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Prioritising the sources of pollution in European cities: do air quality modelling applications provide consistent responses?

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Abstract. To take decisions on how to improve air quality, it is useful to perform a source allocation study that identifies the main sources of pollution for the area of interest. Often source allocation is implemented with a Chemical Transport Model (CTM) but unfortunately, even if accurate, this technique is time consuming and complex. Comparing the results of different CTMs to assess the uncertainty on the results is even more difficult. In this work we compare the source allocation on 150 major cities in Europe based on the results of two CTMs (CHIMERE and EMEP), approximated through the SHERPA (Screening for High Emission Reduction Potential on Air) approach. Even though the two CTMs use different input data and configurations, in most cases the source allocations with the SHERPA simplified models give similar results. But there are also cases where results are contradictory.

1. Introduction

Air quality models are useful tools to perform a variety of tasks like assessment (simulating the concentrations fields at a given moment), forecasting (reproducing future concentrations) and source allocation/planning (evaluating priorities of interventions, and the impact of potential emission reduction policies on concentrations). For assessment (Alvaro Gomez-Losada et a., 2018) and forecasting (Corani et al., 2016), it is possible to compare the model results with observations. FAIRMODE[1] (the Forum for air quality modelling in Europe) i.e. provides tools to assess the quality of the models like the Model Quality Indicator and Model Quality Objective (Pernigotti el al., 2013b; Viaene et al., 2016). However, for source allocation and planning, there is no benchmark against which to compare the model results. In this context air quality models are simulating the impact of theoretical emission reduction scenarios on concentrations, for which no measurements are available. These scenarios are usually implemented considering alternative policy options that might never become real. So, even if they are very useful to evaluate ex-ante the impact of possible policy options, it is hard to judge the uncertainty associated to these results. So, the uncertainty on the source allocations given by an air quality model can be evaluated by comparing it with the results of other models (Thunis et al., 2007; Cuvelier et al., 2010; Pernigotti et al., 2013). Both the absolute and relative impact of emission reductions can be compared. Even if models disagree about the absolute concentration reductions, they might still

[1] The Forum for Air quality Modeling (FAIRMODE) was launched in 2007 as a joint response initiative of the European Environment Agency (EEA) and the European Commission Joint Research Centre (JRC). The forum is currently chaired by the Joint Research Centre. Its aim is to bring together air quality modelers and users in order to promote and support the harmonized use of models by EU Member States, with emphasis on model application under the European Air Quality Directives. For more details, see https://fairmode.jrc.ec.europa.eu/.

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identify the same sources as main contributors to the air pollution in the area of interest. If model results are consistent one can assume that policies based on these results will be effective.

As an initial phase to design an air quality plan, one can be interested in checking the main sources of pollution for a given domain (Isakov et al., 2017). This step is defined in literature as source allocation. By 'source allocation' (Thunis et al., 2019) we mean the techniques applied to understand the key contributors to air pollution at a given location. This source allocation then serves as the corner stone to choose the sector or geographical area on which to focus when designing measures for an air quality plan. Following this initial phase, a model can then be run in 'planning mode', to evaluate the impact of specific emission reduction scenarios on air quality.

The problem to use a CTM for source allocation is the long computation time. Hence, the number of sources that can be analysed, both in terms of locations, sectors and precursors is limited. The SHERPA (Screening for High Emission Reduction Potential on Air) approach (Thunis et al., 2016; Pisoni et al., 2017) has been developed with the aim of providing information on source allocation. SHERPA implements a source-receptor relationship approach, to mimic the behaviour of a full Chemical Transport Model. Its main advantage is the important reduction of the computational time required to perform one simulation, in comparison to a CTM. With this approach the impact of emission reductions for many different combinations of sectors, geographical areas and precursors can be determined quickly. This would be impossible with a full Chemical Transport Model due to time constraints.

In this work, we used the SHERPA approach to produce a source allocation for 150 cities in Europe. A SHERPA approximation of two CTMs, CHIMERE and EMEP, was build. With these two SR models the contribution of 100 sector-area-precursor combinations on the concentration in the city centre was determined. We assessed the similarities and differences between these two set of results. Obviously some of the differences are caused by the fact that the two CTM models rely on different formulations and parametrisations but also on the fact that they are use different input data (emissions, meteorology…). The objective of this work is therefore not to assess the sensitivity of the results to a given parameter (e.g. emissions) but rather to assess the overall uncertainty (or better, variability) attached to source allocation.

The paper is structured as follows. We briefly present the two Chemical Transport Model and their set-up in Section 2. We then describe the SHERPA methodology and its assumptions in Section 3. Section 4 details the methodology followed for the source allocation, while the inter-comparison of the results is presented in Section 5. Conclusions are proposed in Section 6.

2. CHIMERE and EMEP Chemical Transport Models: set-up and simulations

In this work, we used two set of model simulations, performed with two of the leading air quality models in Europe: CHIMERE and EMEP. More details on the models can be found in Mailler et al., 2017 and Couvidet et al., 2018 (for CHIMERE) and Simpson et al., 2012 (for EMEP). A brute force source allocation for 150 cities with these models would be too time consuming; instead here we use a training set of about 20 CHIMERE and EMEP simulations to develop a set of SHERPA Source Receptor Relationships (SRR). This SRR set is then used to perform directly the source allocation. Details on the SHERPA training and validation for CHIMERE can be found in Clappier et al., 2015, and for EMEP in Pisoni et al., 2019.

