

The design of long-term air quality monitoring networks in urban areas using a spatiotemporal approach

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Abstract The implementation and maintenance of an air pollution monitoring program can be expensive and time consuming, especially when the aim is for long-term monitoring over a significant area. Consequently, it is essential that sites are optimized to provide the best representative cover while minimizing costs. In the past, there has been a tendency to locate sampling stations at pollution hot-spots. While this is acceptable for determining a maximum potential exposure or identifying the extent of a risk, there are limitations to this approach when assessing the potential impact of any future abatement strategies or determining the level of exposure outside the vicinity. This paper presents an approach in which representative air quality assessments can be undertaken

for an urban area using the minimum number of measurement sites. A novel methodology is described that involves site selection to capture the maximum variance in measured pollutants, while minimizing spatiotemporal autocorrelation between the selected sites. A case study is presented for Yazd, Iran. Overall, the results show that the proposed methodology can be effective and enable the long-term monitoring of air pollution to be undertaken on a cost-effective basis in urban areas. In addition, there is the potential for the methodology to be utilized for other forms of pollution (e.g., water, soil, and noise).

Keywords Air pollution · ArcGIS · Spatiotemporal · Monitoring network · Urban areas

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Introduction

Increasing concerns about the health effects of air pollution have underlined the need for regulatory authorities to monitor and assess pollution levels, especially in urban areas. In many cases, there is a statutory requirement to provide a quantitative assessment, so that air quality objectives can be shown to be achieved or so that any need for abatement strategies can be identified. The optimization of any monitoring network is highly desirable, since this enables it to meet these

objectives (Briggs et al. 2000), while minimizing costs by reducing the overall number of sampling locations.

Several studies (Baldauf et al. 2002; Silva and Quiroz 2003; Chen et al. 2006; Kao and Hsieh 2006; Kumar et al. 2007; Ott et al. 2008) have attempted to optimize air pollution network design in urban areas. The main idea behind such studies is to capture intra-urban variations in air pollution levels using the least number of monitoring sites. This minimizes the costs of implementation and maintenance of the network. There is some scope for further improvement in such studies however, since most utilize a spatial approach when being designed for a particular area. This is not always ideal because the levels of air pollutants usually vary from day to day and thus, it could be useful to consider temporal trends in many cases also. In addition, some studies have been orientated towards a specific parameter and have ignored any spatial and temporal auto-correlation. For instance, Baldauf et al. (2002) established a monitoring network at locations according to maximum anticipated concentrations and highest population densities.

In order to optimize the location of monitoring sites, it is usual to divide the study area into parcels or zones and consider the centroid of each parcel as a possible candidate site. Ideally, an estimate of the levels in each parcel would be available, so that the density of the monitoring network can be weighted accordingly. However, such information is not always known with the necessary spatial or temporal resolution and estimates need to be made by generating a pollution map using available data. Various techniques can be used to achieve this, but the two most commonly used ones are Land Use Regression Models and Interpolation Techniques. The former provides an estimate of a pollutant level at a location based on the surrounding land use (Briggs et al. 2000), although there might be some auto-correlation among the regressed variables using this method (Kumar 2009). An interpolation technique predicts unknown values at given points from a limited number of nearby measurements through a fitted model and can be used for almost any type of geographically distributed data (including elevation, rainfall, chemical concentra-

tion, noise level, etc.). Figure 1 illustrates the results of an interpolation technique where the part on the left shows a point dataset of known rainfall-level values and part on the right shows the generated raster.

The assumption that makes interpolation a viable option is that spatially distributed objects are also spatially correlated; in other words, things that are close together tend to have similar characteristics. For instance, if it is raining on one side of the street, it is possible to predict with a high level of confidence that it is raining on the other side of the street. However, it would be less certain that it was raining across town and even less certain still if it was raining in the next county. In air pollution studies, it is assumed that spatially distributed pollution levels are linearly (or otherwise) correlated when using an interpolation technique.

