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A Methodology for Designing Short-Term Stationary Air Quality Campaigns with Mobile Laboratories Using Different Possible Allocation Criteria

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Abstract: Air quality monitoring and control are key issues for environmental assessment and management in order to protect public health and the environment. Local and central authorities have developed strategies and tools to manage environmental protection, which, for air quality, consist of monitoring networks with fixed and portable instrumentation and mathematical models. This study develops a methodology for designing short-term air quality campaigns with mobile laboratories (laboratories fully housed within or transported by a vehicle and maintained in a fixed location for a period of time) as a decision support system for environmental management and protection authorities. In particular, the study provides a methodology to identify: (i) the most representative locations to place mobile laboratories and (ii) the best time period to carry out the measurements in the case of short-term air quality campaigns. The approach integrates atmospheric dispersion models and allocation algorithms specifically developed for optimizing the measuring campaigns. The methodology is organized in two phases, each of them divided into several steps. Fourteen allocation algorithms dedicated to three type of receptors (population, vegetation and physical cultural heritage) have been proposed. The methodology has been applied to four short-term air quality campaigns in the Emilia-Romagna region.

Keywords: design mobile laboratory campaign; air pollution concentration; population exposure to air pollutant

1. Introduction

Air quality monitoring and control are key issues for environmental assessment and management in order to protect public health, ecosystem services and physical cultural heritage (intended as physical artefacts in outdoor spaces). Therefore, local and central authorities have developed measuring systems to evaluate air pollution and to provide strategic indications to improve air quality and optimize its monitoring.

The most critical situations occur in urban areas, where emission sources (e.g., urban traffic, domestic heating) and sensitive receptors (e.g., population, physical cultural heritage) are concentrated. According to the data reported by the United Nations in its special edition on progress towards the Sustainable Development Goals [1], about 7 million people died as a result of high levels of air pollution, both ambient and household, in 2016. The same document reports that about 90% of people living in urban areas were still breathing

air that did not meet the World Health Organization's air quality guideline values for particulate matter.

In such a context, governments and environmental protection agencies monitor ambient concentrations of air pollution in many parts of the world as part of regulatory programs designed to protect public health and the environment [2,3]. Historically, the most extensive monitoring systems were mainly developed in the United States and Western Europe, where regular monitoring of ambient air quality has been implemented since the mid-1970s [4]. Today, in Asia (especially Japan and China with a strong increase since the 2000s) there are extensive monitoring networks [5,6]. At the European level, the reference regulation for the monitoring and evaluation of air quality is set by Directive 2008/50/EC and subsequent amendments and additions [3]. This legislation establishes that fixed measurements shall be used to assess ambient air quality. These fixed measurements may be supplemented by modelling techniques and/or indicative measurements to provide adequate information on the spatial distribution of air pollutants.

Fixed monitoring stations represent the most conventional, consolidated and widespread approach for air quality monitoring and evaluation but have some limitations: (1) monitoring is usually limited to a small set of strategically placed locations and the assessment results are significant only for specific areas; (2) fixed monitoring stations have low flexibility. In the last ten years, the existing monitoring networks have been adjusted at European level in order to meet regulatory requirements (Directive 2008/50/CE) and cost efficiency. The following objectives are pursued: (1) to create a uniform and comparable network for wide areas (for example, all European States); (2) to reduce the number of stations, currently higher than required by the legislation [7]; (3) to optimize the spatial representativeness of the networks. In order to achieve these objectives and foster a thorough knowledge of an area even with a smaller number of fixed stations, mobile laboratories [8,9], mobile monitoring campaigns [10,11], low-cost sensors [12–14] and predictive mathematical models [15,16] have been applied. In order to maximize the effectiveness and efficiency of these alternative monitoring tools, it is necessary to adopt an appropriate allocation methodology, able to include spatial and temporal variables to design the short-term air quality campaigns. Recently, mobile laboratories for short-term stationary measurements (laboratories that are either fully housed within or transported by a vehicle and maintained in fixed location for a period of time) are spreading with good results (e.g., [17,18]).

Because operations research (OR) offers a structured method to solve complicated decision problems, several authors have proposed different OR approaches for air quality network design (see Table 1).

Table 1. Operation research approaches proposed to design air quality network: main characteristics.

Authors	Objectives	Variable/s of Action	Constraint/s	Sensitive Receptor/s
[19]		Pollution dosage	Exposure time to pollutant	
[20]		Maximum concentration values	Single source, pollutant and meteorological conditions	
[21]	Number and placement	Exceeding the law limits	Number of points defined before single pollutant	Population
[22–25]		Information associated to the signal	Previously measured data	
[26–29]		Spheres of influence	Data from air quality dispersion model	
[30]		Pollution exposure gradient	Previously measured data	

Table 1. *Cont.*

Authors	Objectives	Variable/s of Action	Constraint/s	Sensitive Receptor/s
[31]		Weighing function of maximum concentration values, exceeding the law limits, cost of the network and data validation	Previously measured data Economic aspect	
[32,33]		Site redundancy	Previous network	
[34]		Exceeding the law limits Protection capability Average daily concentration	Data from air quality dispersion model	
[35,36]		Information gain	Adding new stations	
[37–39]		Pollution exposure	Single pollutant Previously measured data	
[40]		Overall function of maximum concentration values, maximum dosage, maximum network coverage, maximum population protection	Applied to pollution from industrial districts	
[41–43]		Exceeding the law limits	Number of points defined before Number of points defined on the economic basis	
[44]		Cluster analysis procedure	Previously measured data	
[45]		Multiple criteria	Available budget	
[46]		Entropy-based Bayesian optimizing approach	Available budget	
[47]		Detection of higher pollutant concentrations "Protection capability" for areas with higher population density	Distribution of population, budget	
[48]		Population and emission sources		
[49]		Pollution exposure		

As it is possible to observe from Table 1, the objectives (typically: "choice of the optimal number of monitoring points and their spatial distribution") and constraints appear to be similar among the approaches. The studies differ in the choice and combination of the variables and in the formulation of the objective function: for example, Reference [49] applying population exposure as a decision variable, Reference [33] analyzing the redundancy of information provided by measuring stations and [29] using the spatial representativeness of the detected signal. The authors often propose a single objective function (e.g., [43,49]), always oriented towards the evaluation of the effects of air pollution on the resident population. Systematically, the authors deal with the placement of fixed air monitoring networks, considering the spatial aspect, but not the temporal one, as a decision parameter since fixed stations measure air quality continuously all year long (e.g., [19,25,48]). Conversely, algorithms to locate mobile stations must consider both spatial and temporal variables. In fact, mobile laboratories are used for short-term campaigns (a few days or a few weeks) and the temporal context must be given appropriate attention to maximize the representativeness of the campaign. To the best of our knowledge, there are no OR studies specifically developed to design mobile measurement campaigns for air quality, capable of simultaneously considering the spatial and temporal aspects in the sampling configuration.

