# A comparative analysis between sampling patterns for airborne PM10 mapping in the extractive sector

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***Abstract*—Designing a sampling strategy for any environmental variable with the aim of defining a contour map from field surveys entails making decisions about sampling pattern and number of samples. This paper is aimed to assess the influence of sampling strategies on the spatial estimation of PM10 concentration in a quarry environment. An intensive field survey consisting in more than two hundred samples was planned to fully investigate the spatial variability of the selected area. Then systematic, random and stratified random sampling schemes were compared by means of several iterative sub-samplings of the well known data set deriving from monitoring campaigns. Different grid resolutions were selected and their correspondent variograms plotted. The corresponding structural analysis, when compared with output from raw data, allowed to point out the best sampling approach for this phenomenon**

***Keywords: sampling strategy; variogram computation; spatial analysis; PM$_{10}$; quarrying areas***

## I. Introduction

The environmental impact assessment is an important step towards verifying the environmental compatibility of industrial extractive sites with sensitive surrounding areas ([1], [2], [3]).both during the planning stages of the site and while carrying out the urban planning of the adjoining areas ([4], [5]). In this framework, the spatial analysis of typical pollutants such as airborne PM10, [6], rather than noise levels ([7], [8]) or ground vibrations plays a key role when a real time monitoring activity rather than a forecast is required to check the effect of emissions are compatible with land use, ([9]) limitations imposed by Laws. Therefore the pollution tests must be carried out not only at the beginning of the activity, but will need to be constantly updated as the work advances and as the work face of the quarry changes, [10]. Furthermore, while the work is underway it will be necessary to monitor the effects generated on certain receptors (generally those located in a built up area) where the influence of these agents is greater.

For these reasons, in the extractive sector it may be necessary to include air quality measurements from the field, which regularly check that emissions remain within the limits consented by the law, alongside forecasts based upon PM10 dispersion models in the atmosphere.

In any case a space or space-time map ([11]), based on data field, describing the airborne concentration all over the selected domain is required and at least useful for periodical checks. In this research the main sampling schemes ([12], [13], [14], [15]) are tested taking into account not only the systematic or random approach but also including the influence that data deriving from sampling campaign, such as meteorological ones ([16]), reflect on the total amount of samples required to describe the spatial trend. The main finding consists in the selection of stratified random sampling as the most suitable tool in such a phenomenon thus determining a reduction of costs and resources in sampling activities without a quality reduction in the estimation or output map.

Traditionally, modelling methods can be classified into two main categories: deterministic and stochastic ([17]). A review of the literature indicates that continuing improvements in remote sensing and geographic information systems ([18], [19]) have led to the incorporation of data mining models for the evaluation of local airborne concentration. So, many deterministic approaches always more detailed and sensitive in quarry environment ([20], [21]) and geostatistical ones ([22], [23], [24], []25) have been integrated by means of hybrid approaches ([26], [27]).

In this framework sampling strategy is a very important aspect of spatial analysis since the information deriving from hard data are deeply influenced by sample locations and their distribution in spatial domain ([28], [29]). In particular, with fixed economic availability and with the consequent fixed number of potential samples, the quality of representation of variability structure of the variable is strictly dependent on the way the available information sources are located in the spatial domain.

As just focused, each sampling strategy is opportunely applied in any well defined situation, but all the methods are grouped into two main divisions which are systematic strategies and random ones. The first group concerns all the methods based on regular division of the spatial context and the systematic allocation of samples, while the second one regards a random distribution of information sources. Systematic sampling strategies are based on regular distribution of sites of investigation, based on a simple division of the spatial domain in a regular grid, or by following some specific demand, as isovalues lines or transects. The main typologies are:

- pure systematic sampling, that is based on the simple division of the spatial domain in a regular grid and on the sample allocation in each cell of such grid;
- transect sampling, that is based on the distribution of each sample along defined transects;
- isovalues sampling, that is based on the distribution of samples along isovalue lines of the investigated variable (whereas they are known).

The main feature of such kind of methods is the capacity to cover uniformly the whole domain of investigation, and to explore with details the elements of the system that are partially known.

