SPATIAL REPRESENTATIVENESS OF AIR QUALITY MONITORING STATIONS IN ITALY

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Abstract: Supporting the design of the Italian Network of Special Purpose Monitoring Stations, a comprehensive study on spatial representativeness of air quality monitoring sites is presented, to be used in model validation and population exposure studies. Different methodologies are being evaluated, in order to find out one or more fit-to-purpose approaches to spatial representativeness. In this work, we present preliminary results for 3 methods: one uses station measurements and land cover data, other two are based on air quality model simulations, using respectively emissions variability and concentration time series. Strengths and weaknesses of the methods are assessed and on-going developments are presented.

Key words: *air quality monitoring station, spatial representativeness, land use, air quality model, FAIRMODE*

INTRODUCTION

The spatial and temporal representativeness of an air quality monitoring station is of fundamental relevance in air quality assessments. The identification of an area of representativeness allows to extend the information retrieved in an observation point to a wider area surrounding the point, therefore allowing to appropriately design and optimize an air quality monitoring network (avoiding redundant measuring nodes and focusing on hot-spots) and to correctly compare observed data with model simulations (the spatial representativeness of the station must be at least of the same order of magnitude than the model grid box).

The assessment of station spatial representativeness can be based on various sources of information such as additional air pollutant measurements, modelled air pollutant concentrations, spatial surrogate data (e.g. land-cover characteristics and emissions sources). Several approaches are available in literature so far (Nappo et al., 1982; Blanchard et al., 1999; Larssen et al., 1999; Spangl et al., 2007; Henne et al., 2010; Janssen et al., 2012), but a standard procedure that can be applied to different monitoring networks in different regions is not recognised at international level, as stated very recently in the recommendations to the review of the EU Air Quality Policy compiled by FAIRMODE (Forum for Air Quality Modelling in Europe) (http://fairmode.ew.eea.europa.eu/guidance-use-models-wg1/directive-revision/fairmode-recomm_final.docx).

Therefore, the assessment of spatial representativeness of air quality monitoring stations is a prevailing issue of relevant scientific interest at national and international level.

ENEA is supporting Italian Ministry of Environment in building the National Network of Special Purpose Monitoring Stations, a national reference for monitoring long-term evolution of atmospheric concentrations of ozone and its chemical precursors, PM2.5 chemical composition, heavy metals (Arsenic, Cadmium, Nickel, Mercury) and carcinogenic PAHs. In the frame of this agreement, according to the state of the art assessment of spatial representativeness, different methodological approaches are being examined.

This paper presents some preliminary results of three implementations: a statistical method based on objective factors (namely, land cover), a method based on the knowledge of the spatial distribution of emissions, a method based on model simulated concentration fields. Presently, studies are in progress for a fourth method, based on the analysis of backward trajectories, due to be completed by June 2013. The four methods were designed to cover different assessment situations and targets. For the presented methods, the application to selected pollutants and monitoring sites is presented and the principal strengths and drawbacks are discussed.

All methods except the first were implemented using specific datasets produced by MINNI (www.minni.org), which is the Italian Integrated Assessment Modelling System (AMS) for supporting the International Negotiation Process on Air Pollution and assessing Air Quality Policies at national/regional level (Mircea et al., 2011). The AMS simulates 3-dimensional meteorology and air quality fields for the entire Italian region, on a national domain (20 km resolution on horizontal grid) and on 5 nested regional domains (4 km resolution on horizontal grid). The model implements an integrated and multi-pollutant approach for calculating hourly concentrations of all pollutants regulated by the Air Quality Directive (SO_2, NO_2, ozone, PM10, PM2.5, NH_3, Heavy Metals, PAHs, etc.) plus the depositions of sulphates and nitrates, using a mesoscale Chemical Transport Model.

METHOD 1: OBJECTIVE FACTORS (LAND COVER)

A first methodological approach relies on a simplified description of atmospheric pollution processes: an empirical relationship is assumed between physical objective factors influencing air pollution (i.e., wind direction and speed, orography, land cover, urbanized areas, large point emission sources) and concentrations recorded by air quality monitoring stations. This approach is widely used in air quality assessment, in particular when insufficient data on emissions and meteorology and/or limited resources prevent a detailed representation of pollution processes.