This study aims to develop an OR methodological approach for optimizing the short-term air quality monitoring campaigns with mobile laboratories, by considering spatial and temporal variables in order to obtain measurements as representative as possible of the investigated area. The methodological approach has been structured using the typical scheme of the OR which, by using appropriate selection functions, is able to find the optimal (or suboptimal) solution to a decision problem. The proposed approach has been applied to four case studies. The study area is the province of Ravenna (northern Italy), made up of 18 municipalities that periodically sign a memorandum of understanding with Arpae (Regional Agency for Prevention, Environment and Energy of Emilia-Romagna) on monthly air quality monitoring campaigns by using a mobile laboratory. The four examples refer to areas with different features and extensions and with a significant difference: the Ravenna municipality is already largely covered (from the spatial point of view) by fixed monitoring stations, whereas the other areas are completely devoid of them.

2. Materials and Methods

2.1. Description of the Methodology Development through Operations Research

To be solved, a decision problem needs a question to answer, the data that contextualize the choice, and a criterion for making the choice [50]. As widely used in the literature, operations research (OR) is defined as "*a discipline that deals with the application of advanced analytical methods to help make better decisions*" and "*arrives at optimal or near-optimal solutions to complex decision-making problems*".

Through OR, a decision-making problem is mathematically described with functions that represent the logical relationships among the decision objectives, variables and constraints. A decision objective is the desired solution to which the decision-making process tends (e.g., minimum cost, maximum gain, etc.) (*S* in Equation (1) reported below). A variable of action is a quantity of the system, the value of which is unknown, and on which it is possible to act to determine different alternative solutions to the problem (e.g., the number of measuring points, items sold, etc.). The constraint(s) describe the conditions of admissibility of the solutions (e.g., technical constraints to indicate the maximum availability of resources, sign constraints). They are mathematical relationships that describe the conditions of admissibility of the solutions and are used to discriminate the combinations of values of the decision variables that represent acceptable solutions to the problem, from those that are not [51,52].

These three elements are formalized mathematically through a function (called "objective function") consisting of *n* variables and *m* constraints. It represents the objective to be maximized or minimized, mathematically formulated as a function of the decision variables and influenced in the resolution by the constrains.

$$
\begin{aligned}
&Min\ (or\ max)\ f(x)\\
&\quad x \in S
\end{aligned}
\tag{1}
$$

where: $f(x)$ is the objective function to be minimized (or maximized); S is a set of possible values of the independent variables of the problem; x is n-dimensional vector variables. Solving an optimization problem formulated through an objective function consists in determining the values of the variables x that satisfy all the constraints and minimize (or maximize) the value of the objective function in S. The value of x that minimizes (or maximizes) $f(x)$ represents the optimal (or suboptimal) solution of the problem.

The decision problem studied by this work (where to measure the air quality by using mobile laboratories?) has been structured with the OR approach. The methodology integrates to the optimal spatial distribution another two fundamental aspects: (i) the best time period for carrying out the short-term monitoring campaign; (ii) the possibility of pursuing several objectives (e.g., monitoring the exposure of a group of residents, evaluating the impact of an emission source, evaluating the effectiveness of specific territorial policies, etc.).

The approach is structured in 2 distinct operational phases. Phase 1 is dedicated to the characterization of the study area through the collection of data and their processing. The result of phase 1 is a database that collects all the data. Phase 2 is the allocation procedure; its result is the identification of the optimal sites. It is noteworthy that phase 1 needs to be applied just once (obviously data may be updated), while phase 2 may be applied as many times as the number of the necessary measurement campaigns. In this way, numerous short-term air quality campaigns can be designed on the area of study, always applying the same database.

In the proposed methodological approach, phase 1 consists of the following four steps: (i) selection of the area of study; (ii) cell classification; (iii) quantification of air pollutant concentration; (iv) identification and distribution of sensitive receptors.

The first step consists of the identification of the study area and its division into square cells of equal size. Each cell is the basic assessment unit of each algorithm. All the information necessary for the allocation choice must be quantified for each cell (e.g., concentration of pollutants, sensitive receptors, type of cell, objective functions, and so on). A specific cell will be the final result of each allocation procedure.

The second step aims to classify each cell according to the type of prevalent emissive sources present inside it. What is interesting is the classification established by the European Directive 2008/50/EC [3]: (a) urban traffic (T): cells located in urban areas and near roads with heavy vehicle traffic; (b) industrial (I): cells located within or close to industrial areas; (c) urban background residential (BU-Res): cells located in urban areas with high population density and not crossed by roads with high traffic; (d) urban background (BU): cells located preferably within public green and/or pedestrian areas (parks, schools) and not directly subject to specific sources of pollution such as vehicle traffic and industrial emissions; (e) suburban background (B-SubU): cells located in suburban areas characterized by the transport phenomena from outside the city and phenomena produced inside the urban area; (f) rural background (BR): cells located outside the major cities, in predominantly rural/agricultural areas, also subject to phenomena of photochemical pollution, downwind of the direction of the wind field and most likely not in the immediate area of maximum emissions of pollutants; (g) remote background (B-Rem): cells located at natural areas (natural ecosystems, forests) at a great distance from urban and industrial areas.

The third step quantifies the air pollutant concentrations of interest. Many air quality mathematical models are suitable for this purpose, as explained previously. Whatever model is applied, a high-resolution estimation is necessary to answer the monitoring site allocation problem [30,47]. In the case of brief monitoring campaigns, as in this study, an adequate time resolution (preferably hourly or daily) is required, too. This aspect can be a problem for the management of a very large amount of data.

The fourth step enables the identification and spatial distribution of the sensitive receptors to air pollutants. It is necessary to define the spatial distribution of the resident population, the presence of sensitive vegetation and the presence of relevant physical cultural heritage.

Phase 2 consists of five steps. Each step allows for the selection of different elements of the monitoring campaign and the development of many different combinations, each of which determines a different configuration of the campaign. The graphical representation of phase 2 is shown in Figure 1. The first step is the selection of the spatial domain. The monitoring campaign could affect the entire study area selected during phase 1, or one of its subspatial domains. Using a square grid, it is possible to select only the cells of a subarea of interest. The second step is the selection of the temporal domain. This step allows for the identification of a specific time period in which to conduct the campaign (e.g., a day, a month, a season, a whole year). This is closely related to the temporal resolution used to define the pollutant concentration field during phase 1. The selection of the area type is the third phase, it helps to identify areas with homogeneous characteristics from the point of view of pollution and/or presence of emission sources. It allows the selection of cell type. The fourth step is the selection of one

