ASSESSMENT OF WATER QUALITY IN LAGUNA DE BAY AND ITS TRIBUTARY RIVERS BY EXAMINING PHYSICOCHEMICAL PARAMETERS THROUGH GEOSTATISTICAL ANALYSIS

Submitted by:

Aurellano, Venes Bolo[1]

Gabayan, Joshua Lou Allen Mamades[2]

ABSTRACT

This paper examined different physicochemical parameters obtained from Laguna de Bay and its tributary lakes in order to assess the water quality through mapping the distribution of these parameters in the whole study region. Spatial interpolation methods, specifically ordinary kriging and universal kriging, were carried out to estimate the values of the physicochemical parameters at unsampled locations. Results of the study showed that universal kriging performed better compared to ordinary kriging in interpolating values of most of the parameters. Furthermore, half of the physicochemical parameters considered in the study failed the DENR Water Quality Guidelines. This only means that the life of Laguna de Bay is in danger. The national government as well as the local governments of municipalities around Laguna de Bay must do a collaborative effort in cleaning Laguna de Bay. Rehabilitation of the said lake just like the one done in Boracay can also be done in order to save it from further damage.

Keywords: spatial data analysis, water quality parameters

---

[1]vbaurellano@up.edu.ph [2]jmgabayan@up.edu.ph

I. INTRODUCTION

BACKGROUND OF THE STUDY

The Philippines is rich in terms of water resources due to the fact that it is an archipelago with more than 7,101 islands and is surrounded by different bodies of water, with South China Sea on its north and west, the Pacific Ocean on its east, and the Celebes Sea on its south. The country has a total of 59 lakes and 421 river basins with drainage area ranging from 40 to 25,649 km^2. Among the principal river basins, 18 were major river basins with drainage areas of at least 1,400 km^2 and the other small river basins gave areas of at least 50 km^2. In addition, there are approximately 1,000 km^2 of freshwater swamps and approximately 50,000 km^2 of groundwater reservoirs which has a storage capacity of up to 251 km^3 (NSCB, 2005).

Among all other lakes in the country, Laguna de Bay is considered as the largest, and when compared to others in the Southeast Asia region, it comes third after Lake Toba and Lake Songkhla in Thailand. It is enclosed by the provinces of Laguna and Rizal, and some parts of Metro Manila like Pasig, Taguig, and Muntinlupa. The lake also has a total surface area of 92 km^2 when it hits its average highest elevation of 12.50 meters and approximately 760 km^2 when it is at its average lowest elevation of 10.50 meters. The enormous lake is surrounded by the Sierra Madre mountain ranges on its northeast, the Caliraya volcanic plateau on its east, mountains of Laguna and Batangas such as Banahaw and Makiling on its south and southeast. It has a total volume of around 3.2 billion m^3 with a shoreline extending up to 220 kilometers. The lake also has an average depth of 2.5 meters.

There are around 100 rivers and creeks which flows into the lake, 28 of which are tributary. These are the Marikina River, the Bagumbayan River and Buli Creek from Taguig, the Mangangate River and the Tunasan River from Muntinlupa, the San Pedro River, the Biñan River, the Sta. Rosa River, the Cabuyao River, the San Juan River, the Molawin Creek from Los Baños, Laguna, the Bay River, the Pila River, the Sta. Cruz River, the Pagsanjan River, the Pangil River, the Siniloan River, the Sta. Maria River, the Jala-jala River, the Pililla River, the

Tanay River, the Baras River, the Morong River, the Manggahan Floodway from Taytay, Rizal, the Sapang Bato River from Cainta, Rizal, the Angono River, and the Teresa River (LLDA, n.d.).

The lake is the most important source of living among people residing near it, perhaps for fishing, irrigation, and domestic needs. In fact, the bulk of the catch of major fish species in inland fisheries comes from the lake. It also serves as a temporary reservoir, a home especially to the smallest commercial fish in the world called sinarapan (*Mistichthysluzonensis*) (FAO, 2014). Interestingly, a transport route is being developed for tourists by the local government today (De Guzman, 2018).

However, the life of Laguna de Bay is in jeopardy as it faces a lot of environmental issues such as overfishing, pollution coming from the households, commercial areas, and industries as well as massive sedimentation and illegal reclamation which minimize its capacity. In a recent assessment conducted by the Laguna Lake Development Authority (LLDA), from “A” to “F”, with “F” being the worst, the lake got a grade “C-” for water quality and “F” for fisheries.

The major threat that the lake is experiencing is nutrient pollution which causes eutrophication. Eutrophication, or having excessive enrichment in a body of water, is caused by a runoff of nutrients, especially nitrogen and phosphorus usually coming from fertilizers, detergents, and harmful wastewater. Because of this event, plant growth is triggered and animal lives beneath are reduced due to lack of oxygen. Massive fish die-offs have also been reported in Laguna de Bay. Meanwhile, sewage and sedimentation slowly harms the life of the lake, too. Due to lack of proper sanitation facilities inside the households, a large number of informal settlers living at the lake shore is found to be directly disposing their waste into the body of water. Furthermore, an increasing amount of soil and debris has been entering the lake, affecting the capacity of the lake and thus, minimizing its productivity (UN Environment, 2017).

It is not just the Laguna de Bay that is facing serious environmental issues. The crisis has extended at the national level. The Environmental Management Bureau (EMB) reported that only 47% of the country’s 127 freshwater bodies were found to have a good water quality. Also, 58% of the groundwater reservoirs were found to have presence of coliform. What is more alarming is that the cost of water pollution crisis in the country exceeds $1.3 billion USD every year (Andrews, 2018).

Water is considered an essential resource to every individual. Particularly, a lot of Filipinos are living by the waters and are dependent with the resources provided by the ecosystem. In addition, the 6th and 14th sustainable development goals (SDG) set by United Nations (UN) to improve economic growth and productivity are to "ensure availability and sustainable management of water and sanitation for all" and to "conserve and sustainably use the oceans, seas, and marine resources for sustainable development" (UN, n.d.). However, these goals are yet to become true. Looking at the state of waters in the country today, the ambition of providing clean and sustainable water for everyone is hard to reach and requires much time and effort yet it is not impossible. Water shortages have happened. The issue of having a clean water even in urban areas is alarming. But by studying the quality of water, the local government units (LGUs) and other agencies will be guided on what certain policies should be implemented in order to help minimize the environmental threats faced by the system today thus stabilizing it in the near future and for the next generations to use.

OBJECTIVES OF THE STUDY

Generally, this study aims to investigate the water quality in Laguna de Bay and its tributary rivers using data from the 4th quarter of 2018 by examining the physicochemical parameters measured at certain water stations inside and surrounding the body of water. Furthermore, the researchers aims to construct a model for the spatial variability of each physicochemical parameter considered. Specifically, this study aims to:

1. Predict all values of each parameter throughout all parts of the lake other than those in water monitoring stations.
2. Determine through visual inspection on which regions of the lake a certain parameter concentrates.
3. Describe and compare the predicted concentration levels of each parameter.
4. Compare the performance of the two most common spatial interpolation methods.

SCOPE AND LIMITATIONS

This study only focuses on certain physicochemical parameters measured in Laguna de Bay and its tributary rivers during the months of October, November, and December of 2018. Thus, data outside the area and time frame of interest is not within the scope of this research. Furthermore, the sample points considered in this study are the Laguna Lake and tributary rivers monitoring stations identified by the LLDA only. The parameters included in this study are those released in the agency's quarterly water quality report only, except the total (for Laguna Lake stations) and fecal (for Tributary river stations) coliform since the two measure differently. Hence, the findings of this study may not be applied to other areas and time frame of interest.

II. REVIEW OF RELATED LITERATURE

PHYSICOCHEMICAL PROPERTIES

The physicochemical parameters play an important role in assessing the quality of water as it indicates how the body still gives, produces, and sustains life beneath its waves. Changes in these attributes usually led to the conclusion that the quality of water has also changed (Djukie et al., 1994).

