

A novel model evaluation approach focussing on local and advected contributions to urban PM_{2.5} levels – Application to Paris, France

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Abstract

Aerosol simulations in chemistry transport models (CTMs) still suffer from numerous uncertainties, and diagnostic evaluations are required to point out major error sources. This paper presents an original approach to evaluate CTMs based on local and imported contributions in a large megacity rather than urban background concentrations. The study is applied to the CHIMERE model in the Paris region (France) and considers the fine particulate matter (PM_{2.5}) and its main chemical constituents (elemental and organic carbon, nitrate, sulfate and ammonium), for which daily measurements are available during a whole year at various stations (PARTICULES project). Back-trajectory data are used to locate the upwind station, from which the concentration is identified as the import, the local production being deduced from the urban concentration by subtraction. Uncertainties on these contributions are quantified. Small biases in urban background PM_{2.5} simulations (bias of +16%) hide significant error compensations between local and advected contributions, as well as in PM_{2.5} chemical compounds. In particular, wintertime OM imports appear strongly underestimated while local OM and EC production are overestimated all along the year. Erroneous continental woodburning emissions and missing SOA pathways may explain errors on advected OM, while carbonaceous compounds overestimation is likely to be related to errors in emissions and

1 dynamics. A statistically significant local formation of nitrate is also highlighted from
2 observations, but missed by the model. Together with the overestimation of nitrate imports, it
3 leads to a bias of +51% on the local PM_{2.5} contribution. Such an evaluation finally gives more
4 detailed insights on major gaps in current CTMs on which future efforts are needed.

5

6 **1 Introduction**

7 Fine particulate matter (PM_{2.5}, particulate matter with aerodynamic diameter below 2.5 µm)
8 pollution is well-known to produce adverse health effects (Chow et al., 2006), and to affect
9 ecosystems and monuments through acidic deposition soiling (Likens et al., 1996; Lombardo et
10 al., 2013). It also impacts on climate directly through its diffusing and absorptive properties and
11 indirectly through various modifications of cloud properties (Lohmann and Feichter, 2005),
12 leading to changes in the earth radiative balance (Forster et al., 2007).

13 In the European Union, many member states, including France, still fail to reach both daily and
14 annual PM standards (EEA, 2012). Besides some rural areas (e.g. Po valley and Silesia), the
15 exceedences of air quality standards mainly occur in cities that gather population and
16 associated anthropogenic activities. In 2010, about 21% of EU urban population has been
17 exposed to levels not complying with the PM₁₀ daily limit value (daily 50 µg m⁻³ concentration
18 exceeded less than 35 days per year). During the 2001-2010 period, all regulated EU pollutant
19 emissions contributing to fine particles have decreased: by about -15% for PM_{2.5} (decrease in
20 all source sectors except non-industrial fuel combustion that increases), and for its gaseous
21 precursors by about -54% for SO₂, -27% for NO_x, and -10% for NH₃. Nevertheless, trends in
22 PM_{2.5} concentrations remain unclear (EEA, 2012), due to variations in meteorological
23 conditions and due to the possibly important contribution of biogenic sources.

24 Chemistry-transport models (CTMs) have become a very useful tool for both air quality
25 forecasting and emission scenario analysis in order to help air quality managers and policy-
26 makers finding appropriate solutions for pollution abatement. Nevertheless, strong uncertainties
27 in emissions, meteorological data, physical parametrisations and chemical schemes still prevent
28 CTMs to correctly retrieve PM concentrations and even more its chemical speciation. In the
29 framework of the Air Quality Modelling Evaluation International Initiative (AQMEII) project
30 (Rao et al., 2011), a recent cross-comparison over a whole year of ten CTMs in Europe and
31 North America has shown a strong variability between models, with root-mean square errors
32 (RMSE) for PM₁₀ around 7.3-15.2 µg m⁻³ (Solazzo et al., 2012). Most of these models tend to
33 largely underestimate PM₁₀ concentrations, with biases ranging from -14 to +1.4 µg m⁻³.

1 Results are better for PM_{2.5}, particularly in terms of correlation (R in the range of 0.4-0.8,
2 compared to 0.2-0.7 for PM₁₀). Authors have underlined that performances and discrepancies
3 between models are also important during specific episodes of enhanced PM levels. By
4 comparing five CTMs during a winter PM episode in Europe, Stern et al. (2008) has shown
5 biases ranging from -15 to +7 µg m⁻³. Many other model studies in Europe (e.g. Sartelet et al.,
6 2007) drew similar conclusions concerning the PM underestimation.

7 Various uncertainty sources are at stake in CTMs. Among them, emissions still remain a
8 critical point, with strong uncertainties both in emission factors and/or spatial distribution for
9 some source sectors, such as biomass burning, road dust re-suspension (usually missing in
10 inventories), agriculture. Even with similar input data, discrepancies can raise from emission
11 preprocessing (Solazzo et al., 2012). Secondary organic aerosol (SOA) formation also
12 represents a large field of research, with various formation pathways still ignored or poorly
13 understood (see for example Hallquist et al., 2009 and references therein). Meteorological
14 errors can also impact on PM levels through advection and dispersion (wind speed and
15 direction, vertical mixing in the boundary layer) or removal by precipitation (Vautard et al.,
16 2012). In their cross-comparison, Solazzo et al. (2012) have underlined that underestimated
17 wind speed and overestimated precipitation frequency can partly explain the negative PM₁₀
18 bias. Because of the lack of measurements, dry deposition represents another important
19 uncertainty source (Nopmongcol et al. 2012).

20 CTM evaluation is traditionally limited to comparison between modelled and measured
21 concentrations at various sites. Nevertheless, such an approach usually conceals the geographic
22 provenance of errors in terms of local emission/production and regional import. This is
23 particularly important for PM_{2.5} since, in addition to direct emissions, it can be formed from
24 gaseous precursors and advected over long distances, due to limited chemical removal
25 pathways for most of PM compounds and slow dry deposition of aerosol present in the
26 accumulation mode (Van Dingenen et al., 2004). This sometimes leads to strong regional
27 background that is advected toward cities and adds to the local urban pollution increment.
28 Large advected PM contributions have already been shown in megacities such as New York
29 through strong proportions of secondary species, with 54 and 24% of organic aerosol (mainly
30 oxidized, at 64%) and sulfate respectively (Sun et al., 2011). Several studies in Paris have
31 indicated the potential significant influence of PM imports (Sciare et al., 2010; Bressi et al.,
32 2013, Zhang et al., 2013). Through a modeling exercise of long-term PM₁₀ concentrations in

1 the Paris region, Hodzic et al. (2005) have pointed out some error compensations between the
2 local production and the rural background.

3 If many PM studies in megacities have recently given rise to a potential strong advected
4 contribution, very few have intended to systematically quantify it. Lenschow et al. (2001) have
5 developed a methodology (that will be detailed in Sect. 4), based on measurements at sites of
6 various typology (rural and urban background, traffic) and applied to the Greater Berlin area, to
7 discriminate these local and regional contributions. This approach turns out to be useful in air
8 quality management to assess both the sources of PM_{2.5} and the relevance to work on local
9 emissions. Results have shown that the long-range transport accounts for about 50% of the
10 Berlin urban background PM₁₀ concentrations.

11 Based on this approach, this paper intends to evaluate the ability of a regional CTM to retrieve
12 the correct share between local and imported PM_{2.5} contributions in a large megacity. Assessing
13 these two contributions separately is a novel and useful approach which goes beyond traditional
14 model evaluation based on simulation-observation comparisons for particular sites. It will be
15 applied to the CHIMERE model in the Greater Paris region. This large urban area gathers all
16 the characteristics of a megacity, including more than 10 million inhabitants and concentrates
17 an important part of the French economic activities.

18 The observational data base used in this paper is based on the results of the one year
19 PARTICULES campaign (AIRPARIF, 2012, Bressi et al. 2013) in the Greater Paris region,
20 that consists in daily PM_{2.5} chemical speciation measurements at various sites.

21 After a short description of the measurement data base (Sect. 2), the CHIMERE model will be
22 presented as well as its configuration used for this study (Sect. 3). Then the methodology to
23 derive the urban and the advected part of PM_{2.5} will be detailed (Sect. 4). Results will be first
24 analysed for each of the main PM_{2.5} compounds and then implications for model evaluation will
25 be discussed (Sect. 5), before conclusion (Sect. 6).

26

27 **2 Measurement data base**

28 In the framework of the PARTICULES project (AIRPARIF-LSCE), daily (from 00:00 to 23:59
29 LT) PM_{2.5} chemical mass closure measurements have been performed in the Paris region and its
30 surroundings during a whole year period, from the 11 September 2009 to the 10 September
31 2010. Six sites have been documented, including an urban background site (PAR) and three
32 rural background sites, respectively in the north-east (RNE), south (RUS) and north-west

1 (RNW) of Paris. Bressi et al. (2013) have described in details the sampling and analytical setup
2 and have presented the experimental database obtained from this campaign. At each site, PM_{2.5}
3 have been collected by two Leckel samplers, one equipped with Teflon filters for gravimetric
4 and ions measurements, the other with quartz filters for carbon measurements. Measurement
5 techniques and uncertainty estimates for main compounds are summarized in Table 1.

6 Three different measurements of PM_{2.5} concentration are available (among which two are
7 independent): the PM_{2.5} concentration measured by TEOM-FDMS considered here as reference
8 (PM_{ref}), the gravimetric measurement at RH below 20% (PM_{grav}), and the chemically
9 reconstructed PM_{2.5} concentration calculated from the aforementioned
10 measurements/estimations of each compound (PM_{chem}). That last value requires OC
11 measurements to be converted into organic matter (OM). The OM/OC conversion factors are
12 taken as 1.95 and 2.05 for the urban and the rural background sites respectively, in general
13 agreement although in the upper range of values given by other studies (Bressi et al., 2013).
14 Using only these conversion factors, correlation coefficients (R^2) between PM_{chem} and PM_{grav}
15 reach more than 0.98 at every site. In order to be consistent with the chemical compounds
16 analysis, notably in terms of contribution, all PM_{2.5} concentrations mentioned in the paper refer
17 to PM_{grav} measurements.

18 It is worthwhile noting that filter sampling can induce significant artefacts especially due to
19 evaporation of volatile compounds (mainly ammonium nitrate and organic species) (Pang et al.,
20 2002), or adsorption and eventually oxidation of some gaseous compounds (such as nitric acid,
21 ammonia, sulfur dioxide or some volatile organic carbons, VOC) (Cheng and Tsai, 1997; and
22 references therein). To assess the uncertainties associated with these filter measurements,
23 Bressi et al. (2013) have performed an intercomparison during 40 days in wintertime for ion
24 measurements with a particle-into-liquid-sampler (PILS) coupled with ion chromatography
25 (IC). A satisfactory agreement has been found, with discrepancies remaining in the range of the
26 measurement uncertainty fixed by the authors, i.e. around 20%. Another intercomparison has
27 been performed for carbonaceous compounds during 70 days in winter and early spring with
28 hourly VOC denuded EC and OC concentrations from OCEC Sunset field instrument, again
29 leading to satisfactory agreement (discrepancies below 25%, i.e. in the range of measurement
30 uncertainties). However, these comparisons have been carried out during a period with
31 potentially low evaporation (low temperature, high RH), whereas various studies have shown
32 that filter measurement artefacts increase with higher temperature (Keck et al., 2005; Yu et al.,
33 2006).

1 Based on TEOM-FDMS measurements (PM_{ref}) available during the campaign, it is possible to
2 derive an upper limit of the error induced by filter measurements. The comparison with PM_{grav}
3 shows that filter artefacts are mostly negative, meaning that evaporation losses on filter exceed
4 adsorption gains (except in August). By assuming that this error mainly affects ammonium
5 nitrate and organic matter, one can estimate the underestimation of the total of both compounds
6 at around -30% in winter and -50% in summer (see analysis in the Supplement, Sect. S.1).

7 Concerning EC, it is to be noted that differences with black carbon (BC) measurements
8 (Andreae et Gelencsér, 2006; Salako, 2012) can lead to misinterpretations of comparisons with
9 model results if emission factors used in the inventory are not consistent with the
10 measurements. In our case, the PM speciation used in simulations is derived from EC (and not
11 BC) emission factors.

12 This study will focus on the main $PM_{2.5}$ components analysed during the PARTICULES
13 campaign: OM, EC, nitrate, sulfate and ammonium. Sea salts and dust were minor compounds,
14 and are not directly used for model evaluation. Note that for $PM_{2.5}$ and these six chemical
15 constituents, depending on the station, the missing data percentage ranges between 2 and 10%
16 of the year.

17

18 **3 Simulations**

19 **3.1 CHIMERE model**

20 Our work in this paper is performed with the v2008b version of the CHIMERE regional CTM
21 (Schmidt et al. 2001; Bessagnet et al., 2009; Menut et al. 2013)
22 (www.lmd.polytechnique.fr/chimere). This model is widely used both in research activities and
23 operational air pollution survey and forecasting in France (ESMERALDA, [www.esmeralda-
25 web.fr](http://www.esmeralda-
24 web.fr), and PREVAIR, www.prevoir.org, platforms run by AIRPARIF for North and West of
26 France and by PREVAIR at the national scale respectively) and European Union (GMES-
27 MACC program). The ESMERALDA project is a pooling of technical, human and financial
28 means for Air quality forecast system and emission inventory set-up by 9 French air quality
29 monitoring networks, Atmo Picardie, Atmo Nord-Pas de Calais (North of France), Atmo
30 Champagne-Ardennes, LIG'AIR (Centre region), Air Normand (Haute-Normandie), AIR
PARIF (Ile de France), ATMOSF'AIR (Burgundy), AIRCOM (Basse-Normandie), AIR

1 BREIZH (Brittany). In the following, a focus will be made on the aerosol module of the
2 CHIMERE model, which is of particular interest for this study.