or more pollutants of interest, based on which the monitoring campaign will be designed. The last step is the selection of allocation criterion. This represents the mathematical expression of the purpose of the measurement campaign (e.g., evaluate the exceeding of legal limits, the exposure of the population, the damage to heritage). This study suggests fourteen objective functions that represent a large number of possible design criteria for short-term air monitoring campaigns, also considering the indications available in the bibliography (see Table S1 of Supplemental Material). Table 2 shows the list and the relative formulation of the proposed objective functions, while Table S1 of Supplementary Material shows any supplementary information necessary for their quantification. There are eleven allocation criteria dedicated to population protection, offering as a factor of choice the exposure of citizens to atmospheric pollutants, the highest concentration values, values above the legal limits, the correlation with the data measured by the AQMS, the spatial gradient of the concentration values. Five allocation criteria are dedicated to vegetation protection: exposure to pollution, values above the limits for the protection of vegetation, the quantities of pollutants that are deposited to the ground through dry and wet deposits. Finally, a specific damage index for physical cultural heritage has been proposed as a specific allocation criterion for its protection.
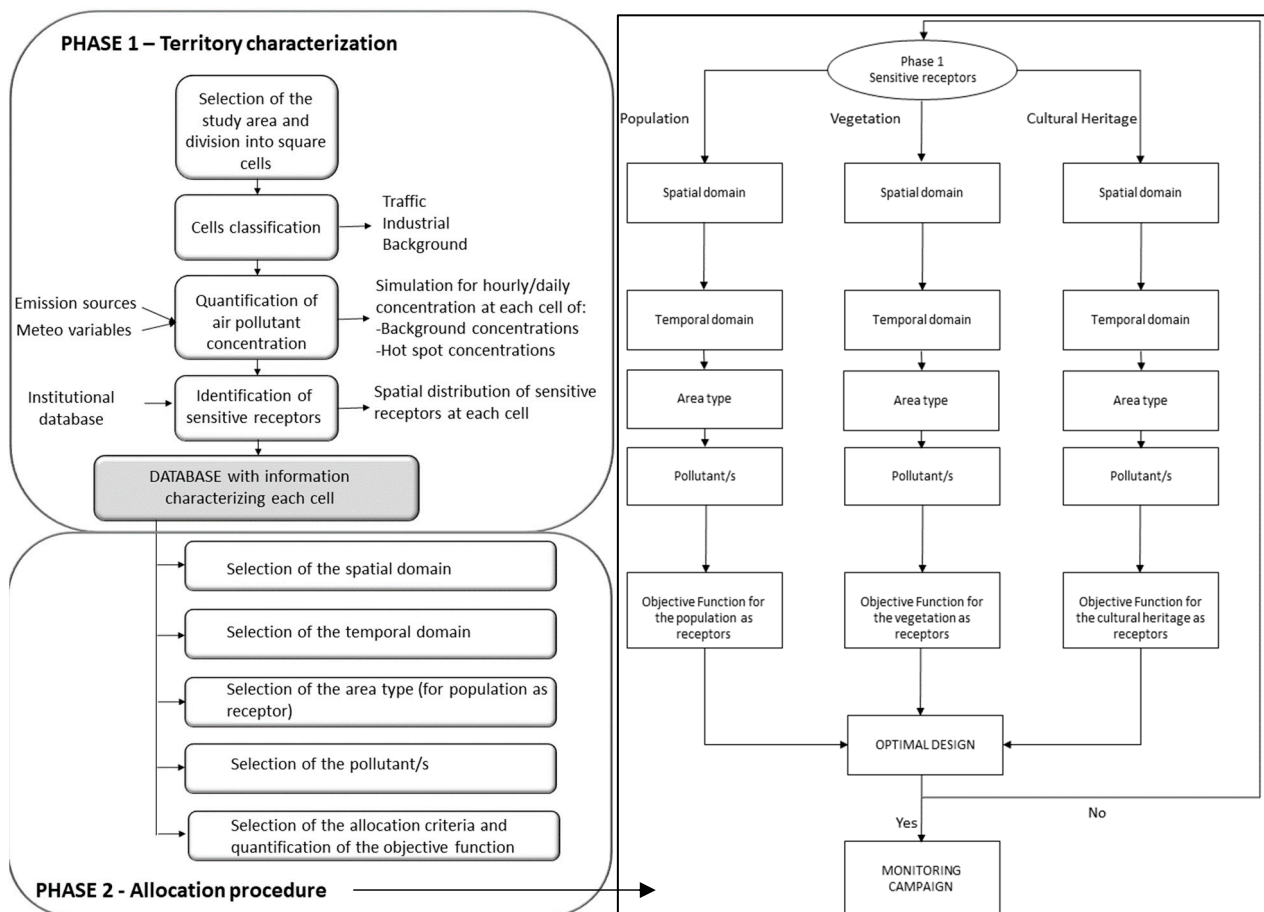

Figure 1. General schematic approach of the proposed design methodology and a specific focus of phase 2—allocation procedure.

2.2. Description of the Study Area

The study area is the Ravenna Province (northern Italy, Figure 2a); the area is 1860 km^2, the population is around 389,000 people [53] and the population density is about 200 inhabitants/km^2. The Ravenna Province is divided into 18 municipalities, each with a different size and features. The study area has a wide air quality monitoring network

(AQMN), mainly concentrated in the municipalities of Ravenna and Faenza (Figure 2b). In the urban centers, air quality is mostly affected by traffic-related air pollution [16] and domestic heating, while some suburban areas are affected by industrial pollution [54]. The study area has been divided into 250 × 250 m cells for a total of 30,618 cells, a compromise between high spatial resolution and computational resources.
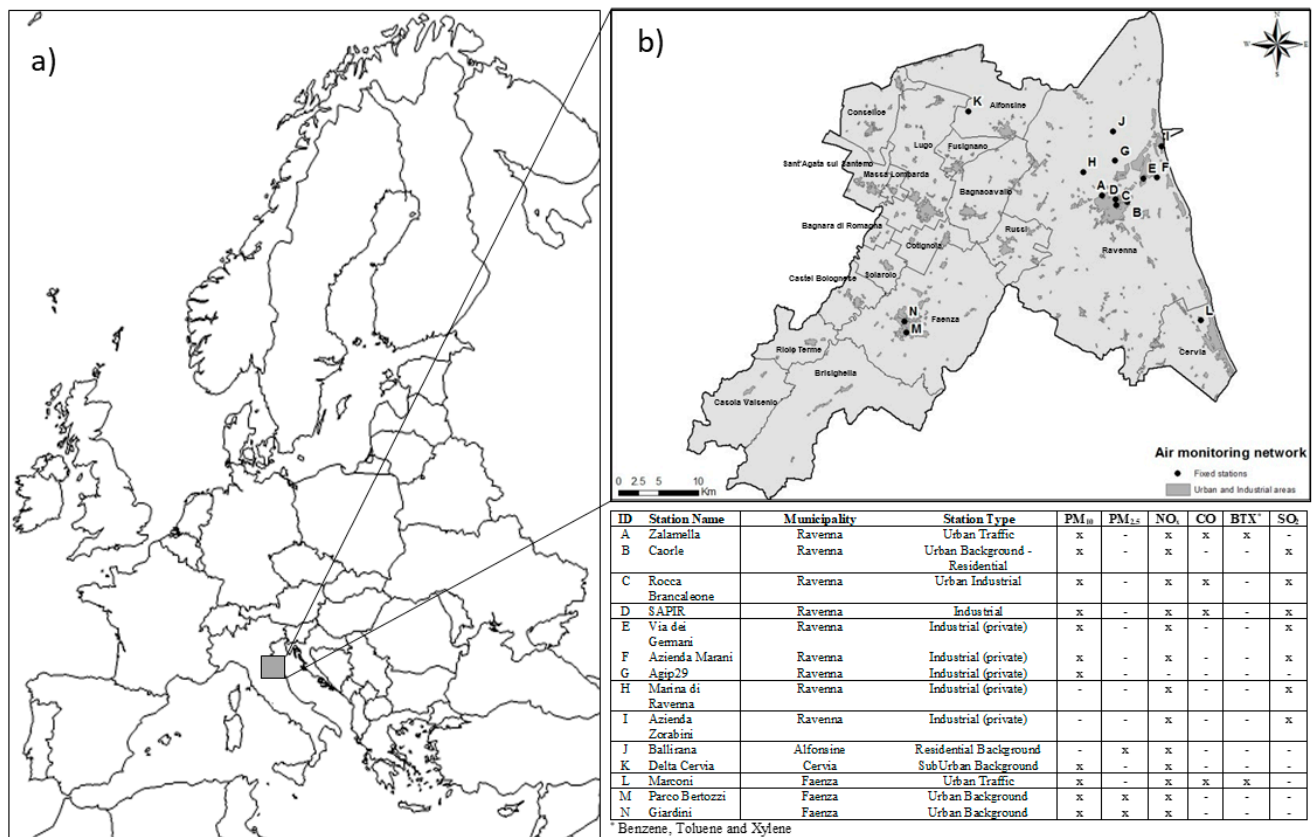