The Department of Environment and Natural Resources (DENR) Administrative Order No. 2016-08 orders the adaption of several Water Quality Guidelines (WQG) and General Effluent Standards (GES) in order to protect, preserve, and revive the quality of fresh, brackish, and marine waters in the country. The WQG has provided parameters to be monitored by the agency. There are ten primary parameters set and these are:

1. Biochemical Oxygen Demand (BOD)
2. Chloride
3. Color in true color unit
4. Fecal Coliform in Most Probable Number per 100 milliliter
5. Minimum Dissolved Oxygen (DO)
6. Nitrate as NO_3-N
7. pH or level of acidity
8. Phosphate
9. Temperature
10. Total Suspended Solids

There are also five secondary inorganic parameters to be measured along with the primary parameters. These are ammonia as NH_3-N, boron, fluoride, selenium, and sulfate. In this study, only six parameters coming from the primary and secondary ones were considered.

The said administrative order also provided classification of water bodies. These are the following:

1. Class AA: Public water supply class I - intended primarily for waters having watersheds, which are uninhabited and/or otherwise declared as protected areas, and which require only approved disinfection to meet the latest PNSDW.
2. Class A: Public water supply class II - intended as sources of water supply requiring conventional treatments (coagulation, sedimentation, filtration, and disinfection) to meet the latest PNSDW.
3. Class B: Recreational water class I - intended for primary contact recreation (bathing, swimming, etc.)
4. Class C: Fishery water for propagation and growth of fish and other aquatic resources; Recreational water class II for boating, fishing, or similar activities; and for agriculture, irrigation, and livestock watering
5. Class D: Navigable waters

Ammonium or nitrogen is known to contribute to the total ionic salinity of the water. This nutrient is known to affect the productivity of water bodies, especially freshwaters (Wetzel, 2001). This is highly due to the presence of sewage and industrial waste pollution or dominance of saline water (Patil et al., 2012).

Biochemical oxygen demand, commonly called as BOD, is defined as the oxygen required for a microorganism to facilitate biological decaying of dissolved solids or organic matter in wastewater under certain aerobic conditions (Solank & Pandit, 2006). It indicates the health of a surface water supply as it naturally treats wastewater present inside the body (Qureshimatva et al., 2015).

A high value of dissolved oxygen implies a good marine life (Yadav et al., 2013). Usually, when the temperature is low, dissolved oxygen is high; otherwise, low value of dissolved oxygen is caused by high temperature or increase of sewage waste (Qureshimatva et al., 2015).

Nitrate is considered as the most highly oxidized form of nitrogen compound usually present in water systems. It is the compound which comes from runoff of agricultural, domestic, and industrial wastes (Solanki, 2012). A high amount of nitrate present in the system supports the algal and plankton growths (Qureshimatva et al., 2015).

The parameter pH measures the level of acidity of a solution at a certain temperature. Scientifically, it is defined as the negative logarithm of hydrogen ion concentration, i.e. pH = -log [H+]. For water, pH ranges from 7.0 to 7.85 (Goher, 2002). Measuring the level of acidity of water is important to maintain a safe environment for most plant and animal species since they only survive at a narrow range of pH condition, not too acidic and not too basic (Qureshimatva et al., 2015).

Similar to nitrate, when water is rich in phosphate, formation of algal blooms becomes evident. Known to facilitate biological metabolism, the nutrient is also present due to domestic waste and sediments entering the body of water (Solanki, 2015).

GEOSTATISTICAL ANALYSIS

Various studies have already employed spatial data analysis in examining the status and pattern of water quality in different water bodies present in their respective regions. A study conducted by Kimleang et al. (2017) assessed the water quality in Tonle Sap Lake. Different interpolation methods were utilized which inverse distance weighted (IDW), simple kriging, and ordinary kriging. After studying the water quality parameters such as dissolved oxygen, total dissolved solids, total suspended solids, and turbidity at the surface layer both kriging methods emerged as a better fit than the inverse distance weighted method.

Shahid et al. (2017) from Pakistan have explored spatial interpolation methods in evaluating the quality of groundwater in Lahore, Punjab, Pakistan. The researchers obtained a total of 73 water samples from tube wells and physicochemical parameters were measured from them. These are alkalinity, calcium, and chlorides, hardness, total dissolved solids, turbidity, and pH. Deterministic interpolation methods such as inverse distance weighting and radial basis functions (RBF) were compared to geostatistical interpolation methods such as ordinary kriging and ordinary co-kriging through the cross-validation process. The analysis showed that co-kriging outperformed ordinary kriging, RBF, and IDW. The researchers were also able to compute the water quality index (WQI) and the findings revealed that 98% of the tube wells in Lahore city has ‘excellent’ to ‘good’ water quality.

Another study conducted by Chang (2008) was able to determine the water quality trends in Han River basin in South Korea using spatial analysis. The researcher gathered eight parameters - biochemical oxygen demand, chemical oxygen demand, dissolved oxygen, suspended sediment, temperature, total nitrogen, total phosphorus, and pH all from 118 sites located in the basin from 1993 to 2002. Initially, the researcher was able to detect either increasing or decreasing trends for variables such as biochemical oxygen demand, chemical oxygen demand, dissolved oxygen, suspended sediment, total phosphorus, and pH. Moreover, as measured by Moran’s I, non-point-source pollution exhibited a strong positive spatial autocorrelation which implies that spatial analysis is vital in examining the spatial patterns of water quality.

Similarly, Jakubek and Forsythe (2004) used data from the 1998 Environment Canada Great Lakes Sediment Assessment Program to investigate sediment contamination in Lake Ontario, Canada. Different variables thought to have major environmental significance were measured such as Sediment Quality Index (SQI), polychlorinated biphenyls (PCBs), mercury, lead, and hexachlorobenzene (HCB). The ordinary kriging spatial interpolation method was used. Cross-validation was also applied to measure the accuracy of the technique. The researchers were able to illustrate prediction surfaces than point patterns for the sediment contamination present in the lake to present images of the overall pollution level.

A study conducted by Velasquez et al. (2002) has shown how water quality parameters are utilized to profile regions in Manila Bay, Philippines with high concentration of dissolved cadmium, copper, and zinc. In the study, the researchers obtained water samples and measured their dissolved oxygen, chlorophyll *a*, salinity, temperature, and particulate organic carbon and nutrients thereafter. The study proves how physicochemical parameters can help the researchers in determining the state and pattern of water quality of a certain region.

III. METHODOLOGY

STUDY AREA

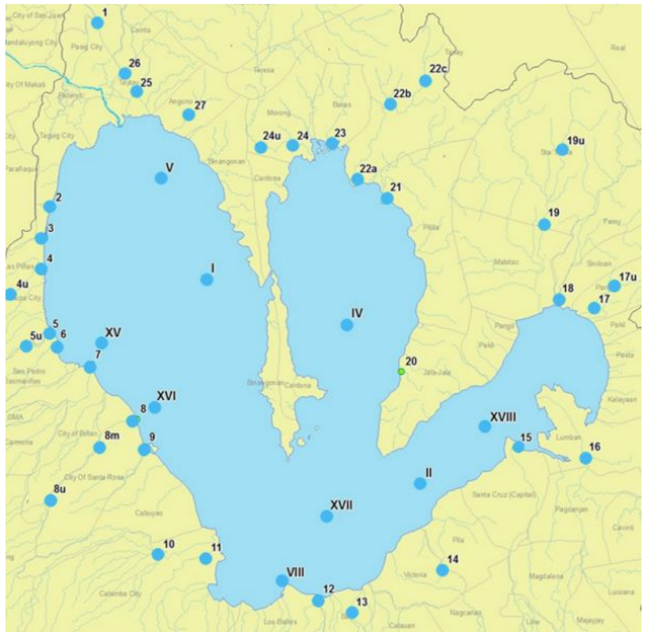


Figure 1. Monitoring Stations in Laguna de Bay and its Tributary Rivers

The figure above shows the map of Laguna de Bay and its surrounding mainland area along with the monitoring stations represented by blue points. There are 9 stations located in the lake itself while 37 stations are situated in the tributary rivers of the lake.

DATA COLLECTION AND SPECIFICATION

The data consisting of water quality parameters for Laguna Lake and its tributary rivers was obtained from Laguna Lake Development Authority (LLDA). It was part of the LLDA Quarterly Water Quality Monitoring Report for the 4th quarter of 2018. Six physicochemical, or basically called water parameters were considered, after excluding the fecal coliform since data for this variable has different unit of measurement for the lake and its tributary rivers.