A main problem with many monitoring networks is that they tend to over-represent pollution hot-spots. While this is desirable from the point of view of assessing maximum exposure, it does not necessarily provide an overall picture of pollution levels. This means that it is not always possible to determine the spatial extent of the risk or to allow the identification of any abatement techniques, which might be necessary (e.g., traffic management). In an effort to overcome these shortcomings, research has been undertaken recently to establish optimized sampling strategies. For example, Kanaroglou et al. (2005) planned a monitoring network using air pollution data and socio-demographic parameters (including the distribution of at risk population) for Toronto, Canada. A main uncertainty relates to why a given number of sites should be determined prior

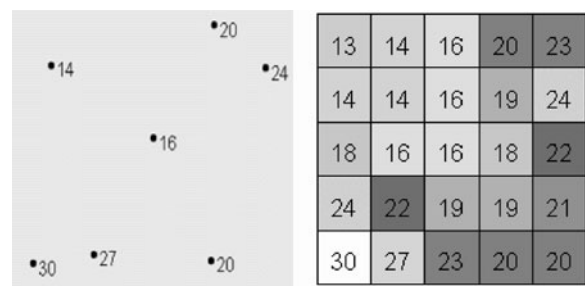


Fig. 1 Interpolated surface using sampling points

to the setting up a network. In this respect, a judgment has to be made between the precision of the mapped pollution data and the costs of operating the network. Kanaroglou et al. (2005) used a Location-Allocation Algorithm (a technique that identifies the optimal locations for a predefined number of air pollution monitors) to optimize the network; however, this approach has been criticized because it has led to the selection of redundant sites (Kumar 2009).

Ott et al. (2008) designed a network to monitor PM_{10–2.5} (coarse particles with aerodynamic diameters between 2.5 and 10 µm) variability with 95% confidence interval. Their study included three 7-day sampling campaigns using passive samplers. They found that the results of the mobile and passive samplers were correlated significantly, although there were clear differences in the measured levels over relatively short distance scales, which they attributed to local sources. The influence of such local sources on network design has been noted by other authors also, as well as the importance of adopting appropriately determined sampling intervals (Chow et al. 2002).

As in the case of spatial covering, temporal resolution (i.e., sampling frequency) is a trade-off between data precision and cost (Chow et al. 2002). There is the potential for local concentrations to behave independently if local sources are dominant. However, synoptic weather patterns can also result in good or poor air quality on a regional scale (reflecting both local accumulation and long-range transport). For the purposes of network design, it is probably preferable to consider long-term (e.g., annual) mean concentrations to be most representative of local sites in a given area when identifying sampling locations, as this minimizes the possible effects of extreme conditions.

This paper investigates a way to reduce uncertainties in the design of air quality monitoring network, while minimizing the number of sampling sites. The main aim is to consider the long-term monitoring of air pollutants taking into account both temporal and spatial autocorrelation between measurement sites and an approach is demonstrated for an intermediate sized city in Central Iran (Yazd) with a population of about 430,000.

Methodological framework

The adopted approach comprises two stages:

1. Establishing a grid of candidate sites based on air pollution data from existing sampling stations, in which each could be weighted accordingly.
2. Distributing an idealized monitoring network across a study area in which the maximum variability is captured and the spatiotemporal autocorrelation is minimized.

In the first stage, interpolated pollution levels are used to determine the spatial distribution of air pollution levels and a pollution map is created using ArcGIS. A grid is then superimposed on a study area and the air pollution level in each cell is estimated from the pollution map.

Creating a pollution map is a two-step process in which inter-site correlation of pollution levels is determined from a series of measurements and then interpolated levels are predicted. A variogram can be used to estimate the inter-site statistical dependence (called spatial autocorrelation) and these are modeled either spatially or temporally (termed variography).

The pollution map is created by Kriging. This is a stochastic technique, (after Krige 1951) and is by default, the geostatistical analytical method that ArcGIS uses for interpolation. It involves determining the time-averaged pollution levels at locations within a minimum spatially bounding box (i.e., the smallest box area that can be created to include all the existing stations) and the estimation of values at other locations by using the distance and the deviation between measured values. Kriging applies a function called semivariance to express the spatial variation; this minimizes the error of predicted values (Andria et al. 2008) that are estimated by a spatial distribution. The general formula for Kriging is:

$$\hat{Z}_i = \sum_{j=1}^N \lambda_j Z_j \quad (1)$$

Where:

\hat{z}_i is the predicted air pollutant level for each idealized location i ;

N is the number of sampling stations around each location;
 λ_j is a weighting factor assigned to each sampling point; and
 Z_j is the measured air concentration at location j .

The weighting factor (λ_j) is based on the distance between the sampling points and each location, and the overall spatial arrangement of the sampling points. In using spatial arrangement in determining the values of λ_j , it is necessary to determine the extent of the spatial autocorrelation (i.e., how pollution levels at individual sites are related at a given time).