ID	Station Name	Municipality	Station Type	PM$_{10}$	PM$_{2.5}$	NO$_x$	CO	BTX*	SO$_2$
A	Zalamella	Ravenna	Urban Traffic	x	-	x	x	x	-
B	Caorle	Ravenna	Urban Background - Residential	x	-	x	-	-	x
C	Rocca Brancaleone	Ravenna	Urban Industrial	x	-	x	x	-	x
D	SAPIR	Ravenna	Industrial	x	-	x	x	-	x
E	Via dei Germani	Ravenna	Industrial (private)	x	-	x	-	-	x
F	Azienda Marani	Ravenna	Industrial (private)	x	-	x	-	-	x
G	Agip29	Ravenna	Industrial (private)	x	-	-	-	-	-
H	Marina di Ravenna	Ravenna	Industrial (private)	-	-	x	-	-	x
I	Azienda Zorabini	Ravenna	Industrial (private)	-	-	x	-	-	x
J	Ballirana	Alfonsine	Residential Background	-	x	x	-	-	-
K	Delta Cervia	Cervia	SubUrban Background	x	-	x	-	-	-
L	Marconi	Faenza	Urban Traffic	x	-	x	x	x	-
M	Parco Bertozzi	Faenza	Urban Background	x	x	x	-	-	-
N	Giardini	Faenza	Urban Background	x	x	x	-	-	-

* Benzene, Toluene and Xylene

Figure 2. The area of study ((**a**) left) and its air quality monitoring network (capital letters) ((**b**) right).

As case study pollutants, PM$_{10}$ and NO$_2$ have been chosen. The concentrations of PM$_{10}$ (daily average values) and NO$_2$ (hourly average values) were estimated for each cell. Background concentrations and concentrations due to local sources were estimated and then combined. The background concentrations were quantified by the geostatistical PESCO (Post-processing and Evaluation with Statistical methods of a Chemistry-transport-model Output) model [55,56]. The package provides the functions to perform data fusion for air quality with hourly temporal resolution, correcting the output of a deterministic chemistry transport model with observed data, through a trans-Gaussian Kriging approach [57]. PESCO model results were provided by the Hydro-Weather-Climate service of Arpae with a spatial resolution of 1 × 1 km^2. The contribution of the local sources was quantified by the advanced Gaussian dispersion model ADMS-Urban [58]. The application of ADMS-Urban (made by the authors) required the identification and characterization of local air pollutant sources. This process was achieved through the spatial disaggregation of the provincial emissions inventory of industrial, road traffic and domestic heating [59] sources. The reference year of the inventory was 2015, the spatial resolution was 250 × 250 m. The pollutant concentrations estimated by PESCO and ADMS-Urban models were combined together using a multiple linear regression (Equation (2)).

$$Y = X\beta = \beta_0 x_{PESCO} + \beta_1 x_{ADMS-URBAN} + \varepsilon \tag{2}$$

where Y is the matrix identifying the dependent variables; it is composed of the values recorded by specific air quality monitoring stations; β are the regression coefficients; x are the pollutant concentrations estimated by PESCO and ADMS models, respectively; ε is the residue. The overall concentration field was then verified by comparing the simulated data and the values measured by the air quality monitoring network, applying specific comparison statistical indices [60,61]. Pearson's product moment correlation coefficient (COR), normalized mean square error (NMSE), fractional bias (FB), factor 2 (FA2) and index of agreement (IA) were employed. They are defined according to the following formulas:

$$COR = \overline{(Co - \overline{Co})(Cp - \overline{Cp})}/\sigma_o\sigma_p \tag{3}$$

$$NMSE = \overline{(Co - Cp)^2}/\overline{CpCo} \tag{4}$$

$$FB = 2(\overline{Cp} - \overline{Co})/(\overline{Cp} + \overline{Co}) \tag{5}$$

$$FA2 = fraction\ of\ data\ for\ which\ 0.5\ \leq Cp/Co \leq 2 \tag{6}$$

$$IA = 1 - (Cp - Co)^2/(Cp - \overline{Cp})(Co - \overline{Co})^2 \tag{7}$$

where: CO and CP are the predicted and observed concentrations, respectively; σ_o and σ_p are the standard deviations of observations and predictions, respectively. *IA*, *COR* and *NMSE* measure the correlation between predicted and measured concentration values, *FB* measures the agreement of the mean concentration values and *FA2* is the fraction of predicted concentrations within a factor of two of the equivalent measured values. Under ideal conditions, *FB* and *NMSE* should be zero, while *COR*, *IA* and *FA2* should be one.

In this study three types of receptors that are sensitive to airborne pollution were selected: resident population, vegetation (natural areas, parks and forests) and physical cultural heritage. Resident population and vegetation were selected as they are the reference receptors in the legislation (e.g., Directive 2008/50/CE). Physical cultural heritage located outdoors was selected as these items are very sensitive to air pollution and have been severely damaged for the last century [62,63]. The spatial distribution of each type of receptor was disaggregated over the territory (250 × 250 m cells) starting from the following aggregated databases: census data of the National Institute of Statistics [53] for the resident population in 2011 (last complete population census available), Emilia-Romagna Region open-data for vegetation [64] and the database of the Italian Ministry of Cultural Heritage for cultural heritage [65].

Table 2. Proposed allocation criteria.