In our study, we chose to analyze land cover near monitoring stations, relying on a causal relationship with concentrations: land cover patterns are representative of actual locations of emissions, and emissions are the main driver of concentrations. Using land cover to assign a georeferenced location to aggregated values recorded in emission inventories is a common practice in air quality modelling.

In compliance with literature studies and in particular Janssen et al. (2008) we developed a synthetic, pollutant dependent, indicator β for the dependency of concentration on land cover, and we studied how β is varying in the neighbourhood of the selected monitoring site. The formulation is

$$\beta = \log\left[1 + \left(\frac{\sum_i a_i \cdot n_{CLi}}{\sum_i n_{CLi}}\right)\right]$$

where, assuming a reference area around the monitoring site, n_{CLi} is the fraction of the area corresponding to CLi class of land cover and a_i is a weight coefficient, determining the influence of CLi class as a potential determinant of pollutant concentration. The factor β is therefore an indicator of "land cover polluting power". However, as an empirical parameter, β absolute values are not physically significant, but relative values are useful to study how this "land cover polluting power" varies around a selected site where concentration is measured. The rationale is that, the more variable is β in the surroundings of the site, the less representative of the air quality in the surroundings of the site are the concentrations measured at the station.

For determining n_{CLi} values, we used Corine Land Cover 2006 database (ISPRA, 2010a), with ad-hoc improvements by means of an aggregation of the original 44 classes into 11 CLi classes and an integration of the road network class, using more detailed layers with national coverage. Spatial treatment of land cover was performed in a GIS (Geographical Information Systems) environment.

The a_i coefficients are calculated from a statistical optimization of the function $C(\beta)=n\beta^2+m\beta+q$, where the dependency of the concentration C on the land cover indicator β is explicated. The optimization was performed using a multivariable regression on measured concentration values from the national database of air quality measurements (ISPRA, 2010b), using 2007 yearly averages.

After the calibration, the calculation of β was performed for 10 monitoring stations for PM2.5 and 12 monitoring stations for ozone or precursors, using circular buffers with 2, 5, 7.5 and 10 km radius centred at each station, thus obtaining an array of values for each station. The spatial representativeness of the station has been quantitatively assessed comparing each buffer's β value with the value in the 2 km radius buffer: a difference of less or more than 20% indicates whether or not the station measurement represents the concentration value inside the buffer. In this analysis a threshold value of 20% was set according to literature (Blanchard et al., 1999; Janssen et al., 2008) and since it is compatible with the quality objectives for most monitoring data included in the Air Quality Directive (15% and 25%, depending on the measured pollutant).

Generally, this approach is useful when annual time series of measured concentrations are available from a consolidated and spatially uniform monitoring network, allowing a good calibration of β. Moreover, using a high-resolution land cover database (like Corine, resolved on 100m square cells) allows detailed assessment of spatial representativeness, very useful for urban and suburban monitoring sites, where land cover is highly variable.

METHOD 2: EMISSIONS VARIABILITY

The second method is based on the correlation between the spatial distribution of atmospheric concentrations of pollutants and the corresponding emissions distribution. This is a simplified modelling approach that leads to a fast and reliable assessment of representativeness, using emission inventory data, commonly available at wider spatial coverage than concentration data. The principle is to define an inversely proportional relation between emission variability around a monitoring site and its spatial representativeness: high emission variability (most likely indicating high concentration variability) means low spatial representativeness, whereas low emission

variability means high spatial representativeness. We took advantage of the MINNI atmospheric modeling system, providing a gridded emission inventory at national scale, with disaggregation (in space, time, chemical speciation and aerosol size profile) for mesoscale Chemical Transport Modeling.
A GIS software was used to perform the analysis of the emissions spatial variability by means of the "neighbourhood statistics" algorithm: for each grid point, the amount of variation in emission values among neighbour cells was derived.
Using the 2005 as the reference year, different time intervals for emission integration were tested (whole year, summer, winter), in order to capture the sensitivity to different patterns of polluting activities (domestic heating prevails in winter, road traffic and industry prevail in summer). The analyses were performed on primary pollutants (PM10, PM2.5, IPA, As, Cd, Ni, Hg).

