

Biochemical Oxygen Demand Level Modeling in Surabaya River using Approach of Cokriging Method

Suliyanto

Department of Mathematics, Universitas Airlangga, Surabaya, Indonesia

Keywords: Surabaya River, BOD, COD, Cokriging Method.

Abstract: National Coordinator of Indowater Community of Practice said that the Surabaya River contains high pollutants that cause pollution. One of the parameters for estimating pollution of Surabaya River is Biochemical Oxygen Demand (BOD). In addition to BOD there are other parameters that have a correlation with BOD, namely Chemical Oxygen Demand (COD). The kriging method is used to estimate the level of water pollution in a new location based on observational data around it using both parameters. The purpose of this research is to estimate BOD levels in three locations around the industry using the method of cokriging. Observation of 10 samples of BOD and COD showed significant correlation for $\alpha = 5\%$ with a correlation value of 99.5% and P-value of 0.000. The result of cross-validation estimation of BOD level sampled using Gaussian model obtained high R^2 value equal to 91.6% and Root Sum Squared (RSS) value is small, that is 0.7057 so it can be said that interpolation result accurate. The results showed that BOD levels leading downstream were lower. This is because the source of pollutants from the upstream of the river that leads to downstream of the river is less affected.

1 INTRODUCTION

According to the monitoring of Jasa Tirta I Public Company, there are five rivers in East Java that do not meet the water quality standard, one of which is the Surabaya River. National Coordinator Indowater Community of Practice, Riska Darmawanti said that the Surabaya River contains high pollutants, evidenced by the level of 420 ng / g plastic samples. In addition there are also organochlorine pesticides and detergent waste (Haq, 2017). The result of the research by pollution index method concluded that the biggest contaminant contributor in Surabaya River is phenol and total suspended solids (Priyono et al., 2013). The pollutant parameters of the Surabaya River are Biochemical Oxygen Demand (BOD) (Trisnawati and Masduqi, 2013). Research on the correlation of Chemical Oxygen Demand (COD) and BOD of liquid waste for pollution monitoring of Surabaya River shows that there is a linear correlation between COD and BOD of Surabaya River water (Razif and Masduqi, 1996). Calculation statistically with descriptive analysis obtained the result that BOD parameter contributes to domestic waste equal to 59.77%, industrial waste 40.05% and agricultural waste 0.18% while for the parameter of COD

contribute domestic waste equal to 54.11%, industrial waste 45.74% and agricultural waste 0.15% (Suwari, 2010). The result of measurement by Surabaya Environment Department (ED) 2016, BOD level at the sample location does not meet the standard quality of class II water quality that has been established. The role of BOD and COD is equivalent to other parameters that are key parameters in relation to alleged pollution by certain activities (Atima, 2014). BOD measurements require a five-day long-term cost and time analysis with complex processes because it takes highly acclimatized and active bacteria seeds in high concentrations (Tchobanoglous, 1991). The measurement of BOD in the Surabaya River undertaken by ED Surabaya is still limited to a few points. One effort to minimize the time and cost of measuring BOD in the Surabaya River is the point estimation method.

Geostatistics is defined as a method that discusses the spatial relationships of several variables to estimate the value of variables located in unobserved locations (Kelkar and Perez, 2002). The appropriate method for use in the data of the sampled BOD level consisting of only one variable is kriging. In fact, the parameters of water pollution in rivers are not only BOD but also COD. Another method that can be used

to solve this case is the cokriging method with attention to other water pollution parameters that is COD to calculate BOD level. BOD is chosen as the primary variable because it is one of the important parameters related to wastewater treatment (Tchobanoglous, 1991). While COD is chosen as a secondary variable because the measurement time is shorter, only for one to two hours only. In addition, COD has also included the level in BOD because COD is a total picture of organic matter while BOD is a description of organic material that easily explained only (Tchobanoglous, 1991). Therefore, BOD can be predicted with COD, but COD may not be suspected by BOD because BOD cannot describe the total organic matter in the waters.

Research using brownig method on river pollution case has never been done. Some research using kriging and cokriging method has been done by Ahmadi and Sedghamiz (2008) using kriging and cokriging method in its application to groundwater depth mapping. The results showed that both methods were acceptable but based on the Mean Square Error (MSE) value, the cokriging method gave more accurate results in mapping the depth of groundwater throughout the study area. Based on the description, the researcher is interested to apply the cokriging method to estimate BOD concentration based on COD concentration observed by ED of Surabaya city, to know BOD concentration at unobserved point specially at points close to industrial or factory that discharges its waste to channel on the Surabaya River as a pollution measure of the Surabaya River.