Allocation Criteria	Sensitive Receptors	Note
Individual exposition to the i-th pollutant in the k-th cell [$\mu g \cdot m^{-3} \cdot h$]	Population Vegetation	Quantifies the exposure of an individual to a specific outdoor pollutant [20,66–68]
Overall exposition to the i-th pollutant in the k-th cell [$\mu g \cdot m^{-3} \cdot h \cdot n$]	Population	Quantifies the overall exposure of all individuals present in a given cell [30,40]
Overall risk to all thepollutants in the k-th cell [$\mu g \cdot m^{-3} \cdot h$]	Population Vegetation	Quantifies the individual risk as the contribution of all the considered pollutants
Correlation between simulated and measured data of the i-th pollutant in the k-th cell	Population	Identifies areas with a good match between the measured data from fixed air quality monitoring stations and concentration data estimated [35,69]
Exceedance of the legal limits of the i-th pollutant in the k-th cell [n.]	Population Vegetation	Identifies the probability of exceeding the legal limits for a specific pollutant [24,31,34–36,41,42,47,68,70]
Maximum concentration value of the i-th pollutant in the k-th cell [$\mu g \cdot m^{-3}$]	Population Vegetation	Identifies the probability of measuring an elevated concentration value for a specific pollutant [34,71,72]

Table 2. *Cont.*

Allocation Criteria	Sensitive Receptors	Note
Minimum index of agreement (IOA) for the *i*-th pollutant in the *k*-th cell	Population	Assess how the values simulated by the model deviate from the values measured by the fixed air monitoring stations
Minimum index of agreement normalized with the resident population (IOAP$_r$) for the *i*-th pollutant in the *k*-th cell	Population	Assess how the values simulated by the model deviate from the values measured by the fixed air monitoring stations, considering also the presence of resident population.
Maximum concentration gradient for the *i*-th pollutant in the *k*-th cell	Population	Assesses how changing the concentration field at a specific point compared to neighboring points [30,39,73]
Maximum air quality index in the *k*-th cell	Population	Assesses the contribution of all the pollutants at the same time [24,74,75]
Minimum concentration difference in the *k*-th cell	Population	Assesses how changing the concentration field at a specific point compared to whole study area [31,73]
Maximum pollutant deposition in the *k*-th cell	Vegetation	Assess the total deposition of the selected pollutants [76]
Maximum PM$_{10}$ deposition in the *k*-th cell	Vegetation	Assess the total deposition of the selected pollutants [76]
Maximum damage index in the *k*-th cell	Physical cultural heritage	Assess the total damage due to erosion blackening pollutants [76–78]

3. Results and Discussion

The results describe the application of the methodological approach developed for the reference study area, presenting some representative case studies of the design of air quality monitoring campaigns aimed at protecting the three types of sensitive receptor selected in the study: population, vegetation, physical cultural heritage.

3.1. Phase 1 Application

The developed methodology was applied in the study area to four specific short-term air quality campaigns. Phase 1 is the same for all campaigns.

As explained in the previous section, all the steps of phase 1 were applied, characterizing each 250×250 m cell with the necessary information and with average values of pollutant concentrations. The campaigns described in this paper use NO$_2$ and PM$_{10}$ as specific pollutants.

Three sets of regression coefficients (β and ε) were calculated: one specific set for cells classified as traffic oriented (category T), one set for industrial cells (category I) and one set for background cells (category BU) (see Section 3.1). Three air quality monitoring stations, one for each cell category, were chosen to provide the values of dependent variable (*Y* in Equation (2)): (a) one traffic oriented station (A-Zalamella); (b) one industrial oriented station (E-Via dei Germani); (c) one background oriented station (K-Delta Cervia) (see Figure 2).

The multiple linear regression analysis applied to NO$_2$ overall concentration field provided the beta coefficients and constants shown below. One dataset consisting of 8760 values each (average concentration data per hour for an entire year) was used to calculate the regression coefficients: the data measured by the fixed air quality monitoring station chosen, the data simulated by the PESCO model and those simulated by the ADMS-Urban model.

$$\text{Traffic area}: \; C_{tot} = (0.60 C_{PESCO} + 0.27 C_{ADMS}) + 13.52 \tag{8}$$

$$\text{Industrial area}: \; C_{tot} = (0.70C_{PESCO} + 0.62C_{ADMS}) + 5.59 \tag{9}$$

$$\text{Background area}: \; C_{tot} = (0.87C_{PESCO} + 0.11C_{ADMS}) + 1.36 \tag{10}$$

For PM_{10}, the coefficients calculated using three datasets of 365 data each (daily average values) are as follows:

$$\text{Traffic area}: \; C_{tot} = (0.55C_{PESCO} + 1.99C_{ADMS}) + 6.89 \tag{11}$$

$$\text{Industrial area}: \; C_{tot} = (0.45C_{PESCO} + 1.65C_{ADMS}) + 4.62 \tag{12}$$

$$\text{Background area}: \; C_{tot} = (0.89C_{PESCO} + 0.58C_{ADMS}) + 1.58 \tag{13}$$

where: C_{tot} is the total concentration; C_{PESCO} and C_{ADMS} are the concentration values simulated by PESCO and ADMS-Urban models, respectively.

The multiple linear regression analysis results for NO_2 show a standard deviation of 10.60, 11.08 and 4.57 and a coefficient of determination (R^2) of 0.52, 0.39 and 0.85, respectively for the stations classified as "traffic", "industrial" and "background". For PM_{10} the values of the standard deviation are 15.07, 13.88 and 11.40, while for R^2 the values are 0.70, 0.61 and 0.83.

The *p*-values for all variables are less than 0.05, showing their statistical significance.

The statistical analysis comparing the measured and predicted total values is shown in Table 3. The correlations between measured and simulated data are always higher than 0.57. In particular for NO_2, there are values that often exceed 0.8. For PM_{10}, the values are between 0.58 and 0.68. The simulated and observed data have small differences in the concentrations values and, consequently, the resulting FB index assume values close to the next optimal results (which corresponds to the value 0). There are some situations with more significant differences (e.g., station "D"), but they are limited to few cases and often linked to areas characterized by highly variable pollution situations due to the proximity of very complex emission sources (the station "D" is inside the industrial and harbor area of Ravenna's city). The FA2 and IOA indices assume values close to ideal performance in many cases. Similarly, also the NMSE index assumes values that are almost ideal (which corresponds to the value 0) in the majority of the considered comparison points.

Table 3. Statistical analysis comparing the measured and predicted NO_2 and PM_{10} concentration values.