3 **3.2 Aerosol module description**

4 The main processes affecting the aerosol size distribution and chemical speciation are
5 represented in the CHIMERE aerosol module. This includes emissions, nucleation, coagulation,
6 condensation, and dry and wet deposition. Through a sectional representation within 8 bins of
7 size (diameter ranging from about 40 nm to 10 μm), the module takes into account various
8 chemical species: primary material — including primary organic aerosol (POA), EC and the so-
9 called mineral particulate matter (MPM) corresponding to the remaining part —, nitrate,
10 sulfate, ammonium, water and SOA compounds.

11 Primary species (POA, EC, MPM) are treated as inert species that can only deposit by wet
12 and/or dry processes. The SOA scheme consists in a single-step oxidation of anthropogenic and
13 biogenic VOC lumped species, giving directly semi-volatile organic compounds that partition
14 between gaseous and particulate phases. SOA yields come from laboratory experiments (Pun
15 and Seigneur, 2007). SOA precursors include five biogenic lumped species — API (alpha-
16 pinene, sabinene), BPI (beta-pinene, delta-3-carene), LIM (limonene), OCI (ocimene,
17 myrcene), ISO (isoprene) — and three anthropogenic ones — TOL (benzene, toluene, other
18 mono-substituted aromatics), TMB (trimethylbenzene, other poly-substituted aromatics) and n-
19 C_4H_{10} (higher alkanes).

20 Absorption processes are considered using a kinetical-dynamical approach, with equilibrium
21 concentrations derived from a tabulated version of the ISORROPIA thermodynamic model
22 (Nenes et al, 1998) for secondary inorganic species, and from a temperature dependent partition
23 coefficient according to Pankow (1994) for semi-volatile organic species. Coagulation (Gelbart
24 and Seinfeld, 1980) and sulfuric acid nucleation (Kulmala et al., 1998) are also included in the
25 model.

26 Aqueous sulfate chemistry is represented (Lee and Schwartz, 1983; Berge, 1993), including
27 iron and manganese catalyzed oxidation reactions of the sulfite ion (SO_3^{2-}) and hydrogen sulfite
28 (HSO_3^-) (Hoffman and Calvert, 1985). Some heterogeneous reactions recommended by Jacob
29 (2000) are also included in the model to take into account the nitric acid formation onto
30 existing particles and cloud droplets. Additionally, the HONO production from NO_2 reactions
31 on wet particles (Aumont et al., 2003) is added.

1 The dry deposition parametrisation follows the traditional resistance analogy (Wesely, 1989).
2 Concerning wet deposition, the model accounts for both in-cloud (Tsyro, 2002 ; Guelle et al.,
3 1998) and sub-cloud wet scavenging.

4 **3.3 Model configuration**

5 Simulations are performed with the ESMERALDA operational modelling platform. Three
6 nested domains — a large (LAR), a medium (MED) and a fine (FIN) one — are considered
7 with horizontal resolution progressively increasing from 0.5° (roughly 50 km) to 15 km to 3 km
8 (see Fig. 1 and description in Table 2), each with eight vertical levels, from 40 m to about 5 km
9 height.

10 Meteorological inputs come from PSU/NCAR MM5 simulations (Dudhia, 1993), performed
11 over three nested domains with increasing resolutions of 45, 15 and 5 km respectively, and
12 using Final Analyses (FNL) data from National Centers for Environmental Prediction (NCEP)
13 as boundary conditions and large scale data.

14 Anthropogenic emissions come from the 1x1km-resolved local ESMERALDA inventory
15 developed by local agencies over the so-called ESM area (delimited by administrative borders,
16 see Fig. 1), e.g. AIRPARIF (2010) for the Paris region and mainly derived from a bottom-up
17 approach. Following the methodology developed in the European FP7/HEAVEN project,
18 traffic emissions are computed from traffic data, fleet description and emission factors using
19 the COPERT IV approach (EEA, 2013). Fuel evaporation emissions are also taken into
20 account. However, road, tire and brake abrasion emissions are ignored, as well as road dust re-
21 suspension. So far, ammonia traffic emissions are not taken into account. The inventory
22 includes emissions from other means of transport (aircraft, shipping, railway). Industrial sector
23 emissions are derived from official statements when they exist or are computed from various
24 types of data (e.g. national raw material consumptions, national productions). Basically,
25 residential emissions are mostly computed using a bottom-up approach, from detailed housing
26 local data (fuel type, housing type, age and size) and associated national consumption
27 estimates. For wood burning related residential emissions, because of the lack of local data,
28 equipment (boiler, open/closed fireplaces, etc.) distribution is taken from national statistics.
29 These ESMERALDA emissions are applied to both the MED and FIN domains, while
30 emissions outside the ESM area are taken from the 0.5x0.5°-resolved EMEP inventory for all
31 primary pollutants (Vestreng et al., 2007). Note that only this last inventory is used in the
32 coarse simulation over the LAR domain.

1 Biogenic emissions (including isoprene, alpha- and beta-pinene, limonene, ocimene, humulene)
2 are computed from MEGAN emission factors (Guenther et al., 2006), apart from the ESM area
3 where refined biogenic emission factors are computed from the 1x1km-resolved French
4 national forest inventory (NFI). The landuse data used to process emissions is taken from
5 Corine Land Cover (EEA, 2000), with a resolution of 250 m over Europe. Table S1 in
6 Supplement (Sect. S.2) gives the speciations of PM_{2.5} into EC, OM, and mineral PM used for
7 both the continental domain (with EMEP emissions) and the two refined domains (with the
8 ESMERALDA inventory). For these latter domains, speciation is based on a bibliographic
9 study carried out by AIRPARIF. Initial and boundary conditions are taken from LMDz-INCA2
10 (Folberth et al., 2006) global model for gaseous species and GOCART (Chin et al., 2000) for
11 particulate species.

12

13 **4 Methodology**

14 **4.1 Determination of the advected and local PM_{2.5} fraction**

15 The local Greater Paris urban contribution to PM_{2.5} levels can be deduced from concentrations
16 measured at rural and urban background sites following the so-called Lenschow approach
17 (Lenschow et al., 2001). Daily PM measurements are available at one urban (PAR (48.849°N,
18 2.365°E)) and three rural background sites located in three directions (RNE (49.088°N,
19 3.076°E), RUS (48.363°N, 2.26°E), RNW (49.063°N, 1.866°E)). Such a data set allows
20 discriminating the local contribution to urban PM_{2.5} levels by subtracting the appropriate
21 upwind rural concentration. To choose the upwind site among the three rural background sites,
22 a rather simple and automatic procedure has been developed, based on back-trajectories.
23 During the whole year, the FLEXTRA model (Stohl et al., 2001) has been initiated each 6
24 hours with 10 particles distributed in the center of Paris, leading to a daily set of 40 back-
25 trajectories. Three main sectors are defined according to the locations of the rural sites with
26 respect to Paris: north-east (0-120°), south (120-240°) and north-west (240-360°). The distance
27 between Paris center and rural stations is about 50 km. By determining the dominant sector for
28 particles in the last four hours before reaching Paris, the upwind rural site can be deduced.
29 Figure 2 gives an illustration for three particular days. Due to the complexity of wind fields,
30 this procedure is certainly too simplistic to account for all meteorological situations that may
31 occur over the Paris region (e.g. back trajectories originating from more than one sector,
32 recirculation). However, all these problems relative to the choice of the appropriate upwind

1 rural site are tackled by the quantification of advected contributions uncertainties in which all
2 the three rural concentration values are included, as described in the next section.
3 Following Lenschow et al. (2001), the methodology thus relies on the assumption that (i) both
4 the PAR station and the upwind rural station are representative of urban background and
5 advected regional background, respectively, and that (ii) no significant changes affect the
6 aerosol chemical composition between rural sites and the edge of the agglomeration (e.g.
7 photochemistry, thermodynamic equilibrium). Concerning this latter hypothesis, the short
8 distance between rural sites and Paris is likely to prevent most SOA production during the
9 transport of air masses, as well as too strong discrepancies in thermodynamic conditions. The
10 validity of the first hypothesis is further discussed in Sect. 4.2. In addition, it should be noted
11 that PM species concentrations are quite similar from one rural site to another, at least in
12 average over the year. However, strong discrepancies sometimes appear for the OM species,
13 larger values at the RNE site being probably related to some local wood burning (domestic
14 heating) emissions at this site. The RNE rural site can thus not be considered as representative
15 of the OM rural background, but this local wood burning pollution is not assumed to impact
16 significantly the other species. In order to avoid invalidating all data from the RNE site, OM
17 concentrations are invalidated only when the discrepancies with the two other sites are stronger
18 than 30% (see analysis and a discussion of this threshold value in Supplement, Sect. S.3).

19 **4.2 Uncertainty discussion**

20 In this section, we first discuss the uncertainties associated to the choice of the up-wind rural
21 station. Uncertainties related to the PM_{2.5} urban background heterogeneity in the Greater Paris,
22 and consequently the representativeness of PAR measurements, are then investigated. Note
23 that, in all the paper, the term “urban” always refers to the urban background concentration in
24 the city, thus including both advected and local contributions.

25 **4.2.1 Uncertainties associated with the up-wind station choice**

26 The methodology is based on the hypothesis that the chosen rural station is representative of
27 the rural background air mass advected toward the city. We investigate here the uncertainty
28 associated with the choice of the up-wind rural station.

29 For each day, up to three rural background stations may be available for estimating the
30 advected contribution toward Paris. Considering the regular distribution of these stations in all
31 directions around Paris, let us assume that the exact value of the advected contribution is
32 bounded by the lowest and highest concentrations among them. For each day i , the

1 concentration range among rural stations can thus be seen as the possible absolute error e_i on
2 advected contribution. Based on our first hypothesis, this value represents an upper limit of the
3 uncertainty since the additional information given by the wind direction that allows the choice
4 of a particular station is not taken into account. Considering a period of n days, from error
5 propagation, the absolute uncertainty on the averaged advected contribution can then be
6 estimated as:

$$7 \quad \overline{e_n} = \frac{1}{n} \sqrt{\sum_{i=1}^n e_i^2} \quad (1)$$

8 **4.2.2 Urban background heterogeneity**

9 The methodology used in this work is also based on the assumption that the PAR station
10 is representative of the Greater Paris urban background. However, the $PM_{2.5}$
11 heterogeneity can be significant in this area. Although the model grid cell corresponding
12 to the measurement site (with 3 km horizontal resolution) has been chosen for comparison
13 purposes, the simulations may not correctly express the larger scale intra-urban variability, or
14 the sub-grid variability. This would partly prevent us from interpreting the observed differences
15 in the local contributions as representative for the whole urban area.

16 Three other TEOM-FDMS are available in the Greater Paris from the AIRPARIF network (in
17 the suburban area of Paris), measuring both $PM_{2.5}$ semi-volatile and non-volatile parts. The top
18 panel of Fig. 3 shows the $PM_{2.5}$ concentration range of this station set including the PAR
19 station, the mean $PM_{2.5}$ concentration of these four stations, and the concentration measured at
20 the PAR station. Discrepancies to the mean daily $PM_{2.5}$ concentration (bottom panel) range
21 from -15.5 to $+22.7 \mu\text{g m}^{-3}$, but most of values (89% of available data) do not differ more than
22 $\pm 5 \mu\text{g m}^{-3}$ from the mean. Large discrepancies may be due to specific local events or stagnant
23 conditions preventing air masses from horizontal mixing. This latter situation occurs for
24 instance the 28 October during which the lowest wind speed of the whole period is measured at
25 the MONTSOURIS meteorological station (48.822°N , 2.337°E) in the center of Paris (daily
26 mean around 1 m s^{-1}). This day corresponds to the third largest $PM_{2.5}$ departure from the mean,
27 which is also visible with PM_{10} or NO_2 (not shown). In average, the $PM_{2.5}$ concentration at the
28 PAR site is slightly lower than the mean urban background concentration, with a discrepancy
29 of $-0.4 \mu\text{g m}^{-3}$.

30 Similarly to advected contributions, we define the absolute uncertainty on the urban
31 background concentration as the maximum concentration range between this panel of urban

1 stations. However, as only PM_{2.5} data are available in the Paris region, the approach cannot be
2 applied to main chemical constituents of PM_{2.5}.

3 **4.2.3 Overall contribution uncertainties**

4 All these uncertainties are given in the Table 3 for all compounds at three time scales (daily,
5 monthly, annual), and reported in Fig. 9 for each month. As local contributions (L) are deduced
6 from advected ones (A) and urban background concentrations (U) by simple subtraction (L=U-
7 A), from errors propagation it follows that these uncertainties on imports (e_A) represent a
8 minimum for the local contribution:

$$9 \quad e_L = \sqrt{e_U^2 + e_A^2} \quad (2)$$

10 to which have to be added the uncertainty associated with the urban background concentration
11 (e_U). As seen before, this latter uncertainty e_U cannot be estimated for PM chemical
12 constituents (as for PM_{2.5} mass) due to missing additional observations. The uncertainty on
13 their local contributions is thus not fully quantified (as for PM_{2.5} mass), but has a low limit
14 given by the uncertainty on their imports. This might lead to an underestimation of this
15 uncertainty.

16 At the daily scale, these uncertainties are quite strong. In relative terms, they prove to be too
17 strong to be compared to model results. Moreover, as most compounds are mainly advected
18 (except EC), uncertainties on local contributions are much stronger than on advected ones
19 (despite their partial quantification). This explains the significant noise in daily time series.
20 They are seriously reduced for monthly contributions, which justifies our choice to discuss
21 results at this time scale. Such a decrease comes from a simple mathematical consideration, that
22 the uncertainty decreases with the root of the number of days, when considering errors on
23 individual days as independent. Except for some chemical constituents during specific months
24 of relatively low imports (EC and OM in October, nitrate in summertime), relative monthly
25 uncertainties on advected contributions remain below ±20%. Concerning monthly local
26 contributions, values remain reasonable for EC (mainly local), ranging between ±4 and ±11%
27 depending on the month. Local OM monthly uncertainties are more critical (±43% in average),
28 particularly during wintertime (January and February, with absolute uncertainties above 1 µg
29 m⁻³ for local contributions below 0.8 µg m⁻³) when they almost reach a factor of two. They are
30 much stronger for secondary inorganic compounds (to a lesser extent for nitrates), due to very
31 low monthly local contributions, often largely below the absolute uncertainty. However, several
32 months show a non negligible local contribution such as: October, December and January.

