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The use of the GIS tools in the analysis of air quality on the selected University campus in Poland

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Abstract: In our article the ordinary kriging interpolation method was used for a spatial presentation of $PM_{2.5}$ concentrations. The data used in the research was obtained from the unique $PM_{2.5}$ measuring system, based on low-cost optical sensors for $PM_{2.5}$ concentration measurements, working on Wroclaw University of Science and Technology campus area. The data from this system was used as an input for the interpolations that were made for three different days characterized by the highest measured values of $PM_{2.5}$ – 20.01.2019, 17.02.2019 and 30.03.2019. For each of the selected days, variants with the maximum and minimum $PM_{2.5}$ values recorded on a given measurement day were presented. In the analyses performed, the ordinary kriging technique and cross-validation, was used as the interpolation and the validation method, respectively. Parameters determining the quality of performed interpolation were Mean Error, Mean Standardized Error, Root Mean Square Error, and Average Standard Error. As the main indicator of quality of interpolation RMSE parameter was used. Analysis of that parameter shows that the higher variability of the data used for interpolation affects its quality. The Root Mean Square Error parameter reached 0.64, 0.94 and 1.71 for the lowest concentrations variants characterized by low spatial variability, and 6.53, 7.51, 11.28 for the highest one, which were characterized by high spatial variability. The obtained results of the research with the use of GIS tools shows that the ordinary kriging method allowed for the correct spatial presentation of the $PM_{2.5}$ concentration variability in areas not covered by the measurement system.

Introduction

Geographic Information Systems (GIS) are multi-component computer tools for data processing, with a particular focus on the comprehensive analysis of spatial data (Urbański 2008). Their main tasks are, among others, data acquisition and collection, data organization, storage, management, updating, analyzing and manipulation of data, including data estimation and spatial modeling. Ultimately, these systems allow for transparent and logical presentation as well as visualization and sharing results in the form of maps, tables or drawings, which are a direct result of work on data spatially associated with the earth's surface – geographical data (Huisman and de By 2009, Urbański 2008). The GIS systems are widely used in assessing the state of the environment, including atmospheric air quality analysis, decision systems and visualization of atmospheric pollution data, such as, for example, carbon dioxide, ozone, nitrogen oxides, sulfur dioxide, odors and particulate matter including PM_{10} and $PM_{2.5}$ (Hen & Lu 2017, Holnicki et al. 2017, Kumar et al. 2015, Núñez-Alonso et al. 2019, Sówka et al. 2017, Tecer and Tagil 2013). The most advanced tools for spatial analysis using GIS are those for surface modeling using spatial interpolation (Sówka et al. 2017).

Spatial interpolation methods including ordinary kriging techniques are often used where for technical and financial reasons or due to the lack of a sufficient amount of time it is not possible to carry out the appropriate number of measurements covering the desired area of research (Sówka et al. 2017, Urbański 2008, Xie et al. 2017).

The purpose of the research was to test the ordinary kriging interpolation technique together with the analysis of errors as a method for air quality assessment at the Wroclaw University of Science and Technology campus area covered with a dense measuring network consisting of $PM_{2.5}$ particulate matter sensors, which is one of the most advanced and only one measuring system currently working at Polish university area that is built on low-cost sensors. The $PM_{2.5}$ measuring system operating at the Wroclaw University of Science and Technology campus area allows to receive spatially related information about $PM_{2.5}$ concentrations. It is possible due to the use of sensors in a fixed location. This allows to use data from the sensor nodes in GIS systems. The main task of the study was to assess whether ordinary kriging is a useful tool that can be used in air quality assessments at points not covered by the measuring system. Research on the selection of a geostatistical tool that could be used to graphically present the spatial distribution of fine particulate matter ($PM_{2.5}$) is important from the point of view of assessing the degree of air pollution because of a large population that is active in the studied area. According to university data (WUST) for 2019, the number of students in the academic year 2019/2020 is about 26,000.