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The CHIMERE and EMEP modelling set-up are different. The key differences between the two modelling configurations are detailed below:

- Grid setting: CHIMERE uses a grid of 0.125 degrees longitude by 0.0625 degrees latitude, corresponding to rectangular cells of more or less 9 by 7 km (in the centre of the domain) whereas EMEP uses a regular grid of 0.1 by 0.1 degrees, corresponding to rectangular cells of more or less 7 by 11 km.
- Emissions: The CHIMERE emission reference year is 2010 with a gridding based on the EC4MACS project proxies (Terrenoire et al., 2015) while EMEP uses a JRC set of emissions (Trombetti et al., 2017) based on 2014 as reference year.
- Boundary conditions: The size of the modelling domains differs. The CHIMERE domain extends from 10.5° East to 37.5° West and between 34° and 62° North while the EMEP domain extends from 30° East to 90° West and between 30° and 82° North.
- Meteorology: The two models use a different reference meteorological year; 2009 for CHIMERE and 2014 for EMEP; both meteorological fields are modelled through the Integrated Forecasting System (IFS) of ECMWF.
- Model Parameterization: Apart from the vertical and/or horizontal resolutions, transport, deposition, chemical processes might be reproduced with different levels of complexity in the two models.

More details on the model simulations and settings can be found in Clappier et al., 2015 and Pisoni et al., 2019. Starting from these results, two set of SRRs have been built to model yearly average PM2.5 concentrations, based respectively on CHIMERE and EMEP data. Before looking at the source allocation results, in the next section a brief description of the SHERPA methodology is proposed.

3. SHERPA methodology

Starting from the simulations performed with CHIMERE and EMEP, two sets of SHERPA source-receptor relationships are built.

Here we briefly summarise how the SHERPA methodology works; please refer to Pisoni et al., 2019 for more details. In the SHERPA approach, the PM concentration change in receptor cell "j" is computed as follows:

$$\Delta PM_j = \sum_{p}^{N_{prec}} \sum_{i}^{N_{grid}} a_{ij}^p \, \Delta E_i^p \qquad (1)$$

where N_{grid} is the number of grid cells within the domain, N_{prec} is the number of precursors, ΔE_i^p are the emission changes, and a_{ij}^p are the unknown parameters to be identified, representing the transfer coefficients between each source cell i and receptor cell j. In SHERPA a_{ij}^p coefficients are cell-dependent, and assume a 'bell shape function'. This bell shape function accounts for variation in terms of distance but is directionally isotropic, and can be defined as follows:

$$a_{ij}^p = \alpha_j^p \left(1 + d_{ij}\right)^{-\omega_j^p} \qquad (2)$$

where d_{ij} is the distance between a receptor cell "j" and a source cell "i". Thus, in SHERPA the matrix of transfer coefficients is known when the two parameters α and ω are identified for a given receptor cell j and a given precursor p (see Equation 2). The final formulation implemented in SHERPA is:

$$\Delta PM_j = \sum_{p}^{N_{prec}} \sum_{i}^{N_{grid}} \alpha_j^p (1 + d_{ij})^{-\omega_j^p} \Delta E_i^p \quad (3)$$

With the SHERPA approach, the key step is so to find the optimal α, ω coefficients. As the number of unknown parameters is equal to 2 (α, ω) for each precursor and receptor cell "j", for the five precursors of PM2.5 (VOC – volatile organic compounds, SO2 – sulphur dioxide, NOx – nitrogen oxides, PPM – primary particulate matter and NH3 – ammonia), ten independent CTM simulations are needed for a given receptor cell. We refer to (Pisoni et al., 2018; Thunis et al., 2016) for additional details about the SHERPA formulation and evaluation process.

Given its cell-to-cell characteristics (Equation 3), the SHERPA formulation can be used to assess the impact of emission reductions over any given set grid cells. Different geographical entities can therefore be freely defined in terms of boundaries, and simulated through SHERPA.

As previously said, in this work the SHERPA approach is used to analyse the differences between two air quality modelling setting, based on CHIMERE and EMEP, referred to in this paper as S-CHIMERE and S-EMEP, respectively.

4. Source allocation methodology

Starting from the S-CHIMERE and S-EMEP SRRs, the aim of this work is to analyse the main contributors to urban pollution in terms of sectors, geographical areas and precursors, as modelled by the 2 modelling configurations. We focus on the PM2.5 yearly average concentrations as target indicator, because PM2.5 is responsible for most of the health related burden in the EU urban areas (EEA 2019). The approach is applied to the 150 cities analysed in the 'PM2.5 Urban Atlas' (Thunis et al., 2018).

As mentioned above, the cell-to-cell characteristics of the SHERPA approach allows the impact of emission reductions over any given set of grid cells to be assessed. Cities, regions or countries can therefore be freely defined in terms of boundaries. Emission reductions can also be freely defined in terms of precursors or sectors. The following single (or combination of) sectors, source areas and precursors are considered.

In terms of sectors, emissions categories follow the CORINAIR SNAP nomenclature:

- Combustion in energy and transformation industries (SNAP 1),
- Non-industrial combustion plants (SNAP 2),
- Combustion in manufacturing industry (SNAP 3),
- Production processes (SNAP 4),
- Extraction and distribution of fossil fuels and geothermal energy (SNAP 5),
- Solvent use and other product use (SNAP 6),
- Road transport (SNAP 7),
- Other mobile sources and machinery (SNAP 8),

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- Waste treatment and disposal (SNAP 9) and
- Agriculture (SNAP 10).

which have been aggregated in this work into five sectors:

- industry (SNAP 1, 3 and 4),
- residential (SNAP 2),
- traffic (SNAP 7),
- agriculture (SNAP 10), and
- others (SNAP 5, 6, 8 and 9).