Fixed Air Quality Monitoring Stations	Measured MEAN ($\mu g/m^3$)	Predicted MEAN ($\mu g/m^3$)	CORR	NMSE	FA2	FB	IOA
NO_2							
B—Caorle	25.35	24.49	0.81	0.20	0.85	0.03	0.90
C—Rocca Brancaleone	32.23	32.15	0.77	0.13	0.92	0.00	0.86
D—SAPIR	47.12	26.64	0.63	0.43	0.58	0.56	0.62
F—Azienda Marani	32.81	26.26	0.60	0.46	0.67	0.22	0.67
H—Marina di Ravenna	21.77	18.90	0.65	0.36	0.73	0.14	0.78
I—Azienda Zorabini	15.72	21.16	0.57	0.75	0.51	0.29	0.71
J—Ballirana	22.63	20.10	0.80	0.18	0.90	0.12	0.88
L—Marconi	34.20	29.98	0.98	0.03	0.99	0.13	0.95
M—Parco Bertozzi	28.54	28.60	0.87	0.14	0.90	0.00	0.93
N—Giardini	21.45	21.27	0.94	0.06	0.95	0.01	0.97
PM_{10}							
B—Caorle	30.83	35.6	0.58	0.30	81.36	−0.14	0.72

Fixed Air Quality Monitoring Stations	Measured MEAN ($\mu g/m^3$)	Predicted MEAN ($\mu g/m^3$)	CORR	NMSE	FA2	FB	IOA
C—Rocca Brancaleone	29.89	34.09	0.67	0.16	89.75	−0.13	0.79
D—SAPIR	44.77	25.71	0.59	0.72	63.46	0.54	0.52
F—Azienda Marani	26.66	21.00	0.60	0.29	83.71	0.24	0.79
L—Marconi	30.90	30.39	0.67	0.15	94.66	0.02	0.79
M—Parco Bertozzi	23.64	27.25	0.68	0.27	88.14	−0.14	0.78
N—Giardini	25.05	32.04	0.61	0.32	78.33	−0.24	0.69

The worst performances were recorded for the stations classified as "industrial", due to the difficulty in characterizing (temporally and spatially) the emissions sources in areas of strong industrial vocation. On the other hand, the best performances were recorded for control stations classified as "background" or "urban".

Because of the good results of the comparative analysis between measured and predicted values, the equations obtained by regression analysis were applied to define the entire concentration fields of NO_2 and PM_{10} concentration in the study area, according to the classification of each cell. Finally, the resident population, vegetation and physical cultural heritage were spatially disaggregated for each cell.

3.2. Phase 2 Application

The four campaigns chosen in order to test the proposed methodology, called Examples n.1–n.4 are described below. Each example simulates the design of a measurement campaign with a mobile laboratory according to the following characteristics (Table 4).

Table 4. Main characteristics of each example.

Decision Criteria	Example n.1	Example n.2	Example n.3	Example n.4
Spatial domain	Territory of the municipality of Ravenna	Territory of the municipality's union of the lower Romagna	Territory of the municipality's union of the Romagna Faentina	Territory of the municipality of Ravenna
Temporal domain	Month of October	Month of July	Month of June	Month of December
Area type	Urban traffic (T)	Urban background residential (BU-Res)	Rural background (BR)	All
Pollutant	NO_2	NO_2	PM_{10}	PM_{10}
Allocation criteria and objective function	Overall exposition to NO_2 of the residential population	Maximum concentration values of NO_2	Maximum PM_{10} deposition	Maximum damage index

3.2.1. Campaign n.1

The objective of this example was to analyze the exposure of the urban population of Ravenna municipality to NO_2. Figure 3 shows the application of phase 2 to the spatial domain (a), temporal domain (b), area type (c) and pollutant (d) identification. These allowed the potential cells for the monitoring activities to be reduced numerically and spatially.

The selected criterion in the first case study was the "overall exposure of the residential population to NO_2". The maximization of the objective function that expressed this allocation criterion (operationally the function is calculated for all the cells resulting from the selection of the first 4 steps of phase 2 and then by selecting those with the maximum values) allowed the identification of only a few cells (Figure 3e). Keeping all the decision variables unchanged and changing only the month of monitoring, Figure 3 shows the

different distribution of the points identified for monitoring. This is due to the different weather conditions and pollutant concentration values.

3.2.2. Campaign n.2

The objective of this example was to analyze the exposure of the population of an urban background area to NO_2. The selection of the spatial domain (a), temporal domain (b), area type (c) and pollutant (d) of the second campaign is shown in Figure 4. The selected criterion in the second case study was the "maximum NO_2 concentration values". Analogous to the previous case, the selection criteria values were calculated on the selection reported in Figure 4d and the optimal points where to place the mobile laboratories were identified among the cells with the highest values (Figure 4e).
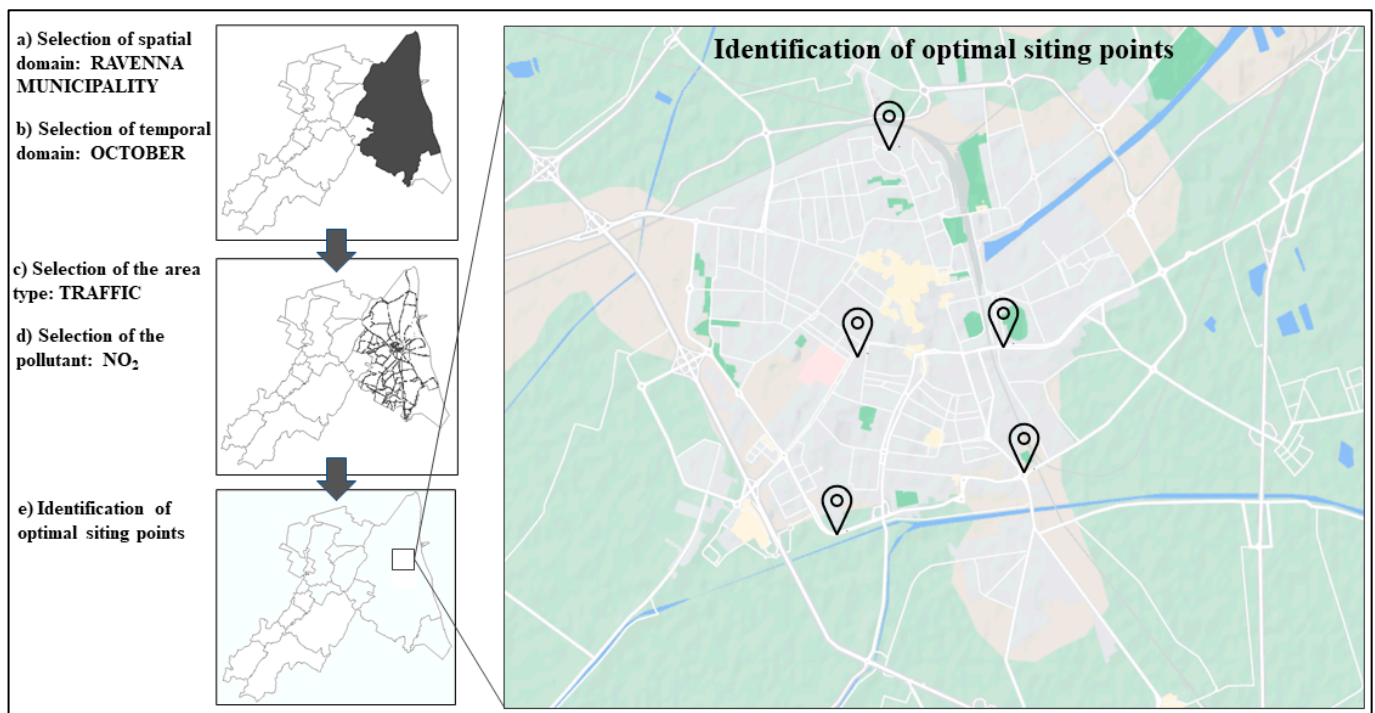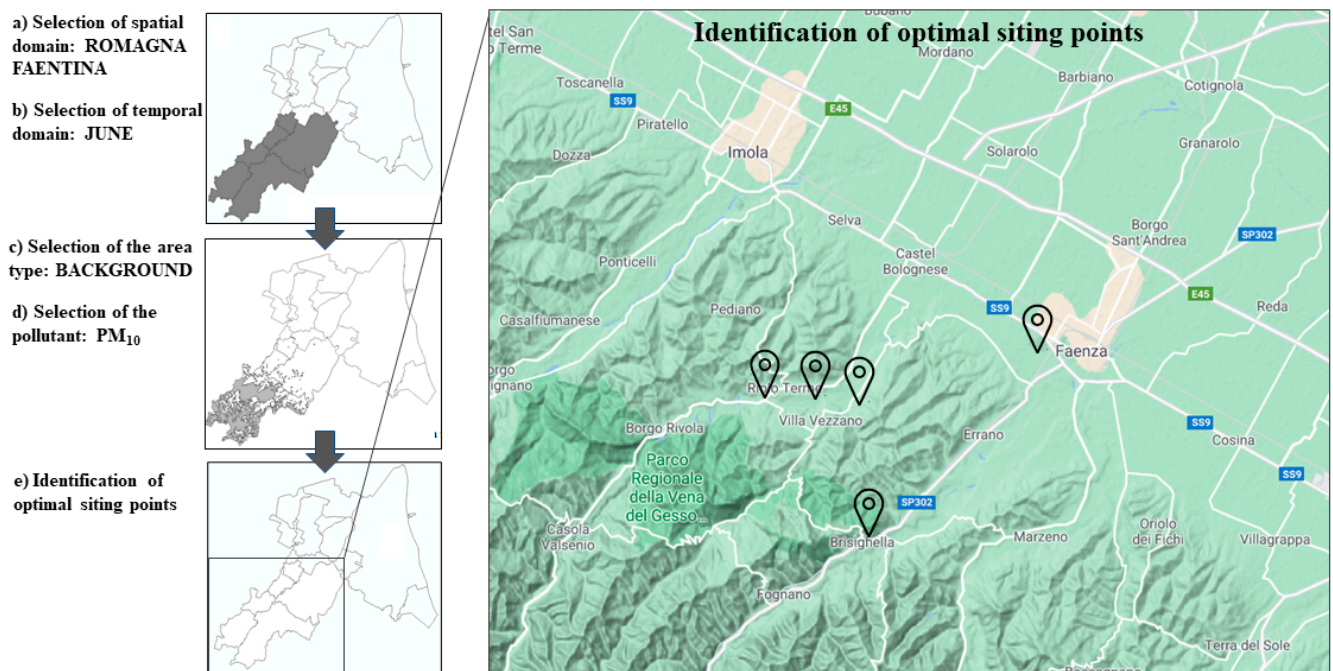

