Response to comments on “Atmospheric inversion for cost effective quantification of city CO_2 emissions” by L. Wu et al.

We thank the three referees for their very detailed reviews. Their comments have allowed us to improve the manuscript by better emphasizing its strength and simplifying secondary discussions in Appendix. As detailed below, this revision focuses on OSSEs as suggested by the reviewers, and accordingly the title was changed to “What would dense atmospheric observation networks bring to atmospheric inversion for the quantification of city CO2 emissions?” A marked-up manuscript is also provided in this response.

Anonymous Referee #1

COMMENT:

Overview: Wu et al. present a manuscript assessing the ability of different observing networks (with different costs) to quantify city CO2 emissions. The paper is appropriately placed in AMT. There is a core of work that appears sounds, and would be a useful contribution to the community.

RESPONSE:

We thank the reviewer for his/her positive assessment of our pseudo-data analysis and for his/her suggestions that have helped improving the manuscript significantly. As detailed below, the paper now focuses on OSSEs, and accordingly the title was changed to “What would dense atmospheric observation networks bring to atmospheric inversion for the quantification of city CO2 emissions?”

COMMENT:

However, as currently presented the manuscript is misleading and improperly substantiated. Most importantly, the paper is written as though it assesses different cost systems for quantifying urban CO2 emissions and derives answers for optimal instrument and network design with wide implications.

RESPONSE:

In the revision, we better separated the pseudo-data analysis on one hand and the discussions on the practical solutions for deploying dense networks on the other hand. The text mainly focused on the former, and we followed the reviewer’s suggestion to re-organize the latter into discussions on the performance requirements for the instruments and inverse modeling framework.

COMMENT:

This is not substantiated.

RESPONSE:

Our study compares networks with few current research-grade instruments to potential future networks with higher density. In this context, it is critical to discuss the development of low cost medium precision (LCMP) sensors (we replaced the term "cheap"). Although LCMP sensors with the precision, systematic error and cost assumed in the initial manuscript are not commercially available yet, present testing with different versions of prototypes within our laboratory (by co-authors of this paper) provide encouraging results for the repeatability and reproducibility of CO2 measurements, when external influences are properly corrected for. As the test will be continued to verify the performance for a least one year, the full study on the sensors shall be published in 2016. Still, we have attached a figure illustrating preliminary work for the reviewers. It indicates that LCMP sensors could yield measurements uncertainties of about 1 ppm for hourly values if regularly calibrated (every few days or weekly). This motivates us to assume that we could use LCMP sensors in the near term to construct dense monitoring networks for atmospheric inversion.

COMMENT:

The authors have done a nice pseudo-data experiment which could be the basis of a re-written publication. I therefore would only recommend publication after major revisions. Writing a manuscript focused on a pseudo-data study evaluating different network performances in a specific inversion framework would be interesting and useful. This should simply state performance of instrument and model that are needed/assumed

RESPONSE:

The text was deeply reorganized in order to avoid misunderstanding about the interpretation of our results. The new text primarily focuses on the pseudo data experiments and on checking the potential of inversions using dense networks within and around city with an accent on targeting precise total and sectorial estimates of the emissions. For such inversions to be practical, we discuss requirements on the instrument performances (Sect. 4.3). Concerning the cost of the atmospheric inversion system, we demonstrated in the new draft that it is impossible to operate very dense monitoring networks if using expensive high precision sensors (~50 k€) currently employed in climatic studies. Running such dense monitoring network would necessitate the use of LCMP sensors (1-5 k€). Please see Appendix B for discussions on the cost requirements of the inversion system if using LCMP sensors. Note that now we do not assume the pre-existence of LCMP sensors for operational use but evaluate the potential of dense networks in improving inversion performance, although we have preliminarily tested such LCMP sensors within our lab.

COMMENT:

(with the model performance equally important to clearly discuss - as unknown biases within are likely the biggest challenge) –

RESPONSE:

The model performance in this study follows Bréon et al. (2015) who assimilated real measurements. Therefore, this performance should be seen as a requirement per se which represents the present skill of mesoscale transport models. Still, we now better acknowledge the problems raised by potential model biases (Sect. 4.3) and perform sensitivity studies that partially account for the unresolved model error (Sect. 3.2).

COMMENT:

and eliminate all the discussion of cost of sensor or network and the discussions and assumptions for MRV.

RESPONSE:

Please see the answer above regarding the cost of the sensors.

The discussion on the cost of future infrastructures for large networks of LCMP sensors was greatly simplified and turned into a series of requirements (Sect. 4.3 and Appendix B). The discussion on the cost of the inventories was also simplified and kept as an indicator for the cost requirements on networks and sensors (Appendix B). All of this is needed to evaluate the relevance of testing 30 to 70 sensors networks in this study but was moved in Appendix and briefly summarized in the discussion section of the paper.

Last, we also significantly revised the MRV part. We provided a brief introduction on MRV systems in order to provide a useful background for city scale atmospheric inversion of fossil fuel CO2 emissions in the introduction, and discussed the relevance of applying the inversion results using dense monitoring networks in the MRV context (Sect. 4.2). Assumptions on MRV (e.g. target definition) have been removed from the text.

COMMENT:

Major Issues:

My major concerns are centered largely on the context and conclusions drawn in the paper. This manifests most notably for a couple topics: Cheap vs. expensive sensors (much of discussion on page 30706, though found throughout): The authors act as though they are rigorously assessing the use of different cost sensor. However, they simply assert a performance capability of cheap sensors that has yet to be demonstrated or tested. This is the extent of the real comparison. The authors basically assert that cheap sensors can work as well as expensive ones in the context of inversions, and then do inversions where the cheap sensors 'win' simply because they are cheaper. This is not any type of real analysis or test. I suggest the authors remove all mentions of cost of sensors and assessment of that. They should instead focus on the pseudo-data study that relies on observations of a certain, assumed quality.

RESPONSE:

Our reply to the general comment underlines that we followed the reviewer's suggestion to better focus on the pseudo-data study. The comparison between cheap vs. expensive sensors was removed from the text. Instead, we explained that it is impossible to set up dense networks (e.g. 30-70 sites) using expensive sensors under acceptable cost. Instead, we discussed requirements in sensor performance and cost on cheap sensors for the inversion system using dense networks to be practical. These were moved into the appendix and shortened in the discussion section. The abstract, introduction and conclusions were revised accordingly.

COMMENT:

Assessment of cost of inventories and networks (mostly on page 30705): This is a very simplistic and naïve assessment. It really seems to be focused on concluding cheap sensors are better, in particular by asserting that original purchase cost dominates total cost.

RESPONSE:

We clarified our discussions on the cost of infrastructure.

COMMENT:

In reality, we don't really know what is needed or necessary for urban co2 emissions quantification.

RESPONSE:

Even though this is an emerging activity, experiments with real data such as that of Bréon et al. (2015) give us robust insights on the requirements for urban CO2 emission quantification.

COMMENT:

This is why a pure pseudo-data study would be useful (and is what I recommend this manuscript be turned into)! Making simple assumptions about cost that ignore practical experiences about measurement location cost and access and calibration/maintenance needs let alone ignoring possible operational personnel costs for mainlining networks and inversion systems renders really makes this analysis portion not relevant and useful.

RESPONSE:

Through the deployment and maintenance of the CO2 Paris network since 2010, we have acquired some solid experience about the requirements and issues for setting-up such urban networks. Also note that the co-authors of this paper gather modelers and experimentalists. The new draft clarified our discussions on the network requirements and we moved them to the appendix and in few sentences of the discussion section.

COMMENT:

Assumptions/assertions of what inversion error is useful: This is again a simplistic analysis that is not robust or really helpful. I would prefer if the authors focus on the capability of different inversion systems as determined by the pseudo-data study with clearly defined assumptions about error and performance of the modeling system.

RESPONSE:

As suggested, we now focus on the capability of the inversion system in our pseudo-data study. The new draft reverted the logic flow for the analysis of the different scores of uncertainties in the inverted emissions. While the analysis of the result ignored any uncertainty target, the discussion section evaluated annual uncertainties (not putting too much weight on such an evaluation) by using different assumptions on the impact of monthly mean uncertainties for the derivation of annual budgets or trends. By such, the new manuscript avoided giving the impression of building its analysis on strong assumptions. We better discuss the assumptions about the error and performance of the modeling system (which is based on real-data studies; Breon et al., 2015; Staufer et al., 2016), and performed sensitivity studies that partially take into account the impact of unresolved model errors.

COMMENT:

As constructed, the author's gives strong weight to total annual CO2 fluxes. These are perhaps not the most useful value from a city network, nor the most robust result from inversions.

RESPONSE:

As indicated previously, we focus more on inversions for the one-month period, and annual uncertainties are discussed only in the final section. Annual estimates provide both the baselines and the trends, which are both required for the analysis of the impact of climate plans. Note that such an application has been the main justification for deploying CO2 urban networks.

COMMENT:

There is relatively little discussion of the bias error problem in inversions in trying to get accurate net annual fluxes.

RESPONSE:

Remember that our inversion configuration follows Bréon et al. 2015 who did not detect major model biases when analyzing misfits between simulated afternoon CO2 gradients and real afternoon CO2 gradients measurements. In particular, data are assimilated in the afternoon only to avoid well known model biases on the vertical transport during nighttime. This supports our assumption that the model is not strongly biased.

Regarding potential biases in the measurements: the paper now better explains requirements on how calibration strategies should allow preventing large biases in the measurements for periods longer than several days to a week. As a consequence, the measurement "biases" are rather seen as error correlations with a timescale of about several days to a week.

We showed sensitivity tests with higher observation (i.e. model + measurement) errors to account for long temporal scales of correlations (which is a better characterization of what could be considered as "model or measurement biases"). These tests are now analyzed and discussed in the main text.

COMMENT:

Actually trends have been though to be easier to detect and help with bias errors- and this is not addressed in here (McKain et al., PNAS).

RESPONSE:

We addressed the matter of detecting trends in section 2.1 of the first version of the manuscript.

Further, model errors are barely "biased" in a mathematical sense. They have tendencies to under-estimate or over-estimate some processes strongly influenced by the large to local scale meteorological conditions and which thus hardly summarize into absolute or relative errors that could be similar for month to month or from year to year or even constant over short time scales. Therefore, it seems difficult to assume that trends could be far more easily monitored than the annual emissions.

COMMENT:

How exactly fluxes are derived, and the details of the 'gradient' method are not clear. This would be much more valuable and useful to spend time discussing in the revision than all the time on cost and MRV.

RESPONSE:

We improved the presentation of the gradient inversion method. Please see our previous responses on cost and MRV.

COMMENT:

Detailed Issues:

Abstract, line 8: This is not really what the authors are doing in this paper Line 14: This is an unsubstantiated claim about cheap sensors

RESPONSE:

The abstract was strongly revised in line with the general corrections to the manuscript discussed above.

COMMENT:

Line 19: Performing the analysis only in January (when biosphere is weakest), and extrapolating to the whole year is an iffy proposition that relies on large assumptions

RESPONSE:

The connection between typical uncertainties at the monthly scale and at the annual scale is now assessed by two extreme cases on the month to month correlations (independent and perfectly correlated), as results in a wide range of annual uncertainties that should cover most realistic month to month correlation scenarios. Our assumption that the scores of uncertainty in winter can be extrapolated to summer month is based on sensitivity tests where the uncertainty in the biogenic fluxes was artificially increased to typical levels for summer months. This would be due to using the gradient approach, which levels down the sensitivity of the inversion to the natural fluxes. This is now better discussed in Sect. 4.2.

COMMENT:

Line 26: Based on the level of assumptions made, would seem unfair to asset the system can meet the requirement on bias errors are essentially unaddressed. Final sentence of Abstract: This is an assertion that is unsubstantiated in this manuscript.

RESPONSE:

Again, the abstract has been strongly revised in line with the general corrections to the manuscript discussed above. Regarding the biases, see our answers to the general comments above.

COMMENT:

The authors have really conducted a pseudo-data experiment and not determined that networks of cheap sensors could actually inverted emissions to within 5% uncertainty.

RESPONSE:

The uncertainty target aimed at helping to analyze the results in the original draft. It is not defined a priori anymore in the new draft, and it was ignored in the result section. As mentioned above, we just gave highlights on the levels of posterior uncertainties in Sect. 4.2 based on the extrapolation of the uncertainties at the monthly scale into a wide range of typical uncertainties at the annual scale.

COMMENT:

p. 30698 line 27-28. This is not a new type of data. There is long literature cited in this paper that is using this data.

RESPONSE:

We meant that the city scale inversion is a recent activity and a source of new types of data for the community of the anthropogenic emissions inventories. Still, we removed "new type of data" in the new manuscript for clarity.

COMMENT:

p. 30699 line 15,15: Should also probably mention at least Salt Lake City which has the longest running urban CO2 network.

RESPONSE:

We agree with the reviewer. We added information on the Salt Lake city network.

COMMENT:

P. 30700 Line 10-11: This really undermines any assessment of cheap versus expensive sensors.

RESPONSE:

See our general answer to the major comments of the reviewer. The large modifications of the text was to better focus on the pseudo data experiments.

COMMENT:

The writing is quite labored and redundant at times, and could really use revision to improve clarity and succinctness. Example of redundancy page 30701, Lines 1-5.

RESPONSE:

Thank you for your suggestions. We checked the redundancy and improved the succinctness and quality of the text.

Anonymous Referee #3

COMMENT:

Overall comments. The paper is an interesting observational system simulation experiment (OSSE) exploring observational network design for estimates of urban emissions of CO2 using atmospheric inversions.

RESPONSE:

We thank the reviewer for his/her comments that helped improving this paper significantly and for his positive assessment of our OSSEs.

COMMENT:

As written, however, the paper has many serious problems. It is limited by a number of severe assumptions embedded in the inversion system, and by the lack of discussion of the vertical resolution of the atmospheric transport model.

RESPONSE:

We now better clarify that the assumptions underlying the configuration of the transport model and of the atmospheric inversion. Our configuration is based on the experiments with real data by Bréon et al. 2015 and a recent publication (Staufer et al., 2016) using year-long real data for the inversion of Paris CO2 emissions. We provided discussions in details on the model error in Sect. 2.5.2 and 4.3. Sensitivity studies with inflated observation error would partially take into account the influence of unresolved model error in inversions.

COMMENT:

The overall conclusions regarding "cheap" vs. "expensive" sensors are invalid,

RESPONSE:

As detailed below in answer to specific comments, this discussion was based on current results regarding the performances of low cost medium precision (LCMP) sensors. We now draw no conclusion regarding "cheap" vs. "expensive" sensors, but focus on the potential of inversion system with dense networks.

COMMENT:

and the alleged ability to deploy sensors at 25m AGL is misleading.

RESPONSE:

25 magl correspond to the typical height of recent buildings in the Paris region. We have already installed measurement sites at the top of such buildings. Please check our responses below as this issue was raised several times in the review.

COMMENT:

The target uncertainties quoted are entirely dependent on the assumed prior uncertainties,

RESPONSE:

No, there were derived independently. However, we removed the definition of uncertainty target from the introduction.

COMMENT:

and these uncertainty assumptions are often unjustified and untested.

RESPONSE:

They are consistent with those used in Bréon et al. (2015) and Staufer et al. (2016). We also conducted sensitivity experiments where observation (model + measurement) uncertainties are inflated to check the robustness of the results. The results of sensitivity tests were discussed in the supplementary material but they are now shown in the main text (Sect. 3.2).

COMMENT:

The discussion of the cost of measurement networks is unrealistic in the extreme and should be deleted.

RESPONSE:

The discussion on the cost of future infrastructures for large networks of LCMP sensors was greatly simplified and turned into a series of requirements (Sect. 4.3 and Appendix B).

COMMENT:

The manuscript contains a core of worthwhile research – an assessment of the sensitivity to a highly idealized inversion system to the network of instruments deployed - but the paper claims to be much more than this. This manuscript requires serious revision before it should be considered for publication. More detail on these points follows.

RESPONSE:

In the new manuscript, we follow this suggestion and focus this study on OSSEs. Accordingly the title was changed to "What would dense atmospheric observation networks bring to atmospheric inversion for the quantification of city CO2 emissions?"

COMMENT:

1. The argument concerning "cheap" vs. "expensive" sensors is misleading, lacks content, and must be deleted.

RESPONSE:

Although LCMP sensors with the precision, systematic error and cost assumed in the initial manuscript are not commercially available yet, present testing with different versions of prototypes within our laboratory (by co-authors of this paper) provide encouraging results for the repeatability and reproducibility of CO2 measurements, when external influences are properly corrected for. As the test will be continued to verify the performance for a least one year, the full study on existing LCMP sensors shall be published in 2016. Still, we have attached a figure illustrating preliminary work for the reviewers. It indicates that LCMP sensors could yield measurements uncertainties of about 1 ppm for hourly values if regularly calibrated (every few days or weekly). This motivates us to assume that we could use LCMP sensors in the near term for atmospheric inversion. Nevertheless, in the new draft, the arguments on favoring one against the other between cheap vs. expensive sensors have been deleted. Instead, we discussed about the requirements on LCMP sensors for the construction of dense monitoring networks in the urban environment.

COMMENT:

The authors state that transport errors are larger than instrument errors, thus instrumental error doesn't matter, and thus "cheap" sensors are just as good as more expensive CO2 sensors. The authors, however, present no quantitative assessment of any real "cheap" sensor or atmospheric transport errors.

RESPONSE:

We improved the presentation of the observation (model + measurement) error configuration in Sect. 3.5.2. Our assumptions/assertions of atmospheric transport errors are based on the works of Breon et al. (2015) and Staufer et al. (2016) in which real data were used to evaluate the model performance. We reverted the logic in that, instead of blindly ignoring the role of the instrument error in the original draft, the requirements are imposed in the new draft on the performance of the LCMP sensors so that inversions would not be greatly affected by poor LCMP sensors.

COMMENT:

The abstract makes it sound like low-cost sensors exist and have been tested and have been shown to perform well. This is wrong. Unjustified assumptions have been made so that sensor performance is irrelevant. This isn't science; it is wishful thinking. Wishful thinking should not be published in ACP.

RESPONSE:

As indicated above, we based our discussion on the cost and precision of the next generation of sensors on actual lab testing, and our assumptions on the accuracy of the model on previous studies using real data. However, following the reviews of our manuscript, we now discuss requirements and expectations on the cost and precision of LCMP instruments in Appendix and briefly in the discussion section, while most of the text focuses on the OSSEs. The abstract was revised accordingly.

COMMENT:

2. The results concerning performance of the inversion system as a function of the number of sensors is defensible within the limits of the many assumptions made by the inverse system, including the uncertainties assumed within the inversion.

RESPONSE:

Again, they have been derived from the diagnostics of Bréon et al. 2015. However, we better highlight the assumptions underlying the OSSEs in the new draft.

COMMENT:

These assumptions, however, are buried deep in the document and in sections that are often very difficult to read.

RESPONSE:

The presentation of the inversion technique and configuration were improved, and we highlighted the inversion results are conditioned on the assumptions made in the abstract.

COMMENT:

The assumptions include prior flux errors, atmospheric transport errors, and assumed coherence in the prior flux errors. Very large coherence is assumed in the prior flux errors. The final error levels are highly dependent on these largely unjustified assumptions.

RESPONSE:

We control budgets of emissions over large areas, but this does not mean that we assume that uncertainties in the distribution of the emissions at high resolution are entirely coherent over such areas. It means that the fine spatial scales of the uncertainty in the emissions should not much affect the type of observation that we select for assimilation (downwind-upwind gradients between distant 25magl sites for elevated wind speeds). Still, the diagnostic of observation errors by Bréon et al. 2015 accounts for the impact of uncertainties in the distribution of the emissions at high resolution (i.e. the so-called "aggregation errors"), see the answer to the detailed comment by the reviewer on this topic). We clarified these in Sect 2.5.1 and 2.5.2.

COMMENT:

As the authors state, deep in the discussion section, these results "should not be over-interpreted." But the abstract says nothing about the numerous assumptions that limit the validity of these results, and states that 5% flux uncertainty can be achieved with 70 sensors: : :with no caveats given whatsoever about the large volume of assumptions that condition this finding. It is even difficult to determine from the abstract that this study is an OSSE. 2.1) These limiting assumptions should be presented prominently and clearly in the methods section. 2.2) These important caveats about the significance of the study results should be made clear in the abstract. The abstract is very misleading and should not be published in its current form.

RESPONSE:

The abstract and the method section were highly modified to better highlight our assumptions, and to be consistent with the strong reorganization of the manuscript.

COMMENT:

3. The method of relating CO2 mixing ratio differences to fluxes is not clear, and is of critical importance to the paper. The method of choosing upwind and downwind sites is described, but how these are related to emissions of CO2 is not described.

RESPONSE:

The presentation of the method, as well as that of the inversion configuration, has been strongly improved. In brief, the atmospheric transport model makes the link between the emissions and the selected concentration gradients as traditionally done in atmospheric inverse modeling, with the difference that instead of sampling concentrations at individual sites from the output of the transport model, here, we sample the differences of concentrations between these sites from the outputs of the model, when the wind criteria for the gradient selection are verified.

COMMENT:

4. The paper is based on a pseudo-measurement network that, as noted in the abstract, collects data at 25 m above ground. The study is based, however, on an atmospheric model that has very coarse resolution – 15 km in the horizontal

RESPONSE:

The horizontal spatial resolution of our atmospheric transport model CHIMERE for Paris metropolitan area is 2 km, with meteorological forcing by ECMWF products at a 15 km resolution.

COMMENT:

and, as best I can determine, about 250 m in the vertical.

RESPONSE:

For efficiency, in general, meteorological, transport, or ocean models do not have regular grid on the vertical in geometric height. They have a much refined grid near the ocean/land-atmosphere boundary. In particular, here, the thickness of the first vertical levels of CHIMERE is about 25 m, and there are ~7 vertical levels in the PBL during the afternoon. Most of the 25 magl stations are located in the second vertical level of the model. We now clarified these in Sect. 2.4.2.

COMMENT:

The model has no demonstrated capacity to represent the complexity of an urban surface either in the vertical or in the horizontal.

RESPONSE:

Bréon et al. (2015) have used this CHIMERE(2km)–ECMWF(15km) model to simulate real measurements of concentrations at less than 25magl in the Paris area. Their model showed similar capability to fit the measurements than the 2km resolution meteorological and transport simulations by Lac et al. (2013) who used a specific scheme to account for the urban heat island in the urban area. The CHIMERE(2km)–ECMWF(15km) model capacity to simulate the measurements is quantified by the estimates of the model errors by Bréon et al. (2015) which are used in our study (i.e. accounted for in the configuration of the observation errors in our inversion system).

COMMENT:

An OSSE is limited by the quality of the modeling system applied to the system design. The authors have no basis for claiming that their results are valid for an observational network deployed at 25 m above ground with a model that has no demonstrated capacity to resolve the details of atmospheric transport in the environment of interest. If the authors must 4.1) discuss the vertical resolution of the model; 4.2) describe how the model simulates the atmospheric surface layer; 4.3) explain the true limits on observational altitude in their study given 3.1 and 3.2; and 4.4) at a minimum note how the complexity of the urban surface in the horizontal, unresolved by their modeling system, could complicate the meteorology in ways that cannot be captured by their modeling system.

RESPONSE:

See the answers above. We added model details on atmospheric surface layer and on how meteorological fields are preprocessed in Sect. 2.4.2. We now better discuss in Sect. 2.5.2 the difficulties related to the modeling or CO2 transport in the Paris area, as is reflected by the high estimates of model errors for the inversion configuration. We now better emphasize that our modeling configuration is derived from that of Bréon et al. (2015) and better present it. And we better highlight the fact that the difficulties related to the modeling of CO2 transport over urban areas explain why we assimilate data under the condition of high wind speed during the afternoon only, when the vertical mixing is high. By this way, the complex impact of local sources and transport should be decreased.