Missing observations were observed from the report and were later known to be caused by non-collection of water samples due to either dense accumulation of water hyacinth or very shallow or dry water during the time of sampling. The average of each parameter for the three months was computed per monitoring station in order to account for missing observations. These averages, together with the coordinates of the monitoring stations obtained from the study of Maruyama and Kato (2017), were then compiled to form the final dataset. It is important to note that not all coordinates of the monitoring stations are obtained from the said study; some are estimated by the researchers (See Appendix A).

STATISTICAL ANALYSES

VARIOGRAM MODELLING

Prior to conducting spatial predictions, a variogram should be constructed first. This study used the robust estimator of semivariances by Cressie and Hawkins (1980). Bailey and Gatrell (1995) further added that a variogram is visualized when a researcher wants to investigate spatial dependence in his observed data, especially in the fields of geology and environmental science. Generally, the estimators of a variogram are more robust to minor departures from the assumption of stationarity in studying the first order component. A natural sample estimator of the variogram is given by:

$$2\widehat{\gamma}(h) = \frac{1}{n(h)} \sum_{s_i - s_j = h} \left(y_i - y_j\right)^2$$

where the summation is divided by all pairs of observed data points within a distance separation *h* and *n(h)* is the total number of pairs. In assuming a stationarity process, a sample variogram should possess two important components: the *sill* which coincides with σ^2 and the *range* or the upper bound of a sill. There are three common variogram models seeked if a researcher wishes to fit a smooth and continuous covariance structure for stationary processes.

1. The spherical model:

   $$\gamma(h) = \sigma^2 \left(\frac{3h}{2r} - \frac{h^3}{2r^3}\right) \; for\ h \le r \text{ or } \sigma^2, \text{ otherwise}$$

   where r is the range and σ^2 is the sill.

2. The exponential model:

$$\gamma(h) = \sigma^2 \left(1 - e^{\frac{-3h}{r}}\right)$$

where again r is the range and σ^2 is the sill.

3. The Gaussian model:

$$\gamma(h) = \sigma^2 \left(1 - e^{\frac{-3h^2}{r^2}}\right)$$

where r and σ^2 is the same as above.

A nugget effect or a discontinuity at the origin and when $\gamma(0) = 0$, which indicates lack of spatial dependence, is then represented by a constant term a. Thus adjustments are made in these three models. After adding the nugget effect, the spherical model changes to $\gamma(h) = a + (\sigma^2 - a)\left(\frac{3h}{2r} - \frac{h^3}{2r^3}\right)$ when $0 \le h \le r$, 0 when $h = 0$, and simply σ^2 otherwise. Meanwhile, the exponential model becomes $\gamma(h) = a + (\sigma^2 - a)\left(1 - e^{\frac{-3h}{r}}\right)$ when $h > 0$ or simply 0 otherwise. Moreover, in a certain interpolation method, a model with the best fit is the one with the smallest sum of squared error (SSError) or the sum of the squared differences between each observation and its respective mean.

KRIGING

Bailey and Gatrell (1995) defined the kriging method as a technique that illustrates spatial patterns, predict values at points other than those in the sample, and evaluate the uncertainty associated with a predicted value at the unsampled locations. The weights used to predict came from the spatial dependence between the sample points as described by the variogram model. It is considered as an optimal spatial linear prediction method since it is unbiased, and it minimizes the mean squared prediction error. There are two models of kriging used in this study: ordinary and universal kriging, both an extension of the simple kriging method.

ORDINARY KRIGING

Ordinary kriging is similar to simple kriging yet it is assumed that the process has an unknown but constant mean. However, this method forms the predicted values, $\hat{y}(s)$, in one step, from the original process $Y(\mathbf{s})$, at $\mathbf{s}$, with weights equal to a linear combination of the observed values y_i at the sample sites $\boldsymbol{s}_i$. To visualize, that is:

$$\widehat{Y}(s) = \sum_{i=1}^{n} \omega_i(s)\, Y(s_i)$$

Typically, the values are chosen for the weights such that the mean value of $\widehat{Y}(s)$ is constrained to be μ, similar to the predicted random variable $Y(s_i)$. Since the mean μ is constant among random variables, the mean for $\widehat{Y}(s)$ will also be μ provided that $\sum_{i=1}^{n} \omega_i(s) = 1$. The objective of this method is to predict all values between $\widehat{Y}(s)$ and $Y(s_i)$ while yielding a minimum expected mean square error. Prediction is unbiased when the expected value of the difference between sample values and estimated values is equal to 0 - if and only if the sum of weights is in unity and mean squared error is minimized.

Moreover, the mean squared prediction error, otherwise known as the kriging variance, will be:

$$\sigma_e^2 = \sigma^2 - c_+^T(s) C_+^{-1} c_+(s)$$

where C_+ is an augmented matrix and $c_+(s)$ is an augmented vector equal to $C_+\omega_+(s)$. To solve for the predicted values, $\omega_+(s)$ to extract $\omega(\mathbf{s})$ so that $\hat{y}(s) = \omega(s)y$ where $\boldsymbol{y}$ is the vector containing the original observations y.

UNIVERSAL KRIGING

To accommodate a global trend and when the mean is unknown and not constant anymore, the method of ordinary kriging is extended to a more general case which they refer to as universal kriging. In this technique, a first order trend component is included.

Similar to ordinary kriging, this method forms a prediction for y in one step and utilizes a linear combination of weights from the observed values y_i at the sample sites $\boldsymbol{s}_i$. Also, the predicted values become unbiased if and only if the sum of weights is equal to 1. The mean square prediction error is still given by:

$$\sigma_e^2 = \sigma^2 - c_+^T(s)C_+^{-1}c_+(s)$$

Universal kriging estimates the trend in order to obtain residuals after modelling the variogram.

CROSS VALIDATION

To evaluate the adequacy of a spatial correlation model and results from kriging, a method is introduced by using the sample data. This method is known as cross validation. This approach can also be used to choose the appropriate lag and angle tolerances for the variogram estimation. Cross validation is done by:

1. First, exclude the observation y_i from the sample points s_i temporarily
2. The observations are then estimated using the remaining points by an estimation method or model
3. The original observations and estimated ones are then compared for all data points

For the method to be valid, the equation below must be approximately equal to zero.

$$\frac{\sum_{i=1}^{n}\left\{\frac{(y_i - \widehat{y}_i)}{\sigma_{-i}}\right\}}{n}$$

where $\widehat{y}_{-i}$ is the predicted observation from all data points except y_i; and

σ_{-i}^2 is the mean squared prediction error of the predicted observations

The equation is above is similar to what Oliver and Webster (2015) defined as the mean squared deviation ratio, or MSDR. For a model to be unbiased, they further added that MSDR should be really close to 1. Furthermore, the square root of the whole equation above with the values inside the summation being squared should approximately be equal to one. This is much similar to the concept of a root mean squared error (RMSE) or simply the root of squared difference between the observed and predicted values all over the number of observations. The use of this statistic is not new especially when comparing spatial interpolation methods. A study conducted by Taylor and Parker (2008) was used to compare and assess the outputs after the interpolation.

Moreover, to determine if a model is a good fit for the data, prediction sum of squares (PRESS) is calculated and it is given by:

$$\tfrac{1}{n} PRESS = \tfrac{1}{n} \sum_{i=1}^{n} (y_i - \widehat{y}_{-i})^2$$

The equation above should yield a small value for a model to be considered as a good fit, perhaps close to zero, since it is aimed that the difference between the original observations and predicted values is also zero or somewhat close to that value. This is called the mean squared error (MSE), a common indicator if a model or estimator fits well.

RSTUDIO FACILITY

The researchers used RStudio, a programming language common to statistical computing and such, to facilitate the compilation of codes for the calculation of relevant statistics and estimates as well as presentation of important graphs and plots used in this study.

IV. RESULTS AND DISCUSSION

DESCRIPTIVE STATISTICS

Table 1. Descriptive Statistics of the Variables in the Study

Variables	N	Mean	Std. Dev.	Minimum	Maximum
Ammonia	46	2.26802	3.47339	0.013	14.975
Biochemical Oxygen Demand	46	24.7754	59.58239	0.833	317.000
Dissolved Oxygen	46	4.41431	3.05161	0.050	9.567
Nitrate	46	0.50297	0.85766	0.044	5.112
pH	46	7.68370	0.59667	6.350	8.733
Phosphate	46	0.59667	0.40620	0.027	2.245

Table 1 presents the descriptive statistics of the physicochemical parameters used in this study. It is important to note the mean, standard deviation, minimum, and maximum value of each variable as they will be useful in comparing and confirming the predicted values presented in the maps as displayed in the next section.

