ACADEMIA ENGINEERING

Research Article
Published: 2023-11-28
https://doi.org/10.20935/AcadEng6149

# Assessing air pollution emissions vs. abatement costs in agricultural practices

Michele Francesco Arrighini[1], Giorgio Guariso[2], Marialuisa Volta[3], Laura Zecchi[1,*]

Academic Editor(s): Muhammad Sultan, Kuok Ho Daniel Tang

## Abstract

Agriculture is a vital component of human civilization, providing food, fiber, and fuel for billions of people worldwide. However, the agricultural sector has also been identified as a significant contributor to air pollution. This study investigates and analyses the impact of agrofarming activities on air pollution in very productive areas such as Northern Italy. It explores the various sources and mechanisms through which agriculture affects air quality compared to all the other emission sectors and the types of pollutants involved, and quantifies the consequences for human health of agricultural emissions. As a further and novel step, it highlights the technologies that can mitigate these negative impacts and promote sustainable agriculture by adopting an integrated assessment modeling approach. This study defines policy recommendations for the area at hand, determining the optimal compromises between air quality improvement and pollution abatement costs. For instance, it shows that it is possible to reduce the average PM2.5 concentration by 17% with an annual expenditure of 300 M€. Four percent of this improvement is due to end-of-pipe abatement measures in the agricultural sector. Such an improvement in air quality would translate into a reduction of tens of thousands of years of life lost by the resident population. This study concludes with an outlook of additional options for addressing the air pollution challenges associated with agro-farming activities that constitute a limit of the current study, but could open new research lines.

**Keywords:** *agrofarming activities, emission abatement, particulate matter, integrated assessment modeling, surrogate models, Northern Italy*

**Citation:** Arrighini MF, Guariso G, Volta M, Zecchi L. Assessing air pollution emissions vs. abatement costs in agricultural practices. *Academia Engineering* 2023;1. https://doi.org/10.20935/AcadEng6149

## 1. Introduction

Agriculture is the backbone of global food production and a fundamental component of human society. It provides billions of people worldwide sustenance, livelihoods, and economic stability. However, as agriculture has evolved and intensified to meet the demands of growing global population, it has also generated a number of detrimental effects, as recently reported by the FAO [1], and in particular, it has become a significant contributor to air pollution [2, 3]. Air pollution, on the other side, is a pressing global environmental issue with adverse consequences for human health, ecosystems, and climate [4–6]. It encompasses a wide array of pollutants, including particulate matter (PM), volatile organic compounds (VOCs), ammonia ($NH_3$), and nitrogen oxides (NOx). The origins of air pollution are multifaceted, with agriculture constituting one of the principal sectors responsible for these emissions [7]. The various activities associated with agrofarming, including crop cultivation, livestock farming, and the use of machinery, fertilizers, and pesticides, lead to the release of a range of pollutants into the atmosphere [8–10]. Agriculture, in particular, emerges as the primary contributor to ammonia emissions [11], a gaseous compound that plays a significant role in the genesis of fine particulate matter PM2.5 [12]. Within the atmosphere, gaseous NH3 interacts with aerosols with sulfuric and nitric acids, culminating in the production of particles such as ammonium nitrate and ammonium sulfate [3]. A chain thus exists linking NH3 emissions, the formation of PM2.5, and the subsequent repercussions of PM2.5 on human health. To disrupt this chain, or at the very least substantially mitigate the associated impacts, a primary approach is the reduction of potential NH3 emissions.

This problem is particularly relevant in countries with intense and widespread agricultural activities [13]. One example is the Netherlands, which has a highly intensive agricultural sector focused on livestock farming. The Ministry of Agriculture has recently implemented a comprehensive approach to address ammonia-related environmental damage, such as the formation of fine particulate matter and acid deposition. This includes implementing strict regulations on livestock housing and manure management to reduce ammonia emissions, encouraging the use of low-emission barn systems and manure processing

[1]Dip. Ingegneria dell'Informazione (DII), Università degli Studi di Brescia, Brescia, Italy.
[2]Dip. Elettronica, Informazione e Bioingegneria (DEIB), Politecnico di Milano, Milan, Italy.
[3]Dip. Ingegneria Meccanica e Industriale (DIMI), Università degli Studi di Brescia, Brescia, Italy.
*email: laura.zecchi@unibs.it

technologies, promoting precision agriculture to reduce fertilizer use and ammonia emissions, and collaborating with farmers to adopt emission-reducing practices while maintaining agricultural productivity. These efforts have significantly reduced ammonia emissions in the Netherlands, improving air quality and environmental conditions [14].

This study analyses the situation of an area, Northern Italy, that resembles the Netherlands for the intensity and importance of agrofarming activities. It aims to quantify the trade-offs between air quality and the cost of emission abatement. This will allow us to understand how much the agricultural sector can contribute to improving air quality and which are the most effective measures to adopt. To solve this problem, an integrated air quality assessment model [15] is used to estimate the variation in PM2.5 and $NO_2$ concentrations and, consequently, the health effects as a function of the emission reduction measures applied.

## 2. Materials and methods

### 2.1. The study area

Northern Italy, including regions such as Lombardy, Veneto, Emilia-Romagna, and Piedmont, almost coincides with the catchment of the Po River, a 71,000 km² area known as Po Valley. It is known for its picturesque landscapes, industrial centers, and cultural heritage. It also hosts most of the national farming activities and is renowned for its intense and qualitatively high agricultural production. This area also faces significant air pollution challenges that impact the environment, public health, and overall quality of life. Several factors contribute to air pollution problems in Northern Italy. It is an industrial hub, hosting numerous manufacturing facilities, including those in the automotive, chemical, and metallurgical sectors. These industries are a major source of emissions, releasing pollutants such as particulate matter, sulfur dioxide ($SO_2$), nitrogen oxides (NOx), and VOCs.

