Who decides what: Spatial issues in environmental decisions

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Abstract: An integrated modelling approach is used in this work to assess the differences in defining air quality policies in spatial domains of different extensions. The tools used, SHERPA and RIAT+, are public domain and allow to rapidly define the emission scenario of the European area under examination and to solve a multi-objective problem to trade-off air quality improvement versus the costs of implementing the pollutant abatement measures. The territory considered is Northern Italy and the pollutant analysed in PM2.5, which is largely of secondary origin. The study demonstrates the importance of a proper definition of the administrative and physical boundaries of the air pollution problem, which may determine higher costs when the correct scale of decisions is missed.

Keywords: Integrated modelling; air quality; multi-objective optimization; Po Valley; PM2.5

1. INTRODUCTION

Environmental problems, such as the management of natural resources, are not usually constrained by administrative boundaries, which have been set in the past for historical reasons. This is the case, for instance, of international river basins where the decisions taken from an upstream country may heavily affect the downstream riparian states. The harsh and long lasting dispute about the construction and management of the Great Ethiopian Renaissance Dam on the White Nile in the Ethiopian territory is opposed by Egypt that has been historically the main user of Nile flow and receive its water thousands of kilometers downstream (Tekuya, 2021).

On a smaller scale, this issue is common in air quality since air masses move easily across administrative borders, particularly when they were defined across rivers and not only on the mountain top. This is a common problem in Europe where, for instance, the French region of Alsace is heavily influenced by the activities across the German border (Skea and Du Monteuil, 2019) or the so-called Black Triangle where the pollutant emissions of Germany, Poland and Czechia mix to produce one of the worst air quality condition in Europe (Grennfelt et al., 2020). The first Convention on Long-Range Transboundary Air Pollution (LRTAP) signed in Geneva in 1979 testifies on how this problem has been on the governments' agenda since long.

When dealing with a decision problem, such as an air quality plan, the issue of the boundary conditions can be critical: what can an environmental authority assume about the decisions of the neighboring territories that influence its local air or water quality? What are the administrative limits of its decisions, and how their effects expand to other areas outside its jurisdiction? Physically based modelling can handle the problem from the mathematical viewpoint. The correct boundary conditions set up for a certain territory is generally addressed in air pollution studies by fixing the pollutant concentrations as far as possible from the region under analysis. To avoid an overwhelming computational effort and necessity of data, the issue is normally tackled by nesting (Pedruzzi et al., 2019). This means a large domain is modelled using a very coarse discretization; its results are used as boundary conditions of a smaller and finer model, and finally, the results of the latter are used for the boundaries of the detailed model of the territory under analysis (see, for instance, Lu et al., 2019; or Carnevale et al., 2014). This approach can partially solve the physical problem but it does not answer the decision problem questions, which can be addressed only by repeating the study with different physical and administrative domains.

This paper illustrates the issue using the example of four regions in Northern Italy that share a common air basin, almost corresponding with the Po River catchment (the so-called Po Valley). Its central part is a flat agricultural and industrial area, where the stagnant atmospheric conditions are well known to generate high air pollution values. Particulate matter, particularly PM2.5, represents a critical pollutant in the area and the main cause of detrimental health effects to the about 15 million people living there.

The case study is dealt with using an integrated modelling approach that allows exploring the different outcomes of decisions taken individually by each region and by all the regions together. The components of the integrated model are briefly described in the next section, which then formulates and solves the two decision problems. Section 3 presents the main data used in the study, and section 4 shows and discusses the results obtained. Section 5 draws some conclusions and proposes some future development of the study.

2. MATERIALS AND METHODS

An integrated assessment suite composed by two open-license tools has been used in this work (see Fig. 1). SHERPA v2.1 (Screening for High Emission Reduction Potential on Air tool - https://aqm.jrc.ec.europa.eu/sherpa.aspx) provides the input data needed to implement a multi-objective optimization problem with RIAT+ (Regional Intergrated Assessment Tool + http://www.riatplus.eu/html/eng/home.html).

