of
191 vehicles in the city and the type of fuel they consume. These categories include busses (consuming

192 diesel, CNG, or electricity), heavy-duty and light-duty vehicles (consuming conventional or Euro
193 1-6 standard petrol), mopeds and motorcycles (consuming conventional or Euro 1- 3⁺ standard
194 petrol), and passenger cars (consuming electricity, or any conventional or Euro 1-6 standard diesel,
195 LPG or petrol).

196 The shares of vehicles before the lockdown were estimated based on the total number of
197 registered vehicles in each category in the city extracted from Automobile Club d'Italia
198 (<http://www.aci.it/>), and the hourly flow extracted from a report by 5T S.r.l. on vehicular mobility
199 in the Piedmont region (5T and Regione_Piemonte, 2019). For the lockdown period, the share of
200 each category in the hourly traffic flow in both working and non-working days was considered in
201 the simulation. Since no data on the share of each of the 44 specified categories in the hourly traffic
202 flow of Turin was available, and this type of data could not be extracted from the recorded traffic
203 flow, an estimation for the share of these vehicles in the traffic flow was made. The data regarding
204 the circulating vehicles was estimated based on the average number of kilometers traveled, and the
205 data regarding the registered vehicles were considered in order to verify the consistency of the
206 disaggregation into categories.

207

208 2.2.3. Emission factors

209 Traffic-induced emissions of NO_x, BaP, PM_{2.5}, TSP, and BC were considered in this research.
210 The emission factors of these pollutants, except for BC, for each of the specified 44 categories of
211 vehicles were extracted from the EMEP/EEA air pollutant emission inventory guidebook 2019
212 (<http://efdb.apps.eea.europa.eu/>). The emission factors for BC were extracted from Krecl et al.

213 (2017) for HDVs, from Ježek et al. (2015) for LDVs and motorbikes, and from Zavala et al. (2017)
 214 for buses. Emission factors for electricity consumption were considered zero. These factors are
 215 reported in Table A1 in Appendix A with a description of the vehicle categories and the average
 216 share of total traffic flow in Turin.

217 Total daily pollutant emission was calculated considering the average hourly share of vehicle
 218 flow for each of the 44 categories. For each hour and each road source, daily pollutant emission
 219 flow of a generic pollutant P was calculated based on Equation (1),

$$P = \sum_i \sum_j \sum_h F_{i,j,h} L_i EF_{P,j} \quad (1)$$

220 where $F_{i,j,h}$ is the traffic flow in road i for vehicle category j at hour h (vehicles h^{-1}); L_i is the
 221 length of the road (m), and $EF_{P,j}$ is the average emission factor of the vehicle category j in terms
 222 of the pollutant P ($g km^{-1} vehicle^{-1}$).

223

224 2.2.4. Meteorology

225 Meteorological data were collected from three different meteorological stations in Turin,
 226 which are managed by the Local Environmental Protection Agency (ARPA) of the regional air
 227 pollution service of Piedmont Region (Figure 1). Hourly observations at the ground level of air
 228 humidity, precipitation, solar radiation, temperature, atmospheric pressure, wind speed, and wind
 229 direction were collected for this research. The radiosoundings from the WMO station of Milano
 230 Linate Airport, which is located approximately 150 km east of Turin, were considered for the
 231 collection of the required upper-air data (<http://weather.uwyo.edu/>). Although this station is rather

232 far from Turin, it is the only source of data in this regard and its soundings can be used considering
233 the relative morphological homogeneity of the western part of the Po Valley (Calori et al., 2006)
234 in which Turin is located. Weather observations were first processed with the CALMET model
235 and then were fed into CALPUFF to conduct the dispersion modeling.

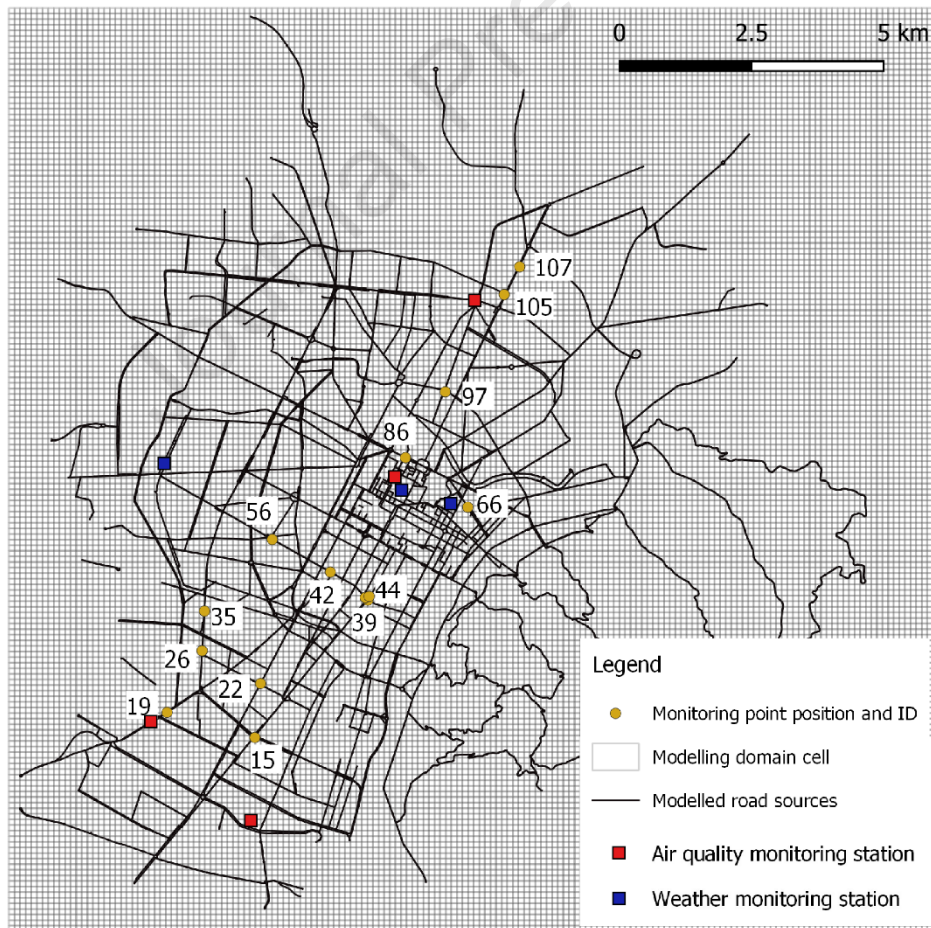
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237 2.3. Dispersion modeling

238 In this study, the dispersion of pollutants was simulated using the CALPUFF modeling system.
239 CALPUFF is a Lagrangian multi-layer, multi-species, non-steady-state puff dispersion model that
240 simulates the effects of time- and space-varying meteorological conditions on pollution transport,
241 transformation, and removal (US EPA, 2011). This model simulates puffs of the materials emitted
242 from the modeled sources, reproducing dispersion and transformation processes along the way.
243 Temporal and spatial variations in the meteorological fields are explicitly incorporated in the
244 resulting distribution of puffs throughout a simulation period.

245 With the release of CALPUFF version 7, the linear sources have been replaced with road
246 sources. A new module for representing roadway emissions in dispersion model simulations has
247 been implemented. The new approach simulates line sources such as roadways using the concept
248 of rod-like puffs. Emitting rods follow the same rules as emitting horizontally symmetric Gaussian
249 puffs, but far fewer rods aligned with road segments are needed to emulate the uniform distribution
250 of emissions along a road segment. Near-field “hot spots” can be resolved as well as the drift of
251 pollutants to sensitive areas further away. . For more technical details on the CALPUFF model
252 structure, see the user’s guide (Exponent, 2019; US EPA, 2011).

253 Simulations were conducted on a domain of $16.6 \text{ km} \times 14.6 \text{ km}$, with 10 vertical layers and a
 254 100 m grid step. A total number of 2,484 road sources was considered in the simulation. Figure 1
 255 illustrates the modeling domain, the road sources, and the measuring points of traffic flow in the
 256 city. A height of 1.5 m was assigned to the emission sources, which are the circulating vehicles
 257 categorized in each of the 44 specified classes. The detailed setting of simulation parameters is
 258 reported in Table A4 of Appendix A. Due to the high number of emission sources, the
 259 computational time required for the detailed simulation was high and therefore, the period of the
 260 simulation was restricted to one week, i.e. from April 12nd to April 19th, 2020, with hourly time
 261 resolution. No chemical transformation scheme was adopted in the simulations.



262

263 *Figure 1. The modeling domain, the road graph, and the location of the monitoring stations.*

264 The output concentrations were averaged over the observation period with the CALPOST
265 processor and represented in the form of maps. Concentration maps of normal days and the
266 COVID-19 country lockdown period were compared, and the reduction of pollutant concentration
267 was calculated. NO_x to NO₂ conversion was modeled in CALPUFF using the MESOPUFF II
268 scheme (Scire et al., 1984). Hourly ozone background concentrations recorded at the Turin
269 Lingotto monitoring station were provided as input to the model.