A semivariance γ , for n sites with a separation distance of h (referred to as lag size), is the average squared difference in z values between pairs of sites i and $j(i+h)$ as in Eq. 2.

$$\gamma(h) = \frac{1}{2N} \sum_{i=1}^N [(z_i - z_j)^2] \quad (2)$$

In practice, a graph of the empirical semivariance is computed when modeling (see Fig. 2) and this provides information on the spatial autocorrelation of the datasets (although not for all possible directions and distances). For this reason, and to ensure that Kriging predictions have positive Kriging variances, it is necessary to fit a model that is a continuous function or curve to the empirical semivariogram. The general mathematical models used to describe the semivariance are spherical, circular, exponential, Gaussian, and linear.

Kriging assumes an isotropic spatial autocorrelation structure. This accepts that the autocorrelation is a function of distance (Mabit and Bernard

2007) and varies similarly in all direction. In contrast, anisotropic spatial autocorrelation (Liu et al. 2004; Sales et al. 2007) occurs when there is a dependence on both distance and direction. The assumption of isotropic spatial autocorrelation is reasonable for a flat area (such as the study area discussed later); however, for areas where the terrain is complex (e.g., a city located in two or more valleys) it is likely that an anisotropic spatial autocorrelation needs to be taken into account prior to creating pollution map.

After the creation of a pollution map, data are imported into MATLAB. MATLAB is a matrix-based programming language and it can be useful for manipulating spatial data when modeling air pollution and the integration of MATLAB and ArcGIS has been used successfully in studies elsewhere (Nejadkoorki et al. 2008). From this map, an idealized monitoring network is determined using a novel approach that minimizes spatiotemporal autocorrelation by capturing the maximum variance as in Eq. 3.

$$\min(z_{ST}) = \frac{1}{n} \sum_{i=1}^n \sum_{d_{ij} > R} (z_i - \bar{z})^2 \quad (3)$$

Where:

- n is the total number of selected sites from all candidate sites;
- z_{ST} is the minimum spatiotemporal autocorrelation in air pollutant concentration;
- $(z_i - \bar{z})$ represents the variability of z for the selected sites;
- d_{ij} is the distance between neighboring sites i and j ; and
- R (range) is the distance at which the modeled semivariograms level off

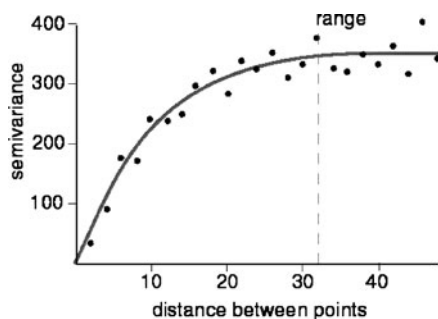


Fig. 2 Empirical semivariogram

R is the minimum distance between two sites to avoid spatial autocorrelation; for example, R would be 32 in Fig. 2 and all points that fall within a distance of 32 from one another would be spatially autocorrelated.

In order to minimize temporal autocorrelation, the air concentration data should span a year (at least), so that any variation on a diurnal, monthly, or seasonal basis does not affect the calculations adversely. In the case when the temporal resolution of the sampling data is insufficient (i.e., less

than a year), an overestimation or underestimation of variance can occur. The usual method to calculate sample size is given in Eq. 4.

$$n_s = \left(1.96 \frac{\sigma}{e}\right)^2 \quad (4)$$

Where n_s is the number of required sites to capture 95% of the observed variability with standard deviation (σ) and an accepted error (e). However, because most air pollution and environmental data exhibit significant spatial autocorrelation (Kumar 2009), there is the potential to over-estimate n and σ .

The approach adopted to minimize the spatial autocorrelation in the current study was to check sites with a distance greater than R for a statistically significant correlation of z . In addition, the number of sites able to capture the maximum variance with minimum spatiotemporal autocorrelation was calculated. Compared to the classical way of calculating the number of sites, the currently described approach normalizes and reduces the total number of sites while determining the spatiotemporal autocorrelation.

Case study (Yazd, Iran)

Study area

There are significant air quality problems in many Iranian cities, including Tehran (Sohrabpour et al. 1999), Shiraz (Hadad et al. 2003), and more recently, Yazd (in central Iran). There are a number of pollution sources that exist already in Yazd (including heavy and light industries, traffic, and construction sites) and concerns over pollution levels in the city have been prompted by an increasing population (currently 430,000; The Office of National Statistics 2007). Yazd is situated around 1,250 m above sea level and the metropolitan area covers about 97 km². The region is relatively flat with no significant topographical features and the prevailing wind direction is from the northwest. The city's climate is very dry.

