A comparative study on NO concentration interpolation in Surabaya City

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Abstract: A NO concentration interpolation is investigated based on a limited number of data available from monitoring stations in Surabaya City. The primary purpose of this study is to identify spatial patterns of NO concentration based on better interpolation results. Because the issue of data limitation often occurs in developing cities, as a preliminary treatment of incomplete data, we compare the performance of two interpolation techniques, i.e., inverse distance weighting (IDW) and ordinary kriging with respect to monthly average data from February 2001 to September 2002, by changing the power parameter of IDW and interval distance of the kriging method. The result shows that the kriging technique with 4000m interval performs better than IDW. Observing the spatial patterns derived, it is confirmed that the concentration in suburban areas is lower than that in other areas. It also shows that the concentration along highways are higher than on trading zone.

Keywords: NO, spatial patterns, inverse distance weighting, ordinary kriging, Surabaya City

1. INTRODUCTION

Air quality indices take an important role of decision making of transport policy. NO and NO_2 are two essential sources of emission due to their roles in the stratosphere in the photochemistry of ozone (e.g., Vaughan *et al*., 2006). NO and NO_2 are also related to photochemical oxidants and elevated surface ozone levels in urban areas (e.g., Peng *et al*., 2006). It is necessary to collect such air quality indices continuously over time and across space to support better transport policy decisions. This is true especially when the growth of vehicle volume almost 50% every year for motorcycle and 100% for private cars. In 2011, motorcycle in Surabaya has reached 5.726.514 units and for private cars, the number reaches almost 1 million units (Anonym, 2012). In Surabaya City, the target city of this study, the concentration of NO is getting more serious depending on the rapid increase of car and motorcycle usage and the tremendous acceleration of vehicle-kilometer by unplanned urban sprawling. There are only five monitoring stations that measure ambient air quality of NO surrounding the stations. To effectively support urban and transport policy decisions reducing environmental impacts from transport activities, it is better to prepare a dataset of air quality that covers the whole urban area. The challenge is how to capture the ambient air quality inside the city at places where there are no monitoring stations, by making full use of the information collected from five stations in Surabaya.

Since Surabaya City only has five monitoring stations, we need to find a suitable method that can reliably predict the air quality level at places without monitoring stations. One of the methods is interpolation technique such as Inverse Distance Weighted (IDW) and kriging (Mercer *et al*., 2011; Tayanç, 2000; Robinson and Metternicht, 2006; Whitworth *et* *al*., 2011). Interpolation techniques ranging from simple formula calculation to complex mathematical equations might be attractive, especially when spatial interpolation assumes that the data attribute are continuous over space. As an empirical case, Mercer *et al*., 2011 mentioned the kriging method performs better than other model such as land use regression. Other reasons are explained in details by Akkala *et al*. (2010) although the performance between both is varied from one to another case as it depends on the power parameters used (IDW) and the nature of the data (Robinson and Metternicht, 2006). Akkala *et al*. (2010) discusses various interpolation techniques, roughly eleven (11) approachese were discussed, along with their advantages and disadvantages. For example, the common method which is often used is splines. It fits a smooth curve to a series of observations. However, its best use is for irregularly-spaced data values. Another example is Trend Surface Analysis (TSA) where it separates the data into local variations and regional trends. Although it assists in eliminating broader trends before analysis, its disadvantage is edge effects and multicollinearity that are generated due to spatial autocorrelation. The present study focuses on the development of spatial interpolation of air quality, in particular NO concentration using IDW and ordinary kriging. The main advantage of IDW is on its simplicity, and ease of use. IDW works well with noisy data. One of its disadvantages is that spatial adjustment of samples does not affect weights. Kriging, on other hand, is a god linear unbiased spatial predictor. However, kriging requires rather sophisticated programming and also its difficulty in handling non-stationarity in data sets.

Few studies employing kriging interpolation in several locations e.g., Texas (Whitworth *et al*., 2011), Los Angeles (Mercer *et al*., 2011), and Istanbul Turkey (Tayanç, 2000) with several discussions, or in a broader area, within European Union (Beelen *et al*., 2007). For example, Whitworth *et al*. (2011) concluded that spatial interpolation for any purpose (e.g., assessing exposure for health effect) is highly affected by the placement and number of fixed monitors collecting air quality, however kriging interpolation was found to outperform LUR model (Mercer *et al*., 2011), Tayanç (2000) used spatial result to obtain concentration of SO_2 over Istanbul. Beelen *et al*. (2007) also stated that one advantage of kriging is the prediction power using three main components that consist of broad scale trend, local spatially variation, and non-spatial random variation. These components outweigh other such model e.g., deterministic approach that requires many detailed input parameters such as terrain surface, other chemical properties that are often difficult to obtain for local and broad scale. There was one study found so far investigating spatial interpolation of air quality in Surabaya City. Djuraidah (2007) implemented spatial interpolation of PM_{10} and ozone using a general additive model based on a multilevel approach. None of studies has been done with respect to NO in Surabaya City.

The present study is therefore designed to initiate such research focusing on traffic-related air quality. Here, we display the performance of two well-known interpolation techniques e.g., the inverse distance weighting (IDW) approach (a non-geostatistical interpolation) and the ordinary kriging interpolation technique in estimating the ambient air quality, in particular NO, at places without monitoring station. Such limited comparisons are because IDW employs a simpler spatial interpolation method than kriging which had been frequently used in the air pollution literature. We would like to determine if non-geostatistical interpolation statistics may aid in obtaining best interpolation method to be applied without using many and complicated test parameters, so we start from the simplest and investigate higher level of spatial interpolation, in this case ordinary kriging. We aim to first identify a better interpolation method, especially under the constraint that there are only a limited number of monitoring stations, and then clarify spatial patterns of air quality in Surabaya City.

