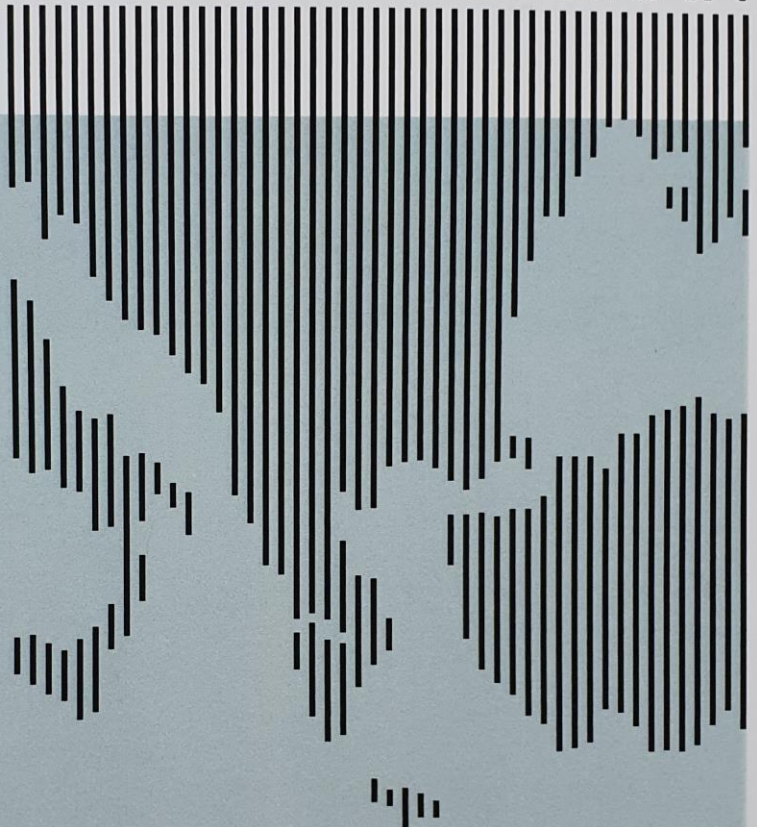


INTERNATIONAL CONFERENCE  
**DECODING BALKAN**



**CONFERENCE PROCEEDINGS**



Министарство просвете,  
науке и технолошког развоја



## Monitoring Air Pollution Using GIS: Case Study for the City of Belgrade

Author 1: Nenad Brodić, Faculty of Civil Engineering - University of Belgrade, Serbia;

Author 2: Stevan Milić, MapSoft d.o.o., Serbia;

Author 3: Momir Mitrović, MapSoft d.o.o., Serbia;

Author 4: Željko Cvijetinović, Faculty of Civil Engineering - University of Belgrade, Serbia;

Author 5: Dragan Mihajlović, Faculty of Civil Engineering - University of Belgrade, Serbia;

Author 6: Jovan Kovačević, Faculty of Civil Engineering - University of Belgrade, Serbia;

Author 7: Nikola Stančić, Faculty of Civil Engineering - University of Belgrade, Serbia.

### Abstract

The methodology for modeling the distribution of certain air pollutant for the city of Belgrade in winter 2015 is presented in the paper. Land Use Regression (LUR) was used for modeling and visualization of spatial distribution of air pollution concentration in the city. NO<sub>2</sub> concentrations were sampled at 46 locations, and predictive variables were calculated based on the road category, traffic intensity, demographic data, altitude, household furnaces and land use. These variables were calculated using buffers of different sizes. Linear regressions between NO<sub>2</sub> and predictive spatial variables were calculated. Afterwards, the most significant predictors were used for multivariate regression model. Quality of the final model was checked using measurement available at certain locations. The RMSE of 9.8  $\mu\text{g}/\text{m}^3$  and the coefficient of determination (R<sup>2</sup>) of 0.6 were obtained. These results indicate that traffic has the largest impact on air pollution concentration especially near the major roads. Prediction should help in deciding which air protection measures are to be taken in order to preserve and improve the city environment. The lack of data that are collected by using quite a few sensor stations is still rather limiting for the successful monitoring of air pollution in the city of Belgrade.

*Key words: Air pollution, Nitrogen Dioxide, Land-use regression, GIS*

## I. INTRODUCTION

Air quality is a very important issue for the sustainable development of a city. Numerous efforts have been made to obtain a reliable assessment this environmental indicator. In the last 30-40 years, there have been various scientific and professional projects funded by

different national and international institutions aimed at obtaining more reliable information on air quality and its environmental impact, primarily on human health.