The region's dense population and urban centers, including Milan and Turin, also experience high traffic congestion [16]. This results in relevant emissions of pollutants from vehicles, including PM, NOx, carbon monoxide (CO), and VOCs. The prevalence of diesel vehicles has been a particular concern due to their NOx emissions [17].

During the colder months, many residents rely on wood-burning stoves and fireplaces for heating. This practice contributes to the elevated levels of PM emissions, especially in rural areas.

Finally, Northern Italy's geographical features, including valleys and basins, can trap air pollutants, exacerbating pollution episodes. Stagnant weather conditions during the winter are well known to further worsen air quality by limiting the dispersion of pollutants.

Agriculture and farming are significant economic activities in Northern Italy, with the region being known for its fertile plains, vineyards, orchards, and diverse agricultural production. While the specific agricultural activities can vary by province and microclimate, some agricultural and farming activities are common to most of the Po Valleys.

This area is one of the leading rice-producing regions in Europe. Varieties like Arborio and Carnaroli are famous for their use in Italian cuisine. Lombardy and Piedmont alone produced approximately 98% of the total Italian yield of 1.5 million metric tons in 2020.

Wheat and corn are staple crops in the area, which produced around 4 million metric tons of wheat and 4.7 million metric tons of corn in 2023.

This territory is also known for the cultivation of fruits such as apples, pears, and peaches and vegetables such as tomatoes, lettuce, and radicchio. Lombardy, Emilia-Romagna, and Veneto are prominent fruit and vegetable producers, and are also important for their well-known viticulture.

Additionally, dairy farming is a significant activity, producing cheese, milk, and other dairy products. Regions like Lombardy and Piedmont are known for their dairy production. In 2021, they produced around 11.7 million metric tons of milk. Northern Italy also has a substantial livestock sector, including cattle (about 4M in 2022), pigs (7.6M), and poultry (more than 110M). Milan and Bologna are major centers for meat processing.

It is important to note that Northern Italy's agricultural landscape is diverse, and the specific crops and activities can vary in terms of region and local climate conditions. Additionally, agricultural practices and production figures can change from year to year based on factors such as weather patterns, market demand, and agricultural policies. Some old farming practices still in use, such as the open burning of crop residues, release relevant quantities of ammonia and other pollutants into the atmosphere.

Despite many technological and institutional efforts, air pollution remains a pressing issue in Northern Italy, necessitating continued vigilance, technological innovation, and public engagement to achieve cleaner air, protect public health, and preserve the region's natural beauty and cultural heritage [18].

### 2.2. The integrated assessment model

An integrated assessment model is formulated and solved to assess the tradeoff between agricultural emissions and abatement costs.

The model minimizes two objectives: on the one side, an air quality indicator (AQI) that is a single value summarizing the air quality conditions over the entire domain under study; on the other side, the cost ($C$) of implementing additional pollution abatement measures in addition to those already mandated by the law (CLE, Current Legislation). The implementation of mandatory measures in 2020 is referred to as the CLE2020 scenario and constitutes the reference situation.

From a formal point of view, the model can be written as follows:

$$\min_{z} J(z) = \min_{z} \left[ \mathrm{AQI}(z) C(z) \right] \tag{1}$$

where the vector $z$ of decision variables represents the "application rates (AR)" of the abatement technologies (also called "end-of-pipe") that can be applied to each of the activities present in the area and categorized in the 11 macrosectors of the CORINAIR European emission inventory [19]. Agriculture is coded as macrosector 10 in such a classification. Equation (1) means that we want to determine the type and extent of the abatement measures to adopt to minimize air pollution and measure implementation costs at the same time. It can also be interpreted as minimizing implementation costs to achieve a given air quality or, on the reverse side, searching for the best air quality achievable with a given budget.

Both the objectives of the above problem can be computed as a function of the emissions, which in turn depend on the problem decision-variables as follows:

$$E^{c,p} = \sum_{k \in K} \left[ A_k^c \cdot ef_k^p \cdot \left( 1 - \sum_{t \in T} eff_t^p \cdot z_k^t \right) \right] \quad (2)$$

where $c$ represents the spatial coordinates of an emission source $k$, $p$ is the specific pollutant, $A$ is the activity level (usually measured in terms of energy used), and $ef$ is the so-called unabated emission factor, i.e., the amount of the pollutant emitted for each unit of activity in the base case, $eff$ is the abatement efficiency of technology $t$, and $z_k^t$ is the fraction of activity $k$ that adopts the technology $t$. In summary, the emission of a certain pollutant in a certain geographical position is the sum of the products of the activities present at that site times the emission factor, which translates each unit of activity into the corresponding emission. This amount can be decreased if a fraction of the activity (the decision variable) adopts a certain technology characterized by a known abatement efficiency.

The above formulation shows that we assume not to change the current activities and sources (i.e., not to change any current production or traffic patterns), but only to introduce abatement techniques to reduce the emissions.

The cost ($C$) is computed as follows:

$$C = \sum_{k \in K} \left[ A_k \cdot \sum_{t \in T} uc_t \cdot z_k^t \right] \quad (3)$$

where $Ak$ represents the total $k$-th activity in the area (i.e., $A_k = \sum_c A_k^c$), and $uc_t$ is the unit cost of the technology $t$. Thus, the total cost is computed as a linear function of the diffusion (application rate) of each technology, the unit cost of which is known.