2 METHODS

2.1 Stationary

Geostatistical data can be analyzed using kriging or cokriging method if it has qualified stationary. The stationary assumptions must be met both stationary in the mean (stationarity of order one) and stationary invariance (second order stationery). According to Kelkar (2002), the first order stationarity can be written mathematically as follows:

$$E[Z_i] = E[Z_{i+h}] \quad (1)$$

With Z_i is variable Z at location i . For the second-order stationarity can be written mathematically as follows:

$$C[Z_1, Z_{1+h}] = C[Z_2, Z_{2+h}]. \quad (2)$$

Covariance in a stationary region is a function of only the vector h , not of the variable itself. That means that as long as the distance and the direction between two points can be predicted the covariance between random variables at two points. No random variable is needed in that location. Therefore, equation (2) can be written as follows:

$$C[Z_i, Z_{i+h}] = C(h), \quad (3)$$

where $C(h)$ is covariance at h distance.

2.2 Spatial Relationships

The most common spatial relationships used in geostatistics are covariance, correlation and variogram.

2.2.1 Covariance

Equations (1) and (2) explain covariance under the assumption of stationarity of order one and two. The covariance of the z variable at location i and the variable z at the location of $i + h$ is

$$c(h) = \frac{1}{N(h)} \sum_{i=1}^{N(h)} Z_i Z_{i+h} - \left[\frac{1}{N} \sum_{i=1}^N Z_i \right]^2. \quad (4)$$

2.2.2 Correlation Coefficient

The correlation coefficient used to describe the spatial relationship. From equation (4) is defined correlation coefficient as follows

$$\rho(h) = \frac{c(h)}{\sigma_i \sigma_{i+h}}, \quad (5)$$

where $C(h)$ is covariance at distance h , σ_i is the standard deviation of data at location i . If a second-order stationary assumption is used, then it is obtained

$$V[Z_i] = V[Z_{i+h}] = C(0). \quad (6)$$

From equation (6) is obtained

$$\sigma_i = \sigma_{i+h} = \sqrt{C(0)} \quad (7)$$

The substitution of (7) to (5) is obtained

$$\rho(h) = \frac{c(h)}{C(0)}. \quad (8)$$

The correlation coefficient at (8) is estimated from the sample as follows:

$$r(h) = \frac{c(h)}{c(0)}, \tag{9}$$

with $c(0)$ is the sample variance.

2.2.3 Variogram

Variogram is a measure of data variance that takes into account distance. A variogram (2γ) is one of the basic geostatistical tools that is used to determine spatial dependence. It is often referred to as a semivariogram (γ), which has exactly the same characteristics (Kis, 2016). According to Kelkar (2002) semivariogram is defined as follows:

$$\gamma(h) = \frac{1}{2}V[Z_i - Z_{i+h}], \tag{10}$$

with $\gamma(h)$ is a semivariogram or semivariance at a distance h . Based on the definition of the variance of equation (10) can be written as follows:

$$\gamma(h) = \frac{1}{2}\{V[Z_i] + V[Z_{i+h}] - 2C[Z_i, Z_{i+h}]\} \tag{11}$$

Substitutions (3) and (6) to (11) are obtained

$$\gamma(h) = C(0) - C(h) \tag{12}$$

There are two types of variograms: experimental variogram and theoretical variogram. According to Kelkar (2002) calculate the value of the experimental variogram as follows:

$$\hat{\gamma}(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)} [z_i - z_{i+h}]^2, \tag{13}$$

with $\hat{\gamma}(h)$ is the semivariance estimate based on the sample data at h distance. Meanwhile, to calculate variogram that there is a cross-link or commonly referred to as cross variance can be written as follows:

$$\gamma_c(h) = \frac{1}{2}E\{[Z_i - Z_{i+h}][Z_{2i} - Z_{2i+h}]\} \tag{14}$$

The estimation of cross variance between variables z and z_2 at (14) is

$$\hat{\gamma}_c(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)} [z_i - z_{i+h}][z_{2i} - z_{2i+h}] \tag{15}$$