Methodology and the scope of research

Characteristic of the $PM_{2.5}$ measuring system

The $PM_{2.5}$ measuring system located at the Wroclaw University of Science and Technology campus area consists of 20 sensor nodes. The core element of the node is the optical sensor A003 from Plantower company, which is the latest device from their product family. The choice of this sensor was motivated by its low price and the promising results of previous long-term test of the older version of device from this family – PMS 7003 with TEOM device (see Badura et al. 2018 for details).

PMS A003 is a small (38×35×12 mm) light-scattering device that composes of a measurement chamber with light-emitting diode, light detector and a set of focusing lenses. The air flow through this sensor is forced by means of a microfan. The detectable size range of particulate matter is 0.3–10 µm. The output signals are digital and have different forms: PM_1, $PM_{2.5}$ and PM_{10} mass concentrations (µg/m^3) and number of particles per unit volume (0.1 l of air) for 6 size bins. In this study signal from $PM_{2.5}$ channel was used. The calibration coefficients were calculated on the basis of averaged values from nearest regulatory monitoring stations in Wrocław. The selection criteria for measuring units, their specifications and characteristics of the sensor network and the setup of sensor nodes are presented in (Badura et al. 2019).

Detailed information on the location of sensor nodes together with their ID's and GPS coordinates is presented in Table 1.

The measuring units are located in different parts of the Wrocław University of Science and Technology campus (Fig. 1a). According to (Badura et al. 2019), fourteen of the twenty devices installed are located on the main campus of the studied university (Fig. 1b), west of the city center near Grunwaldzki Sq. The buildings of this part of the campus are located between two-crucial for transport in the city-streets characterized by high traffic: from the north–west Grunwaldzki street and from the north–east Curie-Skłodowska street. From the south, the University buildings border by Wybrzeże – Wyspiańskiego street and the Odra river. The other six devices are installed outside of the main campus, on different University buildings: Na Grobli, Bujwida, Prusa, Długa and Wittiga streets. The potential sources of $PM_{2.5}$ particulate matter emissions located near the sensor nodes are mainly transport (linear sources) and individual heating systems (low-stack emission sources). According to that some assumptions were made. It was assumed that the readings from sensor nodes located at the main campus area (sensor nodes no. 1–9, 15–18, 20) are mostly influenced by the linear sources of $PM_{2.5}$ emissions. The main campus area is bordered by high traffic roads as mentioned before. When it comes to the sensor nodes located outside of the main campus area (sensor nodes no. 10–14, 19) the assumed potential source of $PM_{2.5}$ is also traffic and additionally, the readings could be influenced by the individual heating systems. Concentrations of particulate matter near all sensor nodes could be potentially affected by the incoming air masses. None of the 20 sensors neighbors any of industrial dust sources in their immediate vicinity. For the purposes of this paper, data from sensor nodes located at higher floors (sensor nodes no. 11, 17, 18 and 20)

Table 1. Detailed information on the location of sensor nodes.

MASQ ID	Campus	Building name	Floor	Longitude	Latitude
1001	Main	D-2	1	17.0565	51.1099
1002	Main	D-1	1	17.0585	51.1105
1003	Main	H-4	0	17.0544	51.1086
1004	Main	C-6 (outdoor)	0	17.0601	51.1085
1005	Main	C-5	0	17.0588	51.1092
1006	Main	A-1	0	17.0623	51.1073
1007	Main	H-6	0	17.0592	51.1070
1008	Main	B-5	1	17.0651	51.1084
1009	Main	D-3	1	17.0571	51.1098
1010	Wittiga St.	T-19	1	17.0854	51.1032
1011	Wittiga St.	T-19	11	17.0854	51.1032
1012	Gdańska St.	F-3	0	17.0669	51.1167
1013	Na Grobli St.	L-1	0	17.0551	51.1044
1014	Długa St.	M-2	0	17.0133	51.1264
1015	Main	H-6	0	17.0593	51.1068
1016	Main	H-4	0	17.0546	51.1087
1017	Main	C-5	6	17.0588	51.1092
1018	Main	C-5	3	17.0588	51.1092
1019	Prusa St.	E-1	1	17.0538	51.1191
1020	Main	C-5	9	17.0588	51.1092

was excluded from analyses. Only data from sensor nodes located at floor 0 and 1 were considered.