To solve the two-objective problem, first we must define the AQI formulation. This study will assume the yearly spatial average of PM2.5 concentration as an AQI. It is strongly connected to the health conditions of the resident populations [20]. It is also representative of the PM10 situation, since PM2.5 is about 70% of the mass of PM10 [21].

Then, a chemical-transport model (CTM) is used to determine the pollutant concentration as a function of a given emission field. The CAMx model [22] has been selected in the case at hand. CAMx is a powerful tool for studying air quality and understanding the complex interactions between emissions, meteorology, and atmospheric chemistry. It is particularly suited for the study of PM2.5 in Northern Italy because a large portion of this pollutant is of secondary origin, meaning that PM2.5 concentration (sometimes exceeding 50%) is not due to emitted PM2.5 (i.e., the primary PM), but forms in the atmosphere through the chemical and physical reactions of precursor gases.

Based on the CTM results, we develop a surrogate model to directly link the AQI to the emission field. This step is necessary to allow a workable solution to the two-objective problem, since using the original CTM requires unacceptable computer times. Thus, it can be used only for the surrogate's training phase.

Finally, the problem of determining the Pareto frontiers is solved by a classical constraint algorithm [23] with two different assumptions: in the first case, the set of variables $z$ includes the abatement measures that can be applied in all macrosectors except agriculture; in the second case, it comprises all the possible measures. The difference between the two cases quantifies the advantage of acting also in the agricultural sector. It can be noted that acting on agricultural emissions alone does not provide the same results, given the non-linearity of the PM formation process. The full implementation of such a procedure was made possible by using the Multi-dimensional Air Quality (MAQ)-integrated modeling software [15, 24] developed by the authors in previous studies.

### 2.3. Surrogate model development

Using surrogate models to solve air pollution planning problems is a valuable approach to efficiently address complex, computationally expensive, or data-intensive tasks. Surrogate models, also known as response surface models, approximate the relationships between input variables (e.g., emission sources, meteorological conditions, and policy measures) and output variables (e.g., air pollutant concentrations and health impacts) without representing all the internal factors determining such a relation. The correct use of surrogate models for air pollution planning requires:

Clear articulation of the air pollution planning problem to address. This could involve optimizing emission reduction strategies, assessing the impact of policy measures, or predicting pollutant concentrations in various scenarios.

Identify the specific objectives and performance metrics one wants to optimize. In this particular case, the selected metric is the least squared difference between the CAMx and the surrogate model's average PM2.5 concentration.

Collect sufficient emission inventories, meteorological data, and air quality values computed by the selected CTM. In the case at hand, CAMx was run 16 times for one year at an hourly time step, designing these experiments to show the consequences of substantial variations of the main emitted gases, namely $SO_2$, NOx, primary PM10 and PM2.5, $NH_3$, and VOC. Emissions of these gases varied between a maximum equal to 110% of those corresponding to CLE2020 and a minimum equal to 90% of the Maximum Feasible Reduction (MFR), which implies the full implementation of the best abatement technologies to all the emission sources.

Select and train a sufficiently general model structure. Feed-Forward artificial neural networks were trained to provide an almost instantaneous link between the emissions of precursor gases and the average PM2.5 concentration over the domain. More in detail, the network input was made by the precursor emissions in the surroundings of each cell of the domain (a radius of 24 km was considered) and the spatial coordinates of each cell [25]. The output was the average yearly concentration value in each cell, and then averaged over the entire domain to determine the selected AQI. It must be noted that despite the CAMx model and any other CTM using hourly emission values as input, these hourly values are obtained starting from the yearly values available in the emission inventories and distributing them in time through known daily and hourly patterns. It is thus meaningful to assume that the yearly emission is indeed the most significant variable.

Using surrogate models in air pollution planning can streamline decision-making, reduce computational burden, and provide valuable insights into the relationships between emissions, air quality, and policy measures. However, it is essential to choose the most suitable modeling technique, validate the model rigorously, and consider the specific characteristics of the problem at hand to ensure the model's reliability and usefulness.

### 2.4. The input dataset

The simulation domain is a rectangular area covering the whole of Northern Italy (**Figure 1**). The reduction policies are applied only to the areas of the regions of Piedmont, Lombardy, Veneto, and Emilia-Romagna, which are by far the most important ones for their intensive agricultural activities. The whole study domain is subdivided into 92 × 59 cells of 6 × 6 km² each.

The emission sources and total emissions must be identified for each cell of the domain. The emission datasets used are the regional emission inventory (INEMAR 2017 inventory, carried out in the LIFE PREPAIR project: PREPAIR – LIFE15 IPE IT 013, https://www.lifeprepair.eu), which specifies the emissions by source in each municipality, and the 2020 Outlook GAINS scenario (https://gains.iiasa.ac.at/models/gains_models4.html), which contains the emission factors and possible abatement technologies for each emission source. **Table 1** summarizes the emissions by the macrosector and by precursor summed over the four main regions of the domain.