In particular, we now better discuss our assumptions (in Sect. 2.5.2) and corresponding requirements (in Sect. 4.3) regarding the capability to model measurements in the core of the Paris urban area. The networks tested in our OSSEs include a significant number of sites in this core. However, Bréon et al. 2015 diagnosed very high model errors for such measurements and thus avoided assimilating them in their inversions (see more detailed discussions on this topic in our answer to specific comments 3 and 38 as well as Sect. 4.3 in the text).

Finally, the sensitivity tests where the observation (model + measurement) errors are inflated are now presented in Sect. 3.2 rather than in the supplementary material to better discuss the weight of model errors.

COMMENT:

5. The manuscript needs further editing. It is full of detail that is hard to follow and at times extraneous to the central message of the paper. The figures are out of order, and often the figure quality is marginal. The writing quality is poor and must be improved before this manuscript is suitable for publication.

RESPONSE:

We now focus on the central message about the potential of atmospheric inversion using dense networks with OSSEs. We improved the quality and concision of the text and the quality of the figures.

COMMENT:

6. The economic justification for "cheap sensors" contains a great deal of unjustified wishful thinking.

RESPONSE:

See our answers to the comment 1.

COMMENT:

For example, Appendix B states that, "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 oprocedures 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 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 authors are thus proposing that a 70-instrument network sprawling across a large metropolitan region would have all of the instruments replaced every 1-2 days. The cost, however, is cited to be "very limited," and Table B1 shows no added cost for personnel for replacing 70 instruments every day. I would expect that such a schedule for instrument replacement alone would take 2-3 full time personnel. Further, Table B1 assumes that 70 free platforms with suitable characteristics for monitoring greenhouse gas emissions are available! This discussion is 1) unrealistic in the extreme and 2) unsuitable for publication. This unrealistic and misleading attempt at evaluating the economics of observational systems must be deleted from this document. It has no scientific value that I can discern.

RESPONSE:

We improved and simplify the discussions on the network cost and turned it into series of requirements. They were put into Appendix and summarized in the discussion section. The aim of this cost analysis is now to provide insights on whether the deployment of 30 to 70 sensor networks could be envisaged in the near future. We think that it is critical to develop this discussion after having analyzed results of OSSEs with such networks.

COMMENT:

Detailed comments.

1. Page 2, Lines 13-15. What sensors are "currently developed?" As best I can tell, no actual sensors are evaluated. This text is extremely misleading and must be modified to represent the actual content of the paper, which assumed instruments with no bias and insignificant random error exist.

RESPONSE:

We clarified the fact in the discussion section that new prototypes of LCMP sensors are presently tested at LSCE and yield promising results regarding the requirements that the manuscript derives from the OSSEs. Note that now we do not assume the pre-existence of LCMP sensors for operational use but evaluate the potential of dense networks in improving inversion performance, although we have preliminarily tested such LCMP sensors within our lab. We strongly revised the abstract.

COMMENT:

2. Page 2, Lines 13-15 What defines expensive?

RESPONSE:

The new abstract now explain that the deployment of dense networks makes it necessary to decrease the price of the sensors whose typical cost is presently 50 k€.

COMMENT:

What defines a "megacity?" Is this different than the cities that emit 44% of global CO2 emissions?

RESPONSE:

The world "megacity" was deleted from the abstract. The 44% direct emissions correspond to all urban areas. The megacities are usually referred to urban areas whose total population exceeds 10 million people.

COMMENT:

3. Page 2, Line 17. "25 m above ground level." Why are the imagined sensors located at 25m above ground?

RESPONSE:

We have chosen 25 magl since this is the common height for high public or private buildings in the Paris area, and since much of them are convenient to install measurement sites on their roof. Building and managing dedicated tower sites for measuring CO2 at higher heights would be impossible (too expensive) if considering 30 to 70 site networks. We also selected this height since Bréon et al. 2015 assimilated measurements from stations at less than 25magl (the modeling skills generally increase with the height).

COMMENT:

Can this altitude be treated realistically in the inversion system? This is a strong recommendation that is not justified by the content of the paper. This must be carefully justified by showing that the model can simulate measurements collected at 25 m AGL or deleted.

RESPONSE:

As said above, Bréon et al. (2015) assimilated data from stations at less than 25magl. Local sources and transport may impact the concentration measurements at 25 magl in a way that is difficult to characterize using a mesoscale atmospheric transport model. This is why we select data under conditions of high wind speed for the afternoon only when the vertical mixing is high. Of note is that most of the site locations investigated in the study are outside the dense parts of the city, and they are all located without a precise definition of their specific location within the 2km x 2km grid cells of CHIMERE. This means that specific studies can be led to select locations less prone to a complex local situation (using mobile campaigns of measurements and local scale transport modeling), which has been recently done at LSCE when setting up new sites around Paris.

Still, assimilating 25magl measurement in the core of the urban area (which corresponds to a considerable number of sites in this study) is challenging and had not been attempted by Bréon et al. (2015) even though they derived typical estimates of the model error for such measurements (that have been used to set-up our inversion system). This requires being able to filter the local scale signal from the measurements at such locations (there are definitely some ideas for such filtering). These considerations are now better discussed in Sect. 2.4.3 and 4.3.

COMMENT:

4. Page 3, lines 5-12. These statements are not justified or quantified, thus not useful. 1) Certainly additional measurements such as CO might improve an urban inversion, but this is not a new result. This paper adds nothing to the body of literature on this topic. Without new results, this should be deleted.

RESPONSE:

Following your suggestion, the statements about CO were deleted in the abstract.

COMMENT:

2) The statement that "cheap" sensors can improve urban emissions estimates says nothing about the quality or characteristics of the so-called "cheap" sensors. Sensor performance should be quantified, or this text should be deleted. This is wishful thinking, not a conclusion from any research performed in this manuscript.

RESPONSE:

The whole abstract was rewritten in line with the general reorganization of the paper that is explained in answer to the previous comments of the reviewer.

COMMENT:

5. Page 3, line 26 – page 4 line 3. This is a run-on and confusing sentence.

RESPONSE:

We rewrote this sentence.

COMMENT:

6. Page 4, line 4. What is the "city mitigation potential?"

RESPONSE:

We have clarified it.

COMMENT:

7. Page 4, Line 6. English needs work.

RESPONSE:

We rewrote this paragraph to improve the language and avoided such a use of the terminology from climate economics.

COMMENT:

8. Page 4, line 29. economics.

RESPONSE:

We kept "climate economy" to be consistent with existing publications (please check some paper titles in the reference).

COMMENT:

9. Page 6, line 10. "required qualities"? What are "qualities?" Please be more precise.

RESPONSE:

We rewrote the sentence and changed required qualities to "accurate emission accounting method".

COMMENT:

10. Page 6, line 14. Involves.

RESPONSE:

Corrected.

COMMENT:

11. Page 6, line 27. The use of continuous CO2 measurements to monitor urban emissions is far from a new idea. Please do not claim that this is a "new type of data."

RESPONSE:

We removed "new type of data".

COMMENT:

12. Page 8, lines 3-7. The authors do not employ an economic model to determine the costs of MRV vs. atmospheric inversions. They simply take the costs of these systems today, and make many unrealistic assumptions about these costs. Costs are not fixed, and today's costs should not be used to plan tomorrow's monitoring systems. Further evaluation of this text (Appendix B) reveals many other problems, noted above in point 6 of the overall comments.

RESPONSE:

The present costs of inventories are still indicative about the typical order of magnitude of the costs in the near term. However we now improve and shorten this analysis to provide very simple notions regarding the typical requirements on the cost of the sensors and networks in appendix, and, briefly, in the discussion section.

Please see also our responses above to overall comment 1 and 6.

COMMENT:

13. Page 8, line 10. "are currently developed." If they are currently developed, please provide some citations that describe the performance characteristics of these sensors. Some imagined sensor characteristics are described in Appendix A, but without any evidence of the realism of these claims.

RESPONSE:

As detailed in our responses to the main point 1, currently prototypes for such LCMP sensors are tested at LSCE and we illustrate first results that are promising regarding the potential for having instruments with such specifications in the near term. This work has been funded by the climate KIC innovation projects, such as MIRIADE and SMEVOUCHER (http://www.climate-kic.org/projects/miriade/), and publications are planned for 2016. See also our answer to overall comment 1.

COMMENT:

14. The introduction has a long discussion of greenhouse gas emissions targets and issues, but presents little insight into the performance of existing urban inversions.

RESPONSE:

The discussion on the uncertainty targets was removed (as discussed above). We feel that the discussions on MRV systems provide useful insights on the context for the monitoring of city CO_2 emissions. Therefore we would like to keep it but we tried to clarify it.

COMMENT:

15. Page 9, lines 17-24. This text needs considerable editing. It is very difficult to understand.

RESPONSE:

We have deleted discussions on target derivation for MRV of city CO_2 emissions.

COMMENT:

16. Page 9, lines 23-24. What are "city inventories that would not have access to the same level of information as national inventories."?

RESPONSE:

This was removed due to the reorganization of the manuscript.

It was connected to the part of the introduction stating that "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 total amount of fossil fuel that has been consumed within the cities."

COMMENT:

17. This entire paragraph on "notional targets" should be simplified and clarified.

RESPONSE:

We do not define such notional targets a priori anymore. Instead, we just give highlights on the levels of posterior uncertainties from the different OSSEs in Sect. 4.2 based on the extrapolation of the uncertainties at the monthly scale into a wide range of typical uncertainties at the annual scale.

COMMENT:

18. Page 10, line 25 – page 11, line 2. I believe these are hypotheses, not statements of fact. Please clarify. If they are facts, please include appropriate citations.

RESPONSE:

These are not statements of facts, neither hypothesis. They are deduction based on physical basis (sectoral emissions are driven by different dominant factors) and mathematical reasoning (split of budgets for different sectors implies negative correlations). We modified the text accordingly and we better discussed the assumptions underlying this derivation (now in Sect. 3.1).

COMMENT:

19. Page 11, lines 2-3. I don't understand this sentence.

RESPONSE:

We do not discuss notional target anymore, and this sentence was deleted.

COMMENT:

20. Page 11, line 8. reducing the reduction?

RESPONSE:

We corrected the text. We wanted to write "reducing the emission". These lines of text was moved into into Sect. 4.2.

COMMENT:

21. Page11, line 4. What is the purpose of this paragraph?

RESPONSE:

We wanted to connect the uncertainties in the monthly to annual budgets of the emissions to that in the trend monitoring, since trends are key indicators for climate plans. This analysis was moved into Sect. 4.2.

COMMENT:

22. Page 11, line 14. This paragraph is very difficult to follow and requires significant editing. Please explain the methods and assumptions clearly.

RESPONSE:

The connection between typical uncertainties at the monthly scale and at the annual scale is now assessed by two extreme cases on the month to month correlations (independent and perfectly correlated), as results in a wide range of annual uncertainties that should cover most realistic month to month correlation scenarios. Our assumption that the scores of uncertainty in winter can be extrapolated to summer month is based on sensitivity tests where the uncertainty in the biogenic fluxes was artificially increased to typical levels for summer months. This would be due to using the gradient approach, which levels down the sensitivity of the inversion to the natural fluxes. This is now better discussed in Sect. 4.2.

COMMENT:

23. Page 12, line 11. I don't understand the purpose or content of this paragraph.

RESPONSE:

The aim of this paragraph (now sketched in the discussion section) was to provide a way of extrapolating (with a wide range of uncertainty) results of uncertainties at the monthly scale to the annual scale since the inversion are applied to a 1-month period only while the annual scale is more relevant politically and correspond to that of most of the inventories.

Now we do not rely on such definition of levels of uncertainty for discussions of the inversion results, but assess what are the implications and the relevance of the uncertainties in emissions estimates brought down by inversions in the context of MRV (Sect. 4.2).

COMMENT:

24. Section 2.2. Notional costs. This section of the paper has serious problems. There is little information that serves as the basis for the cost of conducting an urban emissions inventory of a given accuracy. There are questionable assumptions about the cost of an atmospheric inversion (e.g. cost of sensors is the primary cost). The assumption about "cheap" sensor accuracy and precision makes the distinction among sensors meaningless, but there is no actual evaluation of any sensors. There are no assessments of actual transport errors. Assumptions about costs made in Appendix B appear to be extremely unrealistic. The claim that this study examines the benefits of low cost, poor performance vs. high cost, high performance sensors is false and should be eliminated from the paper. The assumptions about the costs of inventory vs. inversion are also highly questionable and should also be deleted.

RESPONSE:

As already mentioned in answer to the overall comments 1 and 6 and detailed comment 12 by the reviewer, we now focus the paper on OSSEs. These discussions on the costs were greatly shortened and took form of requirements. See our response to overall point 6 for the aim of this cost analysis.

COMMENT:

25. Section 3.1. This introduction to the mathematics needs to utilize terminology that is specific to an urban atmospheric inversion. A "background" estimate of what, for example? Observations of what? The theory is not new. The application must be clear.

RESPONSE:

The atmospheric inverse modeling community has hardly managed to use common mathematical terminology and we cannot say that, today, urban atmospheric inversion has already developed into a widespread activity involving a large community. However, we tried to clarify this section and modified our terminology.

COMMENT:

26. Page 15, line 8. "control a vector x?" What does that mean?

RESPONSE:

The control vector is the set of variables that are controlled by the inversion, and we tried to improve its presentation. There is no misuse of the term control here. The atmospheric inverse modeling community generally erroneously call it the state vector even though it is not the state vector of a dynamical system (because of adopting the vocabulary of meteorological data assimilation for which the control vector is the state vector of the meteorological dynamical system, while, in atmospheric inversion, this is the input vector of the considered dynamical system i.e. the transport model).

COMMENT:

27. Section 3.2 The terminology in the section "control variables" should be replaced with physically meaningful terms.

RESPONSE:

The inversion controls scaling factors to be applied to emission budgets over various time periods, areas and set of sectors of activity. We tried to replace control variables by emissions wherever the text does not need to be rigorous (which we have done as in Fig. 1) but some parts of the text have to stick to the mathematical reality.

COMMENT:

28. Page 16, line 14-15. I do not believe that computational constraints are a primary limit on the resolution of the inversion. Either modify this discussion or provide a citation that demonstrates this claim.

RESPONSE:

The inversion relies on the full computation of the matrix corresponding to the linear observation operator. This full computation requires in principle as many transport simulation over 1 month as the number of control variables. The inversion also requires the inversions of matrices whose size is the number of control variables, which is another source of computing limitations. This is now better explained in Sect. 2.2.

COMMENT:

29. Page 16, line 27. "rest" is an unfortunate choice, since it has another meaning. "Remainder" would be better.

RESPONSE:

We followed your suggestion and change "rest" to "remainder".

COMMENT:

30. Page 17, line 1. Again, why are computational constraints invoked? What computational constraints? It is entirely possible to resolve an urban region at high resolution given current computing resources. This is not a real limit on urban inversion systems. The true reasoning for this coarse spatial resolution should be explained.

RESPONSE:

Without spending too much time on discussing each type of inversion systems, we just remind that some of them are easily limited, due to computational constraints, in term of the size of the observation vector (e.g. analytical systems which base the computation of the matrix corresponding to the observation operator on computations of the sensitivity of each assimilated data to the fluxes), others in term of the size of the control vector (e.g. analytical systems which base the computation of the matrix corresponding to the observation operator on computations of the impact of each controlled flux into the atmospheric concentration). At first glance, variational system could appear not to be limited for the size of the control vector nor for that of the observation vector, but actually, it is limited in terms of number of minimization iteration, and the larger the control space is, the more iterations should be needed to converge. And computing uncertainty covariance matrices from variational systems requires a large number of OSSEs which is extremely difficult due to computational limitations. Finally, all types of system need to address the inversion of covariance matrices whose size is a function of the number of control variables. Addressing the computation of $\mathbf{H}^T\mathbf{R}^{-1}\mathbf{H}$ can be another source of limitation regarding the size of the problem.

Here, we use the type of inversion that is the most adapted to the test of a very large number of different observation networks with a large number of station locations. See above for the description of its computational limitations.

COMMENT:

The atmospheric transport resolution applied for this study is exceptionally coarse.

RESPONSE:

Again the horizontal resolution of CHIMERE simulations for the Paris area is 2 km. There are 19 vertical layers up to 500 hPa with a 25m resolution close to the surface. The original ECMWF 15 km meteorological data were interpolated to the CHIMERE grid. See our answer to overall comment 4 on this topic.

COMMENT:

31. Figure 2. The regional colors and regional boundaries are not clear. There are lines on the map that do not correspond to the colors. What are the regional boundaries?

RESPONSE:

The colors marked out five zones of (2 km x 2 km) grid cells actually used for the definition of the control vector in the inversions. These five zones are meant to evenly split the Ile-de-France region, and do not necessarily follow the boundaries of the different administrative borders in this region (black lines in Fig. 2). It is now clarified in the caption of Fig. 2.

COMMENT:

32. Page 17, line 18. Nordbo et al (2012) reported no flux tower measurements that were carbon neutral. Every observational data point in their paper reported a net annual carbon source to the atmosphere. The paper cannot be used to justify that urban areas are carbon neutral. (Nordbo et al (2012) also referred to Minnesota as a city, and used 500 m resolution data to derive urban fraction for flux tower sites.)

RESPONSE:

Nordbo et al (2012) performed regressions between green-area fraction and urban emissions and *estimated* that a city with 80% green-area fraction would be carbon-neutral. We rewrote this sentence for clarity.

COMMENT:

33. Page 18, lines 4-5. Please define afternoon and high wind speeds. The details are important.

RESPONSE:

They were detailed in Sect. 2.4.3 in the revision. We added a pointer ("see Sect. 2.4.3 for details") to the text.

COMMENT:

34. Page 18, line 3. How are upwind and downwind sites defined?

RESPONSE:

This was also detailed in Sect. 2.4.3 in the revision.

COMMENT:

35. Figure 3 caption. "uniform" not unifrom.

RESPONSE:

Corrected.

COMMENT:

36. Page 19, line 3. What is the purpose of random selections of networks? It isn't likely that networks will be determined via a random process.

RESPONSE:

Indeed, the idea of comparing random samples is to investigate whether one can improve the results by conducting network design studies with OSSEs. Presently, the design of the network is more generally driven by practical issues regarding the infrastructure (agreements with potential hosts of the site, ability to fix inlets at height, and the rest of the infrastructure at a given site). Both considerations could contribute to the design of the network. Here, the samples are driven by some practical consideration so they are not totally random. Still, in some cases we see significant sensitivity to the sampling and thus the asset of conducting network design studies. This is now better discussed in Sections 3.1 and 4.4.

COMMENT:

37. Page 19, line 6. Figure 5 is referenced before Figure 4.

RESPONSE:

We rearranged the order of figures.

COMMENT:

38. Page 19, lines 13-15. How does sampling at 25m above ground, "avoid dominant influence of local emissions on concentration observations?" I don't know of any published work that shows that 25m is high enough above the surface to avoid being dominated by local emissions. I don't know how "avoiding dominant influence" or "local emissions" are defined. See the 4th main comment above. This is an unjustified and highly misleading claim that should not be published.

RESPONSE:

See our answers to the general comment 4 and minor comment 3 on the same topic. Again, Bréon et al. successfully assimilated real measurements from peri-urban sites at less than 25 magl by selecting data under specific wind conditions and during the afternoon only, and we derive our estimate of the model transport errors at such sites from their diagnostics. We rely on assumptions regarding the ability to exploit 25magl measurements in the core of the city (by filtering the local scale signal from urban measurements), which was termed as requirements in the new version of the manuscript.

Furthermore, the 25 magl height corresponds to the installation of the sensors on pre-existing infrastructures such as the roof of public/private buildings.

We improved the text to better discuss these points.

COMMENT:

39. Page 19, line 18. I cannot understand what the authors are trying to say about H1. Please rewrite in clear language.

RESPONSE:

We tried to clarify this section.

COMMENT:

40. Page 20, line 7. Is a 15km resolution ecosystem flux model appropriate for an urban scale study? This seems exceptionally coarse.

RESPONSE:

Paris is an intensive urbanized area. As the computation and gradient assimilation technique focus on the urban area where ecosystem plays small role, the coarse resolution of the vegetation flux simulation should not have significant impact on our inversion results. Indeed, we use the same vegetation flux simulation as in Bréon et al. 2015 where real data are assimilated. Furthermore, the spatial resolution of the NEE should not have a high impact on the assessment from OSSEs. The role of having high resolution product is to increase the fit with the "actual" fluxes but the gain from this improvement for inversion would be small, as can be seen by our sensitivity studies about NEE.

COMMENT:

41. Page 20, line 28. Figure 4? The figures are out of order.

RESPONSE:

We now pay attention to the order of figures.

COMMENT:

42. Page 21, line 16-18. What is the area covered at 2km x 2km resolution? There are 2km x10km grid boxes? Why?

RESPONSE:

As we used the same modeling framework as Breon et al. (2015), we referred to it for details about the CHIMERE model grid (see Fig. 1 in Breon et al. (2015) and Supplementary Fig. S1). The 2 km x 2 km area covers Ile-de-France, and the 2 km x 10 km grid boxes are defined for areas outside of Ile-de-France. We used coarser resolution for these outside areas (our objective is

Paris urban emissions) to save computational time. A figure showing the model grid is now provided in supplementary material.

COMMENT:

43. Page 21, H2: The transport model is only a 15km resolution model with 19 levels up to 500 hPa? This is very coarse resolution. Each vertical level, if evenly spaced, is approximately 250m. It is not unusual for coarse resolution models to have very unrealistic surface layer behavior when they are applied to CO2 simulations, and a 15 km horizontal resolution model cannot take into account realistic structures in the urban surface energy balance and changes in urban roughness. How can this model be used to evaluate the suitability of measurements 25 m AGL over the highly complex urban surface? What is the profile of CO2 close to the surface? The lack of description of the fidelity of this model for this task is a major weakness of the document. The OSSE is only as good as the model used for the OSSE. No relevant model evaluation is presented in this document.

RESPONSE:

Again, we use the same modeling framework as Breon et al. (2015) where model evaluation is presented. Please see our responses to specific comments 3, 30 and 38 and to general comment 4 for details on model resolutions and on our assumptions regarding the ability to fit with 25 magl measurements. We now emphasize that the configuration of our inversion system is strongly connected to that of Bréon et al. (2015).

COMMENT:

44. Page 21, lines 25-27. I don't understand "depending on the simulation: : :" Sometimes you have initial and boundary conditions, and sometimes you don't? Please clarify. How are boundary and initial conditions optional? What determines whether or not you include CO2 boundary and initial conditions?

RESPONSE:

When willing to compare the model to the data, we need to account for boundary and initial conditions. However, for OSSEs, we do not need to account for CO2 boundary initial and conditions (i.e. they are not included in the control vector) if assuming that uncertainties in such conditions can be accounted for in the observation error R (as done here). The mathematical framework of the inversion explains it. We tried to make it clearer through improving the explanation of the mathematical framework (see Sect. 2.4.2).

COMMENT:

45. Page 23, line 1. What does "read from the ECMWF meteorological product" mean?

RESPONSE:

We rephrased it.

COMMENT:

46. Page 23, line 11. Why 22.5 degrees? Is there any justification for this value? Plume dispersion widths will vary with wind speed, wind shear and turbulent intensity. What is the origin of this fixed value? What limitations does this fixed value place on the results of this study?

RESPONSE:

22.5° is clearly resulting from a trade-off between the need to select enough data so that the observational constraint is strong and not too much hampered by model and measurement errors, and the need for ensuring that we do not depart too much from the objective of assimilating "downwind-upwind" gradients. This value has definitely some arbitrary nature. But we recently publish results from a 1-year inversion experiment using real data demonstrating that this yield very good results unlike wider wind ranges for the selection of gradients (Staufer et al., 2016).

Having an even more complex strategy defining the wind range as a function of other meteorological conditions could be more adapted, but this is a first step in this direction and for the OSSEs here, it would not have been relevant.

It is now better discussed in Sect. 2.4.3.

COMMENT:

47. Page 23, line 13. Is that 7-16% of observations once the afternoon hours have been selected? Or is that 7-16% of the total number of possible observations?