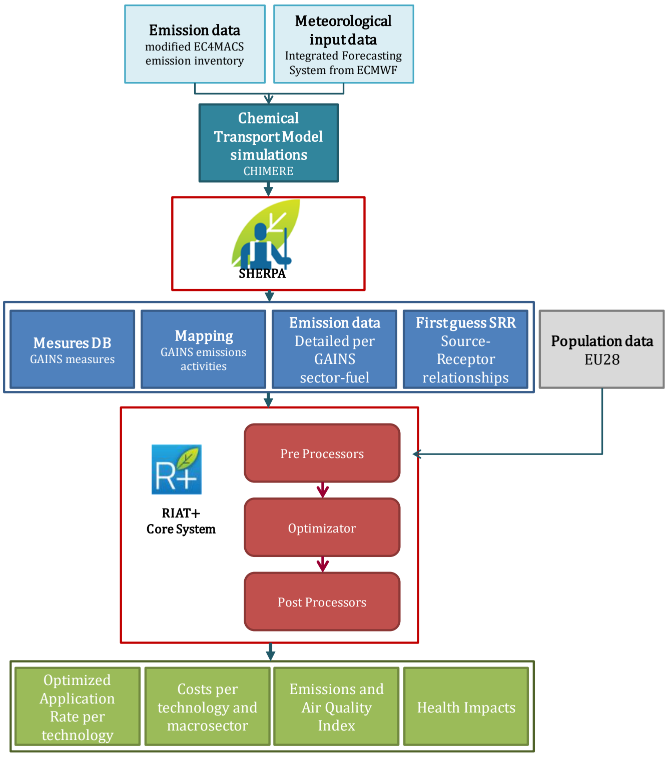

Figure 1. Integrated Assessment System composed by SHERPA v2.1 and RIAT+.

2.1 SHERPA

SHERPA v2.1 is a Java/Python tool (Thunis et al., 2016; Pisoni et al., 2019) developed by the EU Joint Research Center. It allows a quick exploration of potential air quality improvements resulting from emission abatement measures defined at national, regional or local level. The tool may be used to support environmental authorities at different administrative levels in the design and assessment of air quality plans.

SHERPA includes a set of source/receptor relations (surrogate models), which approximately relate the local emissions to concentrations in each cell of the domain under analysis, and a data base of the most important abatement measures that can be applied in each country. It can thus provide a first guess of the effects of local emission reductions with a minimum computational effort. It is available with EU-wide data on main pollutant emissions (nitrogen oxides - NOx, volatile organic compounds - VOC, ammonia - NH3, primary PM10 and PM2.5, sulfur dioxide - SO2) with a spatial resolution of roughly 7x7 km^2, so that it allows working on domains of different sizes and location in Europe. Using such information, it can perform scenario analyses that answer questions related to the effects of local abatement actions, the efficiency of the different local measures, the differences between applications of measures at different scales.

2.2 RIAT+

RIAT+ (Carnevale et al., 2012; Relvas et al., 2017) is the Regional Integrated Assessment Modelling tool developed within the OPERA project (LIFE09 ENV/IT/000092). It has been designed to help decision makers in determining optimal regional air pollution reduction policies that improve air quality at minimum costs. This means it solves a multiobjective problem whose decision variables are the measures to be implemented and whose solution is a set of non-dominated choices (the Pareto front) showing the maximum improvement in air quality that can be reached with a given investment in the implementation of abatement measures. To achieve this, the system incorporates the specific features of the area of interest through an input dataset with the:

- Precursor emissions of local and surrounding sources
- End-of-pipe abatement measures described per activity sector and technology with information on application rates, emission removal efficiency and cost
- The effects of meteorology, boundary conditions and prevailing chemical regimes using site-specific source-receptor functions.

The surrogate models can be as simple as a linear relationship, or as complex as a chemical transport model. To limit the computational time, RIAT+ currently uses linear regression models (provided by SHERPA) or nonlinear relations identified by means of Artificial Neural Networks (ANNs). These must be tuned to replicate the output of a limited number of simulations, previously performed, usually with deterministic chemical and transport model (CTM) calibrated for the specific site. One key feature of the tool is that the surrogate models directly determine the value of an air quality index (*AQI*) without computing intermediate concentration values (i.e., the output of the CTM). Indeed, examples of possible *AQIs* are average yearly concentrations of various pollutants as well as the well-known SOMO35 or AOT40 values used to evaluate ozone dynamic. The selection of the suitable *AQI* for a given problem should be guided by its relation with the known impacts that air pollution causes to society (e.g., health problems, crop reduction, and damages to structures). For instance, considering yearly average PM2.5 concentration in a territory allows estimating the effects on the mortality and morbidity of the resident population, through the standard health impact approach.

The main outputs of RIAT+ are the Pareto front providing the efficient solutions of the AQI ranked by costs; a summary of the application rates of the different measures and corresponding emission reductions for any selected point of the Pareto curve; the geographical maps of the selected AQI, and of the concentrations and emissions for the different pollutants.