270

271 3. Results

272 3.1. Traffic flow

273 Average real-time traffic flow in each hour of the day during the lockdown is compared with
274 the average flow in a normal period, and the flow reduction during the working and non-working
275 days are reported in Tables 2A and 3A in Appendix A, respectively. The same tables also report
276 the average and standard deviation of the traffic flow reduction in each point and each hour of the
277 day. During the working days, 69-88% reduction has been observed in the traffic monitoring points
278 considered. If different hours of the day are examined, traffic flow reduction ranges from 66% to
279 96% during the day. Furthermore, during the non-working days, 74-92% reduction has been
280 perceived in the studied monitoring points. If considering different hours of the day, a range of 49-
281 99% is recognized for the reduction in traffic flow.

282

283 3.2. Pollutants emission and dispersion

284 The average traffic flow F in each road source during the COVID-19 lockdown days was
 285 calculated by scaling the flow in normal days for the average hourly flow reduction observed in
 286 the 15 monitoring points reported in Tables A2 and A3 in Appendix A. The results are reported in
 287 Table 1 and show an emission reduction between 71.4% (PM_{2.5}, working days) and 85.5% (BaP,
 288 non-working days).

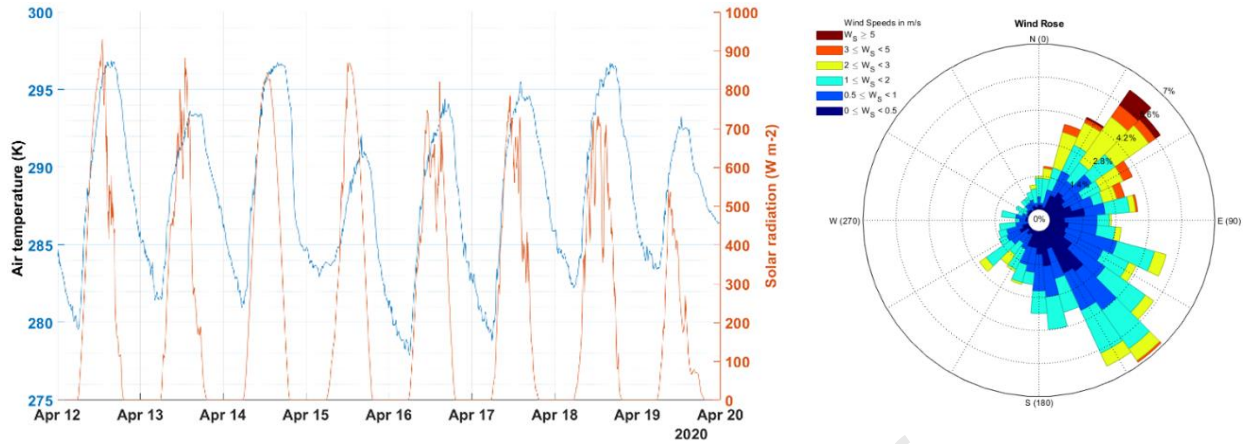
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290 *Table 1. Daily pollutant emissions of Turin road traffic in normal days and during the COVID-19 lockdown.*

Pollutant	Daily emission in normal working days (kg/d)	Daily emission during the lockdown working days (kg/d)	Emission Reduction (working days) (%)	Daily emission in normal non- working days (kg/d)	Daily emission during the lockdown non- working days (kg/d)	Emission Reduction (non-working days) (%)
NO _x	4,501	1,259	72.0	2,404	383	84.0
BaP	6E-03	1.6E-03	73.3	3.8E-03	5.5E-04	85.5
PM _{2.5}	114	32.5	71.4	65	11.1	82.9
TSP	621	174	72.0	337	54.3	83.9
BC	45.4	12.2	73.1	23.7	3.45	85.4

291

292 During the simulation period, there was no rainfall in Turin, except on April 19th, when a total
 293 amount of 1.6 mm of rain was recorded. The temperature and solar radiation, and wind distribution
 294 during this period are also presented in Figure 2. The wind rose in this figure shows two prevailing
 295 wind typologies, which are typical of the area and the period considered. One of them includes
 296 moderate winds ($2 - 5 m/s$) typically occurring during daytime with prevailing direction NE, and
 297 the other includes low winds ($0 - 2 m/s$) typically occurring during nighttime with prevailing
 298 direction SE.

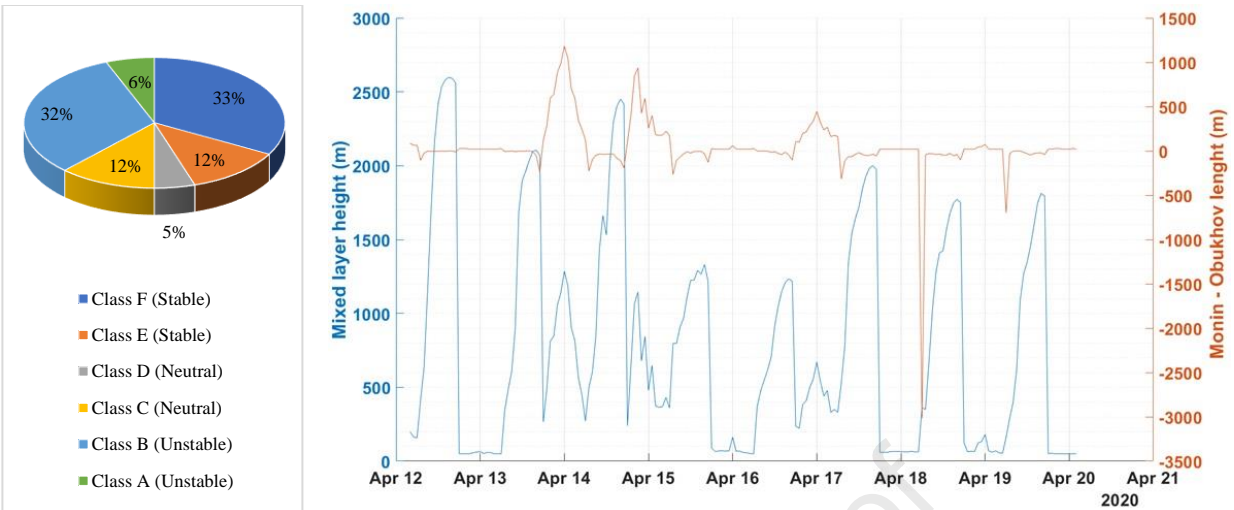


299 *Figure 2. Temperature and solar radiation (left) and wind distribution (right) in Turin during April 12-19, 2020*

300

301 Figure 3 displays the distribution of the atmospheric stability class, and the height of the mixed
 302 layer, and Monin-Obukhov length (L_{mo}) during the simulated period. According to this figure,
 303 stable (class F with a share of 33% and E with 12%) and unstable (class B with 32%) conditions
 304 were prevailing, while neutral conditions (class C with 12% and D with 5%) were less frequent.
 305 This trend is consistent with the general conditions observed during this period. Positive L_{mo} and
 306 limited height of the mixed layer on April 14th, 15th, and 17th indicate that stable atmospheric
 307 conditions were prevailing on these days, while negative L_{mo} values observed on the other days
 308 show the prevalence of unstable conditions, in particular during the daytime.

309

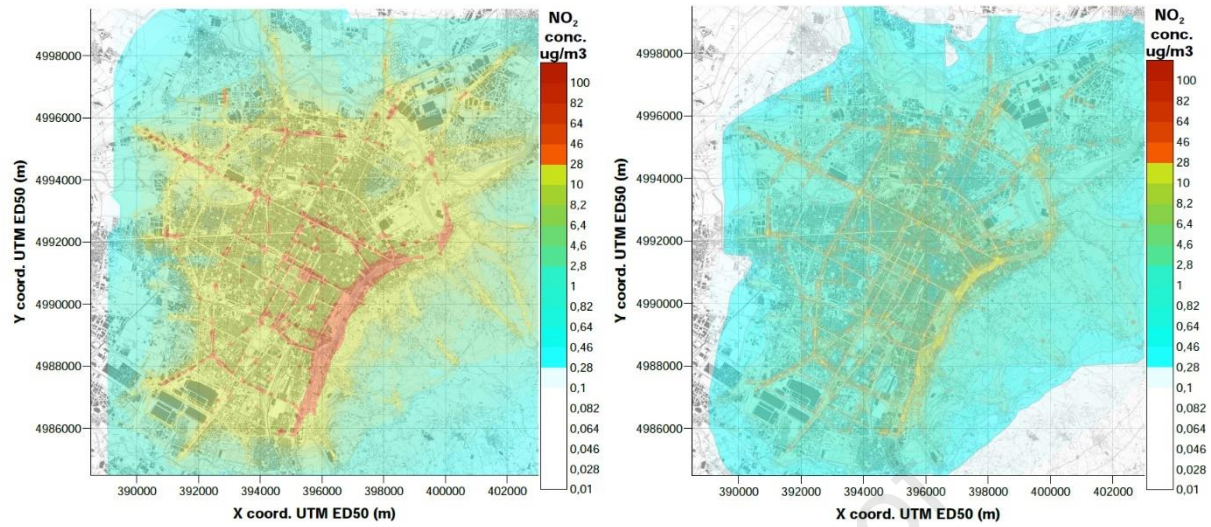


310 *Figure 3. Distribution of the atmospheric stability class (left) and height of the mixed layer and Monin-Obukhov*
 311 *length (L_{mo}) (right) in Turin during April 12-19, 2020.*