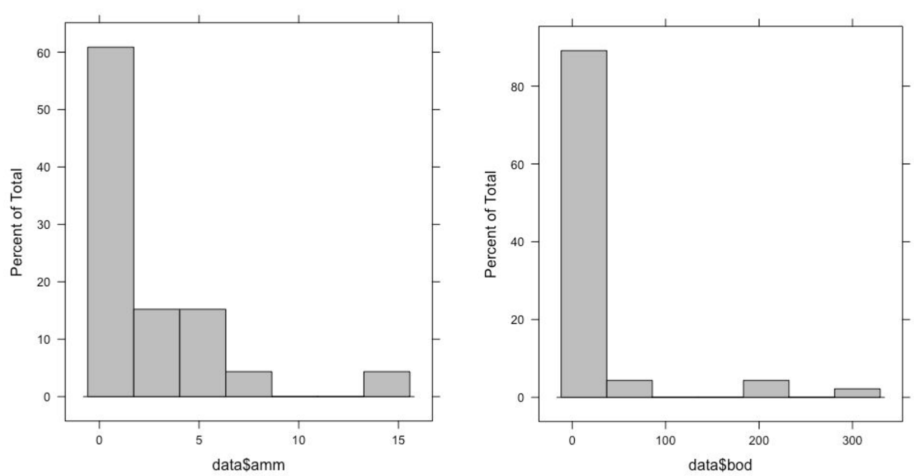
EXPLORATORY DATA ANALYSIS

Table 2. Correlation Coefficients of the Different Variables

	lat	**long**	**x**	**y**	**bod**	**oxy**	**ph**	**amm**	**nit**	**pho**
lat	1	-0.08897575	-0.08223228	0.99996306	0.09856899	-0.06730878	-0.10571051	0.18331348	-0.12806342	0.07628263
long	-0.08897575	1	0.99997702	-0.09752917	-0.42520157	0.60962266	-0.01626996	-0.57965608	0.02166494	-0.53556789
x	-0.08223228	0.99997702	1	-0.09079092	-0.42474811	0.6094671	-0.01705767	-0.57873591	0.02076556	-0.53538119
y	0.99996306	-0.09752917	-0.09079092	1	0.10225707	-0.07259711	-0.10561285	0.18824576	-0.12825325	0.08087962
bod	0.09856899	-0.42520157	-0.42474811	0.10225707	1	-0.50860576	-0.48858725	0.40314235	-0.16565203	0.23461102

oxy	-0.06730878	0.60962266	0.6094671	-0.07259711	-0.50860576	1	0.57680148	-0.67894023	0.12293374	-0.63156757
ph	-0.10571051	-0.01626996	-0.01705767	-0.10561285	-0.48858725	0.57680148	1	-0.28015546	-0.05547948	-0.18059856
amm	0.18331348	-0.57965608	-0.57873591	0.18824576	0.40314235	-0.67894023	-0.28015546	1	-0.09006479	0.86176274
nit	-0.12806342	0.02166494	0.02076556	-0.12825325	-0.16565203	0.12293374	-0.05547948	-0.09006479	1	0.12658249
pho	0.07628263	-0.53556789	-0.53538119	0.08087962	0.23461102	-0.63156757	-0.18059856	0.86176274	0.12658249	1

First, the correlations of the different variables to each other were inspected in order to aid in deciding which covariate to be used in predicting a specific variable. The covariate is taken as a good prediction estimator when the correlation is strong. Good correlation refers to the correlation coefficient that lies between -0.5 to -1 and +0.5 to +1. As seen in table 1, *bod* has good correlation with *oxy*, *oxy* has a good correlation with *amm*, *amm* and *pho* have strong correlation with each other, and *nit* has the highest correlation with *bod* though it is not good enough.



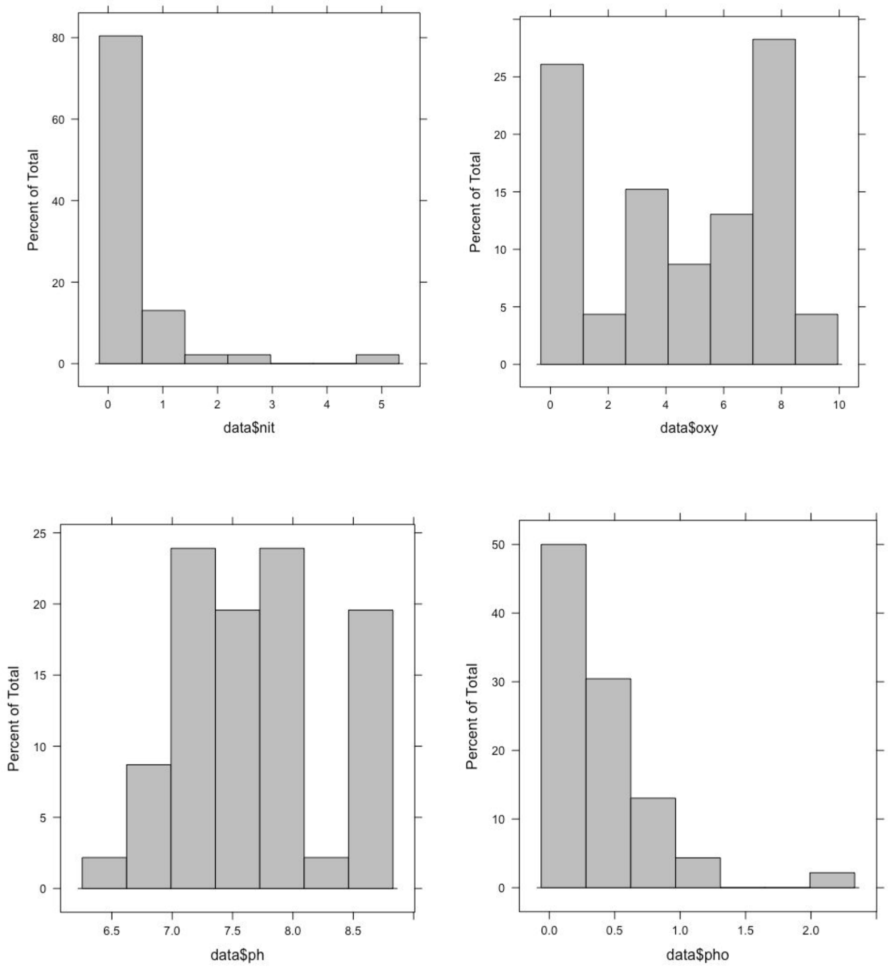


Figure 1. Histograms

A good dataset must have a histogram that has a normal curve, i.e. bell-shaped. The breaks and differing amounts can be an indication of clustering in the dataset. As seen in Figure 1, values for all the variables except *oxy* and *pho* were highly skewed. For this reason, these variables were transformed in order to achieve a bell-shaped histogram. Log-transformation was applied.

AMMONIA

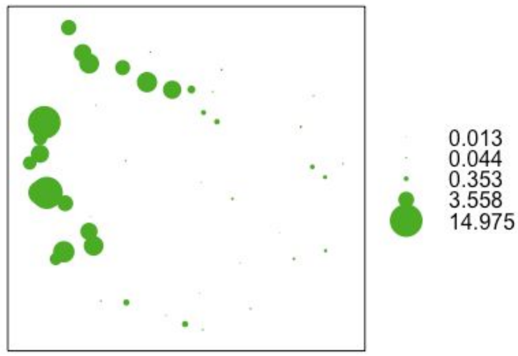


Figure 2. Bubble Plot of Ammonia Concentration

There is relatively high level of ammonia in the northwest of Laguna de Bay. This area consists of rivers flowing around Manila area, Rizal area, and western Laguna.