2. METHODOLOGY

Here, we adopt the IDW and ordinary kriging technique, which belongs to the interpolation methods. Interpolation is a method to obtain values based on several known values. In the mapping process, interpolation is an estimation process or a prediction for a point where there is no value measured. The process forms a contour map of values under study. During the interpolation, errors usually occur due to mistakes of sampling methods, biases in the measurement process, and/or analysis errors.

2.1 Features of the IDW Interpolation Method

The IDW method itself belongs to a deterministic estimation group, where the interpolation is computed based on simple mathematical calculation. In contrast, the kriging method is categorized into a stochastic estimation method, where the calculation is done statistically to produce interpolation, where the randomness of data can be reflected.

The IDW method assumes that the value at a given point is similar to those at other points, which are close to the given point, than those points far from the given point. Such distance-dependent feature of interpolation is reflected by introducing a weight parameter, which is inversely and non-linearly proportional to the distance to a reference point. The IDW method is generally used in the mining industry because of ease of use in practice (one study in Indonesia was conducted by Pramono (2008)). The formula of IDW method (Bivand *et al.*, 2008) is shown in equations (1) and (2).

$$\hat{Z}(s_0) = \frac{\sum_{i=1}^{n} w(s_i) Z(s_i)}{\sum_{i=1}^{n} w(s_i)} \tag{1}$$

$$w(s_i) = \|s_i - s_0\|^{-p} \tag{2}$$

Here, weights are calculated based on the distance to the interpolation point.

The choice of power p for the IDW method highly affects interpolation results. Larger power value assumes that better interpolations can be derived by using the values of closer neighboring points.

The main disadvantage of the IDW method is interpolation results are highly dependent on the observed values available within the sample data. The influence of sample data on interpolation results is called isotropic. In other words, since this method uses (positively) weighted values from the sample data, the value interpolated will never be smaller than the minimal observed value or higher than the maximal observed value. Accordingly, the highest peak or deepest valley cannot be derived from this interpolation. To obtain better results, data used must be dense spatially. If the sample data are sparse and not equally distributed across space, more unexpected outcomes might be produced.

2.2 Features of the Kriging Interpolation Method

The kriging method is a stochastic estimation method which uses linear combinations from weighting systems to estimate values between data samples (Pramono, 2008). The assumption made for this method is that distance and orientation between data samples show strong spatial correlations. Spatial correlations mean that, part of the application of geostatistics is the presence of spatial structure where observations or values close to each other are more alike than those that are far which indicate spatial autocorrelation (Robinson and Metternicht, 2006)

Unlike the IDW method, the kriging method generates errors of interpolation and confidence levels. This method employs a semivariogram to estimate spatial correlations and also describes weights used for interpolation. It is calculated based on semivariogram sample with the distance, point difference or observation value Z and data samples which is shown on the formula (3) below (Robinson and Metternicht, 2006).

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \quad (3)$$

Where *N(h)* is the number of data pairs within a given class of distance. If the It is assumed that the variance of Z is constant. Therefore, the spatial correlation solely depends on separation distance. As can be seen, the value of the experimental variogram for a lag distance (separation distance) of *h* is half the average squared difference between observation values at $z(x_i)$ and the observation value at $z(x_i+h)$. Figure 1 shows graphics of semivariogram which plots semivariances (vertical axis) and distance (horizontal axis). When the distance is short, the semivariance is small, but for higher values of distance, semivariance gradually increases up to a certain distance and after this distance, semivariance is any longer correlated with the distance of point sample. On the other hand, if on the higher distance semivariance gives lower value, this shows that the variation of the observation value does correlate with the distance of the sample, otherwise there is bias.

To produce an interpolation, we use a variogram. It is a simulation based on observations on points. In building variogram, we set an interval parameter. Interval parameter is the width of distance interval over which data pairs are averaged in bins (Bivand *et al.*, 2008; Robinson and Metternicht, 2006). The consequence of setting of interval will affect how variogram is build and formed. Higher interval may result in limited points that form variogram as in higher width interval, more components are captured based on distance between monitoring stations (points).

Variance of the interpolation must be non-negative. To ensure the non-negative variances, the semivariance value inside a matrix that contains observed values and predicted values must be non-negatively definite. For this purpose, simply processing sample variogram values are not adequate, and therefore we need to adopt a parametric variogram model built from the data. There are many parametric models, but these are not equally useful in practice. Most used models adopt exponential, spherical, Gaussian, and circular functions. Accordingly, to figure out a better variogram model, we need to take several steps (Bivand *et al.*, 2008):

Step 1: Build a variogram
Step 2: choose suitable parametric models (Gaussian, spherical etc)
Step 3: choose initial values for partial sill, ranges
Step 4: fit the model

