Fuzzy environmental analogy index to develop environmental similarity maps for design air quality monitoring networks on large-scale

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Abstract
All activities aimed to study primary causes and effects of air pollution cannot disregard the fact that is necessary to have an optimal Air Quality Monitoring Network (AQMN) for assessing population exposure to air pollution and predicting the magnitude of the health risks. In the framework of a cooperation between ARPA Sicilia organisation and Department of Engineering, University of Palermo, researches were performed to develop an innovative methodology useful to define environmental similarity maps, aimed at supporting the design of air quality monitoring networks at regional scale. This approach is based on new index, called fuzzy environmental analogy index (FEAI), based on fuzzy theory. FEAI is deduced by combining two indexes: meteorological pressure indicator (MPI) and anthropic pressure indicator (API). MPI allows to investigate, for the examined territory, analogies relevant to meteorological conditions, API emphasizes the importance of impacts related to anthropogenic or natural sources at regional scale. Finally, FEAI applications for a case study, related to Sicily region, Italy, are also described. The obtained results allow to confirm the capability of FEAI index to investigate similarities between neighboring areas, in terms of environmental pressures due to anthropic and natural sources, and so to identify gaps of the monitoring network used to define existing air quality conditions.

Keywords: environmental similarity maps, fuzzy environmental analogy index, air quality monitoring network, environmental pressures, anthropogenic or natural impacts

1 Introduction

Today impacts of anthropic pressures on the environment remain a critical global problem and, in this field, it is very important to design regional air quality monitoring networks (or to qualify those already existing) with the purpose of providing efficiently control of impacts related to, for example, routine emissions; releases due to nuclear power plant accidents, or, more generally, conditions involving emissions of hazardous substances. The risk management should be targeted at choices generating strategies focused on accurate knowledge of territorial relationships between environmental pressures, anthropogenic impacts, and reconstruction of atmospheric depositions (EPA, 2003; Buchholz et al., 2010; Florent and Didier, 2014; Li et al., 2014; Giardina et al. 2017; Giardina and Buffa, 2018; Connan et al., 2018; Giardina et al. 2019).

In this field, numerous approaches, such as the environmental impact assessment indices, allow to analyses the environmental risks, for example, by dealing with local effects on health and environment (EPA, 2006; Gómez-Navarro et al., 2009; Li et al. 2014; Li et al., 2015; Saib et al., 2015). In recent years, various methodologies have been proposed to evaluate air quality conditions, among these the fuzzy logic is used to reduce uncertainty and imprecision in air quality index (AQI) computational models (Kentel and Aral, 2007; Carbajal-Hernández et al., 2012; Elshout et al., 2014; Olvera-García et al., 2016; Singh et al., 2017; Debnath et al., 2018; Di Nardo et al., 2018).

AQI index is evaluated in different ways around the world and relationships are defined to take into account pollutant toxicity levels, as indicated by national and international legislations.

The common factor of these methodologies is that AQI is based on pollutant concentration data obtained from the monitoring stations strategically located across the country. Therefore, a protocol for quality assurance strongly rely on measured concentrations and, in this respect, data are often insufficient to be representative of the people exposure over an area. Many researchers tried to give an answer about areal extensions of population exposures by using, for example, site-specific correction factors and statistical weighting of individual stations by population densities (Plaia and Ruggieri, 2011).

It is evident that a basic cognitive and assessment tool for all the activities related to the accurate definition of air quality, as well as its geographical extension, cannot disregard the fact that is necessary to have an optimal Air Quality Monitoring Network (AQMN) for assessing population exposure to air pollution and predicting the magnitude of the health risks (ZoroufchiBenis et al., 2015).

In a recent survey of views of Member States (MS) and other stakeholders on the revision of the EU ambient air quality directive (AAQD), further harmonisation of the networks, in particular regarding station siting (and representativeness), was high on the priority list (Hout et al., 2012).

In this field, the Commission of the European Union appointed a working group for the revision of the annexes of the Council Decision 97/101/EC of 27 January 1997 where it is established a reciprocal exchange of information and data from networks and individual stations measuring ambient air pollution within the MS. The Directive 2008/50/EC of 21 May 2008 recognize that modelling techniques should be applied to enable point data to be interpreted in terms of geographical distribution of concentration. This could serve as a basis for calculating the collective exposure of the population living in the area. It is recommended to use “ad hoc” models to support the interpretation and spatial extrapolation of the results of measurements in existing networks (Duyzer et al., 2015).

It is clear that there is a need to develop tools able to identify zones characterized by environmental similarities, such data should be useful for understand the resilience capacity of a monitoring network used to define existing air quality conditions in a geographical area or region.

These tools, for being useful in the above described context, should to take into consideration and elaborate environmental parameters such as emissive sources, that are on the territory; analysis of meteorological data from the surrounding zones; and orographic complexity in the area of interest.

In the framework of a cooperation between ARPA Sicilia (Agenzia Regionale per la Protezione dell’Ambiente), Sicily, and Department of Engineering, University of Palermo, research efforts were performed in order to provide solutions on these issues developing environmental similarity maps based on a new index, called fuzzy environmental analogy index (FEAI). This tool, applicable across a regional scale, is useful to maximize the capability to highlight environmental analogies between bordering areas and so to qualify, or design, air monitoring networks that are active in the territory.

FEAI is derived by combining two indexes: meteorological pressure indicator (MPI) and anthropic pressure indicator (API).