1 Local PM_{2.5} contribution uncertainties show an average value around ±41%, with strongest
2 values exceeding ±40% in September, February and March (±51, ±47 and ±52% respectively).
3 Uncertainties at the annual scale are below ±5% for advected contributions, and below ±20%
4 for local contributions for most compounds (except ammonium and sulfate that have almost
5 negligible annual local production).

6 Based on these results, it follows that the choice of the up-wind rural station does not affect
7 very much the discussion of monthly advected contributions, compared to measurement
8 uncertainties. However, most of local contributions show larger uncertainties (particularly local
9 OM) that, even if they are usually associated with very low contributions, have to be taken into
10 account in the discussion of the comparison with simulation results.

11

12 **4.3 Model evaluation**

13 The idea of the approach developed in this paper consists in evaluating separately the local and
14 advected contributions. After interpolation of concentrations at all four sites, simulated
15 contributions are derived in the same way as observed ones. We will attempt to answer the
16 following question: is the CHIMERE model (as implemented in the ESMERALDA platform)
17 able to correctly simulate both advected and local contributions for the main chemical
18 constituents of PM_{2.5}? Comparisons between measurements and simulations will be achieved
19 on an annual and monthly basis.

20 Statistical metrics used in this paper are defined as following:

21 • Mean bias: $MB = \frac{1}{n} \sum_{i=1}^n (m_i - o_i)$ (3)

22 • Normalized mean bias: $NMB = \frac{\frac{1}{n} \sum_{i=1}^n (m_i - o_i)}{\bar{o}}$ (4)

23 • Root mean square error: $RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (m_i - o_i)^2}$ (5)

24 • Normalized root mean square error: $NRMSE = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (m_i - o_i)^2}}{\bar{o}}$ (6)

1 • Correlation coefficient: $R = \frac{\sum_{i=1}^n (m_i - \bar{m})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^n (m_i - \bar{m})^2 \sum_{i=1}^n (o_i - \bar{o})^2}}$ (7)

2 Where m_i and o_i are the modelled and observed concentrations at time i , respectively, and \bar{m}
 3 and \bar{o} their average over the period.

4

5 Results

6 This section presents the model evaluation results. In a first part, the meteorological simulation
 7 is evaluated in the center of Paris (Sect. 5.1). A quick overview of observed pollution regimes
 8 during the whole year is presented in a second part, with annual average results from
 9 observations (Sect. 5.2). Simulation annual results are then described (Sect. 5.3), followed by a
 10 description of results for each individual main chemical constituents of $PM_{2.5}$ focussing on
 11 seasonal variations (Sect. 5.4 to 5.7). Implications for model evaluation are finally discussed
 12 (Sect. 5.8).

13 5.1 Meteorology evaluation

14 Current meteorological parameters — temperature, wind speed and direction, relative humidity
 15 (RH) and precipitation — are measured in the center of Paris at the MONTSOURIS station.
 16 Figure 4 shows the comparison with MM5 simulations used in the CHIMERE CTM, statistical
 17 results are given in Table 4.

18 The model simulates well temperature and RH, with only a slight bias of -1°C and $+3.1\%$,
 19 respectively, while NRMSE remains low (around 13% for RH). According to diurnal profiles
 20 (not shown), these biases occur mainly during the night and in the morning. Wind speed also
 21 shows a very low bias ($+0.1 \text{ m s}^{-1}$ or $+2\%$ in relative), but with a stronger NRMSE around 30%.
 22 Again, discrepancies are stronger during the night, the early morning and the early evening.
 23 With mean discrepancies around 11.8° , simulation of wind direction appears to be satisfactory
 24 as well. Considering the difficulty to correctly simulate precipitations, the bias in simulations ($-$
 25 0.02 mm or -34% in relative) is quite good. The model is nevertheless not able to correctly
 26 catch all the events or sometimes wrongly predicts events, leading to an important NRMSE
 27 (around 850%, reduced to 205% with daily values). However, such a large error is expected
 28 since rain episodes can be very local, making difficult to properly locate them in the
 29 meteorological models.

1 Boundary-layer height (BLH) estimations are available during the PARTICULES campaign
2 from an aerosol lidar at the SIRTA platform (48.712°N, 2.208°E), located in the Paris suburban
3 background at about 20 km in south-west of the city center (Haeffelin et al., 2011). Figure 5
4 shows modelled and observed diurnal profiles.

5 On a yearly average over the whole year, the model overestimates the BLH at each hour of the
6 day except between 16:00-19:00 UTC, and more particularly during night-time (by about a
7 factor of two). However, these averaged results hide very different monthly tendencies, with
8 the strongest overestimations in November, December, February and March, and better results
9 in September and October. However, such comparisons remain quite tricky since strong
10 uncertainties still affect observed BLH estimations, particularly during transition to nocturnal
11 stable BL in the afternoon (because of the development of a residual BL) and during nighttime
12 or in the presence of clouds (Pal et al., 2013; Cimini et al., 2013). Additionally, algorithms do
13 not work in case of rain.

14 It has also to be noted that urban heat island (UHI) effects are not taken into account in input
15 meteorological data, which can lead to an underestimation of the simulated BLH in the city
16 center (mostly in winter), due to unaccounted anthropogenic urban heat fluxes. For the Paris
17 megacity, urban-rural temperature contrasts up to 7°C have been noticed at night (Lac et al.,
18 2013). Since SIRTA is a suburban site, the BLH overestimation may be compensated in Paris
19 by this UHI effect not accounted in the model. In the framework of the CO2-MEGAPARIS
20 campaign in March 2011, the UHI effect in the Paris agglomeration (with eight deployed
21 lidars) has been investigated, leading to nocturnal BL differences between urban and adjacent
22 suburban areas of +63 m (+45%) on average (Pal et al., 2012). These authors also measured a
23 slower urban BLH decay during the late afternoon/evening transition (500 m h⁻¹ against 600 m
24 h⁻¹ in suburban areas). These results may thus indicate a reduced model error in the Paris center
25 (since BLH average simulations in the city center and at SIRTA only slightly differ). Note that,
26 to balance that missing UHI effect, a minimum BL height is fixed in the model over urban
27 areas. In our case, the value of 150 m is chosen for a 100% urban cell (and decreases
28 proportionally to the amount of non-urban landuse within the cell), based on the 2nd percentile
29 (120 m) of BLH measured at the SIRTA suburban site.

30 **5.2 Annual average speciation budget overview**

31 In this section, the focus is put on observation results, while model results will be investigated
32 in the next sections.

1 The annual mean PM_{2.5} concentration at the PAR site measured with the gravimetric method is
2 15.1 µg m⁻³, with daily values ranging from 4 to 63 µg m⁻³ over the year (Fig. 6). The
3 variability (standard deviation of 8.6 µg m⁻³) strongly depends on the wind regime, with large
4 episodes mostly linked to advection of continental air masses from the north-east wind sector as
5 indicated by back trajectories over a few days. This leads to much stronger mean PM_{2.5}
6 concentrations during this regime than during the two other ones (average concentration of 20.9
7 µg m⁻³, against 14.4 and 11.7 µg m⁻³ for south and north-west sectors, respectively). Back-
8 trajectory results give an occurrence frequency of 30%, 26% and 44% for NE, S and NW
9 sectors, respectively (4 hours before Paris).

10 Most PM_{2.5} advection episodes occur during winter and spring, few others at the end of
11 September and October. Independently to the wind regime, PM_{2.5} appears to be mostly
12 advected over Paris. Table 5 clearly shows that strongest aerosol loads are brought by north-
13 east winds, with much larger variations compared to the two other sectors.

14 The mean chemical composition of observed urban background PM_{2.5} is composed by 11% of
15 EC, 43% of OM, 14% of nitrate, 13% of sulfate and 8% of ammonium. Figures 7 and 8 present
16 the local and advected contributions for PM_{2.5} and its main chemical constituents. Model results
17 are also reported on these figures but will be discussed in the next section. Relative contribution
18 values are reported in the Table 6. It confirms the importance of imports in the PM_{2.5} urban
19 background (71%). Estimated daily local contributions remain below 20 µg m⁻³ during the
20 whole period and show a large day-to-day variability, partly due to the previously mentioned
21 uncertainties in the estimation method.

22 Observed imports are mainly composed of OM and secondary inorganic species (respectively
23 41% and 42% of total advected PM_{2.5}, respectively), while production within the Paris region
24 mainly consists of carbonaceous compounds: OM contributes to 45% of the total local PM_{2.5}
25 and EC to 29%. This local contribution represents 74 and 31% of the urban EC and OM,
26 respectively. Secondary inorganics species are essentially advected from outside.

27 Negative values can be observed for local contributions. They are related either to noise in the
28 analysis procedure (see Sect. 4.2), but can also reflect losses on the way from the rural to the
29 urban site, due to dry and wet deposition, chemical lost and/or thermodynamical equilibrium
30 changes for secondary inorganic and organic aerosol.

31

1 **5.3 CHIMERE average budget results**

2 Statistical results over the whole period are given in Table 7. On average, the CHIMERE model
3 rather well retrieves the urban background PM_{2.5} concentrations, with a slight positive bias
4 around +16%, i.e. in the range of uncertainty of filter measurements. With a correlation (R) of
5 0.59 and a NRMSE around 56%, the PM_{2.5} scores are in the upper range of CTM performances
6 computed by Stern et al. (2008) for several models, over a European domain and a 80-day
7 period. For the main chemical PM constituents, the poorest results concern EC which is
8 significantly overestimated (NMB of +70% and NRMSE 104%). Nitrate and ammonium are
9 overestimated in the model (+23% and +10% respectively) which may be partly explained by
10 negative sampling artefacts as discussed previously. Conversely, OM underestimation (-21%)
11 may be even stronger due to possible negative artefacts. Carbonaceous compounds and sulfate
12 show the lowest correlation (R below 0.54), while ammonium nitrate variability is correctly
13 captured by the model with correlations above 0.7. Note that an overestimation of simulated
14 dusts in the fine mode also affects the results on PM_{2.5}.

15 However, these urban background results hide a more complex picture in terms of imported
16 versus local contributions. Indeed, results on imported PM_{2.5} contributions show a reasonable
17 agreement with observations (NMB of +1.1%), but with large error compensations between
18 ammonium nitrate and the other compounds. The nitrate overestimation (+63%) is too strong to
19 be fully explained by the filter measurement uncertainty. Despite its large RMSE (more than a
20 factor of two), this compound has the best correlation (0.73), and may significantly contribute
21 to the good correlation obtained for the imported PM_{2.5} (0.58). The lowest correlation concerns
22 OM (0.33) that goes also with a strong negative bias (-59%). Negative biases are rather small
23 for sulfates and EC (below -18%), but errors and correlations remain poor (NRMSE above 57%
24 and R below 0.48).

25 The CHIMERE ability to simulate local contributions appears even more critical. Local PM_{2.5}
26 appears overestimated (+51%), with errors stronger than a factor of two (117%) as well as low
27 correlation (0.41). Statistical results are bad for most individual compounds, carbonaceous
28 species being overestimated by about a factor of two (+103 and +76% for EC and OM,
29 respectively), and inorganic species underestimated also by a factor of two (except for sulfate
30 which local contribution remains close to zero). Errors typically range between a factor two to
31 four, while correlations are rather low, 0.45 for EC, 0.23 for OM and around 0.1-0.3 for
32 inorganic compounds. Spatial and temporal heterogeneities in emissions and in dispersion
33 conditions not expressed in the model in spite of its 3 km horizontal resolution probably

1 explain a part of these large RMSE values on locally emitted compounds (e.g. carbonaceous
2 compounds).

3 Modeled and observed imported and local contributions for PM_{2.5} and its main chemical
4 components are represented in Fig. 9. Monthly contribution observations uncertainties
5 quantified in Sect. 4.2 are also reported. The following sections investigate in more detail these
6 model results for each individual compound.

7 **5.4 Elemental carbon local and imported contributions**

8 Urban background observations show that elemental carbon in the Greater Paris region is
9 mainly due to local emissions, with an advected contribution of around 1/3 of the yearly mean
10 concentration. Simulated and observed imported EC levels show a clear seasonal variation with
11 higher concentrations in wintertime and in the early fall period (September and October). The
12 CHIMERE model retrieves quite well the imported EC during most of the year, with a negative
13 bias of -18% (except during the early fall period where bias is significantly higher). This bias
14 falls in the range of measurement uncertainty of 20 %, and the $\pm 25\%$ maximum monthly
15 uncertainty in determining background condition (see Sect. 4.2). In addition, regional EC
16 emissions still have large uncertainties. Even at the global scale, considering uncertainties in
17 emission factors, types of emissions, fuel use, EC emissions uncertainties have been estimated
18 around a factor of two by Bond et al. (2013). Also model transport and sink processes by
19 deposition are uncertain (Solazzo et al., 2012; Vautard et al., 2012). Given all these error
20 sources, the agreement can be regarded as satisfactory.

21 Conversely, local EC contributions are significantly overestimated by the model, with a relative
22 mean bias around a factor of two. The observed month-to-month variability is quite low
23 (monthly averages around $1 \mu\text{g m}^{-3}$), in contrast with a larger simulated variability with
24 monthly peak values in September, October and January. Surprisingly, while imported EC
25 shows a seasonal variation with stronger values during cold months, we do not observe similar
26 variability for the local (Paris region) contribution of EC, although higher local emissions
27 associated with domestic wood burning and lower mixing heights are expected in winter. This
28 may indicate a predominance of traffic related EC at the local scale, compared to woodburning
29 EC for which contribution is expected to increase further away from the Paris center.
30 According to the ESMERALDA inventory used, road and non-road transport represent 63 and
31 13% of the EC emissions in the Greater Paris agglomeration, respectively, while 20% comes
32 from residential heating. This is confirmed by an independent study during the MEGAPOLI

1 winter campaign in which 88% and 12% of EC particle mass was apportioned to fossil fuel and
2 biomass burning, respectively, using the ATOFMS data, compared with 85% and 15%
3 respectively for BC estimated from the aethalometer model (Healy et al., 2012).