Figure 3. *Cont.*

Figure 3. *Cont.*

Figure 3. Example n.1—spatial domain (**a**), temporal domain (**b**), area type (**c**), pollutant selection (**d**) and extremes of the exposure value that identify the optimal monitoring points (**e**). The other figures show how the distribution of optimal points changes as a function of time.
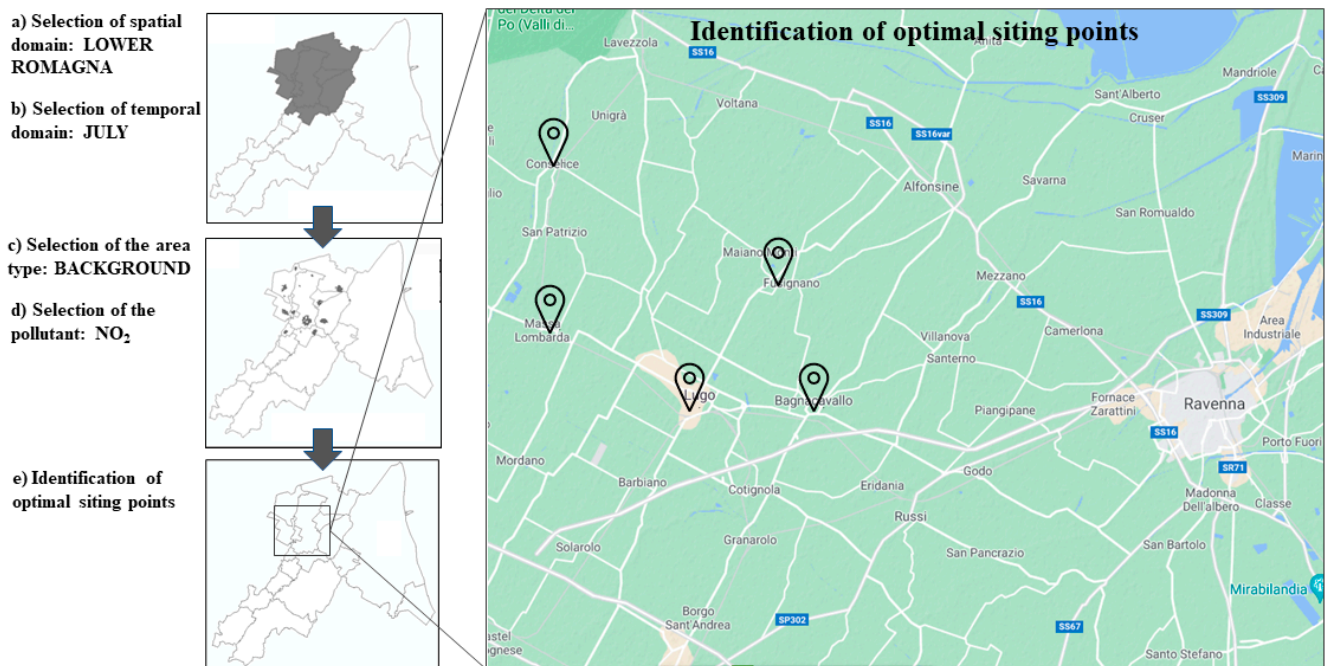
Figure 4. Example n.2—patial domain (**a**), temporal domain (**b**), area type (**c**), pollutant selection (**d**) and extremes of the exposure value that identify the optimal monitoring point (**e**).

3.2.3. Campaign n.3

The objective of this example was to analyze the PM_{10} deposition to assess the effect on sensitive vegetation. The selection of the spatial domain (a), temporal domain (b), area type (c) and pollutant (d) of the third campaign is shown in Figure 5. The selected criterion in the third case study was the "Maximum PM_{10} deposition". Analogous to the other case-studies, the selection criteria values were calculated on the selection reported in Figure 5d and the optimal points where to place the mobile laboratories were identified among the cells with the highest values (Figure 5e).

Figure 5. Example n.3—spatial domain (**a**), temporal domain (**b**), area type (**c**), pollutant selection (**d**) and extremes of the deposition value that identify the optimal monitoring points (**e**).