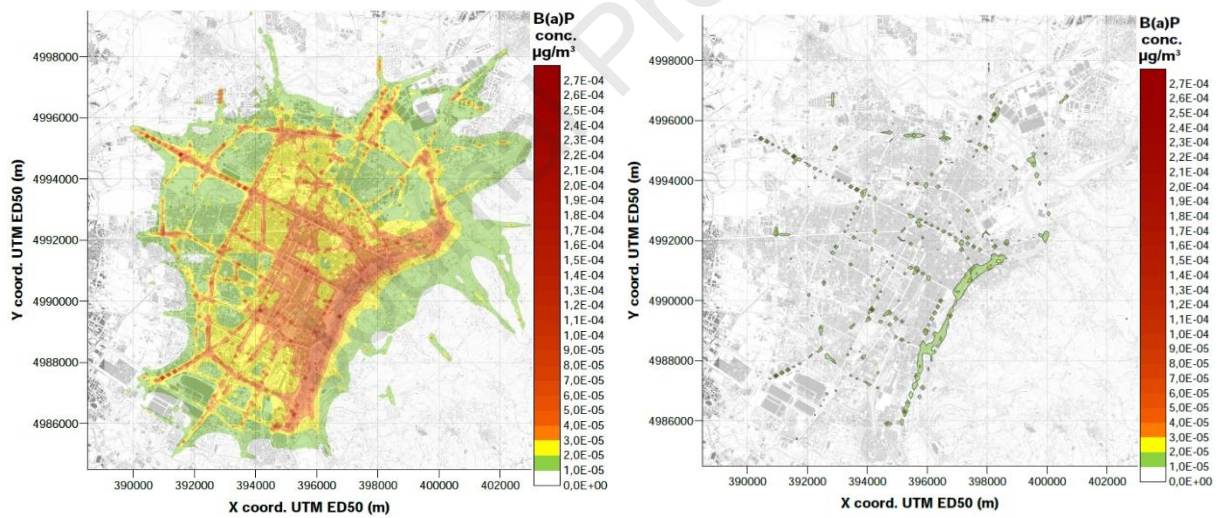
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313 Considering the average traffic flow before and during the lockdown, the share of each type of
 314 vehicle from the flow, and the meteorological conditions during the studied period, the average
 315 pollutant concentration maps are reported in Figure 4 to Figure 8. In these maps, pollutant
 316 concentrations generated by urban road traffic on normal days are compared with those generated
 317 during one week of the COVID-19 lockdown (April 12nd to April 19th, 2020) based on the same
 318 meteorological conditions. The average concentration reduction is reported in Table 2 and finally,
 319 presented in Figure 9.

320



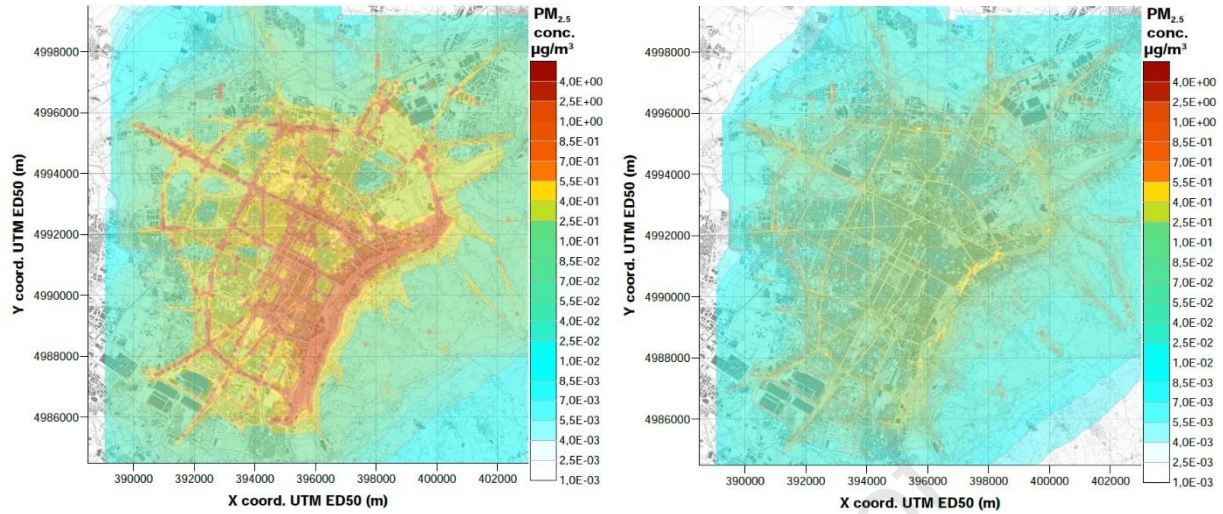
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322 *Figure 4. Maps of NO_2 concentration in the Turin area generated by road traffic sources during normal days (left)*323 *and COVID-19 days (right).*

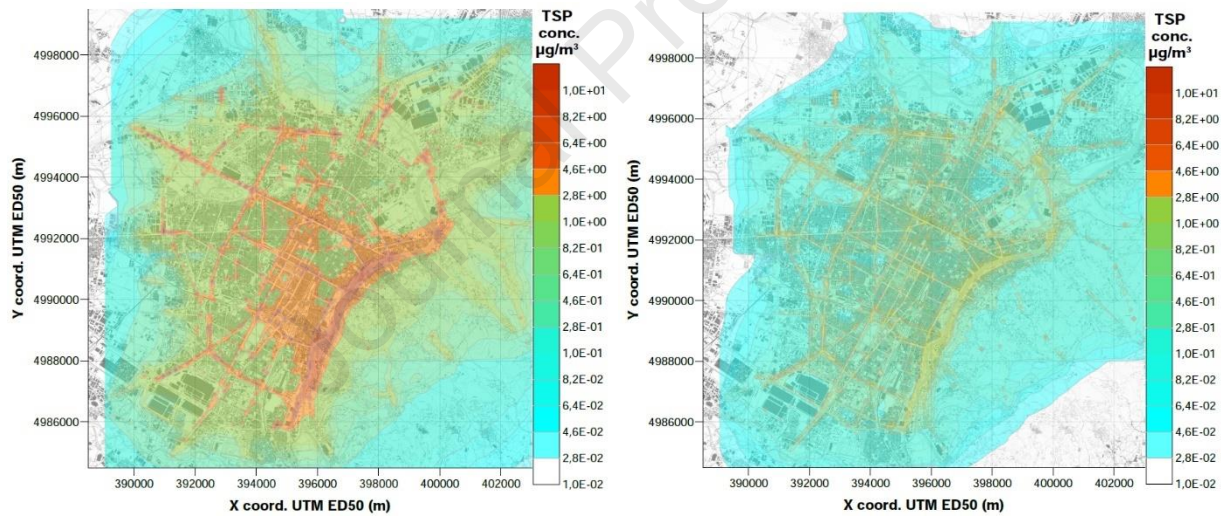
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325 *Figure 5. Maps of BaP concentration in the Turin area generated by road traffic sources during normal days (left)*326 *and COVID-19 days (right).*

