Atmos. Chem. Phys. Discuss., 15, 30693–30756, 2015 www.atmos-chem-phys-discuss.net/15/30693/2015/ doi:10.5194/acpd-15-30693-2015 © Author(s) 2015. CC Attribution 3.0 License.



This discussion paper is/has been under review for the journal Atmospheric Chemistry and Physics (ACP). Please refer to the corresponding final paper in ACP if available.

Atmospheric inversion for cost effective quantification of city CO₂ emissions

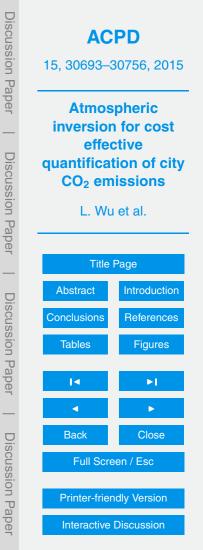
L. Wu¹, G. Broquet¹, P. Ciais¹, V. Bellassen^{2,a}, F. Vogel¹, F. Chevallier¹, I. Xueref-Remy¹, and Y. Wang¹

¹Laboratoire des Sciences du Climat et de l'Environnement (LSCE), UMR CEA-CNRS-UVSQ, Gif sur Yvette, France ²CDC Climat, 75009 Paris, France ^anow at: INRA, UMR 1041 CESAER, 21000 Dijon, France

Received: 6 August 2015 - Accepted: 3 October 2015 - Published: 5 November 2015

Correspondence to: L. Wu (lwu@lsce.ipsl.fr)

Published by Copernicus Publications on behalf of the European Geosciences Union.

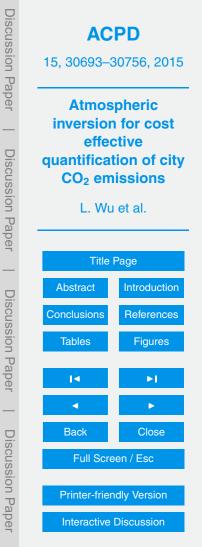




Abstract

Cities, currently covering only a very small portion (< 3%) of the world's land surface, directly release to the atmosphere about 44% of global energy-related CO₂, and are associated with 71–76% of CO₂ emissions from global final energy use. Although

- ⁵ many cities have set voluntary climate plans, their CO₂ emissions are not evaluated by Monitoring, Reporting and Verification (MRV) procedures that play a key role for market- or policy-based mitigation actions. Here we propose a monitoring tool that could support the development of such procedures at the city scale. It is based on an atmospheric inversion method that exploits inventory data and continuous atmospheric
- ¹⁰ CO₂ concentration measurements from a network of stations within and around cities to estimate city CO₂ emissions. We examine the cost-effectiveness and the performance of such a tool. The instruments presently used to measure CO₂ concentrations at research stations are expensive. However, cheaper sensors are currently developed and should be useable for the monitoring of CO₂ emissions from a megacity in the
- ¹⁵ near-term. Our assessment of the inversion method is thus based on the use of several types of hypothetical networks, with a range of numbers of sensors sampling at 25 m a.g.l. The study case for this assessment is the monitoring of the emissions of the Paris metropolitan area (~ 12 million inhabitants and 11.4 TgC emitted in 2010) during the month of January 2011. The performance of the inversion is evaluated in terms of
- ²⁰ uncertainties in the estimates of total and sectoral CO₂ emissions. These uncertainties are compared to a notional ambitious target to diagnose annual total city emissions with an uncertainty of 5 % (2-sigma). We find that, with 10 stations only, which is the typical size of current pilot networks that are deployed in some cities, the uncertainty for the 1-month total city CO₂ emissions is significantly reduced by the inversion by ~ 42 % but
- ²⁵ still corresponds to an annual uncertainty that is two times larger than the target of 5 %. By extending the network from 10 to 70 stations, the inversion can meet this requirement. As for major sectoral CO_2 emissions, the uncertainties in the inverted emissions using 70 stations are reduced significantly over that obtained using 10 stations by 32 %





for commercial and residential buildings, by 33 % for road transport and by 18 % for the production of energy by power plants, respectively. With 70 stations, the uncertainties from the inversion become of 15 % 2-sigma annual uncertainty for dispersed building emissions, and 18 % for emissions from road transport and energy production.

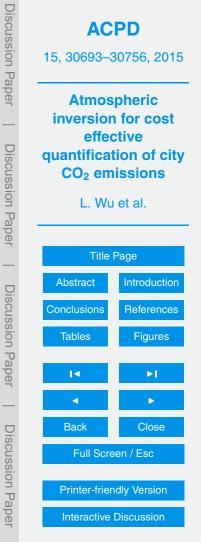
- ⁵ The inversion performance could be further improved by optimal design of station locations and/or by assimilating additional atmospheric measurements of species that are co-emitted with CO₂ by fossil fuel combustion processes with a specific signature from each sector, such as carbon monoxide (CO). Atmospheric inversions based on continuous CO₂ measurements from a large number of cheap sensors can thus deliver a valuable guantification tool for the monitoring and/or the verification of city CO₂
- 10^{-11} emissions (baseline) and CO₂ emission reductions (commitments).

1 Introduction

At the 2010 Cancun summit, parties from United Nations Framework Convention on Climate Change (UNFCCC) agreed to set up a target of keeping global warming under ¹⁵ 2°C compared to pre-industrial levels (UNFCCC, 2011; Meinshausen et al., 2009; Ciais et al., 2013). Shah et al. (2013) showed that this 2°C global warming target is economically and technically feasible, albeit demanding a mitigation of the Greenhouse Gases (GHG) emissions across all sectors of anthropogenic activities. Many developed and developing countries consequently make commitments/pledges to reduce their emis-²⁰ sions under UNFCCC. National commitments/pledges focus on the land use sector or on economy-wide activities such as electricity production and industrial processes,

nevertheless appear to be insufficient for achieving the global warming target (UNEP, 2013).

Cities occupy only less than 3% of the world's land surface (Liu et al., 2014), but ²⁵ directly release about 44% of the global energy-related CO_2 and are responsible for 71–76% of CO_2 emissions from global final energy use (Seto et al., 2014). This urban share of the anthropogenic emissions will continue to increase (IEA, 2008) in an accel-



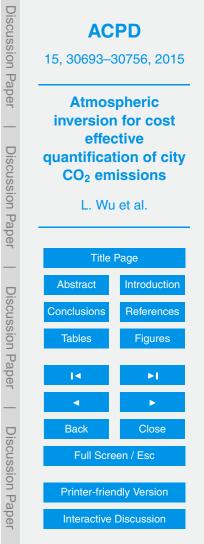


erating urbanization process: the global urban population having grown from 746 million in 1950 to 3.9 billion in 2014 while, by 2050, it is expected to grow by 2.5 billion people, with nearly 90% of them living in Asia and Africa (UN, 2014).

- Unlocking the city mitigation potential may significantly reduce the gap of emission ⁵ reductions between national commitment/pledges and scenarios consistent with a 2 °C limit. A plausible additional city contributions to global emission mitigation was estimated to cover ~ 15 % of the total required global emissions reduction, which represents up to two-thirds of the national commitments/pledges (Erickson and Tempest, 2014). Large urban areas have a strong potential to achieve economies of scale in per capita CO₂ emissions for some important sectors (e.g. transportation and heating)
- where clusters of population and economic activities can share common infrastructures (Bettencourt et al., 2007; Dodman, 2009; Glaeser and Kahn, 2010; CDP, 2012). Practical city mitigation actions are for instance the improvement of public transportation infrastructure such as Mass and Rapid Transit (MRT) systems, building retrofits and energy/waste recycling, and district heating/cooling plants (Sugar and Kennedy, 2013;
- Erickson and Tempest, 2014).

Thousands of cities declared to be willing to take actions to report and reduce their CO₂ emissions (Rosenzweig et al., 2010; Reckien et al., 2013). Such efforts can decrease their climate vulnerability and foster co-benefits in terms of air quality, energy access, public health, and city livability (Seto et al., 2014). They also may foster significant local economic development through advances in green technology. For instance, the London low carbon environmental goods and services is estimated to have generated more than GBP 25 billion revenue for 2011/12 (BIS, 2013).

To check whether claimed reduction targets are fulfilled, city emissions will have to be known accurately for present-day conditions to define a baseline upon which reductions are defined, and then monitored over time during any agreed-upon reduction commitment period. Such quantification of emissions and emission reduction echoes the concept of Monitoring, Reporting, and Verification (MRV) that is the cornerstone of most market- or policy-based mechanisms in climate economy (Bellassen and Stephan,





2015). The MRV concept integrates three independent processes, namely Measuring or Monitoring (M), Reporting (R), and Verification (V). It ensures that the mitigation actions are properly monitored and reported, and that the mitigation outcomes can be verified. The MRV has been widely applied in many contexts such as projects, orga-

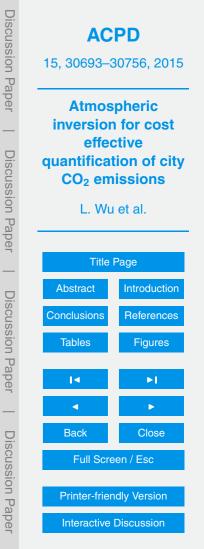
⁵ nizations, policies, sectors, or activities within territories (see Bellassen and Stephan, 2015, and the references therein). For diverse applications, MRV can rely upon different standards, but requires transparency, quality, and comparability of information about emission accounting and the mitigation action implementations.

The first urban mitigation actions relevant for MRV are those whose impacts are relatively easy to measure, e.g., projects and Programmes of Activities (PoA) under the Clean Development Mechanism (CDM) as well as efforts on emission reductions for large factories and buildings under the Tokyo Emission Trading Scheme (ETS) (Clapp et al., 2010; IGES, 2012; Marr and Wehner, 2012; UNEP, 2014). However, there is a lack of technical capacity for accurate accounting of diffuse sources, e.g. transportation and residential buildings. This lack of capacity makes MRVs for citywide emissions

- tion and residential buildings. This lack of capacity makes MRVs for citywide emissions challenging (Wang-Helmreich et al., 2012; UNEP, 2014), and may hinder citywide mitigation implementation in absence of strong political will, sufficient institutional governance and financial support. Hitherto MRV practices for urban mitigation actions are still limited and the majority of sources within the city territory remain uncovered. For instance, the Takue FTC.
- instance, the Tokyo ETS the most advanced urban ETS scheme only regulates less than 20 % of the city's total emissions (TMG, 2010).

As such, there is a keen need to scale up policy instruments and market mechanisms to foster broader access of supports at various scales from international to local, for enabling citywide mitigation actions (World Bank, 2010; Wang-Helmreich et al.,

25 2012; The Gold Standard, 2014). This gap may be reduced by new mechanisms such as the Nationally Appropriate Mitigation Actions (NAMAs; recent move to raise pre-2020 emission reduction ambitions by increasing access to climate financing) and the New Market-based Mechanism (NMM; currently in negotiation for post-2020 carbon financing about crediting and trading of mitigation outcomes). Both mechanisms are



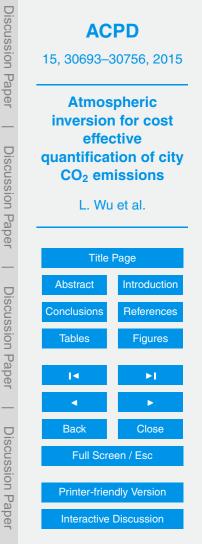
designed under UNFCCC to increase the flexibility of mitigation actions so that broader segments of economy or policy-making can be included in developed and developing countries (Howard, 2014; UNEP, 2014). Based on estimates of emissions from the major sectors, a conceivable approach would be to set up city overall mitigation tar-

- gets and then negotiate specific targets for individual sectors or groups of sources. Empowered by city-scale MRV (see UNEP (2014) for current developments), city mitigation implementation could be (1) credited or traded under designed mechanisms, and (2) registered for receiving international aide through climate finance. Importantly, all these provisions for citywide mitigation actions and their MRV necessitate the avail ability of emission accounting methods with required qualities (moderate or stringent;
 - an issue we will discuss in following sections).

The emission accounting methods that are usually suggested are inventories based on statistical data (World Bank, 2010; Wang-Helmreich et al., 2012). Developing cityscale inventories, and updating them over time, involve extensive collection of con-

- sistent and comparable emissions data, which measures the level of activities (e.g. energy use statistics, or in a more sector-specific manner, kilometers driven by vehicles, and volume of waste provided to landfill) and the activity-to-carbon conversion rates (i.e. emission factor). In the past, cities have followed diverse guidelines or protocols for emission inventory compilation, and recently there is a trend of centralization
- e.g. with the newly proposed Global Protocol for Community-Scale Greenhouse Gas Emission Inventories (GPC; Fong et al., 2014) and the UNFCCC reporting platform NAZCA (climateaction.unfccc.int). Admittedly, inventories of city emissions are known to suffer from incomplete and uncertain data (see Appendix A for a brief review of city inventories). For instance, there is usually a lack of precise statistics regarding the to-
- tal amount of fossil fuel that has been consumed within the cities. This issue of data availability and quality impedes the practical use of city inventories in climate economy.

To improve the quality of emission accounting, here we propose using a new type of data – continuous CO_2 concentration measurements in the atmosphere made on a network of stations around and within cities. Accurate measurements of the atmospheric





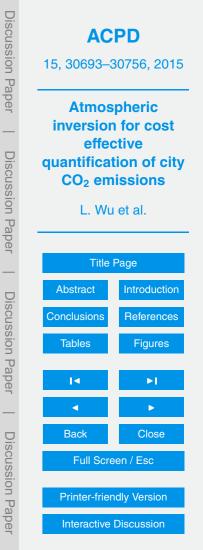
signals, e.g. the CO₂ concentration gradients, contain information about the emissions that are independent of inventories. A statistical method known as atmospheric inversion, which has been used for decades for improving the knowledge of global and continental scale natural CO₂ fluxes (Enting, 2002; Bousquet et al., 2000; Gurney et al., 2002; Peters et al., 2007; Chevallier et al., 2010; Broquet et al., 2013), can exploit this information from actual atmospheric measurements for quantifying CO₂ emissions at city scale (McKain et al., 2012; Kort et al., 2013; Lauvaux et al., 2013; Hutyra et al., 2014; Bréon et al., 2015). The principle of an inversion is to combine information from inventory data with atmospheric CO₂ measurements to deliver improved emission estimates, i.e. emissions with a reduced uncertainty, compared to the inventory. An inversion generally uses a 3-D model of atmospheric transport to relate emissions with observations. In just a few years, a number of city atmospheric CO₂ measurement networks have been deployed for pilot studies. Examples of cities where such networks have been deployed are Toronto (with 5 sites), Paris (with 5 sites), Sao-Paulo (with 2 sites) and the fourth of the inventory of the sites of the analysis of cities where such networks have been deployed for pilot studies. Examples of cities where such networks have been deployed for pilot studies. Examples of cities where such networks have been deployed for pilot studies. Examples of cities where such networks have been deployed are Toronto (with 5 sites), Paris (with 5 sites), Sao-Paulo (with 2 sites).

sites), Los Angeles (~ 10 sites), and Indianapolis (with 12 sites). This creates a need to better document the theoretical potential of atmospheric inversions to monitor emissions and their changes or to independently verify inventories, with a quality relevant for city MRV applications.

In this paper, we assess the performance of atmospheric inversions for the monitoring of total and sectoral fossil fuel emissions in the Paris metropolitan area (the Île-de-France (IDF) region, which has ~ 12 million inhabitants). The most resolved regional bottom-up inventory estimates that this area emitted 11.4 TgC in 2010 (AIR-PARIF, 2013), an amount equivalent to ~ 12% of the fossil fuel CO₂ emissions from the whole France (Boden et al., 2013). Urban emissions are mainly connected to emissions from fossil fuel combustion, as other sources of urban emissions are biofuel

sions from fossil fuel combustion, as other sources of urban emissions such as biofuel uses are usually very limited. Hence, for simplicity, we assume that urban emissions are all from fossil fuel combustion in our study.

In general, there exists no formal agreed-upon minimum requirement about desirable uncertainties in emissions estimates relevant for MRV use. However, such require-

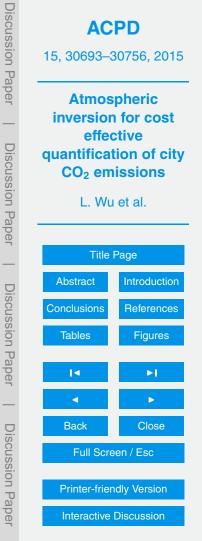




ments would give some solid basis to MRV practice for citywide emission mitigation. Therefore, we will first attempt at defining notional targets in terms of uncertainties in the emissions estimates for inversion systems at city scale (Sect. 2.1). In Sect. 2.2, we will then discuss the cost of the observing and modeling systems that are required

- for atmospheric inversions. This cost, ideally, should be comparable to or even smaller than that of high quality inventories. The observation networks to be tested will be dimensioned to ensure that they fit within this cost. The CO₂ measurement instruments presently used for atmospheric inversion in the scientific community are rather expensive which explains the limited size of the existing city networks. However, cheap sen-
- ¹⁰ sors are currently developed and we assume here that such sensors will be useable for the inversion of city emissions in the near-term. We will thus assess the performance of the inversion that relies on hypothetical networks similar to the existing ones (limited number of sensors at current cost), or includes a larger number of cheap sensors. The theoretical framework of the inversion allows for the derivation of uncertainty reduction
- from such hypothetical networks given the statistical description of the sources of error in the inversion configuration. This study is based on the inversion configuration and results using CO₂ measurements from 3 stations in the Paris area, published by Bréon et al. (2015) (hereafter referred to as B15). Taking into account the limited information content from this small network, B15 did not attempt to estimate sectoral emissions
- ²⁰ separately but rather focused on quantifying total CO₂ emissions from the Paris urban area. The principle of our inversion system extends that of B15 to separate sectoral emissions using larger networks of measurement sites. The use of a large numbers of stations also leads us to conduct network design studies in order to optimize, for a given number of stations, the performance of the inversion as a function of these ²⁵ station locations.