3.2.4. Campaign n.4

The last example that has been described used materials as a sensitive receptor and PM_{10} depositions (which contribute to determining the total damage index, see Table 3) as a choice criterion. The selection steps are shown in Figure 6.

As explained in Section 3, the proposed approach enables the allocation procedure of air monitoring stations including spatial and temporal variables. The inclusion of the temporal variable makes the approach particularly suitable for short-term air quality campaigns. The approach is structured as an actual procedure in phases and steps. This feature has several advantages. The procedural structure guarantees the respect of the principle of replicability that leads to the application of a coherent methodology for the various cases. The presence of two phases permits the simplification of the operations: the two phases are connected to each other, but each phase is able to operate independently from the other. The changes made in one phase determine the variation of the results of the next, but they do not cause a revision of the whole application procedure (which remains standardized). The subdivision in several steps permits transferability: the approach can be adapted to local peculiarity and different objectives. The possibility to choose among many objective functions and different sensitive receptors results in great versatility. Transferability and versatility make the proposed methodology applicable also to low-cost sensors used for air quality monitoring in areas with elevated variations from the spatial and temporal point of views and with low availability of financial resources [79,80].
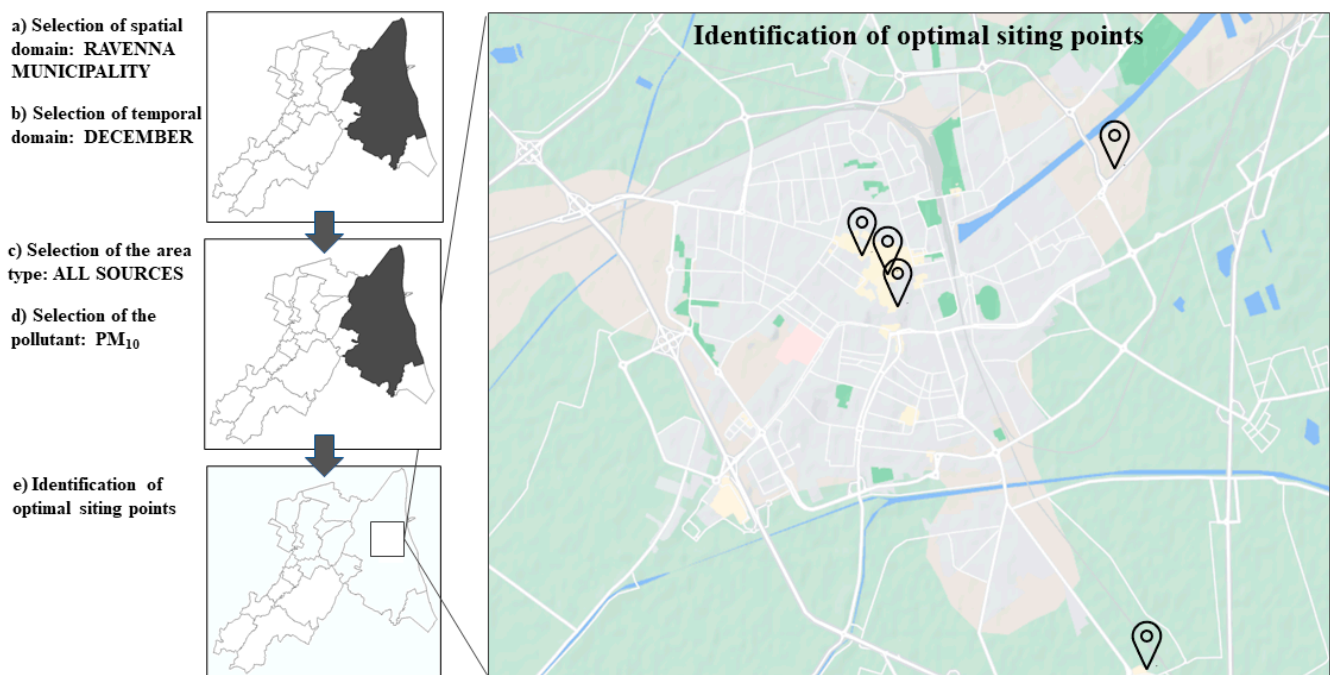
Figure 6. Example n.4—spatial domain (**a**), temporal domain (**b**), area type (**c**), pollutant selection (**d**) and extremes of the damage index values that identify the optimal monitoring point (**e**).

The experimental application of the methodological approach allowed the authors to test each step and to provide the following comments and observations. (i) The proposed methodology requires a preliminary pollutant concentration assessment. In the area of interest, a mathematical dispersion model to assess the background concentration was available (PESCO) and it was integrated by a model to evaluate the local source contributions (ADMS-Urban). Air pollution concentration data, maps and models are easily available in Europe and in other parts of the world [49,81] and the local source modeling requires information which is a part of local authority duties (see the EU Directives in European Union). (ii) Multiple linear regression appears to be a very interesting tool for combining data coming from different predictive models as it is cheap, easy to apply, effective and reliable. (iii) If data are available, the validation of simulated values vs. measured values is always recommended because it permits the adjustment of the assessment process and its strengths and weaknesses to be known. (iv) The spatial disaggregation of the residential population as a sensitive receptor has been done, starting from the national census of the population conducted by the National Institute of Statistics and representing the best available data. The population census is the most detailed information source on the population at different levels and it is very easily available. If the sensitive receptor is vegetation, easy and important sources of information could be lists and/or maps of protected areas, such as national parks, nature reserves and areas of special interest. Lists of national physical cultural heritage are also readily available in many countries. (v) Using all the collected information, processed and arranged through phase 1, the application of the allocation procedure, which constitutes phase 2 of the methodological developed approach, was very simple and fast.

The application of the proposed methodology highlights, also, some weaknesses. The more data used, the higher the resolution and the better the allocation choice, but to process and manage a high quantity of data requires substantial computing capacity that is not always available. Another weak point is that the database and information collection created by phase 1 have to be continuously updated for the approach to be effective. Finally, the allocation choice made by the proposed methodology might not be compatible with practical aspects (e.g., power requirements, security, site permissions, site access, etc.).

A refinement of the methodology could be provided by taking these weaknesses into account. It would be very useful to develop a software tool for the automatization of data loading and update activities. Moreover, it would be convenient to expand the list of objective functions in order to include other sensitive receptors (e.g., fauna) or to further detail the existing categories (population classified in increasing levels of sensitivity to pollutants, such as children and the elderly; cultural heritage classified according to the type of material, such as bronzes and carbonate materials).

4. Conclusions

In conclusion, a new methodology for designing short-term air quality monitoring campaigns has been proposed and tested on a case study area—situated in northeast Italy—through four short-term campaigns. The approach is designed especially for the environmental management and protection authorities but it is also usable by private entities. It is characterized by a high replicability (it is organized as a real procedure in phases and steps) and wide versatility, in fact, it can be adapted and contextualized for situations with very different characteristics (emission, sources, receptors, orography, etc.,) and it can answer very different questions (temporal aspects, different allocation criteria, different receptors, etc.).

Its experimental application has provided satisfactory results (both in terms of time and space) in regard to the objectives of this study by indicating suitable monitoring points.

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