2.3 The decision problem

As anticipated, the decision problem that the regional authorities should solve is formalized as a two-objective optimization that minimizes at the same time the selected *AQI* and the costs *IC* of implementing a set of emission abatement measures. These are the decision variables *z* of the problem and may represent either the measures taken individually by each region or those jointly decided over the entire Po Valley. Both the components of the objective *J* are function of these abatement measures, the *AQI* being the result of an emission scenario (*E*) that depends on *z*. So:

$$\min_{z} J = \min_{z}[AQI(E(z))\ IC(z)] \tag{1}$$

Subject to $z \in Z$.

Z represents the set of feasible actions, which in general differs in the various territorial domains.

The *AQI* assumed in the following is the population-weighted yearly mean PM2.5 concentration over the considered territory, which is well-known to be linked to the main health indicators of a population such as the mortality, measured in terms of years of life lost (YOLL). Indeed, this *AQI* weights more the PM2.5 concentration where population is denser, i.e., in the urban centres, while the values computed outside the towns become almost irrelevant. Its determination is particularly challenging since the main portion of this pollutant is of secondary origin, meaning that it forms in the atmosphere due to the chemical and physical reactions of precursor gases. The reduction of PM2.5 thus implies adopting suitable measures not only to abate primary particulate matter, but also nitrogen oxides and volatile organic compounds such as methane.

More precisely, the emission of a (precursor) pollutant p in a cell d of the considered spatial domain is computed as:

$$E^p(d) = \sum_{a \in A}\left[AL_a(d) \cdot ef_a^p \cdot \left(1 - \sum_{t \epsilon T} re_t^{a,p} \cdot z_t^a\right)\right] \tag{2}$$

where,

- $AL_a^p(d)$ is a measure (usually in terms of energy consumption) of the activity a taking place in cell d;
- ef_a^p is the emission factor of pollutant p for activity a; namely, the amount of pollutant emitted per unit of energy used in that activity;
- $re_t^{a,p}$ is the reduction of emission of p that can be obtained by applying technology t to activity a;
- z_t^a is the decision variable, i.e., the degree of application (between 0 and 100%) of technology t to reduce the emission of activity a.

Eq. 2 states that only the so-called end-of-pipe abatement measures have been considered (D'Elia et al., 2018) and thus no change of the activity level can take place. This means that the residential and industrial structure of the territory is assumed to remain constant (i.e., no change in the use of energy) and emission reductions are obtained by applying emission filters or similar process modifications. It is also assumed that the effects of applying more than one abatement technology are additive and that the same activity is subject to the same reduction over the entire territory. This means, for instance, that the residential buildings apply a given technology, say condensing boilers, in the same proportion *z*, wherever they are. It is indeed a strong assumption that can be more acceptable when the area involved is limited and thus fairly homogeneous. The assumption is more difficult to accept when the considered territory is large and involves a variety of conditions.

3. THE PO VALLEY STUDY

The Po Valley area considered in this study is shown in Fig. 2. This area is often affected by high pollutant concentrations because of the orography and the local meteorology (low wind speed, temperature inversion) leading to the air stagnation (Caserini et al., 2017).

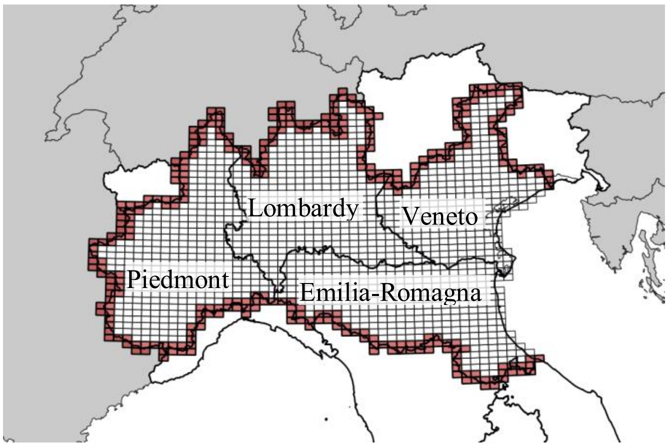

Fig. 2 also shows the 7 x 7 km^2 cell discretization and the boundary elements (in red) of the domain. Each cell is characterized by the presence and value of different activities, whereas the emission factors, the abatement efficiency, and the decision (so-called, application rate of the technology) are common to the domain under consideration. The surrogate models that represent the link between the local emissions and the corresponding value of the *AQI* is also specifically estimated over each cell of the considered domain (Pisoni et al., 2017). Note that, since the surrogate model embeds in some way the effect of the domain boundary conditions, the boundary problem does not enter explicitly into the optimization problem defined by eqs. (1)-(2).