Sections 3 and 4 describe how we use an Observing System Simulation Experiments (OSSE) framework to analyze whether this inversion framework can achieve the uncertainty targets, principally with respect to the number of measurement sensors and their spatial distribution. The inversion methodology and the OSSE setup are described in





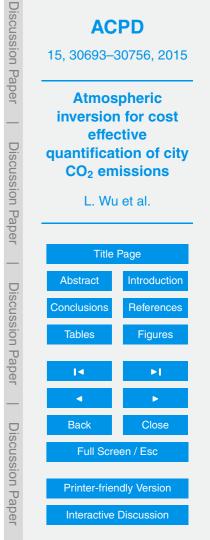
30701

Sect. 3. The inversion results are presented in Sect. 4, and finally some discussions and conclusions are drawn in Sect. 5.

Notional requirements for the inversion framework 2

2.1 Notional targets for uncertainties in inversion estimates

- This section aims at defining a notional target of emission uncertainty for an inversion to be useful in the context of MRV applications. We set the target uncertainty of city annual emissions to be similar to the one of national inventories in OECD countries. reported under UNFCCC and the Kyoto protocol. The main rationale for such setting is that MRVs at national and city scales have similar objectives: supporting determination of baselines and/or reduction of emissions from various sources (e.g. transportation, 10
- building, and industries) for a given geographical area. Hence, the knowledge and experiences accumulated from national MRVs can provide basis for future MRV at city scale. More specifically, the "name and shame" mechanism that was established for countries under UNFCCC and the Kyoto protocol (Chang and Bellassen, 2015) could
- apply to MRV of citywide mitigations, and lead to uncertainty level in citywide emission 15 estimates similar to that in national inventories. The derivation of uncertainty targets for cities from uncertainties of national inventories may look stringent for inversions. Such derived targets are likely stricter than the requirements in uncertainty level for the MRV of emission reductions by actions/policies at city scale, in a situation similar to
- the MRV practice at national scale (Ninomiya, 2012). However, respecting such strict 20 targets ensures the reliability of the annual estimates from atmospheric inversion: the inversion-based estimates of city emissions would then be equivalent or better than that of city inventories that would not have access to the same level of information as national inventories.
- The uncertainty of national inventories is country-specific, but for the seven Annex I 25 countries surveyed by Pacala et al. (2010), the uncertainty in CO₂ fossil fuel emissions



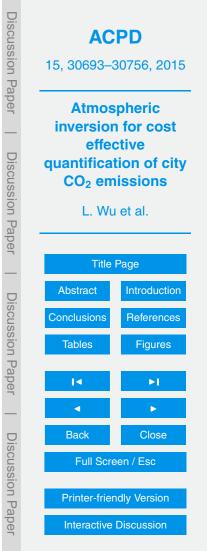


is consistently lower than 10% (2-sigma). For France, the uncertainty of the CITEPA national inventory (annually reported to UNFCCC) is estimated to be of 5% (2-sigma) for year 2012 according to CITEPA (2014). This uncertainty quantification is based on expert judgments as well as error propagation calculations with the IPCC Tier 1

- ⁵ method. Consequently, here we define a 5% 2-sigma annual notional target for the level of uncertainties in annual total fossil fuel CO₂ emission estimates over the territory of a French city (or urban area) to be reached or surpassed by atmospheric inversions. In this study, we investigate the ability of inversions to reach such a target for the Paris metropolitan area.
- ¹⁰ The uncertainty levels for estimates of emissions from different sectors can vary significantly at the national scale (Pacala et al., 2010; CITEPA, 2014). For instance, uncertainties for some activities such as mineral, metal and chemical productions are considerably larger than the 5 % value for total emissions, but the share of these emissions in the total fossil fuel emissions is usually small. However, uncertainties for other
- sectors are closer to 5 % according to CITEPA (2014). The sectoral distribution of uncertainty levels at the city scale can be different from that at the national scale, because the data collected for a given sector in city inventory compilation can have a different level of quality from that in national inventories for the same sector. A recent census by National Physical Laboratory (NPL) based on a group of 26 city inventories reported to
- ²⁰ the carbon *n* Climate Registry (cCR) suggested that the data collected for different sectors can actually have a similar level of quality (report available from www.carbonn.org).

The annual notional target for uncertainties in total CO_2 emissions can be inappropriate for sectoral CO_2 emissions. The sectors of emissions are usually driven by different dominant factors (e.g. temperature for building heating/cooling and commute/vocation

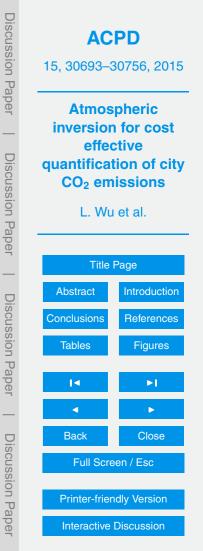
timing for road traffic). Consequently the uncertainties in emission estimates from inventories for different sectors are generally weakly correlated. They can even be anticorrelated when the individual sectoral estimates are based on the split of estimates of budgets derived from fossil fuel consumptions that are shared by these sectors. These weak or negative correlations explain why the uncertainties in individual sec-





toral emission estimates are in general larger than the uncertainties in the aggregated total emission estimate. Due to these reasons, we set notional uncertainty target only for city total emissions estimates in this study.

- Succeeding in delivering a 5% annual uncertainty target for the total emissions of a city would translate into an ability to assess a 25% reduction of total emissions on a 15-year horizon at 95% confidence level (detection interval [18, 32%], p = 0.05 for linear trends of emissions; see Appendix C for numerical details). The Paris climate plan for example, aims at reducing the GHG emission reduction by 25% by 2020 and by 75% by 2050 relative to the 2004 baseline (Mairie de Paris, 2012). This means that a 5% annual uncertainty is also satisfactory to monitor the trend of Paris emissions
- over time. However, the 5% target is not a requirement for such trend detection, since, with an annual estimate bearing 10% uncertainty, a 25% reduction in 15 years would still remain detectable at 95% confidence level (detection interval [11, 39%], p = 0.05).
- So far, practical atmospheric inversion of the Paris city emissions have been performed over 1-month periods, with an interest in inferring monthly emissions, even though emissions have been actually inverted at a higher temporal resolution (B15). However, our notional target of 5% uncertainty is defined at the annual scale. One can nevertheless relate monthly uncertainties to annual uncertainty based on one intermediate and two extreme assumptions regarding the temporal correlations between
- ²⁰ monthly uncertainties: that all monthly uncertainties are independent from one another, that the timescale of these correlations is approximately 2-months, and that all monthly uncertainties are fully correlated. Based on these three assumptions, the annual uncertainty related to the monthly uncertainties can be obtained by simple error propagation. The two extreme cases of null and full positive temporal correlations would
- ²⁵ hardly happen in reality, but they provide an estimate of the range for such targets. We will consider in control runs a 2-month temporal error correlation of uncertainties in monthly inversion emission estimates in order to derive the most likely corresponding uncertainty in the annual inversion estimates. For instance, a 20% 1-sigma monthly uncertainty corresponds to 12, 23, 40% 2-sigma annual emission uncertainties, given





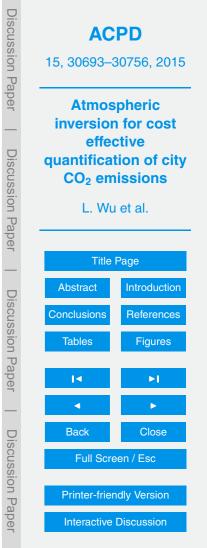
null, 2-month timescale, and full temporal error correlations respectively. In this example of 20 % 1-sigma monthly uncertainty, the most likely annual emission uncertainty is considered to be 23 %, which is much larger than the 5 % 2-sigma target and would not meet our notional requirement. Here, for simplicity, we hypothesize a same level

of uncertainty in inversion estimates of the fossil fuel CO₂ emissions for each month of the year. For instance, months with significant natural vegetation uptake are characterized by a larger influence of the natural vegetation and soil CO₂ fluxes (or Net Ecosystem Exchange, NEE) in the total flux of IDF and a larger uncertainty in NEE fluxes: we checked that both features marginally affect our inversion results (see the supplementary sensitivity analysis).

To facilitate subsequent discussions, we define three levels of 1-sigma uncertainty for monthly emissions estimates, going from less to more stringent levels: level 1 = 15 %, level 2 = 10 %, and level 3 = 5 %. The corresponding most likely 2-sigma annual uncertainties are 17, 11 and 6 % respectively. It can be observed that only level 3 monthly uncertainties can yield annual uncertainties that meet the 5 % uncertainty target for annual estimates. In contrast, monthly estimates with level 1 and 2 uncertainties could be useful for sectoral emissions, for the verification of emission trends, and for the verification of the emission reductions by mitigation policies/actions.

2.2 Notional costs about a city-scale atmospheric inversion system

- ²⁰ The main cost of atmospheric inversion of city emissions being related to the observation network on which it relies, the typical size of the networks to be investigated in this study must be constrained by the definition of a limit for this cost. The order of magnitude of this cost should not exceed that of city inventories that could deliver emission estimates complying with the 5 % notional annual uncertainty. Such high quality inven-
- tories at city scale do not exist yet (see Appendix A). However, the cost of national inventories could give insights on the cost of such city inventories since both types of inventories would adopt similar methodologies and would require similar types of data with the same level of quality.

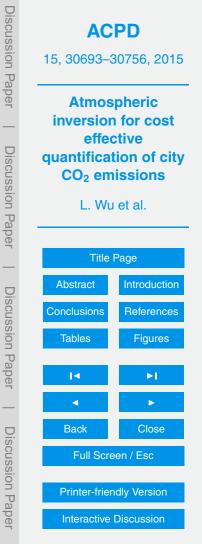




The cost of an inventory involves mainly data collection, and the design and implementation of the inventory methodology. The data (e.g. statistics on energy fuel consumption, transport and industrial activities) required for the development of a national inventory are in general available from national agencies, and the cost of its collection is on the order of several million euros per country per year (Chang and Bellassen, 2015). However, most of the cost incurs from collecting socio-economic data that are primarily obtained for other political/economical/social purposes than emission inventory. The CITEPA is the agency responsible for preparing the French national inventory along the IPCC guidelines. The budget of the activities at CITEPA related to this inventory is on the order of 1 M EUR year⁻¹ (PLF, 2014). This cost covers the compilation of the fossil fuel CO₂ emissions inventory but also (1) the compilation of the inventory for other GHG gases, (2) the compilation of the inventory for GHG emissions due to land use, land use change and forestry (LULUCF), and (3) activities other than monitoring such as the reporting, archiving and annual communication to UNFCCC reviews that

- ¹⁵ are imposed by the IPCC guidelines. It is therefore complicated to assess the part of the cost that is dedicated to the compilation of the CO₂ fossil fuel emissions inventory by CITEPA. As for the city inventory compilation, tracking fuel use statistics from different origins and types and for different sectors might in fact prove more complicated than for a state where national statistics are already firmly established by governmen-
- tal agencies. As a result of the above discussions, we will assume in this study that building and updating each year a city inventory for the Paris metropolitan area that could possibly achieve the 5% notional annual uncertainty target would cost around 0.5 M EUR year⁻¹.

The cost of the observation network for atmospheric inversion is related to that of the measurement instruments and to that of the calibration and maintenance procedures that ensure limited drift and biases in the measurements. We consider two types of sensors that could equip the city observation networks: "high precision sensors" (e.g. existing cavity ring down spectrometers employed by current research networks) and "cheap sensors" currently still in development but likely available in the near future





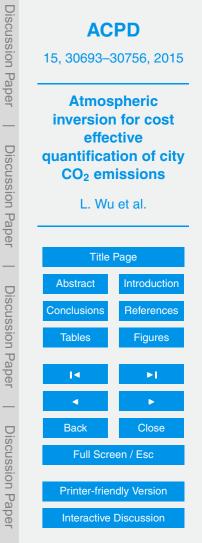
(see Appendix B for details). High precision sensors are instruments with a precision of 0.1 ppm (1-sigma) on hourly measurements. Given the present calibration procedures, such hourly measurements bear additional systematic errors that are smaller than 0.13 ppm for hourly measurements. "Cheap sensors" are expected to have lower precision. The threshold for such precision will be defined in this study to be 1 ppm on

- hourly measurements, and the precision target will be actually 0.5 ppm (1-sigma). We also hypothesize that calibration procedures for the cheap sensors, with costs that are comparable to that for high precision sensors, should ensure that the systematic error in hourly measurements is smaller than 1 ppm. Given that the systematic errors should
- not have long autocorrelation timescales and that precision errors are not autocorrelated in time (see Appendix B), these different errors for both the high precision instruments and the cheap sensors should be far smaller than the errors associated with atmospheric transport modeling and they are thus ignored hereafter (see Sect. 3.5.2 for details). Hence, in this study, the only impact of using one or the other type of sen-
- ¹⁵ sor is thus related to their cost. Given the consideration regarding the limitation of the cost of the atmospheric inversion, this leads to different numbers of stations allowed for the network of measurement sites. With the notional budget of $0.5 \,\mathrm{M\,EUR\,year^{-1}}$, one could afford to operate a network of either ~ 10 high precision sensors or ~ 70 cheap sensors (see Appendix B). We thus evaluate the performance of the inversion in terms of under the performance of the inversion.
- in terms of uncertainty reduction when using hypothetical measuring networks of 10 to 70 sensors.

3 Methodology

3.1 Bayesian inversion

By Bayesian inversion, the information from an observation vector y is combined with a prior (background) estimate x^{b} of a control parameter vector x about CO₂ emissions





to provide an updated estimate x^a (Enting, 2002):

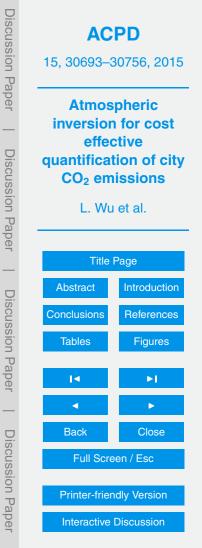
 $\boldsymbol{x}^{a} = \boldsymbol{x}^{b} + \boldsymbol{B}\boldsymbol{H}^{\mathsf{T}}(\boldsymbol{R} + \boldsymbol{H}\boldsymbol{B}\boldsymbol{H}^{\mathsf{T}})^{-1}(\boldsymbol{y} - \boldsymbol{H}\boldsymbol{x}^{b}),$

where **H** the linear matrix operator linking y with x based on the modeling of emissions and atmospheric transport. The errors in y, H and x^{b} are assumed to have statistical distributions that are Gaussian, unbiased and independent of one another. We denote 5 by **R** and **B** the covariance matrices of the observation and background errors respectively. The observation error is a sum of measurement and model errors. Similar to B15, we control a vector x of the budgets of emission estimates, which all together constitute the total emissions of IDF for the month of January 2011. These emissions are defined on a spatial horizontal grid same as that of the atmospheric transport model 10 (see Sect. 3.4.2 for the definition of this grid covering IDF). Here, the observation operator **H** can be decomposed into a chain of three operators: the spatial and temporal distribution of the budgets of emissions within a corresponding area and period of control, the atmospheric transport of CO₂ given these spatial and temporal distributions of the emissions, and a sampling of the resulting simulated CO₂ to be compared with the observations (Fig. 1). These three H components will be detailed later in Sect. 3.4. According to the theory of Best Linear Unbiased Estimation (BLUE), the inversion system (Eq. 1) provides an emission estimate x^{a} with reduced uncertainty (i.e. with "smaller" error covariance matrix compared to **B**):

²⁰ $\mathbf{A} = (\mathbf{B}^{-1} + \mathbf{H}^{\mathsf{T}}\mathbf{R}^{-1}\mathbf{H})^{-1}.$

25

Here we assess the inversion performance by evaluating the ability of inversion to reduce uncertainties in emission estimates, which can be computed by Eq. (2) using realistic prior and observation error statistics. This assessment is done for the estimation of the emissions during the month of January 2011. In the following sections, we detail each component of the inversion system for this computation (see Fig. 1).



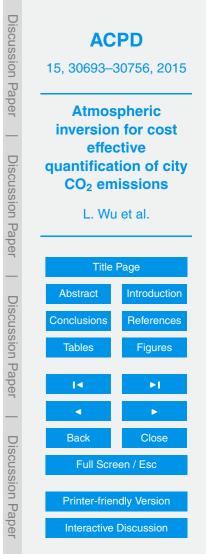
(1)

(2)

3.2 Control vector

Formally, even though this is equivalent in principle, x does not directly contain emission budgets, but scaling factors that are applied to emission budgets included in the observation operator **H**. Each scaling factor in the control vector x corresponds to the

- ⁵ budget of emissions for a given spatial area of the IDF domain, a given temporal window, and a given sector or group of sectors of CO₂ emitting activity. The corresponding ensemble of areas, temporal windows and sectors form partitions of the IDF domain, of the month of January and of the full range of emitting activities respectively, so that the different control variables are associated with a partitioning of the total emissions
- in IDF during January 2011. Hereafter, we will call a "control tile" the combination of an area, a temporal window and a sector (or group of sectors) associated with a control variable. While it is desirable to solve for the emissions at high spatial, temporal and sectoral resolution (in order to avoid aggregation errors, see below), the size of the control vector, and thus this partitioning, must be limited due to computational constraint
- for inversions. In practice, the partitioning described below is adapted to the sectorial, temporal and spatial distribution of the emissions (using insights from the inventory presented in Sect. 3.4.1). We did not estimate the emissions outside of the IDF region. We group the various sectors usually provided by inventories (detailed in Sect. 3.4.1) according to the New Format Reporting (NFR) nomenclature defined by the Long range Transboundary Air Pollution (LRTAP) Reporting Guidelines (EEA, 2013) into seven groups of sectors (see Appendix A for details), namely (1) surface commercial and residential building heating/cooling, (2) road transport, (3) energy production (power plants), (4) combustion and production processes in industries, (5) combustions from agricultural activities, (6) airline traffic, and (7) the rest of all other sectors with smaller emission budgets (e.g. railway, navigation, fugitive emissions, and several minor production processes). These seven sectors are labeled for short as building, road, energy, production, agriculture, airline, and rest, respectively.