In any cases, the common feature of such methodologies is the lack of relation between the spatial behaviour of the variable and the choice on samples allocation. In pure systematic sampling only the resolution of the grid is defined before (usually as function of economic availability), with no consideration on eventual over- or under- estimation of the field, while the other two methods make some assumption on the behaviour of the variable, but with no specific knowledge.

As affirmed in the theory of the regionalized variable (Matheron, 1971, 1973), in some applications environmental variables are assumed to be well described by stochastic modelling, more than by deterministic one and the variable itself may be considered as a random regionalized function while sampled values as realizations of such a function. Following such principle, we can assume that the best way to create an unbiased sampling plan is to define it in a random framework. Nevertheless, a pure random sampling strategy can lead to an excessive economic waste, because a complete coverage of the domain may be achieved only by a large amount of samples. In order to join the unbiasedness of random methods ([32]), and the complete investigation of the site, the random and random stratified strategy have been tested in this paper and then compared with the systematic sampling scheme.

Such methodology is based on the random allocation of each sample in each cell of the regular grid previously created over the domain. In this way the complete coverage of the area is guaranteed by the regular grid and the unbiasedness of the investigation is assured by the randomness of samples position within the grid.

The main problem regarding the bias introduced by sampling strategy regards the relationship between the scale of variability of the field and the scale of the exploration grid ([33]). When the frequency of the sampling method is so precise, the information at that scale are redundant, while the ones at other scales are scarce or totally missing. This is the key concept will be discussed in this paper. In particular, variograms will be used to demonstrate how stratified random sampling is the optimizing method for spatial analysis in such an application. For what concern the influence of sampling approach on the experimental variogram, two main features will be analysed in details: the small scale lags variability and the pairs abundance. Looking at the variograms computed respectively on a systematic and a stratified random sampled variable, we can note how the main differences regard the smallest scale investigable and the distribution of pair abundance among the different spatial scales. In particular, it is clear how in the case of systematic sampling the smallest lag is far to be the smallest investigable spatial scale and the pairs abundance is biased through the different spatial scales. There are many pairs at the multiples of the grid resolution value and very few at the intermediate scales. Such relevant features are very important for the computation of experimental variogram, that is deeply influenced by the pair distribution over the lags and that can be consequently interpreted in a more or less correct way leading to different PM10 concentration maps.

## II. MATERIALS AND METHODS

The research work was developed in a quarry plant in the center of Italy whose aerial view is shown in fig. 1.

Fig. 1. *An aerial view of the quarry.*

The quarrying site extracts limestone, a sedimentary rock comprised mainly of calcium carbonate, which, thanks to its natural presentation, is a highly sought-after non-metal mineral resource. In particular, it plays a key role in the construction industry, not only due to its wide range of applications as a material for construction and decoration, but also since it is one of the main components in the manufacture of cement and lime, amongst other uses. Limestone is produced using opencast mining methods through a multiple bench system which consists in removing material by cutting sub vertically in single elements from the top of the quarry to the quarry floor. This result is achieved with typical operations including drilling and blasting, both designed with a specific fragmentation curve in accordance with the final product to be achieved. After blasting, the fragmented material is loaded and transported to the grinding and sorting plant. The obtained limestone can be used in the aggregate industry or for cement and lime, depending on the dimensional characteristics of the quarried material. The whole quarrying process includes activities generating airborne dust emissions whose characteristics have been defined by specific Norms ([34], [35]). Consequently the airborne dust concentration represent a severe and critical issue all over the productive area and it is periodically checked by means of sampling campaigns.

By collecting data deriving from seasonal checks of airborne PM10 a detailed database was assembled consisting of more than 250 samples all over the property involving not only the processing plant but also the extractive area and the haul road zone connecting the plant to the blasting and drilling zone.

To carry out the monitoring program three nephelometers were utilised. These devises are based on the light scattering method for measuring mass concentration and are based on the Mie scattering theory of particles. When light strikes suspended particles in the air, the light scatters. For some certain particle properties, the intensity of the light scattered off the particle is proportional to its mass concentration. By measuring the intensity of the scattered light, the particle mass concentration can be obtained by applying the conversion coefficient.This method allowed a fast sampling time. In this study each sample had a three minute duration.

Although sampled values were collected in different periods referred to about two months, under the hypothesis of stationarity, they were considered as contemporary.