Generally, there are two approaches for solving the problem of modeling air pollution:

- using spatial interpolation methods,
- using dispersion modeling methods for emitted particles.

Spatial interpolation provides the prediction of air pollution at an arbitrary location using measured pollution at other locations (measurement stations). Plethora of used spatial interpolation methods for solving this problem can be found in Xie et al. (2017), Deligiorgi et al. (2011) and Sertel et al. (2008).

Dispersion modeling methods use mathematical simulation of the dispersion of pollutants to model the propagation of pollutants in the air. The simulation is performed using known data on the source and emission of pollutants, data on the modeling space (digital terrain model, surrounding objects, etc.), meteorological data, but also information about the nature and mode of the distribution of the specific pollutant. Various dispersion models have been developed for air pollution such as Wang et al. (2008), Gulliver et al. (2011) and Al-Naimi et al. (2015).

The city of Belgrade is facing serious problems regarding air pollution. The city management allocated significant resources to tackle this issue. The decision has been made to design and implement a system for the monitoring of air quality within the city Department for environmental protection. Suitable software and hardware is obtained and designated for this purposes. It is planned to use the data that are constantly collected on more than 30 stations distributed all over the city area.

## 2. METHODOLOGY

Previous research suggests that one of the most optimal methods for determining the concentration of air pollutants in urban areas is spatial prediction using global regression on cheap-to-measure attributes. When this prediction method is applied to modelling air pollutants distribution, it is called Land-Use Regression modelling (LUR) in the scientific literature (Oxford, 2015). Land-use regression (LUR) models have been developed and utilized to model traffic pollutants such as NO<sub>2</sub> and PM<sub>2.5</sub> (Briggs et al., 1997; Brauer et al., 2003; Gilbert et al., 2005; Ross et al., 2006; Habermann et al., 2015). A

comprehensive review of LUR models has been given in Hoek et al., 2008. Generally, the LUR model has been utilized to characterize air pollution exposure and health effects in urban areas. For the application of LUR method in Europe, the project called ESCAPE (*European Study of Cohorts for Air Pollution Effects*) was very important (ESCAPE, 2010). The goal of the project was to investigate long-term effects of exposure to certain pollutants on human health in Europe. The project carried out research and verification of the mentioned methodology in 44 cities across Europe, but cities from Serbia did not participate (Eeftens et al., 2012). In order to meet the objectives of the project, it was necessary to have relevant data on the presence of pollutants in the air in the areas where the population is most exposed to them.

### **Predictors**

Predictors are spatial variables that can be easily measured and these are also dependent of the pollutant that should be predicted. Several data sources for the calculation of possible predictors have been considered:

1. Road network and streets with increased traffic load: street and road geometry were given as polylines with attributes such as road category and others; also, vehicle count was provided for 208 crossroads in tabular format for the central area of the city; all of this data was integrated in order to have geometry of roads with information about traffic load for each road segment;
2. Demographic data - number of residents per each statistical circle from 2011 year assigned to polygons for the administrative territory of Belgrade;
3. Furnaces - point data as locations of chimneys with number of individual furnaces per one address; this layer has 48,302 chimneys with a total of 130,641 furnaces;
4. Altitude data - digital elevation model, grid DEM with 100m spatial resolution;
5. Buildings - polygons with building heights for old, central area of the city;
6. Land use - polygons limiting specific land use.

By using above mentioned data a set of predictors have been generated (Table 1).

*Table 1: Set of predictors (each combination of predictor short name + buffer size)*

Predictor	Short name	Buffer size	Description
High population density	HDRES	100m,300m,500m	High population density in buffers around sampling point
Low population density	LDRES	100m,300m,500m	Low population density in buffers around sampling point
Industrial land use	IND	100m,300m,500m	Majority of Industrial class in buffers around sampling point
Green spaces in urban	URBGREEN	100m,300m,500m	Majority of Green in urban class in buffers around sampling point
Population	POP	100m,200m,300m	Population density in buffers around sampling point
Elevation data	SQRALT	-	Square root of DEM values
Furnaces	FURN	100m,300m,500m and 1000m	Emissions solid fuel combustion from winter heating
Inverse distance to the closest road	INVDIST	-	Inverse distance from object to the closest road
Traffic intensity on closest road and inverse distance	INTINVDIST	-	Product of traffic intensity on closest road and inverse distance from object to closest road
Total traffic load	TRAFLOAD	25m,50m,100m, 200m and 300m	Total traffic load off all roads inside buffer (sum of products of traffic intensity and total length of all corresponding segments)
Closest road	DISTNEAR	-	Distance to the closest road
Closest major road	MAJDIST	-	Distance to the closest main road
All road segments nearby	ALLROADS	25m,50m,100m, 200m and 300m	Total length of all road segments inside buffer
Major road segments nearby	MAJROADS	25m,50m,100m, 200m and 300m	Total length of all main road segments inside buffer