The efficient solutions that minimize both costs and *AQI* are obtained by the classical constraint method (fix the value of an objective and optimize the other, then parametrically vary the first value). The set of all these solutions forms the so-called Pareto front, which thus constitutes the result of the optimization. Pareto fronts obtained on every domain are plotted in the objective space (costs vs. *AQI*), showing the trade-offs between air quality and implementation costs. In order to make the decisions over each region comparable with those taken on the overall Po basin, the following procedure is applied.

- An efficient point of the Po Valley Pareto front is selected.
- The costs and *AQI* corresponding to each region is extracted from the scenario.
- The costs to be borne by each region to obtain the same *AQI* by acting individually are determined.
- The *AQI* obtained by each region when investing the costs determined above is computed.

4. RESULTS

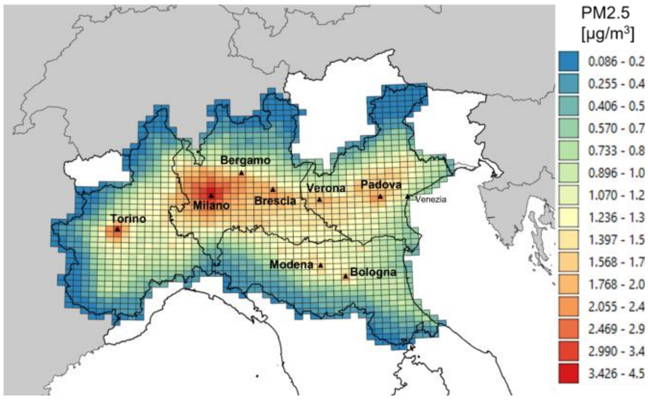

Figure 5. Spatial distribution of the PM2.5 concentration reductions. The strongest reductions are on the urban centers.

Fig. 3 (left) presents the Pareto front obtained for the Po Valley. It is compared with a similar figure (Fig. 3, right) where the simple average spatial concentration of PM2.5 is used as *AQI*. The annual costs on the horizontal axes of the graphs are computed as additional costs besides those required by the application of local, regional, national and European policy in force in 2020. The adoption of the measures required by the Current Legislation scenario or CLE2020 thus corresponds to zero cost in the graphs. While the two curves in Fig. 3 are clearly similar, the values on the vertical axis differ significantly. Indeed, the application of 2020 current legislation corresponds to an average spatial value of about 15 µg/m^3, and the population-weighted average is almost 19 µg/m^3, which clearly indicates that the most dangerous air conditions are found over urban centers. Fig. 4 reports the values corresponding to the four separate regions with Lombardy alone on the right since both the values on the horizontal (cost over CLE) and population-weighted

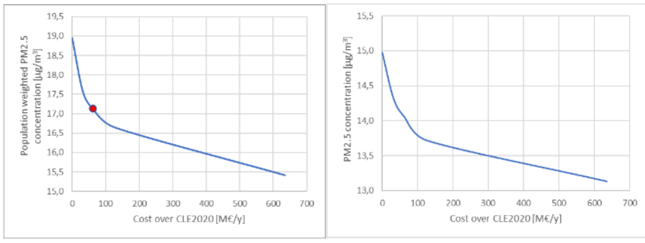

Figure 3. The Pareto fronts of the Po Valley domain: population weighted (left) and simple spatial (right) average PM2.5 concentration.

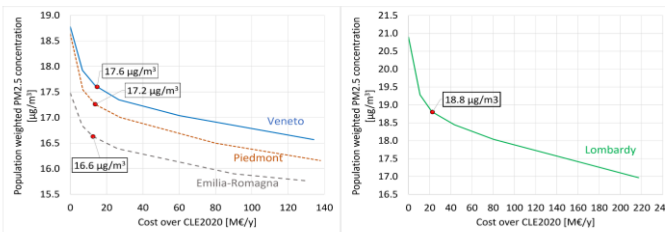

Figure 4. The Pareto fronts of the separate regional domains: Veneto, Piedmont, Emilia-Romagna (left) and Lombardy (right).

concentration are definitely higher. The population-weighted CLE in Lombardy reaches a value of about 21 μg/m^3 definitely higher than the other regions, because of both the highest density of the population and the highest concentration of pollutants.