RESPONSE:

It is for the total number of possible observations. We clarified it.

COMMENT:

48. Figure 6. The wind rose graphics are too small to read.

RESPONSE:

We improved Figure 6.

COMMENT:

49. Page 23, line 21. This paragraph is incomprehensible.

RESPONSE:

We rewrote the paragraph to clearly present how we assess the contribution of individual flux components to CO_2 concentrations.

COMMENT:

50. Figure 7. Why are any differences that are not in the afternoon hours displayed? They are irrelevant to this OSSE.

RESPONSE:

We removed plots of data that are not in the afternoon hours.

COMMENT:

51. Page 24, lines 5-9. A modeling system with 250m vertical resolution will have difficulty representing mole fraction differences at 25m above ground at any time of day. Figure 7 displays time series and differences that might be seriously influenced by the ability or inability of this modeling system to represent vertical mixing very close to strong sources and sinks at the earth's surface. Evaluation of the near-surface vertical profiles created in the model is essential to ensure that these results are not simply artifacts of unrealistic surface layer mixing. The quantitative horizontal gradients (the focus of the following paragraph) are very dependent on this vertical mixing.

RESPONSE:

Please see our response to specific comments 3, 30 and 38 and general comment 4 on the vertical resolution of the model. We generally have something like 7 model vertical levels within the PBL during the afternoon.

COMMENT:

52. Page 25, line 16, delete "can". "Even though a few cities: : :" Why is this relevant?

RESPONSE:

We deleted "can". We just wanted to indicate that the setup of the prior uncertainties may have to be higher for other cities for which the quality of the prior knowledge (of the available bottom up inventories) is not as good. Our posterior uncertainties in the inverted emissions could thus be viewed as being optimistic for the "average city case". This is now rewritten in Sect. 2.5.1.

COMMENT:

53. Page 26, line 2. I do not see how Figure 9a illustrates the point being made in the text. This needs significant work. What happened to figure 8? I see that Figure 9 is a correlation matrix, but no dimensions are described. As presented, this is nearly incomprehensible. It is very good that the authors are trying to explain these critical assumptions, but the presentation is not sufficient to understand the assumptions.

RESPONSE:

We improved the text related to the original Fig. 9 (now Fig. 8 in the new draft) as well as its caption. The dimension in Fig. 8 in the new draft is 834, same as the dimension of the control vector. The corresponding scaling factors are grouped by sectors. Prior sectoral estimate errors were assumed to be independent, as can be read in Fig. 8a in the new draft as zero correlations.

COMMENT:

54. Section 3.5.2 states that the R matrix is assumed to be diagonal, but then notes that the errors are reduced for intersite differences because of the large coherence in space in errors between stations. This is inconsistent. What is the impact of this inconsistency on the validity of the results?

RESPONSE:

The R matrix applies to "downwind-upwind" gradients. Assuming that R is diagonal means that there is no temporal autocorrelation for such gradients between two sites, or that there is no correlation of the errors in the direction orthogonal to the wind. When we claimed that there is a large coherence in space of the errors, we meant that this error was highly correlated when following an air parcel, i.e. along the wind direction. We still acknowledge that some source of model error could be correlated between different gradients corresponding to close locations. However, formulating the spatial correlation in model error is a very challenging. Its detailed investigation would be beyond the scope of this paper. We followed Breon et al. (2015) to set a diagonal **R**. We now clarify and better discuss this in Sect. 2.5.2.

COMMENT:

55. Page 27, lines 8-10. The assumed transport errors are huge, and are a critical set of assumptions in your study.

RESPONSE:

This comment that the assumed transport errors are huge contradicts the previous concerns raised by earlier comments 30 and 38, the corresponding general comment regarding the ability of the model to fit the observation. Those numbers arise from diagnostics by Bréon et al (2015). They account for the difficulty to model the measurements in the Paris area with our inverse modeling configuration.

COMMENT:

The lack of spatial and temporal correlation is also a significant assumption.

RESPONSE:

Bréon et al. 2015 did not account for such spatial and temporal correlations. See also our answer to the previous comment on the spatial correlations of the observation errors.

However, the sensitivity tests (originally presented in the supplementary material and now in Sect. 3.2 of the paper) check the impact of inflating R, which can be viewed as a test of sensitivity of temporal correlations in R. Indeed increasing the standard deviation of the observation errors instead of modeling their autocorrelations is a common technique in atmospheric inversion, e.g. see Chevallier, GRL, Impact of correlated observation errors on inverted CO2 surface fluxes from OCO measurements, 2007. When analyzing the fluxes at the monthly scale, it is critical to know what is the resulting observation error for data averaged at the weekly to daily scale. Whether a given uncertainty on these averages arises from a high STD of the observation error at the hourly scale but low temporal correlations or a lower STD but significant temporal correlations should not play a critical role for monthly mean results. This is now better discussed in Sect. 3.2 and 4.3 .

COMMENT:

I find it very surprising that the sensitivity of your results to these assumptions is insignificant (line 10). I do not have supplementary figure S1. The results of the paper should depend heavily on these assumed errors. A statement that says the dependence is insignificant with no results presented to justify this statement is not defensible.

RESPONSE:

If assuming a 0D inversion problem (with one control variable and one observation) where the observation operator is an identity matrix, the posterior variance will be written BR/(B+R). Depending on the relative weight between B and R, we can see that the result can be weakly impacted by large changes to R (if the weight of B is far larger). The problem is even more complex when accounting for the transport. It is not surprising to find such a low sensitivity to R at the monthly scale, which is a scale at which the projection of the uncertainty in the prior emission into the concentration space is very high. This is now discussed in the Sect. 3.2.

COMMENT:

Results. 56. How is the mixing ratio difference between two sites attributed to a flux correction? This is not clear. This is fundamental and must be defined.

RESPONSE:

The link between flux and gradients is based on the sampling of the gradients from the output of the atmospheric transport model forced by the fluxes, and recovering flux from measured gradients relies on the inversion approach. In this study, we focus on the diagnostic of the uncertainty reduction enabled by the inversion (since the inversion is a statistical approach), and for this we do not need to derive, in practice, flux corrections. This is now better explained in the beginning of Sect. 2.

COMMENT:

57. Page 27, lines 19-22. Airlines, power plants and nighttime emissions from all sectors will have essentially no observational constraints from the methods proposed, save for extreme assumptions about the coherence of the errors. While there is some reason to believe that corrections to daytime emissions from roads or buildings might have some coherence with nocturnal emissions from roads and buildings, there is no reason to believe that airport emissions will be detected by two sites that are located in a region that contains an airport, but which do not encompass the emissions from the airport. It is fundamentally incorrect to say that the proposed network would reduce uncertainty in total emissions.

RESPONSE:

We have defined specific control variables for the airports and the power plants. Therefore, if the system diagnoses uncertainty reduction for these sources, it is because their signature is detectable in the set of observation that is assimilated. It does not rely on extreme assumptions regarding the correlations between uncertainties in airport or power plant emissions and in other sectors since we ignore such correlations in our inverse modeling set up.

Regarding daytime and nighttime emissions, we control them separately. As mentioned by the reviewer, there is some reason to believe that corrections to daytime emissions from roads or buildings might have some coherence with nocturnal emissions from roads and buildings.

Finally, if we reduce strongly the emissions for some specific sectors, mathematically, we reduce uncertainties in the total emissions. Reducing the uncertainty in total emissions does not require reducing uncertainties for all sectors of emissions.

COMMENT:

58. Page 28, line 4. Define "gain." Or do you mean uncertainty reduction?

RESPONSE:

Yes, it is uncertainty reduction in percentage compared to prior uncertainty. However we removed "gain" to avoid unnecessary complication.

COMMENT:

59. Figure 8. The total uncertainty in your inversion approaches an asymptote as the total number of sites increases. Why? What is the limiting factor in your inversion system?

RESPONSE:

We examined in details this slowdown effect in Sect. 3.1 using DFS which quantifies the efficiency of the observations assimilated. As the number of sites increases, it was shown that the information from observations becomes more redundant, in a manner specific to the network type. When using denser networks, the overall observation constraint from the network on inversions increases, but such observation constraint becomes less efficient because the approaching stations raise some redundancy in representing areas of emissions within IDF. Still, the densification of the network up to 70 sites cannot totally bridge lack of sensitivity to fluxes for periods other than daytime, to emissions when the wind conditions do not correspond to the gradient selection criteria, and to sectors dominated by local sources for which assimilating gradients between sites that are distant by less than 5km would be required. This is now better discussed in Sect. 3.1.

COMMENT:

60. Page 29, line 8. DFS/d <10%? When you divide DFS by d, you get a number less than 10%? Please clarify. Do you mean DFS gained per measurement pair added is less than 10%?

RESPONSE:

We mean the DFS gained per measurement (concentration gradient) is less than 10%. Each measurement has a maximal DFS of 1, and a minimal value of 0. The maximal DFS value for the inversion system equals to the number of measurements (d), hence DFS/d accounts for the percentage of observations (related to the signal but not the noise) that are effectively assimilated by inversions. We clarified this in Sect. 3.1.

COMMENT:

61. Page 29, line 10. English, "the Iowa state of USA?"

RESPONSE:

We removed it from the text.

COMMENT:

62. Page 29, lines 11-12. The authors state, "Such small amounts result from the diffuse nature of atmospheric transport and from the uncertainty in atmospheric modeling." The authors, however, have utilized only crude assumptions about atmospheric transport modeling. Their assumptions are not the truth about atmospheric transport errors. This statement appears to be unjustified.

RESPONSE:

Again, see our previous answers to your comments atmospheric transport errors.

COMMENT:

63. Page 29, line 13. "the rate of effectively assimilated gradients decreases." What does this mean? This does not make sense.

RESPONSE:

It is related to the slowdown effect discussed in answer to comments 59 and 60. We commented in the text that this is related to the redundancy of the gradient information.

COMMENT:

64. Page 29. Lines 12-17. I cannot understand this sentence. Is this a comparison to the network studied in the Wu et al (2011) paper?

RESPONSE:

These lines explain how the redundancy (quantified by DFS) of the information from observations for inversions evolves with denser networks. This paragraph was improved for clarity.

COMMENT:

65. Page 29, line 28. "this corresponds to a level 1 quality." What does this mean? What is a "level 1 quality?"

RESPONSE:

In the original draft, we introduced three levels of quality for the convenience of discussions on uncertainty targets in the MRV context. We deleted such discussions on levels of quality, as the concept of uncertainty target has been removed from the new draft.

COMMENT:

66. Page 30, line 3. The entire discussion of network design vs. uncertainty reduction is entirely dependent upon the assumed nature of coherence in the flux errors. Huge spatial coherence is assumed (entire regions have a single correction factor for a single sector of emissions). This assumption is severe and is likely to dominate any results regarding optimal spatial network design. The results, however, do not note any dependence on the assumed uncertainties in the prior flux errors. The results also reportedly show insignificant dependence on very large assumed atmospheric transport errors, but this lack of sensitivity is not shown. Page 32, line 24, admits these limitations, but this is buried into the recesses of the paper. It is dishonest not to present these limitations prominently in the abstract. As noted by the authors, "The results obtained in this study should not be over-interpreted." That sentence belongs in the abstract, and it needs to be explained in the abstract.

RESPONSE:

Regarding the coherence of the error, controlling large regions with a single correction factor does not mean assuming that errors at higher resolution are entirely correlated. This means that uncertainties in the emissions at higher resolution must be accounted for in the computation of the model errors (we call it the aggregation errors, see Kaminski et al. (2001)). The diagnostics of model error by Bréon et al. (2015) include a diagnostic of the aggregation errors since in their framework they apply emission correction factors for the full Ile-de-France region. Here, the control resolution is higher and smaller aggregation errors could be expected.

The list of networks to be tested and the control areas have been built consistently to avoid artefacts from the aggregation. With our configuration, even though a single correction factor for a large area is used, having as much sites as possible around the most prominent sources of the area would give a better control on the average budget. And, indeed, in the end, as would have been expected with a high resolution inverse modeling system, the "best" networks definitely correspond to those providing a strong constraint on most the largest sources within the areas. So the results do not seem to be biased by the coarse scale of the control vector.

The total prior uncertainty is fixed to 20% in this study and follows the setup of Bréon et al. (2015). This number is based on the expert judgement regarding uncertainties in regional inventories such as that of AIRPARIF for the Ile de France area as discussed in Appendix A. This prescription on prior uncertainty was also followed by Staufer et al. (2016) in which year-long real data were successfully assimilated to estimate the budget of emissions from IDF.

Still, some approximations in our setup of the sectorial uncertainties can impact the results of the computation of uncertainty reduction. It could raise concerns regarding the analysis of the absolute values of uncertainty reduction for a given network. However, the comparative analysis of the uncertainty reductions when using different networks but the same inversion setup (i.e. the network design analysis) should bring more robust conclusions.

Regarding the lack of sensitivity to the observation errors, see our previous answers to comments on atmospheric transport error.

We better discussed all these points in Sect. 2.5.1, 2.5.2, 3 and 4.3 and better focus on the network design (OSSE) component of the study. We rewrote the abstract accordingly.

COMMENT:

67. Page 33, line 3. From this point on, the text has no specific connection to the results of this study. This text is extraneous and should be deleted.

RESPONSE:

We agree that these texts are not directly related to the results. These are about the perspectives on how to further improve inversion performances for practical atmospheric inversion of citywide CO_2 emissions. They were considerably shortened and reoriented to discussions on sectoral inversions in the new draft. We kept the discussions concerning inventories and inversions in the end of the paper.

Anonymous Referee #4

COMMENT:

The paper by Wu et al., entitled "Atmospheric inversion for most effective quantification of city CO2 emissions" seeks to answer the question: how much uncertainty reduction in carbon emissions from cities can urban networks observing atmospheric CO2 yield? This is a very timely topic, as the COP21 meeting is underway in Paris as I write this review. The paper is written well, and the *inversion methodology is sound. However, I have one major concern regarding the assumptions underlying cheaper sensors that may render results from the "cheap" network overly optimistic. I would like the authors to address this concern before the paper is published in its final form.*

RESPONSE:

We thank the reviewer for this positive general comment on the paper, and for having helped the paper better focusing on its strongest material and better discussing the assumptions on the low cost sensors.

COMMENT:

MAJOR COMMENT:

The authors appear to be making a lot of assumptions regarding "cheap sensors" that are not substantiated by evidence. In short, I am not aware of cheap sensors that can perform as well as the authors assumed. Can the authors cite specific peer-reviewed references that illustrate the ability for these sensors to perform as well as assumed?

RESPONSE:

This study analyzes the potential improvement on inversion performance when using much denser networks. This raises the need for low-cost medium precision (LCMP) sensor instead of state of the art high-precision instruments. Although LCMP sensors with the precision, systematic error and cost assumed in the initial manuscript are not commercially available yet, present testing with different versions of prototypes within our laboratory (by co-authors of this paper) provide encouraging results for the repeatability and reproducibility of CO_2 measurements, when external influences are properly corrected for. This and previous work have been funded by the climate KIC innovation projects, such as MIRIADE and SMEVOUCHER (http://www.climate-kic.org/projects/miriade/). As the test will be continued to verify the performance for a least one year, the full study on the sensors shall be published in 2016. Still, we have attached a figure illustrating preliminary work for the reviewers. It indicates that LCMP sensors could yield measurements uncertainties of about 1 ppm for hourly values if regularly calibrated (every few days or weekly).

The paper now better focuses on the OSSEs. Accordingly the title was changed to "What would dense atmospheric observation networks bring to atmospheric inversion for the quantification of city CO_2 emissions?" We do not assume the pre-existence of LCMP sensors any more, but discuss now the accuracy of the LCMP sensors and the cost of network infrastructure in terms of requirements in the discussion section and in appendix.

COMMENT:

If there are systematic errors in the cheap sensors there could very well be erroneous emissions that would be solved for by the inversion system. For instance, if the cheap sensors measure systematically higher CO_2 mixing ratios over several hours, the inversion would retrieve higher emissions, naturally. This could require such sensors to be calibrated at significantly higher frequency (e.g., hourly), rather than the multi-day frequency assumed by the authors. Would this be feasible?

RESPONSE:

When analyzing the fluxes at the monthly scale, it is critical to know what is the resulting observation error for data averaged at the weekly to daily scale. Whether a given uncertainty on these averages arises from a high standard deviation (STD) of the observation error at the hourly scale but low temporal correlations or a lower STD but significant temporal correlations would not play a critical role for monthly mean results.

A consideration has led inverse modelers to compensate (assuming it would raise exactly the same results over monthly to seasonal scales) 1-hour to several day temporal autocorrelations of the measurement errors that they could not explicitly set up in their systems by increasing the STD of the measurement errors at the hourly scale (Chevallier, 2007). With that in mind, we consider that our tests of sensitivity to the observation errors, increasing the STD of the hourly scale errors, which are now described in the main text, address the potential impact of systematic errors on 1-month mean results. In these tests, we implicitly require calibrations to prevent systematic errors with temporal autocorrelation of more than a few days/week. Therefore, we now use these sensitivity tests to raise requirements on the accuracy and frequency of the calibration for the sensors rather than derive a fixed measurement errors based on assumption for such an accuracy for a given calibration strategy. We remark that, actually, our preliminary calibration results with LCMP sensors favor achieving such requirement. This is now better discussed in Sect. 4.3.

COMMENT:

Note that the comment about "systematic errors should not have long autocorrelation timescales" on Page. 30706 Lines 9_10 is erroneous. By definition, systematic errors have a non-negligible autocorrelation timescale!

RESPONSE:

Calibrations prevent systematic errors from having long autocorrelation timescales. There is no strict definition of systematic errors. But for such sensors, they characterize the instrument drifts and biases that can be corrected for through regularly applied calibrations, with a residual error that haves some temporal autocorrelations whose timescales should not exceed the calibration periods.

COMMENT:

A type of measurement network that the authors have yet to explore is the combination of deploying both high-precision and cheap sensors in the field, which may be a likely way forward in the near-term, while the cheaper sensors are still undergoing improvement. The high precision sensor(s) would help detect gross errors in the cheap sensors, helping to prevent systematic errors in the retrieved fluxes, as mentioned in the aforementioned scenario.

RESPONSE:

This is a very nice suggestion. We can see that potential of using travelling high-precision instruments (Hammer et al. 2013, http://www.atmos-meas-tech.net/6/1201/2013/amt-6-1201-2013.pdf) within the network to verify the LCMP performance. This would be consistent with what has been done for the atmospheric CO2 European network. In fact, in the original draft, we mentioned such strategy of a mix use of expensive high precision sensors and LCMP sensors in appendix. In this new draft, as we now focus on the OSSEs and address the cost and accuracy of the LCMP sensors in terms of requirements, these instrumental details have been removed from the text and appendix.

COMMENT:

MINOR COMMENTS:

1) Page 30696, Line 12: The "Glaeser and Kahn 2010" reference appears to be missing

RESPONSE:

Thank you for pointing out this. We added this reference.

COMMENT:

2) Page 30701, first paragraph: I found this paragraph difficult to follow, and it took several readings for me to rasp the main ideas. Reword?

RESPONSE:

We do not rely on the uncertainty target any more in the new draft. This paragraph have been greatly shortened and moved it into Appendix A.

COMMENT:

3) Sect. 3.4.3 H3: It would help the reader to explain here the scientific reason for why the CO2 gradients are considered. I realize that the reason can be found in the Breon et al. (2015) paper, but it helps the reader with a sentence like what is mentioned later: "": : :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." I suggest this point to be mentioned earlier, in Sect. 3.4.3

RESPONSE:

Thank you for your suggestion. We followed it. More generally, we improved the general presentation of the method.

COMMENT:

5) Page 30718, Line 21: "not correlated in time neither in space" => "not correlated in time or in space"

RESPONSE:

We rewrote the text.

COMMENT:

6) Page 20725, Line 20: a missing key reference on the use of stable carbon isotope measurements to partition anthropogenic vs biogenic sources is Pataki et al. [2003]: Pataki, D. E., D. R. Bowling, and J. R. Ehleringer (2003), Seasonal cycle of carbon dioxide and its isotopic composition in an urban atmosphere: Anthropogenic and biogenic effects, Journal of Geophysical Research, 108(D23), 4735, doi:4710.1029/2003JD003865-004735, doi:003810.001029/002003JD003865.

RESPONSE:

Thank you for your suggestion. We added this reference.

~~Atmospheric inversion for cost effective~~What would dense atmospheric observation networks bring to the quantification of city CO_2 emissions?

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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 CO_2, ~~and~~but are associated with 71-76% of CO_2 emissions from global final energy use. Although many cities have set voluntary climate plans, their CO_2 emissions are not evaluated by the Monitoring, Reporting and Verification (MRV) procedures that play a key role for market- or policy-based mitigation actions. Here we ~~propose~~analyse the potential of 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 CO_2 concentration measurements from a network of stations within and around cities to estimate city CO_2 emissions. ~~We examine the cost-effectiveness and the performance of such a tool. The instruments presently used to measure CO_2 concentrations at research stations are expensive. However, cheaper sensors are currently developed and should be useable for the monitoring of CO_2 emissions from a megacity in~~

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~~the 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 meters above ground level. The study case for this assessment is the monitoring of the emissions of~~This monitoring tool is configured for the quantification of the total and sectoral CO_2 emissions in 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~~ Its performances are evaluated in terms of ~~uncertainties in the estimates of total and sectoral CO_2 emissions. These uncertainties are compared to a notional ambitious target to diagnose annual total city emissions~~uncertainty reduction based on Observing System Simulation Experiments (OSSEs). They are analyzed as a function of the number of sampling sites (measuring at 25 meters above ground level) and as a function of the network design. The instruments presently used to measure CO_2 concentrations at research stations are expensive (typically ~50 k€ per sensor), which has limited the few current pilot city networks to around ten sites. Larger theoretical networks are studied here to assess the potential benefit of hypothetical operational lower-cost sensors. The setup of our inversion system is based on a number of diagnostics and assumptions from previous city scale inversion experiences with ~~an uncertainty of 5% (2-sigma).~~ real data. We find that, given our assumptions underlying the configuration of the OSSEs, with 10 stations only, ~~which is the typical size of current pilot networks that are deployed in some cities, the~~ the uncertainty for the ~~1-month~~ total city CO_2 ~~emissions~~ emission during one month is significantly reduced by the inversion, by ~42~~% but still corresponds to an annual uncertainty that is two times larger than the target of 5%. By~~%. It can be further reduced by extending the network, e.g. from 10 to 70 stations, ~~the inversion can meet this requirement. As~~which is promising for ~~major sectoral CO_2 emissions~~MRV applications. With 70 stations, the uncertainties in the inverted emissions ~~using 70 stations~~ are reduced significantly over ~~that~~those 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~~and by 31% for ~~dispersed building~~total emissions~~, and 18%~~. These results indicate that such a high number of stations would be likely required for the monitoring of sectoral emissions~~ from road transport and energy production. The inversion performance could be further improved by optimal design of station locations and/or by assimilating additional~~. They demonstrate some high potential

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Mis en forme : Anglais (Royaume-Uni) that atmospheric ~~measurements of species that are co-emitted with CO_2 by fossil fuel combustion processes with a specific signature from each sector, such as carbon monoxide (CO). Atmospheric~~ inversions ~~based on continuous CO_2 measurements from a large number of cheap sensors~~ can ~~thus deliver a valuable quantification tool for~~contribute to the monitoring and/or the verification of city CO_2 emissions (baseline) and CO_2 emission reductions (commitments)~~).~~) and the advantage that could be brought by the current developments of lower-cost medium precision (LCMP) sensors.

1 Introduction

At the 2010 Cancun summit, parties from the United Nations Framework Convention on Climate Change (UNFCCC) agreed to set up a target of keeping global warming under 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~~have made commitments~~/pledges~~ to reduce their emissions under the 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~~. There is however a gap between these commitments and the requirements on the emission reductions (often referred to as "emission gap") for achieving the 2°C global warming target (UNEP, 2013).