In order to save computations, for most of these sectors (isolated energy and production point sources, agriculture, airline and rest), we consider that the spatial area of control for the inversion is the whole IDF area. However, for the two important building and road emissions, we spatially partition IDF into five zones for which the fluxes will be optimized: a central zone (approximately the administrative definition of the city of

Paris, which is very densely populated) and four surrounding areas (the north-west, south-west, north-east and south-east areas of the remaining IDF region, with borders adapted to the distribution of the building and road emissions, see Fig. 2).

Regarding the temporal partitioning, for the three sectors which have the smallest ¹⁰ budgets of emissions (agriculture, airline, and rest), the temporal resolution of the control vector is daily. For the four other sectors (building, road, energy and production), we refine the temporal resolution to control separately the daytime (09:00–18:00 LT) and night-time (18:00–09:00 LT) emissions for each day, in order to account for the large diurnal variations in the emissions.

- Atmospheric CO₂ observations are sensitive to vegetation-atmosphere CO₂ fluxes in addition to fossil fuel CO₂ emissions. For cities surrounded by vegetation or containing green areas, the impact of vegetation-atmosphere CO₂ fluxes on city carbon balance can be significant. For instance, Nordbo et al. (2012) estimated that a city is carbon-neutral when its green-area fraction is about 80 %. However the impact of nat-
- ²⁰ ural vegetation on our results for the highly urbanized IDF region is found limited (see the Supplement). In our inversion, we account for the influence of NEE by including, in the control vector, the scaling factors for the budgets of NEE in the full modeling domain (see Sect. 3.4) and for the four different 6 h windows of the day (i.e. 00:00–06:00, 06:00–12:00, 12:00–18:00, and 18:00–24:00 h LT) over different 5-day periods during
- January 2011. The number of NEE scaling factors included in the control vector is thus 24, and the total number of scaling factors is 834 (see Table 1 for details).



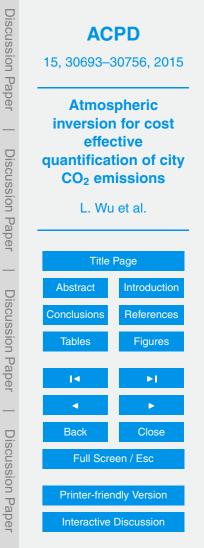


3.3 Observations

We use an inversion system similar to that of B15, in which observations are taken to be CO₂ atmospheric concentration gradients between city upwind and downwind stations. B15 also suggested assimilating only afternoon gradients when the wind speed
⁵ is above a given threshold. By selecting afternoon gradients, we avoid biases in the vertical mixing during nighttime, mornings and evenings when mesoscale transport models have difficulties in representing the planetary boundary layer (Seibert et al., 2000; Steeneveld et al., 2008). Selecting data for high wind speed limits the signature in the atmospheric measurements of local sources that are in the vicinity of the
¹⁰ measurement sites and that cannot be represented correctly by the transport model.

For investigating the potential of the inversion as a function of the observation network, we consider three strategies to deploy a given number of stations. These strategies define three corresponding types of networks: the Elliptical (E), Uniform (U) and Random-even (R) networks (Fig. 3). The E networks surround emissions in the city

- ¹⁵ center, and appear suitable to the assimilation of city upwind-downwind gradients. The E networks consist in three concentric ellipses or rings of stations around the main part of the Paris urban area (the Paris administrative city and its 3 surrounding administrative circumscriptions), encompassing almost all the urban area of IDF. The U networks are defined by a positioning of the stations on a regular grid. The R networks aim at
- ²⁰ balancing the positioning of stations near the city center and in the surrounding areas. The R networks have thus denser coverage over the city center and fewer stations in the surrounding zones than the U networks, but they still cover the whole IDF domain. Apart from the E networks, the U and R networks have stations both close to the emissions in the Paris urban area and in rural areas in its vicinity.
- We assess the potential of the inversion when using these networks with either 10, 30, 50, or 70 stations. For a given network, the station locations are chosen as a subset of a predefined set of 90 candidate locations, depending on the type of the network. For example, 14, 24 and 52 of the 90 candidate stations for R networks are located in



the urban center, the suburban area, and the rural area respectively. For each type of network and a given number of stations *n*, 10 networks are selected for the inversion out of an ensemble of 100 networks that are generated by selecting randomly *n* stations from the set of 90 candidate locations. The selection of such sets of 10 networks is
⁵ based on ad hoc verifications that the station locations should be evenly distributed in

the urban, suburban and rural areas. Figure 5 shows an example of an R network of 10 stations resulting from the above selection procedure.

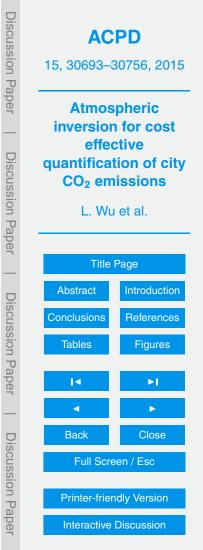
The strategy to properly combine stations from the different selected networks for city upwind-downwind gradient computation (and thus for the precise definition of the character) is detailed in Sect. 2.4.2 as part of the description of the character.

observation vector) is detailed in Sect. 3.4.3 as part of the description of the observation operator. In this synthetic study, we assume that the measurements are taken continuously at a height of 25 ma.g.l. at all stations during the month of January 2011. Sampling at this height would be feasible in the urban environment with existing or new infrastructure and avoid dominant influence of local emissions on concentration observations.

3.4 Observation operator

In this section, we detail the three operators that jointly construct the observation operator ($\mathbf{H} = \mathbf{H}_1 \mathbf{H}_2 \mathbf{H}_3$, Fig. 1). \mathbf{H}_1 provides the spatial and temporal distribution of the anthropogenic emissions or of the natural fluxes within each control tile. This distribution is given at the resolution of the anthropogenic emission of the natural fluxes within each control tile.

- ²⁰ tion is given at the resolution of the atmospheric transport model and is based on an emission inventory or on an ecosystem model simulation. It implicitly bears flux budgets within each control tile. Applying \mathbf{H}_1 to the control vector consists in rescaling the flux map and time series in a uniform way within each control tile, and, as a consequence, the flux budgets, using the control scaling factors. This generates fields of
- ²⁵ CO₂ fluxes on the transport modeling grid (see Sect. 3.4.2). H_2 is the mesoscale atmospheric transport model that maps from the gridded fluxes from H_1 to simulations of the CO₂ concentration fields at 2 to 10 km horizontal resolution and 1 h temporal resolution, in a Northern France area encompassing the IDF region. H_3 is a linear algorithm



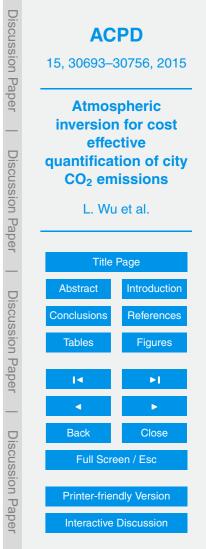


that computes Paris upwind-downwind CO₂ gradients between measurement stations, extracting the simulated observation vector from the CO_2 field from H_2 .

3.4.1 H₁

For the distribution of NEE at the spatiotemporal resolution of the atmospheric transport model, we interpolate the NEE simulations from the land surface model of the short-range forecasts of the European Centre for Medium range Weather Forecasts (ECMWF) at a spatiotemporal resolution of 15 km and 3 h (Boussetta et al., 2013). For the distribution of sectoral fossil fuel CO₂ emissions, we rely on an inventory from the Institute of Energy Economics and the Rational Use of Energy (IER) at the Univer-

- sity of Stuttgart at a high spatial resolution of 1 km × 1 km (Latoska, 2009). This IER inventory accounts for direct CO₂ emissions within IDF. It disaggregates the annual emissions of France in 2005 (according to the national inventory submissions 2007 from UNFCCC, http://www.unfccc.int) into IDF, making use of extensive data from diverse databases for point, line, and area emissions, and of proxy information such as
- population and land cover maps. As for the temporal distribution of the emissions, we 15 apply monthly, weekly and hourly temporal profiles, which are also from IER, to derive hourly emission maps. These temporal profiles are defined for France as functions of each sector but not of the spatial location. There are 51 sectors indexed by NFR code in the IER inventory.
- We compute the emission budgets for all 51 NFR sectors of the IER inventory, and 20 re-aggregate them into the seven groups of sectors defined in Sect. 3.2 (see Table A1). The emission budget of the three major sectors (energy, road, and building) represents ~ 84.4 % of total fossil fuel CO₂ emissions over IDF according to the IER inventory. Figure 2 shows, for the seven sectors, the spatial distribution of the emissions among the 5
- distinct geographic zones of IDF that are used to define the control tiles. The northwest 25 and southeast zones have more emissions than the other three zones, mainly due to the presence of large point sources, e.g. the EDF power plants and the TOTAL Grandputs refinery, in these zones (see Figs. 2 and 4c). Building and road emissions, on the





other hand, are distributed rather evenly in space over the five zones. The budgets of the emissions related to production (7.4 % of total), agriculture (3.7 %), airline (3.3 %) and rest sectors (1.2 %) are relatively small compared to that of the first three sectors. Figure 4 shows the spatial distributions of the emissions from the seven sectors de-

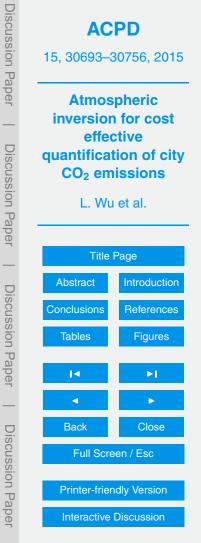
rived for January based on the IER inventory and on the temporal profiles from IER. The IER inventory is not fully faithful to the actual emissions from IDF, for instance, data corresponding to the year 2005 were used to simulate the emissions in 2011, but this would have very limited impact on the theoretical computation in our OSSE framework of inversion.

10 3.4.2 H₂

25

Following B15, we use the mesoscale atmospheric chemistry-transport model CHIMERE (Menut et al., 2013) to simulate the signature of CO₂ fluxes in the atmosphere over the IDF area. This model has successfully served for air quality applications in megacities (Couvidat et al., 2013; Zhang et al., 2013). The CHIMERE model domain in this study, same as that in B15, covers an area of about 500 km × 500 km in northern France that is centered on IDF. Its horizontal resolution is 2 km × 2 km over IDF and its vicinity, and 2 km × 10 km to 10 km × 10 km over the rest of the domain (see Fig. 1 in B15). As such there are 118 cells × 118 cells in the model horizontal grid. Vertically there are 19 layers from the surface up to 500 hPa. The meteorological fields driving the CHIMERE simulation come from the ECMWF analysis at 15 km resolution.

The exchange of CO_2 between the CHIMERE 3-D regional domain and the surrounding atmosphere depends on the wind conditions from the ECMWF product and the CO_2 concentrations at the domain boundaries. These exchanges characterize the signature of remote fluxes outside the modeling domain that impact the observed and simulated atmospheric CO_2 in IDF. Depending on the simulations, we may account for these CO_2 boundary concentrations and for the CO_2 concentration field at the initial date of the simulations (i.e. the CO_2 initial condition). The boundary conditions are





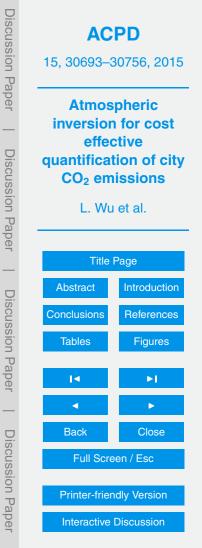
This product has a resolution of 3.75° (longitude) × 2.5° (latitude), which gives about 2–3 cells at each CHIMERE domain lateral boundaries, yielding a smooth influence in both space and time from the CO₂ boundary conditions. The CO₂ initial condition is built from the interpolation of CO2 given by that global inversion product. Note that we do not control these CO₂ boundary and initial concentrations in our inversion system.

- Therefore, in principle, they should be associated with an affine term in the observation operator that is separated from the linear operator **H**. However, mathematically, they can be ignored in the OSSE framework (we only need to account for potential errors from these conditions in the configuration of the observation error), which explains why
- we simplify the notations of the observation operator. The initial and boundary conditions will thus only be used for illustrating the CO₂ variations in IDF based on model simulations.

3.4.3 H₃

For a given network, the operator H_3 consists in a combination of three operations: the linear interpolation of concentrations from the transport model grid to the actual point at which CO₂ measurements are collected, the selection of afternoon CO₂ concentration data (12:00–17:00) at each station (upwind or downwind) when the wind speed from the transport model is higher than $3 \, {\rm m \, s}^{-1}$ at the downwind station, and the CO₂ city upwind-downwind gradient computation. While B15 consider gradients between pairs

- ²⁰ of stations downwind and upwind the full Paris urban area, this study assesses the potential of assimilating gradients between stations that are located within either urban or rural area. The gradients are thus representative of local urban emissions, but not limited to the citywide emissions. The assimilation of all gradients should help better constrain the spatial and sectoral distribution of the emissions.
- ²⁵ The CO₂ gradient computation requires selecting pairs of upwind and downwind stations. For each observation at a given time, the station at which that observation is made is first considered to be a downwind station. We then select, for that observation, a matching observation at an upwind station, based on the wind direction at the



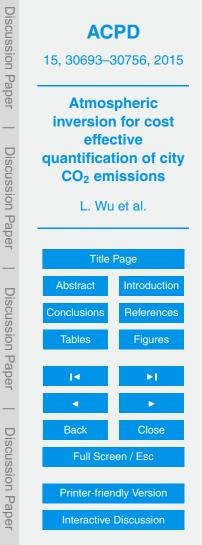


downwind station (read from the ECMWF meteorological product). We impose that the direction angle between the upwind and downwind stations should be comprised between $\pm 11.25^{\circ}$ of the wind direction at the downwind station (defining a 22.5° angle of selection). Figure 5 shows the wind direction for a downwind observation and the area

- that covers its corresponding upwind candidate stations. Then we further impose that the distance between the upwind and downwind stations should be larger than 5 km and as close as possible to 10 km. This distance would correspond to the advection of an air parcel during 1 h with a wind speed of 3 m s⁻¹ (i.e. our threshold on the wind speed for the assimilation of gradients). Here, we ignore the time lag needed to advect
- an air parcel from upwind to downwind stations and compute gradients between simultaneous hourly mean observations. We discard the observations for which no upwind station can be found based on our selection rules. About 7–16% of observations are retained for gradient computation with this data selection procedure, depending on the size and type of the networks.
- Figure 6a shows the afternoon hourly wind conditions at an example station called EVE26 during January 2011, and Fig. 6b shows the wind directions corresponding to the selection of upwind stations when EVE26 is downwind. Winds over station EVE26 blow prevailingly along the southwest-northeast direction for this period (Fig. 6a). Since EVE26 is located to the northeast of the urban center (Fig. 6c), upwind stations for
 gradient computation are mostly selected in the southwest direction (Fig. 6b and c).

Eight CHIMERE simulations with, in input, respectively the simulation of the NEE in Northern France and the inventories for the 7 sectors of the fossil fuel emissions in IDF described in Sect. 3.4.1 are used to check the contributions of each flux component to the CO_2 mixing ratio variations at network stations. This corresponds to applying **H** to

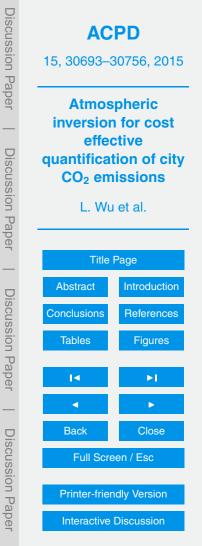
²⁵ control vectors with scaling factors corresponding to the NEE or to a specific sector of emission set to 1 and others to 0, ignoring CO_2 boundary conditions. Figure 7 plots the resulting CO_2 mole fractions at 10 stations of an R network (which are indicated by red triangles in Fig. 5) including 2 urban stations (EVE07 and EVE11 in Fig. 6c) and 8 rural stations.