Yazd has an existing air sampling site capable of measuring PM₁₀, CO, SO₂, NO, NO₂, NO_x, and O₃, but the need for a comprehensive network has been identified because of the recent

urban growth. Total suspended particulate material (TSP) has been identified as a priority pollutant, because background (i.e., natural) levels can be high and it is considered to have a potentially important effect on health. In addition, many of the pollutant sources in the city (i.e., industry, construction, and traffic) are potentially significant sources of TSP.

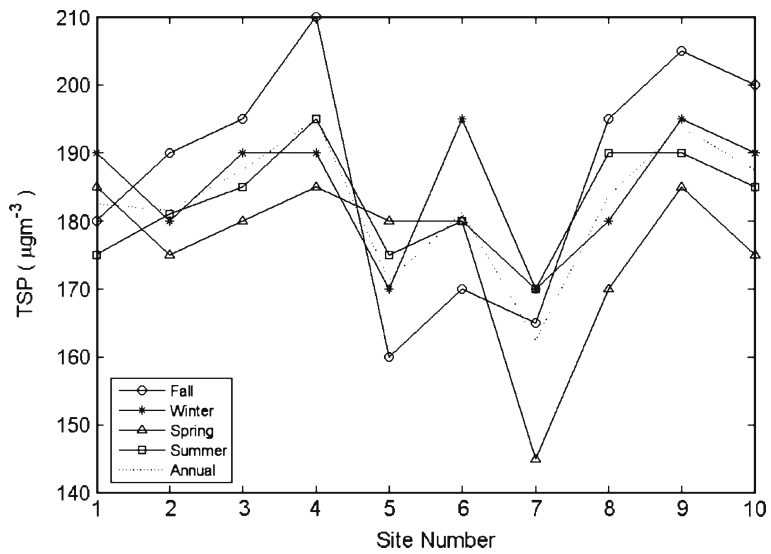
Fortunately, TSP was the pollutant that was known with the most detailed temporal resolution in Yazd (Ehrampoosh 2003). Levels had been measured at 10 sites across the city in 1997, by collecting TSP on filters (aspirated at 3 l min⁻¹ and analyzing these gravimetrically). The results are given in Fig. 3, which shows the seasonal, as well as inter-site, differences in air concentrations. The seasonal mean values were considered to be a useful representation of pollution levels, since human health effects can be dependent on weather conditions also (Goldberg et al. 2006). These values and the locations of the measurement sites were incorporated into the mapping exercise (see below).

TSP mapping

A grid of 9,742 unit cells, each measuring 100 × 100 m, was created that covered the city boundaries of Yazd. The central point of each cell was considered as a candidate sampling site. A preliminary map of TSP levels was created using ArcGIS. However, the measurement data did not cover the entire study area and it was necessary to estimate some levels at some locations on its periphery by extrapolation. There are inherent difficulties in extrapolating data and certain assumptions need to be made to get reliable estimates. However, since the study area was relatively small, it was assumed that such data extrapolation would not present a major problem.

In order to distribute the candidate sites, their identities and positional co-ordinates were determined for each cell of the grid covering the city. These were then imported into MATLAB as a matrix. R was determined using an empirical semi-variogram (see “Methodological framework”) to avoid spatial autocorrelation and a program in MATLAB was used to run Eq. 1 to assist in the

Fig. 3 TSP measurements of the passive sampling sites



design of an optimized sampling network in which spatiotemporal autocorrelation was minimized.

Results and discussion

In order to examine the impact of temporal autocorrelation on spatial autocorrelation and the

number of required sites, the methodology was applied for different seasons to the existing sites. Usually, spatial autocorrelation is analyzed by plotting a semivariogram (as in Fig. 2) and a continuing increase in with distance would indicate its existence. This appeared to be the case in some instances (see Fig. 4); thus, it can be concluded