In terms of geographical sources, four areas are considered for the analysis:

- the core city,
- the commuting zone,
- the rest of the country and
- international (what is outside the considered country).

The commuting zone is defined as that area surrounding the city where at least 15% of the population commutes daily to the core city. The combination of the core city and the commuting zone is referred to as the functional urban area, or FUA[2].

Finally, the precursors considered are NOX, VOC, NH3, PPM and SO2.

This leads to 100 (4 areas x 5 precursors x 5 sectors) runs for each model and city. For small cities (66 out of 150) the core city covers too few grid cells which would lead to discretization errors. In such case the analysis is restricted to the FUA. For these cities, 75 runs (3 areas x 5 precursors x 5 sectors) per city and model were therefore performed. With 150 analysed cities for two CTM models, it is interesting to note that the SHERPA approach allows for a comparison that would have implied 26700 ((66x75 + 84x100) x 2 models) independent air quality simulations with a full Chemical Transport Model. Note that the same amount of runs has been done with the SHERPA simplified model, but with only a few minutes required to perform one scenario. The results for S-CHIMERE were published in the 'Urban PM2.5 Atlas' (Pisoni et al., 2018). For this paper the same runs are done with S-EMEP, and a comparison between the 2 is provided.

Each run performed with the SHERPA SRRs provides a concentration change (ΔC) that results from an emission reduction (ΔE) imposed on a given precursor, for a given sector and within a given area. While the ΔC from SRRs are representative for emission reductions of α=50%, results are then scaled to 100% to obtain the total impact of a given source ($\Delta C/\alpha$). The 50% represents a threshold below which the quasi-linearity of the model responses is preserved, at least when considering yearly average concentrations of PM2.5 (Thunis et al., 2015). In other words, with this approach the model response in terms of concentration change is proportional to the emission change of a given source. It important to stress that this threshold is only valid for PM2.5 and for yearly averages concentrations, as considered here. Because of this 50% threshold, it is also worthwhile to note that the source allocation results discussed here provide information on the impact of potential emission reductions up to that level of 50% (not beyond).

[2]See https://www.oecd.org/cfe/regional-policy/functionalurbanareasbycountry.htm for details.

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The 'relative potential' of a given precursor-sector-area combination is expressed as $\Delta C/\alpha C$, (Thunis and Clappier, 2014). This indicator represents the share of a particular emission source to the concentration. From a policy point of view, high 'relative potential' sources are the ones to be addressed at first to achieve the largest improvements. To compare the 'relative potentials' from S-CHIMERE and S-EMEP, we calculate the correlation between the relative potentials. A high correlation means that both models agree well on the emission sources (sectoral and/or geographic) that contribute most to the concentration for a given city. The main advantage of a correlation indicator is that it ignores systematic differences. In other words, the fact that one model might predict systematically higher concentration changes than the other will not be detected by the correlation metric. This is a desirable characteristic because from the policy perspective, it is the 'relative ranking' among the sources contributions that counts rather than their absolute values.

5. Comparison of the results

In this study we compare the contributions for 150 cities, based on the two SHERPA implementations, S-CHIMERE and S-EMEP. The source allocation is provided for the city location characterised by the worst value of its target indicator (i.e. the most polluted cell in the considered city). We first discuss the results for a few cities, before moving to an EU wide perspective.

Tables 1 to 4 show, for each emission area, sector and precursor, the 'relative potential' for the 2 models (in % of the total concentration, 'chimere_rp' and 'emep_rp') and the resulting ranking in terms of importance ('emep.rank' and 'chimere.rank), for 4 cities, selected to represent different behaviours in terms of SRRs comparison. In addition to this, Figures 1 to 4 show the 'relative potentials' for the 2 models (S-CHIMERE and S-EMEP), for the different types of considered aggregations (area, sector, area-sector, …) and their corresponding correlations, for the same cities.

For Liege (Belgium) the overall (all sectors, precursors and areas included) Pearson correlation between the relative potentials of both models is the highest among the 150 cities (r=0.99, see Figure 1). Both models identify ammonia emissions from agriculture, outside Belgium, as the main contributor to local PM2.5 concentrations. Primary PM from local industry comes second and NOx from international traffic third. Although the lower ranked combinations are not identical, they are quite similar. From a policy perspective, the fact that both modelling applications provide similar information is a sign of robustness. It increases our confidence in the priority of interventions (which sectors-areas to act at first to achieve the maximum air quality improvement) proposed by each model. The values of the different sector-precursor-areas contributions (expressed as relative potentials) are reported in Table 1.

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area	sector	precursor	emep_rp	emep.rank	chimere_rp	chimere.rank
International	Agriculture	NH3	22.9	1	20.6	1
FUA	Industry	PPM	12.6	2	12.4	2
International	Road Transport	NOx	7.5	3	6.9	3
International	Industry	NOx	4.9	5	5.2	4
National	Agriculture	NH3	4.2	6	4.6	5
International	Industry	SOx	5.1	4	2.3	10
International	Residential	PPM	2.2	7	2.5	8
FUA	Road Transport	PPM	2.1	10	2.9	6
International	Industry	PPM	2.2	8	2.4	9
FUA	Industry	SOx	1.9	15	2.7	7
International	Other	NOx	2.2	9	1.9	13

Table 1: Top 10 area-sector-precursor combinations contributing to the PM2.5 concentrations in Liege (B).