 CO_2 series from Northern France NEE in January have small daily variations compared to that of CO_2 from the fossil fuel emissions in IDF and show very similar patterns at all the ten stations. During night-time, CO_2 emitted by the ecosystem respiration or by the anthropogenic activities is trapped within the usually stratified nocturnal plane-

- tary boundary layer, which generates peaks in the CO_2 time series (Fig. 7). However, as explained in Sect. 3.3, the representation of the nighttime variations (in particular of their amplitude) by the transport model is not reliable. The diurnal variations of CO_2 are driven by the diurnal variations of the NEE (with a sink of CO_2 due to photosynthesis during daytime) and of the CO_2 emissions from building, road and energy sectors.
- ¹⁰ There are strong positive CO₂ concentration gradients between the urban-urban and urban-rural pairs of stations when analyzing the signature of the main sectors of anthropogenic emissions (Fig. 7). Figure 7i shows histograms of simulations of the concentration gradients corresponding to the observation vector when using this 10-stations R network for inversion. These simulations are obtained by forcing CHIMERE with the
- estimates of the total NEE and anthropogenic emissions described in Sect. 3.4.1 (i.e. by applying **H** to control vectors with all scaling factors set to 1 and accounting for the CO_2 boundary conditions described in Sect. 3.4.2). The three different histograms contain the gradients between 2 rural, 2 urban or 1 rural and 1 urban station respectively. All the concentration gradients between downwind urban and upwind rural stations
- ²⁰ are positive, carrying a mean CO_2 gradient of ~ 14 ppm with a standard derivation of ~ 4 ppm. In contrast, the concentration gradients between downwind rural and upwind urban stations have 20 % negative values, with a mean of about -3 ppm and a standard deviation of ~ 7 ppm. The gradients between rural downwind and rural upwind stations have a mean of ~ 5 ppm, a standard derivation of ~ 7 ppm, and ~ 13 % negative val-
- ²⁵ ues. Most of these rural-rural negative gradients were found at station pairs where the upwind rural station is much closer to the city center than the downwind rural station (e.g. EVE34 and EVE85 whose distance is ~ 23 km). Ignoring the time lag that is required for an air parcel to be transported from the upwind to the downwind stations when computing the CO₂ gradients explains a large portion of these negative gradi-





ents. The emissions vary in time, and, at a given time, the upwind rural station can bear a signature of a peak dominated by the emissions from the upwind nearby city center while this signature has not reached the distant downwind rural station yet for appropriate gradient computation. Occasional changes in the wind directions between the upwind to the downwind stations may also explain that, sometimes, air masses reaching the downwind stations have not necessarily been transported over the areas with high fossil fuel emissions.

3.5 Accounting for uncertainties

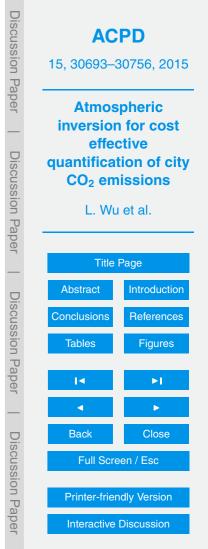
3.5.1 Prior uncertainties

5

Formal statistical methods, such as Monte Carlo approaches, for estimating errors due to uncertain activity data and emission factors are used to infer uncertainties in inventories at the global/national scale (Fauser et al., 2011; Wang et al., 2013). However, to our knowledge, there are currently no studies evaluating uncertainty in existing inventories at city scale. B15 used the AIRPARIF 2008 inventory as a prior emission estimate for their inversions, and assigned a 20% 1-sigma uncertainty in the monthly estimate of the total emissions from IDF. Even though few cities can benefit from such local inventories (see Appendix A), following B15, we set a prior 1-sigma uncertainty in monthly total emissions of about 20%, which corresponds to a 23% 2-sigma annual uncertainty, assuming a temporal correlation of approximately 2 months between
 monthly uncertainties (see Sect. 2.1).

We assume that there is no correlation between the prior uncertainties in scaling factors for different sectors of emissions (see Fig. 9a). For a given sector, the correlations of the uncertainties in scaling factors are given by the Kronecker product between spatial correlations (if there are different control areas for this sector) and temporal cor-

²⁵ relations. We set a value of 0.6 for the spatial correlations between prior uncertainties in scaling factors for building or road emissions that correspond to two different geographical areas (Fig. 2). The temporal correlation of the prior uncertainties in scaling





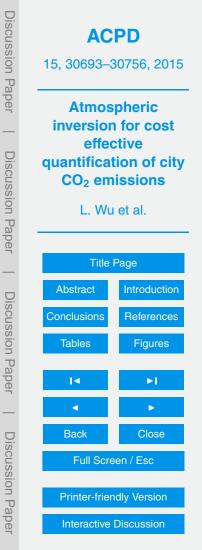
factors is modeled using an exponentially decaying function with a characteristic correlation length of 7 days for each sector (Fig. 9a). Uncertainties in individual scaling factors for a given control tile are derived based on these correlation settings as well as two rules: (1) the aggregation of uncertainties in all the individual scaling factors leads

to an overall 20% 1-sigma uncertainty in total 1-month emissions, and (2) the 1-sigma uncertainties for the seven sectors of 1-month emissions are approximately equal to one another as discussed in Sect. 2.1. By construction, the resulting uncertainties in the budgets for the seven sectors of emissions are larger than that in the total emission estimate, each approximately equal to 36% (Fig. 8). We set, similar to B15, a prior
 uncertainty in the NEE scaling factors of about 70%.

3.5.2 Observation uncertainties

As explained in Sect. 2.2, we ignore measurement errors for the configuration of the observation errors since these measurement errors should be dominated by the model errors (i.e. the errors from the observation operator). Model errors are mainly a combi-

- nation of the aggregation errors due to uncertainties in the spatial and temporal distribution of the fluxes within a control tile that is not resolved by the inversion, the representativeness error (the difference in terms of spatial representativeness between the measurements and the CO₂ simulated with a 2 to 10 km horizontal resolution model), and the atmospheric transport modeling error.
- Following B15, we assume that the model errors for the CO_2 gradient observations are not correlated in time neither in space. The **R** matrix is thus diagonal in our inversion configuration. Based on statistics on the model-measurement misfits, B15 diagnosed that the model error should be on the order of 5 and 10 ppm for individual hourly CO_2 data at rural and urban stations respectively, and of 3 ppm for hourly city
- ²⁵ upwind-downwind gradients between rural stations. They explain the smaller model errors for gradients than for individual CO₂ data by the high spatial correlations between model errors at different stations. These spatial correlations are due to the large spatial coherence of the errors from the model boundary conditions and from the estimate of





the fluxes outside the IDF area, whose cancelling is the main aim of the gradient computation. Even though their system potentially bears higher aggregation errors since using a coarser control vector, this should not be highly significant and we derive the estimate of the model errors for our study based on their diagnostics and on a simple

- derivation of the spatial correlations of the model error between the stations that can lead to their results. This leads us to assign a standard deviation of 3.5, 5.6, and 7 ppm respectively for the observation error on gradients between rural stations, between rural and urban stations and between urban stations. Alternative settings such as inflated (50 % larger) or shrunk (50 % smaller) standard deviation of the observation errors lead to incignificant changes in inversion results (see Supplement Fig. S1).
- ¹⁰ to insignificant changes in inversion results (see Supplement Fig. S1).

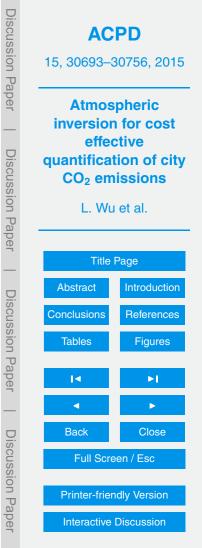
4 Results

15

We conduct inversions of sectoral and total emissions during the month of January 2011 using E, R and U networks with 10, 30, 50 and 70 stations. The inversion results are analyzed in terms of posterior uncertainties in the inverted fluxes and in terms of uncertainty reduction by the inversion (Fig. 8). The uncertainties discussed here are relative uncertainties, which are defined as the uncertainty budgets in percentage to the budgets of the corresponding prior emissions obtained from the IER inventory.

We find that, with small E, R or U networks of 10 stations (i.e. the size of some of the existing networks), inversions are effective in reducing uncertainties in total emissions as well as in the emissions from the three major sectors (building, road and energy). The inversion reduces on average the 1-sigma uncertainty in the total emissions estimates from ~ 19% a priori down to ~ 11% a posteriori (a 42% uncertainty reduction). This posterior uncertainty would correspond to a 13% 2-sigma uncertainty in annual inverted emissions if assuming approximately 2-months temporal correlation

In annual inverted emissions if assuming approximately 2-months temporal correlation between monthly uncertainties (see Sect. 2.1). This level of posterior uncertainty does not meet the notional target of 5 % 2-sigma annual uncertainty. The 1-sigma uncertain-

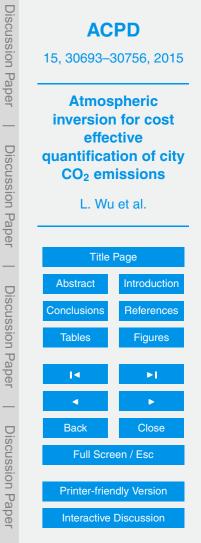




ties in building, road and energy emission estimates for the month of January 2011 are reduced on average from $\sim 36\%$ (prior uncertainty) down to about 23, 27 and 24\% respectively. Even though it represents high uncertainty reductions (about 35, 23 and 31\% of gain respectively over the prior uncertainty), these levels of posterior uncer-

- tainties are above the threshold of level 1 quality that has been defined in Sect. 2.1. In contrast, the uncertainty reduction is very limited for emissions from agriculture, airline, production, and rest sectors. However, the contribution of these four sectors of emissions to the total budget is rather small, which represents only ~ 16% of the total emissions in IDF according to the IER inventory (Fig. 8e). Note that, in order to limit
- the influence of specific station locations, we performed inversions with 10 random networks of the same type and size. These random networks differ from one another in their station locations, but still keep the feature of the type of network (see Sect. 3.3 on how we generated these random networks). The variation (error bars in Fig. 8) in inversion performance due to the influence of station locations is in general small, compared
- ¹⁵ to the variations influenced by the network type and size (see Fig. 8). This influence of station locations for the agriculture sector is significant, but the budget of agriculture emissions is very small.

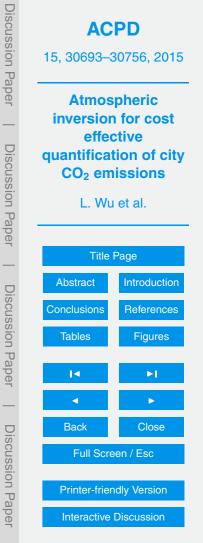
The gain in uncertainty reduction by inversions increases with larger networks. However, this increase slows down and is rather weak once the networks have more than 30 stations (Fig. 8a–c). While there is not much difference between the uncertainty reduction for energy emission estimates when using 30-station or 70-station E networks (Fig. 8a), the increase in uncertainty reduction for building emissions when using 30station or 70-station U networks is still significant. To further illustrate this saturation effect, we assess the number of Degrees of Freedom for the Signal (DFS) of the different networks (Fig. 10a). The DFS describes how many degrees of freedoms of measurements are related to the signal. The simplest illustrating case is that a measurement *y* estimates an emission *x* with an error e: y = x + e, where the prior and measurement errors are independent of each other with variances being v^b and v^e respectively. The measurement *y* will provide one degree of freedom about *x* if there is



no measurement error ($v^e = 0$) or if there is no prior information ($v^b = \infty$). In the case of highly uncertain measurements ($v^e = \infty$), the measurement y will provide zero DFS, or one degree of freedom for the noise. The DFS for this simplest case is $v^b/(v^b + v^e)$, and for general cases of BLUE analysis (Eq. 1) the DFS equals to the trace of the matrix (**B** – **A**)**B**⁻¹ (Rodgers, 2000). Inversion systems with larger DFS values assimilate observations more effectively. For our Paris case study, we find that the amount of information extracted from the assimilated concentration gradient observations is small (DFS/d < 10%, where d is the number of gradient observations). We also found

- a small amount of extracted information in a regional inversion study using eight towers from the Ring 2 network located around the Iowa state of USA (DFS/d < 20%; Wu et al., 2011). Such small amounts result from the diffuse nature of atmospheric transport and from the uncertainty in atmospheric modeling. When using denser large networks, the rate of effectively assimilated gradients decreases. In this case, the dis-
- tances between the upwind and downwind stations selected for gradient computations
 are smaller, and the distances between different upwind stations or between different downwind stations are also smaller, as yields some redundancy of the information from the gradients regarding the budgets of sectoral or total emissions over the full IDF area. This is especially true with the E network for energy emissions, where the candidate locations of stations are closer to one another and cover only the urban area of IDF.
- ²⁰ Consequently, the average DFS decreases as the network size increases, and the gains in uncertainty reduction tend to saturate with larger networks (most evident for the E network).

The 1-sigma posterior uncertainties obtained with 70-station network of either E, R or U type are on average 32, 33 and 18% smaller than those obtained with 10 stations for building, road, and energy emissions estimates respectively (Fig. 8a–c). When compared to the prior uncertainties, inversions with 70-station networks achieve an uncertainty reduction of 56% on average and a 16% 1-sigma posterior uncertainty for the building emission estimates. This corresponds to a level 1 quality. In contrast, the 1-sigma posterior uncertainties in road and energy emission estimates are 18 and

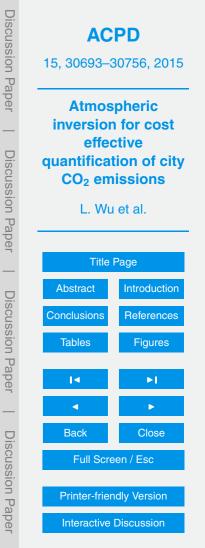




20% respectively. Large networks are more promising for the estimation of dispersed surface emissions such as that from the building sector.

An important finding of our study is that different types of networks show distinct ability for monitoring emissions, which is usually sector-specific. For instance, using a U 5 instead of a E 70-station network leads to 18 vs. 22 %, 18 vs. 19 %, 15 (i.e. a level 2

- quality) vs. 18%, and 6 (i.e. a level 3 quality) vs. 9% (i.e. a level 2 quality) differences in the posterior uncertainty in the estimates of the energy, road, building and total emissions (Fig. 8d). Therefore, with 70-station U networks, the target of 5% 2-sigma annual uncertainty for the total emission estimate can be met. Compared to the U networks,
- the E networks result in larger DFS values (Fig. 10a) but worse performances in uncertainty reduction for total emission estimates (Fig. 10b). The stations in the E network are around the area of high emissions (in particular central Paris), therefore their concentration gradients would be overall more sensitive to the nearby emissions (hence with larger DFS values). However, focusing only on central Paris makes the E network
- ¹⁵ less efficient for controlling the emissions in the rural area (see the spatial distribution of the energy, building and road emissions in Fig. 4a–c). This is because there are large point sources (e.g. the EDF Porcheville power plant and the TOTAL Grandpuits refinery from the energy sector; Fig. 2) and considerable building emissions located outside of the largest ring of the E networks (Figs. 3 and 4). The more extended U
- networks perform better than the smaller U networks and the equal-sized E networks in clarifying the negative cross correlations in errors of emission estimates for different sectors (see Fig. 9b–d for cross correlations between building, road, and energy sectors). The enhanced negative correlations would lead to decreased uncertainties in the total emission estimate that is the sum of sectoral emission estimates. This is a re-
- ²⁵ sult that can also be found in finance where diversification in assets (weak and negative correlations between assets) reduces the portfolio risk (uncertainty in total assets). Notably, the E networks perform better than the U networks for estimating emissions from the airline sector. This is due to the fact that airport emissions (see Figs. 2 and 4f) are located between the two outer rings of the E networks. Moreover, the E networks per-

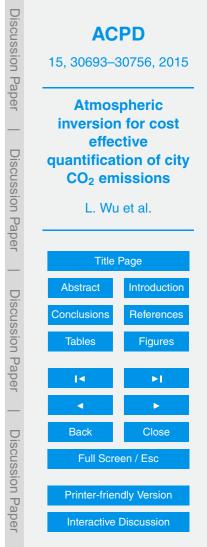




form well to reduce uncertainty in road emission estimates, although a portion of road emissions can occur in rural areas (not covered by the E networks). This is probably because (1) the smallest inner ring coincides with the heavy-loaded Paris peripheral boulevard (25% of the traffic in Paris); (2) the Paris road network (Fig. 4b) sprawls mainly at the urban and suburban area, being enclosed by the largest outer ring; and (3) the station pairs from the E networks (as well as that of the R networks; Fig. 3) may characterize sufficiently well the concentration gradients resulting from the difference between onroad and nonroad emissions.

5 Discussions and conclusions

- ¹⁰ We developed an atmospheric inversion method to quantify city CO₂ emissions using networks of measurement sites within and around a city. This method combines a prior emission estimate from an inventory, with the information from concentration gradient measurements (independent of the inventory) to provide updated emission estimates with reduced uncertainty. Such an inventory can be obtained for instance directly from
- ¹⁵ local agencies or interpolated from regional inventories developed by public research establishments. We examine the ability of the inversion system to reduce uncertainty in emissions estimates for diverse emitting sectors. Our study case is the monitoring of the emissions from the Paris metropolitan area (~ 12% of France's CO₂ fossil fuel emissions). The relevance of the atmospheric method in the MRV context requires
- enquiring the uncertainty level in emission estimates and their associated cost. To this end, we defined a notional uncertainty target for cost-effective total emission estimates based on national MRV practices: a 5 % 2-sigma annual uncertainty for total emission estimates that equates to the uncertainty in France's national inventory reported to UNFCCC.
- ²⁵ We performed inversions over a one-month period in winter (January 2011) using several types of networks of stations sampling at 25 m above ground level. Under the configuration of current networks of the order of 10 stations, the inversion considerably

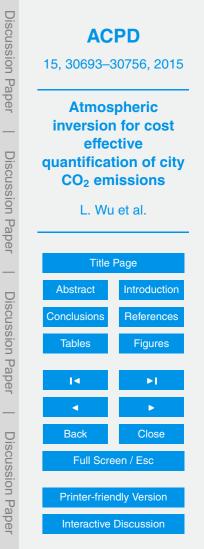




reduced the uncertainties in total emission estimates (by ~ 42%). However, if deriving the corresponding annual uncertainty through the propagation of the uncertainty assuming approximately 2-month temporal correlation between monthly uncertainties, the inversion with ~ 10 stations failed to meet the 5% notional annual target for MRV

- ⁵ use. We thus extended the measuring network. Large extensions should be possible in the near term through the inclusion of sensors that are cheaper than the ones used presently, and whose price could allow the set-up of nearly 70 stations under a budget constraint of 0.5 M EUR year⁻¹. This budget corresponds to the order of the cost to compile, for MRV use, a high quality inventory of city fossil fuel CO₂ emissions.
- ¹⁰ We observed further significant reductions of uncertainties in emission estimates using more stations in inversions. With 70 stations, the inversion can provide total emission estimates that meet the 5% notional annual uncertainty target. The decrease of the uncertainties in the inverted emissions when using 70 stations over using 10 stations are significant: by 32% for commercial and residential buildings, by 33% for
- ¹⁵ road transport and by 18% for the production of energy by power plants, respectively. These three major sectors comprise most of the emission budget according to the IER inventory used in this study. The inversion is especially efficient for decreasing uncertainties in the budget of dispersed emissions from residential and commercial heating. The 1-sigma monthly uncertainty of these building emission estimates can be brought
- down to 15%, which provides valuable information to verify sector-wide mitigation policies/actions or to check whether sectoral mitigation targets are fulfilled. In contrast, the remaining uncertainties for transport and energy emissions estimates are slightly larger (with 1-sigma monthly uncertainties reduced to 18%).