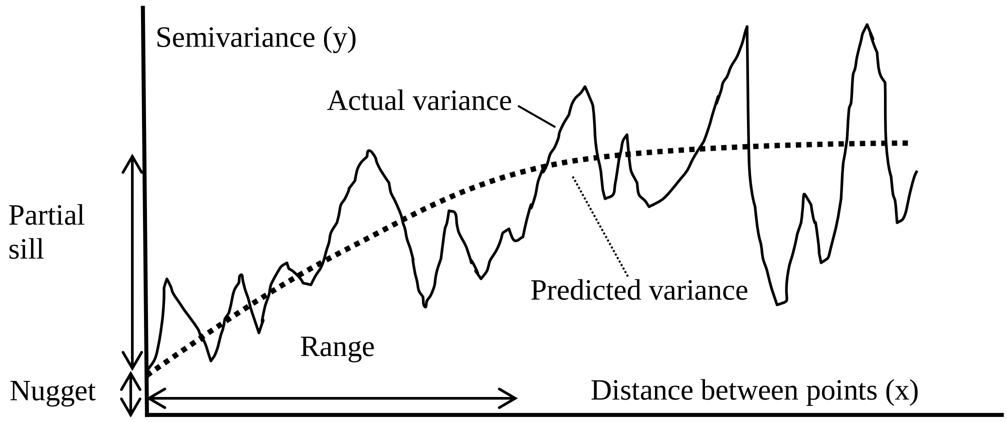


Figure 1. Semivariogram

Reflecting the above steps, the kriging method in this paper is applied in the following way: 1) to analyze statistic characteristics of the sample data, 2) to build variogram models, 3) to generate interpolation results, and 4) to analyze variance values.

3. DATA

3.1 Study Area

Data used for this paper is air quality data of Surabaya City. Surabaya is the capital city of East Java Province and it is also acknowledged as the second largest city in Indonesia with approximately 374.78 km^2 with more than 2.7 million population. The city consists of 31 counties. Surabaya City is located in the Northen Coast of East Java Province. The neighbors city consist of Madura strait in the north and east, Sidoarjo in the south, and Gresik in the west side. The land is dominated by lowlands type with height ranging from 3 m to 6 m above sea level, excluding those in the south. There are two sloping hills in the south part of Surabaya with attitude between 25-50 m above sea level. In regards to air pollution study and the attractiveness of Surabaya, among other cities that operate monitoring stations, the data required for the present study, is relatively available, despite of limited number of locations and missing data rate.

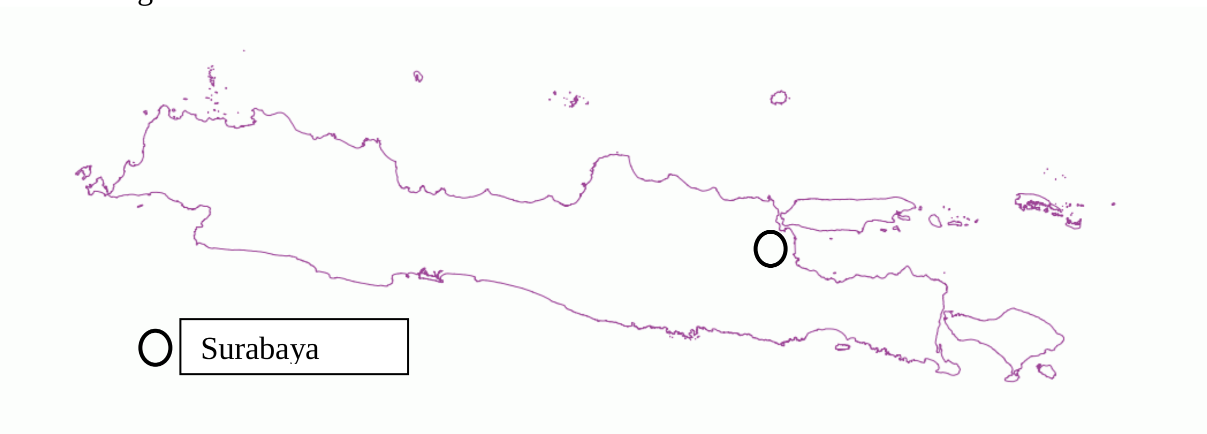


Figure 2. Study area: Surabaya City

3.2 Data Collection

Data used was obtained from Laboratory of Air Quality Department of Environment of

Surabaya City. We use nitric oxide (NO) which represents emission from transportation, taken from five monitoring stations in Surabaya City (Figure 3). They represent the land use pattern in Surabaya. They are:

Station 1. Yard of Achievement Park, Ketabang Kali St.: the Center of the City, housing, office and trading land use (Central Surabaya, located in the Genteng District)

Station 2. Yard of Village Chief Perak Timur, Selangor St.: the housewares and industrial land use (North Surabaya, located in the Pabean Cantikan District)

Station 3. Yard of Assistance Major Office West Surabaya, Sukomanunggal St.: the housing and rural land ue (West Surabaya, located in the Sukomanunggal District)

Station 4. Yard of Gayungan Subdistrict Office, Gayungan St.: the housing land use (near Surabaya Highway By Pass – Gempol – South Surabaya, located in the Gayungan District)

Station 5. Yard of Convention Hall, Arief Rahman Hakim St.: the housing, campus, office land use (East Surabaya, located in the Sukolilo District)