Moreover, since a full regular ten meter lag grid was difficult to create because of some knots were not accessible, an infilling procedure was carried out by means of a specific Gaussian simulation.

These simulated values (32) allowed to fulfill the domain and to explore the variability structure in a more detailed way.

In order to test the differences between the systematic and random sampling strategies and to analyse their influence on the variogram computation, is proposed the simulation of several iterative sub-samplings of the known data set with different grid resolutions, and the computation of variographic analysis on them.

The sampled airborne PM10 concentrations were assumed to be realizations of a random field Y=Z(x).

The field Z was first assumed to be isotropic, thus leading to semivariogram functions γ(h) that were only functions of a single scalar variable, while in the case of the flexible variogram model of the field was assumed to be anisotropic and a semivariogram function γ(h) h∈R^2 was considered. The first step in the applied procedure is the choice of an appropriate variogram model to describe the spatial correlation structure of the data. For the estimates based on isotropic variogram models, an empirical semivariogram was computed by the Matheron estimator (1973):

$$\gamma(h.k) = \frac{1}{2|N(h_k)|} \sum_{(i,j)\in N(h_k)} \left|z(x_i) - z(x_j)\right|^2$$

where h_k k=1,2,N denotes a finite set of distance ranges for which the variogram is estimated, N(h_k )denotes the class of all pairs of measurement points whose distance is comprised in the interval [h_(K-1/2),h_(k+1/2) ] and N(h_k ) is the number of pairs in the class h_k.

## III. Results and Discussion

The first experimental step consists in the statistical exploration of the raw data set.

TABLE I. BASIC STATISTICS

| ***Parameter*** | ***Basic statistics $PM_{10}$ concentration [µg/m3]*** |
|---|---|
| Min | 0.93 |
| Max | 38.57 |
| Mean | 16.60 |
| Median | 16.55 |
| Variance | 104.58 |
| St. dev. | 10.23 |
| Skewness | -0.04 |
| Kurtosis | 2.11 |

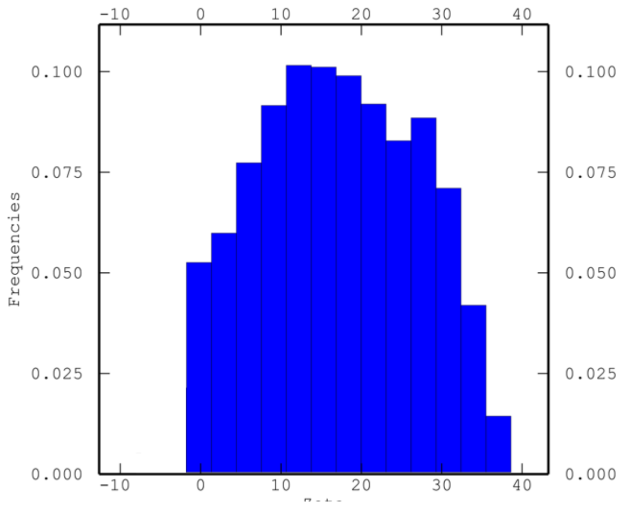


Fig. 2. : *Data histogram*

Experimental omnidirectional variogram was computed for lag = 10 mt.; # of lags = 35.