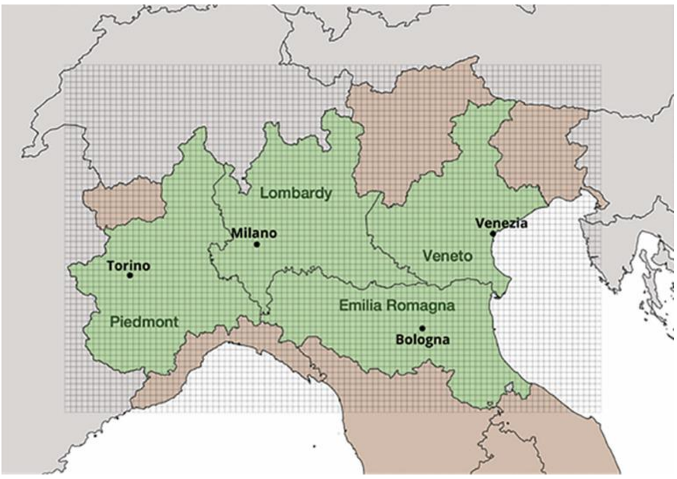


**Figure 1•** The study domain.

Agriculture thus contributes only marginally to the emission of most pollutants, except for ammonia where it represents 97% of the total.

**Table 1 •** Yearly emission per macrosector in the four main regions of the study domain

| **Total emissions (kt/year)** | | | | | | |
|---|---|---|---|---|---|---|
| Macrosector | NOx | VOC | $NH_3$ | PM10 | PM2.5 | $SO_2$ |
| 1. Combustion in energy and transformation industries | 20.5 | 2.0 | 0.1 | 0.3 | 0.2 | 5.1 |
| 2. Non-industrial combustion plants | 29.0 | 29.9 | 1.2 | 30.6 | 28.8 | 1.7 |
| 3. Combustion in manufacturing industry | 36.1 | 8.0 | 0.4 | 2.8 | 2.0 | 13.4 |
| 4. Production processes | 7.2 | 35.3 | 0.2 | 1.5 | 0.8 | 8.1 |
| 5. Extraction and distribution of fossil fuels and geothermal energy | 0.0 | 17.5 | 0.0 | 0.0 | 0.0 | 0.0 |
| 6. Solvent and other product use | 0.4 | 165.4 | 0.0 | 1.8 | 1.6 | 0.0 |
| 7. Road transport | 142.2 | 35.9 | 2.3 | 12.1 | 6.0 | 0.2 |
| 8. Other mobile sources and machinery | 37.6 | 4.6 | 0.0 | 2.0 | 1.9 | 0.6 |
| 9. Waste treatment and disposal | 0.9 | 0.6 | 1.5 | 0.8 | 0.7 | 0.2 |
| 10. Agriculture | 1.7 | 173.2 | 220.2 | 2.3 | 0.5 | 0.1 |
| 11. Biogenic | 1.2 | 182.7 | 0.3 | 3.3 | 2.7 | 0.2 |
| TOTAL | 276.8 | 655.1 | 226.2 | 57.5 | 45.2 | 29.6 |

## 3. Results

The two lower curves in **Figure 2** represent the Pareto frontiers of the two-objective problem defined above under the assumption of limiting the decision variables to the macrosectors 1–9 (red) or including macrosector 10. i.e., agriculture (blue).

The analysis of **Figure 2** allows several considerations. First, the range of variation of the AQI is quite limited. Even in case all feasible measures are adopted, one can simply move from 13.2 to 10.6 μg/m³. This means that the maximum possible variation is just about 20% of the initial value. Second, the maximum curvature of the Pareto frontiers is around a cost of 200 M€ of additional yearly costs above those mandated by law (CLE2020). Let's consider, for instance, a total cost of 300 M€ for the abatement measures (see points A and B in **Figure 2**). The inclusion of agriculture in the decision variables means a reduction of the AQI of around 0.5 μg/m³ (almost 4%) or, alternatively, we can reach an AQI of 11.3 μg/m³ (18% less than the base case), sparing about 100 M€ by also including agricultural measures.

The relevant role of agriculture can also be appreciated by looking at the upper curve in **Figure 2**. It represents the Pareto front in the unrealistic assumption of reducing only the emissions of the agricultural sector. It shows that a reduction of almost 0.8 μg/m³ is possible. This emphasizes the secondary origin of particulate matter in the area since agriculture mainly emits ammonia and a minimal amount of PM. Ammonia, however, is a precursor of secondary PM2.5, and thus, its reduction produces a benefit in terms of the selected AQI.

**Figure 3** shows how the cost of pollution reduction is subdivided among the different macrosectors. Besides agriculture, the other actions, and consequent costs, involve macrosector 2 (non-industrial combustion plants), which includes domestic heating, and macrosector 8 (other mobile sources and machinery), which includes tractors and other operating machines used for agriculture operations.

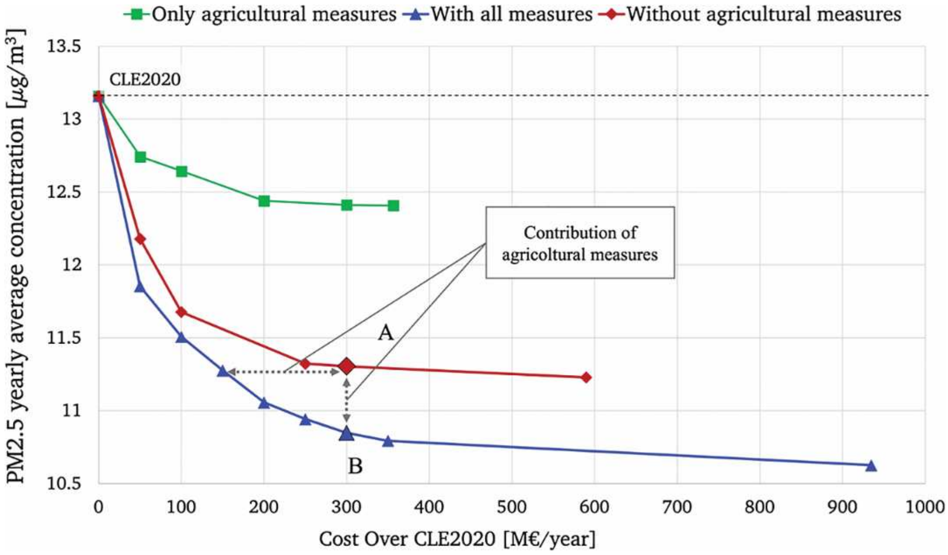


**Figure 2** • Pareto curve obtained by optimizing only agricultural measures (green) without agricultural measures (red) and all end-of-pipe measures (blue).

