



HAL
open science

Assessing the Effectiveness of an Urban CO₂ Monitoring Network over the Paris Region through the COVID-19 Lockdown Natural Experiment

Jinghui Lian, Thomas Lauvaux, Hervé Utard, Francois-Marie Breon, Grégoire Broquet, Michel Ramonet, Olivier Laurent, Ivonne Albarus, Karina Cucchi, Philippe Ciais

► To cite this version:

Jinghui Lian, Thomas Lauvaux, Hervé Utard, Francois-Marie Breon, Grégoire Broquet, et al.. Assessing the Effectiveness of an Urban CO₂ Monitoring Network over the Paris Region through the COVID-19 Lockdown Natural Experiment. *Environmental Science and Technology*, 2022, 56 (4), pp.2153-2162. 10.1021/acs.est.1c04973 . hal-03604090

HAL Id: hal-03604090

<https://hal.science/hal-03604090v1>

Submitted on 31 Mar 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Copyright

1 Assessing the effectiveness of an urban CO₂
2 monitoring network over the Paris region through
3 the COVID-19 lockdown natural experiment

4 *Jinghui Lian^{1,2,*}, Thomas Lauvaux², Hervé Utard¹, François-Marie Bréon², Grégoire Broquet²,*
5 *Michel Ramonet², Olivier Laurent², Ivonne Albarus^{1,2}, Karina Cucchi¹ and Philippe Ciais^{2,3}*

6 ¹ Origins.S.A.S, Suez Group, Tour CB21, 16 Place de l'Iris, 92040 Paris La Défense Cedex,
7 France

8 ² Laboratoire des Sciences du Climat et de l'Environnement (LSCE), IPSL, CEA-CNRS-UVSQ,
9 Université Paris-Saclay, 91191 Gif sur Yvette Cedex, France

10 ³ Climate and Atmosphere Research Center (CARE-C), The Cyprus Institute, 20 Konstantinou
11 Kavafi Street, 2121, Nicosia, Cyprus

12 **KEYWORDS**

13 CO₂ emissions, city, atmospheric inversion, COVID-19 lockdown

14 **ABSTRACT**

15 The Paris metropolitan area, the largest urban region in the European Union, has experienced
16 two national COVID-19 confinements in 2020 with different levels of restrictions on mobility
17 and economic activity, which caused reductions in CO₂ emissions. To quantify the timing and

18 magnitude of daily emission reductions during the two lockdowns, we used continuous
19 atmospheric CO₂ monitoring, a new high-resolution near-real-time emission inventory and an
20 atmospheric Bayesian inverse model. The atmospheric inversion estimated the changes in fossil
21 fuel CO₂ emissions over the Greater Paris region during the two lockdowns, in comparison with
22 the same periods in 2018 and 2019. It shows decreases by 42~53% during the first lockdown
23 with stringent measures, and by only 20% during the second lockdown when traffic reduction
24 was weaker. Both lockdown emission reductions are mainly due to decreases in traffic. These
25 results are consistent with independent estimates based on activity data made by the city
26 environmental agency. We also show that unusual persistent anticyclonic weather patterns with
27 north-easterly winds that prevailed at the start of the first lockdown period contributed a
28 substantial drop in measured CO₂ concentration enhancements over Paris, superimposed on the
29 reduction of urban CO₂ emissions. We conclude that atmospheric CO₂ monitoring makes it
30 possible to identify significant emission changes (>20%) at subannual time scales over an urban
31 region.

32 **SYNOPSIS**

33 This study quantifies the impact of COVID-19 on CO₂ emissions over Paris via an inverse
34 modeling technique using in situ atmospheric CO₂ observations.

35 **1 Introduction**

36 The world economy has been strongly impacted by the COVID-19 pandemic with many
37 countries enforcing a wide range of measures to limit the spread of the virus. One side effect has
38 been a strong reduction in fossil fuel use, which led to a reduction in global carbon emissions in
39 the first half of 2020 as compared to the same period in 2019^{1,2}. Although the emissions

40 recovered later in the year, 2020 emissions were reported at several percent less than those of
41 2019, i.e. 4% from Carbon Monitor (<https://carbonmonitor.org/>), 6.4% from Tollefson³, and 7%
42 from Le Quéré et al.⁴.

43 At the city scale, the reduction of human and economic activities during the lockdown periods
44 led to measurable decreases in urban anthropogenic CO₂ emissions. The COVID-19 lockdowns
45 provide a testbed to assess the effectiveness of various methods that estimate city-scale CO₂
46 emissions. CO₂ gridded emission maps at fine space and time scales are more informative than
47 city-level inventories. However, these estimates are prone to large uncertainties⁵. To constrain
48 spatial and temporal bottom-up emission estimates, independent information is needed, which
49 motivates the use of atmospheric measurements. Ground-based in situ continuous urban CO₂
50 monitoring stations are usually equipped with high-precision cavity ring-down spectroscopy
51 (CRDS) CO₂ analyzers. Other complementary CO₂ observing systems include low-cost but
52 lower accuracy sensors⁶, localized eddy covariance flux towers⁷, carbon isotope measurements⁸,
53 periodic automobile and aircraft campaigns⁹, as well as satellite and remote sensing¹⁰.
54 Atmospheric measurements can be collected in near-real-time and assimilated with models to
55 constrain emissions with low latency. This is an advantage insofar because most city emission
56 inventories have a lag of at least 1 year. The statistical approach that combines atmospheric
57 measurements with emission inventories and high-resolution transport modeling is called urban
58 atmospheric inversion. Over the last few years, urban inversions mainly based on Bayesian
59 methods, combined with either Lagrangian-based or Eulerian-based atmospheric transport
60 models have been applied to quantify CO₂ emissions on monthly time scales over several
61 metropolitan areas, e.g., Paris, Boston, and Indianapolis^{11,12,13}. However, few inversions have
62 demonstrated the ability to detect and quantify short-term urban emission changes arising from a

63 sudden change in human activities like the COVID-19 pandemic¹⁴. Two recent studies have
64 quantified the reductions of emissions in the San Francisco Bay area, Los Angeles and
65 Washington DC/Baltimore metropolitan areas in the US^{6,15}. These studies have used an inverse
66 method based on the Lagrangian approach. In addition, few inversions have separated emissions
67 from different districts or administrative units within a megacity, mostly because of scarce
68 atmospheric measurements.

69 In France, national authorities implemented two nationwide lockdown periods in 2020: March
70 17th to May 11th (55 days) and October 30th to December 15th (46 days). These two periods were
71 associated with reductions of mobility measures, although with marked differences, with the
72 spring confinement being much stricter than the autumn one. They provide a unique opportunity
73 to evaluate how a Eulerian-based atmospheric inversion system can quantify subannual changes
74 in urban CO₂ emissions from city centers to suburban areas in a timely manner.

75 This study analyzes CO₂ emission changes with Bayesian atmospheric inversions assimilating
76 CO₂ observations from six high-precision in situ stations located in and around the Paris
77 metropolitan area with a high-resolution WRF-Chem transport model and a newly developed
78 near-real-time emission inventory. These inversions are based on an updated version of the
79 Parisian inversion system developed by Bréon et al.¹⁶ and Staufer et al.¹¹, using a well-calibrated
80 version of WRF-Chem intensely evaluated against meteorological and CO₂ measurements by
81 Lian et al.^{17,18,19}. Meanwhile, compared to previous inversion studies over Paris, our observation
82 network grew with two newly built urban stations and four suburban stations operated since
83 2014. Only three suburban sites, operational during the period 2010-2011, were used by Staufer
84 et al.¹¹.

85 In the following, section 2 describes the fossil fuel CO₂ emission inventory, the CO₂ monitoring
86 network, and the city-scale atmospheric inversion system deployed for Paris. Section 3 analyzes
87 in detail the measured CO₂ concentrations and the inversion results. A discussion is given in
88 section 4.