The sensor system presents data in the form of 15-minute moving averaged values in relation to one-hour concentrations from automatic measuring stations. As a result, it is possible to present the most current data on air quality in terms of $PM_{2.5}$ particulate matter.

Characteristic of interpolation method

One of the most commonly used geostatistical methods in data interpolation, including interpolation relating to atmospheric pollution, are kriging methods (Deligiorgi and Philippopoulos 2011, Kiš 2016, Núñez-Alonso et al. 2019, Sówka et al. 2017, Wong et al. 2004), which assume that the spatial variability of continuous data is too complex to be represented by simple mathematical equations. For the estimation of variables at points where the values were not measured, they used a moving weighted average of known values at the measuring points located in their vicinity (Sówka et al. 2017, Zhu 2016). These techniques assign weights based on the spatial variability of the examined points. They use an autocorrelation model, which determines the statistical relationships between the measured points. Autocorrelation is based directly on Tobler's law (ESRI 2019, Urbański 2008).

In order to analyze the spatial variability of interpolated data, variogram evaluation was used. It is one of the primary tools in geostatistics that allows determining the dependence/degree of spatial relationship of the studied data (Borkowski and Kwiatkowska-Malina 2017, Deligiorgi and Philippopoulos 2011). The semi-variogram function is used for this, which is described as half the difference of squares between two points spaced apart by a certain distance represented by a vector (Kwiatkowska-Malina and Borkowski 2014, Wong et al. 2004). The spatial relationship is then presented with the use of a graph of the semi-variogram dependence on the distance between points (Borkowski and Kwiatkowska-Malina 2017, ESRI 2019, Kwiatkowska-Malina and Borkowski 2014). It provides information on autocorrelation for data sets, a semi-variogram value is obtained for distance ranges that cover many points.

Analyzing all possible distances and combinations of data requires remodeling with the use of a parametric model (Deligiorgi and Philippopoulos 2011, ESRI 2019, Wong et al. 2004). The most commonly used are trigonometric, spherical, exponential, gaussian or linear functions (ESRI 2019). In the kriging methods, the variogram is directly used for calculating weights, which allows minimizing the variance of the predicted values (Wong et al. 2004).

In the conducted analyzes, as a method of data interpolation for the spatial representation of $PM_{2.5}$ concentrations, the ordinary kriging method was chosen, as the standard method among various kriging techniques (Borkowski and Kwiatkowska-Malina 2017). Ordinary kriging in its calculation scheme assumes that the average of the data set is unknown and is calculated during the interpolation process, while weights are calculated based on linear equations that minimize data variance. This method uses the variogram analysis mentioned above (Wong et al. 2004, Zhu 2016). Interpolation was performed with ESRI's ArcGIS Pro software with the use of the Geostatistical Analyst tool.

Validation of interpolation methods

Data validation methods allow for the analysis of how the obtained data interpolation results agree with the initial model assumptions. They provide information on how the made model performs in predicting values. Their results provide information on how to optimize/calibrate the used model and allow comparison of different data interpolation methods (Ding et al. 2018, Ogryzek and Kurkowska 2016).

As part of the research and analysis, the cross-validation method was used, which is one of the frequently used data validation methods (Ding et al. 2018). The cross-validation scheme consists in removing a known measuring point with a known value from the data set and estimating it using the built model. This method, in combination with the applied geostatistical method of data interpolation, allows to evaluate the accuracy of the performed interpolation along with the assessment of errors related to the estimation of values not covered by the measurement system. It is possible by comparing predicted values with real measured values.

Validation was carried out with the use of the Geostatistical Analyst tool of ArcGIS Pro software, which allowed the analysis of parameters such as Mean Error (ME), Mean Standardized Error (MSE), Root Mean Square Error (RMSE), and Average Standard Error (ASE).