MPI and API have been developed by using fuzzy set theory, which allows interpretation of imprecise (vague) information and recognition of uncertainty due to fuzziness.

In particular, MPI is derived by fuzzy meteorological pressure indicators to study the influence of wind speed and its frequency distribution in neighboring areas of the territory of interest.

Wind speed and frequency data are calculated by using simulations of CALMET (California Meteorological Model) code, a meteorological model that allows assessments of horizontal and vertical wind profiles and turbulence intensity within user-specified atmospheric boundary layers (Scirè et al., 1999). CALMET enables to the user to define a vertical layer, as the midpoint between two faces (i.e., nine faces corresponds to eight layers, with the lowest layer always being ground level of 10 m) for applications to overland and overwater grid cells.

API is evaluated by using fuzzy anthropic pressure indicators, which provide elaborations of parameters related to orography complexity and pollutant mass flow rates (also of natural origin), released from sources distributed on regional scale.

FEAI application for a case study, related to Sicily region in Italy, was performed to validate the proposed methodology. In particular, air pollutant emissions of PM10, SOx, and NOx, and meteorological conditions for five years (from 2010 to 2014) were examined in order to build FEAI maps. In the examined period, several accidental events occurred in the industrial and petrochemical areas (some accidents caused fires that lasted about 48 hours).

Preliminary applications of the proposed methodology concerned these pollutants because they are considered significant for the Sicilian territory, given to the presence of petrochemical plants that extend for 2,700 hectares, health impacts related to road traffic (focused in particular in urban area) and significant deposition processes of particulate such as dust from Sahara desert. The main results are reported and commented in this paper.

Finally, it is worth pointing out that the proposed fuzzy model was already used by ARPA to determine the sub-sets of air monitoring stations useful for reciprocal exchange of information and data from networks and individual stations measuring ambient air pollution within the MS, as established by Council decision 97/101/EC above mentioned.

2 General considerations about fuzzy sets and fuzzy logic

2.1 Fuzzy sets and fuzzy logic

The fuzzy logic model was introduced by Zadeh to address problems in which phenomena are imprecise and vague or to model experiences defined by linguistic expressions (Zadeh, 1975; 1992).

As known, the most important use of fuzzy set theory is the definition and construction of fuzzy rule systems that can be applied successfully to a wide range of problems in which uncertainty and imprecision occur in different ways (Pedrycz, 1996; Casamirra et al., 2009; Castiglia et al., 2010; Renjith et al., 2018; Mahmoudi et al., 2019). A source of imprecision that may lead to uncertainty is scarce or incomplete data, measurement error or data obtained from expert judgment or subjective interpretation of available information (Kentel and Aral, 2004; Sadiq and Tesfamariam, 2009)

We often don’t think with calculations and numbers, but with logical thoughts, linguistic expressions and non-probabilistic uncertainties (intrinsic to the phenomenon itself, not its occurrence).

Therefore, a fuzzy logic model can be useful in areas such as environmental modeling that often involves the processing of a significant number of data that are the subject of inaccuracies. So the fuzzy models, which are robust (noise tolerant capability), allow to manage uncertain information by using multivalent logic rules.

Traditional set theory is based on a bivalent logic, where a number, or object, is either a member of a set or not. In contrast, let X be a collection of numbers or objects (fuzzy set) called the universe of discourse, whose elements are denoted by x; a fuzzy subset A in X is characterised by a membership function $\mu_A(x)$ that associates each element x in X with a real number in the range [0, 1]. The function $\mu_A(x)$ represents the degree of membership of x in the fuzzy set A.

The most commonly used fuzzy numbers are set up as triangular or trapezoidal fuzzy relationships as follows:

$$\mu_A(x) = \begin{cases} \dfrac{x - x_1}{x_2 - x_1} & x_1 \le x \le x_2 \\ \dfrac{x - x_3}{x_2 - x_3} & x_2 \le x \le x_3 \\ 0 & \text{otherwise} \end{cases} \qquad \text{for triangular membership function} \qquad (1)$$

$$\mu_A(x) = \begin{cases} \dfrac{x - x_1}{x_2 - x_1} & x_1 \le x \le x_2 \\ 1 & x_2 \le x \le x_3; \\ \dfrac{x - x_4}{x_3 - x_4} & x_3 \le x \le x_4 \\ 0 & \text{otherwise} \end{cases} \qquad \text{for trapezoidal membership function} \qquad (2)$$

For triangular fuzzy numbers, x_2 yields the maximum value of $\mu_A(x)$, i.e., $\mu_A(x_2) = 1$, making this the most plausible value, whereas x_1 and x_3 are the lower and upper bounds of the variable area of the evaluated data. For trapezoidal fuzzy numbers, the most plausible values of $\mu_A(x)$ fall in the interval [x_2; x_3], whereas x_1 and x_4 are the lower and upper bounds of the variable area for the evaluated data.

For brevity, triangular and trapezoidal fuzzy numbers are often denoted as (x_1, x_2, x_3) and (x_1, x_2, x_3, x_4), respectively.

Basically, for the operations on fuzzy sets Zadeh (1975) suggested the minimum operator for intersection and the maximum operator for union.