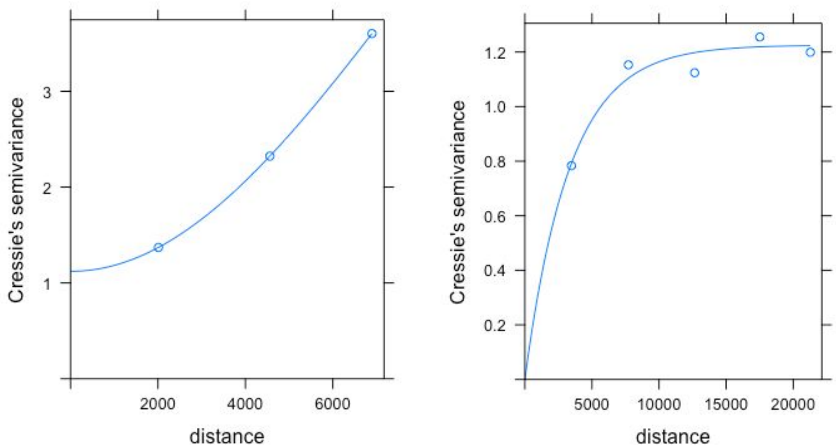


Figure 3. Variogram Models for Ordinary Kriging (left) and Universal Kriging (Right)

Prerequisite to kriging is modelling of the variogram. The Gaussian model yields the best fit for the ordinary kriging while the exponential model yields the best fit for the universal kriging. The Gaussian model is best illustrated as $\gamma(h) = 7.811759\left(1 - e^{\frac{-3h^2}{11152.95^2}}\right)$ with a nugget effect equal to 1.120995. Also, after estimating the coefficients, the exponential model is best illustrated as $\gamma(h) = 1.2256\left(\frac{3h}{2(3342.311)} - \frac{h^3}{2(3342.311)^3}\right)$ when $0 \le h \le 3342.311$, as simple as 0 when $h = 0$, and $\sigma^2 = 1.2256$ otherwise. Furthermore, log(*pho)* was used as a covariate for log*(amm)* in performing universal kriging.

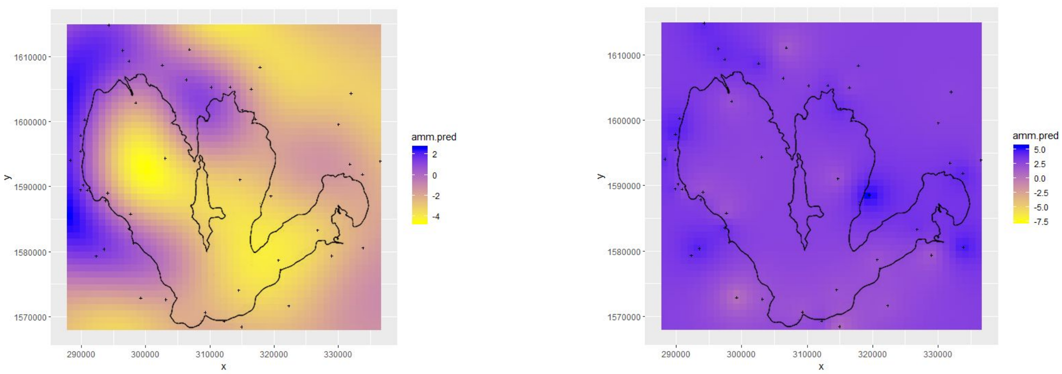


Figure 4. Estimates of Log-ammonia Concentration from Ordinary (left) and Universal Kriging (right)

Figure 4 shows the prediction maps obtained from the interpolation methods. The maps above show different estimates of log-ammonia concentration. In ordinary kriging, it can be seen that high log-ammonia level is present in northwest part which is inline with the findings from the bubble plot earlier. However, estimates from universal kriging showed that the log-ammonia concentration in the whole study region as well as those areas outside it is somewhat constant (value of about 2.5) but there are some areas which have higher concentration compared to the rest as seen in the blue dots.

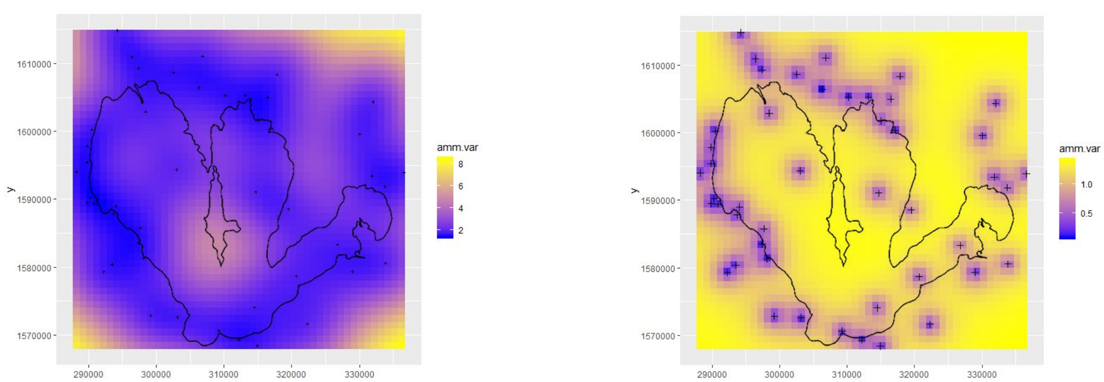


Figure 5. Prediction Variances from Ordinary (left) and Universal Kriging (right)

Figure 5 shows the prediction variances obtained from the two interpolation methods performed. It can be seen that there is small error in prediction in areas with sampled points and those that are close to them for ordinary kriging. However in universal kriging, error is small in the sampled points and areas where there is no sampled point has twice as large error as there is an sampled point. It is also noteworthy that the errors obtained from universal kriging are smaller compared to that of ordinary kriging.

Table 3. Cross-validation Results

	Ordinary Kriging	**Universal Kriging**
RMSE	2.1143	1.1750
Mean Error	-0.1215	-0.0411
MSDR	2.0044	1.3582

Results of cross-validation for ordinary and universal kriging showed that the performance of universal kriging is better than that of ordinary kriging. This is evident in universal kriging's root mean square error (RMSE) which is closer to 1, mean error closer to 0, and mean square deviation ratio (MSDR) closer to 1. These indicates that the estimates from universal kriging are unbiased and represent a good prediction compared to ordinary kriging.

BIOCHEMICAL OXYGEN DEMAND (BOD)

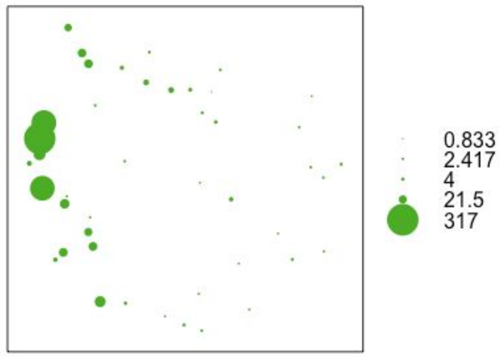


Figure 6. Bubble Plot of BOD Concentration

The bubble plot shown above indicates that there is relatively high BOD concentrations in the northwest of Laguna de Bay. High levels of BOD indicates organic water pollution and attention must be given to these areas since they are at risk of water contamination.

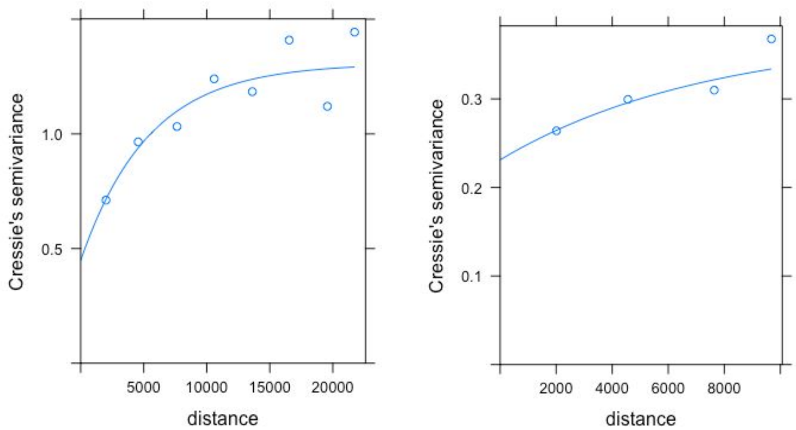


Figure 7. Variogram Models for Ordinary Kriging (left) and Universal Kriging (Right)

As before, variogram was first obtained before performing kriging. The exponential model yields the best fit for both ordinary and universal kriging. The exponential model under ordinary kriging is $\gamma(h) = 0.4480383 + (0.8587912 - 0.4480383)\left(1 - e^{\frac{-3h}{5388.079}}\right)$ when $h > 0$ and 0 otherwise. On the other hand, the exponential model under universal kriging is $\gamma(h) = 0.2312038 + (0.1409128 - 0.2312038)\left(1 - e^{\frac{-3h}{7441.523}}\right)$ when $h > 0$ and also equal to 0 otherwise. Furthermore, *log(oxy)* was used as a covariate for log*(bod)* in performing universal kriging.