89 **2 Methodology**

90 **2.1 Fossil fuel CO₂ emission inventory**

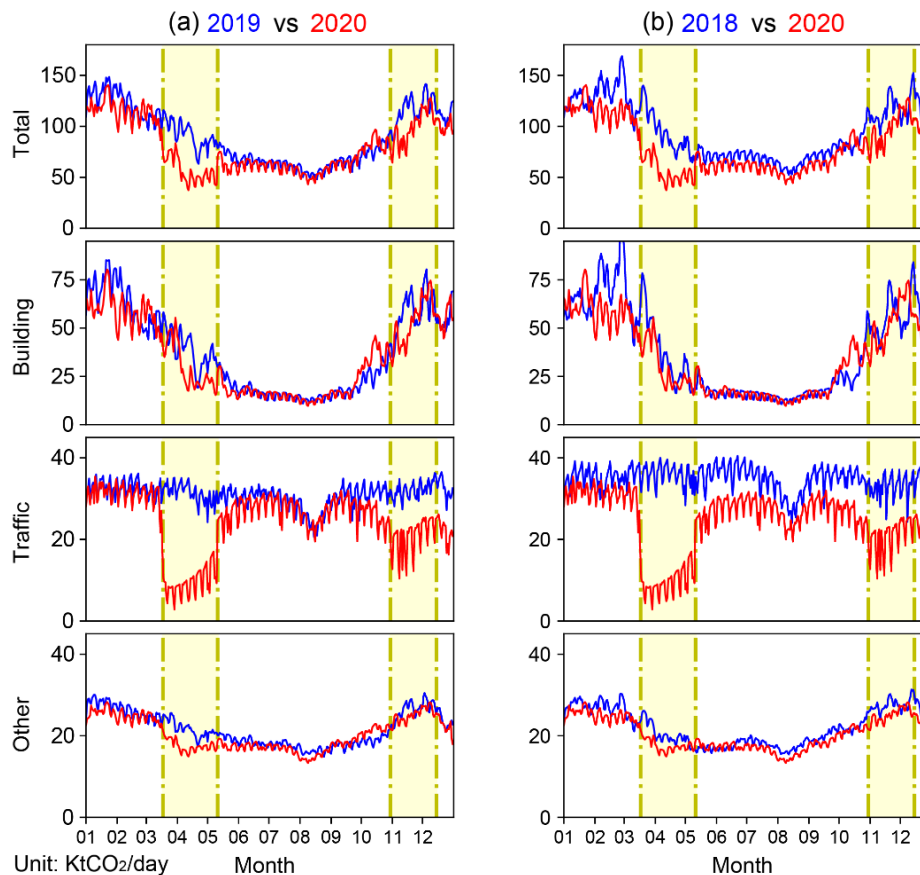
91 This study uses a novel near-real-time data set of fossil fuel CO₂ emissions for the Paris region
92 developed by Origins.earth (<https://www.origins.earth>). The Origins bottom-up inventory
93 provides the Scope 1 hourly gridded CO₂ emissions over Paris from 2018 until the present time
94 for six activity sectors, namely transportation, residential, tertiary, industry (including cement),
95 energy, and waste. CO₂ emissions are available at the hourly time scale and at 1 km × 1 km
96 spatial resolution (SI Appendix, Text S1).

97 The spatial distribution of the total fossil fuel CO₂ emissions from March 17th to May 10th for the
98 years 2018, 2019 and 2020 shows that the emissions are highly concentrated over the city of
99 Paris and its vicinity, mainly due to the high population density, various commercial activities
100 and a high volume of traffic (Figure S1). With the implementation of lockdown measures in
101 2020, a decrease in CO₂ emissions is observed over the center of Paris and the location of
102 highways when compared with the previous 2 years. Figure 1 shows the daily fossil fuel CO₂
103 emissions for 12 calendar months of the year 2020 with comparison to 2018 and 2019 over the
104 entire domain shown in Figure S1. We group the Origins emissions into three main sectors: i)
105 traffic which includes both on-road and nonroad transport, ii) building which includes residential
106 and commercial activities, iii) all other emissions from the remaining sources including industry,

107 energy and waste. The emission budgets of the building sector are 3.43, 3.48 and 2.90 MtCO₂,
108 representing 39.9%, 41.6% and 47.0% of total emissions from March to May for 2018, 2019 and
109 2020 respectively (Figure S2). The traffic sector emissions are of 3.30 MtCO₂ (38.4% of the total
110 emissions from March to May), 2.88 MtCO₂ (34.5%) and 1.54 MtCO₂ (25.0%) from 2018 to
111 2020.

112 The lockdown measures caused a clear decrease in the total CO₂ emissions according to the
113 Origins inventory, as well as in the diurnal and weekly variations (Figures 1 and S3). The most
114 pronounced decline is for the traffic sector as a consequence of the mobility restrictions. A large
115 and sudden decrease in traffic emissions was observed at the beginning of the first lockdown
116 period, followed by a progressive increase over time. The traffic estimates remained below
117 typical levels after the end of the first confinement until mid-June. Starting in July, the traffic
118 emissions recovered to pre-pandemic levels and were at a comparable level to that of the previous
119 years. The traffic emissions in summer showed a small reduction linked to the summer vacation
120 period in July and August. The second lockdown period also led to a drop in CO₂ emissions, but
121 less pronounced than the first one. Less stringent measures were adopted such as keeping schools
122 open and more tolerance to commute to work when needed²⁰. The 2019-2020 emission changes
123 in other sectors are of a smaller magnitude than those of the traffic. Figure 1 shows that CO₂
124 emissions from the building and industry sectors in April and May 2020 were lower than those of
125 2019, which could be interpreted as a consequence of the lockdown. However, as the building
126 emissions are very sensitive to the temperature, one must analyze the interannual temperature
127 anomalies before reaching a causal relationship. Indeed, according to the Météo-France climate
128 bulletin²¹, April and May 2020 were 2.7°C and 2.2°C warmer than 2019, respectively, so that
129 lower emissions are expected, without a COVID-19 effect. Further analyses²² clearly show that,

130 after the correction for temperature anomalies, the daily gas consumption within the city of Paris
131 was still lower in 2020 than it was in 2019.



132
133 **Figure 1.** Comparison of the daily fossil fuel CO₂ emissions for different sectors, namely total,
134 traffic, building (residential and commercial), other (industry, energy and waste) for 12 calendar
135 months of the year (a) 2019 and 2020, (b) 2018 and 2020. The yellow shaded areas indicate the
136 lockdown periods.

137 2.2 CO₂ monitoring network and meteorological measurements

138 Hourly CO₂ measurements collected at six sites, including two urban and four suburban stations,
139 were used in this study. The locations of the stations are shown in Figure 2. Two stations (JUS
140 and CDS) are located within the center of Paris in a dense urban environment where the emission

141 density is the highest. The other four stations (AND, GNS, OVS, SAC) are located at the edges
142 of the urban and built-up areas in mixed urban-rural environments. All of these stations are
143 equipped with high-precision CRDS CO₂ analyzers, with an accuracy that is on the order of a
144 fraction of a ppm with reference to the World Meteorological Organization (WMO) international
145 mole fraction scale²³. The air sampling inlets are installed on rooftops or on towers to extend the
146 footprint of the measurement and reduce the potential impact of local emissions. Apart from the
147 CO₂ measurements, the hourly wind speed and wind direction are measured at a height of 100
148 meters above the ground level at the SAC station. The model-observation misfits for wind are
149 used to filter the CO₂ data to be assimilated in the inversion.

150 **2.3 City-scale atmospheric inversion system**

151 The CO₂ atmospheric inversion system is Bayesian with priors and all error statistics being
152 assumed to be Gaussian (SI Appendix, Text S2). The assimilation of downwind-upwind
153 gradients in CO₂ concentrations for city-scale inversion has been used in this study^{11,16,24}. Using
154 the concentration gradients, rather than the absolute concentrations, in the assimilation system is
155 an effective way to decrease the uncertainties in biogenic and remote fluxes¹⁹. The principles of
156 the inversion used here are similar to those of Bréon et al.¹⁶, Staufer et al.¹¹ and Wu et al.²⁴.
157 However, it uses a specific partition of the emissions in the Île-de-France (IdF) region to support
158 the focus on the emissions from the Greater Paris region. Furthermore, the system has been
159 adapted to assimilate data from the current Parisian CO₂ monitoring network, and to use the 1
160 km-resolution WRF-Chem transport modeling framework developed by Lian et al.^{18,19} (SI
161 Appendix, Text S3).