Let A and B be fuzzy sets from the same universe X, with membership functions μ_A and μ_B, the fuzzy intersection and fuzzy union are as follows (Hong and Leeb, 1996):

$$A \cap B \equiv \{\langle x, \mu_{A\cap B}(x)\rangle \mid x \in X \text{ and } \mu_{A\cap B}(x) = \min[\mu_A(x), \mu_B(x)]\} \qquad (3)$$

$$A \cup B \equiv \{\langle x, \mu_{A\cup B}(x)\rangle \mid x \in X \text{ and } \mu_{A\cup B}(x) = \max[\mu_A(x), \mu_B(x)]\} \qquad (4)$$

The combination of these two operators are generally used in fuzzy *if-then* base rules (fuzzy inference operation). Each fuzzy *if-then* rule has antecedent linguistic values and a single consequent class, as described in the following section.

2.2 Fuzzy inference system

As it is known, the most important application of fuzzy set theory is the fuzzy rule-based systems, successfully applied to a wide range of problems from different areas presenting uncertainty and vagueness in different ways (Pedrycz, 1996; Castiglia et al., 2008; Casamirra et al., 2009; Castiglia et al., 2010).

Generally, the functional operations in fuzzy rule-based systems proceed in the following steps:

- Fuzzification,
- Fuzzy Inference System (FIS),
- Aggregation of all outputs,
- Defuzzification.

Fuzzification is the process of changing real scalar values into fuzzy sets. This is achieved with the different types of construction of fuzzy sets, e.g. by using membership functions described in previous section.

Fuzzy inference is the process of mapping that allows to switch from a given input to an output by using fuzzy logic. This process involves all the pieces discussed in the previous sections (membership functions, fuzzy logic operators) together with the construction of *if-then* rules (i.e. FIS).

A rule consists of a collection of fuzzy *if–then* rules to map from fuzzy sets in the input universe of discourse $X \subset R^n$ to fuzzy sets in the output universe of discourse $Y \subset R^m$, based on fuzzy logic principles (Zadeh, 1992).

The fuzzy *if-then* rules can be described as follows:

Rule R_j: ***If*** x_1 *is* A_{j1} ***and*** … ***and*** x_n *is* A_{jn} ***then*** y *is* B_j j=1, 2,…m (w_j) (5)

where A_{ji} and B_j are the linguist variables defined in X and Y fuzzy sets, quoted as input and output universes of discourse. The *if* part of the rule "x_n *is* A_{jn}" is called the antecedent, or premise, while the *then* part of the rule "y *is* B_j" is called the consequent.

The parameter w_j in Eq. (5) denotes the degree of importance of the rule in the range [0, 1]. Often this factor is used to describe the uncertainty of an expert's assessment of the rule.

There are several ways to combine all the rules of FIS into a single fuzzy set, such as the Min–Max inference method (Zadeh, 1992) widely used in literature. In Fig. 1 an example of Min–Max inference application is shown.

Min–Max inference application starts with the selection of the minimum membership function (i.e. intersection obtained by using Eq. 3) in *if* parts of each rule (see x_1 and x_2 for different antecedents A_{ij} in Fig. 1). The final output membership function is the aggregation (i.e. union obtained by using Eq. 4) of the fuzzy sets, after cutting the degree of membership values at the degree of membership of the corresponding minimum of antecedents (cut-off of B_j sets in Fig. 1).

If Eq. (5) is used with weight w_j, the winner rule is modified by using the following relationship:

$$\mu_j^*(x) = \max\{w_j\, \mu_j(x) : j=1, 2, ..m\} \quad (6)$$

In Fig.1 an example of aggregation of fuzzy outputs without weight is shown as grey area, the aggregation of fuzzy outputs with weight is shown as black area.

The finally step is the defuzzification which maps the output from the fuzzy domain (i.e. the result of fuzzy aggregation operation) back into the crisp domain. This step consists of averaging the outputs from all of the individual fuzzy rules into a single output decision (crisp value).

Many defuzzification methods have been proposed and centre of gravity (COG) is widely used because of its straight forward geometric meaning (Hellendoorn and Thomas, 1993; Ramli and Mohamad, 2009; Castiglia et al., 2011; Castiglia et al., 2015).

The crisp value, obtained by using the COG method, is the centre of "gravity" of the area produced by the combination of the membership functions in the fuzzy inference step, i.e.:

$$COG^* = \frac{\int x\, \mu^*(x)\, dx}{\int \mu^*(x)\, dx} \quad (7)$$

where $\mu^*(x)$ is calculated by using Eq. (6), if the aggregation process of fuzzy outputs is used with weight.

3 Fuzzy sets and fuzzy rule-based system to evaluate MPI and API indexes and FEAI calculation

3.1 Classifying of fuzzy sets to evaluate MPI and API and reasoning process

As described in section 2.2, the first step, called fuzzification, consists in transforming the numeric input data (crisp) into linguistic terms by assigning fuzzy sets, expressed via verbal labels (e.g. low, medium, high etc..) and fuzzy membership distributions defined on the universe of discourse. Therefore, syntactic representations, framed in terms of predicates, are given by sets of labels which can help to construct roles with respect to information structure of the studied system.

The linguistic aggregations operators are based, for example, on linear ordering, such as the linguistic max and min operators (Xu, 2012).

As highlighted in (Tang and Zheng, 2006), semantic relations among linguistic labels capture the vagueness in most natural language. For instance, if we have linguistic labels as {Low, Medium, High, Very High}, on the view point of linguistic semantic relation, we think that very high is much closer to High than Medium, and High is much closer to Medium than Low.