327



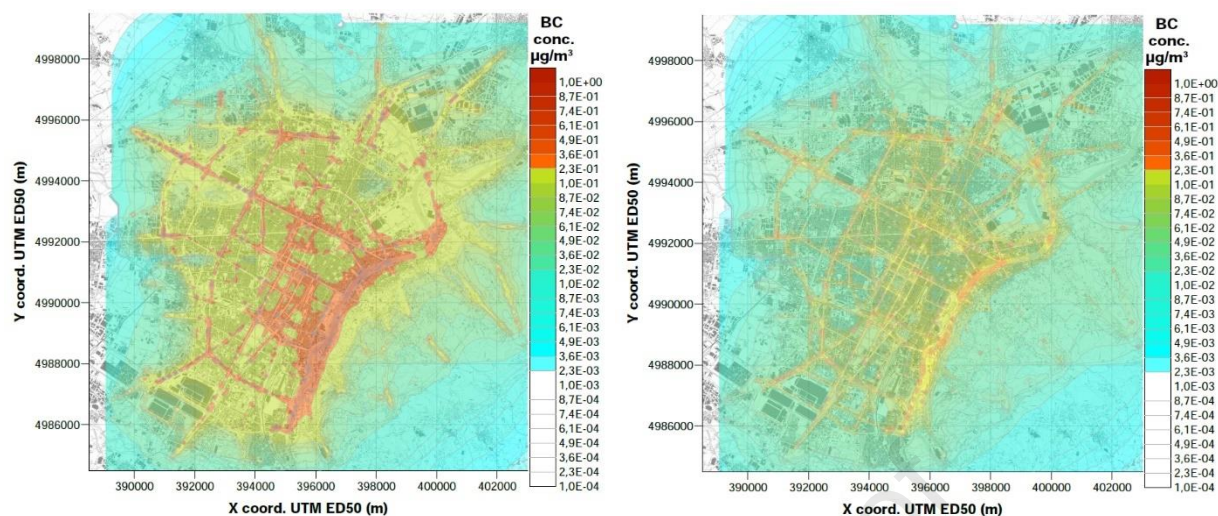
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329 *Figure 6. Maps of PM_{2.5} concentration in the Turin area generated by road traffic sources during normal days (left)*330 *and COVID-19 days (right).*

331

332 *Figure 7. Maps of TSP concentration in the Turin area generated by road traffic sources during normal days (left)*333 *and COVID-19 days (right).*

334



335

336 *Figure 8. Maps of BC concentration in the Turin area generated by road traffic sources during normal days (left)*337 *and COVID-19 days (right).*

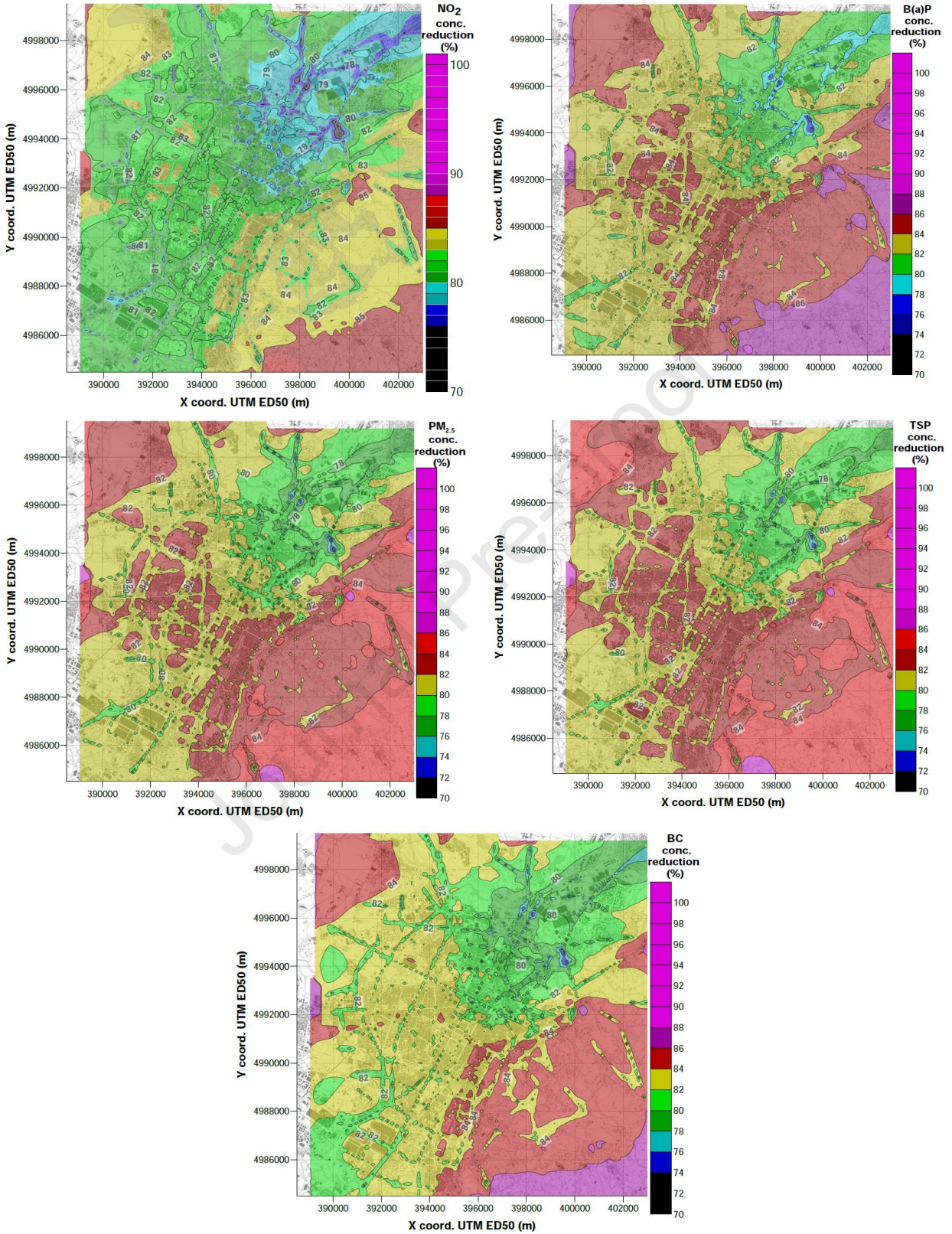
338

339 *Table 2. Pollutant concentration reduction attributed to traffic in the Turin area during COVID-19 days concerning*340 *normal days.*

Pollutant	Traffic concentration reduction (%)		
	min	mean	max
NO _x	70.7	82.2	87.0
BaP	73.5	83.7	88.1
PM _{2.5}	70.0	81.9	86.8
TSP	70.6	82.2	86.9
BC	72.1	83.0	87.9

341

342



343 Figure 9. Maps of pollutants concentration reduction during COVID-19 days concerning normal days.

344

345

4. Discussion

346 The real-time traffic monitoring in Turin during the whole country lockdown period from
347 March 9th to May 18th, 2020, indicated a significant traffic flow reduction in this metropolitan area.
348 Several companies have published periodic mobility reports based on the location data collected
349 through their services, including Google LLC (2020) and TomTom International BV (2020), or
350 have shared their data through analytical platforms, such as Apple Inc. (2020). The data reported
351 in these reports are consistent with the results obtained in our study, all indicating a flow reduction
352 of around 80%. Tables A2 and A3 presented in the Appendix show that traffic flow had a varying
353 reduction depending on the road and hour of the day. Spatial variations are mainly attributed to
354 the road typology. In general, larger roads (e.g. points 15 and 105), which serve as connections
355 between different areas of the city showed lower reductions, while inner roads serving residential
356 areas (e.g. points 39 and 42) showed larger reductions.

357 The decrease in road mobility resulted in a significant reduction in the emission of the
358 considered pollutants during the studied period in Turin, similar to many other cities in Italy
359 (Gualtieri et al., 2020) and other countries (Chen et al., 2021; Collivignarelli et al., 2021b)
360 reporting significant reductions in the traffic-induced emissions during the lockdown restrictions.
361 Comparing the daily emissions of NO₂, BaP, PM_{2.5}, TSP, and BC resulting from the road traffic
362 on normal days and during the COVID-19 lockdown shows that the city experienced more
363 reduction in the emission of air pollutants during non-working days than working days. This
364 difference is mainly due to the activities of some occupations that could not be postponed,
365 canceled, or done from home during the lockdown. Moreover, among the five studied pollutants,

366 BaP had the highest percentage of reduction, while $PM_{2.5}$ showed the lowest percentage of
367 decrease. Different reduction rates may be associated with the difference of emission factors
368 among vehicle typologies. The reduction of traffic flow observed involved mainly a decrease of
369 passenger cars, as this is the most used vehicle typology (81%). For the pollutants whose emission
370 factors for passenger cars have the same order of magnitude as LDVs and HDVs (e.g. BaP, BC),
371 the emission reduction was higher. Conversely, for the pollutants whose emission factors for LDVs
372 and HDVs are higher than those of passenger cars (e.g. NO_x , $PM_{2.5}$), the emission reduction was
373 lower. Although this aspect should be deepened in future studies on traffic flow analysis, the results
374 confirm that the limitation of mobility with private means is of primary importance for
375 administrations (Shams Esfandabadi et al., 2020). These findings are in line with the results of the
376 research conducted by Collivignarelli et al. (2021b), which reports a significant reduction in the
377 concentration of NO_2 during the lockdown period in London, Milan, and Paris and highlight the
378 importance of rethinking vehicles and urban vehicular traffic.