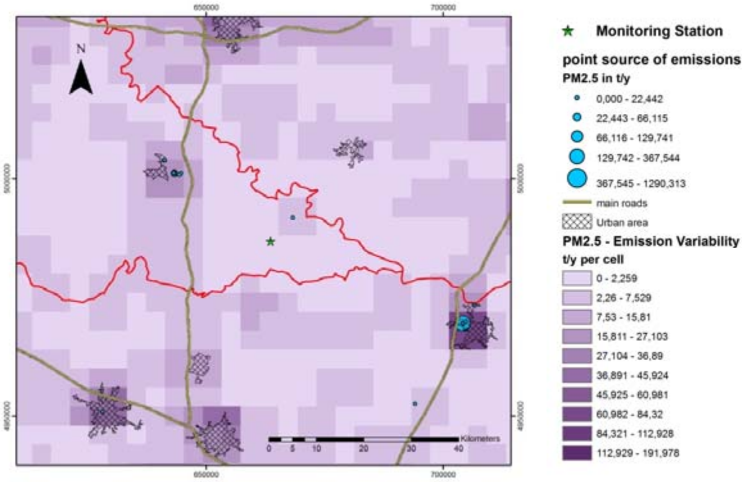

Figure 1. PM2.5 emission variability (violet cells) around Schivenoglia background rural station (green star in the center). Approximate area of representativeness is in the two lightest colour ranges.

As an example, Figure 1 shows PM2.5 emission variability for Schivenoglia station. Light areas (reporting low variability values) prevail around the station, and dark areas (high variability values) are located far from the station and over cities (Mantua 25 km NW, Ferrara 50 km SE). Then, the more detailed evaluation is semi-quantitative and based on an automatic classification of range of values (natural breaks): the two lowest ranges (corresponding to high representativeness) cover the station grid cell and a large area around (about 10^3 km^2), extended in all directions but excluding cities, where emission variability is in the highest ranges. This means that, for this station, spatial representativeness is high but does not include cities.

METHOD 3: CONCENTRATION SIMILARITY

The third selected approach to the evaluation of representativeness is the most intuitive: the concentrations recorded at the site of interest are directly compared with concentrations recorded at selected points in the surrounding area, in a fixed time interval. The monitoring station is representative of a wider area if all measurements in this area differ by less than a threshold from the station measurements.
For quantitative assessment of spatial representativeness of atmospheric monitoring stations, Nappo et al. (1982) give a useful and detailed definition: "a point measurement is representative of the average in a larger area (or volume) if the probability that the squared difference between point and area (volume) measurement is smaller than a certain threshold more than 90% of the time".
As for Method 2, we applied the methodology by adopting the MINNI model dataset, using in this case concentration fields. The comparison between concentrations is performed at high time resolution and no proxy variable is used, as MINNI model takes into account atmospheric dynamics and chemistry, with wide spatial and temporal coverage and consolidated validation against real measurements (Mircea et al. 2011).
On the methodological basis proposed by Nappo et al. (1982), assuming the model concentrations as "measurements", we developed a procedure for recursively comparing the concentration time series. At each time step, the difference between the concentration values measured at the site of interest (coordinates X_{site},Y_{site},Z_0) and at each grid point (coordinates x,y,Z_0) in the model domain has been calculated. A threshold value of 20% was set, following the choice explained in Method 1 paragraph, for the difference between concentrations, in order to assess the condition of "concentration similarity".

A 2-dimensional frequency function $f_{site}(x,y)$, specific of each site of interest, counting positive occurrences of "concentration similarity" for each grid point of the model domain, was defined and finally spatial representativeness area of the site of interest was assessed (i.e. $f_{site}(x,y)>0.9$ is verified).
The described procedure was applied on model results for PM10, PM2.5 and ozone. As MINNI model dataset covers a wide range of reference situations, a detailed sensitivity analysis was performed on input data: different meteorological years (2003, 2005, 2007, their average), emission inventory sources (national CLRTAP, national GAINS) and years (2005, 2015 projections), producing different concentration fields, were used for assessing representativeness at the selected stations. Furthermore, the variation of $f_{site}(x,y)$ corresponding to variations in the time averaging of concentrations was tested, in compliance with the Air Quality Directive requirements for each pollutant. Seasonal representativeness assessment variability was also evaluated.