Fig. 4 Semivariogram for the passive sampling sites

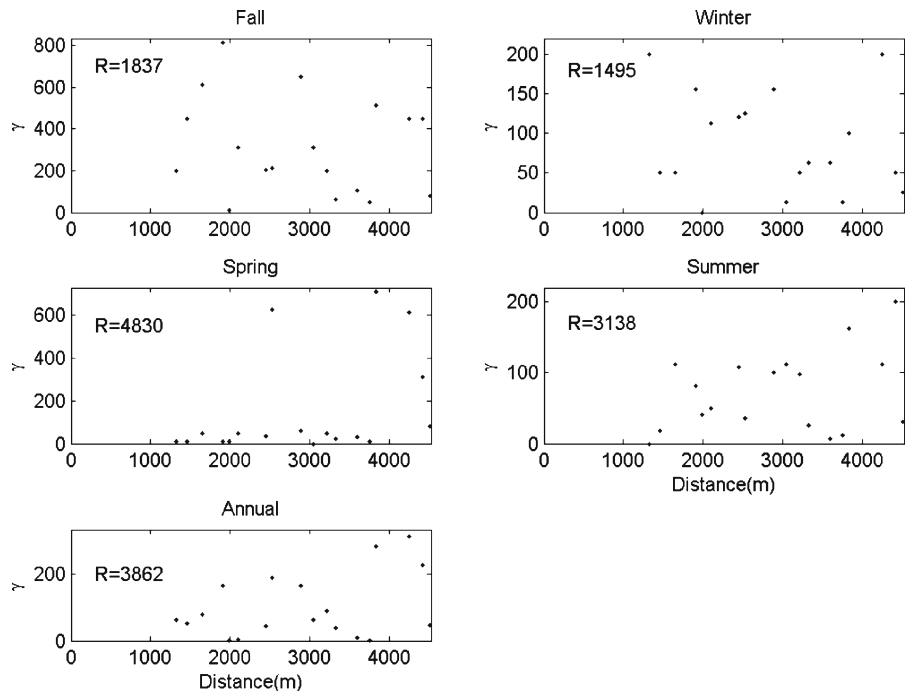
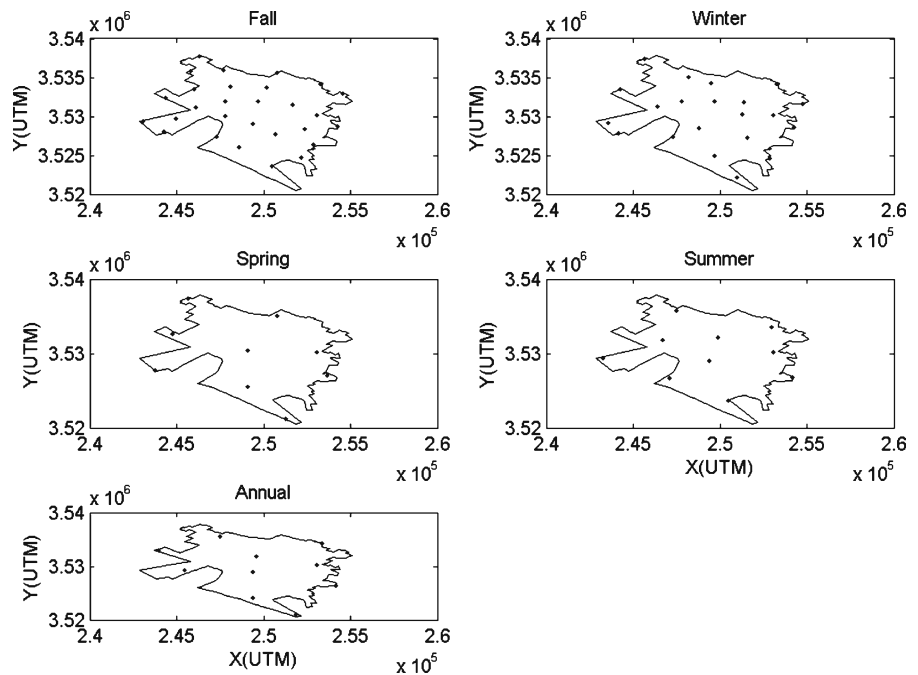