A breakdown analysis is proposed in Figure 1 where correlations are expressed for different data aggregations. In addition to the overall correlation (75000 values), values are also proposed for data grouped by sectors (150 cities x 5 sectors), by area (150 cities x 4 areas) or by area/sectors (150 cities x 5 pr3ecursors x 5 pollutants). In the case of Liege, all correlations are consistently very good.

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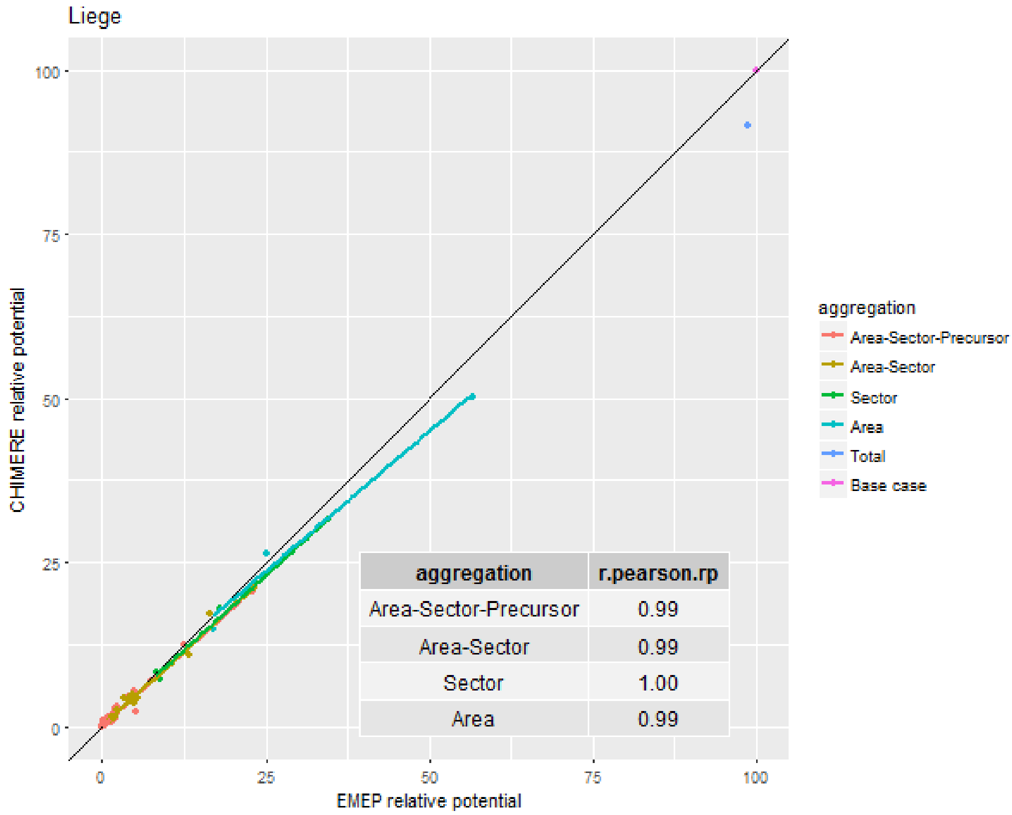

Figure 1: Correlation between relative potentials of S-EMEP and S-CHIMERE for different aggregations in Liege (B).

Unfortunately, the agreement is not always as good. For the city of Genova (Table 2 and Figure 2), both models agree that national/international ammonia emissions from agriculture areas are the largest contributor to local PM2.5 (see Table 2). But the third position in the priority ranking is occupied by NOx from national traffic for S-EMEP while it is PPM from the national residential sector for S-CHIMERE. However, the correlation still reaches 89% and the absolute values of the third ranked sectors are quite close. The agreement between the two models is therefore still satisfactory. It is interesting to note that for relative potentials aggregated per area, the correlation drops to 42%, pointing to differences in the spatial distribution of the two emission inventories.