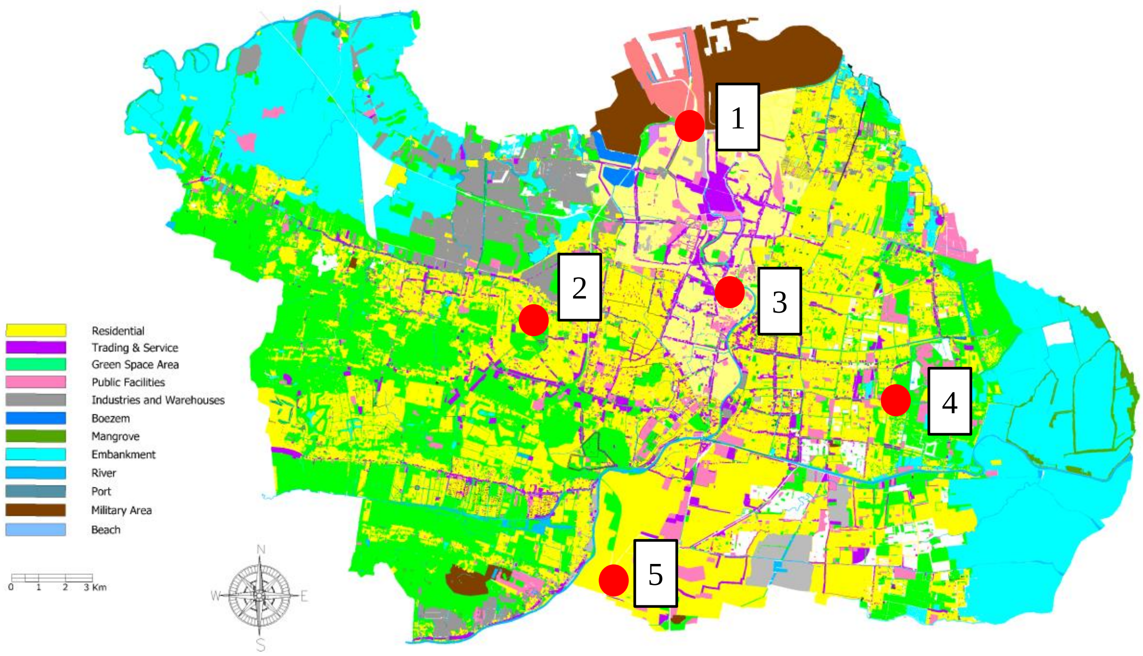


Figure 3. Five monitoring station locations in Surabaya City and the sensor

For interpolation, we take average monthly data from February 2001 to September 2002 because of data availability on that particular period. However, there are some missing data, the rate is shown on Table 1. To deal with missing data, we use missing value imputation using the bootstrap to approximate imputed values from a full Bayesian predictive distribution. The mechanism is explained elsewhere (Herrell, 2013), we use direct *aregImpute* available in package *Hmisc* within R software. The candidate of impute values are averaged and imputed to the missing indices. Latitude and longitude of each station was measured using GPS onsite.

Table 1. Percentage of data availability on 5 zones

Monitoring Station (number)	NO morning	NO_2 morning	NO evening	NO_2 evening
City Center (1)	96.07%	97.2%	96.07%	97.36%
Trading zone (2)	92.75%	89.62%	92.75%	89.3%
Suburban1 (3)	92.1%	93.41%	92.1%	93.41%
Highway (4)	92.26%	92.75%	92.26%	93.1%
Suburban2 (5)	50.74%	51.24%	50.74%	50.58%

3.3 Data Interpolation

To run simulation, we use the open source statistical software "R" to compute the interpolation. Before calculation, we square root all NO concentration to form a homogenous normal distribution of data. For running the IDW method, we implement simulations by changing the values of power parameter numbers while for the ordinary kriging method, we change interval parameters. Power parameters used are one, two, three, and four. For kriging, the interval parameters are 100m, 1000m, and 4000m. Station monitoring were installed to capture concentration within buffer zones. We determine these buffer zones within 2 km, and we try to determine if smaller range (interval) would increase accuracy. Grid data of interpolation results have a resolution of 200 m. Table 2 presents average concentration every month.

Table 2. NO concentration each station from February 2001 to September 2002 (ug/m3)

Month	Stations				
	1	2	3	4	5
2001					
February	16.95	18.08	7.44	17.215	6.76
March	28.59	30.54	15.48	26.27	13.11
April	19.17	17.16	11.27	21.62	9.14
May	12.73	10.09	8.33	17.95	5.47
June	18.01	15.54	9.05	22.58	8.53
July	14.09	10.24	8.25	18.31	5.16
August	10.66	8.05	3.03	14.21	5.25
September	13.68	8.34	3.74	15.09	6.81
October	17.54	15.05	6.19	19.97	8.45
November	18.39	17.39	6.12	20.64	9.54
December	19.67	19.47	6.28	21.10	9.86
2002					
January	20.98	21.87	7.19	23.27	10.30
February	16.53	22.03	6.47	21.17	9.18
March	19.56	19.85	8.76	26.14	10.81
April	16.15	15.84	8.66	20.31	8.20
May	12.28	8.59	5.68	17.50	6.36
June	10.46	7.79	3.84	14.21	6.54
July	11.15	9.32	3.32	15.29	6.40
August	11.11	8.45	2.78	14.51	6.41
September	11.96	2.11	2.41	14.53	6.67
Coordinates					
X	692435.9	691397.4	687148	689483.2	696975.2
Y	9196961	9201134	9196062	9188505	9193914

3.4 Model Validation

We run interpolation techniques IDW and kriging which yield predicted value across spaces. To validate the accuracy of interpolation, we use cross-validation by eliminating observation or information, estimating the value at that particular location with the remaining data and compare the difference between estimated and measured values (Robinson and Metternicht, 2006). Ideally, we take draws from interpolation model and compare it with observation values by random samplings. However, in the present study, we cross-validate these models using observed value on Station 1, which is located in city center. The reason we choose Station 1 is because it is located in the middle of the other 4 stations. We compare predicted values and observed values on Station 1 for 20 months and regress them to obtain R^2, i.e., coefficient of determination. A value of R^2 close to 1 indicates strong relationship if the regression line fits the data well.