Input data

As an input data for the interpolation, data from $PM_{2.5}$ measuring system was used. Only data from sensor nodes located at floor 0 and 1 were considered. The data was fed into the GIS software as 15-minute moving averaged values in relation to one-hour concentrations from automatic measuring stations. In order to perform interpolation, 3 days during the winter time were selected with the highest recorded $PM_{2.5}$ concentrations in relation to the other measurement days. Selected days are 20.01.2019, 17.02.2019

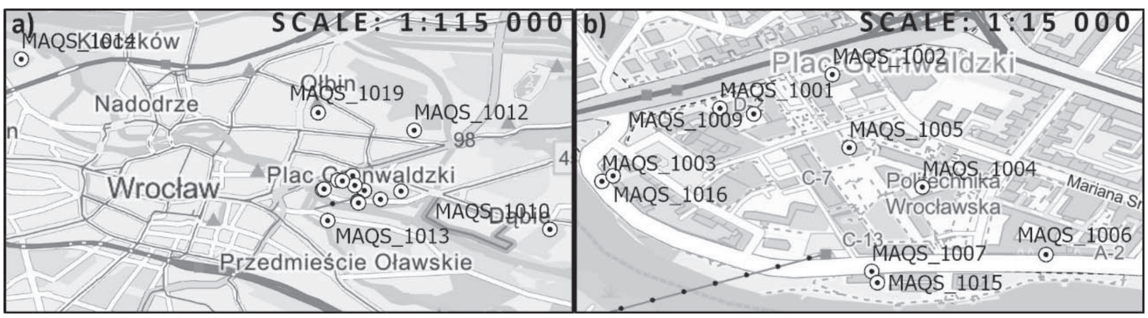


Fig. 1. Location of the measuring devices: a) all units in the Wrocław city area, b) units located on the main campus area (map source: OpenStreetMap 2019)

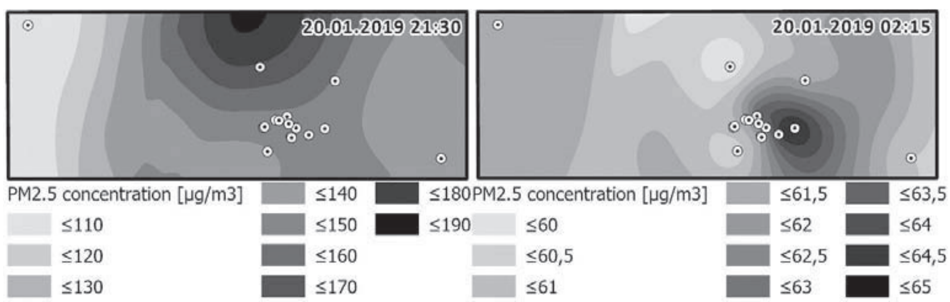
and 30.03.2019. For each of the selected days, scenarios with the maximum values (variants A, C, E) and minimum values (variants B, D, F) of particulate matter recorded on a given measurement day were considered. The basic characteristics of selected days are presented in Table 2. The highest concentrations on 20.01.2019 were recorded at 21:30 (variant A), the lowest at 02:15 (variant B), on 17.02.2019 the highest concentrations at 08:45 (variant C), the lowest at 16:15 (variant D), on 30.03.2019 the highest concentrations were recorded at 01:00 (variant E) and the lowest concentrations at 15:30 (variant F).

Results and discussion

Figures 2–4 show examples of spatial distributions of particulate matter obtained with the use of the ordinary kriging method for selected episodes of high $PM_{2.5}$ concentrations, as observed in Wrocław during the winter in the dates: 20.01.2019 (Fig. 2), 17.02.2019 (Fig. 3) and 30.03.2019 (Fig. 4). In each of the analyzed cases (variants), a continuous surface was obtained, characterized by a sufficient degree of smoothing (no rough edges in the concentration classes specified and presented in Figures 2–4) representing the spatial distribution of air pollutants based on the readings from measuring devices. The concentration distributions presented in Figures 2–4 allowed for obtaining information on the predicted values of dust pollution in places not directly covered by measuring devices, this is particularly visible in the western, northern and north--eastern part of the examined area, where the coverage with measuring devices is low or there is no coverage at all.