The cross covariance equation is

$$C_c(h) = E[Z_i Z_{2i+h}] - E[Z_i]E[Z_{2i+h}] \tag{16}$$

The cross-covariance estimation between the z and z_2 variables at (16) is

$$c_c(h) = \frac{1}{N(h)}\sum_{i=1}^{N(h)} [z_i - z_{2i+h}] - \frac{1}{N(h)}\sum_{i=1}^{N(h)} z_i \times \frac{1}{N(h)}\sum_{i=1}^{N(h)} z_{2i+h} \tag{17}$$

According to Isaaks and Srivastava (1989), there are several components in the variogram of sill, nugget, and range. Sill ($C_0 + C$) is the value of the variogram in the upper part of the variogram (level off), can also be interpreted as the "amplitude" of a particular component of the variogram. Range (A_0) is the distance at which the variogram reaches the sill. In theory, the initial value of the variogram is zero. When the lag approaches zero the value of the variogram is referred to as the nugget. The nugget (C_0) represents a variation in the very small distance (lag), including error in measurement.

2.2.4 Theoretical Variogram

The theoretical variogram is a variogram that is arranged by function or has a curve shape close to the experimental variogram. For further analytical purposes, the experimental variogram should be replaced by the theoretical variogram. This substitution aims to model the variogram according to the characteristics of the estimated variables. There are two types of theoretical variogram: isotropic variogram and anisotropic. According to LeMay (1995) variogram which depends only on distance and point on the direction called isotropy variogram. According to Kelkar (2002), there are four models of the isotropic variogram, i.e., linear, spherical, exponential, and Gaussian models. The isotropic variogram equation for linear model (figure 1) is

$$\gamma(h) = C_0 + \left[h \left(\frac{C}{A_0} \right) \right]. \tag{17.a}$$

The isotropic variogram equation for spherical model (figure 2) is

$$\gamma(h) = \begin{cases} (C_0 + C) \left[\frac{3}{2} \left(\frac{h}{A_0} \right) - \frac{1}{2} \left(\frac{h}{A_0} \right)^3 \right]; & h \leq A_0, \\ C_0 + C & ; \quad h > A_0, \end{cases} \tag{17.b}$$

With $\gamma(h)$ is a spherical model at a distance of $A = A_0$. The corresponding covariance equation is

$$\gamma(h) = \begin{cases} (C_0 + C) \left[1 - \frac{3}{2} \left(\frac{h}{A_0} \right) + \frac{1}{2} \left(\frac{h}{A_0} \right)^3 \right]; & h \leq A_0, \\ 0 & ; \quad h > A_0. \end{cases}$$

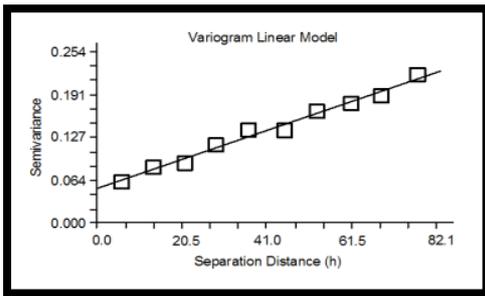


Figure 1: Theoretical Variogram of Linear Model.

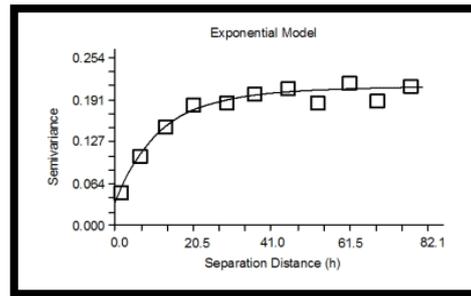


Figure 3: Theoretical Variogram of Exponential Model.

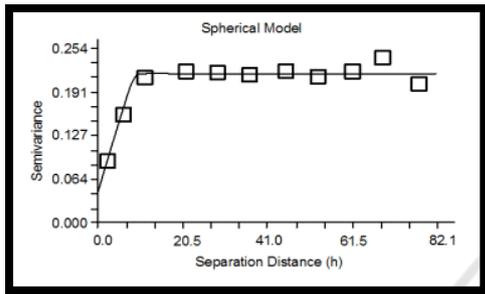


Figure 2: Theoretical Variogram of Spherical Model.