We also measure Root Mean Square Error (RMSE) to obtain bias in each method. RMSE computes the differences between predicted values by an interpolation model and the observed values from the point being modeled. Better model is indicated by a low value of RMSE and higher value of R^2.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \tag{4}$$

Here, y_t is observed value, $\hat{y}_t$ indicates predicted value, and n refers to the number of observations.

4. Results and Discussion

This section shows the results of interpolation using the IDW and kriging methods.

4.1. Inverse Distance Weighting Interpolation

We interpolate observed values to obtain concentration values at points where there are no available monitoring station. We observe the concentration of NO using different power parameters: 1, 2, 3, and 4. Power parameter is used to determine the value of point samples for interpolation. Local interpolation can be changed into a more global one by changing the power value. Low power value means more influence from the surrounding point data.

First, we observe the predicted values over time span of 20 months. We extract simulated (predicted) values on Station 1 and compare them with the measured values over the same 20 months. Figure 4 shows four contour maps resulted from the IDW method with different power parameters, taken on August 2002. The concentration at suburban area is lower than trading and highway zones for all power parameters. We also note that higher power reflects wider range of neighboring areas because the surrounding point data give less effect than lower power parameters.

We collect predicted values over 20 months and compare the results with the observed values. We determine the performance in terms of R^2 and RMSE. It can be seen that using power 1 yields the best result compared to other power parameters. R^2 is 0.8853, while in case of power parameters 2, 3, and 4, R^2 is 0.8751, 0.8644, and 0.854, respectively (shown in Figure 5).

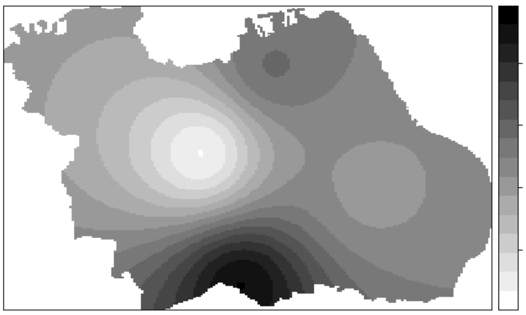
RMSE for power parameter of 1 is in agreement with the results obtained above because it is lower than power parameters 2, 3, and 4. RMSE for power parameters 1, 2, 3, and 4 are 0.736, 0.775, 0.78, and 0.765, respectively.

It can be concluded that the best power parameter for the IDW method is the value 1, as it yields better performance than any other power parameters. This result is in agreement with the implementation of IDW to interpolate soil parameters, it was found that power parameter of one (1) was the best result among other power parameters of two, three, and four (Robinson and Metternicht, 2006). Higher power reflects weaker influence of nearest points, and therefore, it produces wider range of interpolations. The result also shows that the concentration in the city center highly depends on its surrounding factors, less influence by concentration on other zones. This means that the concentration in city center is affected by its surrounding values that subject to further investigate by proposing spatial variables.

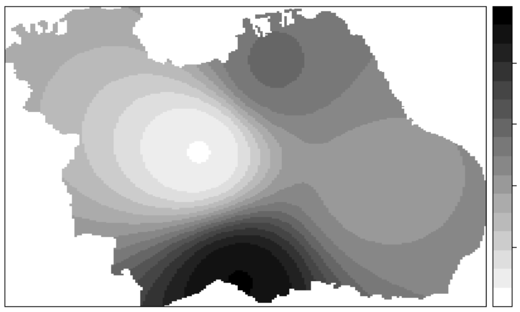
4.2. The Kriging Interpolation

Interpolation with the ordinary kriging method requires statistic computation from each sample. We calculate statistic using semivariogram. First, we determine intervals, in this study we use intervals of 100 m, 1,000 m, and 4,000 m that define the distances between monitoring stations and how many pairs are included inside the bin from the stated interval. For each interval, each month, we investigate best type of model of a semivariogram. The kriging method can be done by using five or more approaches: spherical, circular, Gaussian, exponential, and linear forms. In this study, we use and compare spherical, Gaussian, and exponential forms. We obtain that most of the data are best fitted by using the Gaussian model (variogram not shown).

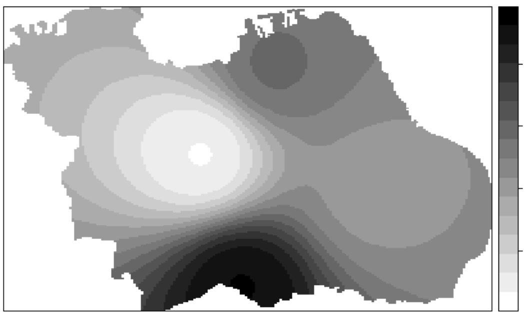
Figure 6 shows the interpolated map using the kriging with different intervals. We can observe that the pattern is monotonous circle range surrounding the point. Ordinary kriging used in this figure also shows that the concentration on the suburban are relatively lower than other zones as also produced from the IDW method. Besides the pattern of interpolated values, the predicted values yielded different values.