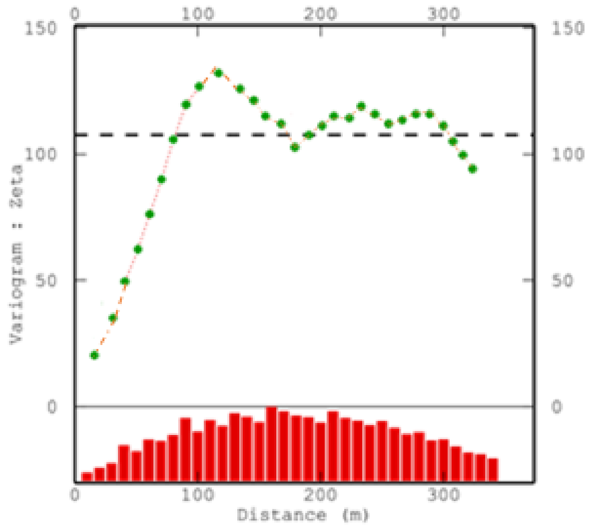


Fig. 3. : *Variogram of raw data*

As mentioned before, in order to examine the differences between the two kind of sampling procedures (the systematic one and the random one), an iterative subsampling of the original dataset has been implemented with different spatial resolutions. The ISATIS package from geovariances allows to compute two kinds of sampling selections on points: i) a regular one in which, once defined the resolution, samples are selected at the centre of each cell, and ii) a random one in which, once defined the grid, the samples are chosen in random way within each cell. Subsampling selection has been carried out for resolutions 20, 30, 40, 50, 60, 70 meters respectively for regular and random method, and experimental variogram has been computed for each subset. In the fig. 4 and 5, an example of regular and random subsampling for 20 mt. resolution is shown.

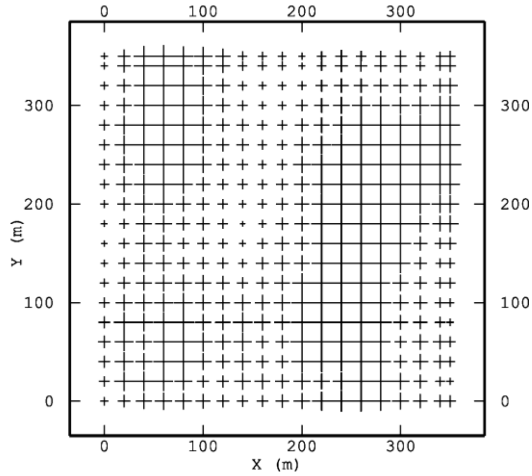


Fig. 4. : *Systematic sampling pattern*

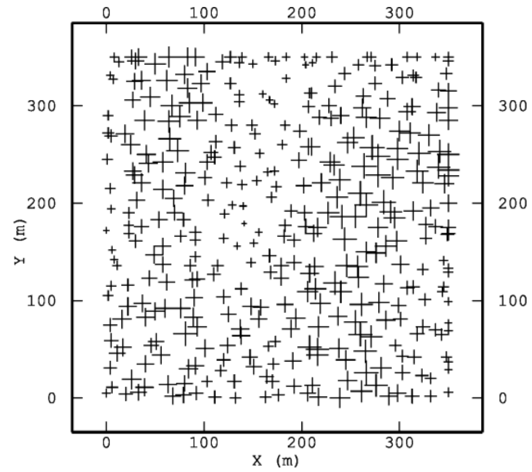


Fig. 5. : *Random sampling pattern*

It is clear how the total amount of spatial scales covered by random sampling is much more than the one of regular sampling, while a complete coverage of the spatial domain is guaranteed by both the methods. Structural analysis has been computed on both the sub sampled datasets and shown in figures 6, 7, 8 and 9.