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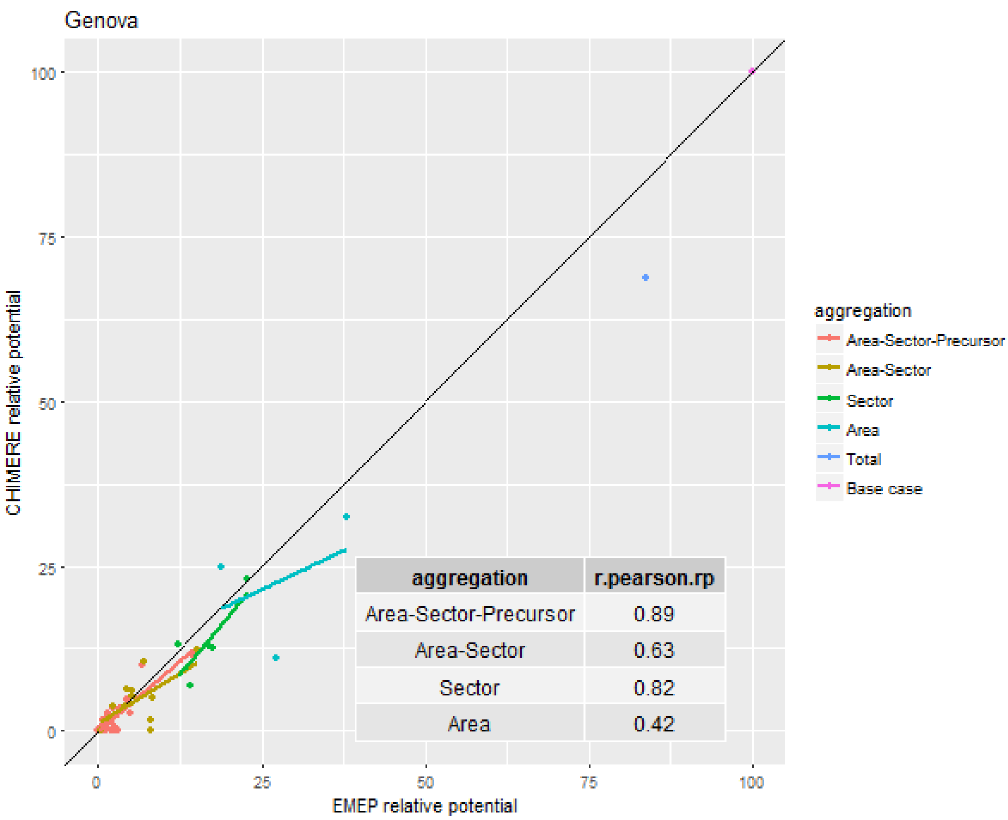
area	sector	precursor	emep_rp	emep.rank	chimere_rp	chimere.rank
National	Agriculture	NH3	14.5	1	11.3	1
International	Agriculture	NH3	6.8	2	10.1	2
National	Residential	PPM	4.3	4	4.7	3
FUA	Residential	PPM	3.2	5	3.5	4
National	Road Transport	NOx	4.9	3	2.6	8
FUA	Road Transport	NOx	3.2	6	2.8	7
International	Industry	SOx	2.2	10	3.4	5
National	Industry	SOx	1.7	15	2.5	9
International	Residential	PPM	1.4	18	2.8	6
FUA	Road Transport	PPM	1.4	17	2.1	10
FUA	Other	NOx	2.5	8	0.7	21
FUA	Industry	NOx	2.4	9	0.0	59
FUA	Industry	SOx	3.1	7	0.0	62

Table 2: Top 10 area-sector-precursor combinations contributing to the PM2.5 concentrations in Genova (IT).



aggregation	r.pearson.rp
Area-Sector-Precursor	0.89
Area-Sector	0.63
Sector	0.82
Area	0.42

Figure 2: Correlation between relative potentials of S-EMEP and S-CHIMERE for different aggregations in Genova (I).

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In the case of Torino (Table 3 and Figure 3), the two models give contradicting recommendations. While S-CHIMERE points to city residential heating as main contributor to PM2.5, S-EMEP points to national agriculture ammonia emissions. The model disagreement extends to the top 5 ranking. As indicated, the problem is probably related to the sectoral (R2=0.78) rather than to the geographical dimension (R2=0.97). Nevertheless, the overall correlation (0.81) is not too bad, and can be explained by the fact that the relative potential values are not too different from each other (although the ranking is quite different).

area	sector	precursor	emep_rp	emep.rank	chimere_rp	chimere.rank
FUA	Residential	PPM	8.6	2	13.3	1
National	Agriculture	NH3	10.6	1	5.9	4
FUA	Industry	PPM	6.4	3	13.3	2
FUA	Road Transport	NOx	6.2	4	4.8	6
National	Residential	PPM	4.9	7	5.4	5
International	Agriculture	NH3	6.1	5	4.2	8
FUA	Industry	NOx	5.2	6	4.7	7
FUA	Road Transport	PPM	2.6	13	8.4	3
FUA	Other	PPM	2.9	12	3.5	10
International	Residential	PPM	2.0	16	4.0	9
National	Road Transport	NOx	4.3	8	1.3	18
FUA	Residential	NOx	3.8	9	1.0	23
International	Road Transport	NOx	3.1	10	0.8	25

Table 3: Top 10 area-sector-precursor combinations contributing to the PM2.5 concentrations in Torino (I).

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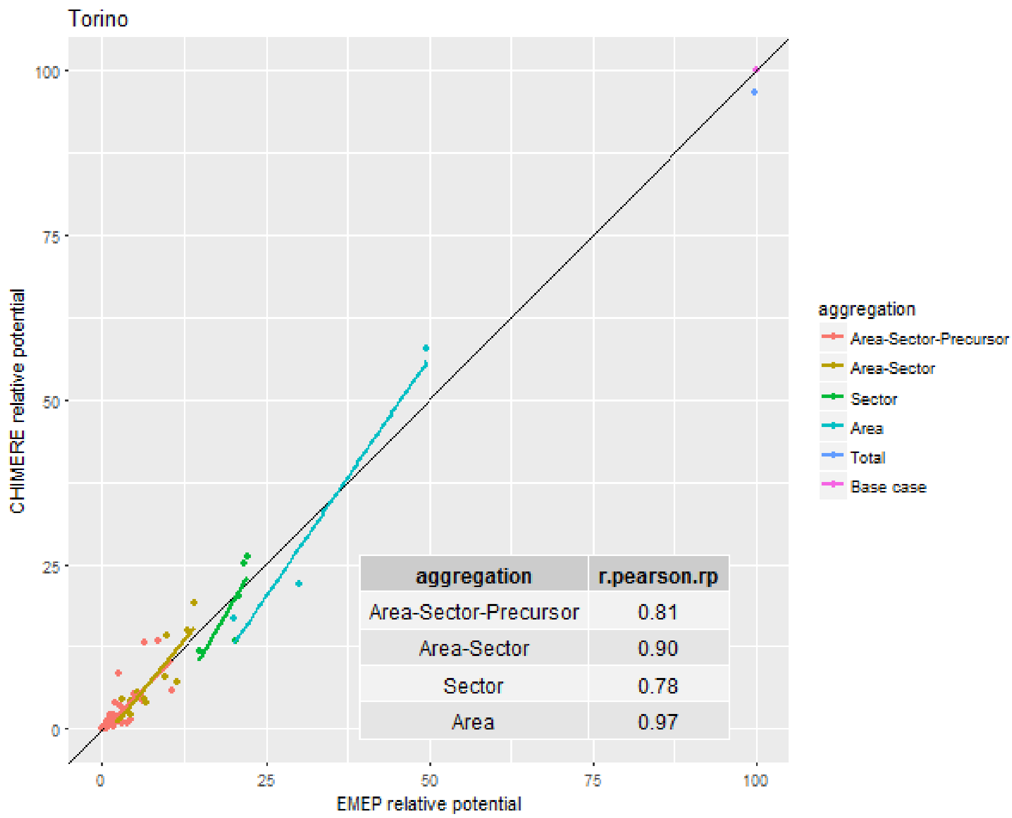