The results obtained in this study should not be over-interpreted, since (1) we worked ²⁵ under synthetic settings for large city networks, and (2) the configuration of our inversion system may fail to be fully faithful to reality (e.g. the idealized parameterization of the prior uncertainties in scaling factors defined for different sectors and spatial zones, and of the assumed independent errors in concentration gradient observations). Never-





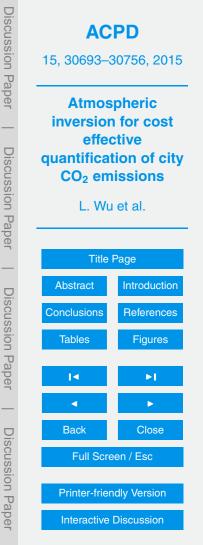
theless our inversions were based on the experience from Bréon et al. (2015) in which real data from a few number of stations around Paris were used.

Two strategies may improve the performance of atmospheric inversion for MRV use at the city scale when using real data. First, the inversion framework can incorporate

- ⁵ much richer sets of atmospheric observations. Recently, city networks have become increasingly densified, embracing other types of CO₂ measuring platforms such as eddy-covariance flux towers (Nordbo et al., 2012; Velasco et al., 2014), ground-based remote sensing instrument (Gisi et al., 2012), aircraft and satellites (Kort et al., 2012; Silva et al., 2013; Buchwitz et al., 2013). The benefit from assimilating these measure-
- ¹⁰ ments however needs to be assessed. For instance, the inversion may suffer from limited representativeness of observations in space (e.g. 0.2–5 km² for eddy-covariance flux measurements; Christen, 2014) or in time (e.g. aircraft campaigns being relatively short due to their cost), or from a weak sensitivity of the observations to emissions (e.g. satellite column measurements). In contrast, some atmospheric tracers other than CO₂
- ¹⁵ can carry distinct signatures from different sectors, thereby their assimilation will certainly improve the ability of inversions to separate emissions from major sectors. For instance, radiocarbon (¹⁴C) measurements can serve for separating anthropogenic (fossil fuel combustion) and biogenic (biofuel and human and plant respiration) sources, and stable carbon isotope measurements (¹³C) can further distinguish combustions
- ²⁰ from gas or liquid fuel (Lopez et al., 2013; Vogel et al., 2013). CO, NO_x and other coemitted gases can be used as proxies for the estimation of sectoral CO₂ emissions (Vogel et al., 2010; Lopez et al., 2013; Turnbull et al., 2015). For example, NO_x has a short life time. Therefore it is an appropriate tracer of local road transport emissions. The ratios between CO and fossil fuel CO₂ vary as a function of the local emission ²⁵ scenarios e.g. residential heating, road transport and industrial combustions, but note

that this variation is ambiguous (Ammoura et al., 2014).

Second, further designs of the inversion system may be beneficial for improving the performance of the inversion. For instance, the procedure for selecting upwind stations can be refined by introducing time lags between downwind and upwind observations





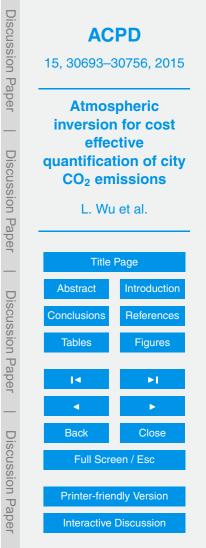
that are computed taking into account the wind directions and magnitudes precisely. We have shown in this study that the inversions are sensitive to the network type. This motivates optimal network design studies, which can be performed by some empirical rules (e.g. redistributing more stations along road network or around power plants

- to better distinguish emissions from road transport and energy production). Advanced network design topics include optimization algorithms that select optimal locations for the redistribution of stations (Wu and Bocquet, 2011) and tracking algorithms that select optimal locations for mobile stations (Abida and Bocquet, 2009). Given a fixed network, the sensitivity of concentration gradients to emissions may be increased by design and the sensitivity of concentration gradients to emissions the sensitivity of concentration gradients to emissions.
- ¹⁰ designing an adaptive spatiotemporal resolution of the emissions to which the scaling factors apply (Wu et al., 2011). When both the network and the resolution of emissions are fixed, the errors in the observations and in the prior emissions can be estimated for more credible inversions (Wu et al., 2013).

Further developing the current city scale inventories is a natural choice for emission accounting, following the applications of national inventories under UNFCCC and the Kyoto Protocol. Such refinement requires tedious efforts in order to continuously collect detailed and high-quality local data. In this paper, we demonstrated that atmospheric inversion could in principle achieve the same level of quality desired for estimates of total emissions at the same cost level.

²⁰ Atmospheric inversion distinguishes itself in a number of ways for the quantification of city CO₂ emissions. First and foremost, it would provide an estimate using another method than inventories based on IPCC guidelines. Estimating the same source of emissions with two different approaches remains the best way to detect biases, even when the approaches may not be fully independent. Second, in addition to the ver-

ification of inventories, atmospheric inversion can also incorporate, whenever available, better inventories into its modeling framework to produce better emission estimates. Third, the inverse modeling system assimilating a cohort of measurements can provide a unique platform to investigate the urban carbon cycle (e.g. the anthropogenic/biogenic land-atmosphere carbon exchange of the urban ecosystem, and the





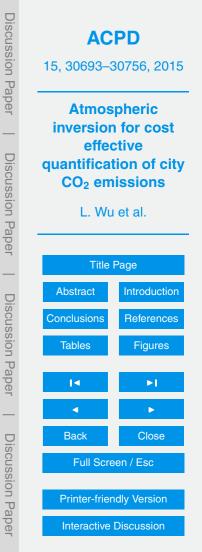
carbon flows into and out of the urban area) and its implication in policy-making. Finally, with its uncertainty reduction ability for emissions from individual sectors, atmospheric inversion would bring a continuous monitoring of emissions changes (e.g. larger heating emissions during cold spells, and larger than usual traffic emissions during specific

⁵ events) which offers important possibilities for infrastructure operators to take appropriate measures with a fast response time. This is in particular helpful to verify city climate mitigation actions, when their impacts could be seen objectively in measured atmospheric signals. Thanks to these features, atmospheric inversion could be a new promising quantification tool for MRV use to mitigate city CO₂ emissions.

Appendix A: Brief review of existing city emission inventories

Inventories of CO₂ emissions are mostly based on a calculation methodology that multiplies activity data by emission factors and sums the resulting multiplications over various sectors of sources. The level of source disaggregation ranges from very small (e.g. using an average emission factor for all vehicles and a single traffic index for transport emissions) to very detailed (e.g. using different emission factors for different vehicle types, age, driving habits, traffic types, and road states). Very detailed inventories are more costly than simple ones because they imply collections of larger datasets, often including specific field or laboratory measurements of emission factors. This is especially true for city inventories which are driven by complex socio-economic

- ²⁰ and technical factors, and can strongly vary in time and space. Such complexity may question the underlying assumption of linear emission models, and certainly leads to high uncertainties in both activity data and emission factors, with a typical case being insufficient representation of source- or context-specific activities using proxy data or default/generalized emission factors. This would raise an issue of inventory verification.
- ²⁵ The existing city inventories, in our opinion, can be roughly catalogued into three types depending on the methodology used to derive them, on their availability and on their uncertainty. The type 1 inventories are based on existing low cost frame-



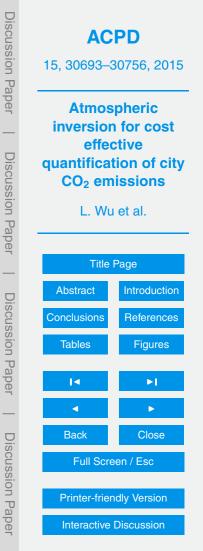


works. They only report at the annual and community resolution (Bertoldi et al., 2010; Cochran, 2015). Many of them adopt the 2006 IPCC Guidelines with adjustments to specific city context (City of Rio de Janeiro, 2011; Dienst et al., 2013) but without uncertainty quantification (Bellassen and Stephan, 2015); others follow the guidelines or

- ⁵ methodologies developed by national/regional/local governments or non-profit local organizations/institutes (e.g. the Bilan Carbone methods in France; ADEME, 2010), as well as by international organizations – such as the newly proposed GPC standard designed by C40, Local Governments for Sustainability (ICLEI) and World Resources Institute (WRI) in the support of the World Bank, UN-HABITAT and UNEP. This type
- ¹⁰ of inventories can cover indirect or embodied emissions that are linked with cities activities but occur outside the considered territories [the Scope 2 emissions related to the consumption of purchased electricity, heat or stream; and the Scope 3 emissions related to the consumption of other products and services not covered in Scope 2; see WRI/WBCSD (2011)]. In practice, the compilation of type-1 inventories can be per-
- ¹⁵ formed with a limited cost that scales with the size of cities (e.g. ~ 18 k EUR year⁻¹ for ~ 1 million inhabitants excluding Scope 3 emissions; Cochran, 2015). To date, the type-1 inventories bear high and more importantly *undocumented* uncertainties.

The type 2 inventories are those that can be derived from global or regional gridded maps of emissions estimates which have been mainly used by the scientific community to model the atmospheric transport of CO_2 . Examples are the Emissions

- ²⁰ community to model the atmospheric transport of CO₂. Examples are the Emissions Database for Global Atmospheric Research (EDGAR) from the European Commission Joint Research Centre (JRC) and the Netherlands Environmental Assessment Agency (http://edgar.jrc.ec.europa.eu), the global/regional inventory developed by the Institute of Energy Economics and the Rational Use of Energy (IER) at the University
- ²⁵ of Stuttgart (Pregger et al., 2007), and the global fossil fuel CO₂ emission map from the Peking University (PKU-CO₂; Wang et al., 2013). The activity data and emission factors entering in the fabrication of type-2 inventories are usually defined from scales coarser than the city scale, which leads to large and, again, *undocumented* uncertainty





locally. The type-2 inventories are free of charge for research purpose, and the fee for commercial use is insignificant.

The type 3 inventories are compiled based upon local data down to the building/street scale at the urban landscape. They are arguably more realistic than the two previous
ones, but available for a small number of cities to our knowledge. Examples of this type are the AIRPARIF inventory for IDF (AIRPARIF, 2013), the London Atmospheric Emissions Inventory (LAEI; GLA, 2012), and the inventory from the HESTIA project for Indianapolis (Gurney et al., 2012). Developing a type-3 inventory is time consuming: it usually demands institutional efforts and requires a high level of expertise. Type-3 inventories can only be established in cities where good activity and/or fuel consumption data are accessible. The inventory quality would be better, if some central authority is responsible for ensuring that adequate data are consistently, transparently and timely

reported by public and private players responsible for emissions. Uncertainty quantification for a type-3 inventory, being a difficult issue due to their complexity, nevertheless

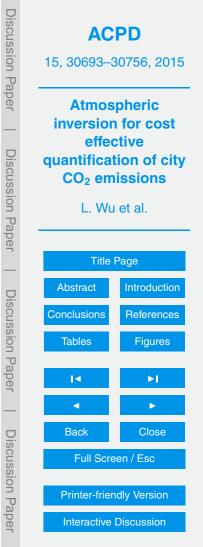
can be performed in an approximate way according to the expert judgment of the inventory compilers. As an example, the monthly uncertainty in the Paris type-3 inventory is estimated to be of the order of 20% by the AIRPARIF engineers (see Bréon et al., 2015). The cost of type-3 inventories consists of data collection fee, salaries, and operation cost, and in general can be considered as at least one order of magnitude less
 than the notional cost target: 0.5 M EUR year⁻¹.

²⁰ Inan the hotional cost target: 0.5 M EUR

Both type 2 and 3 inventories mainly account for direct emissions generated within the considered territories, which are the Scope 1 emissions. Scope 2 emissions for cities can be obtained from Scope 1 emissions. For instance, redistributing national/regional power plant emissions from type-2 inventories to urban areas can ap-

²⁵ proximate a Scope 2 analysis (Marcotullio et al., 2013). Taking into account the energy produced outside of cities but consumed by cities will complete type-3 inventories to provide Scope 3 city emissions as well (AIRPARIF, 2013).

Whether belong to type-1, type-2 or type-3, the inventories at city scale are not frequently updated because the necessary data are usually disclosed and processed long





after emissions actually happened. In case of revisions in calculation methods, such as the correction of emission factors or the addition of emitting activities that were ignored in the previous versions, the entire emission inventory has to be recomputed, which imposes a traceability framework for comparing different versions. In the case of

⁵ the Paris type-3 inventory, there is only a new update every 2 years with a 2-years lag between the date of release and the corresponding year of emissions.

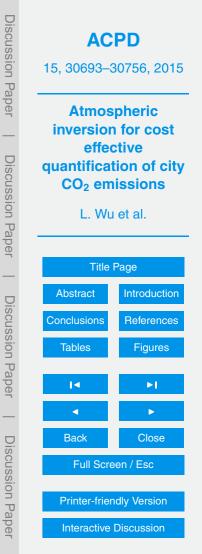
The IER inventory used in this OSSE study incorporates local data to provide a gridded inventory at 1 km and 1 h resolution. We detail this inventory in the main text of the paper (Sect. 3.4.1). Here we group the 40 sectors from this IER inventory into seven aggregate larger sectors, and list their annual budgets in Table A1.

Appendix B: Network cost and instrumental details

10

We detail the network cost in Table B1, in which both expensive high precision sensors and cheaper sensors with limited, but acceptable precision are listed. The network cost includes not only the price of the sensors, but also other supplement items of equip-¹⁵ ment, network installation, maintenance, quality assurance and data processing. The estimated sensor cost is based on commercial available and prototype sensors being tested at the Laboratory of Climate and Environmental Sciences (LSCE). The cost of calibration is estimated to be of the same order for high precision and cheap sensors. The calibration for cheap sensors can be more frequent (e.g. two days) than for

- high precision sensors (e.g. one week), but needs less samples of calibration gas. In addition, innovative calibration procedures for cheap sensors are possible for further reductions of the calibration cost and the temporal correlation in instrument bias. For instance, a calibration center can be set up using high precision sensors to calibrate cheap sensors. One can manage two sets of cheap sensors: one in the calibration center-
- ter and the other in situ in measuring. The calibration is simply performed by replacing the measuring sensors with recently calibrated ones from the calibration center. Since this new calibration method is free of calibration gas, and since the cost of replacing





sensors is very limited, one can maintain a high frequency of calibration (e.g. daily). Note that the network cost can, furthermore, be reduced when pre-existing infrastructure is available, for instance the installation could be free of cost if sharing with existing air quality monitoring platforms.

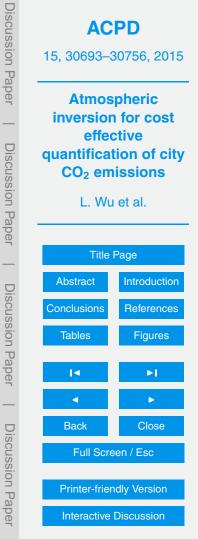
- The total number of deployable monitoring sites is limited by the cost of the network. Given an budget limit of ~ 0.5 M EUR year⁻¹, one can include either ~ 10 high precision sensors when starting from nothing or ~ 70 low cost sensors with minimal installation and maintenance costs (Fig. B1). The local inventories may impose some case-specific additional cost (data fees or funding for a project), but this additional cost is at most an order of magnitude lower than the budget of ~ 0.5 M EUR year⁻¹.
- $_{10}$ order of magnitude lower than the budget of ~ 0.5 M EUR year .

Appendix C: Trend detection under different levels of uncertainties in annual emission estimates

Supposing that the annual fossil fuel emissions from the Paris metropolitan area have a linear trend with a 25% reduction in 15 years, and that the annual emission estimates
¹⁵ have an 5 or 10% uncertainty, we perform Monte Carlo simulations to check to what extent that the linear trend can be detected from perturbed annual emission estimates (within the given annual uncertainty) along years. The detection results are shown in Fig. C1. With 5% annual emission uncertainty, the 25% reduction of emissions in a 15-year horizon can be detected within [18, 32%] at 95% confidence level. In
²⁰ contrast, with 10% annual emission uncertainty, the corresponding detection interval is [11, 39%] at 95% confidence level.

The Supplement related to this article is available online at doi:10.5194/acpd-15-30693-2015-supplement.