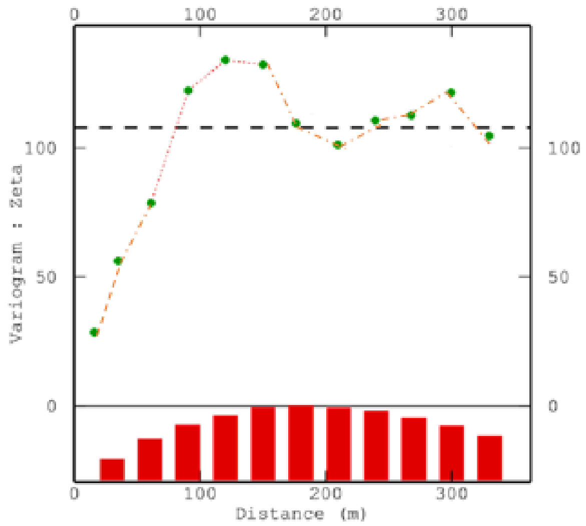


Fig. 6. : *Random sampling lag 30*

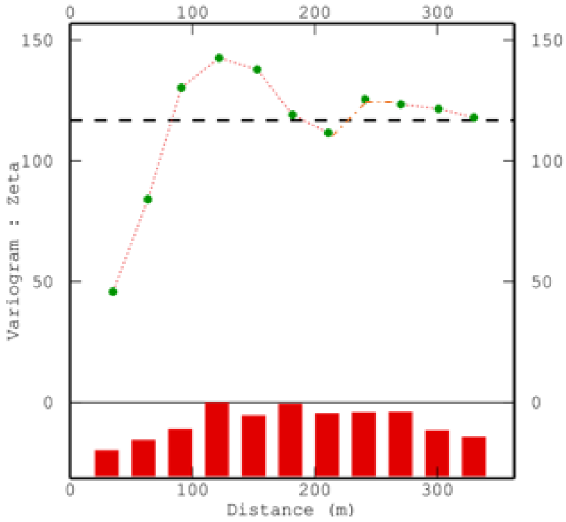


Fig. 7. *: Systematic sampling lag 30*

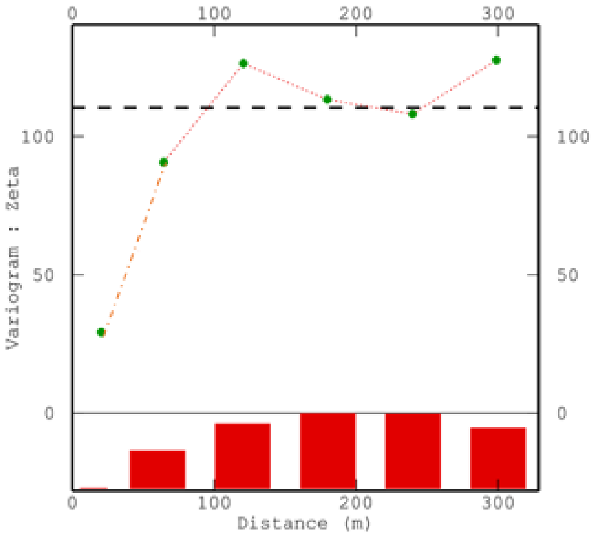


Fig. 8. *: Random sampling lag 60*

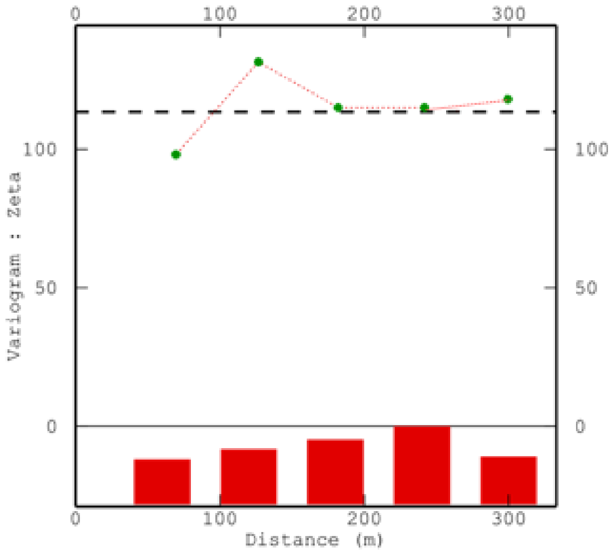


Fig. 9. *: Systematic sampling lag 60*

A general decrease of reliability in variograms may be observed. The main concern is just the way and the rapidity with which such variograms lose sense. The results of variographic analysis reveal the presence of many differences in the behaviour of the two groups of subsets. First of all the change in the histograms of the pairs abundance as shown in the lower part of each variogram. As soon as the subsampling resolution decreases, the numbers of pairs available for semi variance computation decrease uniformly in random approach and irregularly in systematic one. In particular an overabundance of pairs for lags coinciding with sampling scale or multiple of it are relevant in regular approach. The uniformity of information is crucial for an unbiased computation of semi variance values that, in this case, results poorly reliable. The irregular oscillation of variogram values, as in 10 mt. scale in regular sampling, can be connected just with such unbalanced abundance of pairs. Conversely, in random sampling, the pairs quantity decreases in regular way, so that, even the variogram being less reasonable, the semi variance values contributing to its shape are wholly consistent and affordable.