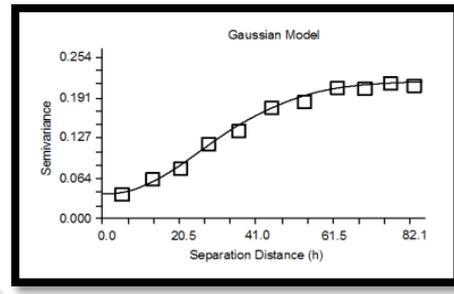


Figure 4: Theoretical Variogram of Gaussian Model.

The isotropic variogram equation for exponential model is

$$\gamma(h) = (C_0 + C) \left[1 - \exp\left(\frac{-3h}{A_0}\right) \right], \quad (17.c)$$

with $\gamma(h)$ is an exponential model at a distance of $A = 3A_0$. The corresponding covariance equation (figure 3) is

$$C(h) = (C_0 + C) \left[\exp\left(\frac{-3h}{A_0}\right) \right].$$

The isotropic variogram equation for gaussian model (figure 4) is

$$\gamma(h) = (C_0 + C) \left[1 - \exp\left(-3 \frac{h^2}{A_0^2}\right) \right], \quad (17.d)$$

with $\gamma(h)$ is a gaussian model at a distance of $A = \sqrt{3}A_0$. The corresponding covariance equation is

$$C(h) = (C_0 + C) \left[\exp\left(-3 \frac{h^2}{A_0^2}\right) \right].$$

Root Sum Squared (RSS) validation information is used to determine the variogram model match. The best isotropic theoretical variogram model is the model with the smallest RSS value.

2.3 Cokriging Method

The cokriging method is the interpolation method used to estimate the level of a variable with respect to other variables (Isaaks and Srivastava 1989). The estimation equation of cokriging according to Kelkar (2002) is

$$Z_0^* = \lambda_0 + \sum_{i=1}^N \lambda_{Z_i} Z_i + \sum_{k=1}^M \lambda_{Z_2k} Z_{2k} \quad (18)$$

with Z_0^* is the estimated value at the new location, λ_0 is the browning weighter for variable Z at the alleged location, λ_{Z_i} is the brown weighing for the variable Z, λ_{Z_2k} is the brown weighing variable Z2, Z_i is the value of variable Z at location i , Z_{2k} is the value of variable Z2 at location k .

2.3.1 Unbiased Condition

If Z_0^* is the value of a variable in a new location that is not sampled it will be estimated, then Z_0 is an unbiased estimator for Z_0^* which satisfies the following equation

$$E[Z_0 - Z_0^*] = 0. \quad (19)$$

Substitutions (18) to (19) are obtained

$$E[Z_0] = E[\lambda_0 + \sum_{i=1}^N \lambda_{Z_i} Z_i + \sum_{k=1}^M \lambda_{Z_{2k}} Z_{2k}]. \quad (20)$$

From (20) under the assumption of a first-order stationer is obtained

$$m_Z = \lambda_0 + m_Z \sum_{i=1}^N \lambda_{Z_i} + m_{Z_2} \sum_{k=1}^M \lambda_{Z_{2k}}. \quad (21)$$

From (21) obtained

$$\lambda_0 = m_Z (1 - \sum_{i=1}^N \lambda_{Z_i}) - m_{Z_2} \sum_{k=1}^M \lambda_{Z_{2k}}. \quad (22)$$

The value of λ_0 at (22) is considered 0 to be obtained

$$\sum_{i=1}^N \lambda_{Z_i} = 1 ; \sum_{k=1}^M \lambda_{Z_{2k}} = 0. \quad (23)$$

Two constraints within (23) produce an ordinary cokriging system. If (23) is substituted to (22), then $\lambda_0 = 0$ is obtained, so that from equation (18) is obtained the estimated variable in the new location as follows

$$Z_0^* = \sum_{i=1}^N \lambda_{Z_i} Z_i + \sum_{k=1}^M \lambda_{Z_{2k}} Z_{2k}. \quad (24)$$

2.3.2 Minimum Variance

The estimation of the cokriging equation (24) is obtained by minimizing the variance as follows:

$$\hat{\sigma}_E^2 = V[Z_0^* - \sum_{i=1}^N \lambda_{Z_i} Z_i - \sum_{k=1}^M \lambda_{Z_{2k}} Z_{2k}]. \quad (25)$$

with constraints (23). Parameter estimation of the cokriging model (24) uses the Lagrange multiplier method by minimizing F function as follows:

$$F = \hat{\sigma}_E^2 + 2\mu_Z (\sum_{i=1}^N \lambda_{Z_i} - 1) + 2\mu_{Z_2} (\sum_{k=1}^M \lambda_{Z_{2k}}) \quad (26)$$

3 RESULTS AND DISCUSSION

The data used in this research are BOD and COD concentration at ten location points in Surabaya River in 2016. Before estimating the level of river pollution using BOD level at a new location or location to be expected, it is necessary to validate by estimating the observation data which has been obtained.