379 As illustrated in the maps of the pollutants concentration reduction in Figure 9 and reported in
380 Table 2, BaP and $PM_{2.5}$ also represent the maximum and minimum percentage of reduction,
381 respectively, in terms of concentration. These results show similar trends for all pollutants, with
382 some minor differences. Regarding $PM_{2.5}$, making a comparison between the results obtained and
383 the existing studies on the COVID-19 lockdown period is difficult. This is because only primary
384 $PM_{2.5}$ emissions were considered in this study. Most of the other studies published recently
385 considered aggregated (primary and secondary) aerosol emissions, highlighting the complexity of
386 the interpretation of $PM_{2.5}$ behavior (Le et al., 2020; Rossi et al., 2020). In general, however, traffic
387 flow reduction was highly reflected in nitrous oxides concentration reduction.

388 Figure 4 to Figure 8 show the spatial distribution of pollutants concentration. The impact is
389 more visible in the proximity of roads, where emissions are generated, but the effects are extended
390 to the whole area. The limited height of sources and the limited dispersion close to the ground are
391 the main factors contributing to the observed trend. These maps also show an uneven distribution
392 of concentration in the area, such that concentrations are higher in the south-eastern part of the
393 town. The presence of a river and reliefs in the eastern part of the city (Figure A1 in Appendix A)
394 contributes to this effect, for two reasons: (1) pollutant dispersion eastwards is limited by the river
395 and reliefs (Ravina et al., 2020a), and (2) traffic is more congested in this area, as the town can
396 only be accessed from north and south. Concentration maps referring to the lockdown period show
397 that the impact, in addition to being reduced, is more limited only to the proximity of the roads.
398 This is an important aspect since consequently, for these pollutants representing a hazard for
399 human health, exposure of the population is limited. Figure 9 shows that the concentration
400 reduction is higher in the north-eastern part of the town. The main reason is that the traffic flow in
401 this area (monitoring points 97, 105, and 107, Table A2 and A3) was less reduced, as mobility in
402 this area is more connected to commercial rather than residential activities.

403 The simulation results for the pollutant NO_2 were compared with the average yearly
404 concentration recorded in four pollutant monitoring stations located in Turin (Rebaudengo,
405 Lingotto, Rubino, and Via Consolata), during the period 2015-2019 and the COVID-19 lockdown
406 period. These monitoring stations record the total ambient concentration of pollutants, which is
407 the result of multiple sources present in the area, as well as the interactions between chemical
408 species and the atmosphere. The comparison is reported in Figure 10. At the Rebaudengo station,
409 the average observed concentration is $65.5 \mu\text{g}/\text{m}^3$ and the simulation model shows a concentration
410 of $41.8 \mu\text{g}/\text{m}^3$. The average observed concentration in the Via Consolata station is $45.3 \mu\text{g}/\text{m}^3$,

411 while the model reports a value of $29.7 \mu\text{g}/\text{m}^3$ for this station. Finally, the Lingotto and the Rubino
 412 stations have recorded the average observed concentration of $33.0 \mu\text{g}/\text{m}^3$ and $31.8 \mu\text{g}/\text{m}^3$,
 413 respectively, while the simulated model shows $25.6 \mu\text{g}/\text{m}^3$ and $15.4 \mu\text{g}/\text{m}^3$ for the two stations,
 414 respectively.

415 These results are also comparable with the source apportionment data reported in Piedmont
 416 Regional Plan for Air Quality (Piedmont Region, 2018). Source apportionment methodology
 417 adopted in this document is based on an integration of modeling and analytical techniques. For the
 418 modeling source contribution, the methodology adopted is the 3D sensitivity runs / Brute Force
 419 Method - BFM. This method involves the creation of a reference simulation (base case) and a
 420 suitable number of sensitivity simulations, one for each emission category to be analyzed. The
 421 contribution of each category is calculated by analyzing the differences between the results of the
 422 sensitivity simulations and those of the base case. Table 3 shows the source apportionment of NO_2
 423 concentrations measured on an annual basis at each of the monitoring stations considered.

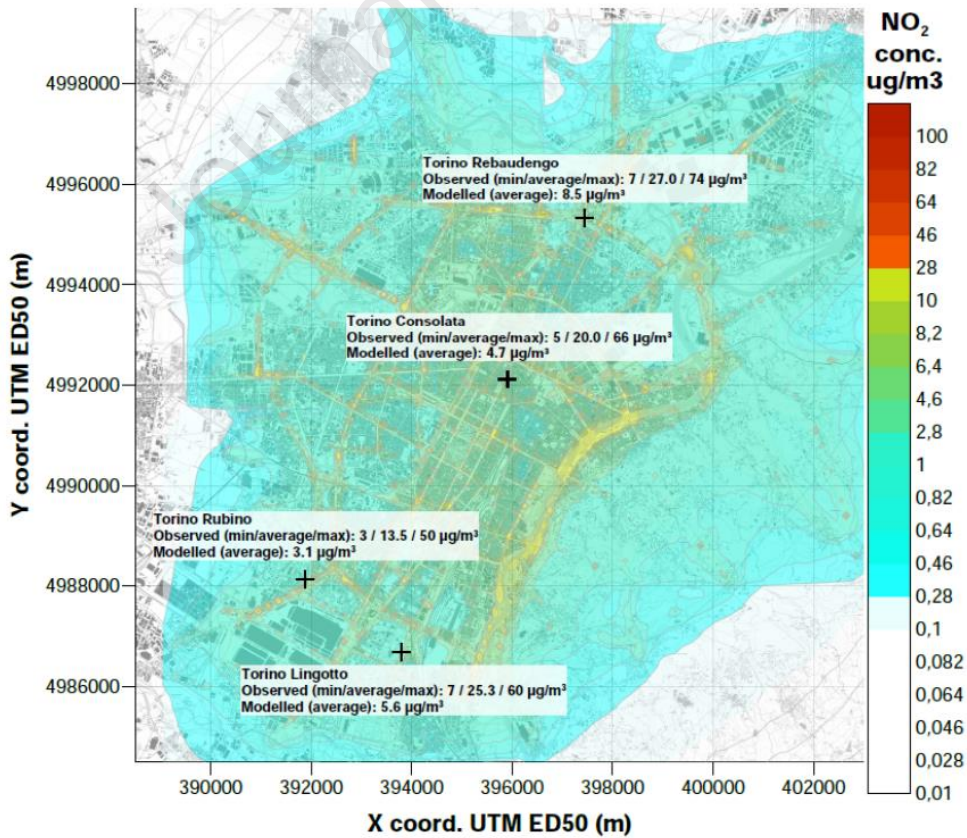
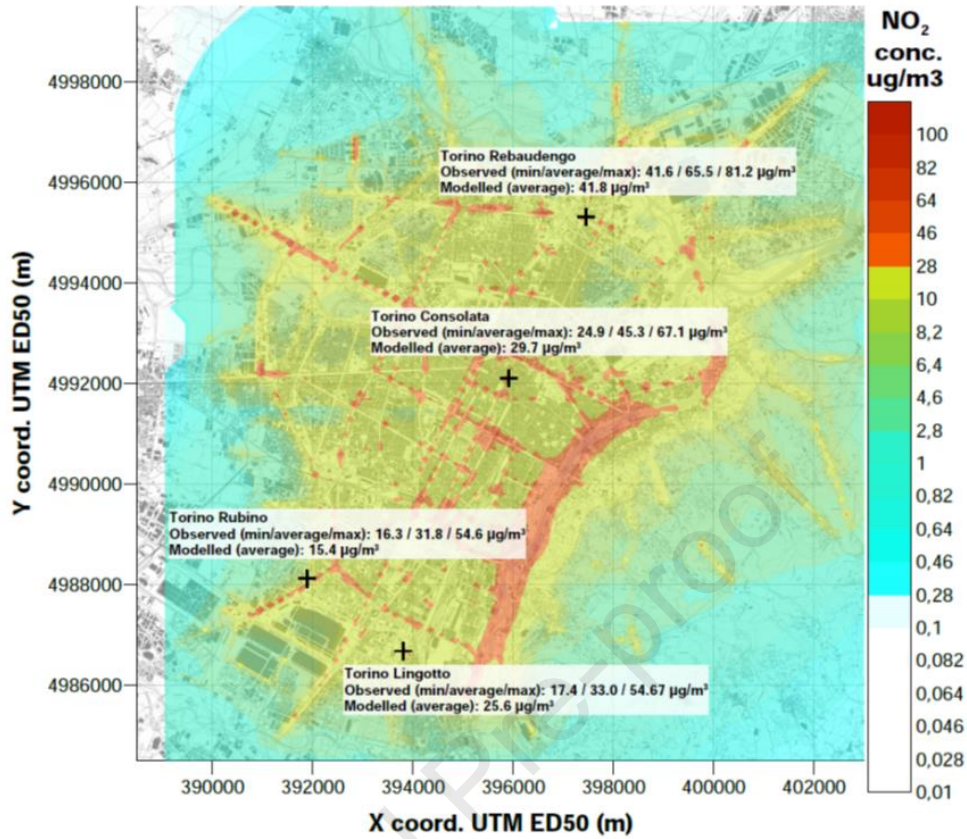
424 *Table 3. Source apportionment of NO_2 concentrations measured on an annual basis at each of the monitoring*
 425 *stations (Piedmont Region, 2018)*