Another very important aspect is the characterization of the small spatial scale variability that is completely lost in regular sampling after the first sampling scales. The systematic sampling assume to have one information on each cell of the grid and consequently to fix the smallest lag exactly to the value of sampling grid resolution. It leads to the complete lack of information regarding the microstructural variability and to the quantification of high nugget effects, often not reflecting the reality. Looking at the experimental variograms of figures 7 and 9 we can note how the small scale variability in systematic sampling is lost immediately and some nugget effect is modelled. Conversely, random sampling represents correctly the uniform variation of the first lags that reveals the homogeneity of the variable if compared with variogram of raw data. Going on with subsampling scale, we can note how the nugget effect modelled by systematic sampling variograms is even more evident, while random subsets show only a bit increase of it. Eventually, at the scale 60-70 mt. the systematic sampling variogram is somewhat a pure nugget model, while the random one still preserve the correct shape. A further step of such a comparison consists in quantifying the influence of sampling strategy reflects on the data set dimension. To this aim, the small scale variability was compared in terms of nugget variance while varying the sampling dataset consistency. In fact taking into account that, especially when the target is an environmental variable, high variations at very small scales are unreliable, the non zero value of the nugget effect, rather than be constituted by analytic variance, can be explained only by the sampling strategy that has been not able to model correctly the uniformity of the variable. An analytical nugget variance was so assessed by means of a fitting procedure in which the inference of the experimental variogram is based on a least square fit of the experimental values of semivariance for each lag. Such fit was made by a series of nested authorized models. Among isotropic variograms, we have considered exponential, Gaussian, spherical and Nugget variogram models. Only exponential and spherical variogram models appeared to yield results sufficiently close to the corresponding empirical variogram over the whole range of spatial lags.

So, by fitting a continuous mathematical function on experimental variogram we can define a nugget variance that is the value at zero distance of the analytical function. This represents an important parameter if referred to the homologous of variogram plotted from the whole data set. The graph in fig. 9 shows the trend of nugget variance with the corresponding sampling methods (systematic in violet and random in red) when varying the data set dimension. As expected, the general outcome is that its value tends to decrease and so on to better describe the spatial variability when sample number grow up but a random selection of samples among the full data set determines a reduction by a factor of two of the corresponding nugget value.

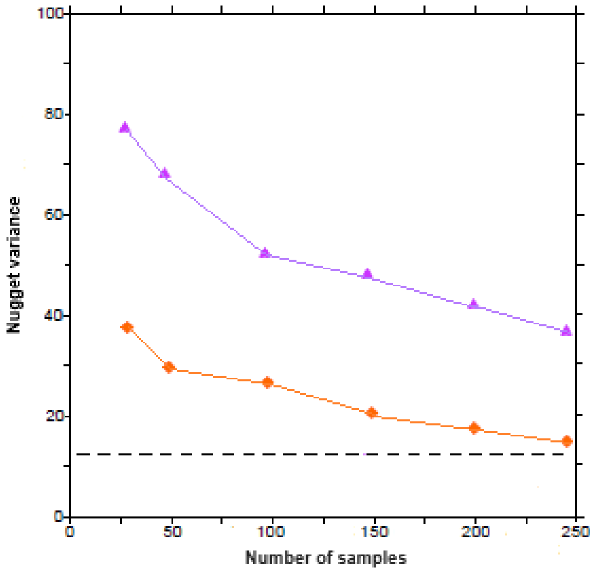


Fig. 10. *: Nugget variance from regular sampling (violet) and random (red)*

It implies the same accuracy in spatial analysis may be achieved by a large reduction of samples when randomly collected.

A further step towards the correct knowledge of the spatial phenomenon is represented by the introduction of anisotropy deriving from field information. In the framework of airborne pollutants in general, and PM10 in particular, the main wind direction in the selected field, plays a crucial role in the study of spatial variability specially dealing with open pit quarrying sites. To this aim, a Calmet simulation was performed to define in a detailed way the wind vectorial field. In particular, taking into consideration meteorological data provided by the real time monitoring station property of Italian Air Force, few kilometres far from the area, the wind vectorial field was drawn. Results are shown in the polar diagram in fig. 11. When main directions are recorded in the selected period, the corresponding sector is marked and so the red zones represent those sectors the sampled wind direction lay in the selected observation time (two months). In fig. 12 a daily trend of wind velocity is represented as for example.