Domain	Cost [M€/y]	*AQI* improvement	
		coordinated	regional
Po Valley	*63.7*	*9.7%*	
Piedmont	13.7	9.3%	4.5%
Lombardy	22.6	13.8%	10.0%
Veneto	14.8	9.7%	6.3%
Emilia-Romagna	12.5	11.8%	7.4%

Given the set of efficient policies corresponding to the front in Fig. 3, a specific point is selected with the criterion of maximum curvature of the Pareto front. It corresponds to the situation of maximum trade-off of both objectives, i.e., improving one objective would entail the strongest decrease of the other. This policy has an implementation cost of 63.5 M€/y and an *AQI* reduction of 1.9 μg/m^3 (9.7%) with respect to the application of CLE. Fig. 5 shows the effects of the application of such policy over the Po Valley in terms of reduction of PM2.5 concentrations with respect to those

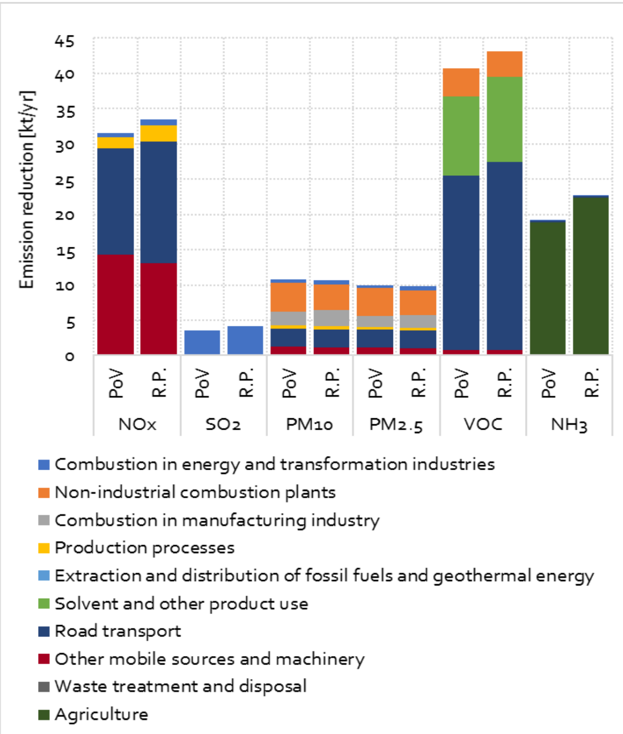

Figure 5. Precursor emission reductions per macrosector needed to implement the coordinated policy (PoV) and the regional ones (R.P.).

corresponding to CLE. It clearly appears that the strongest reductions correspond to the denser urbanization around the main towns. In the red area around Milan, the average yearly reduction exceeds 4 μg/m^3.

To compare the above result with those that can be obtained by individual regional actions, it is necessary to split the total cost into separate regional terms. This is achieved by evaluating the costs related to each cell and summing up those pertaining to each region. When a cell belongs to more than a single region, its costs are split in proportion to the surface belonging to the different regions. Again Lombardy has the highest cost share with over 35% of the total. These costs are used to compute a cost-effectiveness optimization on each region to observe which are the consequences of a region working alone and investing the same budget needed for the Po Valley optimization. The results of this comparison are shown in Table 1 where the *AQI* improvements (with respect to CLE) are reported both when adopting the common policy over the Po Valley and when each region invest the same budget in an individual, uncoordinated policy. The impacts on the Air Quality Index clearly increase when there is a coordinated effort in tackling air pollution. PM2.5 concentration reductions increase of 3.8%, 4.4%, 4.8% and 3.4% respectively in Lombardy, Piedmont, Emilia Romagna and Veneto. Again, Lombardy obtains the largest improvement from a coordinated policy. However, this is true for all the regions: the coordinated policy allows for a better air quality with the same investment by each region.

In quite the same way, one can fix a desired *AQI* result (third column of Table 1) and minimize the cost needed to achieve that *AQI* with actions taken individually by each region. The result of this calculation shows that the total cost would increase to 69.95 M€/y (+3.3%) with the increase practically paid by Lombardy, whereas the cost increase of the other region would be very low.

Fig. 5 shows the reductions of precursor pollutant emissions that must be implemented in case of the coordinated policy on the Po Valley (PoV) and of the separate Regional Policies (R.P.) that achieve the same results in terms of air quality. The emission of PM2.5 precursors are subdivided into the classical SNAP macrosectors. The strongest reductions concern NOx, VOC and ammonia, with the first two mainly due to traffic (SNAP macrosector 7) and the latter to agriculture (macrosector 10). Interestingly, it seems that actions for the reduction of primary particles are not so relevant, and do not differ with the spatial dimension of the reduction plan.