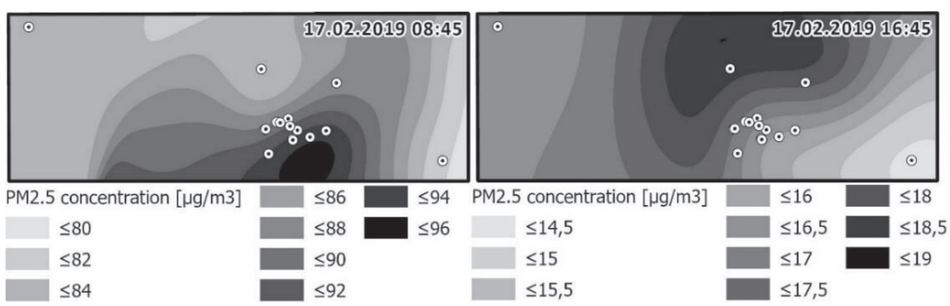
Table 2. The average minimum and maximum concentration values calculated for time intervals in the analyzed variants A–F

–	Variant A	Variant B	Variant C	Variant D	Variant E	Variant F
Maximum concentration in the analyzed variant (µg/m³)	170.19	65.21	99.01	18.35	92.30	17.36
Minimum concentration in the analyzed variant (µg/m³)	102.05	59.09	78.14	14.31	46.01	14.77
Average concentration in the analyzed variant (µg/m³)	143.11	61.73	88.48	16.54	70.32	16.39



(a) (b)

Fig. 2. Data interpolation results with the use of ordinary kriging for 20.01.2019, a) highest concentrations, b) lowest cocnetrations on given day



(c) (d)

Fig. 3. Data interpolation results with the use of ordinary kriging for 17.02.2019, c) highest concentrations, d) lowest cocnetrations on given day

In order to determine the correctness of the obtained surfaces, cross-validation was performed. The validation results are presented in Table 3.

The first two parameters obtained, i.e. ME and MSE from the validation, describe the average errors of interpolation performed – the difference between the estimated values and the measured values. In the situation of a value close to 0, these parameters indicate that estimated values are unbiased, and therefore whether they meet one of the basic assumptions of kriging. As the first of these two parameters is heavily dependent on input data, the most optimal parameter for describing average interpolation errors is the MSE (ESRI 2019). The analyses show that in all scenarios the MSE value is low and is in the range from -0.06 to 0.11. The lowest value equal to 0.02 was obtained for variants D and E. The highest value was achieved in variant C (0.11). The series presenting the quality of the MSE indicator in the analyzed cases is as follows (descending order): Variant D = Variant E> Variant F = Variant B> Variant A> Variant C. Therefore, the analysis of the MSE parameter indicates that the selected interpolation model allowed for obtaining unbiased (located around true values) estimated values.

Another parameter obtained as a result of cross-validation is RMSE. Its value indicates how exactly the interpolation model used predicts true values, i.e. those that were measured and obtained on the basis of interpolation (Ding et al. 2004, ESRI 2019b). The lower the value of the indicator, the better the resulting fit (ESRI 2019b, Ogryzek and Kurkowska 2016). The analyzes (Table 2) show that the values of this indicator differ significantly depending on the variant considered. The lowest RMSE value was obtained in the case of variant F (0.64), and the highest in variant E (11.28). The fit quality series for this indicator is as follows (in descending order): Variant F> Variant D> Variant B> Variant A> Variant C> Variant E. This parameter reached the lowest values in variants F (0.64) and D (0.94), which concern low concentration values in the analyzed cases. Variant B, which also represents low concentrations, reached 1.71. These results, therefore, indicate a potential for better matching of data interpolation models at low concentrations. These concentrations in the analyzed cases are characterized by smaller spatial variability (Fig. 2, Fig. 3, Fig. 4). The obtained values of the RMSE parameter indicate that in the analyzed cases the quality of interpolation depends on the data variability. The larger it is, the larger the errors related to fitting the model.