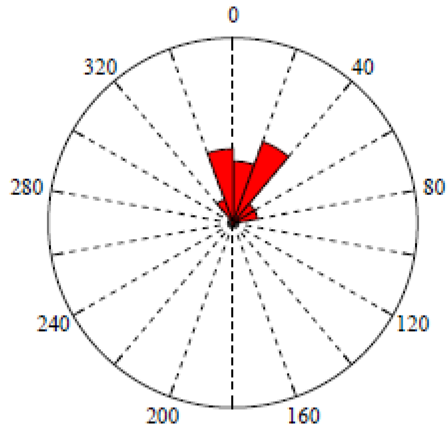


Fig. 11. *: Wind polar diagram of the selected area*

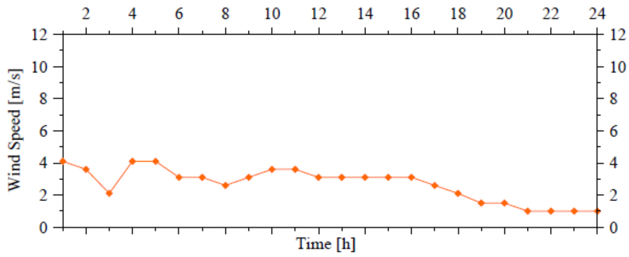


Fig. 12. : Wind polar diagram of the selected area

To appreciate this information, spatial study is enrich with directional variograms drawn for the same lag variation. In the figure 13 and 14, the systematic and the stratified random sampling strategy are compared. Directional variograms are plotted by means of Lag = 25 mt. # of lags = 14.

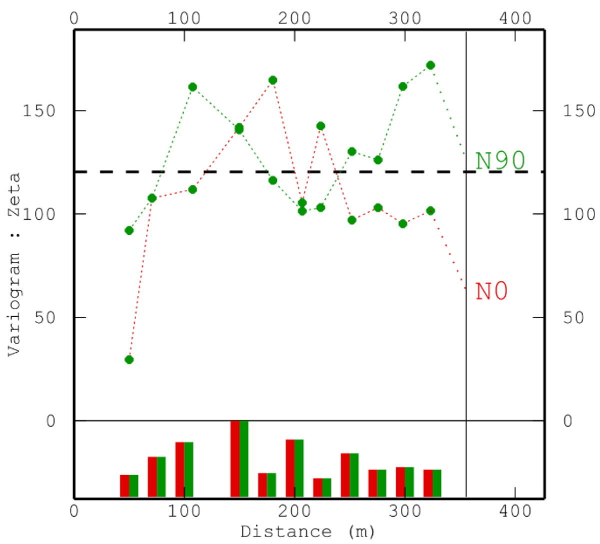


Fig. 13. *: Systematic sxampling lag 50*

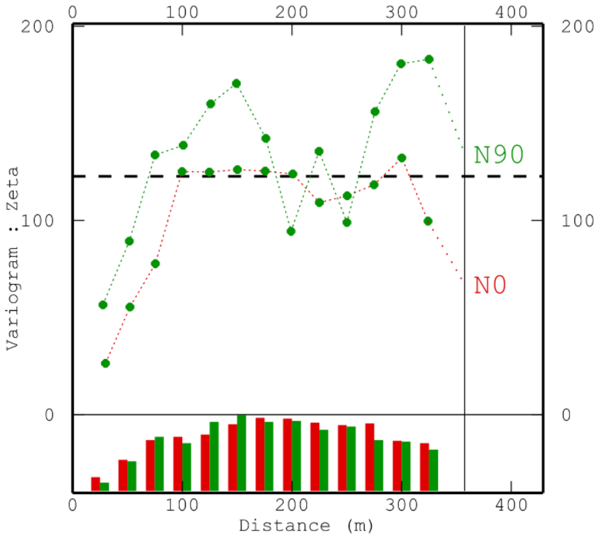


Fig. 14. *: Random sampling lag 50*

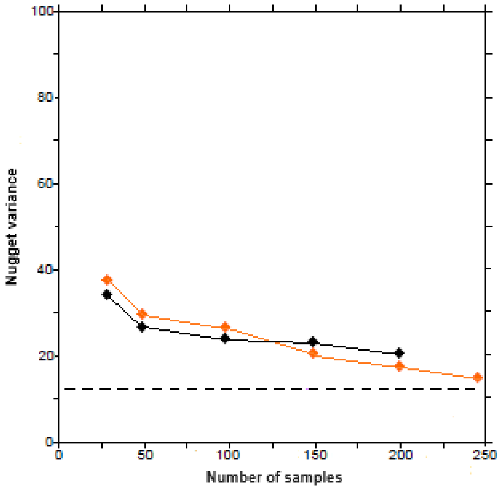


Fig. 15. *: Nugget variance computed from random sampling (orange) and stratified sampling (red).*