Table 1. Cost over CLE2020 and impacts on air quality of the implementation of coordinated and individual regional policies.

As to the reduction distribution among the regions, Fig. 6 shows those required to implement the coordinated policy. Again, Lombardy should implement the strongest reductions, for all pollutants, including VOC emissions in the solvent industry (macrosector 6). It must be noted, however, that CLE2020 emissions for Lombardy are much higher than those of the other regions and the mentioned reductions are of the order of 10-15% of the current values, a percentage that is similar for the other regions.

The key technology to be implemented are:

- Electrostatic precipitator in industry
- Biomass improvement in residential heating
- EURO VI for heavy duty and EURO 5 for diesel light duty vehicles
- Stage 2 and stage 3 on motorcycles

- Low ammonia application in livestock
- Stage 4 on construction and agriculture sources
- Use of water based coating (leather coating)
- Solvent free powder coating in industrial paint

The analysis can be further detailed by transforming the local concentrations into health impact on the resident population according to the classical health impact approach (Bickel et al., 2005.). Table 2 shows the estimated reduction in mortality values measured in terms of Years of Life Lost (YOLL) on the population of the various regions. It is worth noticing that, despite the improvement of the Po Valley policy with respect to CLE2020 is limited to slightly more than 1 μg/m^3, it corresponds to over 250 additional years of life lost by the population every year just because of the high PM2.5 concentrations.

Table 2. Mortality reduction with respect to CLE2020 of the Po Valley policy.

Domain	Mortality [YOLL/y]
Piedmont	40
Lombardy	109
Veneto	59
Emilia-Romagna	45

5. CONCLUSIONS

The use of an integrated modelling system, such as that formed by the SHERPA and RIAT+ tools, allows addressing rather rapidly a set of complex air quality problems thanks to the availability of all necessary data over the territories of the European Union. In particular, it is possible to examine the difference in addressing problems at different spatial scales that correspond in many cases to different levels of decisions.

For the specific situation of the Po Valley, it was demonstrated that a coordination between the regional authorities, which are responsible for air quality in the Italian legislation, might produce better results than policies decided independently by each region. This means the possibility of sparing the implementation costs of abatement measures and/or reducing the average PM2.5 concentrations particularly in urban centers. The study shows, however, that these differences are mainly in the central area of the domain (Lombardy) partly because the assumptions used at the boundaries (constant concentrations) prevent relevant changes in the outer regions. This demonstrates that the definition of the spatial decision domain plays a key role in actual air quality problems and poses a number of interesting political questions. How can decisions involving territory outside an administrative jurisdiction be taken? Should new decision levels be defined? How could benefits and costs be subdivided?

The integrated modelling package can help explore the answers to these questions by allowing splitting all results into the detailed contribution of each territory, determining the most significant pollutants and macrosectors, and going down into the specific set of measures to be applied. Finally, it can interpret the concentration results in terms of their impact on the population measured as average number of life-years lost.

Finally, it is important to highlight that all the end-of-pipe measures considered in this work can modify only marginally the air quality conditions of the Po Valley where we expect average annual values around 20 μg/m^3 in some areas. To reach better values we need to implement other types of measures that partially change also the current activity pattern.

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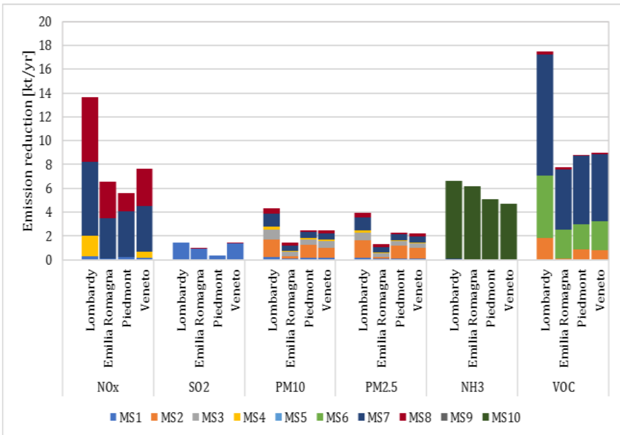

Figure 6. Regional precursor emission reductions per macrosector needed to implement the coordinated policy.

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