Cities occupy ~~only~~ less than 3% of the world's land surface (Liu et al., 2014), but 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 the context of an accelerating urbanization process~~: the~~ (IEA, 2008). The global urban population ~~having~~has grown from 746 million in 1950 to 3.9 billion in 2014 ~~while, by 2050,~~, and it is expected to grow by 2.5 billion people by 2050, with nearly 90% of them living in Asia and Africa (UN, 2014).

~~Unlocking the city~~City mitigation ~~potential may~~options, such as the improvement of public transportation infrastructures using Mass and Rapid Transit (MRT) systems, of building retrofits, and of energy/waste recycling, and the development of district heating/cooling plants

(Sugar and Kennedy, 2013; Erickson and Tempest, 2014), can significantly ~~reduce~~contribute to bridging the ~~gap of~~ emission ~~reductions between national commitment/pledges and scenarios consistent with a 2°C limit. A~~gap. This plausible additional city ~~contributions to global emission mitigation was estimated to~~ contribution could cover ~15% of the total emission reduction required to reach the 2°C global ~~emissions reduction, which~~warming target, and represents up to two-thirds of the level of emission reduction covered by the national commitments~~/pledges~~ (Erickson and Tempest, 2014). Large urban areas have a strong potential to ~~achieve economies of scale in~~decrease per capita CO_2 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 CO_2 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 may also~~ may~~ foster significant local economic development through advances in green technology. For instance, the London low carbon environmental goods and services sector is estimated to have generated more than £25 billion revenue for 2011/12 (BIS, 2013).

To check whether claimed reduction targets are fulfilled, the present-day city emissions ~~will~~ have to be known accurately ~~for present-day conditions~~ to define a baseline upon which reductions are defined, and ~~then~~ these emissions will have to be monitored over time during ~~any~~the 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, organizations, 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 challenging (Wang-Helmreich et al., 2012; UNEP, 2014), and may hinder citywide mitigation implementation in the 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 Tokyo ETS – the most advanced urban ETS scheme – only regulates less than 20% of the ~~city's~~city total emissions (TMG, 2010).

~~As such~~In this context, 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~~better support citywide mitigation actions (World Bank, 2010; Wang-Helmreich et al., 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 city mitigation targets 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~~However, ultimately, all these provisions for citywide mitigation actions and their MRV necessitate the availability of accurate 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 city-scale inventories, and updating them over time, ~~involve~~involves extensive collection of consistent 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 total amount of fossil fuel that has been consumed within the cities. ~~This issue of data availability and quality~~This limitation impedes the practical use of city inventories in climate economy.

~~To improve the quality of~~ An improved emission accounting~~, here we propose using a new type of data —~~ could rely on continuous ~~CO_2 concentration~~ atmospheric measurements ~~in the atmosphere made on a network~~of CO_2 concentrations by networks of stations around and within cities. ~~Accurate measurements~~Indeed, accurate measurement of the atmospheric signals, e.g. the CO_2 concentration gradients, ~~contain~~provides information about the emissions that ~~are~~is independent ~~of~~from the inventories. ~~A~~The statistical method known as atmospheric inversion, which has been used for decades for improving the knowledge of global and continental scale natural CO_2 fluxes (Enting, 2002; Bousquet et al., 2000; Gurney et al., 2002; Peters et al., 2007; Chevallier et al., 2010; Broquet et al., 2013), can be used to exploit ~~this information from actual~~ atmospheric measurements for quantifying CO_2 emissions at the 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 CO_2 measurements to deliver improved emission estimates, i.e. ~~emissions~~estimates with a reduced uncertainty, compared to the prior inventory. An inversion generally uses a 3D model of atmospheric transport to relate emissions ~~with~~to observations. In just a few years, a number of city atmospheric CO_2 measurement networks have been deployed for pilot studies. Examples of cities where such networks have been deployed are Toronto (with ~~5~~3 sites), Paris (with 5 sites), Recife (with 2 sites), Sao-Paulo (with 2 sites), Salt Lake City (~7 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 (AIRPARIF, 2013), an amount equivalent to ~12% of the fossil fuel~~ ~~CO_2~~ ~~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 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 requirements 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~~ ~~CO_2~~ ~~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 sensors 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~~

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~~results using CO_2 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 separately but rather focused on quantifying total CO_2 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 station locations.~~

~~Sections 3 and 4 describe how we use an Observing System Simulation Experiments (OSSE) framework to analyze whether this~~ Bréon et al. (2015), hereafter referred to as B15, used CO_2 measurements from 3 stations in the Paris area and a Bayesian inversion methodology to estimate CO_2 fossil fuel emissions in the Paris metropolitan area (the Île-de-France – IDF – region, which has ~12 million inhabitants) in winter 2010. The most resolved regional bottom-up inventory estimates that this area emitted 11.4 TgC in 2010 (AIRPARIF, 2013), an amount equivalent to ~12% of the CO_2 fossil fuel emissions from the whole France (Boden et al., 2013). B15 did not attempt to estimate sectoral emissions separately due to the very limited size of the measurement network they used. They rather focused on quantifying total CO_2 emissions from the Paris urban area. Staufer et al. (2016) refined the configuration of the inversion system of B15 and applied it for a one-year inversion of the Paris emissions.

In this paper, we assess the performance of atmospheric inversion for the monitoring of total and sectoral fossil fuel emissions in the Paris metropolitan area when using denser networks, based on Observing System Simulation Experiments (OSSEs). The objective is to analyze the sensitivity of this performance to the size and design (i.e. the location of the stations) of such networks, and thus to derive requirements on the configuration of the atmospheric inversion to provide different levels of accuracy on the estimates of the total and sectoral city emissions. We base our inversion methodology and the configuration of the OSSEs – notably the assimilation of concentration gradients and the practical configuration of the inversion parameters – on the system, expertise and diagnostics documented in B15 and Staufer et al. (2016). The use of much larger measurement networks still necessitates some assumptions regarding the inversion framework and the characterization of the sources of errors.

The CO_2 measurement instruments presently used for atmospheric inversion in the scientific community are rather expensive (typically ~50 k€ per sensor) which explains the limited size of the existing city networks. To bridge this data gap, national and European innovation projects (e.g. http://www.climate-kic-centre-hessen.org/miriade.html, MIRIADE-ANR: ANR-11-ECOT-0004) have been proposed to test lower cost (typically ~1 k€ per unit) sensors (called hereafter low-cost medium precision – LCMP – sensors) and to develop a corresponding calibration strategy which would enable the measurement of CO_2 concentrations with a precision and an accuracy that would be acceptable for city scale inversions (but maybe not for other scales, for which more expensive instruments may still be needed for the foreseeable future). This motivates our tests, in this study, of networks with up to 70 sensors.

The principle of the inversion ~~framework can achieve the uncertainty targets, principally with respect to the number of measurement sensors and their spatial distribution. The~~performance assessment, the inversion methodology and the OSSE setup are described in Sect. ~~3~~2. The inversion results are ~~presented~~analyzed in Sect. ~~4, and finally some discussions and conclusions are drawn in~~ 3. Based on these results, Sect. ~~5.~~

~~2 Notional~~4 discusses requirements on the configuration of the observation network for ~~the inversion framework~~

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~~2.1 Notional~~achieving different targets ~~for uncertainties~~of accuracy in ~~inversion~~the 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, 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 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 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~~ of ~~national inventories is country-specific, but for the seven Annex I countries surveyed by Pacala et al. (2010), the uncertainty in CO_2 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 method. Consequently, here we define a 5% 2-sigma annual notional target for the level of uncertainties in annual total fossil fuel CO_2 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.~~

~~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 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~~ and 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 anti-correlated 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 sectoral 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.~~ from the Paris area. Conclusions are drawn in Sect. 4.

~~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 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 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 CO_2 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 CO_2 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~~

~~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 inventories 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€ per year (CITEPA, personal communications). This cost covers the compilation of the fossil fuel CO_2 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 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 CO_2 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 governmental 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€ per year.~~

~~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 sensor 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 M€ per year, 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 uncertainty reduction when using hypothetical measuring networks of 10 to 70 sensors.~~

~~3~~2 Methodology

The principle and the configuration of our atmospheric inversion system are close to those of B15. The general principle is to estimate the emission budgets for different sectors of anthropogenic activity, areas and time windows, which all together constitute the total emissions of IDF for the month of January 2011. It corrects a prior estimate of these emission budgets given by an inventory to better fit observed concentration gradients between pairs of sites along the wind direction, in and around the Paris area, since such gradients characterize the enhancement of atmospheric CO_2 due to the Paris emissions. An atmospheric transport model is used to simulate the gradients corresponding to a given estimate of the emissions.

The atmospheric inversion theory relies on a statistical framework which accounts for the uncertainties in the prior estimate of the emissions, in the transport model and in the measurements, and which diagnoses the uncertainty in the estimate of the inverted ("posterior") emissions as a function of the observation location and time, of the atmospheric transport, and of these prior, model and measurement uncertainties. This diagnostic is used in this study as a natural indicator of the inversion performance. Since it depends neither on the actual value of the observations that are assimilated, nor on the actual value of the prior estimate of the emissions, nor on the actual value of the corrections applied by the inversion on the prior emission estimates, it allows conducting OSSEs without generating synthetic gradient observations for the hypothetical networks that are tested and without conducting practical emission estimates.

~~3.1~~2.1 Theoretical framework of the Bayesian inversion

By Bayesian inversion, the information from an observation vector **y** of CO_2 concentration gradients is combined with a prior ~~(background)~~ estimate $\mathbf{x}^b$ ~~of a control parameter~~of the CO_2 emissions budget for various sectors, areas and time windows (i.e. of the vector ~~**x** about CO_2 emissions~~ of parameters controlled by the inversion **x**, or "control vector" hereafter) to provide an updated estimate of the control vector $\mathbf{x}^a$ (Enting, 2002):

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

where **H** ~~the~~is a linear matrix operator linking **y** with **x** based on the modeling of the spatial and temporal distribution of the emissions ~~and~~ at high resolution and the modeling of the atmospheric transport~~.~~ at high resolution. The ~~errors~~uncertainties in **y, H** and $\mathbf{x}^b$ are assumed to have statistical distributions that are Gaussian, unbiased and independent of ~~one another. We denote by **R** and **B** the covariance matrices of the observation and background errors respectively.~~each other. The ~~observation error is a~~linking of **y** with **x** in general suffers from some deficiencies in the measuring instruments and the atmospheric modeling. The sum of the 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~~ is called the observation error whose covariance matrix is denoted **R**. We denote **B** the error covariance matrix for the ~~month of January 2011. These emissions are defined on a spatial horizontal grid same as that of the atmospheric transport model (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 CO_2 given these spatial and temporal distributions of the emissions, and a sampling of the resulting simulated CO_2 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~~prior estimate ~~$\mathbf{x}^a$ with reduced~~of the control parameters. The uncertainty ~~(i.e. with~~in the estimate $\mathbf{x}^a$ given by (Eq. (1)) is Gaussian and unbiased and its covariance matrix (which is "smaller" ~~error covariance matrix compared to~~than **B**~~):~~) is:

$$\mathbf{A} = (\mathbf{B}^{-1} + \mathbf{H}^T\mathbf{R}^{-1}\mathbf{H})^{-1}. \tag{2}$$

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~~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~~The comparison between this posterior error covariance matrix and the prior one, starting from realistic prior and observation error statistics~~. This assessment is done~~ , allows us to quantify the inversion performance. We pay a specific attention to the diagnostic of the relative difference between the posterior and the prior uncertainties for the ~~estimation~~total and sectoral budgets of the emissions during the month of January 2011.

In the following sections, we detail each component of ~~the~~our inversion system ~~for this computation~~ underlying Eq. (2) (see Fig. 1).

~~3.2~~2.2 Control vector

~~Formally, even though this is equivalent in principle, **x**~~ Our control vector **x** does not directly contain emission budgets, but rather scaling factors that are to be applied to the emission budgets which are included in the observation operator **H**. For the sake of simplicity, Fig. 1 presents the inversion framework as if the emission budgets themselves were controlled, which is quite equivalent to the strict implementation of the inversion system. Each scaling factor in ~~the control vector~~ **x** corresponds to the emission 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 CO_2-emitting activity. The corresponding ensemble of areas, temporal windows and sectors ~~form~~ partitions ~~of~~ the IDF domain, ~~of~~ the month of January 2011 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~~parameter.

While it is desirable to solve for the emissions at high spatial, temporal and sectoral resolution, computational constraints, such as the inversion of **B** and $(\mathbf{B}^{-1} + \mathbf{H}^{T}\mathbf{R}^{-1}\mathbf{H})$ in Eq.

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(2) and the computation of **H** which requires in principle as many transport simulations as control parameters, limit the size of the control vector **x**. 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~~2.4.1) 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~~remainder 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~~remainder, respectively.

In order to save computations, for ~~most of these~~the less important sectors (isolated energy and production point sources, agriculture, airline and ~~rest~~remainder), 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~~can 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 budgets of emissions (agriculture, airline, and ~~rest~~remainder), 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 12h and control separately the daytime (7–19h) and night-time (19–7h) emissions for each day, in order to account for the large diurnal variations in the emissions.

Atmospheric CO_2 observations are sensitive to vegetation-atmosphere CO_2 fluxes in addition to fossil fuel CO_2 emissions. For cities surrounded by vegetation or containing green areas, the impact of vegetation-atmosphere CO_2 fluxes on city carbon balance can be significant. For instance, Nordbo et al. (2012) ~~estimated~~extrapolated from their measurements, that ~~a city is carbon-neutral when its~~an 80% green-area fraction ~~is about 80%. However the impact of natural vegetation on our results for the highly urbanized IDF region is found limited (see the~~

~~supplementary material).~~would approximately make cities carbon-neutral. In our ~~inversion~~inversions, we account for the influence of the natural vegetation and soil CO_2 fluxes (or Net Ecosystem Exchange, NEE) by including, in the control vector, the scaling factors for the budgets of NEE in the full modeling domain (see Sect. ~~3~~2.4) and for the four different 6-hour windows of the day (i.e. 0-6h, 6-12h, 12-18h, and 18-24h local time) 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~~2.3 Observations

We use an inversion system similar to that of B15, in which observations are taken to be CO_2 atmospheric concentration gradients between ~~city upwind and downwind stations.~~upwind and downwind stations (see Sect. 2.4.3 for details). The use of concentration gradients rather than concentrations well cancels out the pervasive large scale influence from remote fluxes outside of the city domain and informs about the local emissions between upwind and downwind stations. B15 also suggested assimilating only afternoon gradients when the wind speed 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 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 center, and appear suitable to the assimilation of city ~~upwind-~~downwind-upwind 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 whole urban area of IDF. The U networks ~~are defined by a positioning of~~position the stations on a regular grid. The R networks aim at balancing the ~~positioning~~position 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~~of either 10, 30, 50, or 70 stations. For a given network, the station locations are chosen as a sub-set 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~~For a given number of stations n, 10 networks are selected for the inversion out of an ensemble of 100 networks that are generated by randomly selecting~~ randomly~~ n stations from the set of 90 candidate locations. The selection of such sets of 10 networks is based on ad hoc verifications that the station locations should be evenly distributed in the urban, suburban and rural areas~~. Fig. 5 shows an example of an R network of 10 stations resulting from the above selection procedure.~~ as would have been done for the design of real networks. This selection limits the range of the random generation of networks to a set of sensible networks for which a further discrimination should rely on the type of network performance assessment that is conducted in this study. Fig. 4 shows an example of an R network of 10 stations resulting from the above selection procedure. The design of current real city networks is much influenced by administrative and technical issues (e.g. agreements with potential hosts of the site and ability to fix inlets at desired height). Here we simplify such considerations and assume that the measurements are taken at 25 meters above ground level (magl) at all stations as discussed in more details in Section 2.4.3.

The strategy to properly combine stations from the different selected networks for city ~~upwind-~~downwind-upwind gradient computation (and thus for the precise definition of the 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 meters above the ground level 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.~~2.4.3 as part of the description of the observation operator.

~~3.4~~2.4 Observation operator

~~In this section, we detail the three operators that jointly construct the~~ The observation operator ~~($\mathbf{H} = \mathbf{H}_1\mathbf{H}_2\mathbf{H}_3$, Fig. 1). $\mathbf{H}_1$ provides~~$\mathbf{H}$ that links the scaling of surface emission budgets to CO_2 concentration gradients in the atmosphere can be decomposed into a chain of three operators ($\mathbf{H} = \mathbf{H}_1\mathbf{H}_2\mathbf{H}_3$; Fig. 1): the spatial and temporal distribution of the ~~anthropogenic emissions or of the natural~~CO_2 fluxes within ~~each~~a corresponding control tile~~. This distribution is given at the resolution of the~~ $\mathbf{H}_1$, 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~~ of CO_2 given these spatial and temporal distributions of the fluxes $\mathbf{H}_2$, and a sampling of the resulting simulated CO_2 to be compared with the observations $\mathbf{H}_3$.

$\mathbf{H}_1$ maps the scaling factors in 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 CO_2~~ to the CO_2 fluxes on the transport modeling grid ~~(see Sect. 3.4.2). $\mathbf{H}_2$~~. It uses an emission inventory and an ecosystem model simulation to prescribe the small-scale spatiotemporal distribution of the gridded CO_2 fluxes. Applying $\mathbf{H}_1$ to a scaling factor uniformly rescales the prescribed CO_2 fluxes within each control tile, and thus adjusts the emission budget of that control tile. $\mathbf{H}_2$ is the mesoscale atmospheric transport model that maps ~~from~~ the gridded fluxes ~~from $\mathbf{H}_1$~~generated by $\mathbf{H}_1$ to simulations of the CO_2 concentration fields on the transport model grid (at 2 to 10 km horizontal resolution and 1h temporal resolution, ~~in~~for a Northern France area encompassing the IDF region~~.~~). $\mathbf{H}_3$ is a linear algorithm that computes Paris ~~upwind~~ downwind-upwind CO_2 gradients between measurement stations, extracting the ~~simulated observation vector~~observations from the CO_2 field ~~from~~simulated by $\mathbf{H}_2$.

~~3.4.1~~2.4.1 $\mathbf{H}_1$

~~For the distribution of NEE at the spatiotemporal resolution of the atmospheric transport model, we interpolate the~~The NEE simulations from C-TESSEL – 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~~).~~) – is interpolated to derive the distribution of NEE at the spatiotemporal resolution of the atmospheric transport model.

~~For the distribution of sectoral fossil fuel CO_2 emissions, we~~We rely on an inventory of the French emissions from the Institute of Energy Economics and the Rational Use of Energy (IER) at the University of Stuttgart to derive the distribution of sectoral fossil fuel CO_2 emissions in IDF at a high spatial resolution of 1 km × 1 km (Latoska, 2009).~~ This IER inventory accounts for direct CO_2 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 apply monthly, weekly and hourly temporal profiles~~, which are~~ also ~~from~~produced by 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.~~

There are 51 sectors indexed by NFR code in the IER inventory. We compute the emission budgets for all these 51 NFR sectors~~ of the IER inventory~~, and re-aggregate them into the seven groups of sectors defined in Sect. ~~3~~2.2 (see Table A1). The emission budget of the three major sectors (energy, road, and building) represents ~84.4% of total fossil fuel CO_2 emissions over IDF according to the IER inventory. Fig.~~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 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 Grandpuits refinery~~, in these zones~~ (see Fig. 2 and Fig. ~~4c~~5c). 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~~remainder sectors (1.2%) are relatively small compared to that of the first three sectors. Fig.~~ 4~~ 5 shows the spatial distributions of the emissions from the seven sectors derived 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~~but in principle, this has very limited impact on the theoretical computation in our OSSE framework of inversion.

~~3.4.2~~2.4.2 $\mathbf{H_2}$

Following B15, we use the mesoscale atmospheric chemistry-transport model CHIMERE (Menut et al., 2013) to simulate the signature of CO_2 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, which is the same as that in B15, covers an area of about 500 x 500 km^2 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 supplementary Fig. S1).~~1 in B15). As such~~ In total, there are 118 x 118 cells in the model horizontal grid. Vertically there are 19 sigma-pressure (terrain-following) layers from the surface up to 500 hPa. The top level of the first layer is at about 25 magl, and there are at least 6 layers below 250 magl. The meteorological fields driving the CHIMERE ~~simulation~~simulations come from the ECMWF ~~analysis~~analyses at 15 km resolution. The CHIMERE modeling system prepares meteorological data on its model grid by diagnosing sub-grid processes, such as turbulent mixing and convection (Menut et al., 2013). We use Global Land Cover Facility (GLCF) land use data at 1 km x 1 km resolution for such diagnosis. Simple urban parameterization is adopted to correct wind speed in the surface layer taking into account the increased roughness in the urban area (Menut et al., 2013), since B15 found no significant differences in the simulation of CO_2 mole fractions when advanced urban scheme is used.

The exchange of CO_2 between the CHIMERE 3D 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~~We need to 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~~) when simulating concentrations, which is not the case when applying the analytical computation of the uncertainties in the inverted emissions budgets through Eq. (2). When simulating CO_2 concentration fields for the preliminary illustration of the CO_2 variations in IDF in Sect. 2.4.3, the boundary conditions are derived from the interpolation of ~~a~~the global inversion product of Chevallier et al. (2010). 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 CO_2 boundary conditions. The CO_2 initial condition is built from the interpolation of CO_2 given by that global inversion product. ~~Note that we~~We do not control these CO_2 boundary and initial concentrations in our inversion system~~. Therefore, in principle, they should be associated with an affine term~~ which explains why these components do not appear in the ~~observation operator that is separated from the linear operator **H**.~~computation of the posterior uncertainties given by Eq. (2). However, ~~mathematically, they can be ignored~~as detailed in Sect. 2.5.2, uncertainties in ~~the OSSE framework (we only need to account for potential errors from~~ these conditions still impact the accuracy of the inversion and have to be accounted for in the ~~configuration of the observation error), which explains why we simplify~~model uncertainty. Anthropogenic emissions within the ~~notations of the observation operator. The initial and boundary conditions will thus only be used for illustrating the CO_2 variations in~~ modeling domain but outside IDF ~~based on model simulations~~are not estimated in our inversions.

~~3.4.3~~2.4.3 $\mathbf{H_3}$

For a given network, the operator $\mathbf{H_3}$ consists in a combination of three operations: the linear interpolation of concentrations from the transport model grid to the actual point at which CO_2 measurements are collected, the selection of afternoon CO_2 concentration data (12-17h) at each station (upwind or downwind) when the wind speed from the transport model is higher than 3 m s^{-1} at the downwind station, and the CO_2 city ~~upwind-~~downwind-upwind gradient computation. While B15 consider gradients between pairs 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~~and not ~~limited to~~necessarily of the citywide emissions as in B15. The assimilation of all gradients should help better constrain the spatial and sectoral distribution of the emissions.

In this synthetic study, we assume that the measurements are taken continuously at the height of 25 magl at all stations during the month of January 2011. This height can correspond to the setup of these stations at the top of existing buildings for which 25 magl is a common height in the Paris area. The deployment of large networks with up to 70 stations at this height would thus not have to rely on new infrastructures as if the targeted sampling height was

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significantly higher (which would be a critical barrier for the practical implementation of the network). Local sources and transport that are poorly represented with a 2 km resolution model may have large impact on the concentration measurements at such a height. However, all real data assimilated by B15 were sampled at peri-urban stations at less than 25 magl. By selecting the data during the afternoon only and for high wind speeds, B15 limited such a local impact. Furthermore, their diagnostic of the model error which is used to set-up the OSSEs in this study (see Section 2.5.2) implicitly accounted for this impact. Still, assimilating 25 magl measurement in the core of the urban area (which corresponds to a significant number of the hypothetical sites investigated in this study) is likely challenging due to the high density of strong sources and to the complexity of the urban canopy, and had not been attempted by B15 even though they derived typical estimates of the model error for urban measurements (see Sect. 2.5.2). This will be further discussed in Sect. 4.