Torino Rebaudengo		Torino Consolata		Torino Lingotto		Torino Rubino	
Emission category	Share	Emission category	Share	Emission category	Share	Emission category	Share
Industry	11.2%	Industry	9.1%	Industry	10.8%	Industry	10.7%
Residential heating	9.0%	Residential heating	9.8%	Residential heating	8.8%	Residential heating	8.7%
Road traffic	74.9%	Road traffic	76.5%	Road traffic	76.2%	Road traffic	76.4%
Agriculture	0.6%	Agriculture	0.7%	Agriculture	0.7%	Agriculture	0.7%
Other	4.3%	Other	3.9%	Other	3.5%	Other	3.5%

426

427 In this table, the share of traffic sources from the total NO₂ concentration is reported as 74.9%
428 for Rebaudengo station, 76.5% for Via Consolata station, 76.2% for Lingotto station, and 76.4%
429 for Rubino station. In the simulated concentrations, a share of 63.8% is found at the Rebaudengo
430 station (-11.1% with respect to the inventory data), a share of 65.5% is found at Via della Consolata
431 station (-11.0%), a share of 77.8% is found at the Lingotto station (+1.6%), and a share of 48.4%
432 is found at the Rubino station (-28.0%). Therefore, simulated concentrations of road traffic sources
433 show a similar share with respect to the measured total concentration. The difference does not
434 exceed 11.1% for three over four monitoring stations. The only exception is the Rubino station,
435 where concentrations are underestimated, probably because of the influence of the nearby ring
436 road, which was not included in the study.

437 During the lockdown period, the estimated contribution of traffic emission to the total recorded
438 concentration fell considerably. A share of 22% was found at the Lingotto station, 23% at Via
439 della Consolata station, 31% at Rebaudengo station, and 23% at Rubino station. This reduced share
440 with respect to the normal period, besides the reduced mobility, may also be attributed to the
441 increase of emissions from the residential sector that was confirmed by other studies (Deserti et
442 al., 2020b). Nevertheless, it must be pointed out that the results reported in Figure 10 mainly serve
443 as a piece of indicative information on the validity of the present analysis, which was strictly based
444 on the comparison of primary pollutant emissions, thus does not consider complex aspects of air
445 quality analysis, such as the interaction of multiple emission sources and secondary pollutant
446 transformations.



448 *Figure 10. Comparison of the model output for NO₂ with the average yearly concentration recorded in four*
449 *pollutant monitoring stations in Turin (Rebaudengo, Lingotto, Rubino, and Via Consolata) in normal days (above)*
450 *and during the COVID-19 lockdown (below).*

451

452 5. Conclusion

453 The COVID-19 lockdown period, in its tragic nature, was a unique experience to analyze and
454 confirm the role of traffic emissions in urban areas. However, studies applying real quantification
455 of traffic flows during the pandemic lockdown period are scarce and the literature lacks the
456 application of Lagrangian dispersion models to simulate the dispersion of traffic-induced air
457 pollution during the COVID-19 lockdown.

458 In this research, the effect of the full lockdown period on the reduction of NO₂, BaP, PM_{2.5},
459 TSP, and BC emitted from the road mobile sources, including various types of passenger cars,
460 busses, heavy-duty vehicles, light-duty vehicles, mopeds, and motorcycles in Turin, one of the
461 most polluted cities in Italy, was investigated. To do so, the real-time traffic flow of the city during
462 the first lockdown period of the country was recorded and fed into a Lagrangian dispersion model.
463 In the case study analyzed, it was clear that the reduction in vehicular traffic in Turin significantly
464 contributed to the improvement of air quality during the lockdown days. Studying the emission of
465 pollutants in the city during a one-week period in the full lockdown condition indicated a reduction
466 between 71.4% (referring to PM_{2.5} during the working days) and 85.5% (referring to BaP during
467 non-working days). Furthermore, the reduction in the concentration of pollutants in this period
468 varied between 70% (for PM_{2.5}) and 88.1% (for BaP).

469 In the concluding remarks, it is necessary to report some important considerations regarding
470 the limitations related to the methodology adopted in the present study. The first is that the present
471 study is based only on the dispersion analysis of primary pollutants and does not consider the
472 totality of the sources present in the area under examination and the chemical transformations
473 occurring between the various species. When considering pollutants that do not tend to undergo
474 secondary transformations, the results reported are fully in line with already published studies
475 (Collivignarelli et al., 2020; Xiang et al., 2020). For PM, it should be noted that the reduction
476 obtained refers only to the primary component. As shown in several other studies (Adams, 2020;
477 Huang et al., 2020; Le et al., 2020; Sreekanth et al., 2021), the overall PM trend, also considering
478 the secondary component, has different results due to multiple factors, which are outside the scope
479 of this study. The second limitation of the method is the application of bulk emission factors, due
480 to the lack of sufficiently accurate data of vehicle speed during the COVID-19 lockdown period.
481 It is not possible to quantify to what extent the change in travel speed resulting from the reduction
482 in traffic flow may have affected vehicle emissions. Considering the method applied, it is clear
483 that in the scenarios examined, the reduction in emissions depended mainly on the reduction in
484 traffic flow on the various sections of the road network and the change in the type of vehicles on
485 the road. The results showed that the reduction of emissions, in addition to the renewal of the
486 vehicle fleet, must be mainly linked to the reduction of movements with private means of transport,
487 given that cars are by far the most present type of vehicles on the road. This consideration is
488 particularly important regarding minor pollutants, such as BaP, and BC, which are majorly
489 dangerous for human health.

490 The subsequent phase of analyzing the spatial distribution of concentrations provided
491 important insights. This research was the first to use a Lagrangian dispersion modeling approach

492 to simulate the dispersion of traffic-induced air pollution during the COVID-19 pandemic. Results
493 showed that in conditions of high vehicular flow, these impacts can extend beyond the proximity
494 of traffic routes and affect pertinent residential areas or parks. On the other hand, a marked
495 reduction in vehicular traffic tends to limit the spatial extension of the impacts. Given the
496 complexity of the subject, these results are recommended to be compared and discussed in future
497 analyses. Confirmation or refutation of these results would bring important implications for air
498 quality and mobility planning in urban areas. Such future studies will bring further knowledge if
499 more detailed and accurate datasets on vehicle flow typology and speed are collected and provided
500 by administrations and stakeholders. Similarly, analyzing different urban areas around the world,
501 in various periods, as well as applying different modeling tools will undoubtedly help increase
502 current knowledge of the topic.

503

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Appendix A. Supplementary data

Table A1. Vehicle categories, the share of total vehicle flow in Turin, and related average emission factors

Category	Technology	Fuel	Abatement	Share from the total vehicle flow (%)	Emission factors (g/km)				
					NO _x	BaP	PM _{2.5}	TSP	BC
1	Buses	Diesel	Urban Buses Standard - Euro V - 2008	0.29%	3.09	9.0E-07	0.046	0.498	0.001
2	Buses	CNG	Urban CNG Buses - EEV	0.04%	2.5	0	0.005	0.163	0
3	Heavy-duty vehicles	Diesel	Diesel 7.5 - 16 t - Conventional	0.46%	8.92	9.0E-07	0.334	0.379	0.205
4	Heavy-duty vehicles	Diesel	Diesel 7.5 - 16 t - Euro I - 91/542/EEC I	0.18%	5.31	9.0E-07	0.201	0.379	0.199
5	Heavy-duty vehicles	Diesel	Diesel 7.5 - 16 t - Euro II - 91/542/EEC II	0.37%	5.5	9.0E-07	0.104	0.379	0.100
6	Heavy-duty vehicles	Diesel	Diesel 7.5 - 16 t - Euro III - 2000	0.55%	4.3	9.0E-07	0.088	0.379	0.090
7	Heavy-duty vehicles	Diesel	Diesel 7.5 - 16 t - Euro IV - 2005	0.67%	2.65	9.0E-07	0.016	0.379	0.016
8	Heavy-duty vehicles	Diesel	Diesel 7.5 - 16 t - Euro V - 2008	0.59%	1.51	9.0E-07	0.016	0.379	0.016
9	Heavy-duty vehicles	Diesel	Diesel 7.5 - 16 t - Euro VI	0.81%	0.291	9.0E-07	0.001	0.379	0.016
10	Light commercial vehicles	Petrol	Diesel - Conventional	0.46%	1.66	2.9E-06	0.179	0.179	0.003
11	Light commercial vehicles	Petrol	Diesel - Euro 1 - 93/59/EEC	0.18%	1.22	6.3E-07	0.117	0.179	0.002
12	Light commercial vehicles	Petrol	Diesel - Euro 2 - 96/69/EEC	0.37%	1.22	6.3E-07	0.117	0.179	0.001
13	Light commercial vehicles	Petrol	Diesel - Euro 3 - 98/69/EC I	0.55%	1.03	6.3E-07	0.078	0.179	0.001
14	Light commercial vehicles	Petrol	Diesel - Euro 4 - 98/69/EC II	0.67%	0.831	6.3E-07	0.041	0.179	0.001
15	Light commercial vehicles	Petrol	Diesel - Euro 5 - EC 715/2007	0.59%	1.15	6.3E-07	0.001	0.179	0.001
16	Light commercial vehicles	Petrol	Diesel - Euro 6 up to 2017	0.81%	0.96	6.3E-07	0.001	0.179	0.001
17	Mopeds and motorcycles	Petrol	2-stroke - Mop - Higher than Euro 3	0.96%	0.25	2.3E-06	0.018	0.091	0.004
18	Mopeds and motorcycles	Petrol	2-stroke - Mop - Euro 3	3.60%	0.25	2.3E-06	0.018	0.091	0.004
19	Mopeds and motorcycles	Petrol	2-stroke - Mop - Euro 2	1.54%	0.25	2.3E-06	0.026	0.091	0.004