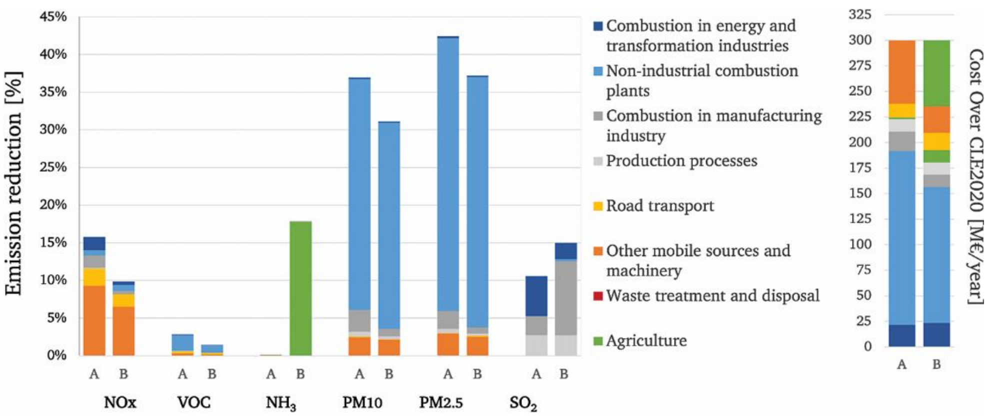


**Figure 3** • Emission variation (%) of A and B alternatives with respect to the base case 2020 per macrosector (left) and the distribution of additional costs (right).

More specifically, the most important actions foreseen by the optimal solutions corresponding to points A and B are reported in **Tables 2** and **3**: the improvement of fireplaces for macrosectors 2, the switch to less polluting diesel standards for macrosectors 8, the substitution of urea and the switch from low ammonia application to a combination of covered outdoor storage of manure, and low ammonia application for agriculture. Correspondingly, one may look at the proposed reductions of the precursor gases. Ammonia should be reduced by more than 18% in alternative B; NOx by 16% in A and 10% in B (mainly for the improvement of diesel engines), and primary PM by some 40%, mainly due to the combustion of wood for domestic heating. Even when considering all emission macrosectors, 20% of the total cost is allocated to the reduction of ammonia in agrofarming activities.

Thanks to the type of surrogate model adopted, which allows a local calculation on a single cell, one can visualize the impact of the suggested policies on the entire territory. **Figure 4** shows the spatial distribution of the PM2.5 concentration in the original condition (i.e., 2020 emission field) (**Figure 4a**), the concentration map when adopting only measures in other sectors (**Figure 4b**) and when including also measures in the agriculture macrosector (**Figure 4c**). The highest concentrations are found in the central flat part of the domain where the main cities are located (like Turin, Milan, and Venice). Peak values exceed 22 μg/m³, whereas the concentrations decrease moving toward the border of the domain, i.e., toward the mountainous areas. In this part, the values may be even lower than 5 μg/m³. Indeed, in the city of Milan, the PM10 concentration exceeded the limit of 50 μg/m³ for 90 days in 2020 instead of the 35 days mandated by European regulation. With the improvement that can be achieved when implementing the suggested policy, again for the yearly cost of 300 M€, the area with concentrations above 20 μg/m³ is reduced (−24% with the set measures of A and −30% with B).

**Table 2** • Main technical measures of Alternative A, their corresponding costs, variation in application (AR), and consequent variation of pollutant emissions

| Macrosector | Sector | Activity | Technology | Cost over CLE [M€] | AR [%] | Emission reduction [kt/year] |
|---|---|---|---|---|---|---|
| Non-industrial combustion plants | Fireplaces | Fuelwood | New fireplace | 106.9 | 57 | VOC: 3.8 |
| Other mobile sources and machinery | Agriculture | Diesel | Switch from Stage 2/3 to Stage 5 | 61.3 | 60 | NOx: 24.6 VOC: 1.9 PM10: 1.3 PM2.5: 1.2 |
| Non-industrial combustion plants | Heating stoves | Fuelwood | New stove – biomass | 32.9 | 48 | VOC: 10.1 PM10: 1.1 PM2.5: 0.4 |
| Combustion in energy and transformation industries | Power & district heat plants – new (excl. coal) | Other biomass and waste fuels | Selective catalytic reduction on new hard coal power plants | 7.2 | 50 | NOx: 1.5 |
| Combustion in the manufacturing industry | Agglomeration plant – sinter | No fuel use | Switch from Stage1/2 to Stage 3 – Process NOx control | 6.5 | 77 | NOx: 0.9 PM10: 0.02 PM2.5: 0.01 |