In this work, sets (or subsets) of fuzzy input values were chosen and modelled in compliance with basic information and knowledge that classify and define objective data, without losing their interpretability (see section 3.2 for more details). The mid linguistic label represents assessment of "indifference" and the rest labels are defined around it.

The method for generating fuzzy rule-based systems (i.e. reasoning process) is based on the approach reported in (Giardina et al., 2014) in which each fuzzy rule is determined taking into account the relative importance of input fuzzy variables and weights of linguistic terms evaluated by assuming linear relationships among labels. In section 3.3 one example of fuzzy rule generating process is illustrated for MPI.

Given that FIS system is evaluated by assuming linear relationships among linguistic terms of input variables, the number of rules in the single knowledge base is well defined, making easier to interpret the model and to verify the partitioning of input spaces when the input–output mapping is applied, eliminating conditions that cause inconsistency.

In order to test linguistic models and FIS implemented for the information structure examined in this work, some reasoning processes performed by using ARPA expert opinions were used and the results compared with those obtained by using the developed tool. In addition, some sensitivity analyses were carried out by varying the partition of input fuzzy sets to verify that the values of the rule selection process parameters are still the same.

The results of these validation works showed that the procedure to evaluate MPI and API seems to approximate the real system with good performances, with the advantage of being easily verifiable, despite the presence of complex information structure.

3.2 MPI and API indexes

MPI index is derived by combining data from the two following meteorological pressure indicators:

- wind speed (WS) [m/s];
- wind frequency (WF), expressed in percentage [%].

Fuzzy classifications of WS and WF are built by using the fuzzy linguistic model reported in Tab.s 1 and 2 and presented in graphical form in Fig.s 2 and 3, respectively.

The Beaufort scale (Barua, 2005), referring to observed wind speed conditions at sea or land, is used to define linguistic representations of WS sets, as reported in Tab. 1. The scale depicts the force of wind by a series of numbers from 0 to 12, on the basis of wind speeds and effects over a large area.

The reasoning to describe the wind speed effects, reported in Beaufort scale, has helped to define the linguistic values and matching the fuzzy sets distributions as reported in Tab. 1.

To give an example, Medium (SM) linguistic label is related to Beaufort number 4, i.e. "Moderate breeze" (with wind speed in the range 5.5÷8 m/s). Trapezoidal membership function of SM is defined around the medium value of about 6.5 m/s.

Beaufort numbers from 1 to 3 correspond to wind speed interval of 0.0÷3.3 m/s, the associated effects are: "calm" (with wind speed in the range 0.0÷0.2 m/s); "Light air" (with wind speed in the range 0.3÷1.5 m/s); and "light breeze" (with wind speed in the range 1.6÷3.3 m/s). The fuzzy classifications in terms of linguistic labels are "Very Low" (SVL), characterized by x variable of Eq. (2) in the range 0.0÷3.3 m/s, and "Low" (SL), characterized by x variable in the range 1.5÷6 m/s. Note that the maximum membership function for "Low" (SL) corresponds to x of 3.3 m/s, whereas the upper bound of the variable data is 6 m/s, which is close to medium value of wind speed for Beaufort number 4 (Moderate breeze).

Fuzzy WF distributions are based on five classes (Tab. 2) expressed by verbal labels from "Very Low" (FVH) to Very High (FL). For example, frequency value of 20% is considered as median value of the set identified with label "High" and as lower limit of the class identified with label "Very High". This derives to attempt to represent results of wind rose analyses carried out for a period of ten years in Sicily. Moreover, by examining frequency results reported in some review of wind speed probability distributions evaluated for other countries (Essa and Embaby, 2005; Carta et al., 2009; Amar and Elamouri, 2011), these classifications seem to be representative and support generalizations made in this study.

Finally, MPI fuzzy output (consequent) is defined by using the linguistic values reported in Tab. 3 and in graphical form in Fig. 4. The domain is based on nine labels to extend the semantic relations of natural languages used by experts.

API index is evaluated by combining the three following fuzzy pressure indicators:

- Orography Complexity Indicator (OCI) [m]
- pollutant mass flow rate emitted from each source (average in a year), normalized with its maximum value (MFR) [-];
- distance of a generic cell of the calculation grid from the cell where the pollutant source is located (D) [km].

The linguistic fuzzy sets of OCI, MFR and D parameters are reported in Tab.s 4 through 6. The output fuzzy linguistic values of API are shown in Tab. 7. As performed for MPI fuzzy output, the domain of API is based on nine labels.

OCI indicator, expressed in meter, is calculated as average of the difference between geodetic height of C[i,j] of the sub-grid and the geodetic height of bordering cells (Fig. 5). This allows to take into account orographic features among neighboring cells, due to landforms such as hills, mountains and valleys which can blocking or breaking pollutants dispersion conditions. The elaborations are performed, with 3x3 km resolution, by using a pre-processing algorithm, developed in R-CRAN programming language, and making use of digital raster elevation maps distributed by USGS. Fig. 6 reports the OCI map obtained by using QGIS software. Comparisons between OCI map and Sicily topography, reported in Fig. 7, highlight a good match of areas with greater orographic complexity respect to the neighboring ones.

OCI fuzzy distributions are based on linguistic variables distributed around the label "Medium Complexity", characterized by x variable of Eq. (1) in the range 225÷325 m (Tab. 4). This takes into account that in UK a standard method is used for defining a mountain and a hill. This is based on height, and for a while US adopted this standard too. Both countries defined a mountain as being about 305 m, or more tall. Any similar landform lower than this height is considered a hill.