4 EC biases in CHIMERE appear highly variable from one month to the other, the strongest ones
5 occurring in September, October and January. Emission related errors are not expected to show
6 a similar month-to-month variability. Alternatively, pollutant dispersion, through vertical and
7 horizontal mixing and advection, may significantly contribute to the simulated month-to-month
8 EC bias. The combination of very weak wind speed (lower than 1.5 m s^{-1}), low BLH (up to 150
9 m, i.e. the user-fixed minimum value in urban areas) and fresh emissions (mostly related to
10 traffic) during several hours may result in very high simulated peaks on particular days. Such
11 peaks are mainly simulated for particular days during the months of September, October and
12 January for which monthly means are affected, while observations do not show such events.
13 These specific days are characterized by episodes usually lasting few hours during morning and
14 evening, with hourly EC concentrations reaching values higher than $10 \mu\text{g m}^{-3}$ (up to $20 \mu\text{g m}^{-3}$
15 the 26 October). A small shift of the time at which convective BL starts to grow can lead to
16 very large discrepancies. Similarly, as previously mentioned, the transition from convective to
17 stable BL in the evening remains difficult to define properly, and is thus associated with
18 significant uncertainties. Also vertical mixing within the boundary layer remains a potential
19 error source that is difficult to quantify in the absence of vertical profile measurements. Local
20 EC simulations with the lowest overestimations appear during months with the highest BLH
21 overestimation (November, December, and February). This suggests a potential overestimation
22 of EC emissions in the local inventory. In addition, the monthly error variability may also be
23 explained by wind speed errors. For instance, November simulation shows the best results, but
24 also the strongest overestimation of wind speed (bias of $+0.91 \text{ m s}^{-1}$, +23% in relative). It is
25 worthwhile noting that an increased uncertainty on locally emitted compounds such as EC (and
26 OC) may arise from the high resolution of CHIMERE simulation and input data (e.g.
27 emissions, meteorology), as it was shown for ozone (Valari and Menut, 2008).

28 In order to minimize errors induced by pollutant dispersion, the local EC contribution can be
29 normalized by the NO_x ($\text{NO}+\text{NO}_2$) concentration measured in the Paris center (PA12 station
30 from the Airparif network (48.838°N , 2.394°E), nearby to the PAR station), as shown in Fig.
31 10. In this approach, NO_x emissions are assumed to be less uncertain than EC ones. Contrary to
32 observations that follow a clear seasonal variation with a winter minimum, simulated EC/NO_x
33 ratios show a very small month-to-month variability, staying in the range $0.024\text{-}0.033 \mu\text{g m}^{-3}$

1 $\mu\text{g}\cdot\text{ppb}^{-1}$, in good accordance with the ratio in the emission inventory of 0.038 given for both the
2 residential and road transport sectors. CHIMERE overestimates this ratio, particularly during
3 winter, when observed ratios decrease.

4 Consequently, the Greater Paris EC emissions in CHIMERE may be overestimated, at least
5 during winter time, by up to a factor of two, while a satisfactory EC/NO_x ratio is found in
6 summer.

7 Such positive biases of EC in Paris have already been reported with the CHIMERE model
8 using a quite similar (at least for Paris region) PM_{2.5} inventory during spring 2007 (Sciare et
9 al., 2010) and summer 2009 (Zhang et al., 2013). However, during that latter period, with
10 similar Paris PM_{2.5} emissions (and quite similar EC speciation for the road transport sector) and
11 another chemistry-transport model, as well as different meteorological data (taken from WRF
12 rather than MM5 model), Couvidat et al. (2013) have found a slightly negative bias in Paris,
13 but a positive one at a suburban site. However, all these studies have considered urban
14 background concentrations, rather than a local increment, and are thus not directly comparable
15 to our work because of (i) significant advected EC contribution (~1/3) and (ii) potential error
16 compensation between imports and local production.

17 **5.5 Organic matter local and imported contributions**

18 On average during the whole year, OM observations show that it is the dominant compound of
19 PM_{2.5}, with a contribution of 42% to urban background PM_{2.5} levels. Observations also show
20 that it is mainly advected (69%), with a strong seasonal variation with maximum imports
21 occurring during winter. Periods with the largest contributions of imported OM are observed
22 from December to February with daily advected contributions reaching up to 20 $\mu\text{g}\cdot\text{m}^{-3}$.

23 The CHIMERE model clearly fails to simulate such high imported OM levels, with, for
24 instance, more than a factor of five of underestimation for the month of January which cannot
25 be explained by the 14% uncertainty in determining imported contribution (see Sect. 4.2) and
26 by the measurement uncertainties. If observed OM values were underestimated, as suggested in
27 Sect. 2, these underestimations would be even larger. In opposition to observations, imported
28 OM simulated by CHIMERE during winter are even lower than during summertime. Due to
29 low photochemical activity in winter, the contribution of imported SOA (relatively to OM) in
30 the model remains small, with values around 20-30% and showing a predominant (70-90%)
31 biogenic origin (BSOA). CHIMERE provides much better results during summer, with much
32 higher simulated SOA imports, accounting for 40 to 80% of OM. Again, this SOA is mostly

1 biogenic (more than 90%), with significant contribution of isoprene oxidation that provides
2 40% of the total SOA. During the whole year, the daily anthropogenic SOA (ASOA) simulated
3 concentration remains below $1 \mu\text{g m}^{-3}$ while BSOA reaches levels above $6 \mu\text{g m}^{-3}$.

4 Underestimated European POA emissions may partly explain the wintertime negative biases in
5 imported OM levels. Indeed, POA emissions still have large uncertainties, because of the
6 various potential sources, e.g. traffic, residential heating (Sciare et al., 2011), or unaccounted
7 cooking (see for instance Crippa et al., 2012) and the difficulty to properly determine emission
8 factors (Bond et al., 2013). As one of the major sources in winter, uncertainties in wood
9 burning emissions are probably responsible to a large extent of this underestimation. This is
10 especially due to the large range of emission factor values depending on the equipment (open
11 fireplace, closed inserts, boilers, stoves) (Nussbaumer et al., 2008), the lack of local data in
12 bottom-up approaches (e.g. consumptions, equipment type) and conversely, the difficulty to
13 find appropriate spatial distribution proxies in top-down approaches (stronger rural than urban
14 per capita emissions). Another factor of uncertainty is the semi-volatile nature of POA
15 emissions (Robinson et al., 2007) ignored in our simulations. Additionally, as the fraction of
16 volatilized POA depends on the ambient OA concentration, no consensus yet exists on the
17 dilution conditions at which POA emission factor (EF) measurements are conducted in lab
18 experiments. While Zhang et al. (2013) consider that these measurements are done at low
19 dilution and thus do not apply any correction to POA emissions, Couvidat et al. (2012) argue
20 that dilution is much stronger and finally use a factor of five of correction. At this stage, no
21 elements allow us to conclude on this point, especially as inventories usually aggregate EF
22 from various databases in which experimental conditions are probably different.

23 Levoglucosan measurements are available during the whole year at the PAR and RUS stations
24 and can be used to quantify the spatial distribution of domestic wood burning in the region of
25 Paris. If we assume that measurements at this rural station are representative of the regional
26 background advected toward Paris, it is thus possible to derive local and advected contributions
27 using the Lenschow approach (Fig. 11). In this figure, levoglucosan appears to be mostly
28 advected, which suggests a significant contribution of wood burning OM imports. A local
29 production in the Paris region also clearly appears (around 30% in December).

30 Wood burning has shown to significantly contribute to urban background $\text{PM}_{2.5}$ levels during
31 winter 2005 in Paris, around $20 \pm 10\%$ (Favez et al., 2009). Sciare et al. (2011) have estimated
32 this wood burning contribution to represent $15 \pm 11\%$ of $\text{PM}_{2.5}$ during winter 2009 at a suburban
33 site of Paris. Positive matrix factorization (PMF) of aerosol mass spectrometer (AMS)

1 measurements gives a SOA contribution of more than 50% of OM in Paris, including also a
2 part of aged woodburning OM (Crippa et al., 2012). As advected OM is mainly composed of
3 POA in the simulation, its underestimation is probably partly related to missing SOA formation
4 pathways in the model. The volatility-basis set (VBS) approach (Donahue et al., 2006) takes
5 into account the POA volatility and reactivity, as well as the chemical aging of SOA (Robinson
6 et al., 2007). In EMEP model simulations over six years, Bergström et al. (2012) have shown
7 that the VBS approach can increase the OA background over France, Benelux, Germany and
8 Eastern Europe from 2-3 to 3-5 $\mu\text{g m}^{-3}$. During wintertime with smaller oxidant levels, non-
9 oxidative SOA formation pathways occurring in the aqueous or aerosol phase and leading to
10 high molecular-weight products are thought to be important (Kalberer et al., 2004, Carlton et
11 al., 2008, Hallquist et al., 2009; Ervens et al., 2011).

12
13 Conversely, simulated local OM appears overestimated, more than the uncertainty of observed
14 contribution ($\pm 69\%$ in average). Note that the unexpected local OM seasonal variation, with the
15 lowest contributions in January and February, and the strongest in October, is still within the
16 range of uncertainty on monthly values for local contributions (up to $\pm 93\%$, Fig. 9). Model
17 biases show a large month-to-month variability during the year, which may be partly due to this
18 uncertainty. In addition, since simulated OM remains predominantly composed of locally
19 emitted POA, a chemically inert species in CHIMERE, the high variability in monthly biases is
20 partly explained by dynamical errors (BLH, wind speed), as indicated by the strong correlation
21 ($R=0.97$) between OM and EC monthly local contributions.

22 By considering the ratio of OM versus EC local contribution, it is possible to investigate in
23 more detail this latter point. Figure 12 shows the evolution of this ratio over the year.
24 Observations show a local average OM/EC ratio around 1.7 with a significant monthly
25 variability, but no clear seasonal variation. Given the measurement uncertainties (around 20%
26 for EC and up to 60% for OM), this is still consistent with the average value of 1.3 found in
27 CHIMERE simulations (NMB of -19%). Assuming that a major part of local OM is of primary
28 origin, the local OM overestimation is thus related to a similar EC overestimation. This
29 indicates that emission errors are probably more related to the total emission amount than to the
30 $\text{PM}_{2.5}$ speciation. The simulated local OM/EC ratio of 1.3, closer to the OM/EC emission ratio
31 of 0.96 for road transport in the Greater Paris region, than to the ratio of 5.76 for residential
32 heating, also reflects a dominant road transport contribution in the city center. It can be noted
33 that the OM/EC emission ratio of 0.96 for road transport is rather consistent with a value of

1 0.78 derived from OM and EC measurements during the PARTICULES campaign at a traffic
2 site (located at the Paris urban highway). Differences could be due either to the specific
3 OM/EC emission factors for diesel and gasoline vehicles, around 0.5 and 2.8 respectively, the
4 representativity of the composition of the vehicle fleet at a given site for urban background, or
5 again to measurement uncertainties.

6 As previously mentioned, another factor of local OM overestimation may be the missing
7 evaporation of semivolatile POA emissions. By considering the Paris ambient conditions (in
8 terms of temperature and OM concentrations), one can derive that as much as 40-80% of POA
9 emissions could be volatilized (see analysis and Fig. S4 in the Supplement). This is expected to
10 partly explain the CHIMERE overestimation of the OM local contribution. However, it is to be
11 noted that, according to this approach, these lower emissions are balanced by the POA
12 reactivity that increases the amount of SOA (i.e. oxidized POA, OPOA), but with a certain
13 delay in time and thus mostly outside of the agglomeration (Zhang et al., 2013). It is also
14 important to remind that large uncertainties exist on the amount of semivolatile organic
15 material taken into account in POA emission factors.

16
17 As a conclusion, the underestimated OM advection during wintertime is probably both due to
18 lacking woodburning emissions and missing SOA formation pathways in the model. Additional
19 SOA formation pathways would also increase SOA advection in summer, as shown by
20 CHIMERE simulations of the MEGAPOLI summer campaign including the VBS scheme
21 (Zhang et al., 2013). Given the possible underestimation in OA due to evaporation (see Sect.
22 S.1 in Supplement), this would not be inconsistent with measurements. Concerning OM local
23 contributions, apart from their uncertainties, errors in PM emissions, combined with the
24 unaccounted POA volatility, and errors in dynamics probably explain a large part of their
25 overestimation as well as the CHIMERE's difficulty to catch their variability.

26 **5.6 Nitrate contributions**

27 Nitrate is the second largest contributor to urban PM_{2.5} in this study. The largest episodes occur
28 in March and April, mostly due to nitrate advection from outside (Fig. 9). This leads to a
29 seasonal variation of imported nitrate with higher concentrations reached during springtime
30 (higher NH₃ emissions due to fertilizer use). Despite the low photochemistry, some strong
31 nitrate episodes are observed in winter. Nitrate formation during these seasons is due to the low
32 volatility of ammonium nitrate at cold temperatures.

1 The CHIMERE model simulates rather well the seasonal variation of the advected contribution
2 (R of 0.73), but with a significant positive bias (+1.4 $\mu\text{g m}^{-3}$, +63% in relative), much larger
3 than uncertainties on advected contribution (below 20% from October to July). The largest
4 overestimations occur in autumn and spring (with more than a factor of two). As explained in
5 Sect. 2, positive biases may be partly due to errors in measurements, related to volatilisation
6 artefacts during sampling. They probably explain a large part of the overestimation, mainly in
7 autumn and spring when temperature and potential filter artefacts increase but temperature
8 remains low enough to allow the existence of particulate-phase ammonium nitrate.