Acknowledgements. This study is a contribution to the project MRV Sector funded by the European Climate Knowledge and Innovation Community (Climate-KIC). Four authors (L. Wu, G. Broquet, F. Vogel and P. Ciais) work with the industrial chair BridGES supported by the

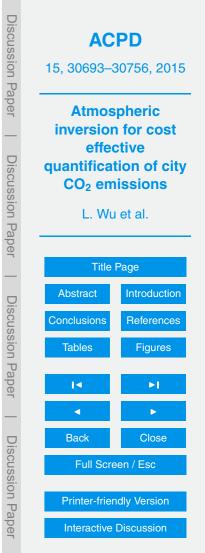


Université de Versailles Saint-Quentin-en-Yvelines, the Commissariat à l'Énergie Atomique et aux Énergies Renouvelables, the Centre National de la Recherche Scientifique, Thales Alenia Space, and Veolia. We thank François-Marie Bréon for assistance.

References

10

- 5 Abida, R. and Bocquet, M.: Targeting of observations for accidental atmospheric release monitoring, Atmos. Environ., 43, 6312–6327, doi:10.1016/j.atmosenv.2009.09.029, 2009.
 - ADEME: Bilan Carbone, Entreprises Collectivités Territoires, Guide méthodologique, version 6.1, objectifs et principes de comptabilisation, available at: http: //associationbilancarbone.fr/fr/download-file/485/field_fichier/479 (last access: 2 November 2015), 2010.
 - AIRPARIF: Bilan des émissions de polluants atmosphériques et de gaz à effet de serre en llede-France pour l'année 2010 et historique 2000/2005: Méthodologies et résultats, AIRPARIF, association de surveillance de la gualité de l'air en Ile-de-France, 2013.
 - Ammoura, L., Xueref-Remy, I., Gros, V., Baudic, A., Bonsang, B., Petit, J.-E., Perrussel, O.,
- Bonnaire, N., Sciare, J., and Chevallier, F.: Atmospheric measurements of ratios between 15 CO₂ and co-emitted species from traffic: a tunnel study in the Paris megacity, Atmos. Chem. Phys., 14, 12871–12882, doi:10.5194/acp-14-12871-2014, 2014.
 - Bellassen, V. and Stephan, N.: Accounting for Carbon: Monitoring, Reporting and Verifying Emissions in the Climate Economy, Cambridge University Press, Cambridge, UK, 2015.
- Bertoldi, P., Cayuela, D. B., Monni, S., and de Raveschoot, R. P.: Existing Methodologies 20 and Tools for the Development and Implementation of Sustainable Energy Action Plans (SEAP), JRC Scientific and Technical Reports, Publication number: JRC 56513, EUR 24309 EN, European Commission Joint Research Centre Institute for Energy, available at: http://publications.jrc.ec.europa.eu/repository/handle/JRC56513 (last access: 2 November 2015), 2010. 25
- - BIS: Low Carbon Environmental Goods and Services: Report for 2011/12, UK Department for Business, Innovation, and Skills (BIS), available at: https://www.gov.uk/government/ publications/low-carbon-and-environmental-goods-and-services-2011-to-2012 (last access: 2 November 2015), 2013.





- 30733
- Ciattaglia, L., Esaki, Y., Fröhlich, M., Gomez, A., Gomez-Pelaez, A. J., Haszpra, L., Krummel, P. B., Langenfelds, R. L., Leuenberger, M., Machida, T., Maignan, F., Matsueda, H., Morguí, J. A., Mukai, H., Nakazawa, T., Peylin, P., Ramonet, M., Rivier, L., Sawa, Y., Schmidt, M., Steele, L. P., Vay, S. A., Vermeulen, A. T., Wofsy, S., and Worthy, D.: CO₂

30

- parameterization, Atmos. Meas. Tech., 6, 3477–3500, doi:10.5194/amt-6-3477-2013, 2013. ²⁵ Chang, J.-P. and Bellassen, V.: Trend setter for territorial schemes: national greenhouse gas inventories under the UNFCCC, in: Accounting for Carbon: Monitoring, Reporting and Verifying Emissions in the Climate Economy, edited by: Bellassen, V. and Stephan, N., Cambridge University Press, Cambridge, UK, 2015. Chevallier, F., Ciais, P., Conway, T. J., Aalto, T., Anderson, B. E., Bousquet, P., Brunke, E. G.,
- Chem. Phys., 13, 9039–9056, doi:10.5194/acp-13-9039-2013, 2013. 20 Buchwitz, M., Reuter, M., Bovensmann, H., Pillai, D., Heymann, J., Schneising, O., Rozanov, V., Krings, T., Burrows, J. P., Boesch, H., Gerbig, C., Meijer, Y., and Löscher, A.: Carbon Monitoring Satellite (CarbonSat): assessment of atmospheric CO₂ and CH₄ retrieval errors by error
- Phys., 15, 1707-1724, doi:10.5194/acp-15-1707-2015, 2015. 15 Broquet, G., Chevallier, F., Bréon, F.-M., Kadygrov, N., Alemanno, M., Apadula, F., Hammer, S., Haszpra, L., Meinhardt, F., Morguí, J. A., Necki, J., Piacentino, S., Ramonet, M., Schmidt, M., Thompson, R. L., Vermeulen, A. T., Yver, C., and Ciais, P.: Regional inversion of CO₂ ecosystem fluxes from atmospheric measurements: reliability of the uncertainty estimates, Atmos.
- Bréon, F. M., Broquet, G., Puygrenier, V., Chevallier, F., Xueref-Remy, I., Ramonet, M., Dieudonné, E., Lopez, M., Schmidt, M., Perrussel, O., and Ciais, P.: An attempt at estimating Paris area CO₂ emissions from atmospheric concentration measurements, Atmos. Chem.
- den Hurk, B., Viterbo, P., Lafont, S., Dutra, E., Jarlan, L., Balzarolo, M., Papale, D., and van der Werf, G.: Natural land carbon dioxide exchanges in the ECMWF integrated forecasting system: implementation and offline validation, J. Geophys. Res., 118, 5923-5946, 10 doi:10.1002/jgrd.50488, 2013.
- Bousquet, P., Peylin, P., Ciais, P., Le Quéré, C., Friedlingstein, P., and Tans, P. P.: Regional changes in carbon dioxide fluxes of land and oceans since 1980, Science, 290, 1342-1346, 5 doi:10.1126/science.290.5495.1342, 2000.
- Boden, T. A., Marland, G., and Andres, R. J.: Global, Regional, and National Fossil-Fuel CO₂ Emissions, Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, US Department of Energy, Oak Ridge, Tenn., USA, 2013.

Discussion 15, 30693-30756, 2015 Paper **Atmospheric** Boussetta, S., Balsamo, G., Beljaars, A., Panareda, A.-A., Calvet, J.-C., Jacobs, C., van inversion for cost

Discussion

Paper

Discussion Paper

Discussion Pape

effective quantification of city **CO₂ emissions**

ACPD

L. Wu et al.





surface fluxes at grid point scale estimated from a global 21 year reanalysis of atmospheric measurements, J. Geophys. Res., 115, D21307, doi:10.1029/2010jd013887, 2010.

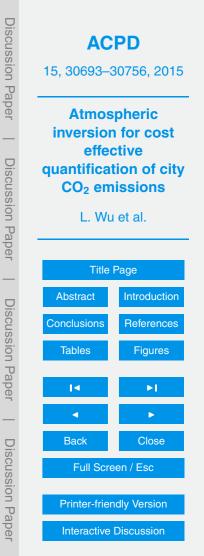
- Christen, A.: Atmospheric measurement techniques to quantify greenhouse gas emissions from cities, Urban Clim., 10, 241–260, doi:10.1016/j.uclim.2014.04.006, 2014.
- ⁵ Ciais, P., Sabine, C., Bala, G., Bopp, L., Brovkin, V., Canadell, J., Chhabra, A., DeFries, R., Galloway, J., Heimann, M., C.Jones, Quéré, C. L., Myneni, R. B., Piao, S., and Thornton, P.: Carbon and other biogeochemical cycles, in: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, 2013.
- 10 CITEPA: Inventaire des émissions de polluants atmosphériques et de gaz à effet de serre en France, Format SECTEN, available at: http://www.citepa.org/fr/activites/ inventaires-des-emissions/secten (last access: 2 November 2015), 2014.

City of Rio de Janeiro: Greenhouse Gas Inventory and Emissions Scenario of Rio de Janeiro, Brazil: Technical Summary, COPPE/UFRJ and Rio Prefeitura, 2011.

¹⁵ Clapp, C., Leseur, A., Sartor, O., Briner, G., and Corfee-Morlot, J.: Cities and Carbon Market Finance: Taking Stock of Cities' Experience With Clean Development Mechanism (CDM) and Joint Implementation (JI), OECD Environmental Working Paper No. 29, OECD Publishing, 2010.

Cochran, I.: Region/city geographical inventorie, in: Accounting for Carbon: Monitoring, Report-

- ²⁰ ing and Verifying Emissions in the Climate Economy, edited by: Bellassen, V. and Stephan, N., Cambridge University Press, Cambridge, UK, 2015.
 - Couvidat, F., Kim, Y., Sartelet, K., Seigneur, C., Marchand, N., and Sciare, J.: Modeling secondary organic aerosol in an urban area: application to Paris, France, Atmos. Chem. Phys., 13, 983–996, doi:10.5194/acp-13-983-2013, 2013.
- Dienst, C., Schneider, C., Xia, C., Saurat, M., Fischer, T., and Vallentin, D.: On track to become a low carbon future city? First findings of the integrated status quo and trends assessment of the pilot City of Wuxi in China, Sustainability, 5, 3224–3243, 2013.
 - Duren, R. M. and Miller, C. E.: Measuring the carbon emissions of megacities, Nature Clim. Change, 2, 560–562, 2012.
- ³⁰ Enting, I.: Inverse Problems in Atmospheric Constituent Transport, Cambridge University Press, Cambridge, UK, 2002.
 - Erickson, P. and Tempest, K.: Advancing Climate Ambition: Cities as Partners in Global Climate Action, Produced by Stockholm Environment Institute (SEI) in Support of the UN Secretary-

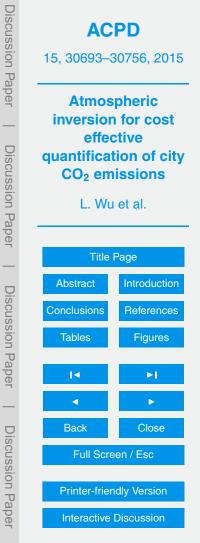




General's Special Envoy for Cities and Climate Change and C40, SEI Working Paper 2014-06, 2014.

- Fauser, P., Sørensen, P. B., Nielsen, M., Winther, M., Plejdrup, M. S., Hoffmann, L., Gyldenkærne, S., Mikkelsen, M. H., Albrektsen, R., Lyck, E., Thomsen, M., Hjelgaard, K.,
- and Nielsen, O.-K.: Monte Carlo (Tier 2) uncertainty analysis of Danish Greenhouse Gas Emission Inventory, Greenhouse Gas Measurement and Management, 1, 145–160, doi:10.1080/20430779.2011.621949, 2011.
 - Fong, W. K., Sotos, M., Doust, M., Schultz, S., Marques, A., Deng-Beck, C., Kovac, A., Bhatia, P., Russell, B., Morris, E., van Staden, M., Arikan, Y., Eichel, A., Dickinson, J., Desai, R., and
- Hoornweg, D.: Global Protocol for Community-Scale Greenhouse Gas Emission Inventories – an Accounting and Reporting Standard for Cities, World Resources Institute, C40 Cities Climate Leadership Group and Local Governments for Sustainability (ICLEI), available at: http://ghgprotocol.org/files/ghgp/GHGP_GPC.pdf (last access: 2 November 2015), 2014.
- Gisi, M., Hase, F., Dohe, S., Blumenstock, T., Simon, A., and Keens, A.: XCO₂-measurements with a tabletop FTS using solar absorption spectroscopy, Atmos. Meas. Tech., 5, 2969–2980, doi:10.5194/amt-5-2969-2012, 2012.
 - GLA: London Atmospheric Emissions Inventory 2010, Greater London Authority, available at: http://data.london.gov.uk/dataset/london-atmospheric-emissions-inventory-2010 (last access: 2 November 2015), 2012.
- ²⁰ Gurney, K. R., Law, R. M., Denning, A. S., Rayner, P. J., Baker, D., Bousquet, P., Bruhwiler, L., Chen, Y.-H., Ciais, P., Fan, S., Fung, I. Y., Gloor, M., Heimann, M., Higuchi, K., John, J., Maki, T., Maksyutov, S., Masarie, K., Peylin, P., Prather, M., Pak, B. C., Randerson, J., Sarmiento, J., Taguchi, S., Takahashi, T., and Yuen, C.-W.: Towards robust regional estimates of CO₂ sources and sinks using atmospheric transport models, Nature, 415, 626–630, 2002.
- ²⁵ Gurney, K. R., Razlivanov, I., Song, Y., Zhou, Y., Benes, B., and Abdul-Massih, M.: Quantification of fossil fuel CO₂ emissions on the building/street scale for a large U.S. city, Environ. Sci. Technol., 46, 12194–12202, doi:10.1021/es3011282, 2012.
 - Howard, A.: FVA, NMA and NMM technical papers, UNFCCC Briefing on the Technical Papers on FVA, NMA and NMM, Lima, Peru, 2014.
- Hutyra, L. R., Duren, R., Gurney, K. R., Grimm, N., Kort, E. A., Larson, E., and Shrestha, G.: Urbanization and the carbon cycle: current capabilities and research outlook from the natural sciences perspective, Earth's Future, 2, 473–495, doi:10.1002/2014ef000255, 2014.

IEA: World Energy Outlook, International Energy Agency (IEA), Paris, 2008.





IGES: Measurement, Reporting and Verification (MRV) for Low Carbon Development: Learning from Experience in Asia, IGES Policy Report No. 2012-03, Institute for Global Environmental Strategies (IGES), Kanagawa, Japan, 2012.

Kort, E. A., Frankenberg, C., Miller, C. E., and Oda, T.: Space-based observations of megacity carbon dioxide, Geophys. Res. Lett., 39, L17806, doi:10.1029/2012gl052738, 2012.

5

30

Kort, E. A., Angevine, W. M., Duren, R., and Miller, C. E.: Surface observations for monitoring urban fossil fuel CO₂ emissions: minimum site location requirements for the Los Angeles megacity, J. Geophys. Res., 118, 1577–1584, doi:10.1002/jgrd.50135, 2013.

Latoska, A.: Erstellung eines räumlich hoch aufgelösten Emissionsinventar von Luftschadstof-

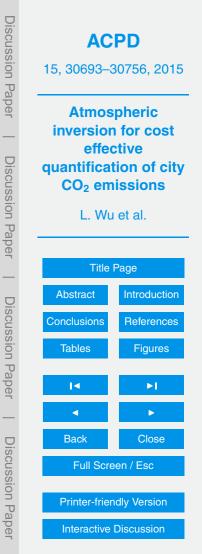
- ¹⁰ fen am Beispiel von Erstellung eines räumlich hoch aufgelösten, Thesis, Institut für Energiewirtschaft und Rationelle Energieanwendung, Universität Stuttgart, 2009.
- Lauvaux, T., Miles, N. L., Richardson, S. J., Deng, A., Stauffer, D. R., Davis, K. J., Jacobson, G., Rella, C., Calonder, G.-P., and DeCola, P. L.: Urban emissions of CO₂ from Davos, Switzer-land: the first real-time monitoring system using an atmospheric inversion technique, J. Appl.
 Meteorol, Clim., 52, 2654–2668, doi:10.1175/jamc-d-13-038.1, 2013.
- Liu, Z., He, C., Zhou, Y., and Wu, J.: How much of the world's land has been urbanized, really? A hierarchical framework for avoiding confusion, Landscape Ecol., 29, 763–771, doi:10.1007/s10980-014-0034-y, 2014.

Lopez, M., Schmidt, M., Delmotte, M., Colomb, A., Gros, V., Janssen, C., Lehman, S. J., Mon-

- ²⁰ delain, D., Perrussel, O., Ramonet, M., Xueref-Remy, I., and Bousquet, P.: CO, NO_x and ${}^{13}CO_2$ as tracers for fossil fuel CO_2 : results from a pilot study in Paris during winter 2010, Atmos. Chem. Phys., 13, 7343–7358, doi:10.5194/acp-13-7343-2013, 2013.
 - Mairie de Paris: BLEU Climat 2012, l'engagement de la collectivité parisienne en matière de lutte contre les émissions de gas à effet de serre et d'efficacité énergétique, available at: http://api-site-cdn.paris.fr/images/110876.pdf (last access: 2 November 2015), 2012.
- http://api-site-cdn.paris.fr/images/1108/6.pdf (last access: 2 November 2015), 2012. Marcotullio, P., Sarzynski, A., Albrecht, J., Schulz, N., and Garcia, J.: The geography of global urban greenhouse gas emissions: an exploratory analysis, Climatic Change, 121, 621–634, doi:10.1007/s10584-013-0977-z, 2013.

Marr, M. A. and Wehner, S.: Cities and Carbon Finance: a Feasibility Study on an Urban CDM, UNEP (United Nations Environment Programme)/Gwangju City, 2012.

McKain, K., Wofsy, S. C., Nehrkorn, T., Eluszkiewicz, J., Ehleringer, J. R., and Stephens, B. B.: Assessment of ground-based atmospheric observations for verification of greenhouse





30737

gas emissions from an urban region, P. Natl. Acad. Sci. USA, 109, 8423-8428, doi:10.1073/pnas.1116645109, 2012.