The CO_2 gradient computation ~~requires~~demands 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~~given by the ECMWF meteorological ~~product).~~data, also used to drive the CHIMERE model). We impose that the ~~direction~~ angle between the direction from the upwind ~~and~~to the downwind stations ~~should be comprised between ±11.25° of the~~ and the wind direction at the downwind station ~~(defining~~is comprised between ±11.25°. The choice of such a ~~22.5° angle~~range of angles for the gradient selection is a trade-off between the need to select enough data to constrain the inversion, and the need for ensuring that we do not depart too much from the objective of assimilating “downwind-upwind” gradients. It is derived from the study of Staufer et al. (2016) who analyzed the impact of such a choice on the results of the inversion when using real data. Fig. ~~). Figure 5 shows~~4 illustrates the principle of the gradient selection by showing the wind direction for a downwind observation and the area that covers its corresponding upwind ~~candidate~~ stations. ~~Then we~~

We further impose that the distance between the upwind and downwind stations should be larger than 5 km (to avoid assimilating gradients that are mostly representative of local sources) and as close as possible to 10 km. This 10 km 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 gradient computation in the reference inversion ignores the time lag needed to advect an air parcel from upwind to downwind stations and ~~compute gradients~~it is based on the difference between simultaneous hourly mean observations. This explains why the 10 km distance is seen as a good trade-off between the need for being representative of large scale emissions and the need to limit the impact of ignoring the time required for transporting air masses from an upwind to a downwind site. We discard the downwind observations for which no upwind station can be found based on our selection rules. About 7-16% of total observations are retained for gradient computation with this data selection procedure, depending on the size and type of the networks.

Fig.~~Figure~~ 6a shows statistics on the afternoon hourly wind conditions at an example station ~~called~~ EVE26 during January 2011, and Fig. 6b shows ~~the wind directions corresponding~~restriction of this statistics to the ~~selection of upwind stations~~ wind conditions at EVE26 when EVE26 is selected as a downwind~~.~~ site for gradient computation. Winds ~~over~~at 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), the corresponding upwind stations for gradient computation are mostly selected in the southwest direction (~~Figures~~Fig. 6b~~ and 6c~~-c).

~~Eight~~As the observation operator is linear, one can evaluate the contribution of a flux component to the CO_2 mixing ratio at the measurement stations by applying the observation operator to that specific flux component, cancelling all other flux components. We thus perform 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~~2.4.1 ~~are used~~ to ~~check~~evaluate the ~~contributions~~contribution of ~~each~~these different types of flux ~~component~~ to the CO_2 ~~mixing ratio~~ variations during January 2011 at ~~network stations~~the hypothetical station locations considered in this study. This corresponds to applying **H** to control vectors with scaling factors corresponding to the NEE or to a specific sector of emission set to 1 and others to 0~~,~~ and ignoring CO_2 boundary conditions. ~~Figure~~Fig. 7 plots the ~~resulting~~ time series of CO_2 mole fractions corresponding to the different types of flux at 10 stations of an R network (which are indicated by red triangles in Fig. ~~5~~4) 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 planetary boundary layer, which generates peaks in the CO_2 time series ~~(~~.~~Fig. 7).~~ However, as explained in Sect. ~~3~~2.3, the representation of the ~~nighttime~~night-time 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 major sectors (building, road and energy ~~sectors~~), and the meteorology within the planetary boundary layer.

There are strong positive CO_2 concentration gradients between the urban-urban and urban-rural pairs of stations when analyzing the signature of the ~~main~~major sectors of anthropogenic emissions (Fig. 7). ~~Figure~~Fig. 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~~ 2.4.1 (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~~ 2.4.2). 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 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 values. 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 CO_2 gradients explains a large portion of these negative gradients. 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~~2.5 Accounting for uncertainties

~~3.5.1~~2.5.1 Prior uncertainties

Formal statistical methods, such as Monte Carlo approaches, ~~for estimating~~can be used to estimate errors due to uncertain activity data and emission factors ~~are used to infer~~and thus the overall 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 the 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~~Following B15, we set a prior 1-sigma uncertainty of about 20% in monthly total emissions ~~of about 20%, which corresponds to a 23% 2-sigma annual uncertainty, assuming a temporal correlation~~from the Paris metropolitan area. In practice, few cities benefit from such high resolution local inventories (Appendix A), and the setup of ~~approximately 2 months between monthly~~the prior uncertainties ~~(see Sect. 2.1).~~for other cities may have to be higher since the quality of the prior knowledge from their available inventories is not as good.

We assume that there is no correlation between the prior uncertainties in the emission budgets (and thus in their scaling factors) for different sectors of emissions (see Fig. ~~9a~~8a). For a given sector, the correlations of the uncertainties in scaling factors for different areas and time windows are given by the Kronecker product between spatial correlations (if there are different control areas for this sector) and temporal correlations. 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~~ 8a). Uncertainties in individual scaling factors for a given control tile are derived based on ~~these correlation settings as well as~~this configuration of the correlations and on the two ~~rules~~following assumptions: (1) the aggregation of uncertainties in all the individual scaling factors leads to an overall 20% 1-sigma uncertainty in total ~~1-month~~ emissions for January 2011, and (2) the 1-sigma uncertainties for the ~~seven sectors~~budget for January 2011 of ~~1-~~

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~~month~~the seven sectors of emissions are approximately equal to one another~~ as ~~. The latter assumption is supported by a recent census, which was conducted by National Physical Laboratory (NPL) based on a group of 26 city inventories reported to the carbonn Climate Registry (cCR) suggesting that the data collected for different sectors can actually have a similar level of quality (report available from www.carbonn.org). The sensitivity of the inversion results to the configuration of **B** and thus the robustness of the inversion are discussed in Sect. ~~2.1~~ 4. By construction, the resulting 1-sigma uncertainties in the budgets for the seven sectors of emissions are larger than that in the total emission estimate~~, each~~. They are approximately equal to 36% (Fig. ~~8). We~~9). As B15, we set~~, similar to B15,~~ a prior uncertainty in the NEE scaling factors of about 70%.

Controlling large control tiles with a single scaling factor does not mean that the uncertainties in the emissions at higher resolution are assumed to be entirely correlated within a control tile. The uncertainties in the distribution of the emissions at higher resolution given by the observation operator must actually be accounted for in the computation of the observation error as indicated in the following section. This part of observation error is generally called the aggregation error.

~~3.5.2~~2.5.2 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 combination of the aggregation errors~~Observation uncertainties arise from both the measurement errors and the model errors associated with the observation operator (including the transport model errors). The precision of the instruments presently used (typically cavity ring down spectrometers) for the climate studies can have a high precision that is better than 0.1 ppm (1-sigma) on hourly mean data. When properly calibrated, typically every 2 weeks to 2 months, these high precision instruments do not bear any significant drifts or biases, and the systematic errors borne by their hourly measurements are smaller than 0.13 ppm. This level of measurement error is negligible compared to the current transport model errors that are detailed later in this section. Even though the deployment of dense networks with up to 70 sites would rely on LCMP sensors and on a different calibration strategy, we conduct the main inversion experiments assuming that they would measure CO_2 with a precision and accuracy still negligible compared to the model error. However, some sensitivity tests will be performed to assess the impact of much larger measurement errors (Sect. 3.2).

The model error, which applies to “downwind-upwind” CO_2 gradients in this study, is mainly a combination of the aggregation error due to uncertainties in the spatial and temporal distribution of the fluxes within a control tile that is not resolved by the inversion, of the representativeness error (the difference in terms of spatial representativeness between the measurements and the CO_2 simulated with a 2 km to 10 km horizontal resolution model), ~~and~~of the atmospheric transport modeling error~~.~~, and of the errors in the model CO_2 initial and boundary conditions.

Following B15, we assume that the observation error covariance matrix **R** is diagonal, which means that the model errors for the CO_2 ~~gradient observations~~ gradients are not correlated in time ~~neither~~or in space. ~~The **R** matrix is thus diagonal~~ This implies that there is no correlation of the model errors in ~~our inversion configuration.~~the direction orthogonal to the wind (see later in this paragraph for a discussion about the direction parallel to the wind). Based on statistics on the model-measurement misfits, B15 diagnosed ~~that the model error should be on~~ the total model error when simulating CO_2 hourly concentrations at individual urban and rural sites and for hourly city downwind-upwind gradients between rural stations. They found that this error is of the order of 5 ppm and 10 ppm for ~~individual~~ hourly CO_2 data at rural and urban stations respectively, and of 3 ppm for hourly ~~city upwind-downwind gradients between rural stations. They~~gradients between rural stations. The high model error at individual stations characterizes the difficulties of atmospheric models to represent the CO_2 transport within and in the vicinity of urban areas, even when selecting data during the afternoon and for high wind speed only. B15 explain the smaller model errors for gradients than for individual CO_2 data by the high spatial correlations between model errors at ~~different stations.~~upwind and downwind sites. These spatial correlations are due to the large spatial coherence of the errors from the model boundary conditions ~~and from~~along the ~~estimate of the fluxes outside the IDF area~~wind direction, whose cancelling is the main aim of the gradient computation. ~~Even though~~In principle, this is not incompatible with the assumption mentioned above that there is no correlation of model errors in the direction orthogonal to the wind since it bases on the idea that the correlation follows the advection of air parcels and of the atmospheric signature of remote sources and sinks. Still, the diffusion of the signature of remote sources and sinks through their ~~system potentially bears higher~~atmospheric transport could correlate the model error between different gradients corresponding to close locations. Characterizing such spatial correlations is very challenging and falls beyond the scope of this paper.

The diagnostics of model error by B15 account for the transport and representativeness errors and of errors in the CO_2 initial and boundary conditions of the same transport configuration as that used in our study. It also accounts for aggregation errors since ~~using~~their inverse modeling framework solves for emissions at a coarser ~~control vector, this~~ resolution than in this study (they apply scaling factors for the 6-hour mean budget of the emissions in IDF). Smaller aggregation errors should ~~not be highly significant and~~ apply in our configuration but we ~~derive the estimate~~conservatively use their diagnostic to assign the model errors in our OSSEs. This setup of the model errors ~~for~~in our study is also based on ~~their diagnostics and on~~ a simple derivation of the spatial correlations of the model error for individual measurements between ~~the~~upwind and downwind stations ~~that can lead to~~ based on 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 insignificant changes in inversion results (see Supplementary Fig. S1).~~

~~4~~3 Results

3.1 Results with the reference inversion configuration

We conduct a series of inversions of sectoral and total emissions during the month of January 2011 using E~~,~~-, R- and U-type 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~~9). The uncertainties discussed here are relative uncertainties, which are defined as the uncertainty budgets in percentage ~~to~~of the budgets of the corresponding ~~prior~~ emissions obtained from the IER inventory~~.~~ (and included in the observation operator).

~~We find that, with~~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 reduces 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 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 uncertainties in building, road and energy emission estimates ~~for the month of January 2011~~ are reduced on average from ~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~~uncertainty reduction respectively over the prior uncertainty~~), these levels of posterior uncertainties 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~~remainder sectors. However, the contribution of these four sectors of emissions to the total budget is rather small, ~~which~~and represents only ~16% of the total emissions in IDF according to the IER inventory (Fig.~~ 8e). Note that, in~~ 9e).

In order to limit the influence of specific station locations~~,~~, and to weight the sensitivity to the network design (and thus the need for network design studies), 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~~ follow their respective network type (see Sect. ~~3~~2.3 on how we ~~generated~~generate these random networks). The variation (error bars in Fig. ~~8) in~~9) of the inversion performance due to changes in the ~~influence of~~ station locations is in general small, compared to the variations ~~influenced by~~ due to the changes of the network type and size (see Fig. ~~8). This~~9). The influence of the station ~~locations~~location is large for the agriculture sector ~~is significant~~, but ~~the~~emission budget ~~of agriculture emissions~~for this sector is ~~very~~ small.

The ~~gain in~~ uncertainty reduction ~~by inversions~~ increases with larger networks. However, this increase generally slows down and is rather weak once the networks have more than 30 stations (Fig. ~~8a~~9a-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~~9a), the increase in uncertainty reduction for building emissions when using ~~30-station or~~ 70-station compared to 30-station U networks is still significant. To further illustrate this ~~saturation~~slowdown effect, we assess the number of Degrees of Freedom for ~~the~~ Signal (DFS~~)~~

~~of the~~ ; Rodgers, 2000) for inversions using different networks (Fig. 10a). The DFS ~~describes how many degrees of freedoms~~characterizes the number of independent pieces of information brought by the observations and therefore the relative weight, of the signal from the observations against the noise from the observations in the analysis. If the uncertainty in the measurement is very high or if the measurements ~~are related to the signal. The simplest illustrating case is that a measurement y estimates an emission x with an error ϵ: $y = x + \epsilon$, where the prior and measurement errors are independent of each other with variances being v^b and v^ϵ respectively. The measurement y~~ bring redundant information, the measurements will provide ~~one degree of freedom about x if there is no measurement error ($v^\epsilon = 0$) or if there is no prior information ($v^b = \infty$).~~a small DFS. In ~~the case of highly uncertain measurements ($v^\epsilon = \infty$), the measurement y will provide zero DFS, or one degree of freedom for the noise. The~~practice, the overall DFS ~~for this simplest case is $v^b/(v^b + v^\epsilon)$, and for general cases of BLUE analysis (Eq. (1)) the DFS equals to the~~ is the trace of ~~the~~ matrix $(\mathbf{B}-\mathbf{A})\,\mathbf{B}^{-1}$ ~~(Rodgers, 2000). Inversion systems with larger DFS values assimilate~~and has a value between zero and the number of observations ~~more effectively.~~ d (Wu et al., 2011). For our Paris case study, we find that the ~~amount of information extracted from the~~ DFS per concentration gradient observation (i.e. the ratio DFS/d) is less than 10%, that is, only a small percentage of observations are effectively 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)).~~and correspond to the signal but not the noise. Such small ~~amounts result~~DFS results from the diffuse nature of atmospheric transport (which weakens the atmospheric signature of the emissions from specific sources and spreads it throughout the different concentration gradients) and from the uncertainty in atmospheric modeling~~. When using denser large networks, the rate of effectively assimilated gradients decreases. In this case,~~ (which weakens the constraint given to observations during the inversion analysis). When using denser networks, the DFS per observation decreases, and the information brought by the different gradient observations on the budgets of sectoral or total emissions over the full IDF area has more redundancy. This is due to the decrease of the distances between the upwind and downwind stations~~–~~, and between the different upwind (or downwind) stations that are 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~~.

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Despite such a densification of the network, many isolated and local sources, which dominate some sectors of emissions, are yet difficult to catch, in particular with our 5 km threshold on downwind-upwind site distance (see Sect. 2.4.3). Additionally, the selection of daytime observations for high wind speed dramatically reduces the observational constraint on the emissions at other periods of time (see Sect. 2.2 for the temporal discretization of the control vector), which, altogether have a large weight on the total emission budget. Therefore, the slowdown 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. Consequently, the average DFS decreases as the network size increases, and the gains in uncertainty reduction tend to saturate with~~ uncertainty reduction when using larger networks ~~(most evident for the E network).~~ is also explained by their convergence to a value which reflects this lack of constraint.

The 1-sigma posterior uncertainties obtained with 70-station ~~network~~networks of type either E, R or U ~~type~~ are on average 32%, 33%, 18% and ~~18~~31% smaller than those obtained with 10 stations for building, road, ~~and~~ energy ~~emissions~~and total emission estimates respectively (Fig. ~~8a~~9a-c). ~~When compared~~Compared to the prior uncertainties, inversions with 70-station networks achieve an uncertainty reduction of ~~56~~60% on average ~~and a 16~~for the total emissions which leads to an 8% 1-sigma posterior uncertainty ~~for the building emission estimates. This corresponds to a level 1 quality.~~. In contrast, the 1-sigma posterior uncertainties in building, road and energy ~~emission estimates~~emissions are 16%, 18% and 20% respectively~~.~~, with uncertainty reductions by 56%, 48% and 43% respectively compared to the corresponding sectoral prior uncertainties. Large networks are more promising for the estimation of dispersed surface emissions such as ~~that~~those from the building sector.

~~An important finding of our study is that different~~Different types of networks show distinct ability for monitoring emissions, which is usually sector-specific. For instance, using a U- instead of a E-type 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)~~9% 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.~~9d). 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 less efficient for controlling the emissions in the rural area (see the spatial distribution of the energy, building and road emissions in Fig. ~~4a~~5a-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 (Fig. 3 and Fig. ~~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~~ 5).

In all experiments, the prior and posterior relative uncertainties in sectoral budgets are higher than that in the total emissions due to the fact that the sectoral budgets from inventories or atmospheric inversions are based on a mix of independent information and on the split of the information on the total emissions (which is characterized by null or negative correlations between the uncertainties in the different sectors). The analysis of the negative correlations between posterior uncertainties in different emission budgets is indicative of the capability of the inversion system to well spread the attribution of an overall concentration increase between them (Fig. 8). Large negative correlations associated with high posterior uncertainties indicate that the posterior uncertainties in the individual budget for the different corresponding emission components arise from improper attributions of budget among these emission components while the sum of the emissions budget of all components may be well constrained by the inversion. The skill of the larger U networks for separating the sectoral emissions budgets is higher than that of the smaller U networks and than that of the equal-sized E networks (see Fig. 8b-d for cross correlations between building, road, and energy sectors).

However~~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 result 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 Fig. 2 and Fig. ~~4f~~5f) are located between the two outer rings of the E networks. Moreover, the E networks perform well to reduce uncertainty in road emission estimates, although a significant portion of the road emissions ~~can~~ occur in rural areas ~~(~~that are 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~~5b) sprawls mainly ~~at~~in the urban and suburban area, ~~being enclosed by~~which are comprised within the largest outer ring; and (3) the ~~station pairs from~~configuration of the E networks (as well as that of the R networks; Fig. ~~3) may characterize sufficiently well~~3) is better adapted than that of the ~~concentration gradients resulting from the difference~~U networks to distinguish between ~~onroad and nonroad~~the signature of the road emissions and that of the other emission sectors.

3.2 Sensitivity to the measurement and model errors, and to the amplitude of the uncertainty in NEE

The results analyzed above are based on the reference inversion configuration detailed in Sect. 2. However, as introduced in Sect. 2.5.2, observation errors could be in practice larger than assumed, either because we would need to use LCMP sensors with smaller accuracy than the present high precision instruments in order to deploy dense networks, or because our assumptions regarding the model errors (derived from the diagnostics of B15 over a small number of sites) would not be adapted to dense measurement locations.

We have thus repeated the inversion tests with values for the observation error standard deviations inflated by 50% compared to those described in Sect. 2.5.2 for the reference configuration (which would corresponds to a dramatic increase of the measurement error or decrease of the modeling skills, see the discussion in Sect. 4). The 1-sigma posterior uncertainties resulting from inversions with inflated (Fig. 11) and reference (Fig. 9d) observation errors when using 70 sites and the type of network providing the best performances (depending on the sector) are (1) 7% and 6%, respectively, for total emission estimates with U networks, (2) 16% and 15%, respectively, for building emissions with U networks, (3) 19% and 18%, respectively, for road emissions with R networks, and (4) 20% and 18%, respectively, for energy emissions with U networks. The increase of the posterior uncertainty in total emission estimates resulting from this inflation of observation error standard deviation is significant (typically 1% of the budget of prior total emissions). However, these increases are relatively modest compared to the typical variations of posterior uncertainties depending on the different networks that are tested. This is likely due to the fact that, at the monthly scale, the projection of the uncertainty in the prior emissions into the concentration space is very high compared to the observation errors, and to the fact that the observation limitation is primarily related to their spatio-temporal coverage rather than to the precision of the hourly measurements and of their simulation by the observation operator.

Our reference experiments apply to a month in winter, when the CO_2 signal from the NEE is low, and the heating emissions are high, which decreases the difficulty to separate it from that of the anthropogenic emissions in the concentration gradients. This could favor the monitoring of the anthropogenic emissions during this season. In order to assess whether the results obtained in this study can be indicative of the performance of the inversion during summer, when the NEE is higher (we ignore here the impact of the decrease in the heating emissions), we run inversions where the prior error standard derivation for the NEE fluxes is inflated/shrunk by 100%, or where the NEE fluxes within the observation operator $\mathbf{H}_1$ (see Sect. 2.4.1) are multiplied by 3 or 5 (which typically corresponds to the ratio between the NEE in July vs. January according to the C-TESSEL simulations). The differences between the uncertainty reductions for the total emission estimates obtained with the reference configuration and when applying these changes are found to be less than 1%. Actually, the correlation between the posterior uncertainties in the NEE fluxes and in the total and sectoral fossil fuel CO_2 emissions (except the building emissions) are nearly zero (Fig. 8b-d), which implies that the different networks are sufficiently dense to provide a clear separation between natural and anthropogenic fluxes within our inversion framework. This explains the weak influence of the prior uncertainty in the NEE for the estimate of the fossil fuel CO_2 emissions.

These sensitivity analyses strengthen the confidence in the robustness of our inversion results that are based on the experiments with real data of B15 and Staufer et al. (2016).

~~5~~4 Discussions and conclusions

4.1 Summary with complementary analysis

We have developed an atmospheric inversion method to quantify city total and sectoral CO_2 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 local agencies or interpolated from regional inventories developed by public research establishments~~.~~ (see Appendix A). We examine the ability of ~~the~~this inversion system to reduce uncertainty in ~~emissions~~emission estimates for diverse emitting sectors~~. Our study case is the monitoring of the emissions from the~~ of the Paris metropolitan area (~12% of ~~France's~~France CO_2 fossil fuel emissions~~). The relevance~~) as a function of the ~~atmospheric method in the MRV context requires enquiring the uncertainty level in emission estimates~~ size 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~~design (i.e. location of the stations) of the observation networks.

We ~~performed~~perform inversions over a one-month ~~period in~~ winter period (January 2011) ~~using~~ under a framework of Observing System Simulation Experiments, in which we test several types of theoretical networks of stations sampling CO_2 atmospheric concentrations at 25 meters above ground level. ~~Under~~ When using 10 stations, which is the ~~configuration~~typical size of the few current networks ~~of the order of 10 stations,~~ , the inversion considerably ~~reduced~~reduces the uncertainties in total emission estimates for January 2011 (by ~42~~%). However, if deriving the corresponding annual~~ %) from a ~20% 1-sigma prior uncertainty ~~through the propagation of the~~ down to ~11% 1-sigma posterior uncertainty ~~assuming approximately 2-month temporal correlation between monthly~~ . The uncertainty reduction for sectoral budgets is also high but the 1-sigma posterior uncertainties~~,~~ ~~the~~ for these budgets is ~25% i.e. more than twice as high as for total emissions. In the prior inventories as in our inversion ~~with ~10 stations failed to meet the 5% notional annual target for MRV use. We thus extended the measuring network. Large extensions should be possible in the near term through the inclusion of sensors~~experiments, the total emissions are better constrained (in relative terms) than the sectoral budgets. The inversion is more efficient in decreasing uncertainties in the budget of dispersed emissions from residential and commercial heating than 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€ per year. This budget corresponds to the order of the cost to compile, for MRV use, a high quality inventory of city fossil fuel CO_2 emissions.~~

~~We observed further significant reductions of uncertainties in~~ in other sectoral budgets. We observe significantly larger uncertainty reduction in sectoral emission budget estimates when 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~~vs. 10 stations ~~are significant: by~~is of 32% for commercial and residential buildings, ~~by~~of 33% for road transport and ~~by~~of 18% for the production of energy by power plants, and of 31% for the total emissions, respectively. ~~These~~The three major sectors ~~comprise~~(building, road, and energy) cover most of the emission budget according to the IER inventory used in this study. ~~The inversion is especially efficient~~Therefore, while the extension of the networks does not seem to be critical for ~~decreasing uncertainties in the budget of dispersed~~ the verification of the city emission total budgets, it likely provides high advantages for the monitoring of sectoral emissions~~ from residential and commercial heating. The~~. When using 70 sites, the 1-sigma monthly posterior uncertainty ~~of these~~in the 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~~% while that for transport and energy emissions estimates ~~are slightly larger (with 1-sigma monthly uncertainties~~is reduced to 18~~%).~~%.