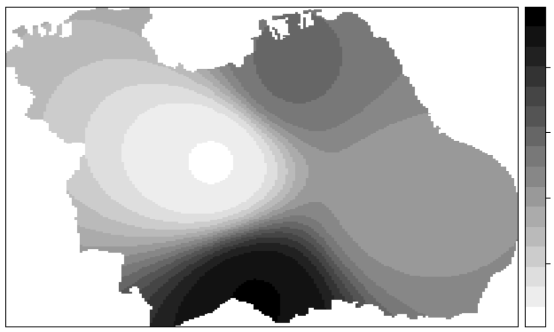
a) Power : 1



b) Power : 2



c) Power : 3



d) Power : 4

Figure 4. Interpolation by IDW using different power values:1, 2, 3, and 4 (August 2002)

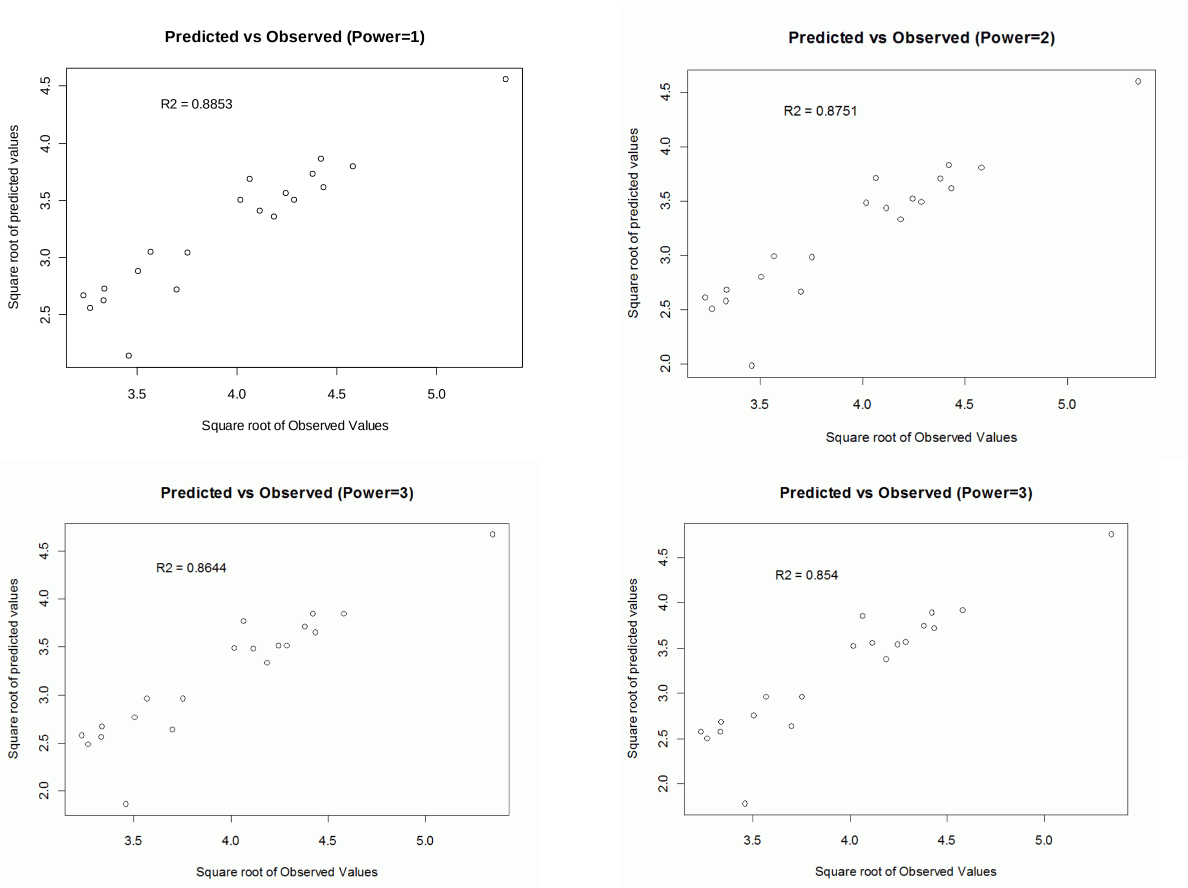
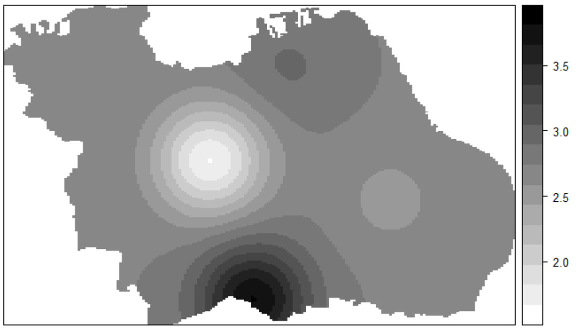
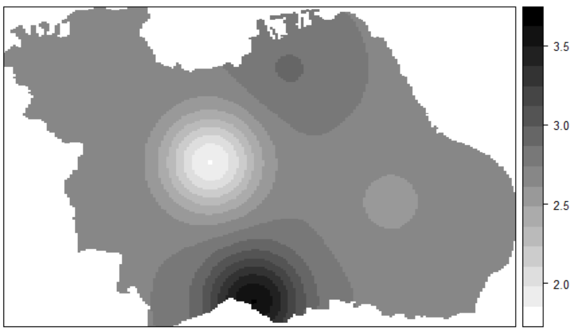