3.1 Validation of BOD Level

Before estimating the level of river pollution using BOD level at a new location to be expected, it is necessary to validate it first by estimating the observed data that has been obtained. It is assumed that BOD and COD level data satisfy stationary assumptions in mean and variance.

The Pearson correlation value between BOD and COD shows p-value equal to 0,000 which means significant at $\alpha = 5\%$. The correlation value between BOD and COD variables is 99.5%. The cokriging method can be continued because BOD and COD variables have a high correlation. Variogram used in this research is theoretical isotropic variogram consisting of four models, namely linear, spherical, exponential, and Gaussian model. Isotropic variogram depends only on distance (h) alone without considering direction. Variogram and cross-variogram theoretical selected to determine the suitability of the model based on the smallest Residual Sum of Square (RSS) value. The result of modeling theoretical isotropy variogram from BOD and COD levels for the four models is presented in the following table 1.

Based on Table 1 obtained the best theoretical variogram model for BOD is the Gaussian model with the smallest RSS value of 2838. In this model, BOD level reaches sill in the range of 2050 meters which means the BOD level will not have any dependencies at distances over 2050 meters. Based on the nugget-sill ratio of theoretical isotropic variograms, BOD levels are included in strong spatial autocorrelation of 0.408%. The best theoretical variogram model for COD is the Gaussian model with the smallest RSS value of 144803. In this model, the COD level reaches sill at 2100 meters range which means COD level will not have dependencies more than 2100 meters. Based on the nugget-sill ratio of theoretical isotropic variograms, COD levels are included in strong spatial autocorrelation of 0.312%. The best theoretical variogram model for cross-variogram of BOD and COD is the Gaussian model with the smallest RSS value of 20297. In the selected model for cross variogram, there is a dependency between BOD and COD level at 2090 meters distances, more than 2090 meters no dependencies between both. The best theoretical isotropic variogram model for BOD level is presented in the following figure 5.

Figure 6 is the best theoretical isotropic variogram model of COD level. While the best theoretical isotropic cross-variogram model of BOD and COD levels as Figure 7.

Table 1: Parameter Estimation Result of Cokriging Model on BOD and COD Data.

Model	Nugget (C _o)	Sill (C _o +C)	Range (A _o)	RSS
BOD				
Linear	8.508	17.05	4987.5	2925
Spherical	5.280	15.88	3580.0	2846
Exponential	6.050	17.33	6420.0	2887
Gaussian	6.760	16.55	2050.0	2838
COD				
Linear	51.879	128.34	4987.5	149374
Spherical	31.500	117.30	3940.0	145603
Exponential	29.300	126.80	6150.0	147688
Gaussian	38.200	122.30	2100.0	144803
BOD x COD				
Linear	21.037	46.58	4987.5	20936
Spherical	12.860	43.02	3770.0	20382
Exponential	14.700	48.50	7170.0	20679
Gaussian	16.660	44.82	2090.0	20297

3.2 Cokriging Interpolation to Estimate the BOD Level

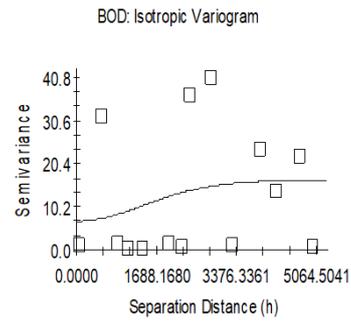
After the best theoretical variogram and theoretical cross-variogram are obtained, then it is used for cokriging interpolation. The purpose of cokriging interpolation is to estimate BOD and COD levels using point estimation because the coverage of measurement region is not broad, i.e. in one river zone. Based on the actual value and estimated value of brown interpolation result, then cross-validation is done to see the good of the interpolation result. The effect of cross-validation obtained by coefficient of determination R^2 value of 91.5% as presented as figure 8.