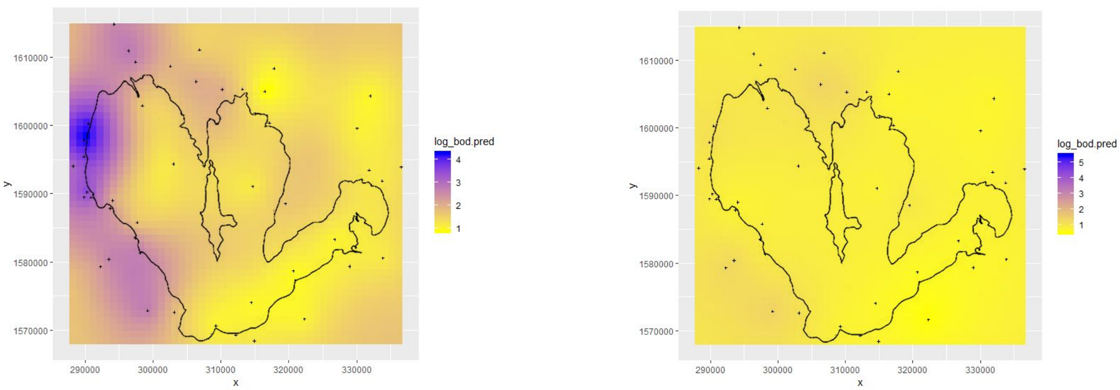


Figure 8. Estimates of Log-BOD Concentration from Ordinary (left) and Universal Kriging (right)

Figure 8 shows the prediction maps obtained from the interpolation methods. The maps above show different estimates of log-BOD concentration. In ordinary kriging, it can be seen that high BOD level is present in northwest part which is inline with the findings from the bubble plot earlier. However, estimates from universal kriging showed that the BOD concentration in the whole study region as well as areas outside it is somewhat constant with a value of 1.

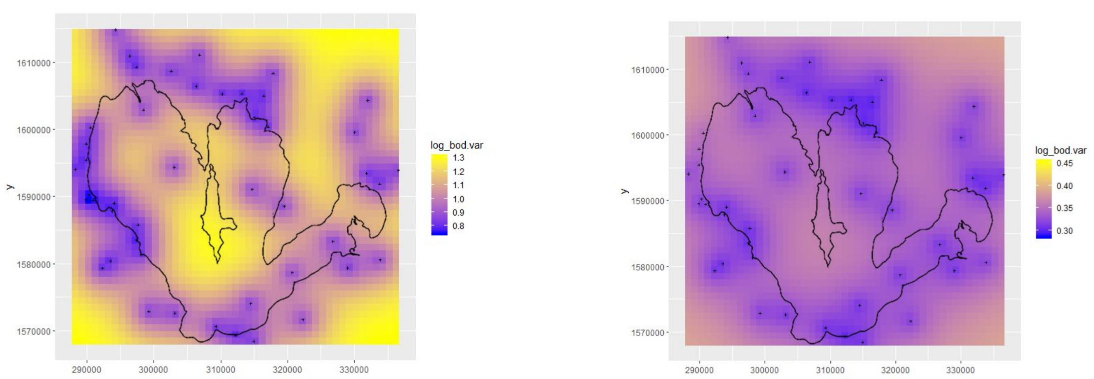


Figure 9. Prediction Variances from Ordinary (left) and Universal Kriging (right)

Figure 9 shows the prediction variances obtained from the two interpolation methods performed. It can be seen that there is a small error in prediction in areas where there is a sampled point and the rest has error in prediction about 1.3. However in universal kriging, it can be seen that areas with sampled points have error about 0.30 and those without have about 0.33.

Furthermore, the prediction variances in universal kriging are smaller compared to that of the ordinary kriging.

Table 4. Cross-validation Results

	Ordinary Kriging	**Universal Kriging**
RMSE	1.0738	0.5443
Mean Error	-0.0443	-0.0011
MSDR	1.1728	0.8876

Results of cross-validation for ordinary and universal kriging showed that the performance of ordinary kriging is better than that of universal kriging. This is evident in ordinary kriging's RMSE which is closer to 1, mean error close to 0, and MSDR closer to 1. These indicates that the estimates from ordinary kriging are unbiased and represent a good prediction compared to universal kriging.

DISSOLVED OXYGEN (DO)

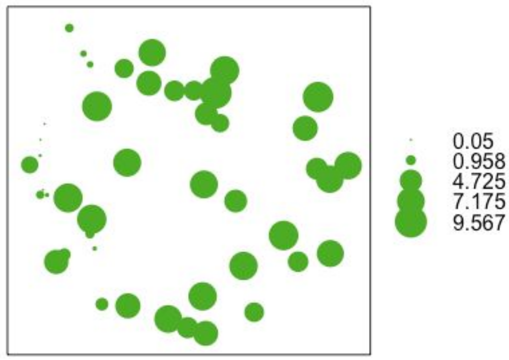


Figure 10. Bubble Plot of Dissolved Oxygen Concentration

The bubble plot above shows high concentration of dissolved oxygen for the whole study region.

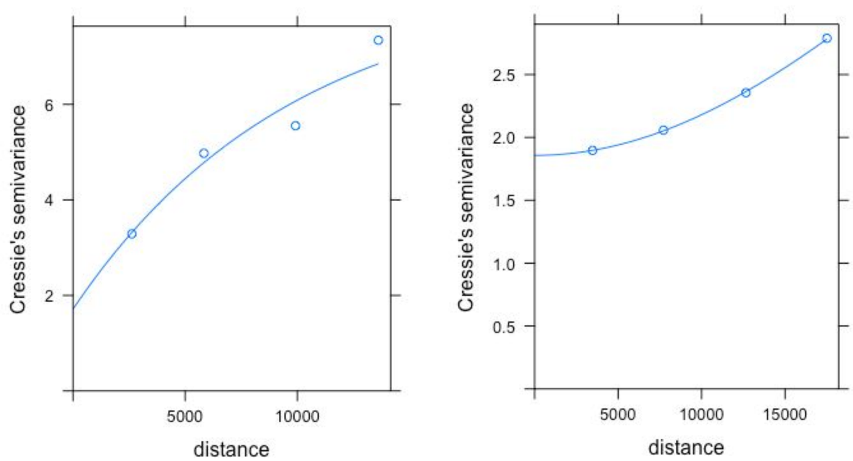


Figure 11. Variogram Models for Ordinary Kriging (left) and Universal Kriging (Right)

As before, variogram was first fitted before performing kriging. The exponential model yields the best fit for ordinary kriging while the gaussian model yields the best fit for universal kriging. The exponential model for dissolved oxygen under ordinary kriging is given by $\gamma(h) = 1.711768 + (9833.878 - 1.711768)\left(1 - e^{\frac{-3h}{6.855187}}\right)$ when $h > 0$ or 0 otherwise. On the other hand, the gaussian model for universal kriging is $\gamma(h) = 4.928672\left(1 - e^{\frac{-3h^2}{38394.46^2}}\right)$ with a nugget effect equal to 1.857170. Moreover, the *log(amm)* was used as a covariate for *oxy* in performing universal kriging.