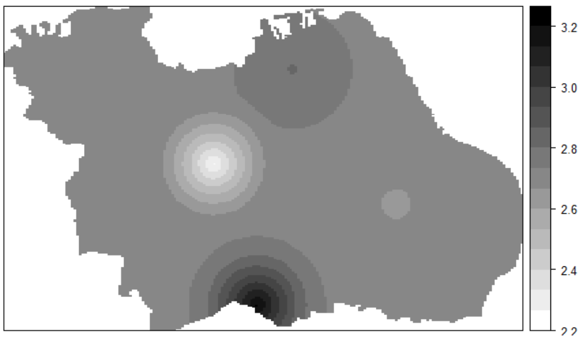
Figure 5. Predicted vs observed values and R^2 value



a) Interval 100 m



b) Interval 1,000 m



c) Interval 4,000 m

Figure 6. Interpolation using the kriging method with different intervals (August 2002)

We compare predicted values obtained from the kriging method with different intervals with respect to the observed values from 20 months of information. Figure 7 displays the predicted values against observed values and we found for all interval type, there are linear correlation, which means ordinary kriging well estimate the concentration on the city center. We estimate the R^2 and have noted that kriging with interval of 4000 m has yielded highest R^2 of 0.8914. Other interval 100 m and 1000 m produce R^2 0.8664 and 0.8806. This is also supported by RMSE where the lowest RMSE (0.653) is produced for map with interval 4000m, followed by 0.67 (interval 1000m), and 0.7 (interval 100m), respectively.

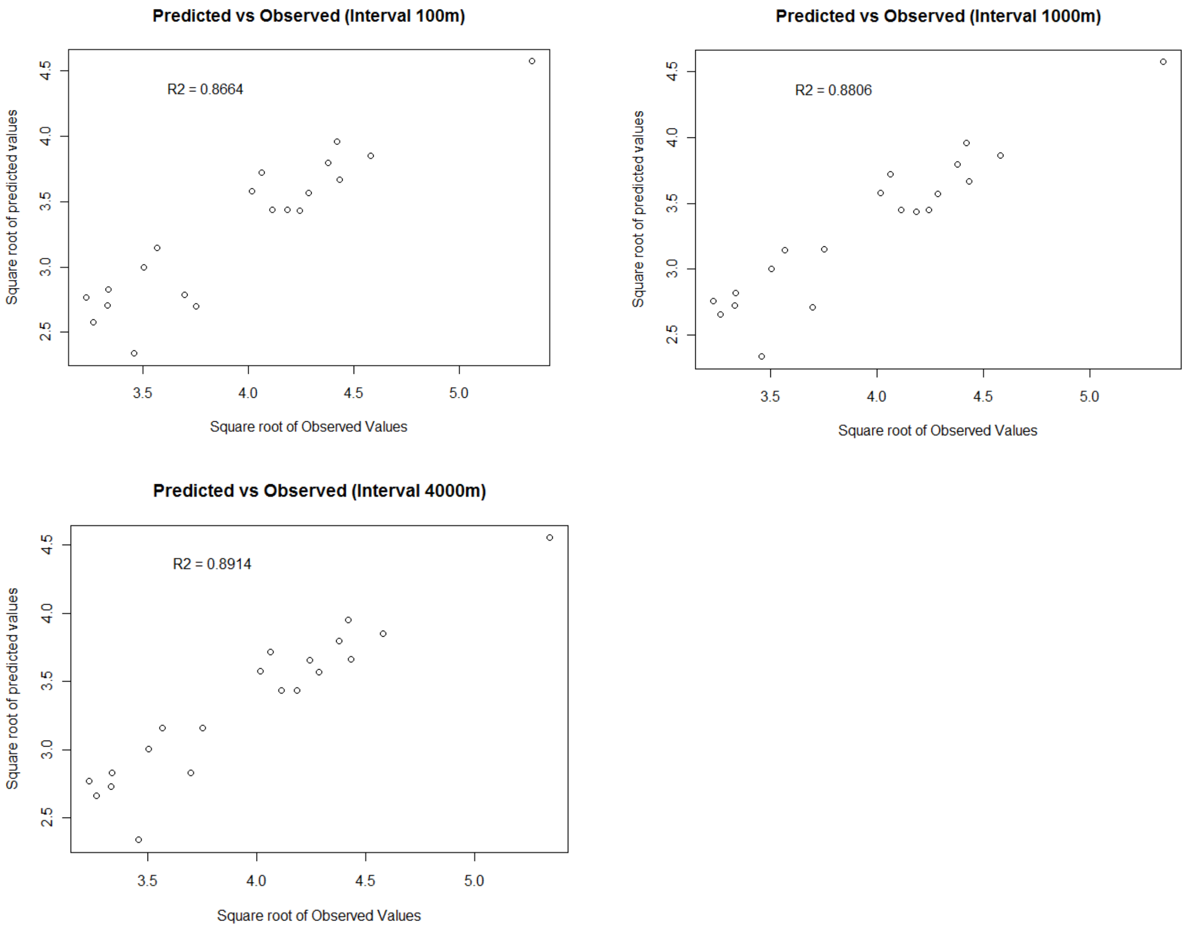


Figure 7. Predicted values vs observed values using kriging with different intervals

5. Conclusion

Using IDW the wider range produce significantly decrease the relationship between predicted values with observed values in the city center. Best power parameter was found to be 1 with R^2 0.8853 and RMSE 0.736. The data over 20 months are found to be best fitted using Gaussian model and we found that the data is well fitted if we use interval distance of 4000m. The R^2 is 0.8914 with RMSE 0.653. Kriging was found to yield better performance than IDW for prediction in Surabaya City. Between interval between station monitoring distance of 100 m, 1000 m, and 4000 m, we found that the performance is better when using 4000 m. We note that the concentration on trading zone is lower than on highway zone on average monthly. This suggests higher traffic activity on highway zone than on trading zone, relatively. As expected, the average NO concentration on suburban areas is lower than trading and highway zones.