For MFR pressure indicator, the normalization of pollutant mass flow rate has facilitated the fuzzy classifications of emissions intensity that, therefore, varies in the range [0, 1] (0 no emission, 1 maximum emission) (Tab. 5).

It should be highlighted that, under reasonably conservative assumptions, the label "Medium" (MFR_M) is defined by x variable of Eq. (1) in the range 0.2÷0.4, the label "Between Medium and High" (MFR_M _H) in the range

0.3÷0.5, and the label "High" (MFR_ H) in the range 0.4÷0.6. Moreover, such a choice is consistent with breakpoint pollutant concentrations for AQI Sub-index used in (Olvera-García et al., 2016; Singh et al., 2017).

In particular, fuzzy classification levels of concentrations of SO2, NO2 and PM10 used to evaluate air quality parameters in (Olvera-García et al., 2016) are considered "High" (with membership function equal to 1) if they vary from 40 to 50% compared to their corresponding maximum values.

Regarding the parameter D, in this work it is considered distance from the source of 12 km like the one at which might match an area suffering the effects of negative environmental pressures, taking into consideration knowledges regarding population density around the locations of sources.

3.3 Determination of the fuzzy rule-based system FIS

Each fuzzy rule of FIS system is determined taking into account the relative importance of input fuzzy variables, reported in Tab.s 8 and 9, and weights of linguistic terms, shown in Tab.s 1÷7, that are evaluated by assuming linear relationships among them.

Let us take input fuzzy sets of WS and WF, with the pertinent weights reported in Tab.s 1 and 2, and MPI fuzzy outputs with the relevant weights shown in Tab. 3.

MPI output linguistic term, to be used within the fuzzy *if–then* rules, is identified by using the weight W_{MPI} calculated by using following relationship:

$$W_{MPI} = R_{WS}\, W_{WS} + R_{WF} W_{WF} \tag{8}$$

where R_{WS} = 0.4 and R_{WF} = 0.6, if the calculation is performed for second or third layer (see Tab. 8). On the basis of the above equation, it is possible to identify the followings *if–then* based rules:

Rule 1: ***If*** wind speed (WS) is *Very Low* (W_{WS}= 0.2) ***and*** wind frequency (WF) is Low (W_{WF}= 0.4) ***then*** MPI is *Between Very Low_Low* with weight W_{MPI}=0.32

MPI consequent part is obtained using Eq. (8), namely W_{MPI}= 0.4 x 0.2 + 0.6 x 0.4 = 0.32. This number is placed between W_{MPI}= 0.222 of MPI as *Between Very Low and Low (MPI_VL_L)* and W_{MPI}= 0.333 of MPI as *Low (MPI_L)* (see Tab. 3), by using minimum condition the result is as follows: MPI is *Between Very Low_Low (MPI_VL_L)* with weight W_{MPI}=0.32

Rule 2: ***If*** the wind speed (WS) is *Very High* (W_{WS}= 1.0) ***and*** wind frequency (WF) is *Very Low* (W_{WF} = 0.2), ***then*** MPI is *Between Low and Medium (MPI_L_M)* with weight W_{MPI}=0.52.

In this case the value of Eq. (8) is W_{MPI}= 0.4 x 1.0 + 0.6 x 0.2 = 0.52. This number is placed between W_{MPI}=0.444 of MPI as *Between Low and Medium (MPI_L_M)* and WRPN = 0.556 of MPI as *Medium (MPI_M)* (see Tab. 3); by using minimum condition the result is as follows: MPI is *Between Low and Medium (MPI_L_M)* with weight W_{MPI}=0.52.

By using the approach described above, a number of 50 FIS rules for MPI (25 rules for the first layer and other 25 rules for the second and third layers) and of 729 FIS rules for API have been developed.

The aggregation process, by which output fuzzy sets of each rule are combined into a single fuzzy set, has been performed by using the Min-Max inference described in section 2.2. Defuzzification step is carried out by using the COG relationship reported in Eq. (7).

For FIS processing of MPI, wind speed and frequency results obtained by using CALMET simulations for the first three layers, that schematize the vertical atmospheric conditions grid of 10, 20, 40 m, are used.

A pre-processing algorithm, written in R-CRAN programming language, reads wind speeds and frequency distribution computed by CALMET code for the eight cells bordering to cell C[i,j] (Fig. 5). These data are used as input in the fuzzy inference procedure to obtain MPI index of C[i,j].

MPI index is attributed to C[i,j], given that it is under goes meteorological pressures by the eight neighbouring cells. This approach allows to take into consideration those wind directions that influence C[i,j] with more frequency (i.e. height number of direction bins: Nord, NE, Est, SE, South, WS, West, NW in Fig. 5).

It should be noted that the procedures to build the FIS systems for layers at 10, 20, 40 m are different. In particular, relative importance of input fuzzy variables relevant to the first atmospheric boundary layer assigns same weight to WS and WF (Tab. 8), whereas, for the second and third layer, a little more weight it is attributed to WF. This is made because frictional drags of earth surface have a little impact on wind speed values in higher layers, consequently low differences of wind speed values can observed among neighbouring zones. So wind frequency is the parameter that better reflects mutual exchanges among bordering cells. MPI index values, obtained for the three layers of C[i,j], are finally added.