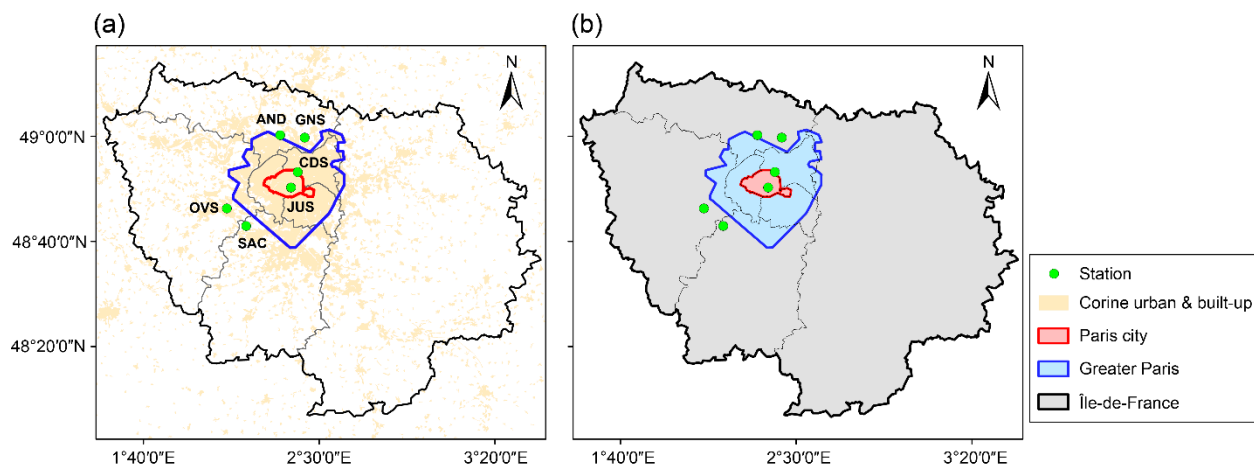
162 The inversion is applied to optimize fossil fuel emissions and biogenic fluxes from March 1st to
163 May 31st and from October 21st to December 23rd for 2018, 2019 and 2020 respectively, which
164 covers the two entire lockdown periods as well as the same periods in the prior 2 years. In the
165 following, section 2.3.1 presents the reference inversion configuration. In section 2.3.2, a set of
166 sensitivity experiments is designed to evaluate the impact of different inversion configurations
167 on the retrieved estimates of fossil fuel CO₂ emissions.

168 **2.3.1 Reference inversion setup**

169 The prior fossil fuel emissions within the IdF region, which includes Paris and its neighboring
170 departments, covering an area of 12012 km² (Figure 2), are based on the Origins inventory.
171 Fossil fuel CO₂ emissions outside the IdF region (but included in the modeling domain, Figure
172 S4) originate from the ODIAC Fossil Fuel CO₂ Emissions Dataset (version name: ODIAC2020)
173 for the year 2018, also at 1×1 km horizontal resolution²⁵. The ODIAC monthly budget was also
174 multiplied by the temporal profiles to account for the weekly and diurnal cycles of the
175 emissions²⁶. Biogenic CO₂ fluxes were simulated with the diagnostic biosphere Vegetation
176 Photosynthesis and Respiration Model (VPRM), coupled online to the WRF atmospheric model
177 used for transporting CO₂, thus ensuring a perfect consistency between the atmospheric physics
178 and the variability in biogenic fluxes^{27,28}.

179 The inversion controls CO₂ emissions by different control vectors that correspond to a sector of
180 activity over a given geographic area and for a given time window. Figure 2, together with Table
181 S1 shows the spatial (i.e. within Paris and outside Paris) and temporal (i.e. 6-hourly windows)
182 resolutions of the control vectors used for the fossil fuel and biogenic fluxes (SI Appendix, Text
183 S4). Concerning the partitioning of fossil fuel emissions, we divided the WRF-Chem innermost

184 domain (Figure S4) into three emitting regions for which the emissions can be optimized: the
 185 Greater Paris region, the rest of the IdF region, and outside the IdF region (Figure 2b). The
 186 Origins inventory estimates that the Paris city, the Greater Paris area (excluding Paris city) and
 187 the rest of the IdF region emitted 4.33, 14.67 and 16.31 MtCO₂, taking up 12.3%, 41.5% and
 188 46.2% of the total fossil fuel CO₂ emissions over the whole IdF region in 2019, respectively.
 189 Note that the sizes of these three regions are significantly different, so that the emissions per unit
 190 area of Paris city is larger than those of the other two, even though its total emissions are smaller.
 191 The inversion system rescales prior estimates over 6-hour time windows (4 unknowns per day,
 192 namely 0:00-6:00, 6:00-12:00, 12:00-18:00, 18:00-0:00 UTC) of the fossil fuel emissions over
 193 the Greater Paris region (including Paris city) that is provided by the Origins inventory. In
 194 addition, we also attempt to further separate the city of Paris (red shaded area in Figure 2b) from
 195 the Greater Paris region (results shown in the discussion section). The inversion system also
 196 optimizes prior estimates of (i) 6 h fossil fuel emission budgets for the rest of the IdF region, (ii)
 197 daily fossil fuel emission budget outside the IdF region, and (iii) daily budget of biogenic fluxes
 198 (net ecosystem exchange - NEE) over the entire model innermost domain provided by the VPRM
 199 model (Table S1).



200

201 **Figure 2.** (a) Yellow shaded areas indicate the Corine urban and built-up land use. The city of
202 Paris is located within the inner red line. The Greater Paris region (blue line) extends over a
203 larger surface, following its administrative boundaries (including Paris city and the three
204 administrative jurisdictions that are around Paris, called “Petite Couronne”). The Île-de-France
205 region (black line) is made up of eight administrative jurisdictions, including the city of Paris,
206 the three Petite Couronne jurisdictions and four other larger jurisdictions with a smaller
207 population density (thin gray lines). (b) Map of the subregions whose fossil fuel emission
208 budgets are controlled by the inversion. In the reference inversion configuration, emissions over
209 three emitting regions are optimized independently: the Greater Paris region (red+blue shaded
210 area), the rest of the IdF region (gray shaded area), and outside the IdF region. Data source: The
211 Corine land cover data are available at [https://land.copernicus.eu/pan-european/corine-land-](https://land.copernicus.eu/pan-european/corine-land-cover)
212 cover.

213 The inversion system assimilates CO₂ concentration gradients between pairs of stations aligned
214 roughly along the wind direction and respectively upwind and downwind a significant area of the
215 city. It is assumed that the signature of remote fluxes is relatively small in such gradients that are
216 dominated by the signature of the city emissions¹¹. The method for the selection of the
217 assimilated CO₂ downwind-upwind gradients was described in detail in Wu et al.²⁴ and is
218 outlined in the SI Appendix (Text S5). The assimilated hourly afternoon CO₂ concentration
219 gradients are given in the SI Appendix (Text S6). The inversion framework also requires
220 prescribing the observation errors and the uncertainties in prior emissions. Assumptions
221 regarding these error covariance matrices are similar to those of Bréon et al.¹⁶ and Wu et al.²⁴,
222 and are detailed in the SI Appendix (Text S7 and Text S8).

223 **2.3.2 Sensitivity tests**

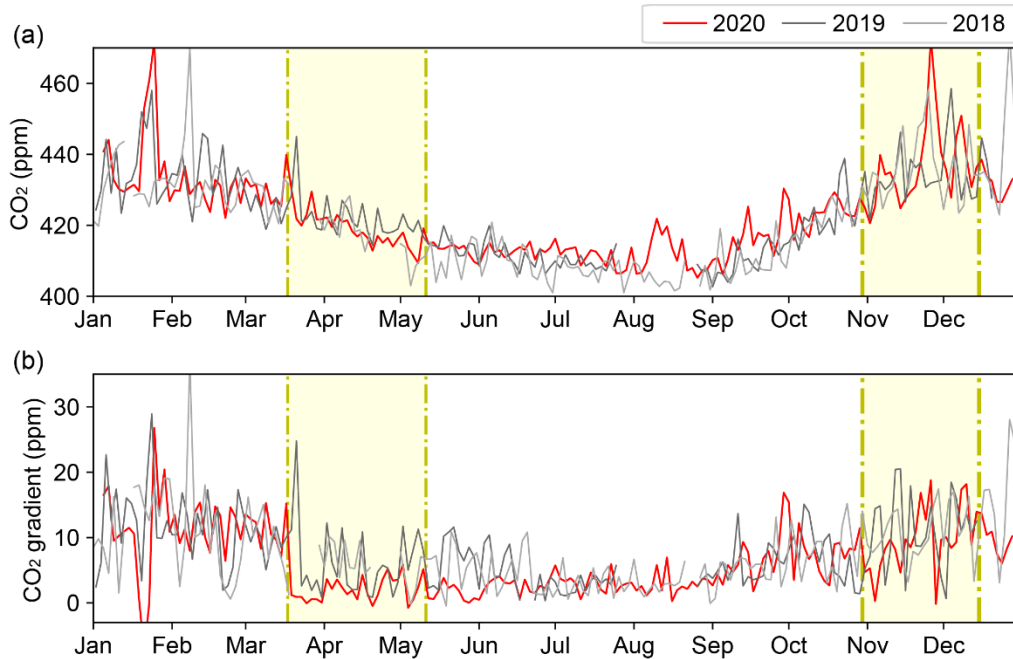
224 To analyze the sensitivity of the results to the inversion configuration, 19 additional inversions
225 were conducted (NO. 2-20 in Table S3). These tests are further classified into three groups. First,
226 three sensitivity tests (NO. 2-4) are designed to analyze the impact of using, or not, the
227 measurements from the two urban stations (JUS and CDS) that lie within the core of the city.
228 Another set of inversions (NO. 5-13) allows us to analyze the sensitivity of the results to the data
229 selection criteria of the assimilated gradients. The third set of sensitivity tests (NO. 14-20) aims
230 at investigating the impacts of uncertainties in prior fossil fuel and biogenic fluxes, as well as
231 their temporal correlations.