Mean Square Error (MSE) value of 0.7057. The value of R^2 is very high, and the MSE value is small, so the interpolation result is accurate. The accuracy of BOD value estimation can also be seen through the plot between the actual value and the estimated value of BOD level as figure 9.

3.3 BOD Estimated on New Location

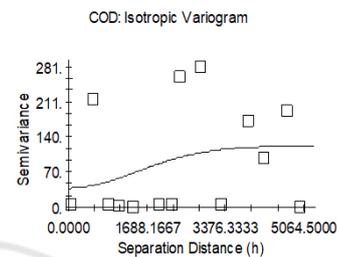
The estimated spread of BOD levels in the Surabaya River is presented in the form of a two-dimensional contour map (figure 10).

The cokriging interpolation results in a range of BOD levels which vary between 6 mg / l to 11.7 mg / l which are grouped into 15 intervals in the form of different color gradations. The area marked by the symbol X is the measurement point for BOD levels in the Surabaya River by ED. The estimated BOD content is dominated at intervals of 7.1 mg / l to 7.5 mg / l which are indicated by gradations of light green.



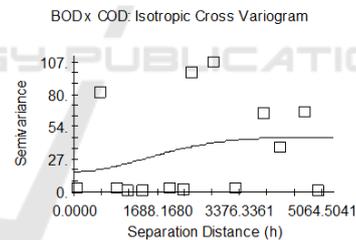
Gaussian model (C_o = 6.760000; C_o + C = 16.550000; A_o = 2050.0000; r₂ = 0.061; RSS = 2838.)

Figure 5: Best Theoretical Isotropic Variogram of BOD level.



Gaussian model (C_o = 38.200000; C_o + C = 122.300000; A_o = 2100.0000; r₂ = 0.078; RSS = 144803.)

Figure 6: Best Theoretical Isotropic Variogram of COD level.



Gaussian model (C_o = 16.660000; C_o + C = 44.820000; A_o = 2090.0000; r₂ = 0.068; RSS = 20297.)

Figure 7: Best Theoretical Isotropic Cross Variogram of BOD and COD levels.

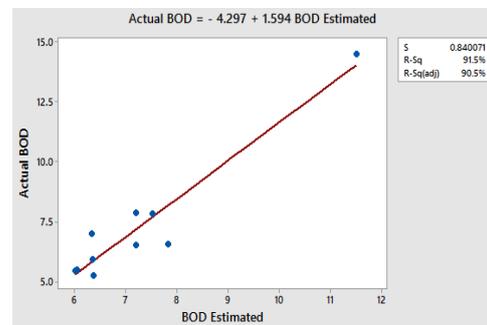


Figure 8: Cross-Validation of BOD Level Estimates at the Observation Locations.

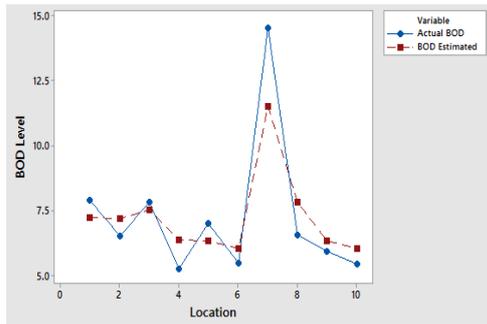


Figure 9: Plot Estimated Value and Actual Value of BOD Level.

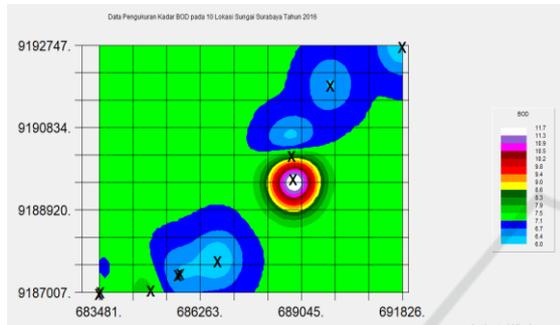


Figure 10: Estimated Spread of BOD Levels at Surabaya River.

The BOD level in the lower reaches of the river is low, this is due to the pollutant source from the upstream of the river that leads to the downstream of the river the smaller the effect.

The new location is estimated to be the location points after the industries because according to the ED information, the three industries are discharging their waste into the channel that leads to the Surabaya River. Selection of these location points is also due to research by Suwari (2010), BOD level contributes a large amount of industrial waste. Industrial waste does not have high volume but its strongest destructive power. The result of BOD level estimation at the new location, namely location 11 with easting coordinate 684505 and northing 9187059 is presented in the form of a two-dimensional contour map as figure 11.