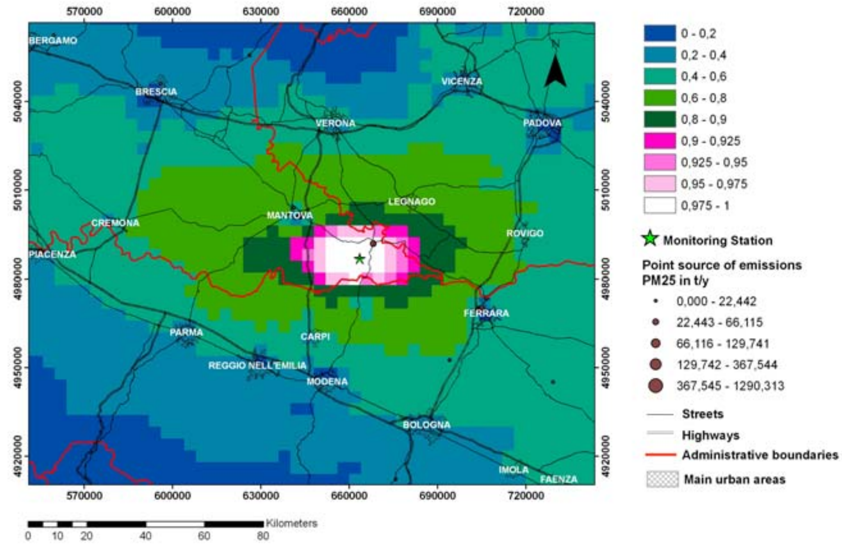

Figure 2. Frequency function $f_{site}(x,y)$ for PM2.5 measurement at Schivenoglia station. Representativeness area is in pink and white.

An example of the obtained results is shown in Figure 2, concerning PM2.5 measurement representativeness assessment at Schivenoglia station (Central Po Valley, Northern Italy). Figure shows $f_{site}(x,y)$ values integrated with supporting thematic layers. Representativeness area ($f_{site}(x,y) > 0.9$) is immediately visible in pink colour tones and can be precisely determined by counting model grid cells verifying the similarity condition.
This method shows very good performances in describing both the extension and the shape of representativeness areas, with results at the same spatial resolution as the input data used for the assessment.

CONCLUSIONS

For the implementation of the Italian Special Purpose Monitoring Network for air quality, ENEA has been testing different methodologies for the evaluation of spatial representativeness of monitoring stations, in order to study how point measures at a single site reflect pollutant concentrations in the area surrounding the site. At present, 3 methodologies were tested, covering different typologies of input datasets and assessment algorithms.
Method 1, based on using land cover data as a proxy variable of concentration, allows to determine spatial variations of the polluting factor in analysis, at increasing distance from the selected site. The empirical relationship has a simplified formulation, therefore the quality of results strongly depends on the selected dataset of measured concentrations, used in the calibration stage. The method looks promising for evaluating urban monitoring sites, due to the free availability of free high resolution datasets of land cover, describing accurately urban environments.
Method 2, using MINNI gridded emission database to analyze emission variability as a proxy variable of concentration, gives a complete picture of spatial variations of the polluting factor in analysis, covering the whole model domain, thus not depending on any monitoring site. This is useful for a comprehensive evaluation of spatial representativeness, e.g. for designing new monitoring networks, though some limits are present (just primary pollutants, semi-quantitative evaluation).
Method 3, directly comparing hourly concentrations at the selected site and in the surrounding by using MINNI gridded concentration database, shows encouraging skills in accurate definition of representativeness area and

shape. The method proved to be particularly robust, as the comparison is performed at high time resolution and no proxy variable is used, as MINNI model takes into account atmospheric dynamics and chemistry, with wide spatial and temporal coverage and consolidated validation against real measurements. As for method 2, using a gridded model means that representativeness is evaluated at the spatial detail of the model grid, not allowing for example an adequate description of urban stations.
Each of the three examined methods has been object of a detailed technical report (Cremona et al., 2013; Piersanti et al., 2013; Vitali et al., 2013). At present, a fourth method, based on backward trajectories of air masses reaching the selected site, is under development, relying on meteorology as a proxy variable of air pollution. In a following phase, the four methods will be applied to all stations of the Special Purpose Monitoring Network, to derive a final evaluation of spatial representativeness.

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