5. ACKNOWLEDGEMENT

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6. REFERENCES

Akkala, A., Devabhaktuni, V., & Kumar, A. (2010). Interpolation Techniques and Associated Software for Environmental Data. *Environmental Progress & Sustainable Energy*, 29(2)

Anonym. (2012). Formulir Penilaian Tahap I Administrasi, Pelaksanaan Kegiatan Penghargaan Wahana Tata Nugraha Tahun 2012. In Appendix.

Beelen R., Hoek G., Pebesma E., Vienneau D., de Hoogh K., and Briggs D.J. (2009) Mapping of background air pollution at a fine spatial scale across the European Union. *Science of The Total Environment* 407, 1852-1867

Bivand, R., Pebesma, E., and Gomez-Rubio, V. (2008). Applied Spatial Data Analysis with R. Springer, New York.

Brauer, M., Hoek, G., Vliet, P. Van, Meliefste, K., Fischer, P., Gehring, U., Heinrich, J., et al. (2000). Estimating Long-Term Average Particulate Air Pollution Concentrations: Application of Traffic Indicators and Geographic Information Systems. *Epidemiology*, 14(2), 228–239

Dijkema, M. B. a, Mallant, S. F., Gehring, U., Van den Hurk, K., Alssema, M., Van Strien, R. T., Fischer, P. H., et al. (2011). Long-term exposure to traffic-related air pollution and type 2 diabetes prevalence in a cross-sectional screening-study in the Netherlands. *Environmental health* 10(1), 76

Djuraidah, A. (2006) Optimasi Penentuan Lokasi Stasiun Pemantau. Forum Statistika dan Komputasi Vol. 11, pp. 1–5 (In Indonesian)

Djuraidah, A. (2007). Model Aditif Spatio-Temporal untuk Pencemar Udara PM10 dan Ozon di Kota Surabaya dengan Pendekatan Model Linear Campuran. IPB (Bogor Agricultural University).

Hart, J. E., Yanosky, J. D., Puett, R. C., Ryan, L., Dockery, D. W., Smith, T. J., Garshick, E., et al. (2009). Spatial modeling of PM10 and NO2 in the continental United States, 1985-2000. *Environmental health perspectives*, 117(11), 1690–6

Herrell, F. E. (2013). Package " Hmisc ". Retrieved from Harrell F.E. (2013) Package "Hmisc". Url: http://cran.r-project.org/web/packages/Hmisc/index.html

Liu, Y., Paciorek, C. J., & Koutrakis, P. (2009). Estimating regional spatial and temporal variability of PM(2.5) concentrations using satellite data, meteorology, and land use information. *Environmental health perspectives*, 117(6), 886–92

Mercer, L. D., Szpiro, A. a, Sheppard, L., Lindström, J., Adar, S. D., Allen, R. W., Avol, E. L., et al. (2011). Comparing universal kriging and land-use regression for predicting concentrations of gaseous oxides of nitrogen (NOx) for the Multi-Ethnic Study of Atherosclerosis and Air Pollution (MESA Air). *Atmospheric environment* 45(26), 4412–4420.

Peng, Y. P., Chen, K. S., Lai, C. H., Lu, P. J., & Kao, J. H. (2006). Concentrations of H_2O_2 and HNO_3 and O_3–VOC–NOx sensitivity in ambient air in southern Taiwan. *Atmospheric Environment*, 40(35), 6741–6751.

Pramono, G. H. (2008). Akurasi Metode IDW Dan Kriging Untuk Interpolasi Sebaran Sedimen Tersuspensi Di Maros, Sulawesi Selatan. Forum Geografi, 22(1), 145–158. (In Indonesian)

Robinson, T.P., and Metternicht, G. (2006). Testing the performance of spatial interpolation techniques for mapping soil properties. *Computers and Electronics in Agriculture*, 50, 97-108

Ryan, P. H., and Lemasters, G. K. (2007). NIH Public Access. *Inhalation Toxicology*, 19, 127–133.

Tayanç, M. (2000). An assessment of spatial and temporal variation of sulfur dioxide levels over Istanbul, Turkey. *Environmental pollution*, 107(1), 61–9.

Vaughan, G., Quinn, P. T., Green, a C., Bean, J., Roscoe, H. K., Van Roozendael, M., & Goutail, F. (2006). SAOZ measurements of NO_2 at Aberystwyth. *Journal of environmental monitoring* 8(3), 353–61.

Whitworth, K. W., Symanski, E., Lai, D., & Coker, A. L. (2011). Kriged and modeled ambient air levels of benzene in an urban environment: an exposure assessment study. *Environmental health* 10(1), 21