The results show that BOD levels at location 11 around PT. An of 7.5 mg / l. This value was far exceeding class II river water quality standard that has been set at 3 mg / l, so that location 11 has been contaminated status. There are several factors that cause high levels of BOD in the location that is because the river flow that still brings the influence of waste from the previous location and also can be expected because the location is close to PT. A which

is the industry with the dominant waste according to Fardiaz (1992) that is hydrargyrum (Hg), cadmium (Cd), chromium (Cr), lead (Pb), and copper (Cu). This illustrates the industrial wastewater treatment system of PT. A has not met the standard.

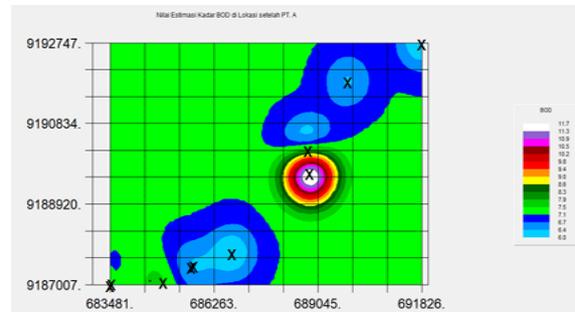


Figure 11: Estimated Spread of BOD Levels at Location 11.

Then the estimation of BOD levels in the new location, namely location 12 with easting coordinate 688519 and northing 9189221 is presented in the form of a two-dimensional contour map as figure 12.

The results show that BOD levels at location 12 around PT. An of 9.9 mg / l. This value is far exceeding class II river water quality standard that has been set at 3 mg / l, so that location 12 has been contaminated status. Several factors cause high levels of BOD in that location, which is due to river currents that still carry the effect of waste from the previous location including the waste of PT. A and may also be suspected because the location of location 12 is close to PT. B which is an industry with dominant waste according to Fardiaz (1992), namely organic matter, suspended solids (SS), dissolved solids (DS) and Cd. This illustrates the industrial wastewater treatment system at PT. B has not met the standard.

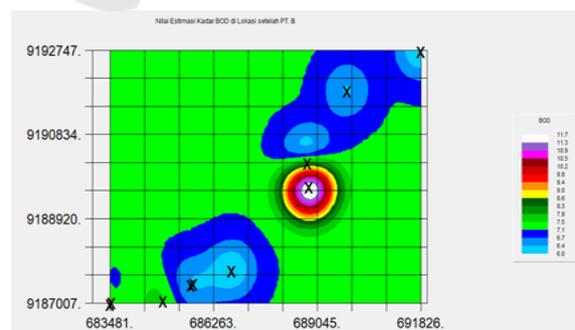


Figure 12: Estimated Spread of BOD Levels at Location 12.

4 CONCLUSIONS

The result of modelling of sample BOD level using cokriging method obtained by the best model based on the smallest RSS value of 2838 is Gaussian model. The value of R^2 is very high of 91.5% and small MSE value of 0.7057. This shows that the interpolation results are accurate with the Gaussian model. The estimation result of BOD level in Surabaya River shows that BOD level leading downstream of the river is lower. This is because the source of pollutants from the upstream of the river that leads downstream of the river is less have an effect. The results show that BOD levels at new location around PT. A, namely location 11 of 7.5 mg / l. This value is far exceeding class II river water quality standard that has been set that is 3 mg / l so it can be said that the location has been contaminated status. Several factors cause high levels of BOD in the location that is because the river flow that still brings the influence of waste from the previous location and also can be expected because the location is close to PT. A which is the industry with the dominant waste that is hydrargyrum (Hg), cadmium (Cd), chromium (Cr), lead (Pb), and copper (Cu). Then the estimation of BOD levels in the new location around PT. A, namely location 12 of 9.9 mg / l. This value far exceeding class II river water quality standard that has been set that is 3 mg / l so it can be said that the location has been contaminated status. Several factors cause high levels of BOD in that location, which is due to river currents that still carry the effect of waste from the previous location including the waste of PT. A and may also be suspected because the location of location 12 is close to PT. B which is an industry with dominant waste, namely organic matter, suspended solids (SS), dissolved solids (DS) and Cd.

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