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New Approaches in Urban Air Quality Monitoring

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Abstract. This paper explores the new methods and techniques to design air quality monitoring networks in urban areas. The different perspectives, from which the air quality variability in urban domains has been dealt with, are summarized. GIS and computer programming applications to capture and manipulate data, extract secondary data, generate database, and implement designing approaches are analyzed. The paper highlights how some of these methodological aspects are being well designed and summarizes the new developments that can be expected in the near future.

Keywords: Component, urban air quality, monitoring network, new approaches

1. Introduction

Urban systems have a limited capacity and concentration of human activities in such systems may lead to environmental problems including air pollution. There has been solid evidence on relationship between serious disease [1, 2] and air pollution in urban areas. However, there are concerns [3-5] on the way which ambient air pollutions are monitored. Therefore several attempts have been made to overcome this and design more representative urban air quality monitoring networks. These are mainly based on using computer programming, GIS and the application of spatial statistics. The different perspectives, from which the air quality variability in the urban domains has been dealt with, are summarized. Geographical Information Systems (GIS) and computer programming applications to capture and manipulate data, extract secondary data, generate database, and implement designing approaches are analyzed. The paper considers the current techniques and explores possible new developments for the future.

2. Designing air quality monitoring networks

Air quality monitoring networks are required to monitor the levels of ambient air pollutants and determine the environmental and health effects in cities. Such networks must consider the monitoring location, sampling duration and frequencies and the pollutants concern [6]. Furthermore these networks are limited by access, available technology and monitoring resources.

Traditional way of establishing monitoring networks is to install samplers in hot-spots. While these locations may give the maximum concentrations, yet there is need to monitor pollutants in other areas especially if an epidemiological evaluation is intended. The most significant approaches to design monitoring networks are based upon statistical concepts as most of measurements are correlated either in time or space. The remaining of this paper deals with the current approaches in urban air quality monitoring networks and their effectiveness.

In an attempt by Kanaroglou et al. [4] a monitoring network was designed for Toronto, Canada using the Location-Allocation (L-A) technique. First the local variability of air pollution at location is obtained as:

$$\gamma(\vec{x},\vec{\mathrm{h}}) = \frac{1}{2}\sum_{h}\left[\left\{\mathrm{z}(\vec{\mathrm{x}}) - \mathrm{z}(\vec{\mathrm{x}}+\vec{\mathrm{h}})\right\}^{2}\right] \qquad (1)$$

The right side of the equation occurs over all possible pairs of locations within distance *h* from *x*. This equation leads to a pollution surface with each cell of the created surface has a value as the intensity of variability. In the next step a weighting scheme is implemented to allocate more monitoring sites in areas where the density of a population of interest is high as:

$$W_R = \frac{P_R/P_T}{y_R/y_T} \qquad (2)$$

Here P_R and y_R are the population and pollution variability in region *R* compared to the total population P_T and variability y_T in the entire study area. The weight W_R is applied for each location that belongs to region *R*. Finally the location of candidate sites are identified by L-A procedure using GIS as:

$$Z = \sum_{i=1}^{k} \sum_{j=1}^{m} w_i \, (1 - bd_{ij}) x_{ij} \qquad (3)$$

Where *K* is the number of demand locations and *m* is the number of candidate locations and W_i at location *i* represents demand. The d_{ij} is distance between *i* and *j*, and x_{ij} is the allocation decision with the value of 1 if the location is served by a station and 0 otherwise.

In the above modelling framework, spatial variability with respect to population is considered. However, there are some areas to improve. A predefined number of sites should be argued and this is important from the economical point of view. Moreover, weighting factor based on population does not necessarily capture air pollution variability[7]. For instance selecting a single site in an area of high spatial autocorrelation is well enough to assess population exposure in that area. In addition, the L-A technique does not take into account spatial autocorrelation. Most of such techniques [3, 4] only use a two-week passive sampling to create initial surfaces. However, a newly research [8] revealed that sampling networks not only have spatial autocorrelation but temporal autocorrelation (e.g. seasonal autocorrelation) and only an annual sampling reduce the temporal autocorrelation.