**Table 3** • Main technical measures of Alternative B, their corresponding costs, variation in application (AR), and consequent variation of pollutant emissions

| Macrosector | Sector | Activity | Technology | Cost over CLE [M€] | AR [%] | Emission reduction [kt/year] |
|---|---|---|---|---|---|---|
| Non-industrial combustion plants | Fireplaces | Fuelwood | New fireplace | 107 | 57 | VOC: 3.8 |
| Other mobile sources and machinery | Agriculture | Diesel | Switch from Stage 1/3 to Stage 5 | 43.6 | 42.6 | NOx: 21.6 VOC: 1.6 PM10: 1.2 PM2.5: 1.1 |
| Agriculture | Pigs | Pigs–liquid systems | Combination of low nitrogen feed. Air scrubber. Covered outdoor storage of manure. Low ammonia application | 19 | 20 | NH3: 16.4 |
| Agriculture | Urea application (incl. ABC) | No fuel use | Urea substitution | 17.7 | 50 | NH3: 14.1 |
| Agriculture | Other cattle | Other cattle–liquid systems | Combination of covered outdoor storage of manure & low ammonia application | 15.7 | 80 | NH3: 13.3 |

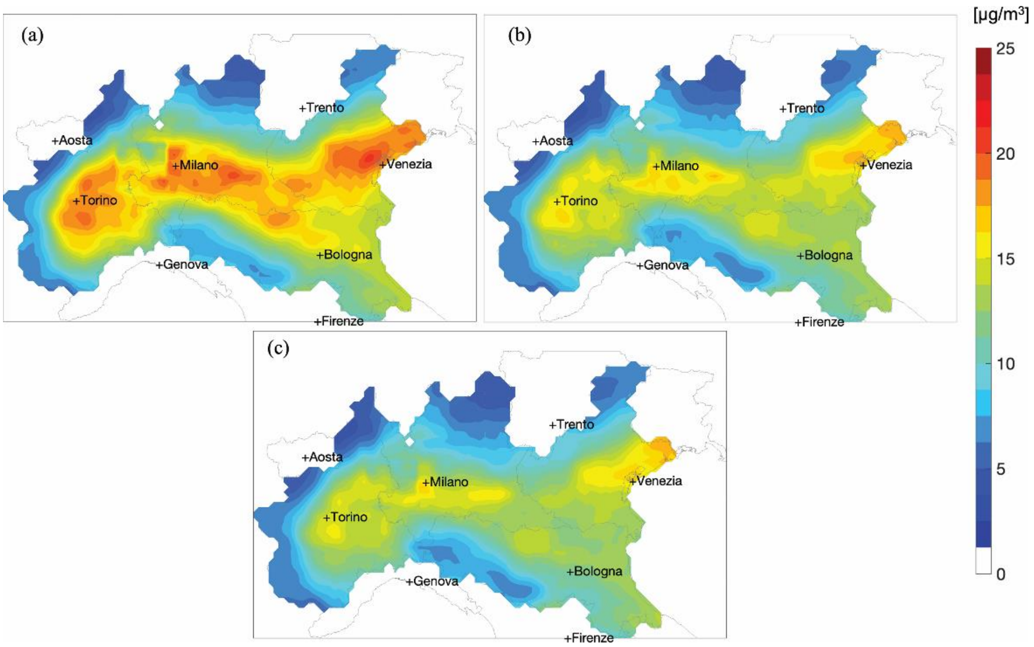


**Figure 4** • Yearly average PM2.5 concentration (μg/m³) in the base case 2020 (a), scenario A (b), and scenario B (c).

The spatial distribution of the average PM2.5 concentration allows us to compute the expected effects on the health of the resident population. This is done by considering the population structure such as children, asthmatic, and elderly, because each class of citizens reacts differently to a decrease (or an increase) in the pollutant concentration.

The three maps in **Figure 5** represent the distribution of the months of life lost (a fraction of the classical YOLL) in each cell by the resident population. Again, the worse conditions occur in the central plain area, where most of the population lives, and where, in 2020, the PM2.5 pollution reduced the expected life length of more than one year.