3.4 MIP and API normalization and FEAI index calculation

The fuzzy rule-based system is applied to evaluate API[i,j] and MIP[i,j] indexes for each cell C[i,j] of the calculation domain.

Due to the diverse nature of fuzzy variables, index values are characterized by different order of magnitude. For this reason MIP and API have to be rescaled to render the variables comparable.

To do this, $\mathrm{MPI[i,j]}$ and $\mathrm{API[i,j]}$ are normalized by using scores in the range [0, 10], attributed by using quantile distribution, similarly to what suggested in (OECD, 2008):

$$\mathrm{MIP\ [i,j], or\ API[i,j]} = \begin{cases} 0 \text{ if } \mathrm{MIP, API} < Q^{0.2} & 5 \text{ if } Q^{0.6} \leq \mathrm{MIP, API} < Q^{0.7} \\ 1 \text{ if } Q^{0.2} \leq \mathrm{MIP, API} < Q^{0.3} & 6 \text{ if } Q^{0.7} \leq \mathrm{MIP, API} < Q^{0.8} \\ 2 \text{ if } Q^{0.3} \leq \mathrm{MIP, API} < Q^{0.4} & 7 \text{ if } Q^{0.8} \leq \mathrm{MIP, API} < Q^{0.85} \\ 3 \text{ if } Q^{0.4} \leq \mathrm{MIP, API} < Q^{0.5} & 8 \text{ if } Q^{0.85} \leq \mathrm{MIP, API} < Q^{0.9} \\ 4 \text{ if } Q^{0.5} \leq \mathrm{MIP, API} < Q^{0.6} & 9 \text{ if } Q^{0.9} \leq \mathrm{MIP, API} < Q^{0.95} \\ & 10 \text{ if } \mathrm{MIP, API} \geq Q^{0.95} \end{cases} \tag{9}$$

where Q^n is n-th quartile of the data set (e.g. $Q^{0.5}$ corresponds to the median of data).

Concerning the aggregation of the normalized indexes, the key matter is to decide whether it is allowed compensability among the various elements or not (OECD 2008), i.e. poor performance in some indicators can be compensated by sufficiently high values of other indicators.

In our case, MPI and API indexes are derived by semantic classifications based on same linguistic attributions that define the intensity of environmental pressures related to physical parameters, moreover FIS system is built by assuming linear relationships among linguistic terms.

In addition, Min-Max transitivity allows to compute with words without loss of information. In this respect, it is worth highlighting that Kundu (1998) demonstrated the superiority of roles based on Min-Max equivalence compared to ones based, for example, on the usual Max-Min form of transitivity.

Therefore it's reasonable to think that it is possible to get a composite index by using an additive aggregation method, preserving all the given information and the required compensability among indicators.

On the basis of the above considerations, FEAI is evaluated by summing normalized MPI and API indexes for each cell C[i,j], as follows:

$$\mathrm{FEAI[i,j]} = \mathrm{MPI[i,j]} + \mathrm{API\ [i,j]} \tag{10}$$

FEAI was applied to build maps of environmental similarity conditions in Sicily region, Italy, for air pollutant emissions of PM10, SOx, and NOx, and meteorological conditions for five years (from 2010 to 2014). In this period, several accidental events occurred in industrial and petrochemical areas (some accidents caused fires that lasted about 4 days). This study allowed to identify vulnerabilities in the Sicilian monitoring networks comparing the model results with real cases that showed inability of monitoring station to address dangerous conditions for the period under review.

4 Data processing and results for a case study

4.1 Description of geographical-economic characteristic of the study area and environmental pressures related to anthropic and natural sources

The case study, reported in this paper, has concerned a domain covering the Sicily's region (Fig. 7), a largest island (25,426 sq. km.) located within Italy and placed in the middle of the Mediterranean area. Its geographical particularity is the varied orographic structure.

The highest mountains lie in the north-east and are Mount Etna (3,350 m), the biggest volcano in Europe, rising between Catania plain and Alcantara river valley, and the Sicilian Apennines, stretching from the Strait of Messina to the Torto valley. Other active volcanoes are Stromboli and Vulcano, in the Aeolians islands in the Tyrrhenian sea.

The Sicilian Apennine range of mountains is divided into three groups: the Peloritani, Nebrodi and Madonie. At the foot of the south slope of Etna is situated the Catania plain, delimited to the south by the Iblei hills, a wide expanse of high ground, up to the Mount Lauro (985 m). The middle of the island is a broken succession of rolling hills, the Erei (lying among Iblei, Catania plain and Salso valley in the center of Sicily) and the low rounded hills called Altopiano Solfifero.

The climate is Mediterranean, i.e. mild wet winters with very dry summers. The larger mountains as well the distance from the sea are causes of high differences in climate. The average annual temperature is around 20 °C, which drops to 10 °C inland, and precipitations are confined mainly in the winter months.

The primary economic sector is the agriculture, characterized by inland areas where wheat is extensively cultivated, and coastal belt with cultivation of citrus fruit, orchards and vineyards.

In the industrial field, petrochemical industries (near Gela, Ragusa, Siracusa and Augusta) are highly important. Petrochemical plants extend for 2,700 hectares and includes a large area from Augusta, passing through Priolo and

Melilli. These plants are considered to be the largest in Europe with numerous oil and chemical refineries and energy production companies.

Coastal area of the Gulf of Milazzo, a natural bay located in the eastern sector of Northern Sicily, is characterized by industries as crude oil refinery and thermal power plant, as well as marina and commercial harbour.