Figure 3: Correlation between relative potentials of S-EMEP and S-CHIMERE for different aggregations in Torino (I).

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In our last example (Madrid - Table 4 and Figure 4), differences are extremely important in terms of relative potentials and ranking, leading to an overall correlation of 41%. All other correlations, with the exception of the spatial ones are extremely poor. Uncertainties for this city are important, and the choice among policy options shows important variability.

area	sector	precursor	emep_rp	emep.rank	chimere_rp	chimere.rank
City	Road Transport	PPM	9.9	2	24.6	1
City	Residential	PPM	6.2	3	8.9	2
City	Other	PPM	2.0	9	5.0	4
National	Agriculture	NH3	2.5	6	2.4	8
Comm	Road Transport	PPM	1.7	11	5.3	3
National	Agriculture	PPM	0.9	13	4.3	5
City	Industry	PPM	2.4	7	1.4	12
City	Other	NH3	2.3	8	1.8	11
Comm	Residential	PPM	1.0	12	2.3	9
City	Industry	SOx	25.4	1	0.8	21
City	Road Transport	NOx	0.8	16	2.7	6
City	Residential	SOx	4.7	4	0.9	20
National	Residential	PPM	0.7	18	2.4	7
National	Road Transport	PPM	0.8	15	2.2	10
National	Industry	SOx	1.8	10	0.8	22
Comm	Industry	SOx	2.8	5	0.4	28

Table 4: Top 10 area-sector-precursor combinations contributing to the PM2.5 concentrations in Madrid (E).

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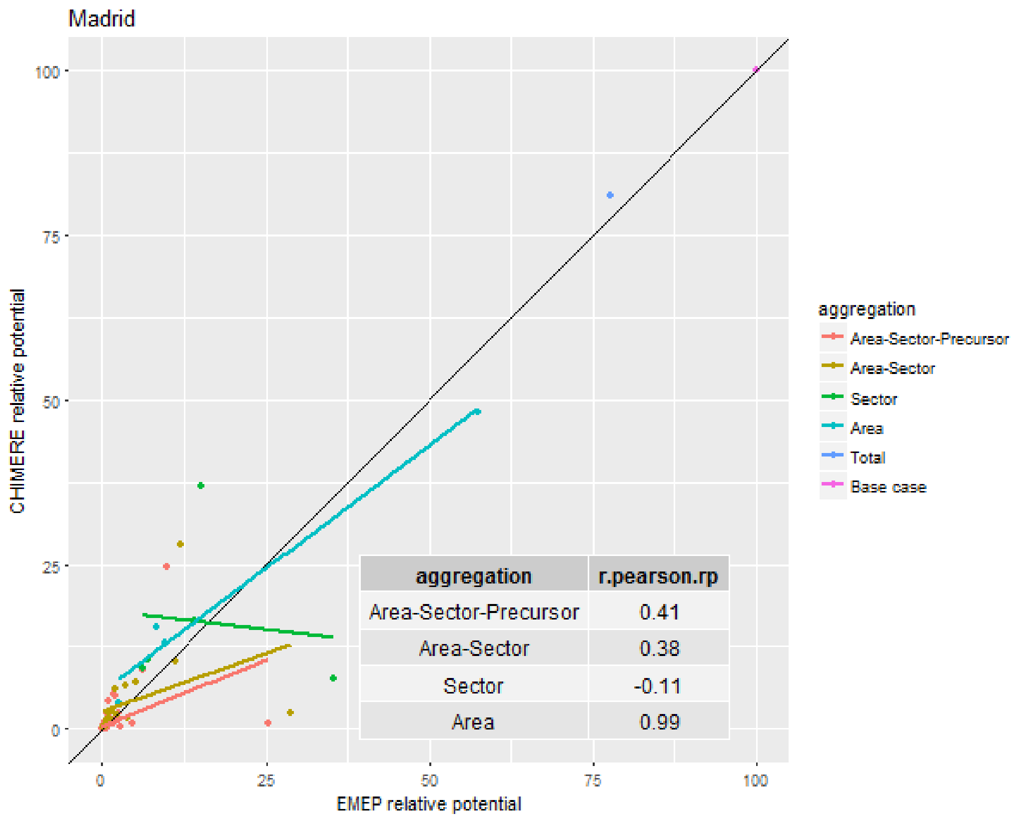

Figure 4: Correlation between relative potentials of S-EMEP and S-CHIMERE for different aggregations for Madrid (E).