20	Mopeds and motorcycles	Petrol	2-stroke - Mop - Euro 1	1.69%	0.25	2.3E-06	0.045	0.091	0.004
21	Mopeds and motorcycles	Petrol	2-stroke - Conventional	3.25%	0.25	2.3E-06	0.091	0.091	0.004
22	Passenger Cars	Diesel	Diesel Medium - Conventional	1.03%	0.546	1.7E-06	0.099	0.099	0.099
23	Passenger Cars	Diesel	Diesel Medium - Euro 1 - 91/441/EEC	0.22%	0.69	1.7E-06	0.084	0.099	0.008
24	Passenger Cars	Diesel	Diesel Medium - Euro 2 - 94/12/EEC	0.84%	0.716	1.7E-06	0.055	0.099	0.042
25	Passenger Cars	Diesel	Diesel Medium - Euro 3 - 98/69/EC I	2.98%	0.773	1.7E-06	0.039	0.099	0.039
26	Passenger Cars	Diesel	Diesel Medium - Euro 4 - 98/69/EC II	6.01%	0.58	1.7E-06	0.031	0.099	0.012
27	Passenger Cars	Diesel	Diesel Medium - Euro 5 – EC 715/2007	6.14%	0.55	1.7E-06	0.002	0.099	0.011
28	Passenger Cars	Diesel	Diesel Medium - Euro 6 up to 2016	11.09%	0.45	1.7E-06	0.002	0.099	0.000
29	Passenger Cars	LPG	LPG - Conventional	0.39%	2.36	1.0E-08	0.002	0.033	0.001
30	Passenger Cars	LPG	LPG - Euro 1 - 91/441/EEC	0.11%	0.414	1.0E-08	0.002	0.033	0
31	Passenger Cars	LPG	LPG - Euro 2 - 94/12/EEC	0.35%	0.18	1.0E-08	0.002	0.033	0
32	Passenger Cars	LPG	LPG - Euro 3 - 98/69/EC I	0.32%	0.09	1.0E-08	0.001	0.033	0
33	Passenger Cars	LPG	LPG - Euro 4 - 98/69/EC II	3.27%	0.056	1.0E-08	0.001	0.033	0
34	Passenger Cars	LPG	LPG - Euro 5 – EC 715/2007	1.85%	0.056	1.0E-08	0.001	0.033	0
35	Passenger Cars	LPG	LPG - Euro 6 – EC 715/2007	3.82%	0.056	1.0E-08	0.001	0.033	0
36	Passenger Cars	Petrol	Petrol Medium - ECE 15/04	5.67%	2.66	4.8E-07	0.002	0.035	0.002
37	Passenger Cars	Petrol	Petrol Medium - Euro 1 - 91/441/EEC	1.11%	0.485	3.2E-07	0.002	0.035	0.002
38	Passenger Cars	Petrol	Petrol Medium - Euro 2 - 94/12/EEC	4.03%	0.255	3.2E-07	0.002	0.035	0.002
39	Passenger Cars	Petrol	Petrol Medium - Euro 3 - 98/69/EC I	4.79%	0.097	3.2E-07	0.001	0.035	0.001
40	Passenger Cars	Petrol	Petrol Medium - Euro 4 - 98/69/EC II	10.02%	0.061	3.2E-07	0.001	0.035	0.001
41	Passenger Cars	Petrol	Petrol Medium - Euro 5 – EC 715/2007	4.86%	0.061	3.2E-07	0.001	0.035	0.001
42	Passenger Cars	Petrol	Petrol Medium - Euro 6 up to 2016	11.33%	0.061	3.2E-07	0.001	0.035	0.001
43	Buses	Electricity		0.01%	0	0.0E+00	0.000	0.154	0
44	Passenger Cars	Electricity		1.15%	0	0.0E+00	0.000	0.033	0

Table A2. Traffic flow reduction in the traffic monitoring points (working days).

Hour of the day	Point	15	19	22	26	35	39	42	44	49	56	66	86	97	105	107	Mean	Std. dev.	
	ID																		
	Coord.	(N W)	7 64666	7 69666	7 64777	7 64663	7 63443	7 63477	7 63477	7 67117	7 67111	7 65555	7 67700	7 66331	7 64008	7 60410			7 67977
00:00 – 00:59		92%	90%	100%	95%	93%	100%	100%	100%	95%	100%	100%	100%	93%	89%	90%	96%	4%	
1:00 – 01:59		100%	90%	100%	90%	85%	100%	100%	100%	100%	100%	100%	100%	85%	92%	91%	96%	6%	
2:00 – 02:59		100%	89%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	72%	87%	86%	96%	8%	
3:00 – 03:59		100%	79%	100%	82%	100%	100%	100%	100%	100%	100%	100%	100%	100%	80%	82%	95%	9%	
4:00 – 04:59		64%	80%	100%	76%	84%	100%	100%	71%	100%	100%	100%	100%	73%	67%	78%	86%	14%	
5:00 – 05:59		44%	60%	86%	71%	72%	67%	75%	71%	86%	70%	72%	76%	71%	60%	76%	70%	10%	
6:00 – 06:59		48%	60%	76%	68%	59%	67%	76%	72%	76%	68%	65%	68%	64%	60%	63%	66%	7%	
7:00 – 07:59		34%	75%	85%	81%	77%	76%	79%	83%	84%	80%	76%	75%	77%	73%	73%	75%	12%	
8:00 – 08:59		55%	74%	78%	80%	75%	78%	78%	74%	83%	74%	77%	73%	74%	73%	76%	75%	6%	
9:00 – 09:59		60%	77%	80%	79%	71%	80%	78%	77%	81%	77%	80%	79%	77%	72%	77%	76%	5%	
10:00 – 10:59		57%	73%	82%	77%	66%	79%	77%	77%	79%	77%	77%	78%	75%	71%	71%	74%	6%	
11:00 – 11:59		61%	74%	84%	76%	65%	77%	77%	77%	75%	75%	76%	78%	73%	69%	70%	74%	5%	
12:00 – 12:59		55%	73%	84%	75%	66%	77%	73%	77%	72%	77%	75%	77%	70%	69%	69%	73%	6%	
13:00 – 13:59		51%	72%	81%	74%	66%	77%	75%	75%	71%	74%	77%	75%	70%	68%	68%	72%	7%	
14:00 – 14:59		57%	76%	81%	74%	68%	79%	78%	81%	79%	79%	77%	79%	74%	72%	70%	75%	6%	
15:00 – 15:59		60%	77%	83%	77%	71%	80%	79%	82%	80%	80%	80%	80%	76%	73%	73%	77%	6%	
16:00 – 16:59		65%	76%	86%	79%	74%	84%	83%	83%	78%	82%	82%	82%	76%	73%	76%	79%	5%	
17:00 – 17:59		71%	77%	85%	78%	74%	84%	82%	84%	77%	83%	79%	80%	76%	74%	78%	79%	4%	
18:00 – 18:59		77%	80%	87%	82%	78%	83%	84%	85%	76%	83%	82%	81%	77%	77%	81%	81%	3%	
19:00 – 19:59		74%	84%	87%	85%	82%	87%	83%	89%	81%	85%	84%	86%	79%	81%	84%	83%	4%	
20:00 – 20:59		76%	86%	92%	85%	81%	88%	86%	89%	87%	86%	85%	90%	82%	85%	82%	85%	4%	
21:00 – 21:59		76%	85%	92%	86%	80%	85%	86%	85%	85%	84%	90%	89%	82%	82%	81%	84%	4%	
22:00 – 22:59		79%	89%	92%	85%	82%	91%	90%	94%	87%	91%	89%	91%	84%	83%	79%	87%	5%	
23:00 – 00:59		90%	90%	96%	92%	89%	96%	96%	93%	94%	95%	94%	95%	91%	85%	91%	92%	3%	
Average		69%	78%	88%	81%	77%	85%	85%	84%	84%	84%	84%	85%	78%	76%	78%	81%	5%	
Std. dev.		18%	8%	8%	8%	11%	10%	9%	10%	9%	10%	10%	10%	8%	9%	8%			

Table A3. Traffic flow reduction in the traffic monitoring points (non-working days).