Comparing the values of ASE and RMSE indicators gives the information on overestimation or underestimation of variability in the data set (Ogryzek and Kurkowska 2016). An ASE value greater than RMSE indicates an overestimation of variability. This situation occurs in the case of variants A, B, C, D, F. ASE values are not significantly larger than RMSE (range from 0.03 to 0.29), therefore it can be concluded that no large overestimation of data was obtained during interpolation. In the case of variant E underestimation of data variability was found (ASE smaller than RMSE by 2.1). As this option applies to high concentrations, the underestimation was not considered significant.

Comparing the obtained cross-validation results (Table 3) and the obtained concentration distributions (Fig. 2–4), it can be concluded that the ordinary kriging method provides the spatial presentation of the measurement data whose source is the $PM_{2.5}$ sensor system located in different parts of Wroclaw University of Science and Technology campus. This method works best for data representing low concentrations (variants B, D and F). This data, obtained from the measuring system, is characterized by low spatial variation, which significantly affects the quality of interpolations. In the case of the high variability of data used for interpolation, the corresponding variants (A, C, E) are characterized by more substantial errors obtained during cross-validation (Table 3), however, in the final assessment, taking into account their level of variability, they allow to obtain qualitatively correct spatial distributions.

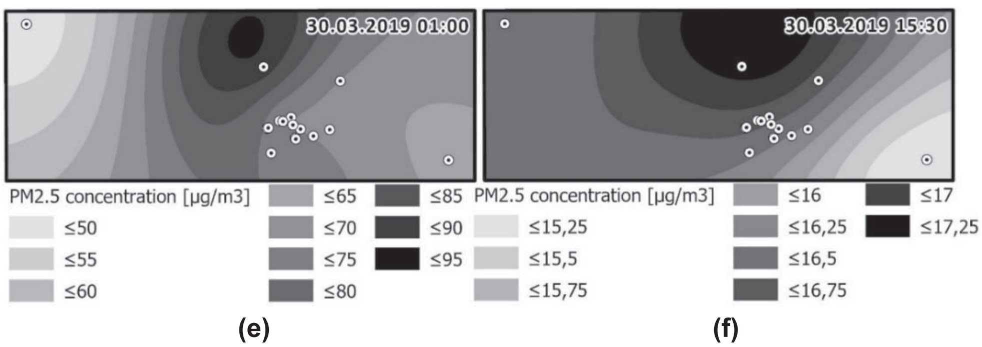


Fig. 4. Data interpolation results with the use of ordinary kriging for 30.03.2019, e) highest concentrations, f) lowest cocnetrations on given day

Table 3. Results of preformed cross-validation

Cross-validation results						
–	Variant A	Variant B	Variant C	Variant D	Variant E	Variant F
ME	-0.68	0.21	1.39	0.12	1.34	0.08
MSE	-0.06	0.05	0.11	0.02	0.02	0.05
RMSE	6.53	1.71	7.51	0.94	11.28	0.64
ASE	6.61	2.00	8.04	1.01	9.18	0.67