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As seen from the city example presented above, we can have both strong (Liege) and weak (Madrid) agreement between the 2 modelling set-up.

Let's now see what comes out when we extend this analysis to all 150 cities, looking at the results in an aggregated view. From the city results, to define if the two modelling applications provide similar responses, we will consider an overall correlation above 95% as very good, between 90 and 95% as good, between 85 and 90% as fair, between 70% and 85% bad and below 70% very bad. This is an arbitrary choice, but can be useful to start grouping and classifying the results. The histogram of the overall correlations for all 150 cities (Figure 5:) shows that the model agreement is good or very good for about half of the cities, satisfactory for another 21%, leaving 32% of doubtful/problematic cities.

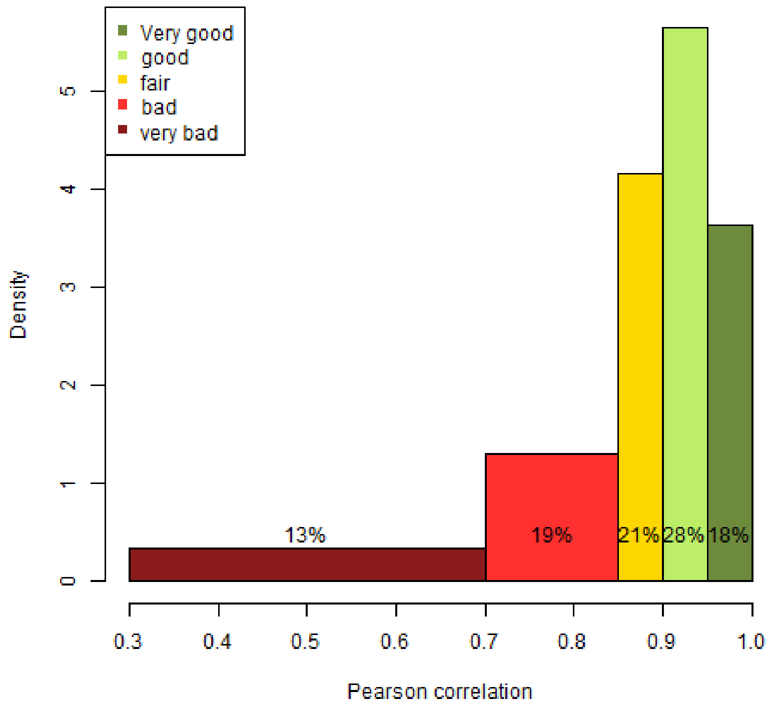

Figure 5: Distribution of the Pearson correlation coefficient between relative potentials, for 150 cities.

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The overall correlation map of Europe (Figure 6) shows that cities with the highest variability are mostly located in Spain, Northern Italy as well as the Baltic countries. Probably for these areas the differences in terms of meteorology, emissions, and their impact on concentrations through the air quality models, is higher than in other areas.