9 Errors in the simulated meteorology, temperature and RH, modifying the thermodynamical
10 equilibria may also partly explain these results (see analysis in Sect. S.5 in the Supplement).
11 Such errors become more problematic at mild to hot periods (June for instance) since, through
12 its dissociation constant, the temperature dependence of the ammonium nitrate thermodynamic
13 equilibria increases with temperature (Seinfeld and Pandis, 2006). Clear temperature
14 underestimation are sometimes observed over all Europe (e.g. in June, see Fig. S7 in the
15 Supplement). This may increase the amount of nitrate in the particulate phase and consequently
16 decrease the dry deposition of HNO_3 (significantly stronger compared to nitrate, Baumgardner
17 et al., 2002). This may finally induce an overestimation of total nitrate (HNO_3 + particulate
18 NO_3^-) reservoir over Europe, which can eventually lead to overestimated nitrate imports,
19 depending on the thermodynamical conditions.

20 The nitrate overestimation may also be related to uncertainties in the simulated precursor gas
21 concentrations (NH_3 , HNO_3). The G_{ratio} metric provides information on which species is the
22 limiting factor in the ammonium nitrate formation (Ansari and Pandis, 1998; Pinder et al.,
23 2008). It is defined as (all concentrations being expressed in mol m^{-3}):

$$24 \quad G_{\text{ratio}} = \frac{[\text{NH}_3] + [\text{NH}_4^+] - 2[\text{SO}_4^{2-}]}{[\text{HNO}_3] + [\text{NO}_3^-]} \quad (8)$$

25 Values above 1 indicate a HNO_3 -limited regime, while values below 1 indicate a NH_3 -limited
26 regime. In this expression, the numerator, also known as the free ammonia indicator (F- NH_x),
27 represents the available ammonia after neutralization of sulfates, one mole of sulfate removing
28 two moles of ammonia. The simulated G_{ratio} indicates a dominant HNO_3 -limited regime over
29 the continent, while the regime is NH_3 -limited over the sea. This result is in accordance with
30 several previous studies performed over Europe (Pay et al., 2012; and references therein).
31 Accordingly, if nitrate overestimation is related to overestimated emissions, this mostly

1 concerns NO_x emissions and chemistry rather than NH₃. However, this would not be consistent
2 with Konovalov et al. (2006) who have shown, through an inverse modelling exercise over
3 Europe with satellite measurements, that NO_x emissions from the EMEP inventory (used in our
4 study, outside the refined domain) have a tendency for an underestimation of several tenths %
5 in the Benelux and Rhine Ruhr region, which are important NO_x sources contributing to nitrate
6 advection to Paris. The nitrate overestimation may also be explained by a too high conversion
7 of NO_x into HNO₃. Such positive biases on nitrates are not in accordance with some recent
8 papers (Pay et al., 2012) that simulate significant negative biases over Europe during a whole
9 year (MB of -1 µg m⁻³, NMB of -50%).

10

11 Concerning local contributions, observations give positive or near zero contributions, with a
12 rather strong month-to-month variability, while the model does not simulate any particular
13 nitrate production in the Paris region. Uncertainties in local contributions are large (Fig. 7), but
14 for several months as October, December and January, local nitrate production is significant,
15 reaching for instance 2.0±0.4 µg m⁻³ in January. According to the model, nitrate production is
16 significantly underestimated. Actually, the Greater Paris region appears to be a nitrate sink,
17 particularly during later spring and early summer. However, these negative local contributions
18 usually remain low. As the G_{ratio} is mostly above unity in Paris (3.2 in average), HNO₃ is
19 usually the limiting species. During winter, uncertainty in the speed of heterogeneous NO_x to
20 HNO₃ conversion, one of the major pathways in simulations, is large (e.g. Jacob et al., 2000)
21 and may explain these discrepancies. It is both related to uncertainty in the conversion
22 mechanism (e.g. accommodation coefficients) and in input data (aerosol surface, relative
23 humidity). On an hourly basis all along the period, a NH₃-limited regime is also sometimes
24 simulated (during about 13% of the period), which may be a factor of nitrate underestimation in
25 case of missing NH₃ emission sources, like the traffic source in our case.

26 **5.7 Sulfate contributions**

27 Observed monthly sulfate imports range from 0.8 to 3.2 µg m⁻³, with the highest values reached
28 in September 2009, spring and winter. Imports are lower in autumn and early winter probably
29 due to the recurrent south-westerly wind regime (particularly in November) associated with low
30 SO₂ emissions in this direction. These low emissions do not appear to be compensated by the
31 higher RH (around 83% in average in November) brought by oceanic air masses that allows
32 fast aqueous phase sulfate formation (Kai et al., 2007; Rengarajan et al., 2011). In winter, the

1 strong monthly contributions are driven by some very high imports of different durations from
2 north-east (Fig. 9), while regional background concentrations remain low. Since
3 photochemistry is expected to be limited during the winter season, these strong imports during
4 the cold season may be mostly related to aqueous phase sulfate formation from the large SO₂
5 emissions in Benelux and Western Germany. The situation is quite different in spring, with
6 lower sulfate peak values during episodes but higher background the rest of the time. This leads
7 to higher monthly values, despite lower SO₂ emissions.

8 On average, the CHIMERE model simulates rather well the advected sulfate, with a mean bias
9 of about -17%. Larger negative biases are found in June, September and winter months, and
10 cannot be explained by uncertainties in the observed advected contributions (below 14%). The
11 underestimations in January, February, June and September are mainly due to missing or
12 underestimated advection events. Apart from uncertainties in their temporal behaviour,
13 SO₂ emissions are expected to be reasonably quantified, and the sulfate underestimation
14 may thus be partly explained by errors on transport and/or gas and aqueous phase
15 sulfate formation. Aqueous phase formation, the major formation pathway at least during
16 winter, depends on several parameters not well constrained in our simulations such as
17 the cloud water content and the pH.

18 Observations show quite low sulfate local production in the Greater Paris, except in January
19 where the monthly production is quite stronger and appears significant ($0.7 \pm 0.1 \mu\text{g m}^{-3}$).
20 During this month, the observed production essentially occurs on January 18 during a fog event
21 associated with low wind speed (around 1 m s^{-1}). Such conditions enhance fast heterogeneous
22 sulfate formation, leading to a daily local contribution above $4 \mu\text{g m}^{-3}$. This event has been
23 more precisely described by measurements during the concomitant MEGAPOLI winter
24 campaign (Healy et al., 2012). As a slow process (except during fog events), sulfate formation
25 thus remains low at the local scale in Paris, and is more likely to occur in the plume of the city.
26 Concerning this particular fog event, the CHIMERE model manages to capture this sulfate
27 production peak, but not to its full extent (negative bias around -70%). Uncertainties in
28 observed local contributions are stronger during the other months, explaining the quite noisy
29 monthly signal and preventing us to conclude on a noticeable sulfate production. Besides the
30 January fog event, the model also simulates very low sulfate production in the Greater Paris,
31 and thus stays reasonably close to observations.

32

1 5.8 Implications for model evaluation

2 As various error compensations in PM_{2.5} simulation have been underlined in the previous
3 sections, it appears interesting at this stage to evaluate the CHIMERE model performance not
4 only in terms of urban background concentrations, but also considering both advected and local
5 contributions.

6 Boylan and Russel (2006) have proposed to evaluate CTMs performance with the Mean
7 Fractional Bias (MFB) and the Mean Fractional Error (MFE), two statistical metrics integrating
8 the fact that both simulations and observations are subject to uncertainties, which appears
9 particularly suited for aerosol in our case. Both statistics are defined as follows:

$$10 \quad MFB = \frac{1}{n} \sum_{i=1}^n \frac{(m_i - o_i)}{(m_i + o_i) * 0.5}$$

11

(9)

$$12 \quad MFE = \frac{1}{n} \sum_{i=1}^n \frac{|m_i - o_i|}{(m_i + o_i) * 0.5}$$

13

(10)

14 Where m_i and o_i are the modelled and observed concentrations respectively at time i .

15 By construction, MFB values are restricted to the $\pm 200\%$ range, while MFE values can spread
16 out from 0 to 200%. Another interesting feature is that they normalize large and small
17 concentrations, which thus avoids giving too much weight to a particular season (e.g.
18 wintertime nitrates). Boylan and Russel (2006) have also proposed some performance criteria
19 and goals for PM depending on the average of the mean observed and mean simulated
20 concentration so that to take into account the minor importance of errors in less abundant
21 compounds (defined by an average concentration below $2.25 \mu\text{g m}^{-3}$, corresponding to 15% of
22 the US EPA annual air quality standard for PM_{2.5}, $15 \mu\text{g m}^{-3}$):

$$23 \quad \bullet \quad \text{MFB goal :} \quad MFB \leq \pm \left[170e^{-(\bar{o} + \bar{m}) * 0.5 / 0.5} + 30 \right]$$

24

(11)

$$25 \quad \bullet \quad \text{MFE goal :} \quad MFE \leq 150e^{-(\bar{o} + \bar{m}) * 0.5 / 0.75} + 50$$

26

(12)

$$27 \quad \bullet \quad \text{MFB criteria :} \quad MFB \leq \pm \left[140e^{-(\bar{o} + \bar{m}) * 0.5 / 0.5} + 60 \right]$$

28

(13)

1 • MFE criteria : $MFE \leq 125e^{-(\bar{o}+\bar{m})^{*0.5/0.75}} + 75$
2 (14)

3 These performance goal and criteria are widely used for CTM evaluation (Milford et al., 2013;
4 Pay et al., 2012).

5 Simulation results for urban concentrations and both advected and local contributions are
6 compared to these criteria in Fig. 13. Urban background concentrations (in black) meet both
7 MFB and MFE goals for all PM_{2.5} compounds, some of them being considered as minor ones.
8 The OM urban concentration MFB and MFE (around -20 and 37% respectively) are in the
9 upper range of CTM performances recently published (Bergström et al., 2012 and reference
10 therein; Lane et al., 2008; Hu et al, 2009; Murphy and Pandis, 2009).

11 However, the previously described error compensations between advected and local
12 contributions, as well as between compounds appear clearly. Concerning the advected part (in
13 green), the nitrate overestimation is compensated by the OM underestimation, leading to very
14 low bias on total PM_{2.5} (MFB of +12%). MFE on these two compounds appears as more
15 critical, satisfying only the performance criteria, but without damaging the PM_{2.5} performance
16 that stays below the 50% threshold (meaning that both biases tend to occur and partly cancel
17 each other out simultaneously).

18 Concerning local contributions, MFB and MFE metrics do not accept negative values. We thus
19 only consider local PM_{2.5}, EC and OM, and ignore secondary inorganic compounds (mostly
20 negative). The local PM_{2.5} contribution only reaches the performance criteria, but not the
21 performance goal (MFB and MFE around +40 and 76% respectively). This is obviously due to
22 the overestimation of EC and OM compounds that only meet the performance criteria thanks to
23 their minor contribution (the performance goal being reached only on the MFE). MFB and
24 MFE results are rather similar for both carbonaceous compounds.

25 Therefore, the overall CHIMERE model ability to reproduce urban background PM_{2.5}
26 speciation appears as rather satisfactory, but the simulation of advected OM and nitrate as well
27 as local carbonaceous compounds still requires improvements to fulfill these performance
28 goals.

29

30 **6 Conclusions**

31 An original approach to evaluate chemistry-transport models in terms of advected and local
32 contributions rather than concentrations is described. Based on observations at both urban and

1 rural background stations, the estimation of advected contributions consists in the choice of the
2 appropriate rural site considering back-trajectories data to localize the air masses origin, while
3 local production is then simply deduced from the urban concentration by subtraction.

4 The methodology is applied to the CHIMERE model in the Paris region with a one-year daily
5 measurements database of PM_{2.5} and its speciation, in the framework of the PARTICULES
6 project. On an annual basis, about 71% of the Paris urban background fine PM is related to
7 imports from outside, mainly from the north-east. These air masses advect 87% of the inorganic
8 secondary compounds, 69% of the OM and 26% of the EC. Artefacts in filter measurements
9 (volatilisation losses of semi-volatile material and adsorption gains of some gaseous species)
10 introduce uncertainties, particularly for ammonium nitrate and organic matter. The net effect is
11 mostly an underestimation of the measured semi-volatile material concentrations, estimated to
12 around -30% in winter and up to -50% in summer.

13 Based on the concentration range between the three rural stations, uncertainties on both local
14 and advected contributions associated with the choice of the up-wind rural station are also
15 quantified. The representativeness of the urban background site is assessed for PM_{2.5} by
16 considering additional measurements at three other suburban stations of the AIRPARIF
17 network in the Greater Paris. It appears that strong uncertainties affect daily local contributions
18 of most compounds, leading to a significant noise in the signal. However, except for local
19 contributions of inorganic species and OM during some months, uncertainties in monthly and
20 annual contributions are significantly reduced and usually remain below measurement
21 uncertainties.

22 The CHIMERE model simulates urban background PM_{2.5} concentrations with only little bias
23 (+16%). This is however due to error compensations between (i) advected and local
24 contributions, (ii) different PM_{2.5} compounds and (iii) periods of the year. Imports appear to be
25 strongly underestimated in winter, particularly for OM and to a lesser extent sulfates, and
26 slightly overestimated during the rest of the year mainly due to ammonium nitrate. Conversely,
27 the local PM_{2.5} production is significantly overestimated, essentially due to OM and EC.