Fig. 5 Proposed monitoring networks

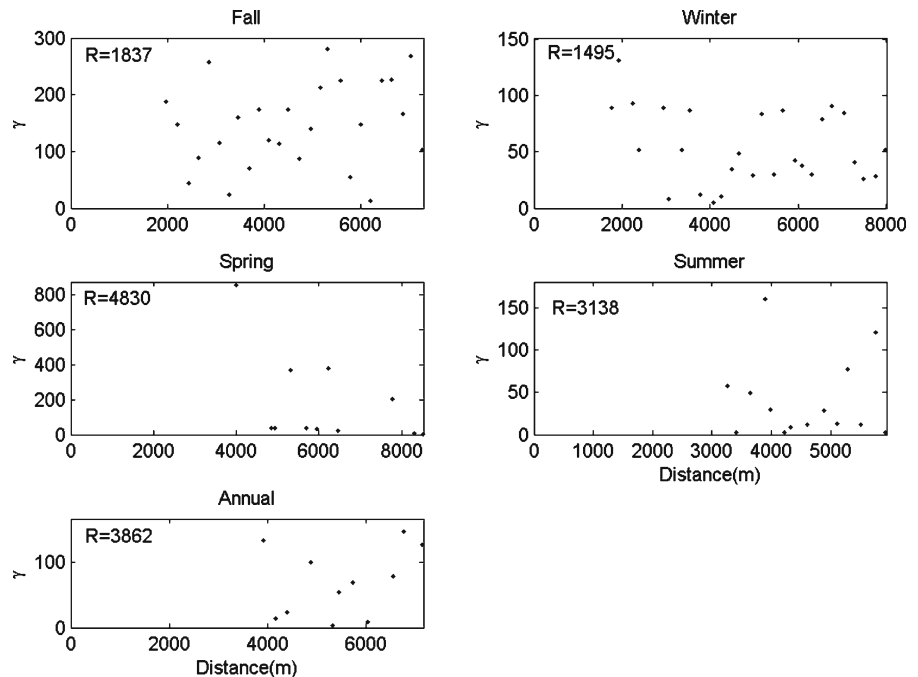


that the existing monitoring network is not ideal and could benefit from being redesigned.

Figure 5 illustrates the locations of idealized sites according to season, where longitudinal and

latitudinal coordinates in Universal Transfer Mercator (UTM-Zone40-N) are given on the *x*- and *y*-axes. The minimum number of required sites with minimized spatial autocorrelation and maximized

Fig. 6 Semivariogram of the proposed monitoring networks for different seasons



variance for fall, winter, spring, and summer are: 28, 21, 9, and 10, respectively. In addition, the proposed sites appeared to be distributed unevenly across the city. Based on the adopted methodology, no season indicated spatial autocorrelation, but a temporal autocorrelation would be seen readily if a long-term monitoring network were to be deployed. Moreover, the minimum number of idealized sites would be subject to spatiotemporal autocorrelation, as illustrated above, because air concentrations are often less variable at certain times of year (i.e., during summer in Yazd). Considering the temporal autocorrelation on an annual scale, the minimum number of idealized sites was found to be 10 with an average distance between them of 7.4 km.

Figure 6 shows the seasonal and annual semi-variograms for the idealized sites. The lack of a relationship between distance and semivariance suggests that the data were independent and that spatial autocorrelation was avoided. Because the mean TSP concentrations appear to be seasonally dependent, an air pollution monitoring network based on an annual mean TSP concentrations might be the best way to reduce temporal autocorrelation in this case.

Summary and conclusions

This paper describes an approach for designing a long-term air pollution monitoring network for an urban area. It consists of creating a set of candidate sites by mapping existing data and then optimizing any proposed network on predicted pollution levels.

The study indicates that in order to avoid spatial autocorrelation, the range should be estimated using an empirical semivariogram which is important when determining both the number of sites and when allocating them to a monitoring network.

For Yazd, it was found that the idealized monitoring network was distributed unevenly across the city and a lack of autocorrelation would indicate that such a network could lead to a better assessment of human health effects than exists currently. The modeling exercise for the existing

data revealed that the temporal autocorrelation (as well as spatial autocorrelation) was significant and this should be taken into account if redesigning the network for the long-term monitoring of air pollution. However, there remain uncertainties about the way that the confidence interval could be calculated for such a network.

Many recent air pollution monitoring studies have been based on measurement data acquired over short time-scales (Kanaroglou et al. 2005; Kumar 2009). The current study suggests that both spatial and temporal autocorrelation might be important and could reflect on the optimum number and distribution of idealized sites. It is considered that the annual mean concentration might be incorporated into calculations whenever possible, in order to minimize temporal autocorrelation effects.

The proposed design for a sampling network could enable a cost-effective solution to environmental monitoring. The approach could allow environmental engineers, local authorities, and epidemiologists to design air pollution monitoring networks for specific purposes by incorporating the relevant input data in the mapping exercise. Consequently, there is scope to develop the methodology for use at other sites and there is the potential for it to be used for other forms of pollution (e.g. water, soil, and noise).

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