Other industrial activities include building and the transformation of agricultural and fish products. The principal industrial areas are around Catania (engineering, pharmaceuticals, electro technical industry, food, building materials) or located in the south-east part of Sicily. Some of these industrial activities are very concentrated in the largest cities of Palermo, Messina and Catania.

Regional communications are highways, that connect Palermo, Messina and Catania, roads that connect Palermo and Trapani, as well as Palermo-Punta Raisi, Catania-Fontanarossa and Trapani-Birgi airports.

Fig. 7 shows with dashed areas the zones where the main industrial activities and urban areas are concentrated.

The report (ARPA, 2012) highlighted that, at regional level, transport contributes for 68% to total NOx emissions and about half of those emissions are due to road transports (56%), while the industrial activities give a contribution of about 22%. The exceedance of NOx limiting values have occurred in urban areas as Palermo and Catania. Other NOx emission sources, that have mass flow rates about equal to those emitted by big cities, are located in Milazzo, Gela, Ragusa, Priolo and Augusta, province of Siracusa, where the contribution of the combustion plants of the energy industry and of other industrial plants are significant (ARPA, 2018).

Industrial combustion plants, refineries and vehicular traffic in urban areas are the main sources of SOx emissions. In particular, in 2012 SOx sources were about 60% due to industrial combustion plants and about 26% for processes without combustion, excluding Volcano Etna contributions. The natural emissions from Etna are higher than Italian sources by a factor of 5.

PM10 emitted in industrial areas represents about 20 % of the total emissions at regional scale (excluding contributions of natural sources). Other sources are road traffic and agricultural activities. Big cities as Siracusa, Ragusa, Caltanissetta, Messina e Palermo are among urban areas that suffer the greatest impacts in Sicily.

Natural sources (around 35% of the total sources) are responsible for 58% of fine particulate production. This is due to various phenomena such as Saharan winds, erosion of coasts, and transport of sea salt resulting from evaporation phenomena.

4.2 Analysis the case study and main results

FEAI index has been calculated for SOx, NOx and PM10 pollutions, by using the models described in section 3.

Applications of the proposed methodology concerned these pollutants because they are considered significant for the Sicilian territory, given to the presence of petrochemical plants that extend for 2,700 hectares, health impacts related to road traffic (focused in particular in urban area) and significant deposition processes of particulate such as dust from Sahara desert. The main results are reported in the following section.

MPI is evaluated by using data of five CALMET simulations, for the years from 2010 to 2014. Each simulation has covered a period of a year with step of 1 hour.

The meteorological simulations were carried out by using observed data of a number equal to 77 surface stations distributed in the Sicilian region and measurements of one upper-air sounding station, located near the airport of Trapani city. These data are provided by a number equal to 60 surface stations of SIAS (Servizio Informativo Agrometeorologico Siciliano) network, with instruments and equipment to measure atmospheric conditions at 2 and 10 m; 13 Surface station of WMO (World Metereological Organizzation) network, and 4 surface stations of Mareografica network. The measurements were used to evaluate the three-dimensional initial conditions of meteorological fields, at 1-h intervals, by using a domain with resolution of 3x3 km.

Emission inventories of SOx, NOx and PM10, used for API assessments, refer to data reported in (ARPA, 2012) for year 2012, both for natural and anthropogenic sources. The emissions data are classified as punctual (power and industrial plants), linear (road transport), and diffuse area (urban area).

By way of example, in Fig. 8 API data are reported for NO_X. These results, processed by software QGIS, are related to Q^n, in Eq. (9), that starts from 85th quantile. Fig. 9 shows MPI results obtained by using CALMET simulations for 2010 year. The MPI and API indicators are shown on a map that reports the autostrada and provincial roads in Sicily.

To identify areas characterized by high similarities for a more significant temporal interval, overlapping procedure of FEAI results for the examined five years has been done using “Addition” blending mode in QGIS software. The option of “Addition” blending mode allows to overlay the raster layers, adding pixel values of one layer with the other.

Fig.s 10 through 12 report, for SOx, NOx, and PM10 pollutions, FEAI intersection maps from 85th quantile of FEAI outcome distributions. In the same figures air quality monitoring stations, used by ARPA Sicilia for SOx, NOx and PM10, are highlighted with numbered squares.

In analyzing the results, some measurement stations are located in zones (white area) that have low environmental analogies for the examined pollutants. Therefore, the measurements are representative of the cell where the station is locate, so it cannot be used as representative data of neighboring cells.

These results are particularly interesting to evaluate the representativeness of air pollution monitoring networks used in industrial areas of Milazzo and Siracusa. Fig. 13 reports details of map shown in Fig. 10 for industrial areas located at Milazzo and Siracusa.

For Milazzo only the stations number 23, 25, and 28 are located in areas characterized by environmental affinity between neighboring cells on the basis of FEAI index values (Fig. 13a), while the stations in Syracuse are "self-referenced" (Fig. 13b). On the basis of a study concerning overcomes of limit values of concentrations of pollutants, only Milazzo stations measured health risk conditions.

It is worth emphasizing that, monitoring station networks, placed in these areas, never measured overcomes of pollutant concentrations, such as SOx, during incidents that occurred in the last years. This led ARPA to reassess the monitoring network set-up.

This need is highlighted by the model proposed in this paper.