It is clear how in the case of directional variograms (with zero angular tolerance) the differences between the two methods are even more evident. First of all for what concern the pairs abundance that are hardly biased and completely absent for lags 50 and 125 meters in systematic approach and then for what concern the shape of the variograms that are much less meaningful and irregular. In stratified random strategy, the structure is kept and the original anisotropy is honoured too. Another consideration consists in investigating how the introduction of field information such as wind map, reflects on the quality of the resulting variogram. Such an objective is investigated by means of a comparison between different data set. From one side, sub datasets are randomly sampled from the original database as shown before, and from the other one a stratified random selection is carried out. In this last one the database is divided into smaller groups according with sample directions and among them a random selection is performed with no replacement. In fig. 12 the two trends are shown. The first consideration to be made is that according to, the introduction of stratified sampling allow to obtain a nugget variance lower if compared with that obtained using the same number of samples with no subsampling categorization. Both the values tend to decrease but the stratified one tends to a more constant value and, when growing the entering data set, is much more representative and finally (250 samples) is not calculated (variogram fitting is not performed) since its consistency is very low.

## IV. CONCLUSIONS

An iterative subsampling of a well known PM10 concentration map all over a selected domain with 10 meter resolution, for six different grid resolutions, from 20 to 70 meters, using a systematic regular sampling strategy and a stratified random one has been simulated. Structural analysis on the subsets have been carried out, computing omnidirectional variograms for each scale and comparing results with the one computed on raw data. Since the first subsets, for which the grid resolution is reasonably high, the differences between the two approaches appear clear. The systematic sampling approach is not able to keep the information of the small scale variability and loses it, assuming an increasing nugget effect whose presence does not correspond to the experimental data outcome. Meanwhile it presents several unreliable oscillations, due to the biased amount of pairs that are denser in scale equal to the sampling one or in the multiples of it and few in the others. Conversely, variograms computed on randomly sampled subsets, preserve the original shape of the raw data variogram and, even decreasing in details with the increase of sampling scale, they represent conveniently the real variability structure of the variable. Such crucial differences reveal the importance of the choice of sampling strategy on environmental analysis planning. Especially for what concerns the spatial estimation of environmental variables, the correct and reasonable representation of the real structure of the field is a crucial aspect that always affects the interpretation step. As known, an unreliable image of the variable represents the base for an incorrect understanding of the real natural processes. If we consider the economic aspect, we can observe how with the same economic waste, we can obtain more detailed information on the subject, simply choosing to locate the samples in a random way and not over a systematic grid. This reduction may be very important if we consider that the same nugget effect is computed for two data set differing each other by a factor of 5. Moreover, with stratified random sampling, we can appreciate a further reduction in the number of samples which is not translated into a corresponding reduction in the quality of the variogram, which on the contrary, remains more or less unchanged.

The major findings may be summarized as follows. A random sampling approach proved to better fit the characteristics of variability of airborne PM10 concentration than a systematic one. The same sample number allowed, in fact, a better variographic output and so on a more detailed corresponding estimation map. A further improvement was observed when the random sampling strategy was enrich with the stratified approach taking into account the main wind direction. This addiction allowed a reduction in the total amount of samples without determining a reduction in the corresponding variogram and estimation map.

In conclusion, a stratified random sampling strategy revealed to be the best approach to better represent the spatial variability of the observed phenomenon. The proposed selection was based on the assessment of the main wind direction in the temporary window in which samples were collected. By performing a cost benefits analysis the final check allowed to reduce the number of periodical check from 250 samples to less than 60 thus determining a huge reduction of costs deriving from equipment usage and staff involvement.

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