### Prediction model of NO<sub>2</sub> concentration with the estimation of model uncertainty

Functional model is presented with the equation of multi-regression that defines dependency between measured pollutant concentration on sampled locations and relevant predictors in the zone around sampled location. Functional model equation is given by:

$$NO_2 = A_0 + \sum_{i=1}^n (A_i X_i)$$

where:

- $X_i$  — value of predictor (independent variables),
- $A_0$  — constant trend for the area of prediction,
- $A_i$  — regression coefficient of predictor  $X_i$ ,
- $n$  — total number of predictors.

Coefficients  $A_i$  that were obtained indirectly are further used to predict air pollution concentration at arbitrary location by considering predictor values at that location.

Input data for the prediction are:

1. Sampling locations where NO<sub>2</sub> concentration has been measured;
2. GIS data (predictors) that cover area of sampling locations and prediction area.

All mentioned data are georeferenced using the State coordinate system of Serbia. Output data of the prediction are:

1. Regression model that describes relation between predictors and measured concentration of NO<sub>2</sub>;
2. Predicted values of air pollution on the sampling locations and quality measures expressed by Root Mean Squared Error (RMSE) and correlation coefficient (R<sup>2</sup>);
3. Predicted values of NO<sub>2</sub> in a form of the raster where digital number value (DN) represent the amount of air pollution at these locations.

### 3. RESULTS

Concentrations of air pollutants were measured at 46 locations irregularly distributed in the area of Belgrade in 2015. The analysis of minimal number of measurements and their distribution over area of interest, suggested that only measured concentration of nitrogen

dioxide fulfilled conditions for providing successful prediction for the central area of the city. Time period for observation of this emission was three months during the winter of 2015 year (January, February and March) due to the very nature of  $\text{NO}_2$  source impact. The result of the prediction is raster with a spatial resolution of 50 meters for the central area of the city of Belgrade (Figure 1).

Regression uncertainty assessment was introduced by two factors: RMSE of prediction that amounts to 9.8 and coefficient of determination ( $R^2$ ) of 0.60. After performed regression with all of the predictors from Table 1, a statistical significance estimation of each predictor was performed. After excluding predictors that were not significant, model was created by using predictors TRAFLOAD50, POP100, SQRALT, HDRES100, HDRES300, FURN300 and INTINVDIST.

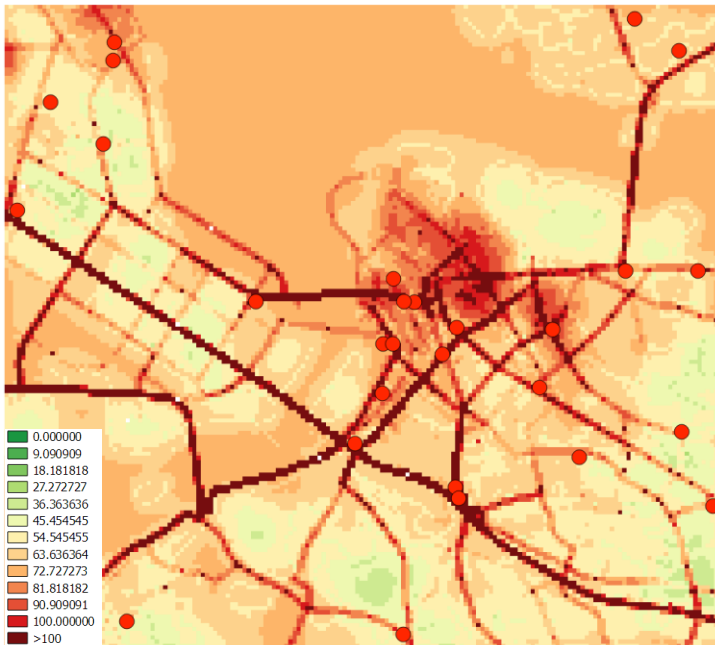


Figure 1: Prediction raster of  $\text{NO}_2$  concentration for the central area of Belgrade for winter of 2015.