On the contrary, for the industrial areas of Gela and Ragusa, the FEAI maps shows that some station positions are optimal for the observations as well as representativeness of the bordering areas. Similar conclusions can be performed for the urban zones.

4.3 Validation works

Cluster analysis (Everitt et al., 2011) was used to validate FEAI results.

As well known, clustering algorithm, also called segmentation analysis or taxonomy analysis, allows to group similar observations into homogenous clusters.

To do this, K-mean method (Hartigan and Wong, 1979) has been employed.

K-mean approach is the most commonly used clustering method for splitting a dataset into k groups, with k fixed a priori. Each cluster is represented by its centroid which corresponds to the mean of points assigned to the cluster.

Determining the optimal number of clusters in a data set is a fundamental issue in partitioning clustering which requires the user to specify the number of clusters k to be generated.

The optimal number of clusters is somehow subjective and depends on the method used for measuring similarities and the parameters used for partitioning.

In this work, to determine the optimal number of clusters, the silhouette method, that computes the average silhouette of observations for different values of k (Rousseeuw, 1987), is used.

For each data x_i, the silhouette width S_{xi} is calculated as follows:

- For each x_i, calculate the average dissimilarity a_{xi} (Duncan and Duncan, 1955) between x_i and all other points of the cluster to which x_i belongs.
- For all other clusters C, to which x_i does not belong, calculate the average dissimilarity $d(x_i, C)$, of x_i to all data of C. The smallest of these $d(x_i,C)$ is defined as $b_{xi}=\min_C d(x_i, C)$. The value of b_{xi} can be seen as the dissimilarity between x_i and its “neighbor” cluster (i.e. the nearest one to which it does not belong).
- The silhouette width of the observation x_i is defined by the relationship $S_{xi} =(b_{xi}-a_{xi})/\max(a_{xi}, b_{xi})$.

The optimal number of clusters k is the one that maximize the average silhouette over a range of possible values for k.

Once identified the k parameter value, K-mean algorithm starts with an initial guess for the cluster centers, and each observation is placed in the cluster to which it is closest. The cluster centers are then updated, and the entire process is repeated until the cluster centers no longer move (Brock et al., 2008).

Comparisons between one of the groups obtained by K-mean analysis for NOx, reported in Fig. 14, and FEAI data of Fig. 10, highlight the coherence among each other.

5 Conclusion

Planning to prevent and reduce air pollution requires a complete understanding of how pollutants are distributed, therefore the placement of an air quality monitoring network is an crucial task to predict impacts on people health (Mofarrah and Husain, 2010; Pope and Wu, 2014).

In this field various studies have been performed. For example, identification of air pollution monitoring stations by applying density and spatial correlation methods including population density, the scale of monitoring pollutants, and economic costs is reported in (Ashrafi et al., 2008). However, a limitation of this study was that the geographical conditions of the region were not considered, aspect that plays an important role in the determination of air quality monitoring stations (Kazemi-Beydokhti et al., 2017).

A challenge is to identify correlations among anthropic or natural sources, meteorological conditions and geographical characteristics of the territory, necessary for example to identify zones characterized by environmental similarities useful for understand the resilience capacity of a monitoring network that is used to define air quality conditions.

In the framework of a cooperation between ARPA Sicilia (Agenzia Regionale per la Protezione dell’Ambiente), Sicily, and Department of Engineering, University of Palermo, research efforts have been performed to provide an innovative methodology useful to define environmental similarity maps, aimed at supporting the design of air quality monitoring networks at regional scale.

To do this, a new index, called fuzzy environmental Analogy Index (FEAI), has been developed.

FEAI is derived by a combination of meteorological pressure indicator (MPI), which investigates the relation with meteorological factors at different height of the atmospheric layer, and anthropic pressure indicator (API), which addresses air pollution sources at regional scale. MPI is evaluated through elaborations of wind speed and frequency data, obtained by using CALMET simulations, a diagnostic 3-dimensional meteorological model. FEAI index was applied for a case study, relevant to the Sicily region, Italy.

FEAI is applied to build maps of environmental similarity conditions in Sicily, for air pollutant emissions of PM10, SOx, and NOx, and meteorological conditions for five years (from 2010 to 2014). In this period, several accidental events occurred in the industrial and petrochemical areas (some accidents caused fires that lasted about 4 days). Moreover, preliminary applications of the proposed methodology concerned these pollutants because they are considered significant for the Sicilian territory, given to the presence of petrochemical plants that extend for 2,700 hectares, health impacts related to road traffic (focused in particular in urban area) and significant deposition processes of particulate such as dust from Sahara desert.

The study allowed to identify vulnerabilities in the Sicilian monitoring networks comparing the model results with real cases that showed inability of monitoring station to address dangerous conditions for the period under review.

In particular, results allowed to test the resilience capacity of air quality monitoring stations used in industrial areas of Milazzo and Siracusa. In fact, in the past during incidents that occurred here, monitoring station networks, placed in these geographical areas, have never measured overcomes of pollutant concentrations such as SOx. This led ARPA to reassess the monitoring network set-up.

The model has highlighted that these areas are characterized by very low FEAI index (low environmental affinity), finding a justification for the failure in measurements by the monitoring systems designed to control environmental pressure of industrial areas.

It is worth pointing out that the proposed fuzzy model was used by ARPA to determine the sub-sets of air monitoring stations useful for reciprocal exchange of information and data from networks and individual stations measuring ambient air pollution within the Member States, as established by Council decision 97/101/EC of 27 January 1997.

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