232 **3 Results**

233 **3.1 CO₂ concentration measurements**

234 Figure 3a shows the time series of the afternoon (12-17 UTC) averages of the observed CO₂
235 concentrations at JUS, an urban station located in the center of Paris, from 2018 to 2020. It
236 shows that the observed CO₂ seasonal variability is mostly driven by the seasonality in regional-
237 scale biogenic fluxes, whereas meteorological conditions significantly impact the short-term
238 variations (i.e. synoptic and daily time scales). During March 2020, low-pressure systems located
239 north of the British Isles resulted in cloudy skies over the Paris region, a common synoptic
240 regime during winter. In mid-March, the Paris region came under the increased influence of the
241 Azores high-pressure anticyclonic system, favoring the predominance of warm and dry
242 weather²¹. The first lockdown period started simultaneously with a change in meteorological
243 conditions. In addition, the aforementioned warm spring in 2020 led to an early start of the
244 vegetation by about 1 week. Consequently, atmospheric CO₂ concentrations during the first
245 lockdown are not only perturbed by emission reductions but are also influenced by unusual

246 meteorological conditions and early vegetation bloom. No anomalous weather regime nor
247 unusual plant phenology was observed during the second lockdown.



248
249 **Figure 3.** Two-day afternoon (12-17 UTC) mean of the observed: (a) CO₂ concentrations at the
250 JUS station, and (b) CO₂ concentration gradients between JUS and SAC stations. The yellow
251 shaded areas indicate the lockdown periods.

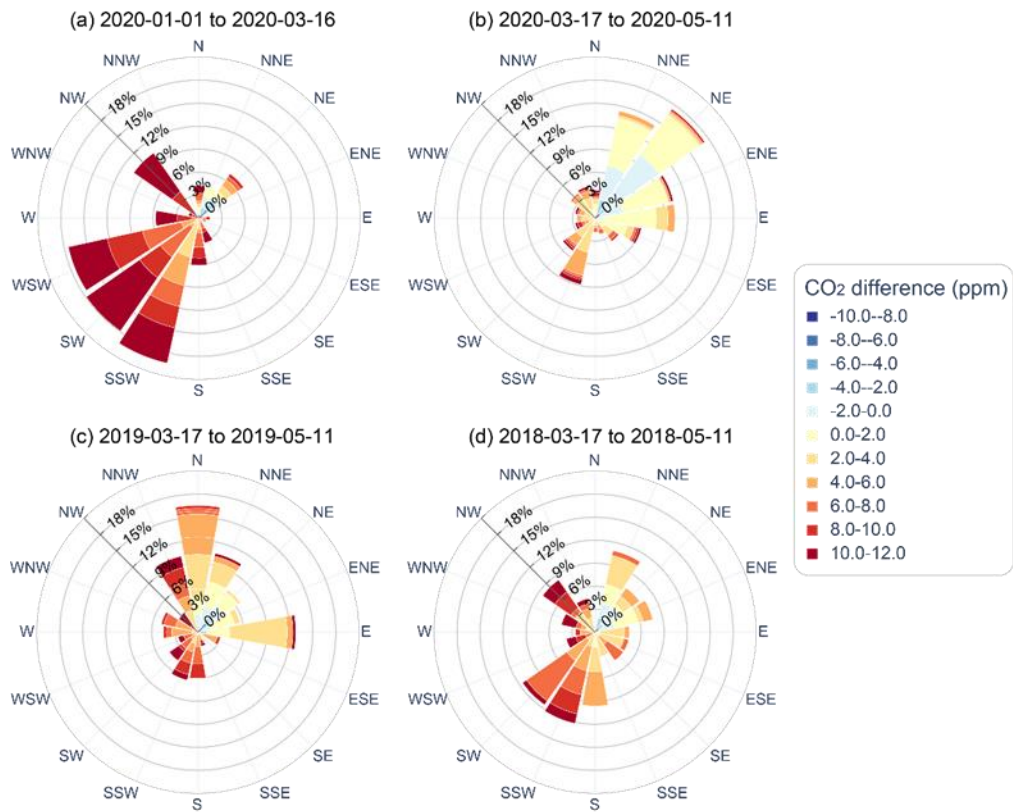
252 The use of CO₂ concentration gradients (downwind-upwind) reduces the impact of boundary
253 CO₂ conditions advected into the Paris area and from remote fluxes in the model domain outside
254 the station's network, facilitating our ability to track CO₂ signals due to fossil fuel emissions
255 from the Paris urban area. We thus computed the differences in CO₂ concentrations between JUS
256 and the SAC station which is located about 20 km southwest of the Paris center in a suburban
257 area. Figure 3b shows that during the first lockdown period, a significant drop in JUS-SAC CO₂
258 concentration gradients is observed with a decrease of 65% when compared to the prelockdown
259 period (SI Appendix, Text S9). However, because the synoptic weather conditions changed at the

260 start of the first lockdown period, analyzing the concentration gradients to determine lockdown-
261 induced fossil fuel CO₂ signals is not possible without filtering specific conditions or using
262 modeling tools, as noted by Ciais et al.²⁹. We therefore show the JUS-SAC CO₂ concentration
263 gradients as a function of wind direction (Figure 4). The hourly afternoon data (12-17 UTC)
264 were classified into different classes ranging from -10 to 12 ppm in steps of 2 ppm. The figure
265 shows the frequency and mean CO₂ difference per bin for the 16 wind direction sectors (22.5°
266 each). For wind fields, we used wind measurements at 100 m above the ground level at the SAC
267 station. The impact of the wind speed is presented in Figure S7, where the JUS-SAC CO₂
268 gradients are shown as a function of wind speed and direction.

269 Figure 4a shows that relatively large CO₂ concentration gradients (8~12 ppm) between JUS and
270 SAC stations are observed during the prelockdown period with prevailing winds from the
271 southwest. These large CO₂ gradients are most likely attributed not only to the high emissions
272 from household heating over Paris but also to the relatively weak vertical mixing in winter.
273 However, the dominant winds changed from southwest to northeast in mid-March 2020,
274 simultaneously with the start of the first lockdown (Figure 4b). The CO₂ wind rose shows a small
275 difference (0~2 ppm) between JUS and SAC in the 22.5-45° sector, which can be expected since
276 the SAC station is downwind of Paris and thus the CO₂ variability is most likely under the
277 influence of the emissions coming from Paris. Moreover, the decrease in CO₂ concentration
278 gradients could also result from a deepening of the mixed layer as well as a reduced household
279 heating demand with increasing temperature. All of these changes obscure the effect of
280 restrictions on fossil fuel emissions during the lockdown.

281 To resolve this question, we compared the CO₂ wind rose during the first lockdown (Figure 4b)
282 to those observed on average during the previous years for the same time interval (Figure 4c and

283 4d). In the 0-90° sector when the wind speeds are lower than 9m/s (Figure S7), the CO₂
 284 concentration gradients between JUS and SAC are smaller in 2020 (< 2 ppm) than in 2018 and
 285 2019 (2~4 ppm). This analysis suggests that the observed drop in the CO₂ concentration gradient
 286 in 2020 is associated with the corresponding reductions of emission sources due to the COVID-
 287 19 lockdown and cannot only be explained by the coincident shift in wind direction. Quantitative
 288 estimation of emissions and biogenic fluxes nevertheless requires an inversion with observed
 289 atmospheric transport fields during the lockdown periods.