- Meinshausen, M., Meinshausen, N., Hare, W., Raper, S. C. B., Frieler, K., Knutti, R., Frame, D. J., and Allen, M. R.: Greenhouse-gas emission targets for limiting global warming to 2°C, Nature, 458, 1158–1162, 2009.
- Menut, L., Bessagnet, B., Khvorostvanov, D., Beekmann, M., Blond, N., Colette, A., Coll, I., Curci, G., Foret, G., Hodzic, A., Mailler, S., Meleux, F., Monge, J.-L., Pison, I., Siour, G., Turquety, S., Valari, M., Vautard, R., and Vivanco, M. G.: CHIMERE 2013: a model for regional atmospheric composition modelling, Geosci. Model Dev., 6, 981-1028, doi:10.5194/gmd-6-981-2013, 2013.
- 10

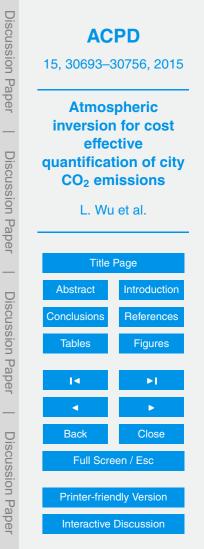
20

5

Ninomiya, Y.: Classification of MRV of Greenhouse Gas (GHG) Emissions/Reductions: for the Discussions on NAMAs and MRV, Institute for Global Environmental Strategies (IGES), Policv Brief. Number 25, 2012.

Nordbo, A., Järvi, L., Haapanala, S., Wood, C. R., and Vesala, T.: Fraction of natural area

- as main predictor of net CO₂ emissions from cities, Geophys. Res. Lett., 39, L20802, 15 doi:10.1029/2012gl053087, 2012.
 - Pacala, S., Breidenich, C., Brewer, P. G., Fung, I., Gunson, M. R., Heddle, G., Law, B., Marland, G., Paustian, K., and Prather, K.: Verifying Greenhouse Gas Emissions: Methods to Support International Climate Agreements, The National Academies Press, Washington, DC, 124 pp., 2010.
- Peters, W., Jacobson, A. R., Sweeney, C., Andrews, A. E., Conway, T. J., Masarie, K., Miller, J. B., Bruhwiler, L. M. P., Pétron, G., Hirsch, A. I., Worthy, D. E. J., van der Werf, G. R., Randerson, J. T., Wennberg, P. O., Krol, M. C., and Tans, P. P.: An atmospheric perspective on North American carbon dioxide exchange: CarbonTracker, P. Natl. Acad. Sci. USA, 104, 18925-18930, doi:10.1073/pnas.0708986104, 2007. 25
 - PLF: État récapitulatif de l'effort financier consenti en 2014 et prévu en 2015 au titre de la protection de la nature et de l'environnement, Projet de loi de finances (PLF) pour 2015 - Jaunes budgétaires, Ministère français des finances et des comptes publics, available at: http://www.performance-publique.budget.gouv.fr/sites/performance publique/
- files/farandole/ressources/2015/pap/pdf/jaunes/jaune2015 environnement.pdf (last access: 30 2 November 2015), 2014
 - Preager, T., Scholz, Y., and Friedrich, R.: Documentation of the Anthropogenic GHG Emission Data for Europe Provided in the Frame of CarboEurope GHG and CarboEurope IP, Final





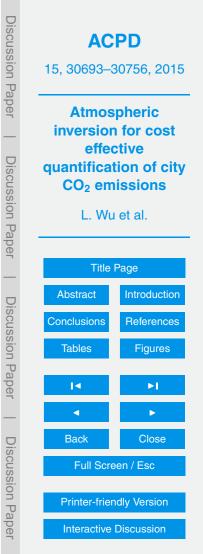
Report CarboEurope-IP, Institute for Energy Econonics and the Rational Use of Energy (IER), University of Stuttgart, Stuttgart, Germany, 2007.

- Reckien, D., Flacke, J., Dawson, R. J., Heidrich, O., Olazabal, M., Foley, A., Hamann, J. J. P., Orru, H., Salvia, M., De Gregorio Hurtado, S., Geneletti, D., and Pietrapertosa, F.: Climate
- change response in Europe: what's the reality? Analysis of adaptation and mitigation plans from 200 urban areas in 11 countries, Climatic Change, 122, 331–340, doi:10.1007/s10584-013-0989-8, 2013.
 - Rodgers, C. D.: Inverse Methods for Atmospheric Sounding: Theory and Practice, Series on Atmospheric, Oceanic and Planetary Physics, edited by: Taylor, F. W., World Scientific Publishing Co. Pte. Ltd., 5 Toh Tuck Link, Singapore 596224, 2000.
- Rosenzweig, C., Solecki, W., Hammer, S. A., and Mehrotra, S.: Cities lead the way in climatechange action, Nature, 467, 909–911, 2010.

10

30

- Seibert, P., Beyrich, F., Gryning, S.-E., Joffre, S., Rasmussen, A., and Tercier, P.: Review and intercomparison of operational methods for the determination of the mixing height, Atmos. Environ., 34, 1001–1027. doi:10.1016/S1352-2310(99)00349-0, 2000.
- Environ., 34, 1001–1027, doi:10.1016/S1352-2310(99)00349-0, 2000.
 Seto, K. C., Dhakal, S., Bigio, A., Blanco, H., Delgado, G. C., Dewar, D., Huang, L., Inaba, A., Kansal, A., Lwasa, S., McMahon, J. E., Müller, D. B., Murakami, J., Nagendra, H., and Ramaswami, A.: Human settlements, infrastructure and spatial planning, in: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assess-
- 20 ment Report of the Intergovernmental Panel on Climate Change, edited by: Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., Kriemann, B., Savolainen, J., Schlömer, S., von Stechow, C., Zwickel, T., and Minx, J. C., Cambridge, UK and New York, NY, USA, 2014.
- Shah, N., Vallejo, L., Cockerill, T., Gambhir, A., Heyes, A., Hills, T., Jennings, M., Jones, O.,
 Kalas, N., Keirstead, J., Khor, C., Mazur, C., Napp, T., Strapasson, A., Tong, D., and
 Woods, J.: Halving global CO₂ by 2050: technologies and costs, Energy Futures Lab and
 Grantham Institute for Climate Change at Imperial College London, 2013.
 - Silva, S. J., Arellano, A. F., and Worden, H. M.: Toward anthropogenic combustion emission constraints from space-based analysis of urban CO₂/CO sensitivity, Geophys. Res. Lett., 40, 4971–4976, doi:10.1002/grl.50954, 2013.
 - Steeneveld, G. J., Vilà-Guerau de Arellano, J., Holtslag, A. A. M., Mauritsen, T., Svensson, G., and de Bruijn, E. I. F.: Evaluation of limited-area models for the representation of the di-





30739

ban Development, available at: http://www.goldstandard.org/sites/default/files/documents/ financingcitiesofthefuture.pdf (last access: 2 November 2015), 2014.

doi:10.1175/2007jamc1702.1, 2008.

5

TMG: Tokyo Cap-and-Trade Program – Japan's First Mandatory Emissions Trading Scheme, TMG, Tokyo, 2010.

The Gold Standard: Financing Cities of the Future: Tools to Scale-up Clean Ur-

- Turnbull, J. C., Sweeney, C., Karion, A., Newberger, T., Lehman, S. J., Tans, P. P., Davis, K. J., 10 Lauvaux, T., Miles, N. L., Richardson, S. J., Cambaliza, M. O., Shepson, P. B., Gurney, K., Patarasuk, R., and Razlivanov, I.: Toward quantification and source sector identification of fossil fuel CO₂ emissions from an urban area: results from the INFLUX experiment, J. Geophys. Res., 120, 292-312, doi:10.1002/2014jd022555, 2015.
- UN: World Urbanization Prospects: The 2014 Revision. HighlightsST/ESA/SER.A/352. 15 available at: http://esa.un.org/unpd/wup/highlights/wup2014-highlights.pdf (last access: 2 November 2015), 2014.

UNEP: The Emissions Gap Report 2013, United Nations Environment Programme (UNEP), Nairobi, 2013.

UNEP: Climate Finance for Cities and Buildings – a Handbook for Local Governments, UNEP 20 Division of Technology, Industry and Economics (DTIE), Paris, 2014.

UNFCCC: Establishment of an Ad Hoc Working Group on the Durban Platform for Enhanced Action, Decision 1/CP.17, FCCC/CP/2011/9/Add.1, available at: http://unfccc.int/resource/ docs/2011/cop17/eng/09a01.pdf (last access: 2 November 2015), 2011.

Velasco, E., Perrusquia, R., Jiménez, E., Hernández, F., Camacho, P., Rodríguez, S., Retama, A., and Molina, L. T.: Sources and sinks of carbon dioxide in a neighborhood of Mexico City, Atmos. Environ., 97, 226-238, doi:10.1016/j.atmosenv.2014.08.018, 2014.

Vogel, F., Hammer, S., Steinhof, A., Kromer, B., and Levin, I.: Implication of weekly and diurnal ¹⁴C calibration on hourly estimates of CO-based fossil fuel CO₂ on hourly estimates of CO-

based fossil fuel CO at a moderately polluted site in southwestern Germany, Tellus B, 62, 30 512-520, 2010.

urnal cycle and contrasting nights in CASES-99, J. Appl. Meteorol. Clim., 47, 869-887, Discussion Paper Sugar, L. and Kennedy, C.: A low carbon infrastructure plan for Toronto, Canada, Can. J. Civil Eng., 40, 86–96, doi:10.1139/cjce-2011-0523, 2013.



Discussion

Paper

Discussion Paper

Discussion Paper

Vogel, F. R., Tiruchittampalam, B., Theloke, J., Kretschmer, R., Gerbig, C., Hammer, S., and Levin, I.: Can we evaluate a fine-grained emission model using high-resolution atmospheric transport modelling and regional fossil fuel CO₂ observations?, Tellus B, 65, 18681, 2013.

Wang, R., Tao, S., Ciais, P., Shen, H. Z., Huang, Y., Chen, H., Shen, G. F., Wang, B., Li, W.,

⁵ Zhang, Y. Y., Lu, Y., Zhu, D., Chen, Y. C., Liu, X. P., Wang, W. T., Wang, X. L., Liu, W. X., Li, B. G., and Piao, S. L.: High-resolution mapping of combustion processes and implications for CO₂ emissions, Atmos. Chem. Phys., 13, 5189–5203, doi:10.5194/acp-13-5189-2013, 2013.

Wang-Helmreich, H., Kreibich, N., Streitferdt, V., Arens, C., and Sterk, W.: City-Wide Pro-

10 grammes of Activities – an Option for Significant Emission Reductions in Cities?, JIKO Policy Paper 04/2012, Wuppertal Institute for Climate, Environment and Energy, available at: http://wupperinst.org/en/publications/details/wi/a/s/ad/1895/ (last access: 2 November 2015), 2012.

World Bank: A City-wide Approach to Carbon Finance, Carbon Partnership Facility Innovation Series. Washington, DC, 2010.

WRI/WBCSD: The Greenhouse Gas Protocol: a Corporate Accounting and Reporting Standard, World Resources Institute/World Business Council on Sustainable Development, Washington, D.C., 2011.

Wu, L. and Bocquet, M.: Optimal redistribution of the background ozone monitoring stations

²⁰ over France, Atmos. Environ., 45, 772–783, doi:10.1016/j.atmosenv.2010.08.038, 2011.

15

Wu, L., Bocquet, M., Lauvaux, T., Chevallier, F., Rayner, P., and Davis, K.: Optimal representation of source-sink fluxes for mesoscale carbon dioxide inversion with synthetic data, J. Geophys. Res., 116, D21304, doi:10.1029/2011jd016198, 2011.

Wu, L., Bocquet, M., Chevallier, F., Lauvaux, T., and Davis, K.: Hyperparameter estimation

- ²⁵ for uncertainty quantification in mesoscale carbon dioxide inversions, Tellus B, 65, 20894, doi:10.3402/tellusb.v65i0.20894, 2013.
 - Zhang, Q. J., Beekmann, M., Drewnick, F., Freutel, F., Schneider, J., Crippa, M., Prevot, A. S. H., Baltensperger, U., Poulain, L., Wiedensohler, A., Sciare, J., Gros, V., Borbon, A., Colomb, A., Michoud, V., Doussin, J.-F., Denier van der Gon, H. A. C., Haeffelin, M., Dupont, J.-C.,
- Siour, G., Petetin, H., Bessagnet, B., Pandis, S. N., Hodzic, A., Sanchez, O., Honoré, C., and Perrussel, O.: Formation of organic aerosol in the Paris region during the MEGAPOLI summer campaign: evaluation of the volatility-basis-set approach within the CHIMERE model, Atmos. Chem. Phys., 13, 5767–5790, doi:10.5194/acp-13-5767-2013, 2013.

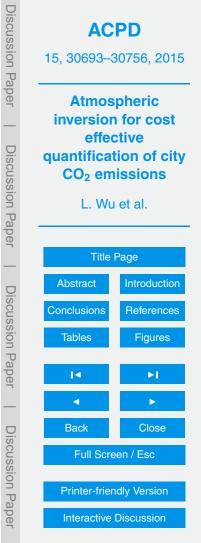


Table 1. Spatiotemporal resolutions of the sectoral control factors for inversions over 30-day
periods (see the main text and Table A1 for more information on aggregate sectors).

Control factors	Spatial resolution	Time resolution	Number of factors
Building	5 zone	Daily daytime and night-time	300
Road	5 zones	Daily daytime and night-time	300
Energy	1 zone	Daily daytime and night-time	60
Production	1 zone	Daily daytime and night-time	60
Agriculture	1 zone	Daily	30
Airline	1 zone	Daily	30
Rest	1 zone	Daily	30
NEE	1 zone	5-day period with four daily 6 h-windows	24
_	_	-	834 (total)

Discussion Paper		PD 30756, 2015				
aper Discussion Paper	inversion effe quantifica CO ₂ en	Atmospheric inversion for cost effective quantification of city CO ₂ emissions L. Wu et al.				
iper	Title	Title Page				
Dis	Abstract	Introduction				
Discussion Paper	Conclusions	References				
on Pa	Tables	Figures				
aper	I	▶1				
—	•	•				
Dis	Back	Close				
Sussi	Full Scr	Full Screen / Esc				
Discussion Pape	Printer-frie	ndly Version				
aper	Interactive	Discussion				



Table A1. Specification of all the 40 sectors in the IER inventory employed in this study. These sectors are grouped into seven aggregate larger sectors listed in Table 1.

Sector	NFR code	Budget (TgCyr ⁻¹)	Comments
Energy	1A1a	3.7205	Public Electricity and Heat Production
	1A1b	0.31007	Petroleum Refining
	1A1c	0.097906	Manufacture of Solid Fuels and Other Energy Industries
Road	1A3bi	3.0287	Passenger cars
	1A3biii	0.78072	Heavy duty vehicles
	1A3bii	0.66808	Light duty vehicles
Building	1A4bi	2.5757	Residential plants
	1A4ai	1.0185	Commercial/Institutional
	1A4bii	0.90577	Household and gardening (mobile)
	1A4aii	0.4489	Commercial/Institutional
Production	1A2fi	1.0724	Fuel Combustion Activities: manufacturing Industries and
			Construction
	1A2c	0.37312	Chemicals
	2A1	0.11867	Mineral Products
	1A2e	0.11245	Food Processing, Beverages & Tobacco
	1A2a	0.09999	Iron and Steel
	1A2d	0.088409	Pulp, Paper and Print
Agriculture	1A4ci	0.32116	Plants in agriculture, forestry and aquaculture
	1A4cii	0.14497	Off-road Vehicles and Other Machinery
Airline	1A3ai(i)	0.58194	International Aviation
	1A3aii(i)	0.34983	Civil Aviation (Domestic)
Rest	2B1	0.075718	Ammonia Production
	6Cb	0.042929	Waste Incineration
	3A2	0.038744	Paint Application
	1A3biv	0.037411	Automobile tyre and brake wear
	1A3e	0.031093	Other Transportation
	2C1	0.020038	Metal Production
	1A3c	0.019035	Railways
	2A7d	0.011561	Mineral Products
	2A4	0.0082194	Mineral Products
	2B5a	0.0075701	Chemical Industry
	3C	0.0056263	Chemical Products, Manufacture and Processing
	2A3	0.0054513	Mineral Products
	1A2b	0.00506	Non-ferrous Metals
	2A2	0.0049208	Mineral Products
	2C3	0.0044444	Metal Production
	1A3dii	0.0039965	Navigation
	2C2	0.0024742	Metal Production
	3B1	0.0017747	Degreasing and Dry Cleaning
	1B1b	0.00018562	Fugitive Emissions from Fuels
	2B3	0.00013253	Chemical Industry

Discussion Paper **ACPD** 15, 30693-30756, 2015 **Atmospheric** inversion for cost effective **Discussion** Paper quantification of city **CO₂ emissions** L. Wu et al. **Title Page** Abstract Introduction **Discussion Paper** References **Tables** Figures 4 Back Close **Discussion** Paper Full Screen / Esc **Printer-friendly Version** Interactive Discussion



30742

AC	ACPD				
15, 30693–3	15, 30693–30756, 2015				
Atmospheric inversion for cost effective quantification of city CO ₂ emissions					
L. Wu	L. Wu et al.				
Title					
Tille	Page				
Abstract	Introduction				
Conclusions	References				
Tables	Figures				
14	۶I				
	•				
Back	Back Close				
Full Scre	Full Screen / Esc				
Printer-friendly Version					
Interactive Discussion					

Discussion Paper

Discussion Paper

Discussion Paper

Discussion Paper

Table B1. Specification of network cost for high precision or cheap sensors.