28 Among the possible reasons for model errors, overestimated particulate matter emissions in the
29 Paris region associated with dynamical errors (mainly boundary layer height) are pointed out to
30 explain overestimations in these local contributions. A better simulation result of the local
31 OM/EC ratio tends to demonstrate that errors are mostly related to the total PM emission
32 amount rather than the PM speciation. Underestimated continental scale woodburning
33 emissions and missing SOA formation pathways are probably responsible for the wintertime

1 underestimation in advected OM. A large part of the nitrate overestimation stays in the range of
2 the filter measurement uncertainties. Influence of temperature and relative humidity errors on
3 thermodynamical equilibria is investigated in Paris, and shows a limited impact on particulate
4 nitrate simulation most of time (positive bias of +10% in average), except during mild to hot
5 periods where errors can reach a factor of two on some episodes. Local and advected sulfate
6 contributions are on the average well simulated, but individual long range transport episodes
7 are missed or underestimated by the model.

8 Finally, the CHIMERE model appears reasonably suited for PM_{2.5} air quality (AQ) forecasting,
9 with urban concentrations fulfilling performance goals in terms of fractional biases and errors.
10 However, efforts are still needed to reduce errors compensations between compounds. The
11 diagnostic evaluation conducted here gives better insights on error origins (e.g. local emission
12 inventories, meteorology), on which further improvements are required for a more detailed
13 investigation of specific sources (e.g. wood burning OM).

14 The underestimation of OM wintertime imports appears as the most critical aspect, and efforts
15 are needed to investigate if an underestimation of regional woodburning OM emissions
16 (through emission factors and/or the dependance on temperature) can provide the missing
17 material and/or if the too simplistic SOA formation scheme is likely to be responsible.
18 Additional efforts are needed to evaluate emissions of carbonaceous material at the local scale,
19 and as well as the local dynamic in urban environment (in particular the boundary layer height).
20 A study of the chemical regime in Paris, in order to investigate which one, among nitric acid
21 and ammonium, is the limited species in nitrate formation is also likely to better target the error
22 source of the underestimated local nitrate production.

23 Such a large advected contribution in urban background PM_{2.5} has important implications on
24 environmental management. It notably shows that pollution reduction measures at the Paris
25 scale alone are inadequate to prevent most exceedances of PM standards, thus underlying the
26 necessity of integrated AQ management at the regional/continental scale. Similar studies should
27 also be undertaken in other megacities in order to highlight the Paris agglomeration special
28 feature (e.g. geographic situation, local orography). This study has focused on PM_{2.5} urban
29 background levels, however stronger local contributions are expected considering urban traffic
30 sites (where most critical PM exceedances in the Paris agglomeration occur) and/or PM₁₀ (for
31 which long-range transport is reduced by faster deposition).

32

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18

1 Table 1: Measurement techniques and instruments for PM_{2.5} and each of its compounds.

Species	Measurement technique	Instrument	Uncertainty/ Sensitivity
PM _{2.5}	Gravimetry	Microbalance Sartorius MC21S	- / ± 1 µg
	TEOM-FDMS		
Organic carbon (OC), elemental carbon (EC)	Thermo-optical	Sunset Laboratory instrument, EUSAAR-2 protocol	20% ¹ 20%
Ions (NO ₃ ⁻ , SO ₄ ²⁻ , NH ₄ ⁺)	Ion chromatography	Dionex DX600	5% ¹

2 (1) measurement error, not including filter sampling errors

3

1 Table 2: Domains description.

Domain name	Cells number (SW corner location)	Resolution
LAR	67x46 (-10.5°; 35°)	~50 x 50 km (0.5 x 0.5°)
MED	68x56 (-5.19°; 45.05°)	15 x 15 km
FIN	150x186 (-0.01°; 46.17°)	3 x 3 km

2
3

1 Table 3: Mean absolute and relative uncertainties on observed imported and local
 2 contributions at three time scales (see text for details), and range of uncertainties among
 3 all monthly contributions over the period.

Contribution	Species	Absolute ($\mu\text{g m}^{-3}$) and relative (%) uncertainty					
		Daily mean		Monthly mean range		Yearly mean	
Advection	PM _{2.5}	4.40	44%	(0.37, 1.88)	(5%, 18%)	0.32	3%
	EC	0.30	87%	(0.04, 0.12)	(11%, 25%)	0.02	5%
	OM	2.77	69%	(0.20, 1.27)	(7%, 30%)	0.21	5%
	Ammonium	0.48	49%	(0.04, 0.33)	(6%, 21%)	0.04	3%
	Nitrate	1.15	>100%	(0.12, 0.57)	(11%, 35%)	0.10	5%
	Sulfate	0.59	43%	(0.08, 0.28)	(5%, 14%)	0.04	2%
Local	PM _{2.5}	7.13	>100%	(0.77, 2.32)	(27%, 66%)	0.46	11%
	EC	*	37%	*	(4%, 11%)	*	2%
	OM	*	>100%	*	(15%, 93%)	*	13%
	Ammonium	*	>100%	*	(18%, >100%)	*	24%
	Nitrate	*	>100%	*	(16%, >100%)	*	17%
	Sulfate	*	>100%	*	(26%, >100%)	*	38%

4 * Idem than advection.

5
 6

1 Table 4: Statistical results for meteorological parameters simulation.

Paris, MONTSOURIS site	MB	NMB (%)	RMSE	NRMSE (%)	R
Temperature (°C)	-1.0	-	1.6	-	0.99
Wind speed (m s ⁻¹)	+0.1	+2.3	0.9	30	0.78
Relative humidity (%)	+3.1	+4.4	9.3	13	0.88
Precipitations (mm h ⁻¹)	-0.0	-33.7	0.6	856	0.19
Boundary layer height (m)	+223.8	+37.8	522.8	88	0.61

2

3

1 Table 5: Average and standard deviation of the advected and local observed PM_{2.5}
 2 contribution ($\mu\text{g m}^{-3}$), depending on the air mass origin.

Air mass origin		All	RNE	RUS	RNW
Rural contribution	Mean	11.3	17.6	8.5	8.6
	Standard deviation	9.0	11.5	5.4	6.2
Urban contribution	Mean	4.0	3.7	6.1	3.0
	Standard deviation	3.6	3.0	4.2	3.0

3

4

1 Table 6: Observed yearly advected and local relative contributions to urban background
 2 PM_{2.5} (and its major chemical constituents) in Paris.

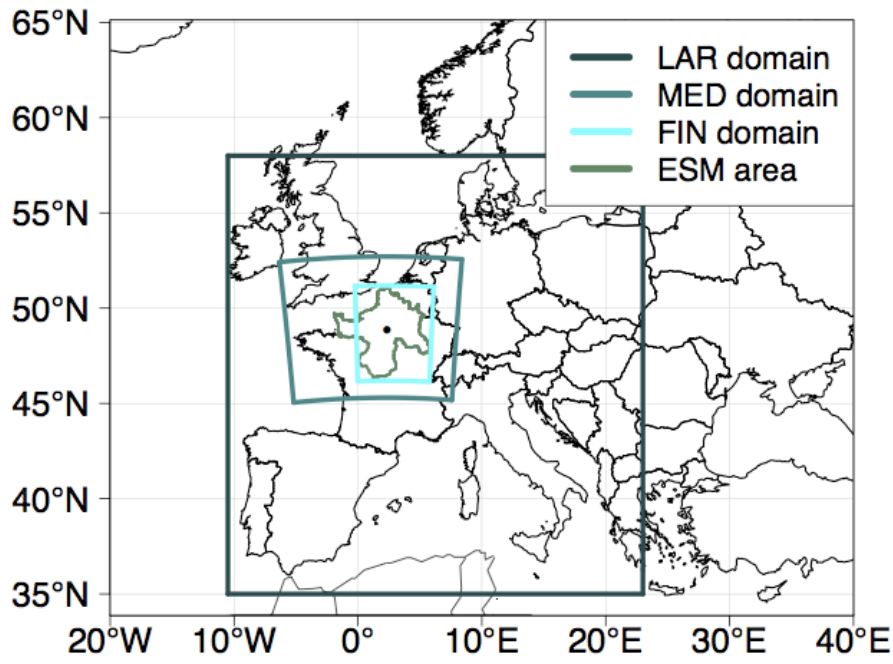
	Contribution to PM _{2.5} (%)	PM _{2.5} compound contribution (%)	
Advected	71.2	EC	3.0
		OM	29
		Nitrate	11
		Sulfate	12
		Ammonium	7.0
Local	28.8	EC	8.4
		OM	13
		Nitrate	3.0
		Sulfate	0.5
		Ammonium	0.8

3

4

1 Table 7: Statistical results for local and advected contribution and urban background
 2 concentration (see metrics definitions in Sect. 4.2, N is the number of daily data).

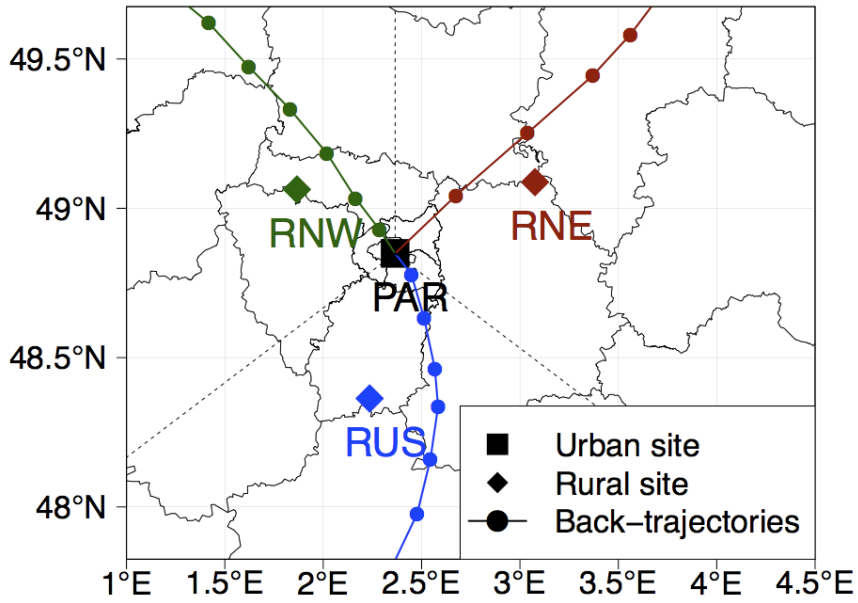
	Chemical constituent	MB ($\mu\text{g m}^{-3}$)	NMB (%)	RMSE ($\mu\text{g m}^{-3}$)	NRMSE (%)	R	N
Local contribution	PM _{2.5}	+2.0	+51	4.71	117	0.41	333
	EC	+1.1	+103	1.50	146	0.45	321
	OM	+1.3	+76	2.55	157	0.23	332
	Ammonium	-0.18	-105	0.53	313	0.27	322
	Nitrate	-0.66	-109	1.44	240	0.31	322
	Sulfate	+0.04	+32	0.59	531	0.11	322
Advected contribution	PM _{2.5}	+0.13	+1.1	7.41	65	0.58	359
	EC	-0.07	-18	0.23	57	0.45	346
	OM	-2.6	-59	4.07	92	0.33	358
	Ammonium	+0.36	+30	1.04	87	0.70	347
	Nitrate	+1.4	+63	2.74	127	0.73	347
	Sulfate	-0.30	-17	1.34	75	0.48	347
Paris concentration	PM _{2.5}	+2.4	+16	8.47	56	0.59	336
	EC	+1.0	+70	1.50	104	0.54	336
	OM	-1.3	-21	3.33	56	0.48	336
	Ammonium	+0.15	+10	1.10	77	0.71	336
	Nitrate	+0.68	+23	2.44	84	0.80	336
	Sulfate	-0.34	-17	1.56	79	0.39	336



1

2 Figure 1: Nested domains used for the simulations, and ESM area of the bottom-up
3 anthropogenic emission inventory.

4

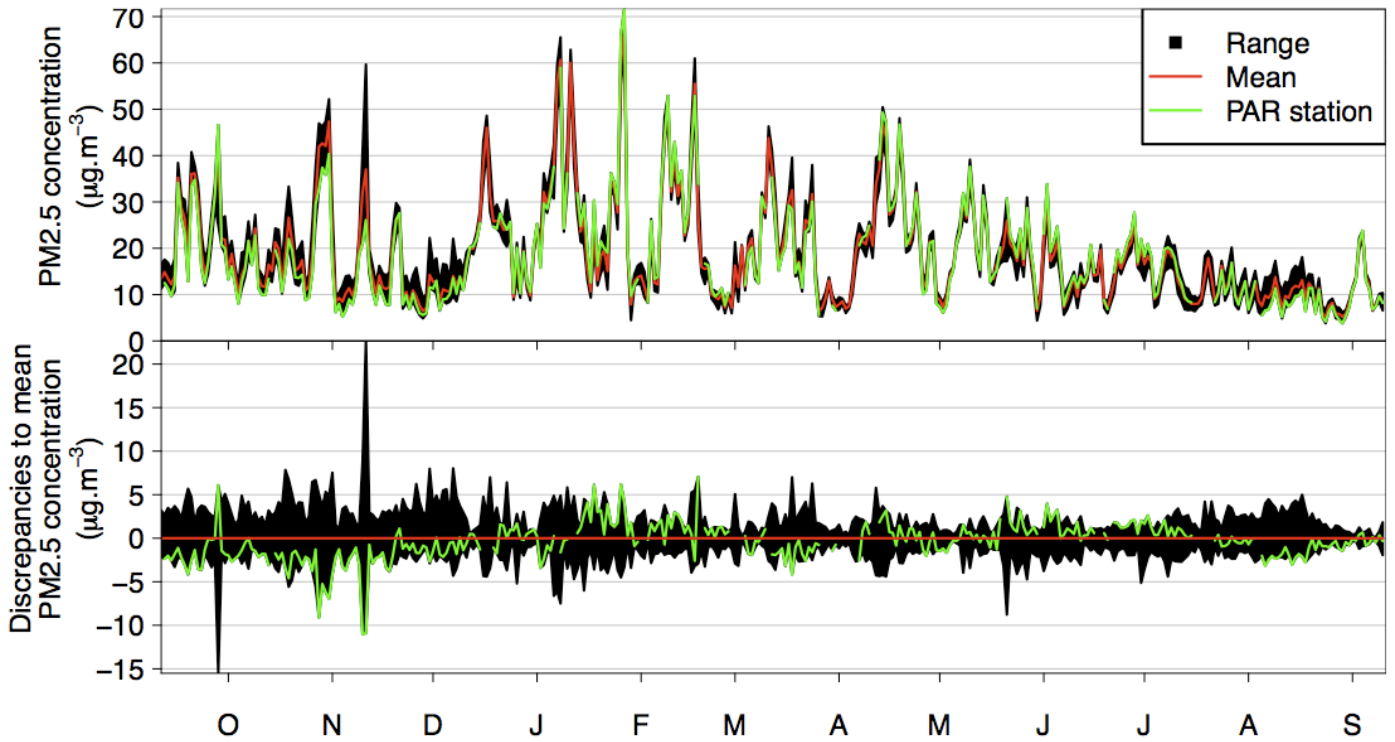


1

2 Figure 2: Location of measurement sites in Paris (urban site, PAR) and around (rural sites,
 3 RNE, RUS, RNW) the Greater Paris. Straight black lines delimit the three wind sectors.
 4 Back-trajectories for three specific days, one for each sector, are also represented by
 5 colored lines. Colored points over back-trajectories indicate air mass location at each
 6 hour.