290

291 **Figure 4.** CO₂ concentration gradients between JUS and SAC stations as a function of wind
 292 direction over: (a) the prelockdown period from January 1st to March 16th 2020, (b)-(d) the first
 293 lockdown period from March 17th to May 11th 2020, and the same periods of the year in 2019
 294 and 2018. The percentages on the axes indicate the frequency of CO₂ concentration differences

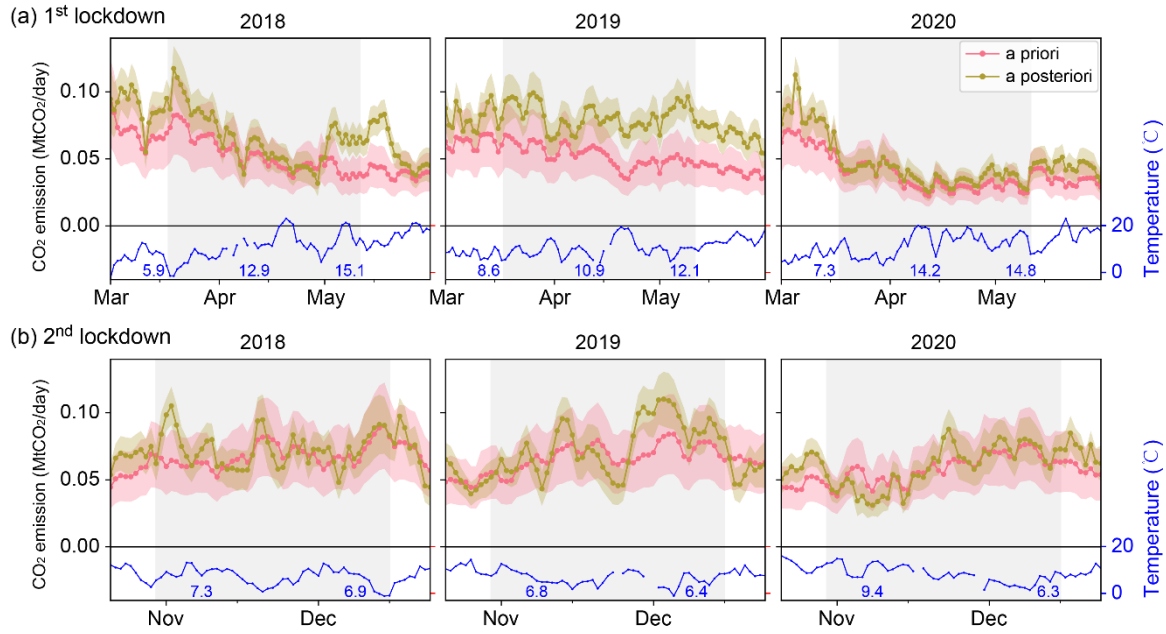
295 within each class interval when winds come from particular directions. Note that only the
296 afternoon data (12-17 UTC) are used in the analysis.

297 **3.2 Inversion results**

298 We first analyze the fit between observed and simulated concentrations from prior and posterior
299 fluxes, as an indication of the efficiency of the inversion in reducing the misfits to the
300 observations. Figure S8 shows that the agreement between the posterior CO₂ concentration
301 gradients as compared to the observations is substantially better than those induced by the prior
302 fluxes (SI Appendix, Text S10).

303 **3.2.1 Daily emission estimates**

304 We use here the reference inversion detailed in section 2.3.1 and focus on the fossil fuel CO₂
305 emissions over the Greater Paris region where most of the emissions are concentrated. The
306 inversion has little impact on the estimate of the fossil fuel fluxes over the rest of the IdF region
307 and the biogenic fluxes (Table S4 and Figure S9), and the reasons are given in the SI Appendix
308 (Text S11).



309

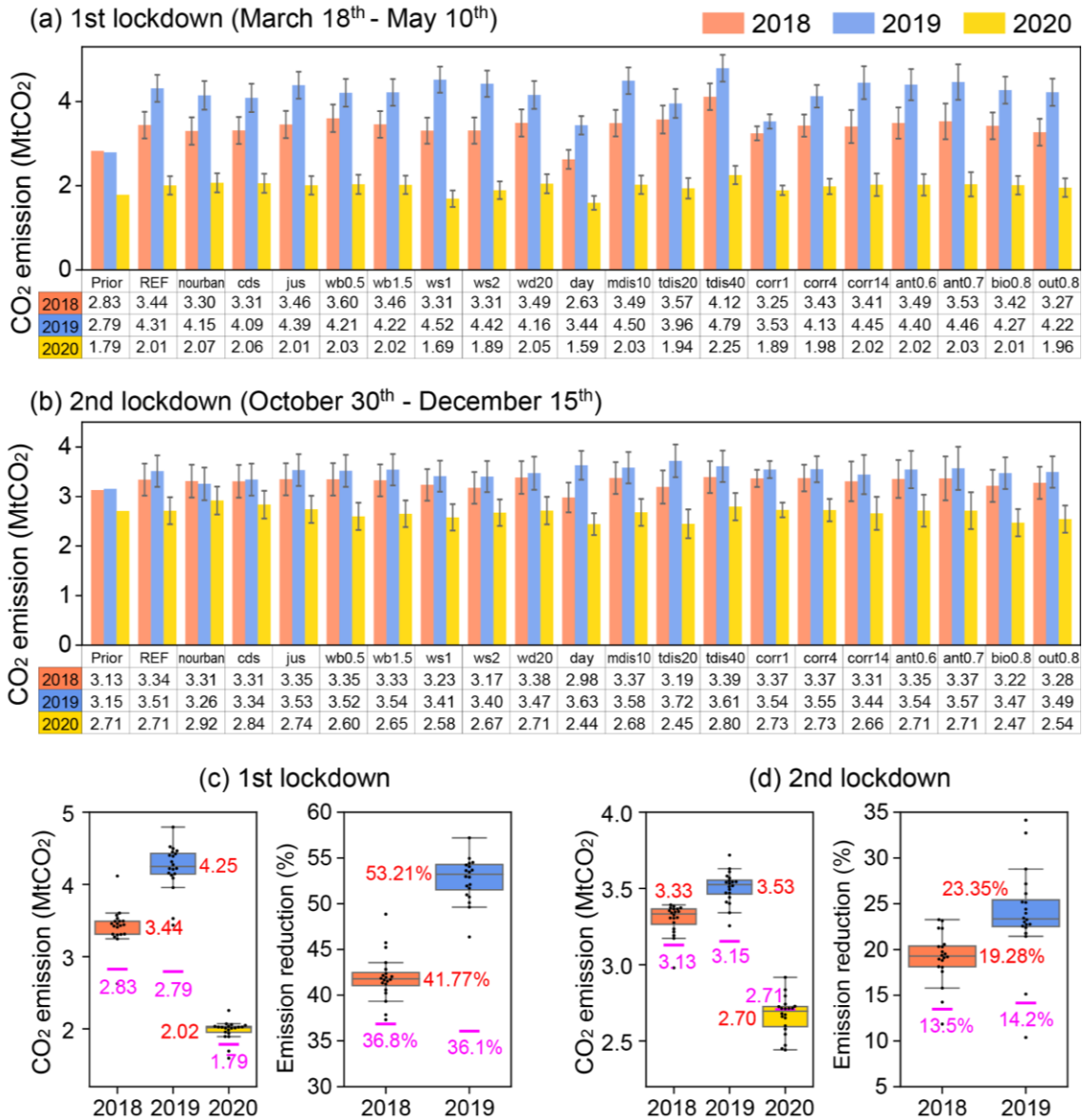
310 **Figure 5.** Daily estimates of the fossil fuel emission for the (a) March 1st - May 31st and (b)
 311 October 21st - December 23rd periods for the years 2018, 2019 and 2020 respectively over the
 312 Greater Paris region. The grey shaded areas indicate the lockdown periods. The pink line and
 313 shading show the prior flux according to the Origins inventory together with its assumed
 314 uncertainty. The yellow and shading show the posterior estimates with their uncertainty ranges.
 315 The blue lines indicate the daily mean temperature measured at 100 m above the ground level at
 316 the SAC station. Numbers in blue at the bottom denote the monthly mean temperature.

317 Figure 5 shows that the posterior emission estimates are generally larger than the prior ones and
 318 have larger temporal variations. Inverse emissions are mostly within the range of the prior
 319 uncertainty. The inversion leads to a reduction of the emission uncertainty by a factor of ~2. We
 320 also found a roughly inverse relationship between the daily mean temperature and daily CO₂
 321 emissions (see the blue line in Figure 5). The highest emission increments are obtained in spring
 322 2019, presumably related to the fact that the monthly mean temperatures in April and May 2019
 323 were lower than those for the other 2 years, by around 2°C.