4.2 Discussion on the levels of posterior uncertainties and on the relevance of the corresponding estimates

We can hardly determine whether the levels of precision in emission accounting obtained by atmospheric inversions would be enough for a MRV framework since the MRV experiences for citywide CO_2 emissions are still very limited (Appendix A). We still attempt at evaluating the usefulness of estimates with these different levels of uncertainties. In MRV practice, mitigation actions and climate plans are usually based on targets for the reduction of annual budgets of the emissions and should thus be evaluated based on the monitoring of annual budgets and/or of their trends. In this study, the accuracy of the inversion is analyzed for a single winter month, and inversion experiments over longer time periods are out of the scope of the paper (for reasons of computational cost). However, results from Sect. 3.2 indicated that its accuracy in spring, summer and fall should be similar. In order to get an indication on the accuracy of the inversion at the annual scale, we thus assume that the scores obtained here apply to all months during the year, and use two opposed and extreme hypotheses regarding the correlations between posterior uncertainties from month to month. The first one is that these uncertainties are fully independent, which can be supported by the independence of the measurements used to constrain the estimates from month to month. The second one is that these uncertainties are fully correlated, which can be supported by the fact that part of the posterior uncertainty is related to residual prior uncertainties that have not been decreased by the inversion, and that the prior uncertainties can be highly correlated from month to month. Actual correlations should lie between these two extreme cases. By doing so, we obtain a simple, conservative and indicative assessment of a typical range of 2-sigma annual uncertainties in the total and sectoral emission estimates from the inversion. With such a conversion, the prior uncertainty in total emissions would range between 12% and 40% while that in the sectoral budgets of the emissions would range between 21% and 72% depending on the sectors. The 2-sigma annual posterior uncertainty in total emissions would range between 4% and 23% when using 10 to 70 sites. The 2-sigma annual uncertainty in the budgets for the three main emitting sectors (building, road, energy) would range between 13% and 59% when using 10 sites, and between 9% and 44% when using 70 sites, while it would systematically exceed 14% for the production sector even when using 70 sites. Such annual uncertainty ranges vary a lot for the secondary sectors of emissions (airline, agriculture, remainder) e.g. from between 7% and 41% for agriculture to systematically higher than 20% for the remainder emissions when using 70 sites.

We compare these numbers to the diagnostic (based on expert judgments as well as error propagation calculations with the IPCC Tier 1 method) of the typical uncertainty in the national inventories in developed countries, which could apply to theoretical city scale inventories under MRV frameworks. The uncertainty in national inventories is country-specific, but for the seven Annex I countries surveyed by Pacala et al. (2010), the uncertainty in CO_2 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). 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. Uncertainties for other sectors are closer to 5% according to CITEPA (2014).

Furthermore, succeeding in delivering a 5% or 10% 2-sigma annual uncertainty 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 a 95% confidence level (detection interval [18%, 32%] or [11%, 39%] respectively, 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 emissions by 25% by 2020 and by 75% by 2050 relative to the 2004 baseline (Mairie de Paris, 2012). This means that a 10% annual uncertainty would be enough to monitor the trend of Paris emissions over time.

Comparing our indicative estimate of the typical range of posterior uncertainties in annual total and sectoral emissions to these 5% and 10% 2-sigma uncertainties confirms the need for dense observation networks if willing to build a valuable MRV framework. A significant part of the range of posterior uncertainties derived for the annual total emissions when using 10 sites is below the 10% 2-sigma uncertainty. However, it does not reach the 5% 2-sigma uncertainty and most of this range is lying above the 10% 2-sigma uncertainty. When using more than 30 sites and U networks, the 5% 2-sigma uncertainty can be reached by the most optimistic estimates of posterior uncertainties in annual total emissions and most of their range lie below the 10% 2-sigma uncertainty. Furthermore, as far as the most optimistic derivation of annual results is concerned, inversions with more than 30 sites would be required to expect that the posterior uncertainties in annual emissions for the three major sectors can be close to 10% 2-sigma uncertainty. This level can be reached with U or R networks of more than 50 stations for building emissions, but it cannot be reached for the road and energy sectors. 70 sites are required to expect posterior uncertainties of less than 10% 2-sigma uncertainty for all these 3 sectors at the annual scale. For the other types of sectors, the inversion with U, E or R networks is likely not adapted to reach the 10% 2-sigma uncertainty level at the annual scale.

With 70 sites, a significant part of the ranges of 2-sigma posterior uncertainties in annual emissions for the three major sectors is below ~15% (for any type of networks). Such a 2-sigma uncertainty at the annual scale still corresponds to an ability to detect the 25% reduction of emissions on a 15-year horizon at a 95% confidence (detection interval [3%, 46%], p = 0.05 for linear trends of emissions; see Appendix C). The 5% and 10% 2-sigma uncertainties can thus be viewed as stringent for the monitoring of sectoral emissions but the comparisons to these levels of uncertainty indicate that dense networks would be necessary to ensure that the inversion has a high potential to verify sector-wide mitigation policies/actions or to check whether sectoral mitigation targets are fulfilled.

4.3 Robustness of the inversion configuration and requirements on the model, methods and instruments supporting such a configuration

The results obtained in this study should not be over-interpreted, since (1) we worked 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). Nevertheless our inversions were based on the experience from ~~Bréon~~B15 and Staufer et al. (~~2015~~2016) in which real data from a few number of stations around Paris were used. In addition, we performed sensitivity analyses by significantly inflating the observation error to account for a potential increase of the measurement and modeling errors when deploying dense networks with many sites in the core of the urban area, and this analysis gave confidence in the robustness of the results obtained with our reference inversion configuration.

~~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 much richer sets of atmospheric observations. Recently, city networks have become increasingly densified, embracing other types of CO_2 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 measurements however needs to be assessed. For instance, the inversion may suffer from limited representativeness of observations in space (e.g. 0.2-5 km^2 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 CO_2 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 (^{14}C) measurements can serve for separating anthropogenic (fossil fuel combustion) and biogenic (biofuel and human and plant respiration) sources, and stable carbon isotope measurements (^{13}C) can further distinguish combustions from gas or liquid fuel (Lopez et al., 2013; Vogel et al., 2013). CO, NO_x and other co-emitted gases can be used as proxies for the estimation of sectoral CO_2 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 CO_2 vary as a function of the local emission 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 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~~ Our tests ignored potential temporal correlations in the model and measurement errors. Increasing the standard deviation of the observation error for hourly data should have a similar impact on results at the monthly scale as accounting for short temporal autocorrelations (over timescales typically smaller than few days). Increasing the standard deviation of the observation errors instead of modeling their autocorrelations is a common technique in atmospheric inversion (Chevallier, 2007).

The results from B15 and Staufer et al. (2016) support the idea that the model has no major biases or errors with large temporal correlations. However, even though B15 diagnosed model errors for measurements in the core of the urban area, they and Staufer et al. (2016) did not attempt at assimilating such measurements. We thus implicitly make the assumption that there is no major model errors with long temporal correlations associated with high local sources for 25 magl locations in the urban environment. This assumption is supported by the idea that relevant investigations (mobile measurement campaigns, high resolution transport modeling) can be led to avoid setting up sites close to such sources. In our study, the hypothetical stations are all located without a precise definition of their specific position within the 2 km x 2 km grid cells of CHIMERE, which are sufficiently large to assume that they encompass areas less prone to local sources. High resolution transport modeling can also be used to develop techniques for filtering the signal from the large scale emissions against that of local sources in the measurements.

The theoretical use of LCMP sensors to allow the deployment of networks of up to 70 sites could be viewed as a source of systematic measurement errors with long temporal scales of autocorrelation. Our results from Sect. 3.2 suggest that if the measurement errors are significant and increase the observation errors by 50%, they can have a significant impact on the accuracy of the inversion. Such an inflation of the observation error would result from 1 ppm systematic errors with 7 day temporal correlations in the hourly measurements (since it would result in ~1.5 ppm systematic error in weekly mean gradients, or, if converting the temporal correlations into an inflation of the hourly standard deviations, in an 8 ppm measurement error for hourly gradients). Therefore, our sensitivity tests indicate that the LCMP accuracy and calibration strategy should ensure that the systematic errors do not exceed 1 ppm, and if they are close to this value, that they are not auto-correlated over more than one week. This recommendation adds to the recommendation that the cost of LCMP sensors should not exceed 1-5 k€ euros (see the discussion in Appendix B).

The choice to rescale the budgets of emissions over large areas and sectors rather than at high resolution could make our results quite optimistic. However, the aggregation errors associated with such a coarse scale rescaling are accounted for in the inversion. Furthermore, the configuration of the networks tested in this study is adapted to that of the “control tiles” which helps avoiding aggregation artefacts. With such configurations, the results show that having as many sites as possible around the most prominent sources of a tile will give a better control on the average budget of that tile. As would have been expected with a high resolution inverse modeling system, our coarse inversion system identifies the networks that can provide a strong constraint on most of the largest sources within the tiles, and it demonstrates some sensitivity to the network types and station locations.

The assumptions underlying our setup of the sectoral uncertainties (in particular for the prior error covariance matrix **B**) can definitely impact the results of the uncertainty reduction. It could raise some concerns regarding the analysis of the absolute values of uncertainty reduction for a given network. However, the comparative analysis of the uncertainty reductions when using different networks but the same inversion setup (i.e. the network design analysis) should bring more robust conclusions.

4.4 Perspectives

While the deployment of dense city networks of more than 30 sites seems presently excessively expensive, the present development and testing of LCMP sensors whose cost would not exceed 1-5 k€ give first hopes that it could become realistic in the near term (see Appendix B).

The potential for monitoring sectoral budgets could be further increased by the use of isotopic measurements such as ^{13}C and ^{14}C (Lopez et al., 2013; Vogel et al., 2013) and of co-emitted pollutants such as NOx and CO (Ammoura et al., 2014) whose ratio to CO_2 depend on the sectors of activity.

Our inversions are shown to be highly sensitive to the types of networks that we have defined, and sometimes (e.g. for the agriculture sector) to the specific station location for given type of network. While the results could be improved if the stations location would follow some empirical rules (e.g. redistributing more stations along road networks or around power plants to better distinguish emissions from road transport and energy production), this motivates optimal network design studies, based on atmospheric inversion OSSEs such as in this study, potentially coupled to optimization algorithms (Wu and Bocquet, 2011).

One may consider further improving the current city scale inventories ~~is~~as a natural choice for emission accounting~~, following~~ in the context of MRV, in a way similar to what is experienced by the applications of national inventories under UNFCCC and the Kyoto Protocol. ~~Such~~However such refinement requires tedious efforts in order to continuously collect detailed and high-quality local data. In this paper~~,~~ we ~~demonstrated that~~ highlight the potential of the alternative approach of atmospheric inversion ~~could in principle achieve the same level of quality desired for~~to provide accurate estimates of the total and sectorial budgets of the emissions~~ at the same cost level.~~.

Atmospheric inversion distinguishes itself in a number of ways for the quantification of city CO_2 emissions. ~~First and foremost, it~~It would provide an estimate ~~using another~~ method other 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~~In addition to the verification of inventories, atmospheric inversion can also incorporate, whenever available, ~~better~~ inventories into its modeling framework to ~~produce better~~improve their emission estimates. ~~Third, the~~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~~on 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 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~~With these features, atmospheric inversion ~~could~~appears to be a ~~new~~ promising ~~quantification~~ MRV tool ~~for MRV use~~ to mitigate city CO_2 emissions.

Appendix A Brief review of existing city emission inventories and discussion on the accuracy of MRV city frameworks

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Inventories of CO_2 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 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.

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 frameworks. 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 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 of inventories can cover not only direct city emissions (i.e. the Scope 1 emissions) but also indirect or embodied emissions that are linked with cities activities but occur outside the considered territories ~~[~~(e.g. 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 performed with a limited cost that scales with the size of cities (e.g. ~~~€18k~~~18 k€ per year 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~~. They have been mainly used by the scientific community to model the atmospheric transport of CO_2. 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 of Stuttgart (Pregger et al., 2007), and the global fossil fuel CO_2 emission map from the Peking University (PKU-CO_2; Wang et al. (2013)). The activity data and emission factors ~~entering in~~for the ~~fabrication~~compilation 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~~was 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€ per year.~~

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 approximate 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,~~. Whatever their type (1, 2 or 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 the Paris type-3 inventory, there is only a new update every ~~2~~two years with a 2-~~years~~year lag between the date of release and the corresponding year of emissions.

The IER inventory used for the practical implementation of the OSSEs in this ~~OSSE~~ study incorporates local data to provide a gridded inventory at 1 km and ~~1h~~1 h resolution. We detail this inventory in the main text of the paper (Sect. ~~3~~ 2.4.1). Here we group the 40 sectors from this IER inventory into seven aggregate larger sectors, and list their annual budgets in Table A1.

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~~Appendix B Network cost and instrumental details~~

~~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 equipment, 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 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€ per year, 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€ per year.~~The uncertainty in city emissions estimates is in general considered as larger than that in national estimates (Duren and Miller, 2012). However, the development of city scale MRV frameworks could foster the development of city scale inventories with an accuracy which is close to that presently diagnosed for national inventories in OECD countries, reported under UNFCCC and the Kyoto protocol (Chang and Bellassen, 2015). The underlying rationale is that MRVs at national and city scales would have similar objectives. Both would support determination of baselines and/or reduction of emissions from various sources (e.g. transportation, building, and industries) for a given geographical area. As mitigation actions against CO_2 emissions are many and various, their MRVs differ from one another accordingly. Ninomiya (2012) classified different existing MRVs and suggested that the MRV of emission reductions by actions/policies would be less accurate than the MRV of national emissions using inventories. If this reasoning is also valid at the city scale, the uncertainty level for total city emissions would be stringent for the MRV of emission reductions by citywide actions/policies.

Appendix B Requirements on the cost of the infrastructure and of the LCMP sensors underlying the deployment and operation of dense networks

The typical cost of existing inventories give ideas on the order of magnitude which could be acceptable for the cost of the overall inversion framework. Since there is presently no MRV framework at the city scale, we investigate the typical cost of national inventories in the MRV framework of UNFCCC. In order to have the same accuracy within the frame of MRV systems, city scale inventories based on similar methodologies would have to rely on data with the same level of quality. The cost of an inventory involves the collection of large datasets, and the design and implementation of the inventory model. 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. For the compilation of a city inventory, tracking fuel use statistics from different origins and types and for different sectors might actually prove more complicated than for a state where national statistics are already firmly established by governmental agencies. The CITEPA is the agency responsible for preparing the French national inventory following the IPCC guidelines. The budget of the activities at CITEPA related to this national inventory is about 1.5 M€ per year (République Française, 2015). This covers not only the compilation of the fossil fuel CO_2 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 are imposed by the IPCC guidelines. It is therefore complicated to assess the budget of the CO_2 fossil fuel emissions inventory at CITEPA. However, it indicates that a reasonable cost for a city inversion framework should not exceed 1-2 M€ on average per year.

Current atmospheric GHG monitoring programs have significant investment and operational costs, for example the KIC Climate CarboCountCity program (http://www.climate-kic.org/projects/carbon-emissions-from-cities/) incurred costs of ~4 M€ for a 3 year project period, which included installation of a few monitoring stations in Paris and Rotterdam (less than 10 sites overall), as well as salaries and mobile campaigns. The typical cost of infrastructure installation for 10-site networks, if excluding the cost of the sensors, is presently of the order of 200 k€ when deploying the network if it does not require the building of dedicated towers (as assumed in our study where stations are located at 25 magl), ~180 k€ euros per year for labor charges (data QA/QC, processing and modelling), and ~5-10 k€ per year per site for maintenance and calibration. From these previous experiments one would estimate the cost of a 70 site monitoring network of the current make to about 10 M€ for a 5 year period. A strategy is required to decrease this cost if we are hoping to benefit from the demonstrated advantages of this study of operating a 30 to 70 site networks instead of a sparse 10 site network. Data hosting, processing and QA/QC costs seem fairly uncompressible and even with more advanced data processing routines, the need to hire at least one expert modeler and field technicians to maintain the network seems unavoidable. With technological development, however, one can hope that the significant contribution of sensor cost could be reduced. Ideally, this cost of the sensors should not be significant to ensure that the budgets remains of the order of 1-2 M€ on average per year (accounting for the depreciation of the initial settings and purchases over ~10 years). Today, the sensors used by the atmospheric monitoring community need to be replaced or a major repair every 5-10 years, which presents a cost of more than 500 K€ per year for a 70 site network (accounting for the depreciation of their purchase over ~7 years). Lower-cost sensors would likely be less robust (shorter life-time) which would imply that their cost need to be at least one order of magnitude smaller to be beneficial i.e. 1-5 k€.

Current LCMP prototypes tested at LSCE in the framework of on-going European innovation projects have promising results regarding their fundamental measurement precision and temporal bias structure and could cost less than 2 k€. Still, the most critical challenge will be to ensure that atmospheric monitoring networks based on such sensors can provide accurate data with a relatively (compared to the present protocols) cheap infrastructure and calibration strategy, which needs to be demonstrated in a future study.

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 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 contrast, with 10% and 15% annual emission uncertainty, the corresponding detection ~~interval is~~intervals are [11%, 39%] and [3%, 46%] respectively at 95% confidence level.

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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 6h-windows	24
--	--	--	834 (total)

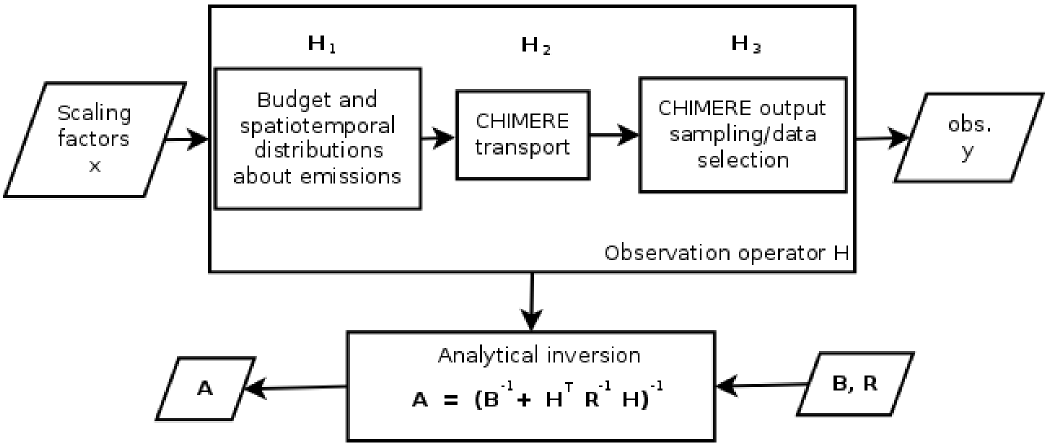
Table A1 Specification of ~~all~~ the 40 sectors in the IER inventory employed in this study. These sectors are grouped into seven aggregate larger sectors listed in Table 1.

Sector	NFR code	Budget (TgC/yr)	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

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

	~~Cost~~			~~Depreciation 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~~
	~~45 k€~~	~~2 k€~~	~~2 k€~~	~~10%-20%~~ ~~(5-10 yr)~~	~~20%-40%~~ ~~(2-5 yr)~~	~~Low precision/high systematic error: 0.5-1 ppm / 1 ppm~~
~~Infrastructure / site~~	~~25 k€~~	~~25 k€~~	~~3 k€~~	~~-~~	~~-~~	~~Minimum (given pre-existing infrastructure and co-funding):~~ ~~Inlet + calibration= 10 k€~~
~~– Container~~	~~10 k€~~	~~10 k€~~	~~2 k€~~	~~-~~	~~-~~	
~~– Inlet system~~	~~5 k€~~	~~5 k€~~	~~-~~	~~10%-20%~~	~~10%-20%~~	
~~– Calibration~~	~~5 k€~~	~~5 k€~~	~~1 k€~~	~~20%-33%~~	~~20%-33%~~	
~~– Installation and others~~	~~5 k€~~	~~5 k€~~	~~-~~	~~-~~	~~-~~	
~~Annual~~						
~~– Infrastructure / site~~	~~10 k€~~	~~10 k€~~	~~0-1 k€~~	~~-~~	~~-~~	~~Cost of e.g. rent, electricity, data…~~
~~– 1 engineer: network~~	~~60 k€~~	~~60 k€~~	~~60 k€~~	~~-~~	~~-~~	
~~– 1 engineer: data~~	~~60 k€~~	~~60 k€~~	~~60 k€~~	~~-~~	~~-~~	
~~– 1 engineer: modeling~~	~~60 k€~~	~~60 k€~~	~~60 k€~~	~~-~~	~~-~~	



~~Figure~~

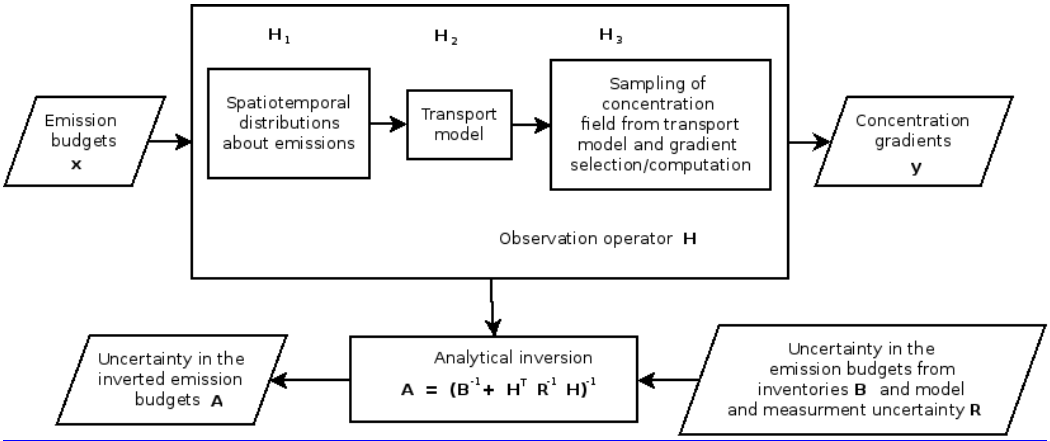
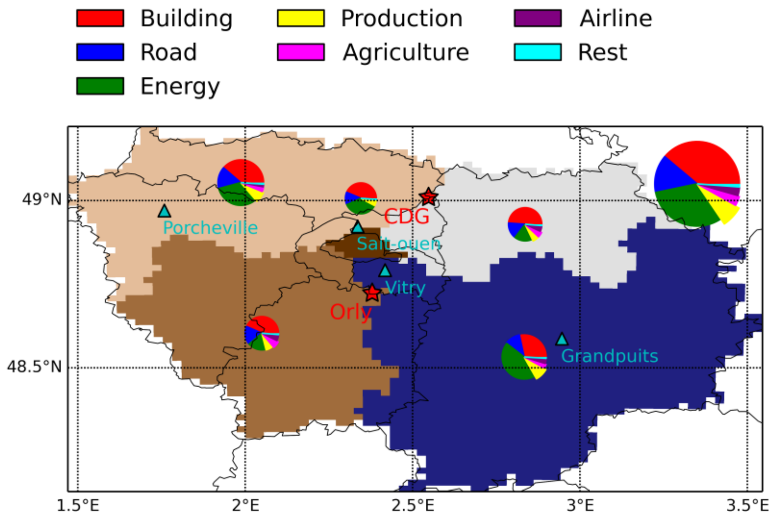


Fig. 1 Diagram of the ~~synthetic study on atmospheric inversion of~~ principle of the city CO_2 emissions~~.~~ inversion system and of the computation of uncertainties in the inverted emission budgets. Note that there is no computation of **x** and **y** vectors in this OSSE study.