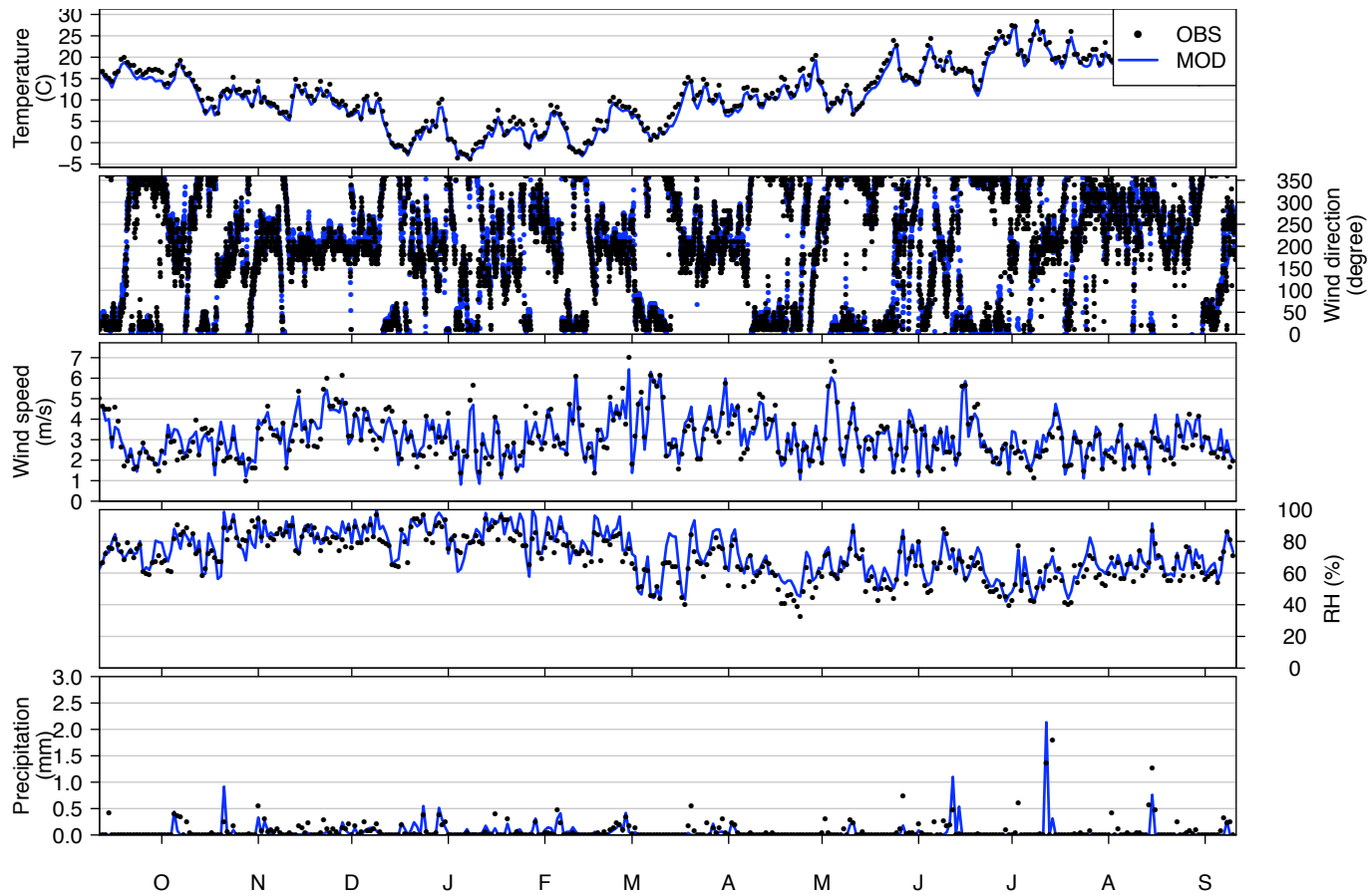
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1



3 Figure 3: Daily PM_{2.5} concentration range (black) from a set of four urban background
4 stations in the Greater Paris (top panel), with mean daily (red) and PAR (green)
5 concentration. Bottom panel: the same minus the mean PM_{2.5} concentration.

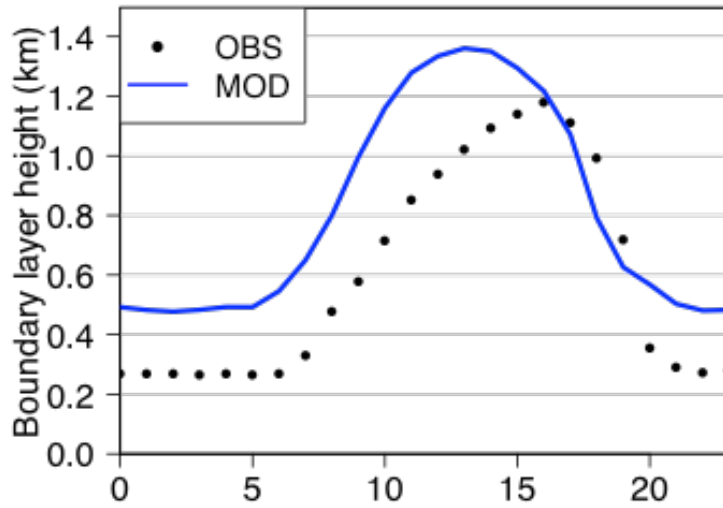
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1

2 Figure 4: Measured and simulated meteorological parameters at the MONTsouris
 3 station (in the center of Paris). Temperature, wind speed, relative humidity (RH) and
 4 precipitations are reported as daily values while wind direction has a 1-h time resolution.

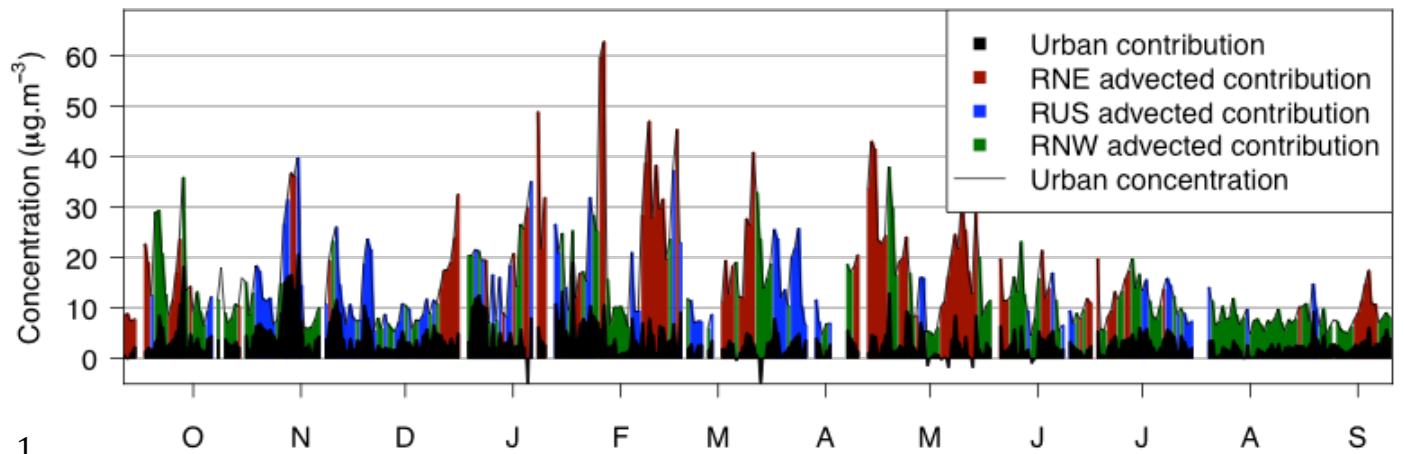
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1

2 Figure 5: Boundary layer height diurnal profile at SIRTA station, measured (in black) and
3 simulated (in blue) during the PARTICULES campaign .

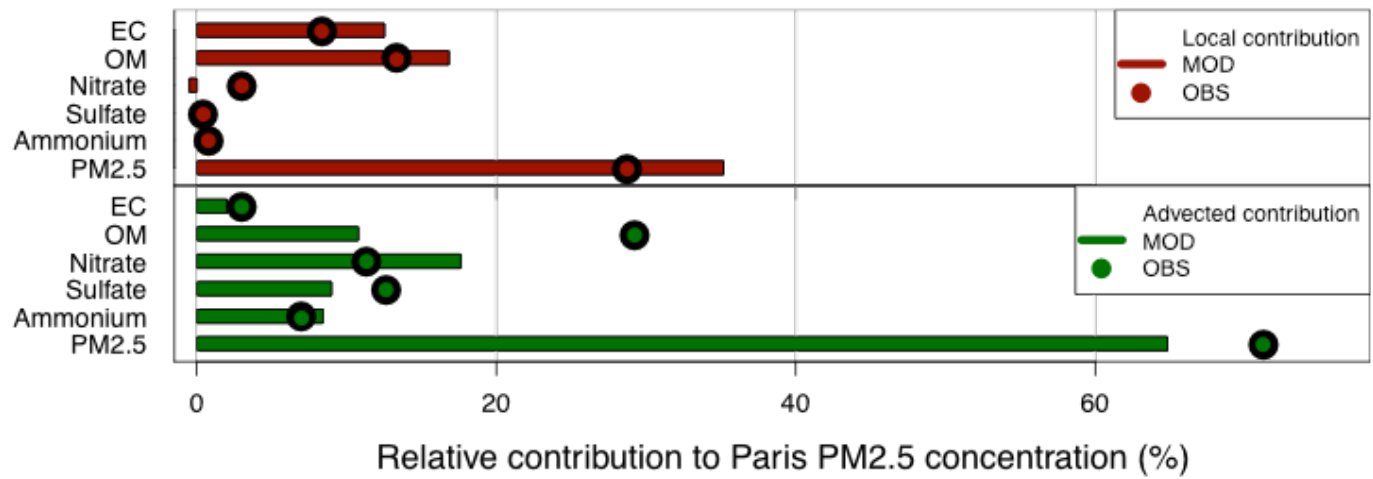
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1

2 Figure 6: Imported and local contributions to the daily observed PM_{2.5} concentrations in
 3 Paris (PAR). The urban local contribution is colored in black. Advected contributions are
 4 represented according to air mass origin in red (for north-east regime), blue (south) and
 5 green (north-west). Note that for several days, no chemical PM_{2.5} speciation is available.

6

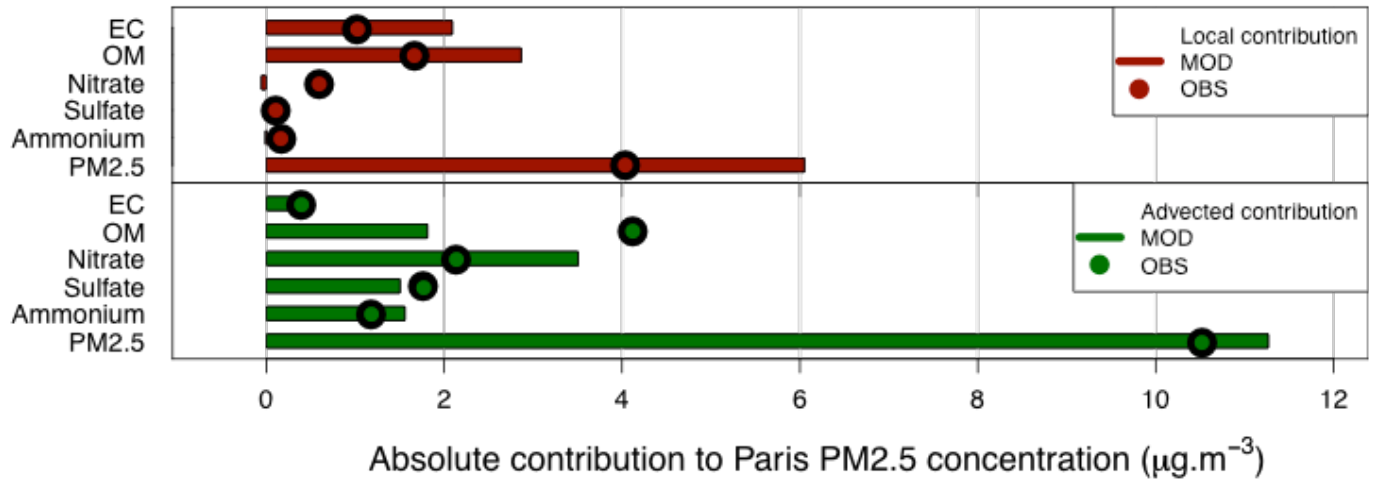


1

2 Figure 7: Mean relative local (top, red) and advected (bottom, green) contributions to the
 3 Greater Paris PM_{2.5} urban background, for CHIMERE (bars) and observations (rounds).