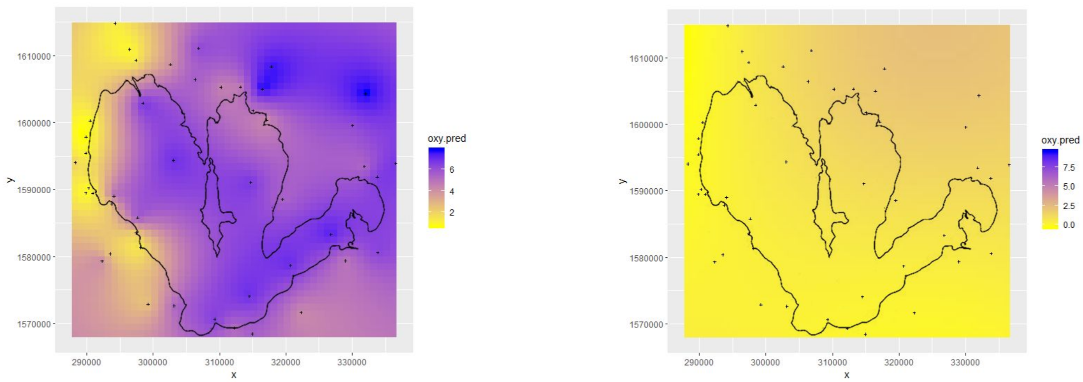


Figure 12. Estimates of Dissolved Oxygen Concentration
from Ordinary (left) & Universal Kriging (right)

Figure 12 shows the prediction maps obtained from the interpolation methods. The maps above show different estimates of dissolved oxygen concentration. For ordinary kriging, it can be seen that the dissolved oxygen concentration inside the study region is about 6, the northwest area outside it has dissolved oxygen concentration about 2, and the northeast area outside it has dissolved oxygen concentration about 8. However, for universal kriging, the dissolved oxygen concentration is constant for the whole study region and areas outside it.

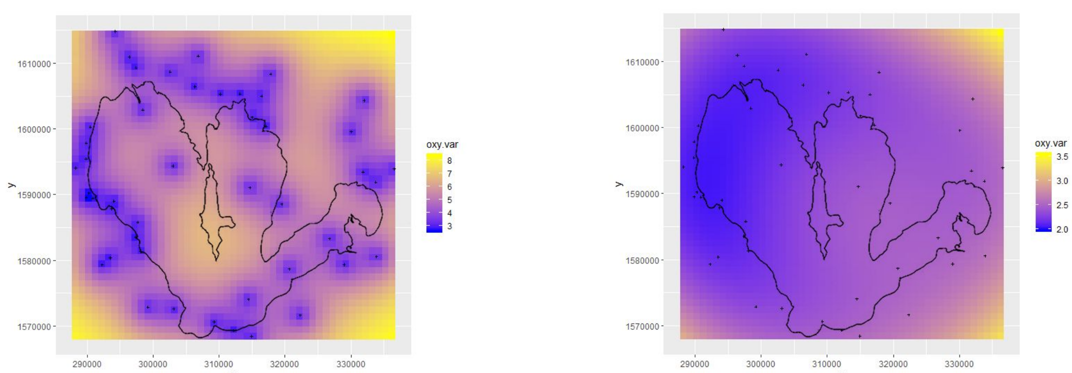


Figure 13. Prediction Variances from Ordinary (left) and Universal Kriging (right)

Figure 13 shows the prediction variances obtained from the two interpolation methods performed. In ordinary kriging, there is a small error in prediction at areas where there is a sampled point and those without has large error in prediction. On the other hand, the whole study region as well as areas outside it has small error in prediction for universal kriging.

Table 5. Cross-validation Results

	Ordinary Kriging	Universal Kriging
RMSE	2.6031	1.7058
Mean Error	0.1236	0.0058
MSDR	1.4991	1.3376

Results of cross-validation for ordinary and universal kriging showed that the performance of universal kriging is better than that of ordinary kriging. This is evident in universal kriging's RMSE which is closer to 1, mean error closer to 0, and MSDR closer to 1. These indicates that the estimates from universal kriging are unbiased and represent a good prediction compared to ordinary kriging.

NITRATE

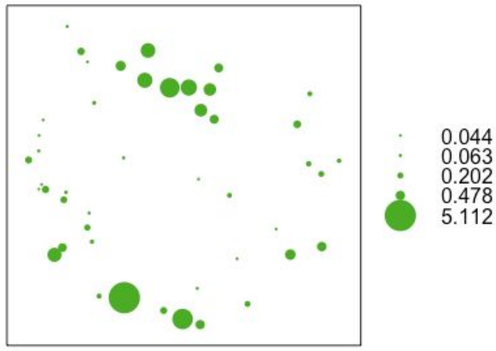


Figure 14. Bubble Plot of Nitrate Concentration

The bubble plot shown above indicates that there is relatively high nitrate concentrations in the northern and southern areas of Laguna de Bay. These areas consist of river flowing around Rizal and southern part of Laguna.

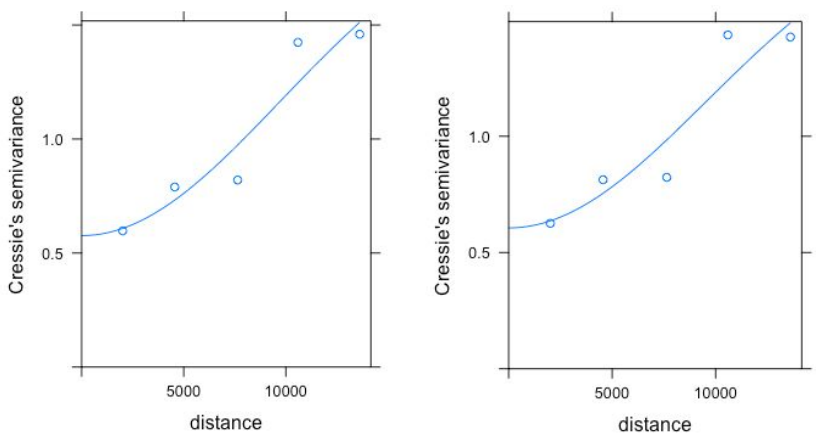


Figure 15. Variogram Models for Ordinary Kriging (left) and Universal Kriging (Right)

The variogram was first fitted before performing kriging. The gaussian model yields the best fit for both ordinary and universal kriging. To illustrate, the gaussian model for ordinary kriging is given by $\gamma(h) = 1.4969034\left(1 - e^{\frac{-3h^2}{13752.24^2}}\right)$ with a nugget effect equal to 0.5764216. Meanwhile, the gaussian model for the universal kriging method for nitrate concentration is $\gamma(h) = 1.3820096\left(1 - e^{\frac{-3h^2}{13501.87^2}}\right)$ with a nugget effect equal to 0.6058362. Furthermore, the spatial coordinates x and y were used as a covariate for log*(nit)* in performing universal kriging since the covariate *bod* which has the highest correlation to the variable of interest didn't yield a linear relationship with log*(nit)*.

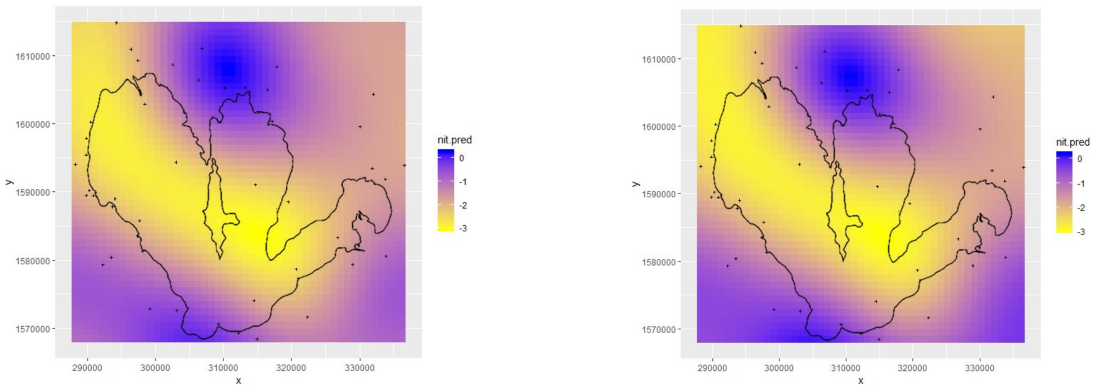


Figure 16. Estimates of Log-nitrate Concentration from Ordinary (left) and Universal Kriging (right)

Figure 16 shows the prediction maps obtained from the interpolation methods. The maps above show similar estimates of nitrate concentration. It can be seen that the nitrate is somehow constant with a value of -3 inside the study region while the nitrate is 0 outside it.