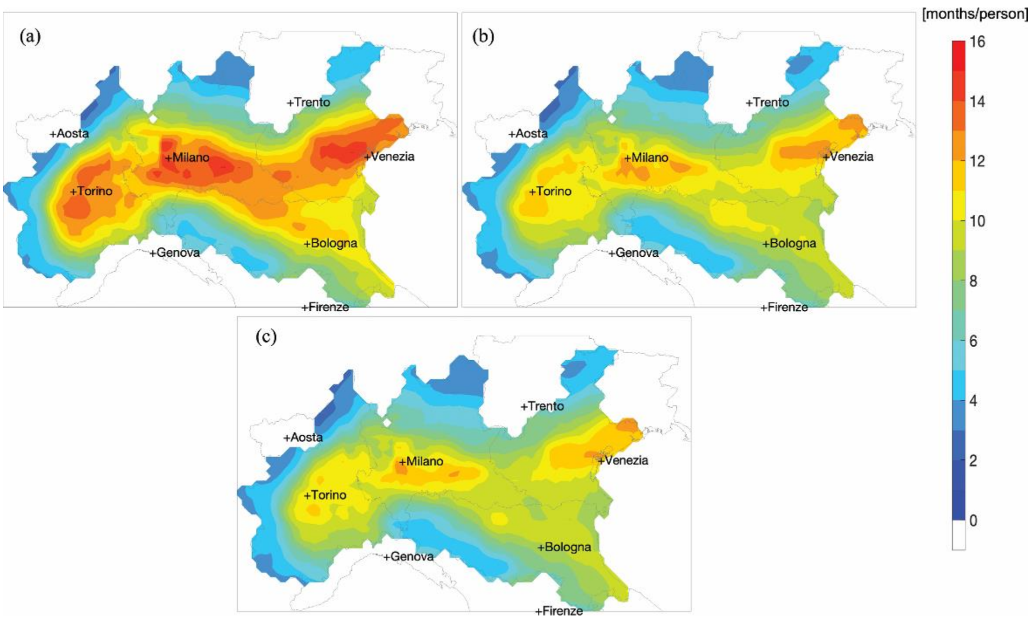


**Figure 5** • Years of life lost (months/person) in the base case 2020 (a), scenario A (b), and scenario B (c).

Overall, the years of life lost by the almost 20M people living in the study domain can be reduced by 47,000 years in case A and 54,000 years in case B compared to the 2020 situation, if the optimal policies at 300 M€ yearly cost are adopted.

Assuming the low standard value of 50,000 € per YOLL, this means that the suggested policy would generate a benefit of about 2.4 B€ in case A and 2.7 B€ in case B even without considering the decrease in morbidity, usually measured in terms of DALYs or disability-adjusted life years. Despite all the uncertainties, this means that the external benefits of air pollution reduction are almost one order of magnitude higher than the implementation costs of abatement measures.

## 4. Discussion and conclusion

The above results highlight the significant impact of the agricultural and livestock sectors on the Po Valley area and the importance of including agricultural policies in developing air quality and carbon emission reduction plans. Interestingly, the suggested policies act mostly on the farming sector (specifically, cattle and pigs), while urea substitution is the only action directly related to agricultural practices. Another action that turns out to be relevant is the modernization of the agricultural machinery to reduce primary PM emissions, besides NOx and VOC.

The surrogate modeling approach adopted in this study seems quite useful for air quality planning studies in different environmental contexts. Once a surrogate model has been developed, it is possible to rapidly test many alternative courses of action thanks to the decoupling of the problems of air pollution evaluation and cost quantification. The surrogate model computes the air quality index given a certain emission field, but the same emission values can be obtained in many different ways and at different costs.

The application of this approach to the highly productive and populated area of Northern Italy shows that a reasonable and efficient compromise solution would require a yearly investment of about 200–300 M€, which would decrease the average PM2.5 concentration of about 15–17% in comparison with the base year 2020. Additional investment, even if decided in the most efficient way, would not provide a significant further improvement of air conditions.

Given the well-known detrimental effect of PM2.5 on the human respiratory system, this improvement would significantly decrease the mortality and morbidity within the resident population. If translated into economic terms, this represents a benefit at least one order of magnitude larger than the corresponding abatement costs. Thus, the suggested solutions also have a considerable economic return.

To further mitigate the negative impact of agrofarming activities on air pollution, various other practices and technologies have been developed and are slowly diffusing in the domain under consideration. They go beyond those considered in this study. For instance, one can consider livestock housing systems that capture and treat manure emissions. Innovative farming techniques, such as controlled-release fertilizers and nitrification inhibitors, can reduce ammonia emissions from fertilizer application. Additionally, cover cropping and reduced tillage can reduce dust emissions and improve soil quality. The impact of these and other very promising techniques, like precision agriculture, was not considered in this study. Precision agriculture, for instance, requires the use of advanced technology to optimize farming practices, including the application of fertilizers and pesticides. By using sensors, drones, and GPS technology, farmers can apply these inputs more efficiently, reducing overuse and the associated emissions of ammonia, VOCs, and greenhouse gases. Its consideration requires a large amount of new data not available at the time of this study.

Organic farming is another important option that is expanding in the area under consideration. These practices emphasize using natural fertilizers, reduced pesticide use, and improved soil health. Organic farming, too, can lead to lower emissions of ammonia, VOCs, and synthetic pesticide compounds. It was not considered because it represents a change of activity with respect to the current situation.

Despite these limitations, the approach presented above proved to help identify the best actions to decrease the impact of agriculture on air pollution and can be equally transferred to other contexts. In the case of the Po Valley, it showed that the contribution of the agrofarming sector to air pollution is substantial, but can be reduced by combining sustainable practices and policy measures and that this reduction is efficient from both the environmental and economic viewpoints.

## Funding

This research was funded by Fondazione Cariplo under the grant “AgriAir: Data science to reduce agri-food impact on air quality in the Po Valley”. Call 2021 “Data Science for science and society”. The authors are grateful to C. Carnevale, A. Tonola, A. Basak (University of Brescia), and L. Ferrari (Politecnico di Milano) for collaborating on the project.

## Author contributions

Conceptualization, G.G., M.V.; methodology, M.A., G.G., M.V. and L.Z.; software, M.A., G.G., M.V. and L.Z.; writing—original draft preparation, G.G.; writing—review and editing, M.A., G.G., M.V. and L.Z. All authors have read and agreed to the published version of the manuscript.

## Conflict of interest

The authors declare no conflict of interest.

## Data availability statement

Emission data are publicly available in the regional emission inventories at www.inemar.eu. Data about measure utilization, efficiency, and cost are available at gains.iiasa.ac.at/models/.

## Institutional review board statement

Not applicable.

## Informed consent statement

Not applicable.

## Sample availability

The authors declare no physical samples were used in this study.

## Additional information

Received: 2023-09-29

Accepted: 2023-10-30

Published: 2023-11-28

*Academia Engineering* papers should be cited as *Academia Engineering 2023*, ISSN 2994-7065, https://doi.org/10.20935/AcadEng6149. The journal’s official abbreviation is *Acad. Engg*.