	Cost			Depreciation	n rate	Comments
Sensors/site	High precision	Cheap old platform	Cheap new platform	High precision	Cheap	High precision < 0.1 ppm and low systematic error < 0.13 ppm
	EUR 45 k	EUR2k	EUR2k	10–20 % (5–10 yr)	20–40 % (2–5 yr)	Low precision/high systematic error: $0.5-1$ ppm $(1 \text{ ppm})^{-1}$
Infrastructure/site	EUR 25 k	25 k EUR	EUR3k	-	_	Mininum (given pre-existing
Container	EUR 10k	EUR 10 k	EUR2k	_	_	infrastructure and co-funding):
Inlet system	EUR5k	EUR 5 k	_	10-20%	10-20 %	Inlet + calibration = 10 k EUR
Calibration	EUR 5 k	EUR 5 k	EUR 1 k	20-33%	20-33%	
Installation and others	EUR 5 k	EUR 5 k	-	-	-	
Annual						
Infrastructure/site	EUR 10 k	EUR 10 k	EUR 0–1 k	-	-	Cost of e.g. rent, electricity, data
1 engineer: network	EUR 60 k	EUR 60 k	EUR 60 k	-	-	
1 engineer: data	EUR 60 k	EUR 60 k	EUR 60 k	-	-	
1 engineer: modeling	EUR 60 k	EUR 60 k	EUR 60 k	-	-	

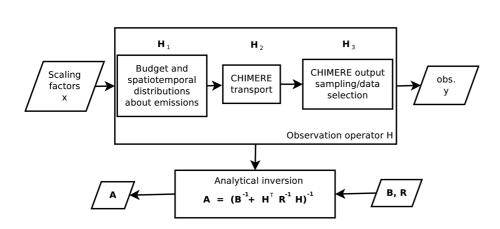
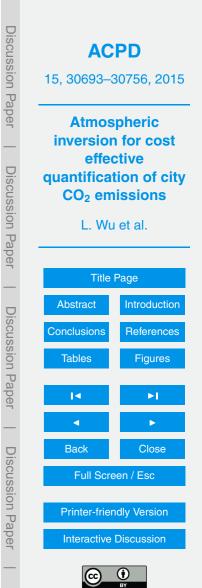


Figure 1. Diagram of the synthetic study on atmospheric inversion of city CO₂ emissions.

30744



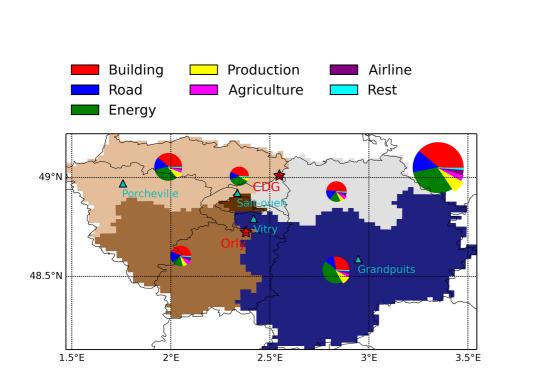
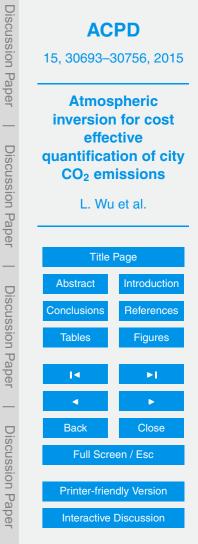


Figure 2. Sectoral budgets of fossil fuel CO_2 emissions from the IER inventory for five zones of IDF for the month of January in 2011 (see the first seven rows in Table 1 for sector specifications). The circle area is proportional to the emission budge. The upper right largest circle shows the total sectoral budgets for all the five zones of IDF. The red pentagons shows the two airports CDG and Orly, and the cyan triangles show several large point emissions such as three EDF power plants and the TOTAL Grandpuits refinery.





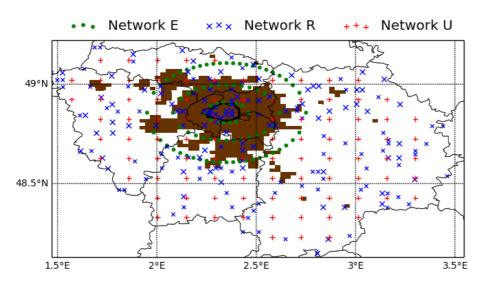
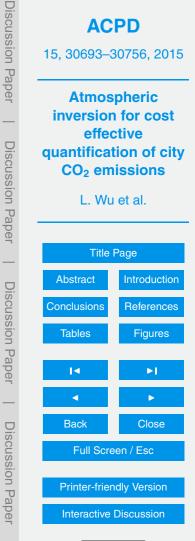


Figure 3. Illustrative locations for the elliptical (E), random-even (R) and unifrom (U) networks over IDF. The brown area marks out where the population density is larger than 1250 people km⁻². The E network marked by green dots consists of three rings surrounding the densely populated urban area in brown. The U network (red crosses) extends to the regular grid points of the IDF domain. The site locations of the R network are randomly selected respectively in three concentric areas: (1) the city center within the peripheral ring (coinciding with the smallest green ring), (2) the suburban area (in brown) with central Paris clipped out, and (3) the rest of IDF.



Discussion Paper



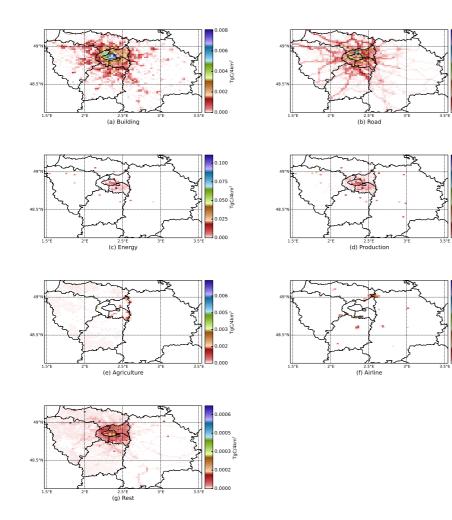
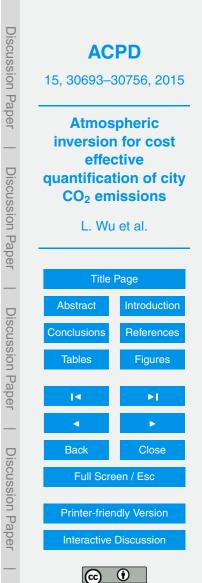


Figure 4. Sectoral and spatial distribution of the IER inventory for IDF for January 2011.



0.004

0.003

0.002 g

0.001

0.000

0.012

0.009

0.006 Š

0.003

0.000

0.008

0.006

0.004 ¥2

0.002

0.000

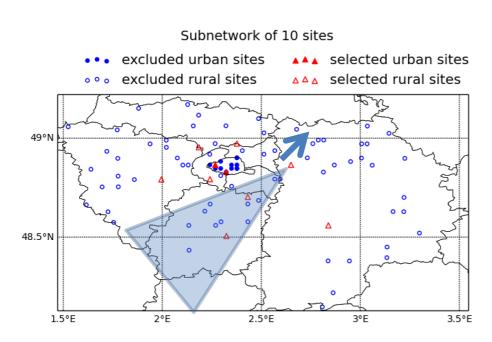
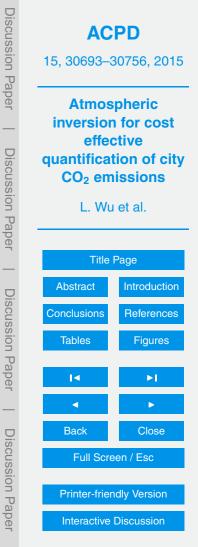


Figure 5. Selection a subset (10 sites marked out in red triangles) from a cloud of candidate locations for the R network to form smaller networks. The circles show the sites that are not selected. The open circles/triangles are for rural sites, and the filled circles/triangles are for urban sites. This figure also shows how the wind direction selects candidates of upwind sites for concentration gradient computations at a downwind station. The blue arrow indicates the wind direction at that downwind station. The two red triangles covered in the shadow area are candidate upwind sites according to the selection procedure detailed in the main text of this paper.





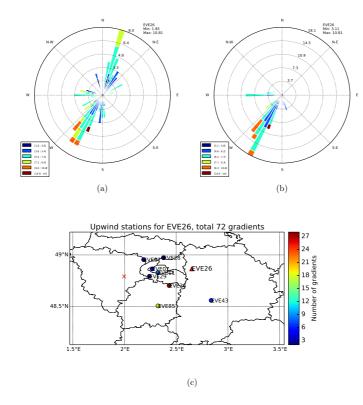
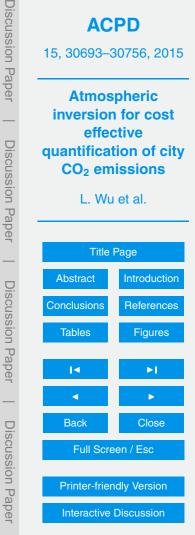


Figure 6. Results of selections of upwind stations for gradient computations for one downwind station for the month of January in 2011. Here we use a R network of 10 stations defined in Fig. 5. The illustrative downwind station in Fig. 5 (named EVE26 in this figure) is chosen for diagnosis. (a) The afternoon wind conditions at EVE26 during the given month; (b) the afternoon wind conditions for selected observations for gradient calculation at EVE26; (c) the counts of times selected as the upwind site for gradient computations at EVE26 for all the other nine stations. The leftmost red cross indicates that this site is never selected for gradient computation for EVE26.



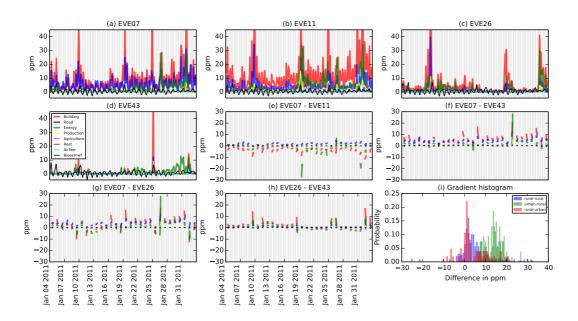
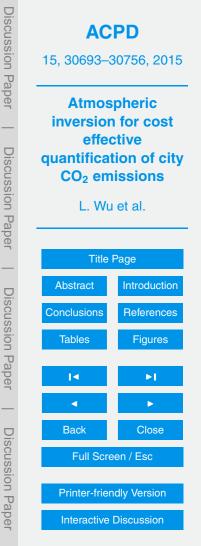


Figure 7. (**a**–**d**) CO_2 mixing ratio series of sectoral CHIMERE simulations at four selected stations of the R network (see Figs. 5 and 6c). EVE07 and EVE11 are urban sites and EVE26 and EVE43 are rural sites but close to large point emissions. The shadow marks out the night time. (**e**–**h**) The time series of the difference in model simulations sampled at several site pairs among the four sites. (**i**) The histogram of afternoon concentration gradients following the data selection procedure detailed in Sect. 3.4.3 for all the 10 stations of the R network. These histograms are grouped according to the type of downwind and upwind stations.





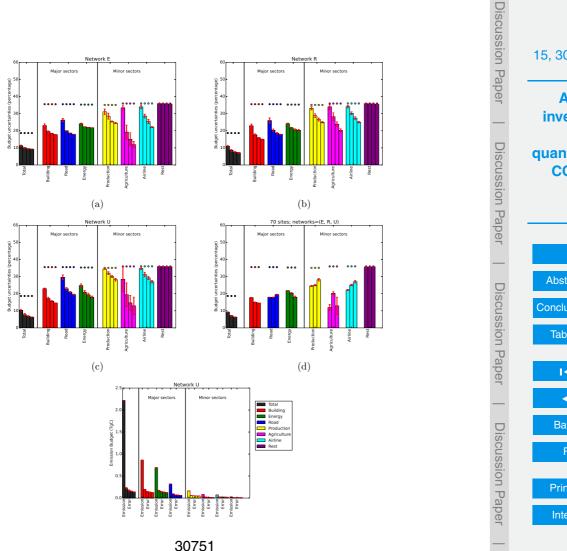




Figure 8. Budget of uncertainties in total and sectoral emission estimates by inversions using three types of networks of different sizes. Each sector has a distinct color. In (a-d), we show the uncertainty budgets in percentage to the corresponding emission budgets computed using the IER inventory. The points indicate the percentage of prior uncertainty budgets before inversion, and the bars demonstrate the percentage of posterior uncertainty budgets after inversion. The error bars show the variations of the uncertainty budget using 10 different networks of same size (10, 30, 50, or 70) constructed as detailed in Sect. 3.3. (a-c) Reduction of uncertainties by inversions using three different types of networks of increasing sizes. For each sector, the numbers of stations corresponding to the four bars from left to right are 10, 30, 50 and 70 stations respectively. (d) Reduction of uncertainties by inversions using three different types of networks of 70 stations. The types of network corresponding to the three bars from left to right are E, R, and U respectively. (e) Comparison between the inventory budgets and uncertainty budgets (both in TgC) using the uniform network of increasing sizes. For each sector, the leftmost bar shows the inventory budget, and the four remaining bars to the right show the budget of uncertainties in posterior emission estimates by inversions using 10, 30, 50 and 70 stations respectively.





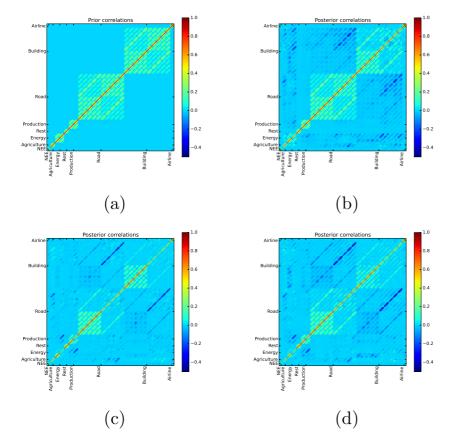
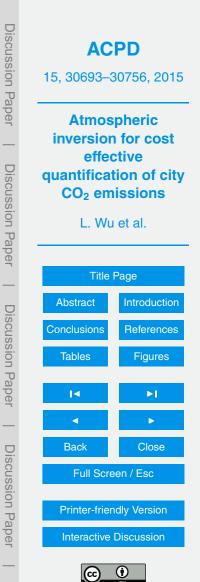


Figure 9. The correlation structures in **(a)** the error of prior scaling factor estimates; **(b)** the posterior error obtained by inversion using a U network with 10 stations; **(c)** the posterior error obtained by inversion using an E network with 70 stations; and **(d)** the posterior error obtained by inversion using a U network with 70 stations.



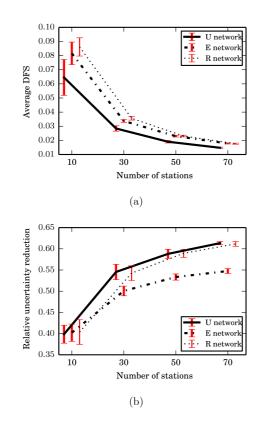
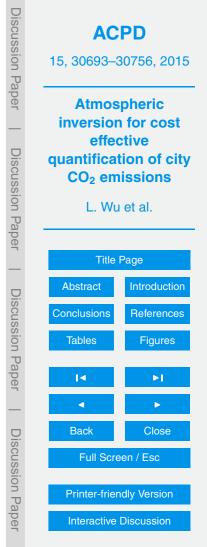
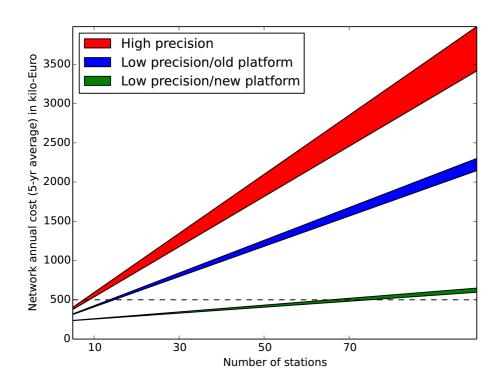
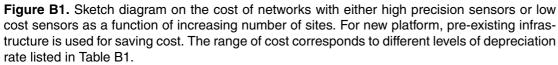


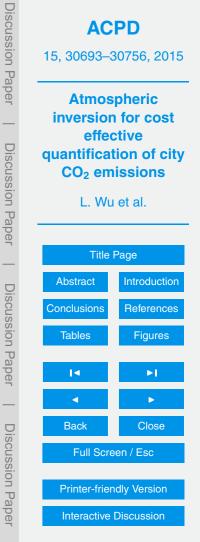
Figure 10. For three types of networks of different sizes, we compute **(a)** the average number of Degrees of Freedom for the Signal (DFS/*d* where *d* is the total number of observations assimilated) accounting for, on average, the independent pieces of information from an observation to resolve emissions; and **(b)** the relative reduction of uncertainties in scaling factor estimates computed by $(\sqrt{1^TB1} - \sqrt{1^TA1})/\sqrt{1^TB1}$, where **1** is an all-one vector. The error bars show variations due to inversions using 10 different networks of same size constructed as detailed in Sect. 3.3.













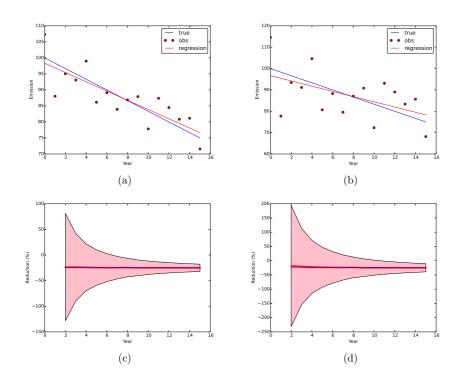


Figure C1. Detection of linear trends using the Monte Carlo method with ensembles of 10 000 simulations. We hypothesize that the emissions decrease linearily from a value of 100 in any appropriate unit to 75 (i.e. a 25% reduction) in a 15-years time horizon. (**a** and **b**) show the linear trends detected by linear regressions (red lines) using series of emissions, which are obtained by perturbing the hypothesized emission values (blue lines) under 5 and 10% 2-sigma annual emission uncertainties respectively (in percentage to the emission value in the initial year). (**c** and **d**) show the increasing 2-sigma accuracy of the trend detections with increasingly available emission data along years. The detection accuracy is calculated from statistics of regression results for 10 000 simulations.