324 Figure 5 also illustrates modeling errors in the inversion procedure. First, the posterior estimates
325 of the daily fluxes show deviations from the prior that might be caused by atmospheric transport
326 model errors from day-to-day or synoptic scales. One example is the large (a factor of ~ 2)
327 decrease of the a posteriori emissions from November 1st to 7th 2020. We investigated the
328 atmospheric model behavior during this period and concluded that WRF poorly simulates stable
329 atmospheric conditions, with an overestimate of the PBL height. We examined other periods
330 (from May 1st to 15th 2018) when the posterior emissions are much larger than the prior, but the
331 simulated meteorological fields (i.e. temperature, wind and PBL height) agree reasonably well
332 with the observations and are not correlated with cold days, suggesting that some of the observed
333 weekly changes might be due to activity changes.

334 Second, it appears that day-to-day variations of the inverse emissions are also driven by the
335 amount of atmospheric data used. Indeed, because of the selection criteria, the number of
336 assimilated gradients varies considerably from one day to another (Figures S5 and S6). When
337 few or no concentration gradients fit the assigned criteria on a given day, the temporal variations
338 in the inverse emissions rely on observations over neighboring days. A typical example is the
339 period around November 25th 2019. The inverse emissions show a gradual decrease with large
340 posterior uncertainties up to this date, followed by a very sharp increase (factor of more than 2).
341 Further analysis shows that the measured concentration gradients are smaller than those
342 modelled on the 25th, and larger afterward, which explains the sharp increase. There are no valid
343 observations for the period from November 16th to 24th, so the posterior estimates start from the
344 prior, and decrease toward the estimates controlled by the observations of the 25th, because of the
345 prescribed 7-day error correlation length for the fossil fuel emissions.

346 **3.2.2 CO₂ emissions budgets during the lockdown**



347

348

349

350

351

352

353

Figure 6. Sensitivity results for the estimates of the total fossil fuel CO₂ emission budgets during the (a) (c) first and (b) (d) second lockdown periods over the Greater Paris region (including Paris) for the years 2018, 2019 and 2020. Panels (c) and (d) present the distribution of the prior and posterior CO₂ estimates, both for the absolute emission budgets and for the relative emission reduction ratio. The midpoint, the box and the whiskers represent the 0.5 quantile, the 0.25/0.75 quantiles, and 0.1/0.9 quantiles respectively. The medium values of the posterior

354 estimates among the sensitivity tests are shown in red. The prior estimates from the Origins
355 inventory are shown in magenta.

356 We then focus on the total fossil fuel CO₂ emission budgets during the first (March 18th - May
357 10th) and second (October 30th - December 15th) lockdown periods, in comparison to the same
358 period in 2018 and 2019 over the Greater Paris region. To get an indication of the robustness of
359 the inversion results, we also look at the total emission estimates obtained with the reference
360 configuration together with the sensitivity tests of the inversion configuration. In Figures 6a and
361 6b, the first column on the left (Prior) shows the prior emissions from the Origins inventory. The
362 second one (REF) shows the posterior estimates derived from the reference inversion. The other
363 columns show the posterior values based on different sensitivity tests described in Table S3, each
364 corresponding to a different set of assumptions.

365 Overall, the results for the emissions over the two lockdown periods show limited sensitivity to
366 the inversion setup. Most of the configurations tend to increase the fossil fuel CO₂ emissions
367 with respect to the prior estimates, which gives us a certain degree of confidence that our prior
368 emissions were underestimated. For the first lockdown period, the inversion increases the total
369 fossil fuel emissions from 2.83 to 3.44 MtCO₂ for 2018, from 2.79 to 4.25 MtCO₂ for 2019, and
370 from 1.79 to 2.02 MtCO₂ for 2020 (the ensemble medians of the posterior estimates from the
371 sensitivity tests are given here). The optimized CO₂ emissions during the first lockdown in 2020
372 show a decrease of around 42% and 53% in fossil fuel CO₂ emissions when compared to the
373 same periods in 2018 and 2019 respectively. For the second lockdown, the changes from prior to
374 posterior total fossil fuel emissions are from 3.13 to 3.33 MtCO₂ for 2018, from 3.15 to 3.53
375 MtCO₂ for 2019, and from 2.71 to 2.70 MtCO₂ for 2020. The total emissions decrease by 19%
376 and 23% in 2020 with respect to 2018 and 2019. In addition, compared to the prior uncertainties,

377 the inverse emissions reach an uncertainty reduction of about 8~10% for the total emissions.
378 Note that the uncertainties discussed here are relative uncertainties, dependent on the prior
379 emission uncertainties assigned to the Origins inventory.

380 We examined the full ensemble of inverse emission estimates to identify the most critical
381 assumptions made in the system. First, the sensitivity tests indicate that the inversion
382 with/without assimilating data from the two urban stations (JUS and CDS) produces similar
383 results (NO. 2-4 in Table S3 with respect to the reference). This could be linked to the large
384 model error that was assigned to the urban stations in the inversion system (SI Appendix, Text
385 S7). Regarding the data selection criteria, when assimilating data during the late morning and
386 afternoon (8-17 UTC) (NO. 10 in Table S3, denoted as “day” in Figure 6), we note that the
387 inversion produces lower fossil fuel emission estimates than the reference (which only uses the
388 afternoon data, i.e. 12-17 UTC). This might be due to biases in modeled PBL heights, or to the
389 inadequate depiction of the near-surface vertical mixing, or incorrect diurnal cycles in prior
390 emissions. The inversion solution is also sensitive to the target distance (NO. 12-13 in Table S3,
391 denoted as “tdis20” and “tdis40” in Figure 6) used in the selection of the assimilated CO₂
392 gradients between pairs of upwind and downwind stations. By filtering out pairs of stations close
393 to each other with a minimum station-to-station distance, we eliminated downwind-upwind
394 gradients that are not representative of a large portion of the urban area. The target distance plays
395 a critical role in determining the number of the assimilated CO₂ data both from the urban-suburb
396 gradients and from the suburb-suburb ones that are representative of urban emissions and the
397 cross-city emissions respectively. This configuration is therefore a primary parameter in our
398 inversion system as the inverse solution is constrained by the selected atmospheric observations.
399 The sensitivity to the temporal error correlations in the prior fossil fuel fluxes is also a critical

400 parameter, especially during weeks with limited observations filtered out following our criteria
401 (NO. 14-16 in Table S3, denoted as “corr1”, “corr4” and “corr14” in Figure 6). The results show
402 that the values of the relative uncertainty in the prior monthly budgets of fossil fuel emissions
403 (NO. 17-18) and biogenic emissions (NO. 19) have little influence on the inverse solution.

404 **4 Discussions**

405 Our analyses show that the substantial drop in the measured CO₂ concentration enhancements
406 over Paris during the first lockdown in spring 2020 is partly due to a change in meteorological
407 conditions that happened coincidentally with the lockdown measures. Nevertheless, inversion
408 results show that the first lockdown in spring 2020 resulted in a large reduction of emissions, of
409 about 53% and 42% for the Greater Paris region when compared to 2019 and 2018 respectively,
410 while the reductions were estimated to be 37% and 36% based on the Origins inventory. This
411 decrease results from both the large reduction in traffic emissions during the lockdown, and the
412 milder temperature than normal, which has an influence on household emissions. The decrease in
413 emissions during the second lockdown is less pronounced (~20%), due to the continuation of a
414 larger share of economic activity and road traffic. Our inversion results are in line with a bottom-
415 up assessment for CO₂ emissions over Paris communicated by the City of Paris (~50% reduction
416 for March 2020)²⁹, suggesting that our inversion system is able to quantify monthly city-scale
417 CO₂ variations. The initial assessments given by the AirParif local air quality agency indicate a
418 decrease of about 30% in total CO₂ emissions over the IdF region at the beginning of the first
419 lockdown (March 17th-20th). It also claimed that traffic emissions decreased by 70% during the
420 first lockdown and only about 20% at the beginning of the second lockdown.