Summary

The use of the ordinary kriging method for interpolation of data from $PM_{2.5}$ sensors located on the campus of the Wrocław University of Technology has shown that this method allows for obtaining correct distributions representing particulate matter concentrations. Cross-validation was the basic tool used to assess the quality of interpolations. The two basic parameters used in the evaluation of interpolation were Mean Standardized Error (ME) and Root Mean Square Error (RMSE). The obtained validation results indicate fulfilment of one of the basic assumptions of kriging. It shows that the estimated values are located around true values, which means that those values are unbiased. The MSE parameter describing this is close to 0 and ranges from -0.06 to 0.11. The RMSE parameter was used to evaluate the interpolation quality. Conducted analysis of this parameter shows that the quality of interpolation is affected by the spatial variability of data used. For the variants related to the low spatial variability of $PM_{2.5}$ concentrations (variants B, D, E) the quality of interpolation is higher – the RMSE parameter ranges from 0.64 to 1.71. In the case of variant related to the higher spatial variability of $PM_{2.5}$ concentrations (variants A, C, E) the RMSE parameter is higher and ranges from 6.53 to 11.28, which means that the quality of interpolation is lower. The cross-validation results combined with obtained graphical representation of spatial distributions of $PM_{2.5}$ pollution indicate that the created maps of the spatial distribution of dust pollutants can be used to determine the variability of the tested pollutants in areas not covered by the measurement system.

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References

Badura, M., Sówka, I., Batog, P., Szymański, P. & Dąbrowski, Ł. (2019). Sensor network for $PM_{2.5}$ measurements on an academic campus area, *E3S Web of Conferences,* 116, pp. 1–8, DOI: 10.1051/e3sconf/201911600004.

Badura, M., Batog, P., Drzeniecka-Osiadacz, A. & Modzel, P. (2018). Evaluation of low-cost sensors for ambient $PM_{2.5}$ monitoring, *Journal of Sensors*, 2018, pp. 1–16, DOI: 10.1155/2018/5096540.

Borkowski, A. Sz. & Kwiatkowska-Malina, J. (2017) Geostatistical modelling as an assessment tool of soil pollution based on deposition from atmospheric air, *Geoscience Journal*, 21, 4, pp. 645–653, DOI: 0.1007/s12303-017-0005-9.

Deligiorgi, D. & Philippopoulos, K. (2011) Spatial interpolation methodologies in urban air pollution modelling: application for the greater area of metropolitan Athens, Grece, *Advanced Air Pollution*, DOI: 10.5772/17734.

Ding, Q., Wang, Y. & Zhuang, D. (2018). Comparison of the common spatial interpolation methods used to analyze potentially toxic elements surrounding mining regions, *Journal of Environmental Management*, 212, pp. 23–31, DOI: 10.1016/j.jenvman.2018.01.074.

Environmental Systems Research Institute ESRI (2019). Support materials provided by ESRI for the Geostatistical Analyst tool (https://pro.arcgis.com/en/pro-app/help/analysis/geostatistical-analyst (date 02.08.2019)).

Han, X. & Lu, X. (2017). Spatial distribution, environmental risk and source of heavy metals in street dust from an industrial city in semi-arid area of China, *Archives of Environmental Protection*, 43, 2, pp. 10-19, DOI: 10.1515/aep-2017-0013.

Holnicki, P., Kałuszko A., Nahorski Z., Stankiewicz K. & Trapp W. (2017). Air quality modelling for Warsaw agglomeration, *Archives of Environmental Protection*, 43, 1, pp. 48-64, DOI: 10.1515/aep-2017-0005.

Huisman, O. & de By, R.A. (2009). *Principles of geographic information system, an introductory textbook (fourth edition)*, The International Institute for Geo-Information Science and Earth Observation, Netherlands 2009.

Kiš, I.M. (2016). Comparison of ordinary and universal kriging interpolation techniques on a depth variable (a case of linear spatial trend), case study of the Šandrovac Field, *Rudarsko-geološko-naftni Zbornik*, 31, 2, pp. 41–58, DOI: 10.17794/rgn.2016.2.4.

Kumar, A., Mishra, R.K. & Singh, S.K. (2015). GIS application in urban traffic air polution exposure study: a research review, *Suan Saiandha Science and Technology Journal*, 2, 1, pp. 25–37.