Building
Production
Airline
Road
Agriculture
Rest
Energy
Porcheville
CDG
Saint-ouen
Vitry
Orly
Grandpuits
49°N
48.5°N
1.5°E
2°E
2.5°E
3°E
3.5°E

~~Figure~~

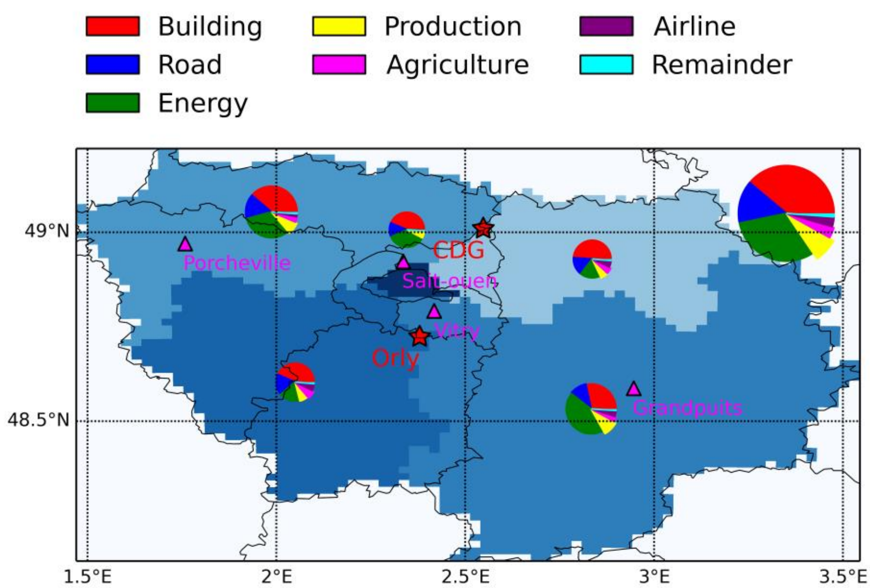
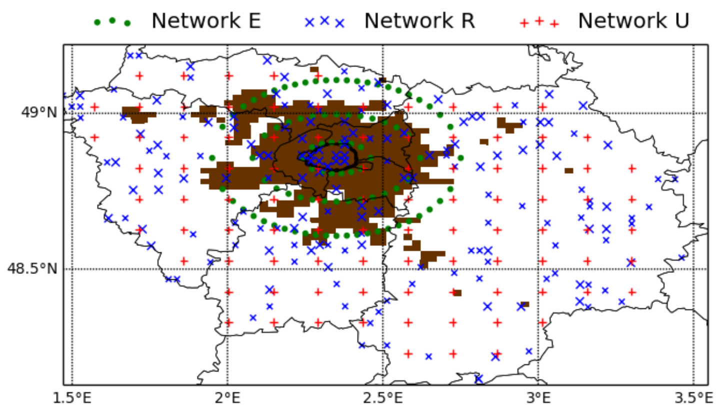


Fig. 2 Sectoral budgets of fossil fuel CO_2 emissions from the IER inventory for the five “control” zones ~~of~~(central Paris in dark blue and four other surrounding areas in light blue) partitioning the IDF region and for the month of January in 2011 (see the first seven rows in Table 1 for sector 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~~areas of IDF. The red pentagons shows the two airports CDG and Orly, and the ~~cyan~~purple triangles show several large point emissions such as three EDF power plants and the TOTAL Grandpuits refinery. Note that these five zones in blue mark out the IDF region, but do not strictly follow the administrative borders (black lines) within IDF.

Mis en forme : Anglais (États Unis)



~~Figure~~Fig. 3 ~~Illustrative locations~~Locations for the elliptical (E), random-even (R) and ~~unifrom~~uniform (U) networks over IDF. The brown area marks out where the population density is larger than 1250 people per 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 (the administrative “city of Paris”) 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.

Mis en forme : Exposant

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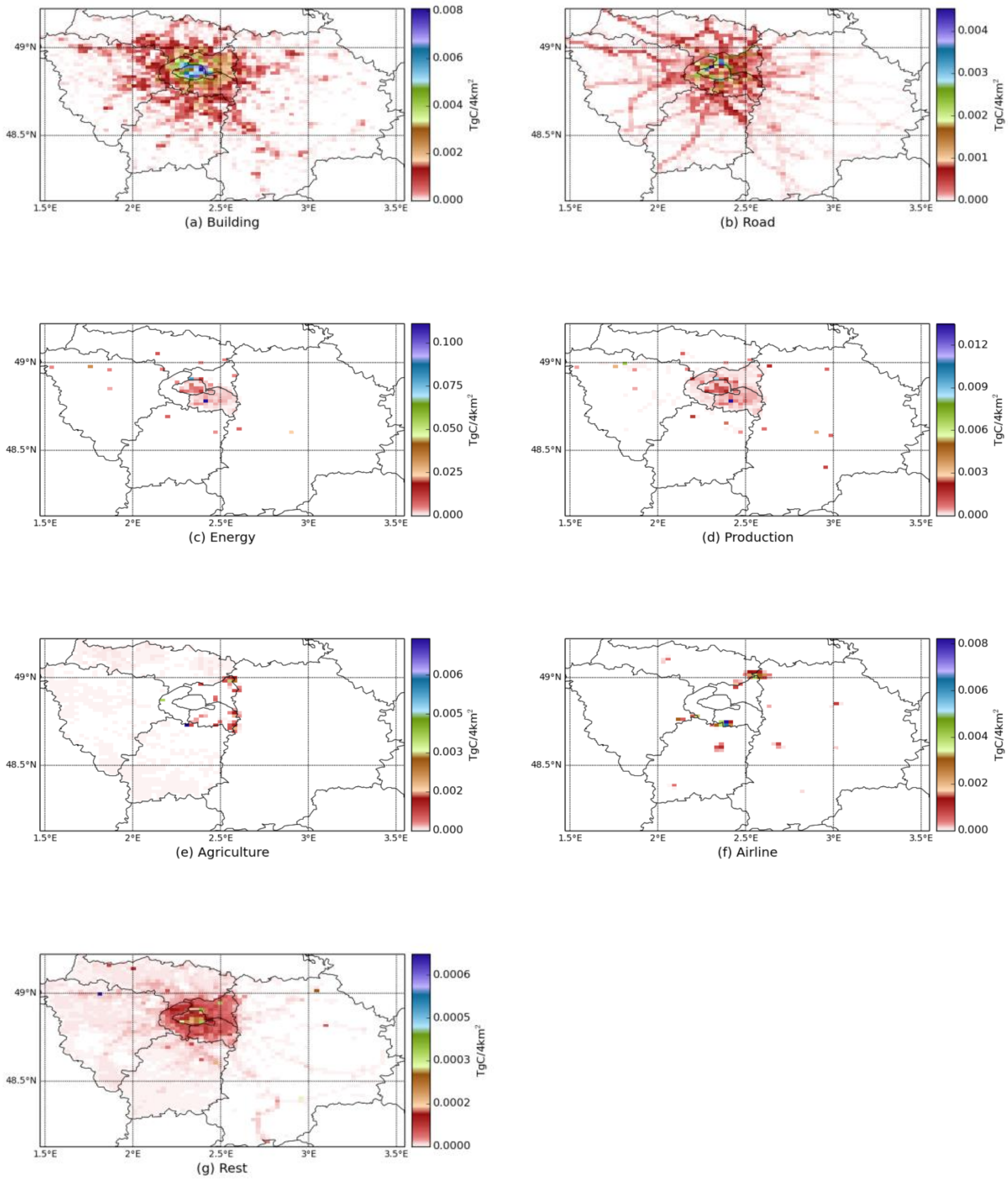
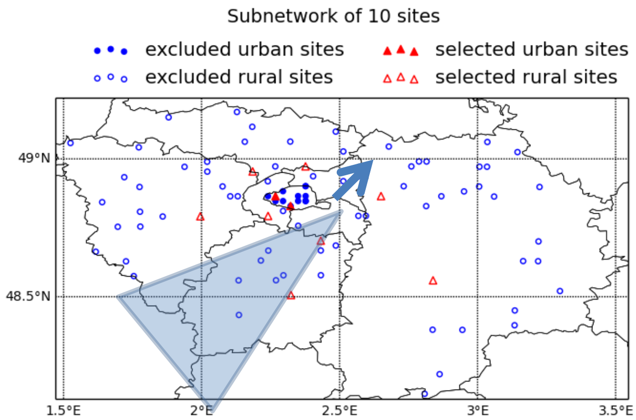
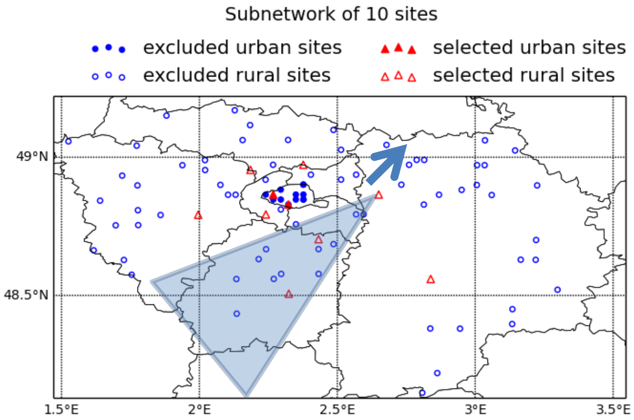




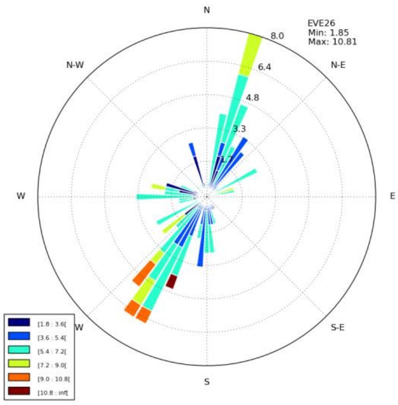
~~Figure~~

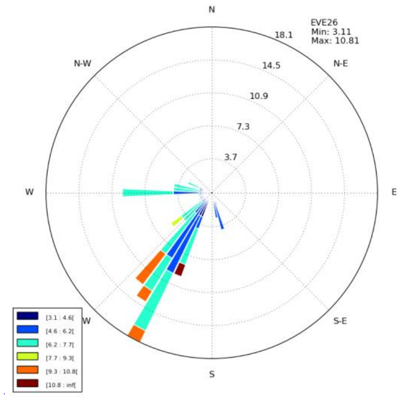
Fig. 4 ~~Sectoral and spatial distribution of the IER inventory for IDF for January 2011.~~

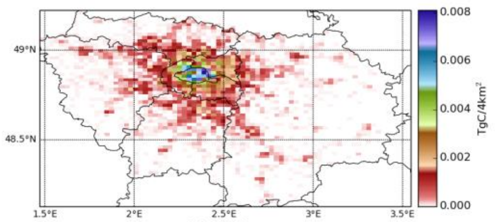
Mis en forme : Anglais (États Unis)



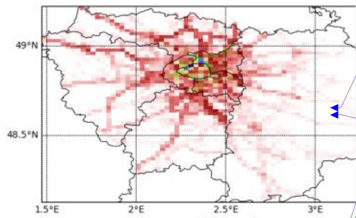
~~Figure 5~~ Selection of a subset ~~(~~of 10 sites ~~marked out in~~ (red triangles) from a cloud of candidate locations for the R network to form smaller networks. The blue circles show the sites that are not selected~~.~~ from available locations. The open circles/triangles ~~are for~~present rural sites, and the filled circles/triangles ~~are for~~present 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~~Sect. 2.4.3.







~~(a)~~ (a) Building



~~(b)~~ (b) Road

Mis en forme : Titre 3

Tableau mis en forme

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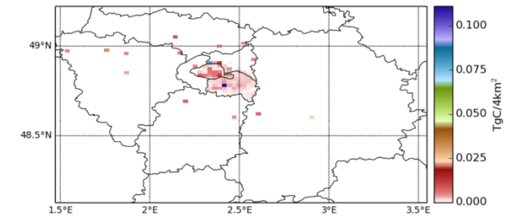
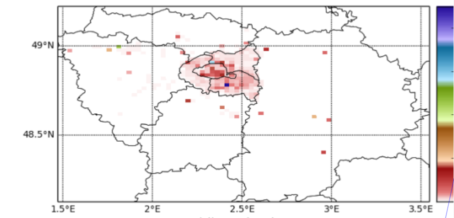
Mis en forme : Français (France)

Mis en forme : Français (France)

Mis en forme : Normal, Gauche, Espace Avant : 0 pt, Sans numérotation ni puces

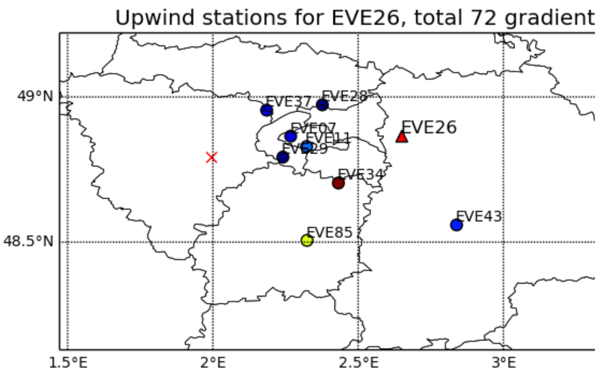


(c) Energy



(d) Production

Cellules insérées



~~(c)~~

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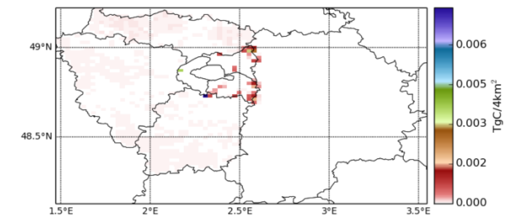
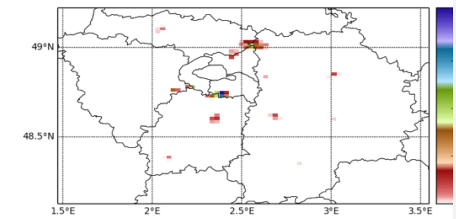
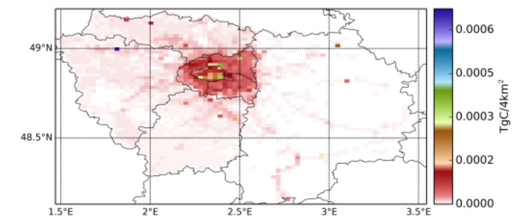
Mis en forme : Français (France)



(e) Agriculture

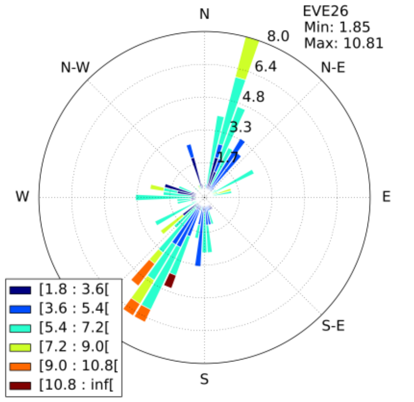


(f) Airline

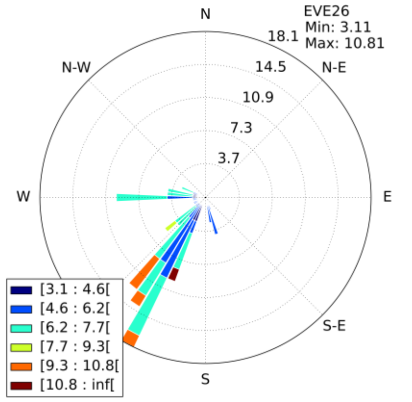


(g) Remainder

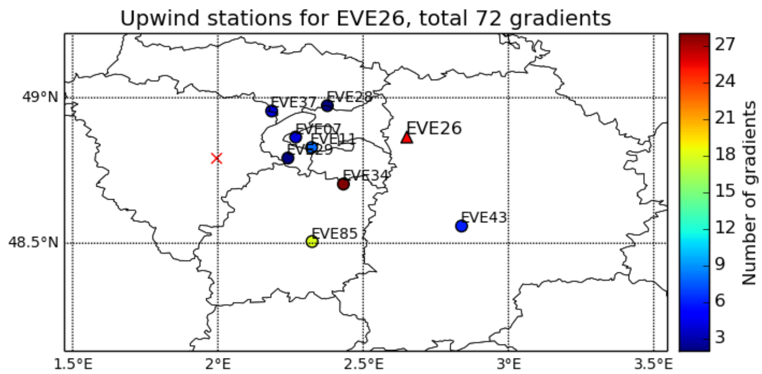
~~Figure~~Fig. 5 Sectoral and spatial distribution of the IER inventory over IDF for January 2011.



(a)



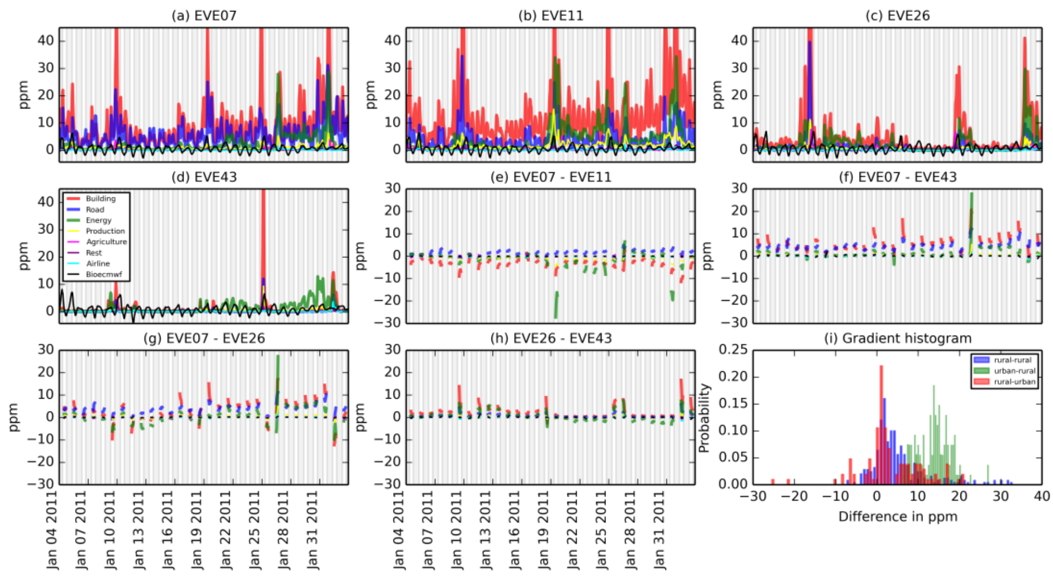
(b)



(c)

Fig. 6 Results of selections of upwind stations for gradient computations for ~~one downwind station~~EVE26 (see Fig. 4; R-type network of 10 stations) for the month of January ~~in 2011. Here we use a R network of 10 stations defined in Figure 5. The illustrative downwind station in Figure 5 (named EVE26 in this figure) is chosen for diagnosis~~2011. (a) The afternoon wind conditions at EVE26 during the given month; (b) the afternoon wind conditions for ~~selected~~the observations selected for gradient calculation at EVE26; (c) the ~~counts~~number of times a site is selected as ~~the~~ upwind ~~site~~ for gradient computations at

EVE26~~ for all the other nine stations.~~. The leftmost red cross indicates ~~that this~~a site that is never selected for gradient computation for EVE26.



~~Figure~~

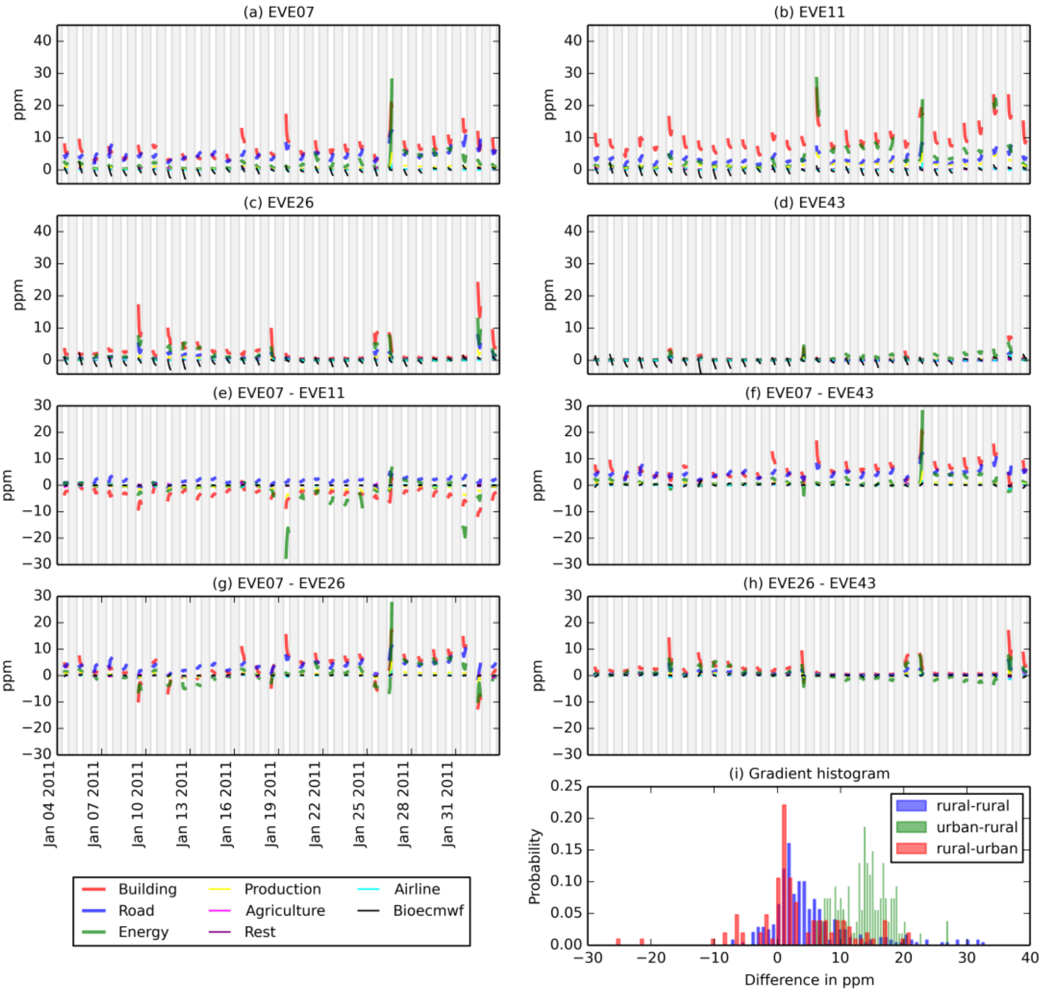
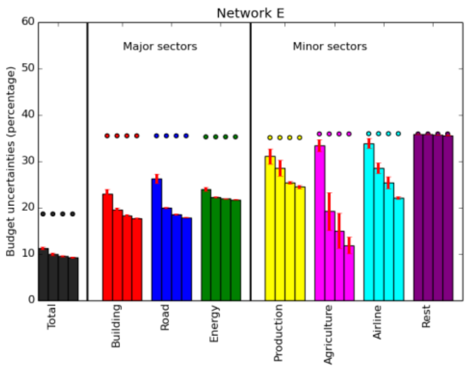
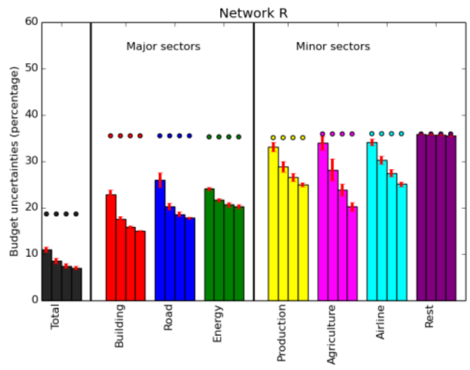
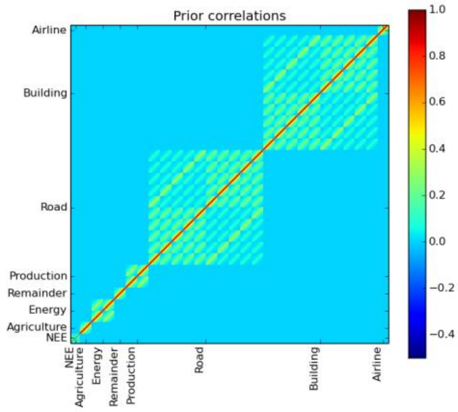


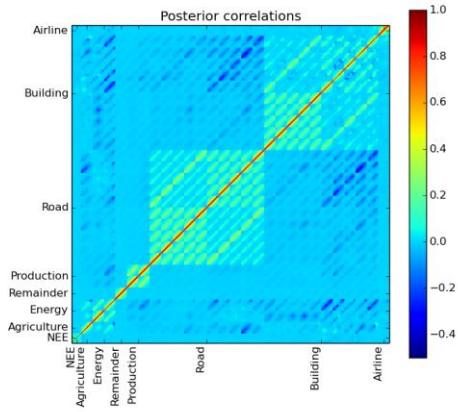
Fig. 7 (a-d) CO_2 mixing ratio series of sectoral CHIMERE simulations at four selected stations of the R network (see ~~Figure 5~~Fig. 4 and ~~Figure~~Fig. 6c). EVE07 and EVE11 are urban sites and EVE26 and EVE43 are rural sites but close to large point emissions. The shadow marks out the night time. (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~~2.4.3 for all the 10 stations of the R network. These histograms are grouped according to the type of downwind and upwind stations.