421 Apart from these encouraging results, several challenges and potential improvements inherent to
422 the city-scale atmospheric inversion should also be noted. Our atmospheric inversion retrieves
423 larger fossil fuel CO₂ emissions over the Greater Paris region than the prior estimates, especially
424 for 2019. At this point, we cannot offer a definitive interpretation of this apparent discrepancy
425 between the inventory and the atmospheric inversion estimate. Other socioeconomic data sets
426 and inventory products may provide further insight when they become available in the future.
427 Nevertheless, to provide an alternative evaluation of the capability of the inversion results, we
428 performed an additional sensitivity test by multiplying the prior fossil fuel fluxes by a factor of 2.
429 The results in Figure S10 show that the posterior estimates tend to converge with the reference
430 inversion results, which suggests that our whole-city inverse solution is mostly constrained by
431 atmospheric observations rather than by the prior emissions from the Origins inventory.

432 Another important aspect of this approach is that the uncertainties in the posterior estimates of
433 CO₂ emissions are caused, to a certain extent, by errors in the spatial and temporal distribution of
434 urban emissions at scales finer than the targeted ones. The configuration of the present inversion
435 systems and the analysis of their outputs primarily target the city-scale monthly budgets rather
436 than emissions at high spatiotemporal resolutions. We limited the spatial resolution of the
437 inversion due to the current configuration of the city observation network with only two stations
438 in the densest part of the urban area (JUS and CDS). Since Bréon et al.¹⁶ and Stauffer et al.¹¹
439 focusing on the year 2011, the number of CO₂ in situ stations has increased to seven since 2014.
440 The present monitoring network used in this study, in particular the two urban sites, provides
441 enough observations to constrain the whole urban area but additional sites will be needed to
442 estimate the fossil fuel emissions over the Paris inner city (red shaded area in Figure 2). The
443 inversion estimates of the total fossil fuel CO₂ emissions over the city of Paris and the Greater

444 Paris region (excluding Paris) during the two lockdown periods are shown in Figure S11. Results
445 indicate a larger reduction (in relative) of CO₂ emissions for the city of Paris than that for the
446 Greater Paris region (excluding Paris). It should be noted that there are only two stations within
447 Paris to constrain the inversion, but the extension of the network will allow future inversion
448 studies to separate the inner city from the large suburban area around Paris.

449 **ASSOCIATED CONTENT**

450 **Supporting Information**

451 The Supporting Information is available free of charge on the ACS Publications website at DOI:
452 Supporting Information.

453 Additional details on Origins fossil fuel CO₂ emission inventory, WRF-Chem model
454 configuration, Bayesian inversion setup and supplementary results.

455 **AUTHOR INFORMATION**

456 **Corresponding Author**

457 * Jinghui Lian (jinghui.lian@suez.com)

458 **Funding Sources**

459 Thomas Lauvaux is supported by the French research program “Make Our Planet Great Again”
460 (Project CIUDAD).

461 **ACKNOWLEDGMENT**

462 The authors would like to thank Suez Group and the City of Paris for the support of these
463 ongoing analyses. Thanks also to OVSQ, to Marc Jamous at CDS, to the IPSL QUALAIR

464 platform team and to Cristelle Cailteau-Fischbach (LATMOS/IPSL) for JUS, and to
465 LSCE/RAMCES technical staff for the maintenance of the CO₂ monitoring network.

466 REFERENCES

- 467 1 Le Quéré, C., Jackson, R. B., Jones, M. W., Smith, A. J. P., Abernethy, S., Andrew, R. M.,
468 De-Gol, A. J., Willis, D. R., Shan, Y., Canadell, J. G., Friedlingstein, P., Creutzig, F., and
469 Peters, G. P.: Temporary reduction in daily global CO₂ emissions during the COVID-19
470 forced confinement, *Nat. Clim. Change*, 10, 647–653, [https://doi.org/10.1038/s41558-020-](https://doi.org/10.1038/s41558-020-0797-x)
471 [0797-x](https://doi.org/10.1038/s41558-020-0797-x), 2020.
- 472 2 Liu, Z., Ciais, P., Deng, Z., Lei, R., Davis, S. J., Feng, S., Zheng, B., Cui, D., Dou, X., Zhu,
473 B., Guo, R., Ke, P., Sun, T., Lu, C., He, P., Wang, Y., Yue, X., Wang, Y., Lei, Y., Zhou, H.,
474 Cai, Z., Wu, Y., Guo, R., Han, T., Xue, J., Boucher, O., Boucher, E., Chevallier, F., Tanaka,
475 K., Wei, Y., Zhong, H., Kang, C., Zhang, N., Chen, B., Xi, F., Liu, M., Breon, F-M., Lu, Y.,
476 Zhang, Q., Guan, D., Gong, P., Kammen, D. M., He, K., and Schnellhuber, H. J.: Near-real-
477 time monitoring of global CO₂ emissions reveals the effects of the COVID-19 pandemic,
478 *Nat. Commun.*, 11, 5172, <https://doi.org/10.1038/s41467-020-18922-7>, 2020.
- 479 3 Tollefson, J.: COVID curbed carbon emissions in 2020-but not by much. *Nature*.
480 <https://www.nature.com/articles/d41586-021-00090-3>, 2021.
- 481 4 Le Quéré, C., Peters, G. P., Friedlingstein, P., Andrew, R. M., Canadell, J. G., Davis, S. J.,
482 Jackson, R. B., and Jones, M. W.: Fossil CO₂ emissions in the post-COVID-19 era, *Nat.*
483 *Clim. Change*, 11, 197–199, <https://doi.org/10.1038/s41558-021-01001-0>, 2021.

- 484 5 Mueller, K. L., Lauvaux, T., Gurney, K. R., Roest, G., Ghosh, S., Gourdji, S. M., Karion, A.,
485 DeCola, P., and Whetstone, J.: An emerging GHG estimation approach can help cities
486 achieve their climate and sustainability goals. *Environmental Research Letters*, 16(8):
487 084003, 2021.
- 488 6 Turner, A. J., Kim, J., Fitzmaurice, H., Newman, C., Worthington, K., Chan, K.,
489 Wooldridge, P. J., Köehler, P., Frankenberg, C., and Cohen, R. C.: Observed impacts of
490 COVID - 19 on urban CO₂ emissions. *Geophysical Research Letters*, 47(22),
491 e2020GL090037. <https://doi.org/10.1029/2020GL090037>, 2020.
- 492 7 Papale, D., Antoniella, G., Nicolini, G., Gioli, B., Zaldei, A., Vogt, R., Feigenwinter, C.,
493 Stagakis, S., Chrysoulakis, N., Järvi, L., Nemitz, E., Helfter, C., Barlow, J., Meier, F.,
494 Velasco, E., Christen, A., and Masson, V.: Clear evidence of reduction in urban CO₂
495 emissions as a result of COVID-19 lockdown across Europe. *Integrated Carbon Observation*
496 *System (ICOS)*, <https://energyexpress.gr/sites/default/files/media/meleti.pdf>, 2020.
- 497 8 Venturi, S., Randazzo, A., Tassi, F., Gioli, B., Buccianti, A., Gualtieri, G., Capecchiacci, F.,
498 Cabassi, J., Brilli, L., Carotenuto, F., Santi, R., Vagnoli, C., Zaldei, A., and Vaselli, O.:
499 Unveiling the changes in urban atmospheric CO₂ in the time of COVID-19 pandemic: A
500 case study of Florence (Italy). *Science of The Total Environment*, 148877,
501 <https://doi.org/10.1016/j.scitotenv.2021.148877>, 2021.
- 502 9 Liu, D., Sun, W., Zeng, N., Han, P., Yao, B., Liu, Z., Wang, P., Zheng, K., Mei, H., and Cai,
503 Q.: Observed decreases in on-road CO₂ concentrations in Beijing during COVID-19
504 restrictions, *Atmos. Chem. Phys.*, 21, 4599–4614, [https://doi.org/10.5194/acp-21-4599-](https://doi.org/10.5194/acp-21-4599-2021)
505 2021, 2021.