Kwiatkowska-Malina, J. & Borkowski, A.Sz. (2014). Application of semivariance analysis for estimating SO_2 concentration in atmospheric air, *Infrastruktura i Ekologia Terenów Wiejskich*, 2, 2, pp. 377–388, DOI: 10.14597/infraeco.2014.2.2.027. (in Polish)

Núñez-Alonso, D., Pérez-Arribas, L.V., Manzoor, S. & Cáceres, J.O. (2019). Statistical tools for air pollution assessment: multivariate and spatial analysis studies in the Madrid region, *Journal of Analytical Methods in Chemistry*, 9, pp. 1–9, DOI: 10.1155/2019/9753927.

Ogryzek, M. & Kurowska, K. (2016). Geostatistical methods preparing of map average transaction prices of agricultural land undeveloped, *Studia i Prace WNEiZ US*, 45, 1, pp. 397–408. (in Polish)

Sówka, I., Grzelka, A., Bezyk, Y. & Miller, U. (2017). GIS-based modelling of odour emitted from the waste processing plant: case study, *E3S Web of Conferences*, 17, pp. 1–8, DOI: 10.1051/e3sconf/20171700085.

Tecer, L.H. & Tagil, S. (2016). Spatial-temporal variations of sulphur dioxide concentration, source, and probability assessment using a GIS-based geostatistical approach, *Polish Journal of Environmental Studies*, 22, 5, pp. 1491–1498.

Urbański J. (2009). *GIS w badaniach przyrodniczych*, Wydawnictwo Uniwersytetu Gdańskiego, Gdańsk 2009.

Wong, D.W., Yuan, L. & S.A Perlin (2004) Comparison of spatial interpolation method for the estimation of air quality data, *Journal of Exposure Analysis and Environmental Epidemiology*, 14, pp. 404–415.

Xie, X., Semanjski, I., Gautama, S., Tisiligianni, E., Deligiannis, N., Rajan, R.T., Pasveer, F. & Philipid, W. (2017). A review of urban air pollution monitoring and exposure assessment methods, *International Journal of Geo-Information*, 6, 12, pp. 1–21, DOI: 10.3390/ijgi6120389.

Zhu, X. (2016). GIS for Environmental Applications: A practical approach, Routledge, London 2016.

Zastosowanie narzędzi GIS w analizie jakości powietrza atmosferycznego na terenie wybranego kampusu uczelni wyższej w Polsce

Streszczenie: W artykule przedstawiono wyniki analiz przestrzennych zmienności stężeń pyłu $PM_{2.5}$ uzyskanych z pomiarów przeprowadzonych przy zastosowaniu systemu nisko kosztowych czujników zlokalizowanych na terenie kampusu Politechniki Wrocławskiej dla scenariuszy trzech dni w okresie zimowym charakteryzujących się wartościami podwyższonych stężeń $PM_{2.5}$ na badanym obszarze – 20/01/2019, 17/02/2019 i 30/03/2019.

Dla każdego z wybranych dni przedstawiono warianty z odnotowanymi maksymalnymi oraz minimalnymi wartościami stężeń $PM_{2.5}$ zanotowanych w danym dniu pomiarowym. W przeprowadzonych analizach jako metodę interpolacji wykorzystano technikę krigingu zwykłego, a jako metodę walidacji walidację krzyżową. Parametrami określającymi poprawność wykonanej interpolacji były Mean Error, Mean Standardized Error, Root Mean Square Error oraz Average Standard Error.

Z przeprowadzonych badań i analiz wynika, iż większa zmienność danych użytych do interpolacji wpływa na jej jakość oraz iż dla wariantów obliczeniowych, w których analizowane były stężenia minimalne w danym dniu pomiarowym uzyskano mniejsze wartości błędów interpolacji. Parametr Root Mean Square Error będący głównym wskaźnikiem jakości wykonanych interpolacji dla stężeń najniższych osiągnął wartość równe 0.64, 0.94 oraz 17.71, w przypadku najwyższych – 6.53, 7.51, 11.28.

Metoda krigingu zwykłego umożliwiła na jakościowo poprawną przestrzenną prezentację zmienności stężeń pyłów $PM_{2.5}$.