Hour of the day	Point ID																Mean	Std. dev.
	15	19	22	26	35	39	42	44	49	56	66	86	97	105	107			
	Coord. (N W)	45.0326, 7 64666	45.0364, 7 67666	45.0413, 7 67666	45.0463, 7 64777	45.0527, 7 63443	45.0550, 7 63477	45.0553, 7 67117	45.0555, 7 67111	45.0593, 7 67700	45.0645, 7 66311	45.0702, 7 64088	45.0780, 7 69410	45.0887, 7 67077	45.1045, 7 68885	45.1090, 7 70115	45.1090, 7 70110	
00:00 – 00:59	94%	96%	100%	97%	97%	100%	100%	100%	100%	100%	100%	100%	98%	96%	93%	97%	98%	2%
1:00 – 01:59	100%	97%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	95%	97%	97%	99%	2%
2:00 – 02:59	100%	96%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	95%	96%	99%	2%
3:00 – 03:59	100%	94%	100%	96%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	94%	94%	99%	2%
4:00 – 04:59	100%	91%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	82%	100%	98%	5%
5:00 – 05:59	48%	61%	93%	59%	50%	84%	100%	71%	83%	80%	79%	84%	78%	72%	72%	74%	14%	
6:00 – 06:59	0%	35%	71%	45%	15%	49%	80%	71%	71%	55%	45%	47%	55%	41%	56%	49%	21%	
7:00 – 07:59	35%	51%	80%	63%	51%	72%	47%	77%	55%	61%	65%	45%	68%	51%	49%	58%	12%	
8:00 – 08:59	58%	68%	82%	75%	69%	74%	76%	82%	72%	68%	67%	73%	76%	67%	71%	72%	6%	
9:00 – 09:59	64%	78%	93%	85%	78%	79%	78%	77%	82%	80%	80%	84%	84%	80%	80%	80%	6%	
10:00 – 10:59	75%	80%	93%	85%	79%	84%	78%	88%	85%	86%	86%	87%	85%	82%	85%	84%	4%	
11:00 – 11:59	78%	85%	91%	85%	79%	81%	78%	85%	82%	80%	81%	86%	81%	85%	84%	83%	3%	
12:00 – 12:59	76%	86%	91%	84%	81%	82%	82%	86%	81%	81%	85%	86%	81%	85%	82%	83%	3%	
13:00 – 13:59	61%	82%	88%	78%	70%	79%	77%	82%	72%	78%	76%	81%	71%	80%	72%	77%	6%	
14:00 – 14:59	54%	77%	90%	79%	71%	79%	80%	88%	80%	80%	81%	85%	75%	80%	79%	79%	8%	
15:00 – 15:59	80%	84%	92%	88%	77%	87%	84%	88%	88%	86%	89%	91%	83%	88%	85%	86%	4%	
16:00 – 16:59	85%	90%	92%	87%	82%	88%	90%	89%	91%	87%	90%	93%	85%	87%	88%	88%	3%	
17:00 – 17:59	87%	90%	92%	86%	78%	87%	88%	92%	90%	87%	89%	93%	85%	88%	89%	88%	4%	
18:00 – 18:59	86%	90%	93%	87%	81%	87%	88%	91%	91%	87%	88%	92%	84%	89%	89%	88%	3%	
19:00 – 19:59	85%	91%	94%	85%	81%	87%	88%	90%	87%	87%	87%	92%	84%	90%	88%	88%	3%	
20:00 – 20:59	81%	89%	94%	85%	80%	87%	85%	88%	86%	82%	84%	91%	82%	90%	85%	86%	4%	
21:00 – 21:59	78%	87%	91%	85%	79%	81%	85%	89%	83%	81%	88%	90%	83%	89%	81%	85%	4%	
22:00 – 22:59	75%	89%	93%	86%	84%	84%	90%	94%	89%	89%	94%	91%	82%	87%	85%	87%	5%	
23:00 – 00:59	87%	92%	98%	94%	87%	94%	95%	92%	93%	94%	93%	94%	90%	91%	90%	92%	3%	
Average	74%	82%	92%	84%	78%	85%	86%	88%	86%	85%	85%	87%	83%	83%	83%	84%	4%	
Std. dev.	23%	15%	7%	13%	19%	11%	12%	9%	11%	12%	13%	14%	11%	13%	12%			

Table A4. Setting of dispersion simulation parameters.

Parameter	Description	Setting
MGAUSS	Vertical distribution used in the near field	Gaussian
MCTADJ	Terrain adjustment method	Partial plume path adjustment
MSPLIT	Puff splitting	allowed
MCHEM	Chemical mechanism	Transformation rates computed internally (MESOPUFF II scheme)
MDRY	Dry deposition modeled	Not modelled
MDISP	Method used to compute dispersion coefficients	Dispersion coefficients from internally calculated sigma v, sigma w using micrometeorological variables (u*, w*, L, etc.)
MTAULY	Method used for Lagrangian timescale for Sigma-y	Draxler default 617.284 (s)
MCTURB	Method used to compute turbulence sigma-v & sigma-w using micrometeorological variables	Standard CALPUFF subroutines
MBCON	Boundary conditions (concentration)	Not modelled

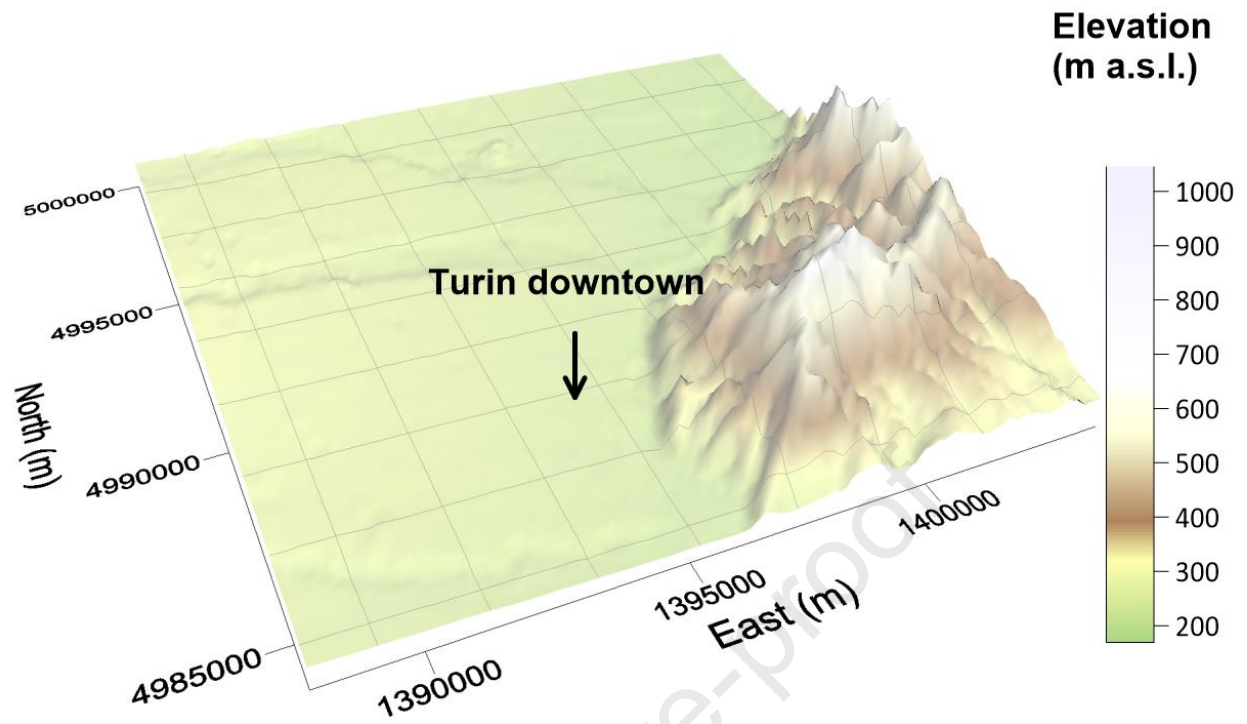


Figure A1. Topography of the modelling domain.