- 506 10 You, Y., Byrne, B., Colebatch, O., Mittermeier, R. L., Vogel, F., and Strong, K.:
507 Quantifying the impact of the COVID-19 pandemic restrictions on CO, CO₂, and CH₄ in
508 downtown Toronto using open-path fourier transform spectroscopy. *Atmosphere*, 12(7),
509 848, <https://doi.org/10.3390/atmos12070848>, 2021.
- 510 11 Stauffer, J., Broquet, G., Bréon, F.-M., Puygrenier, V., Chevallier, F., Xueref-Rémy, I.,
511 Dieudonné, E., Lopez, M., Schmidt, M., Ramonet, M., Perrussel, O., Lac, C., Wu, L., and
512 Ciais, P.: The first 1-year-long estimate of the Paris region fossil fuel CO₂ emissions based
513 on atmospheric inversion, *Atmos. Chem. Phys.*, 16, 14703–14726,
514 <https://doi.org/10.5194/acp-16-14703-2016>, 2016.
- 515 12 Sargent, M., Barrera, Y., Nehrkorn, T., Hutyra, L. R., Gately, C. K., Jones, T., McKain, K.,
516 Sweeney, C., Hegarty, J., Hardiman, B., Wang, J. A., and Wofsy, S. C.: Anthropogenic and
517 biogenic CO₂ fluxes in the Boston urban region. *Proceedings of the National Academy of*
518 *Sciences*, 115(29), 7491-7496, 2018.
- 519 13 Lauvaux, T., Gurney, K. R., Miles, N. L., Davis, K. J., Richardson, S. J., Deng, A., Nathan,
520 B. J., Oda, T., Wang, J. A., Hutyra, L., and Turnbull, J.: Policy-Relevant Assessment of
521 Urban CO₂ Emissions, *Environ. Sci. Technol.*, 54, 10237–10245,
522 <https://doi.org/10.1021/acs.est.0c00343>, 2020.
- 523 14 Lauvaux, T., Miles, N. L., Richards, S. J., Deng, A., Stauffer, D. R., Davis, K. J., Jacobson,
524 G., Rella, C., Calonder, G.-P., and DeCola, P. L.: Urban emissions of CO₂ from Davos,
525 Switzerland: The first real-time monitoring system using an atmospheric inversion
526 technique. *Journal of Applied Meteorology and Climatology*, 52(12), 2654–2668,
527 <https://doi.org/10.1175/JAMC-D-13-038.1>, 2013.

- 528 15 Yadav, V., Ghosh, S., Mueller, K., Karion, A., Roest, G., Gourdji, S. M., Lopez-Coto, I.,
529 Gurney, K. R., Parazoo, N., Verhulst, K. R., Kim, J., Prinzivalli, S., Fain, C., Nehrkorn, T.,
530 Mountain, M., Keeling, R. F., Weiss, R. F., Duren, R., Miller, C. E., and Whetstone, J.: The
531 impact of COVID - 19 on CO₂ emissions in the Los Angeles and Washington DC/Baltimore
532 metropolitan areas. *Geophysical Research Letters*, 48(11),
533 <https://doi.org/10.1029/2021GL092744>, 2021.
- 534 16 Bréon, F. M., Broquet, G., Puygrenier, V., Chevallier, F., Xueref-Remy, I., Ramonet, M.,
535 Dieudonné, E., Lopez, M., Schmidt, M., Perrussel, O., and Ciais, P.: An attempt at
536 estimating Paris area CO₂ emissions from atmospheric concentration measurements, *Atmos.*
537 *Chem. Phys.*, 15, 1707–1724, <https://doi.org/10.5194/acp-15-1707-2015>, 2015.
- 538 17 Lian, J., Wu, L., Bréon, F. M., Broquet, G., Vautard, R., Zaccheo, T. S., Dobler, J., and
539 Ciais, P.: Evaluation of the WRF-UCM mesoscale model and ECMWF global operational
540 forecasts over the Paris region in the prospect of tracer atmospheric transport modeling.
541 *Elem. Sci. Anth.*, 6, 64, <https://doi.org/10.1525/elementa.319>, 2018.
- 542 18 Lian, J., Bréon, F. M., Broquet, G., Zaccheo, T. S., Dobler, J., Ramonet, M., Staufer, J.,
543 Santaren, D., Xueref-Remy, I., and Ciais, P.: Analysis of temporal and spatial variability of
544 atmospheric CO₂ concentration within Paris from the GreenLITE™ laser imaging
545 experiment. *Atmos. Chem. Phys.*, 19, 13809–13825, [https://doi.org/10.5194/acp-19-13809-](https://doi.org/10.5194/acp-19-13809-2019)
546 2019, 2019.
- 547 19 Lian, J., Bréon, F.-M., Broquet, G., Lauvaux, T., Zheng, B., Ramonet, M., Xueref-Remy, I.,
548 Kotthaus, S., Haeffelin, M., and Ciais, P.: Sensitivity to the sources of uncertainties in the

549 modeling of atmospheric CO₂ concentration within and in the vicinity of Paris, Atmos.
550 Chem. Phys., 21, 10707–10726, <https://doi.org/10.5194/acp-21-10707-2021>, 2021.

551 20 Wang, Y., Deng, Z., Ciais, P., Liu, Z., Davis, S. J., Gentine, P., Lauvaux, T., and Ge, Q.:
552 Transportation CO₂ emissions stayed high despite recurrent COVID outbreaks. arXiv
553 preprint arXiv:2101.06450, <https://arxiv.org/abs/2101.06450>, 2021.

554 21 Bulletin Climatique Météo-France:
555 https://donneespubliques.meteofrance.fr/?fond=produit&id_produit=129&id_rubrique=29
556 (last access: 5 July 2021), 2019, 2020.

557 22 Ciais, P., Bréon, F. M., Dellaert, S., Wang, Y., Tanaka, K., Gurriaran, L., Françoise, Y.,
558 Davis, S.J., Hong, C., Penuelas, J., Janssens, I., Obersteiner, M., Deng, Z., and Liu, Z.:
559 Impact of lockdowns and winter temperatures on natural gas consumption in Europe. Earth's
560 Future, <https://doi.org/10.1029/2021EF002250>, 2021.

561 23 Tans, P., Zhao, C., and Kitzi, D.: The WMO Mole Fraction Scales for CO₂ and other
562 greenhouse gases, and uncertainty of the atmospheric measurements, Report of the 15th
563 WMO/IAEA Meeting of Experts on Carbon Dioxide, Other Greenhouse Gases, and Related
564 Measurement Techniques, 7-10 September 2009, GAW Report No. 194, WMO TD No.
565 1553, 152–159, 2011.

566 24 Wu, L., Broquet, G., Ciais, P., Bellassen, V., Vogel, F., Chevallier, F., Xueref-Remy, I., and
567 Wang, Y.: What would dense atmospheric observation networks bring to the quantification
568 of city CO₂ emissions?, Atmos. Chem. Phys., 16, 7743–7771, [https://doi.org/10.5194/acp-](https://doi.org/10.5194/acp-16-7743-2016)
569 [16-7743-2016](https://doi.org/10.5194/acp-16-7743-2016), 2016.

- 570 25 Oda, T. and Maksyutov, S.: A very high-resolution (1 km×1 km) global fossil fuel CO₂
571 emission inventory derived using a point source database and satellite observations of
572 nighttime lights, *Atmos. Chem. Phys.*, 11, 543–556, [https://doi.org/10.5194/acp-11-543-](https://doi.org/10.5194/acp-11-543-2011)
573 2011, 2011.
- 574 26 Nassar, R., Napier-Linton, L., Gurney, K. R., Andres, R. J., Oda, T., Vogel, F. R., and Deng,
575 F.: Improving the temporal and spatial distribution of CO₂ emissions from global fossil fuel
576 emission data sets, *J. Geophys. Res.*, 118, 917–933, <https://doi:10.1029/2012JD018196>,
577 2013.
- 578 27 Mahadevan, P., Wofsy, S. C., Matross, D. M., Xiao, X., Dunn, A. L., Lin, J. C., Gerbig, C.,
579 Munger, J. W., Chow, V. Y., and Gottlieb, E. W.: A satellite-based biosphere
580 parameterization for net ecosystem CO₂ exchange: Vegetation Photosynthesis and
581 Respiration Model (VPRM). *Global Biogeochem. Cy.*, 22, GB2005,
582 <https://doi.org/10.1029/2006GB002735>, 2008.
- 583 28 Ahmadov, R., Gerbig, C., Kretschmer, R., Koerner, S., Neininger, B., Dolman, A. J., and
584 Sarrat, C.: Mesoscale covariance of transport and CO₂ fluxes: Evidence from observations
585 and simulations using the WRF-VPRM coupled atmosphere-biosphere model. *J. Geophys.*
586 *Res.-Atmos.*, 112, D22107, <https://doi.org/10.1029/2007JD008552>, 2007.
- 587 29 Ciais, P., Ramonet, M., Lauvaux, T., Bréon, F. M., Lian, J., Laurent, O., Combaz, D.,
588 Broquet, G., Legendre, V., Delmotte, M., Xueref-Rémy, I., Jamous, M., Cailteau-Fischbach,
589 C., Françoise, Y. : Suivi atmosphérique des émissions de CO₂ de la région parisienne. *La*
590 *Météorologie*. n° 114, 2021.