4 Note: These average values are based on the sub-period with a complete data set for all of
 5 the compounds (87% of the period).

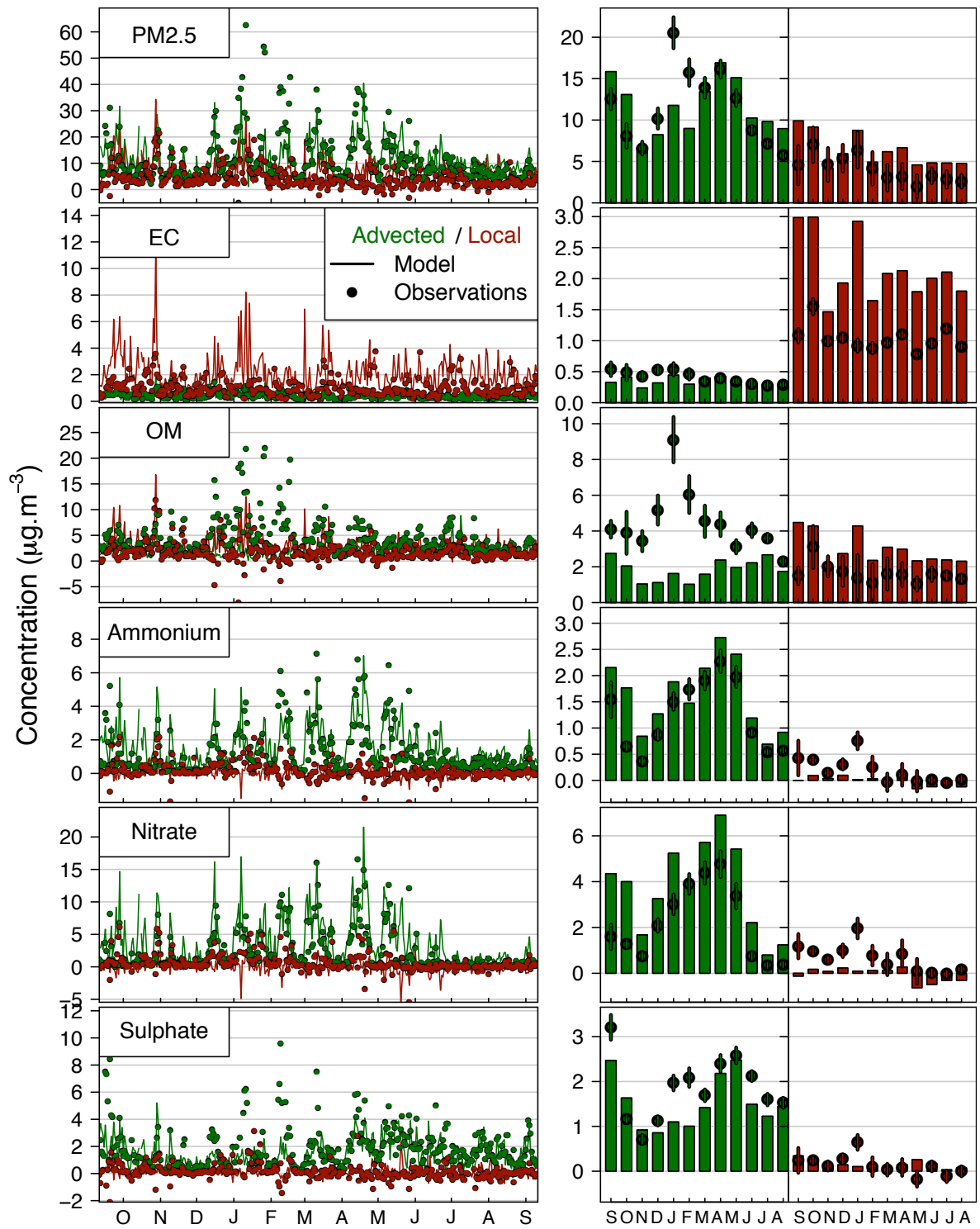
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1

2 Figure 8: Same as Fig. 7, with absolute contributions.

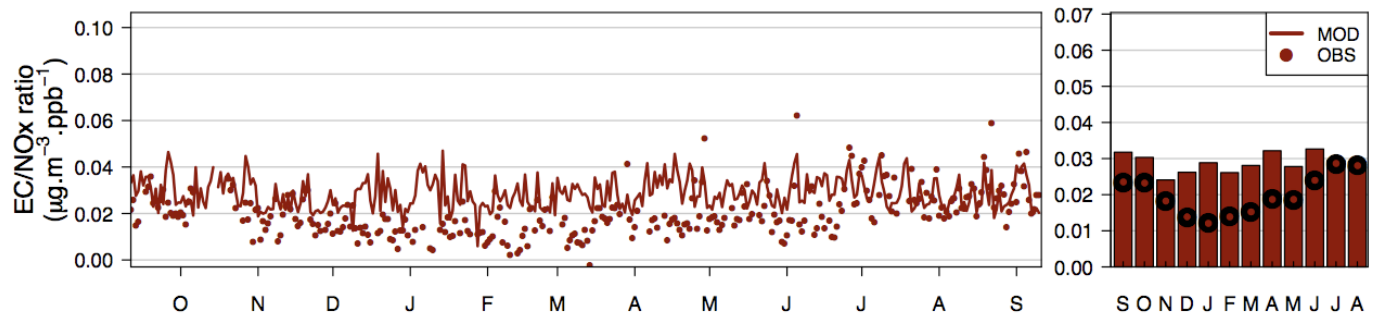
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1

2 Figure 9: Daily time series (left panel) and monthly variations (right panel) of modeled
 3 (lines) and observed (points) advected (green) and local (red) contributions.

4

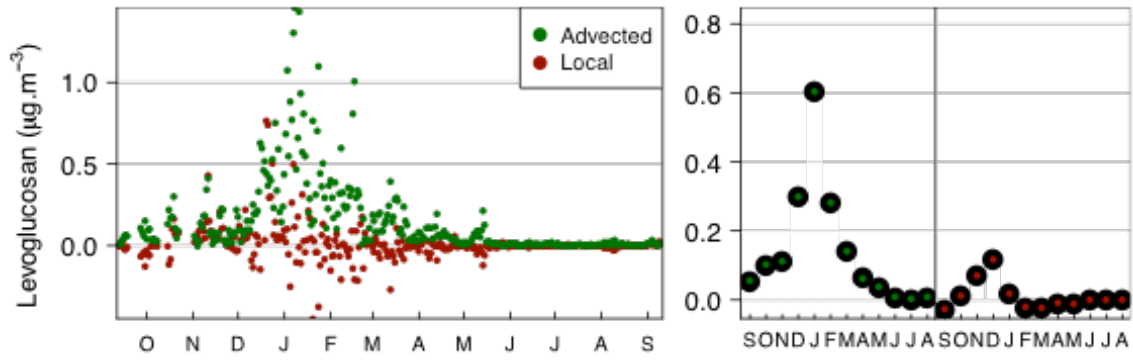


1

2 Figure 10: Local EC/NO_x ratio time series (left) and monthly averages (right) for model

3 (line and bar) and observations (points).

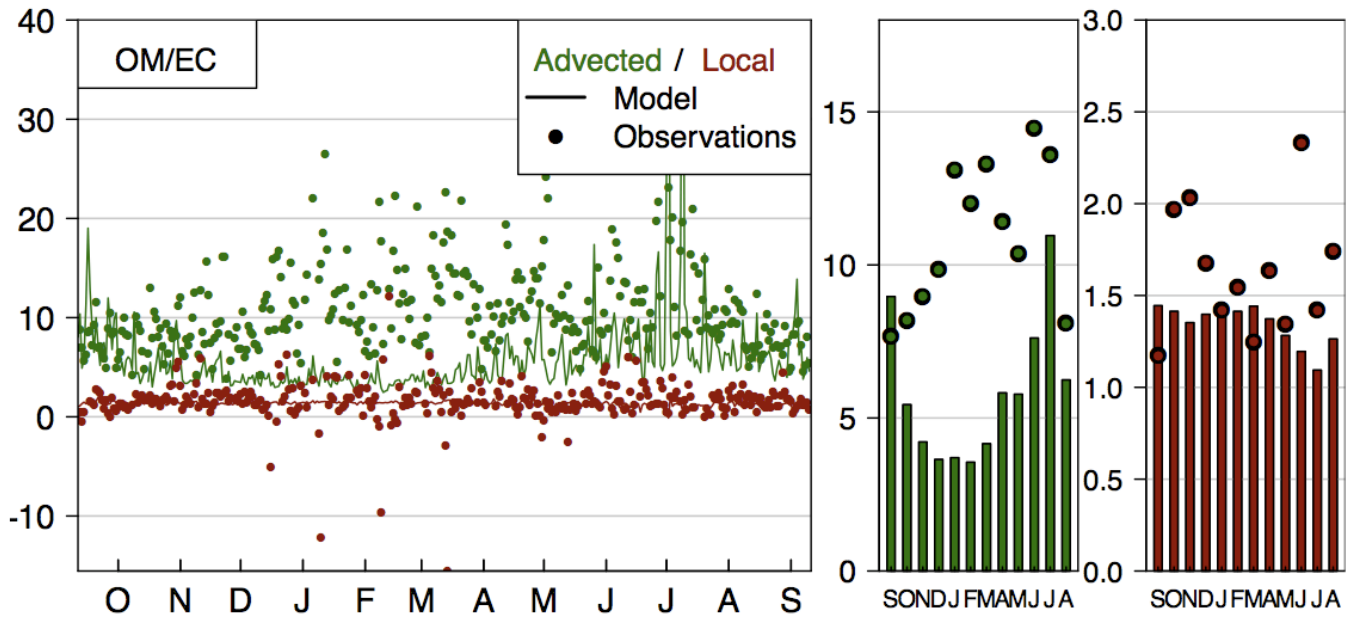
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2 Figure 11: Daily (left panel) and monthly (right panel) advected (green) and local (red)
 3 levoglucosan contributions.

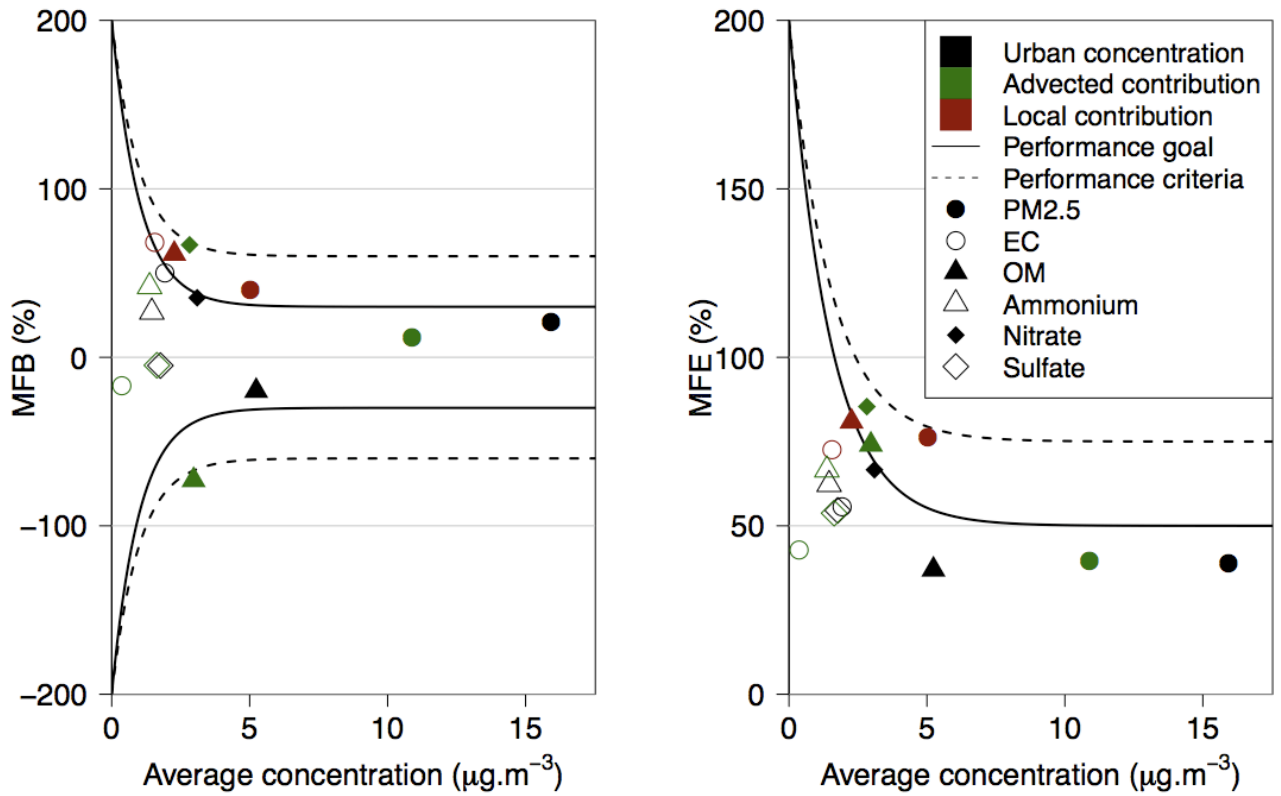
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2 Figure 12: Local OM/EC ratio (unitless) time series (left) and monthly averages (right) for
 3 model (line and bars) and observations (points).

4



1

2 Figure 13: Mean fractional bias (left panel) and mean fractional error (right panel)
 3 depending on the average concentration defined as the average of the mean observed and
 4 the mean simulated concentration. Urban background concentrations, advected and local
 5 contributions of $\text{PM}_{2.5}$ and all its compounds are reported, as well as performance criteria
 6 (dotted line) and goal (continuous line). Secondary inorganics local contributions are not
 7 reported on the graph (see text).

8