#### 4. CONCLUSIONS AND FUTURE WORK

The modelling of air pollution in the city of Belgrade by using measurements of pollution concentration at 46 location and auxiliary data such as: traffic intensity data, demographic data, locations of furnaces, buildings' heights, and DEM and land use data, provided the results that meet ESCAPE requirements. Spatial prediction using global regression on cheap-to-measure attributes, i.e. predictors, prepared by using GIS tools proved to be a good solution. Traffic intensity was the most significant predictor. However, prediction can be improved substantially by increasing a number of measurement locations and more detailed spatial data, such as more detailed terrain and building topography (urban canyons), as well as information on wind (air movement in the city). Accordingly, application of the dispersion modeling methods should be considered in addition to spatial interpolation methods.

#### 5. REFERENCES

- Al-Naimi, N., Balakrishnan, P., and Goktepe, I., (2015). *Measurement and modelling of nitrogen dioxide (NO<sub>2</sub>) emissions: a marker for traffic-related air pollution in Doha, Qatar*, Annals of GIS, 21:3, 249-259, DOI: [10.1080/19475683.2015.1057225](https://doi.org/10.1080/19475683.2015.1057225)
- Brauer, M., Hoek, G., van Vliet, P., Meliefste, K., Fischer, P., Gehring, U., Heinrich, J., Cyrys, J., Bellander, T., Lewne, M., and Brunekreef, B. (2003). *Estimating long-term average particulate air pollution concentrations: Application of traffic indicators and geographic information systems*. Epidemiology 14:228–239.
- Briggs D.J., Collins S., Elliott P., et al. (1997). *Mapping urban air pollution using GIS: a regression-based approach*. International Journal of Geographical Information Science, 11, 699–718. DOI: <https://doi.org/10.1080/136588197242158>
- Deligiorgi, D., and Philippopoulos, K., (2011). *Advanced Air Pollution, Chapter 19. Spatial Interpolation Methodologies in Urban Air Pollution Modeling: Application for the Greater Area of Metropolitan Athens, Greece*, 341-362.
- Eeftens, M., Beelen, R., de Hoogh, K., et al. (2012). *Development of land use regression models for PM(2.5), PM(2.5) Absorbance, PM(10) and PM(coarse) in 20 European Study Areas; results of the ESCAPE Project*. Environmental Science & Technology, 46(20), 11195–205.



ESCAPE Exposure Assessment Manual (2010).

URL: [http://www.escapeproject.eu/manuals/ESCAPE\\_Exposure-manualv9.pdf](http://www.escapeproject.eu/manuals/ESCAPE_Exposure-manualv9.pdf)

Gilbert, N. L., Goldberg, M. S., Beckerman, B., Brook, J. R., and Jerrett, M. (2005). *Assessing spatial variability of ambient nitrogen dioxide in Montreal, Canada, with a land-use regression model*. J. Air Waste Manage. Assoc. 55:1059–1063.

Gulliver, J. and Briggs, D., (2011). *STEMS-Air: A simple GIS-based air pollution dispersion model for city-wide exposure assessment*, Science of the Total Environment 409 (2011) 2419–2429.

Habermann, M., Billgera, M., Haeger-Eugensson, M. (2015). *Land use regression as method to model air pollution*. Previous results for Gothenburg/Sweden., Procedia Engineering 115 (2015) 21 – 28

Hoek, G., Beelen, R., de Hoogh, K., et al. (2008). *A review of land-use regression models to assess spatial variation of outdoor air pollution*. Atmospheric Environment, 42, 7561–78.

Oxford (2015). *Oxford Textbook of Public Health (6. Ed.), Chapter 7.3 Environmental Exposure Assessment: Modelling Air Pollution Concentrations*, Oxford University Press 857-867, DOI: [10.1093/med/9780199661756.001.0001](https://doi.org/10.1093/med/9780199661756.001.0001)

Ross, Z., English, P. B., Scaif, R., Gunier, R., Smorodinsky, S., Wall, S., and Jerrett, M. (2006). *Nitrogen dioxide prediction in Southern California using land use regression modeling: Potential for environmental health analyses*. J. Expos. Sci. Environ. Epidemiol. 16:106–114.

Sertel, E., Demirel, H., Kaya, S., Demir, I., (2008). *Spatial Prediction Of Transport Related Urban Air Quality*, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B2. Beijing 2008, Commission II, WG II/7

Wang, G., van den Bosch, F. H. M., Kuffer, M., (2008). *Modelling Urban Traffic Air Pollution Dispersion*, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B8. Beijing 2008

Xie, X., Semanski, I., Gautama, S., Tsiligianni, E., Deligiannis, N., Rajan, R.T., Pasveer, F., and Philips, W. (2017). *A Review of Urban Air Pollution Monitoring and Exposure Assessment Methods*, ISPRS International Journal of Geo-Information 6(12), 389; DOI: <https://doi.org/10.3390/ijgi6120389>