## Publisher’s note



## Copyright



## References

1. FAO. The State of Food and Agriculture 2023. Revealing the true cost of food to transform agrifood systems. Rome: FAO; 2023. doi: 10.4060/cc7724en
2. DEFRA (Dept. for Environmental Food and Rural Affairs), Air quality strategy: framework for local authority delivery, PB 14818. 2023, Gov.UK.
3. Wyer KE, Kelleghan DB, Blanes-Vidal V, Schauberger G, Curran TP. Ammonia emissions from agriculture and their contribution to fine particulate matter: a review of implications for human health. J Environ Manage. 2022;323: 116285. doi: 10.1016/j.jenvman.2022.116285
4. Cohen AJ, et al. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. Lancet. 2017;389:1907–18. doi: 10.1016/S0140-6736(17)30505-6
5. Aleluia Reis L, Drouet L, Tavoni M. Internalising health-economic impacts of air pollution into climate policy: a global modelling study. Lancet Planet Health. 2022;6(1): e40–8. doi: 10.1016/S2542-5196(21)00259-X
6. European Environment Agency. Air quality in Europe 2022. Report no. 05/2022. 2022. doi: 10.2800/488115
7. Bauer SE, Tsigaridis K, Miller R. Significant atmospheric aerosol pollution caused by world food cultivation. Geophys Res Lett. 2016;43;5394–400. doi: 10.1002/2016GL068354
8. Kammer J, et al. Characterization of particulate and gaseous pollutants from a French dairy and sheep farm. Sci Total

Environ. 2020;712:135598. doi: 10.1016/j. scitotenv. 2019. 135598

9. Yuan B, et al. Emissions of volatile organic compounds (VOCs) from concentrated animal feeding operations (CAFOs): chemical compositions and separation of sources. Atmos Chem Phys. 2017;17:4945–56. doi: 10.5194/ acp-17-4945-2017
10. Tabase RK, Næss G, Larring Y. Ammonia and methane emissions from small herd cattle buildings in a cold climate. Sci Total Environ. 2023;903:166046. doi: 10.1016/j.scitotenv. 2023.166046
11. Yang Y, et al. Comprehensive quantification of global cropland ammonia emissions and potential abatement. Sci Total Environ. 2022;812:151450. doi: 10.1016/j.scitotenv. 2021.151450
12. Giannakis E, Kushta J, Bruggeman A, Lelieveld J. Costs and benefits of agricultural ammonia emission abatement options for compliance with European air quality regulations. Environ Sci Eur. 2019;31(1):93. doi: 10.1186/s12302-019-0275-0
13. Zhang Y, et al. Modeling agricultural air quality: current status, major challenges, and outlook. Atmos Environ. 2008; 42(14):3218–37. doi: 10.1016/j.atmosenv.2007.01.063
14. Velders GJM, et al. Effects of European emission reductions on air quality in the Netherlands and the associated health effects. Atmos Environ. 2020;221:117109. doi: 10.1016/ j.atmosenv.2019.117109
15. Turrini E, Carnevale C, Finzi G, Volta M. A non-linear optimization programming model for air quality planning including co-benefits for GHG emissions. Sci Total Environ. 2018;621:980–9. doi: 10.1016/j.scitotenv.2017.10.129
16. Eurostat. Regions in Europe - 2022 interactive edition. 2022. Available from: https://ec.europa.eu/eurostat/cache/ digpub/regions/#total-population
17. Wilson J, et al. Urban PM2.5 atlas – Air quality in European cities – 2021 report. Publications Office of the European Union. 2021. Available from: https://data.europa.eu/doi/ 10.2760/356670
18. Raffaelli K, et al. Improving air quality in the Po Valley. Italy: some results by the LIFE-IP-PREPAIR Project. Atmosphere. 2020;11(4):429. doi: 10.3390/atmos11040429
19. European Environment Agency. EMEP/EEA air pollutant emission inventory guidebook 2019. EEA Report No 13/2019. Luxemburg 2019. doi: 10.2800/293657. Available from: https://www.eea.europa.eu/publications/emep-eea-guidebook-2019
20. WHO (World Health Organisation). Economic cost of the health impact of air pollution in Europe: clean air, health and wealth. Copenhagen: WHO Regional Office for Europe; 2015.
21. Pietrogrande MC, Demaria G, Colombi C, Cuccia E, Dal Santo U. Seasonal and spatial variations of PM10 and PM2.5 oxidative potential in five urban and rural sites across Lombardia region, Italy. Int J Environ Res Public Health. 2021;19(13):7778. doi: 10.3390/ijerph19137778
22. Ramboll. User's guide: comprehensive air quality model with extensions (CAMx). version 7.00. 2020. www.camx.com
23. Mavrotas G. Effective implementation of the ε-constraint method in Multi-Objective Mathematical Programming problems. Appl Math Comput. 2009;213(2):455–65. doi: 10.1016/j.amc.2009.03.037
24. De Angelis E, Carnevale C, Marcoberardino GD, Turrini E, Volta M. Low emission road transport scenarios: an integrated assessment of energy demand, air quality, GHG emissions and costs. IEEE Trans Autom Sci Eng. 2022;19:37–47. doi: 10.1109/TASE.2021.3073241
25. Ferrari L, Guariso G. Geography-based neural networks for the simulation of air pollution. Proceedings of IFAC World Congress 2023, Yokohama, Japan, 2023 Jul 9–14, ThA24.3.