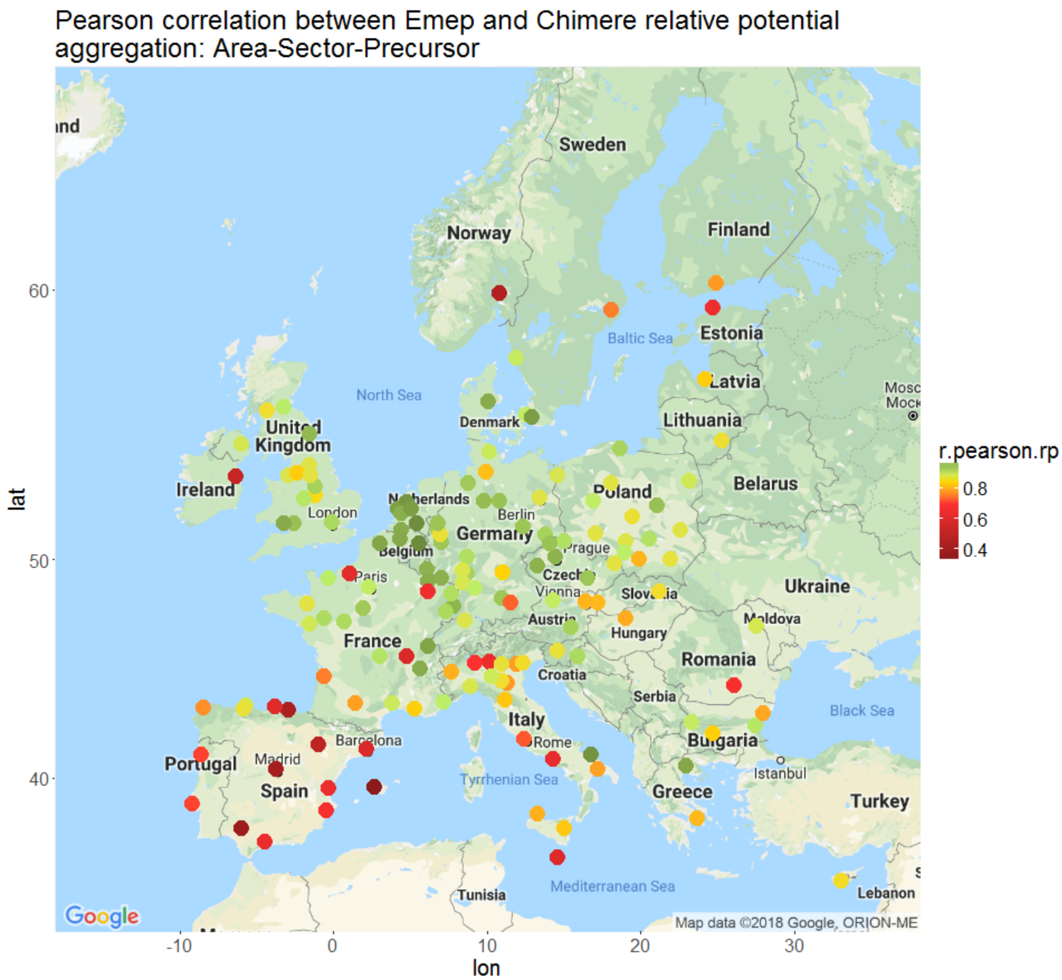

Figure 6: Pearson correlation between EMEP and CHIMERE relative potentials.

To the knowledge of the authors, this is one of the first attempts to systematically compare the sources and causes of pollution in European cities, using a harmonized approach. The reasons for these differences between cities are however not easy to identify. This is because the SRRs used in this study are based on different meteorological years (2009 vs 2014), emissions (2010 vs 2014) and air quality models (CHIMERE vs EMEP). So, even if this analysis provides an overall estimate of the variability of policy responses, it does not allow us to identify a specific cause for the observed differences.

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However, this situation (that is to say, the use of different input and model set-up) represents usual practice whenever air quality models are used at the local scale to assess the impact of air quality plans. Indeed, local/regional authorities generally use only one given set of data, applying a particular model, due to a lack of resources and information. Therefore, only a given meteorology, a given emission inventory for a given reference year and a specific model are used to identify the sources of pollution to target. How this choice influences the results and the subsequent design of an air quality plan is an issue that is often not tackled.

It is probably unreasonable to think that a local authority can evaluate in a comprehensive way the variability of a particular modelling pathway (too much demanding). We however believe that further guidance should be provided to select the proper modelling set-up (choice of meteorological year, emission, model to use) to reduce the uncertainty attached to the results and increase their robustness.

The final goal of this work would be to help decision makers to properly define key sources, so that only 'no-regret' policies are selected. As mentioned above, the present work aims to quantify this variability but it cannot provide explanations for the observed differences. The only process to identify the causes of differences, is to perform regular inter-comparison exercises where the responses of models to emission changes are systematically tested via sensitivity analysis. While exercises of this type occurred in the past years (Colette et al., 2017, Cuvelier et al., 2007, Pernigotti et al., 2013), it is crucial that these are performed on a regular basis as models and input data continuously evolve.

6. Conclusions

Before applying emission reduction measures to improve air quality, it is important to evaluate the importance of the key sources contributing to pollution in a given area. The main methodology to perform this task is referred to as 'source allocation'.

Source allocation can be implemented in various ways. In this paper we use the SHERPA model, a source-receptor relationship mimicking the behaviour of a fully-fledged CTM. With SHERPA one can perform hundreds of simulations in few minutes to test the impact of various geographical, sectoral or precursor-based emission sources, on the concentration at a point of interest. The result is a complete source-allocation study for a given domain explaining the key sources of pollution for a given area.

In this work, we developed two SHERPA versions, based on two modelling set-up using different meteorological reference year, emission inventories and air quality models. Even if these setting are quite different and difficult to compare, they represent what happens in the real-world when designing air quality plans. In fact, different local authorities in Europe are free to use different reference meteorological years, emissions and models. The comparison of these results therefore provide an estimate of the variability attached to source allocation results for a given area.

The two SHERPA SRRs versions (based on CHIMERE and EMEP) have then been used to perform source allocation on 150 main cities in Europe, and results have been presented in terms of priorities of interventions (i.e.: which are the sector/geographical areas/pollutants that are more relevant for air quality in a given city?).

The results are for some cities consistent (changing the modelling set-up we get the same ranking in terms of priorities), while for other cities (a minority) the two SRRs deliver different results. Even if it is not possible in this work to identify the causes for these differences (as the two modelling set-ups are too different) the paper shed light on the fact that one can get quite different ranking of sectors-areas depending on the modelling set-up considered. This is quite logical (different assumptions will deliver different results) but at the same time it is an important issue to be underlined. As this is the current practice in air quality modelling for planning in Europe (in fact one can freely choose meteorological reference years, emissions, models, when building a plan) we conclude that further guidance is needed to understand how to properly define this modelling set-up; and to understand how this choice could impact the selection of priorities for intervention and the variability of the results.

Thanks to the limited number of required simulations to build SHERPA, future work could envisage the implementation of 'constrained setting' to build SRR (i.e. keeping the same air quality model but changing emissions, or keeping the same emissions but changing the model) to be able to discriminate on the relative contributions of the different factors involved. Also, further model inter-comparison works should be fostered.

Code and data availability

The code and data used to perform the analysis presented in this paper is available at https://github.com/enricopisoni/SRR_comparison (Last access: 7th of April 2020). The SHERPA model, providing the source-receptor relationships applied in this paper, is available at https://aqm.jrc.ec.europa.eu/sherpa.aspx (Last access: 7th of April 2020).

Authors contribution

BD developed the methodology, performed all the analysis and drafted a first version of the paper. PT conceived the initial development of SHERPA, and contributed to the structuring and revision of the paper. EP developed the SHERPA tool, contributed to the interpretation of the results and to the preparation of the final version of the paper.

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