1

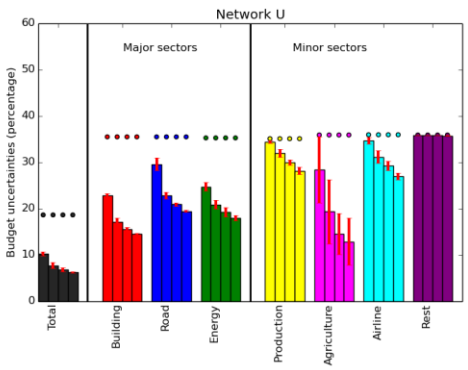


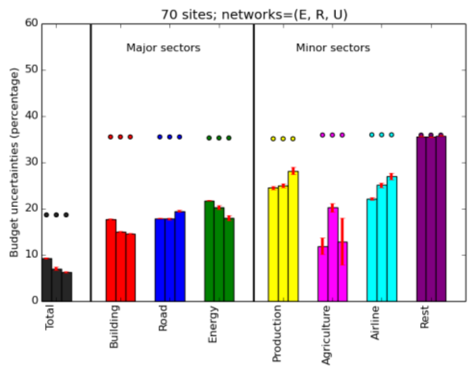






(a) ~~(b)~~ (b)





~~(d)~~

Tableau mis en forme

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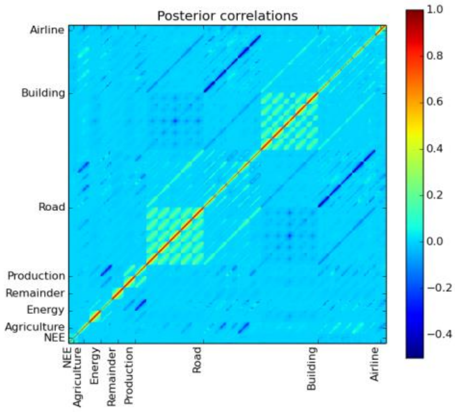
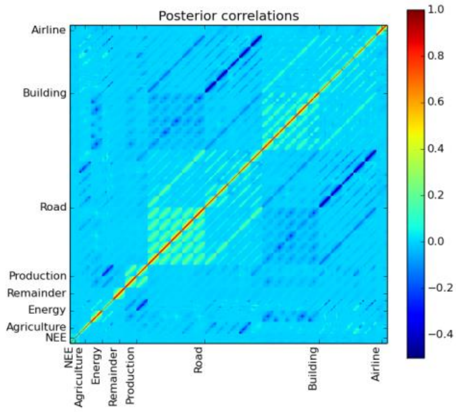
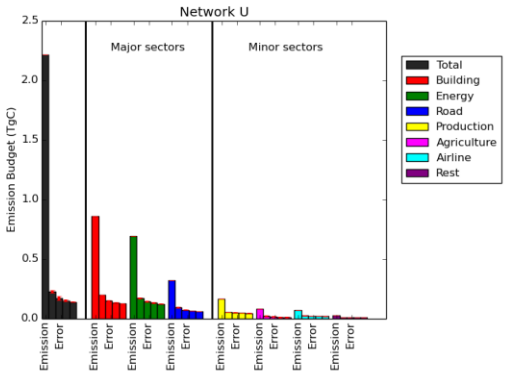




~~(c)~~ (c) (d)



~~(e)~~

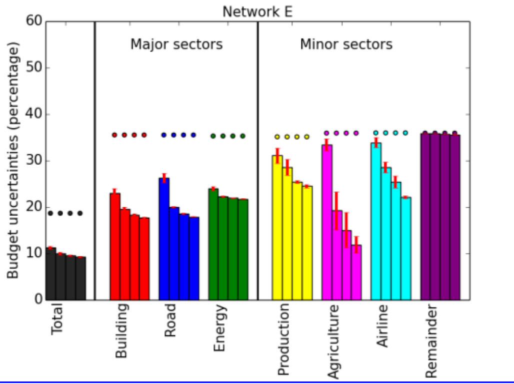
~~Figure 8~~Fig. 8 The correlation structures in (a) the error of prior scaling factor estimates; (b) the posterior error obtained by inversion using a U network with 10 stations; (c) the posterior error obtained by inversion using an E network with 70 stations; and (d) the posterior error obtained by inversion using a U network with 70 stations. Each row or column of the pixels corresponds to the correlation between one scaling factor and all the 834 scaling factors (see Sect. 2.2). For clarity, we group these scaling factors into eight sectors and organize them for each sector according to temporal indices and spatial areas. The tickers show the name of these eight sectors.

Mis en forme : Français (France)

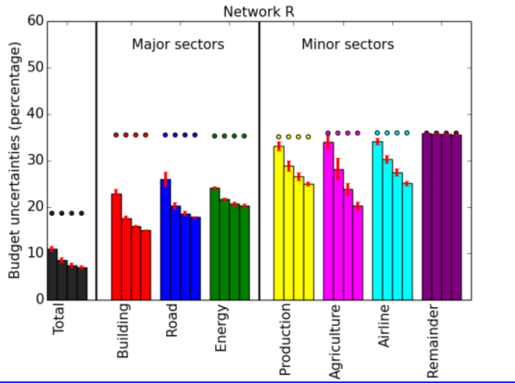
Mis en forme : Français (France)

Mis en forme : Normal, Espace Ava : 0 pt, Sans numérotation ni puces

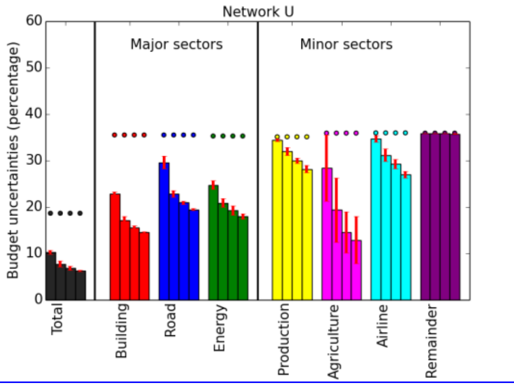
Mis en forme : Centré


Network E
Major sectors
Minor sectors
Budget uncertainties (percentage)
0
10
20
30
40
50
60
Total
Building
Road
Energy
Production
Agriculture
Airline
Remainder

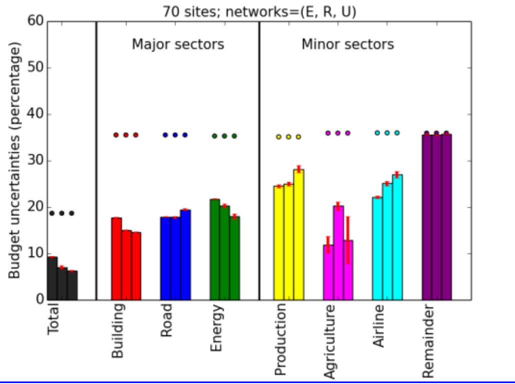
(a)


Network R
Major sectors
Minor sectors
Budget uncertainties (percentage)
0
10
20
30
40
50
60
Total
Building
Road
Energy
Production
Agriculture
Airline
Remainder

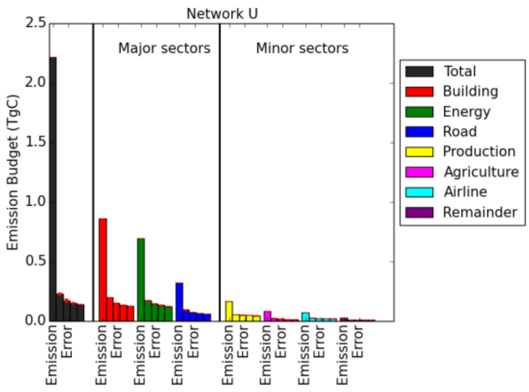
(b)


Network U
Major sectors
Minor sectors
Budget uncertainties (percentage)
0
10
20
30
40
50
60
Total
Building
Road
Energy
Production
Agriculture
Airline
Remainder

(c)

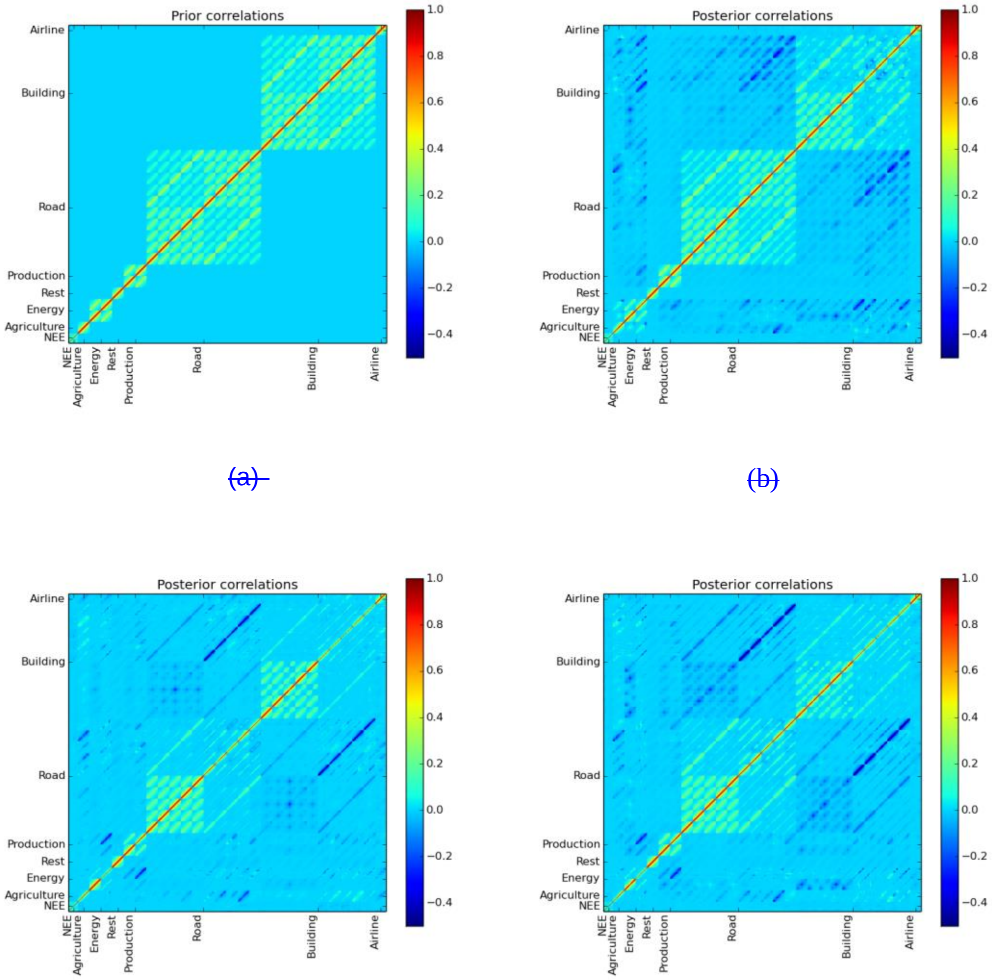

70 sites; networks=(E, R, U)
Major sectors
Minor sectors
Budget uncertainties (percentage)
0
10
20
30
40
50
60
Total
Building
Road
Energy
Production
Agriculture
Airline
Remainder

(d)


Network U
Major sectors
Minor sectors
Emission Budget (TgC)
0.0
0.5
1.0
1.5
2.0
2.5
Emission
Error
Total
Building
Energy
Road
Production
Agriculture
Airline
Remainder

(e)

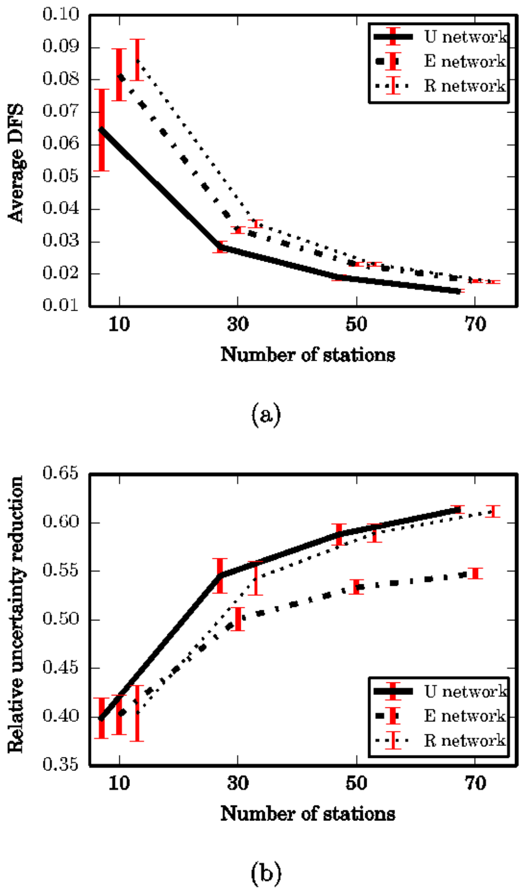
Fig. 9 Budget of uncertainties in total and sectoral emission estimates by inversions using three types of networks of different sizes. Each sector has a distinct color. In (a-d), we show the uncertainty budgets in percentage to the corresponding emission budgets computed using the IER inventory. The 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~~2.3. (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.



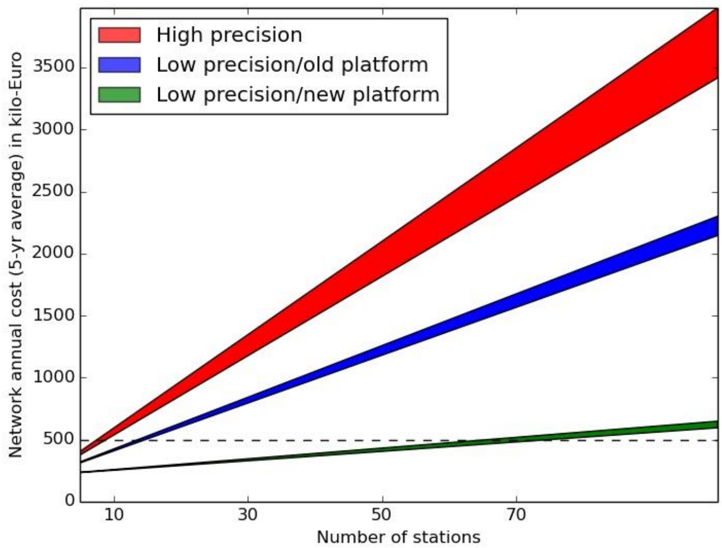
~~(a)~~ ~~(b)~~

~~(c)~~ ~~(d)~~

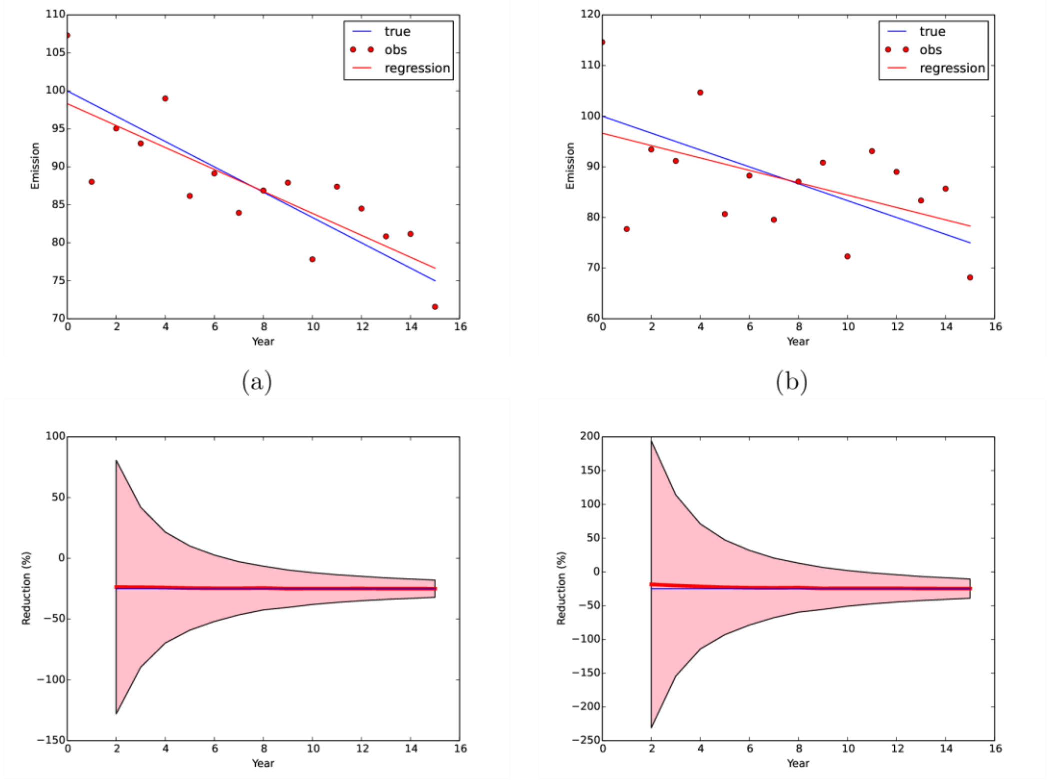
~~Figure 9 The correlation structures in (a) the error of prior scaling factor estimates; (b) the posterior error obtained by inversion using a U network with 10 stations; (c) the posterior error obtained by inversion using an E network with 70 stations; and (d) the posterior error obtained by inversion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



~~Figure~~Fig. 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~~ which is total DFS divided by 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 $(\sqrt{\mathbf{1}^{\mathrm{T}}\mathbf{B}\mathbf{1}} - \sqrt{\mathbf{1}^{\mathrm{T}}\mathbf{A}\mathbf{1}})/\sqrt{\mathbf{1}^{\mathrm{T}}\mathbf{B}\mathbf{1}}$, where $\mathbf{1}$ 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. 2.3.~~3.~~



~~Figure B1 Sketch diagram on the cost of networks with either high precision sensors or low cost sensors as a function of increasing number of sites. For new platform, pre-existing infrastructure is used for saving cost. The range of cost corresponds to different levels of depreciation rate listed in Table B1.~~



(a) (b)

(c) (d)

~~Figure~~

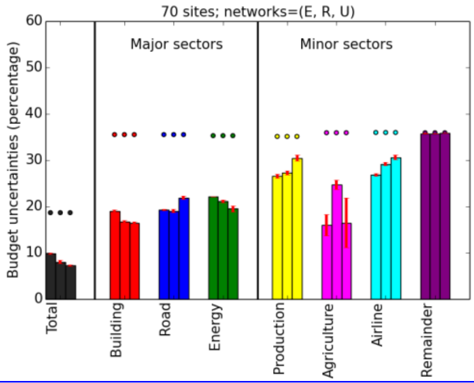
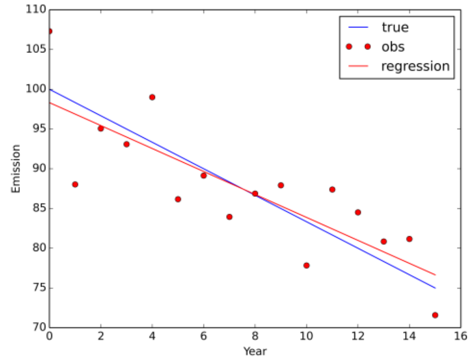
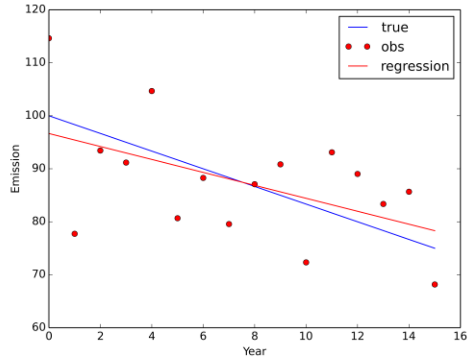


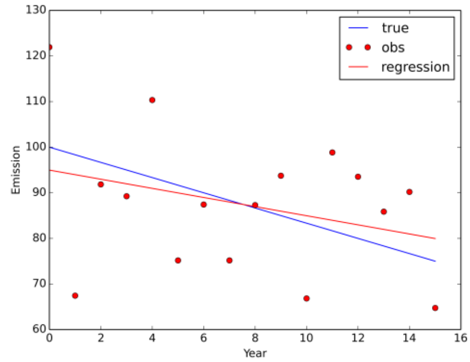
Fig. 11 Reduction of uncertainties by inversions using three different types of networks of 70 stations with inflated observation error standard derivation (50% larger).


true
obs
regression
Emission
Year

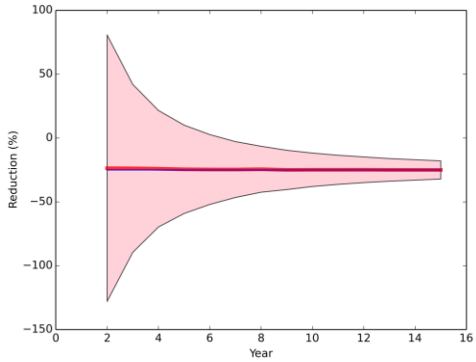
(a)


true
obs
regression
Emission
Year

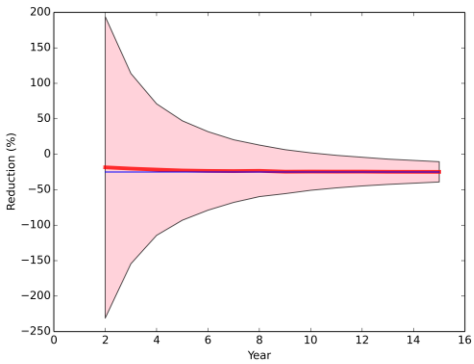
(b)


true
obs
regression
Emission
Year

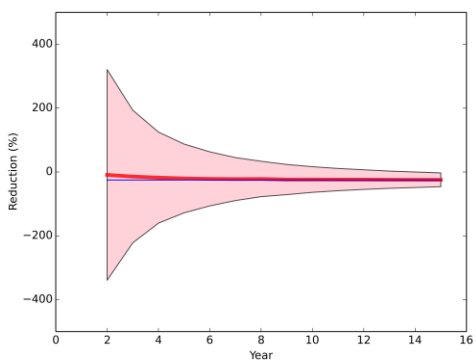
(c)


Reduction (%)
Year

(d)


Reduction (%)
Year

(e)


Reduction (%)
Year

(f)

Fig. C1 Detection of linear trends using the Monte Carlo method with ensembles of 10000 simulations. We hypothesize that the emissions decrease linearly from a value of 100 in any appropriate unit to 75 (i.e. a 25% reduction) in a 15-years time horizon. (a), (b) and (~~b~~c) 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%, 10% and ~~10~~15% 2-sigma annual emission uncertainties respectively (in percentage to the emission value in the initial year). (~~c~~d), (e) and (~~d~~f) 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 10000 simulations.