Kumar et al. [7] developed an improved technique to design a network by capturing maximum variance in air pollution and minimum sample size as:

$$\text{Max}|z| = \frac{1}{n} \sum_{i=1}^{n} (z_i - \bar{z})^2 \quad {}_{z_i \neq z_j}, d_{ij} > h \qquad (4)$$

Where *n* is the sample site, air pollution z_i, observed at the location *i* must be significantly different from that observed at its neighbour sites *j*. The distance between *i* and its neighbours *dij* must be greater than h. Compared to the previous research, this technique highly considers spatial autocorrelation. However, yet there are two parts for improvement namely, number of sites and temporal autocorrelation. Total number of sites *n*, needed to capture observed variability was calculated as:

$$n = \left(\frac{1.96s}{U}\right)^2 \qquad (5)$$

Where *s* is the sample standard deviation, *U* is the accepted uncertainty. This means that the user must include a predefined number of sites regardless the domain of the study area. For instance for a study area of 10 km × 10 km 50 sites may be calculated based on Eq. 5. In the next step considering the condition of $d_{ij} > h$ it is hard to distribute sites within this domain. Secondly similar to the previous approach the issue of temporal autocorrelation is yet a concern.

Most recently an approach was developed by Nejadkoorki et al. [8] to satisfy these issues as:

$$\min (z_{ST}) = \frac{1}{n} \sum_{i=1}^{n} (z_i - \bar{z})^2 \quad {}_{d_{ij} > R} \qquad (6)$$

Where *n* is the total number of selected sites from all candidate sites; z_{ST} is the spatiotemporal autocorrelation in air pollutant concentrations; z_i-*z* represents the variability of *z* for the selected sites; *dij* is the distance between neighbouring sites *i* and *j*; and *R* is the distance at which the spatial autocorrelation is disappeared. Here *R* is estimated based on the empirical semivariogram (figure 1). The semivariance (Y axes) is estimated for points within a separated distance (X axes). Looking at the graph there is a relationship between semivariance and distance. However, after a certain distance (*R*), the semivariance levels out.

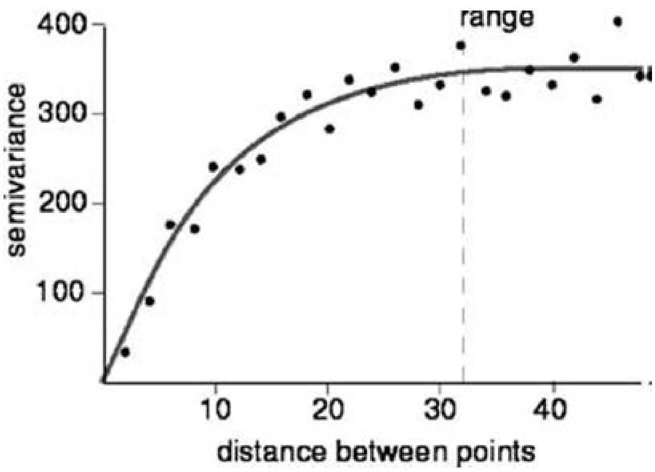

Figure 1. Emperical semivariogram

Nejadkoorki et al. further demonstrated that the current approach generated a rational air quality monitoring network for monitoring particulate matters (i.e. 10 sampling sites) across a study area of 97 km^2. It was also argued that when an annual data was performed, the temporal resolution appeared to be minimum compared to the seasonal scales.

The approach satisfies the limitations of the previous studies by considering temporal autocorrelation. Furthermore, it allows the technique defines the minimum number of sites which effectively reduces the cost of maintaining the monitoring networks. However, one thing is remained to improve is how significant is the number of sites compared to traditional approach (Equation 5).

3. Implementing the Approaches using computer Programming and GIS

Designing urban air quality monitoring networks requires the analysis of air pollution data, spatial data and census data. Air pollution data are initially as vector data (preliminary sampling) and then raster (continues surfaces). Spatial data analysis is an important part of such techniques. GIS is an integration of computer software, hardware, geographical data and grayware (user). Nowadays, there have been tremendous developments in GIS packages (e.g. ArcGIS) in manipulating and visualizing data. Here, GIS can provide an environment to visualize data. However, where a complex analysis such as spatial search algorithms are required [3] yet modelers need to utilize the computer programming.

Computer programming has been integrated with GIS [3, 5, 8-11] to gives a more powerful environment to manipulate spatiotemporal data. Of the computer programs, MATLAB has appeared to be more user friendly with built in algorithms [8].

4. Summary and conclusion

This paper has reviewed most recent developments in designing urban air quality monitoring networks. It was discussed that only a spatiotemporal approach that minimizes the number of sites is the state of the art approach to design urban air quality monitoring networks. It is yet anticipated future works are required to find the statistical significant of air pollution sample size using the third approach. Furthermore, the current approach may be extended for other forms of environmental pollution such as water, soil, and noise.

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