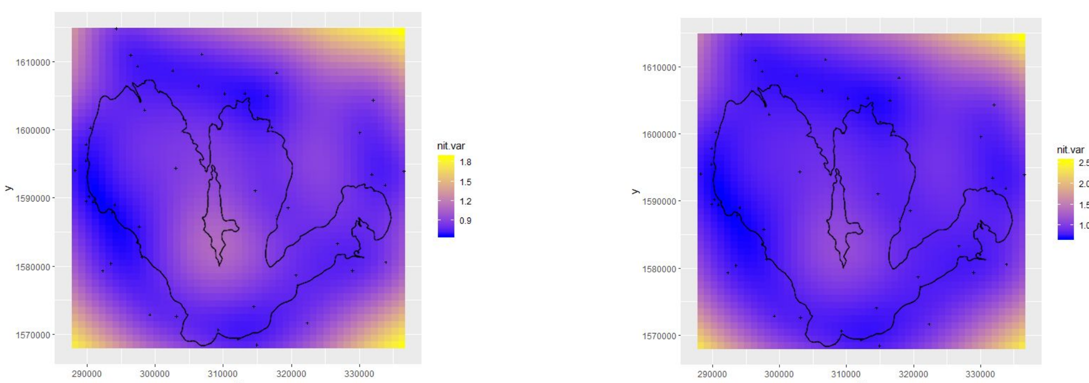


Figure 17. Prediction Variances from Ordinary (left) and Universal Kriging (right)

Figure 17 shows the prediction variances obtained from the two interpolation methods performed. It can be seen that there is a small error in prediction in areas with observed points and those that are close to them. It is also noteworthy that there is a hole seen inside the study region.

Table 6. Cross-validation Results

	Ordinary Kriging	**Universal Kriging**
RMSE	1.9277	1.0176
Mean Error	-0.0676	-0.0225
MSDR	4.6201	1.1726

Results of cross-validation for ordinary and universal kriging showed that the performance of universal kriging is better than that of ordinary kriging. This is evident in ordinary kriging's RMSE which is closer to 1, mean error closer to 0, and MSDR closer to 1. These indicates that the estimates from universal kriging are unbiased and represent a good prediction compared to ordinary kriging.

pH

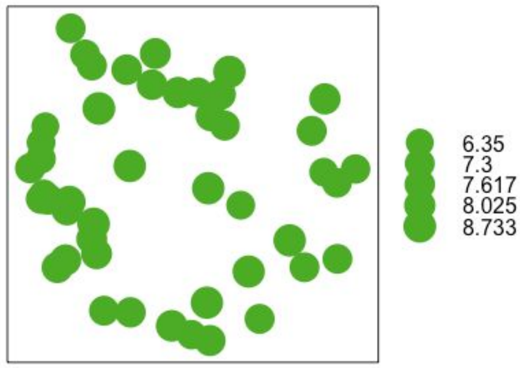


Figure 18. Bubble Plot of pH Level

The bubble plot above shows high level of pH for the whole study region.

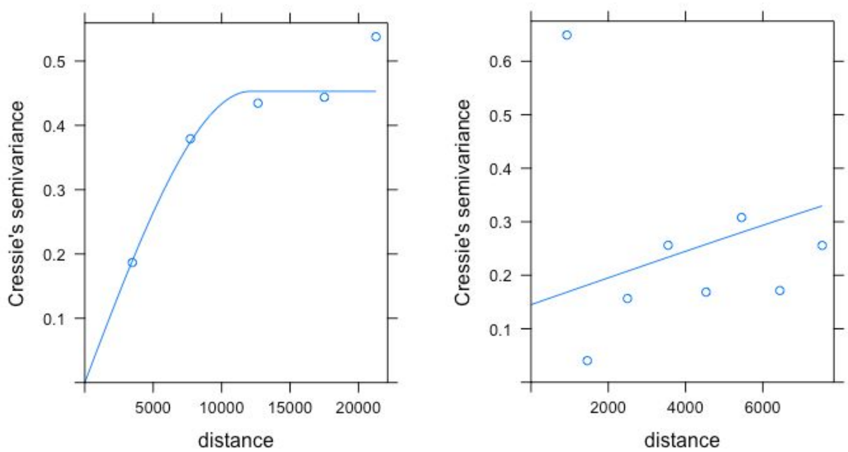


Figure 19. Variogram Models for Ordinary Kriging (left) and Universal Kriging (Right)

The variogram was first fitted before performing kriging. The spherical model yields the best fit both for ordinary kriging and universal kriging. Under ordinary kriging, the spherical model is $\gamma(h) = 0.4529646\left(\frac{3h}{2(12124.25)} - \frac{h^3}{(12124.25)^3}\right) for\ h \leq 12124.25$ or $\sigma^2 = 0.4529646$, otherwise. On the other hand, the spherical model for universal kriging is $\gamma(h) = 0.1450426 + (0.4602812 - 0.1450426)\left(\frac{3h}{2(27494.26)} - \frac{h^3}{2(27494.26)^3}\right)$ when $0 \leq h \leq 27494.26$, as simple as 0 when $h = 0$, or $\sigma^2 = 0.4602812$ otherwise. Furthermore, the spatial coordinates *x* and *y* were used as a covariate for *ph* since the covariate *oxy* which has the highest correlation with the variable of interest didn’t yield a linear relationship with it.

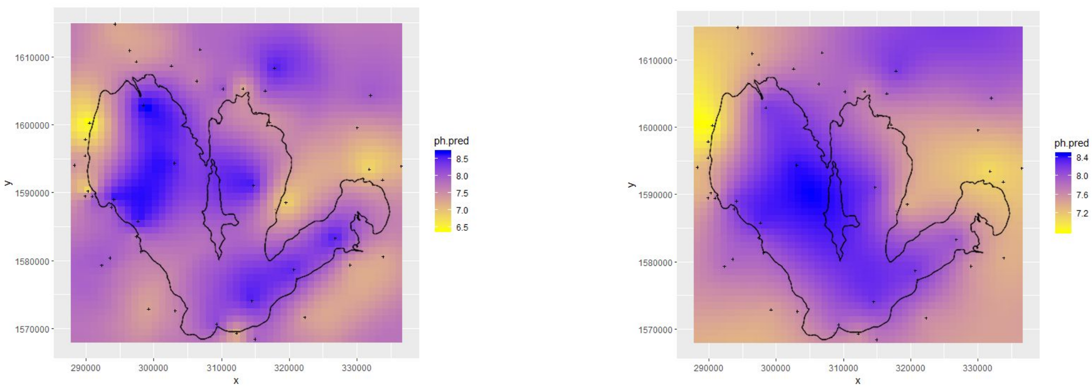


Figure 20. Estimates of pH Level from Ordinary (left) and Universal Kriging (right)

Figure 20 shows the prediction maps obtained from the interpolation methods. The maps above show different estimates of pH level. For ordinary kriging, it can be seen that there is clustering of high pH level in the northern and southern part of the study region. However, for universal kriging, high pH level is evident in the whole region and on the far northeast area.

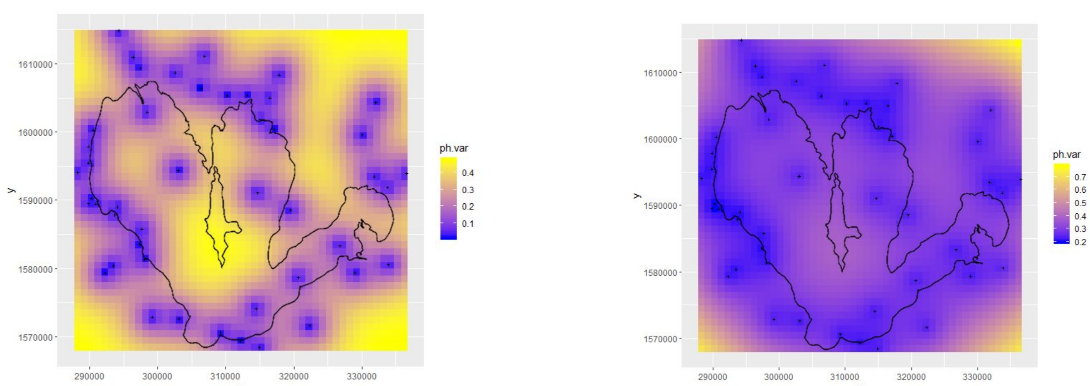


Figure 21. Prediction Variances from Ordinary (left) and Universal Kriging (right)

Figure 21 shows the prediction variances obtained from the two interpolation methods performed. In ordinary kriging, it can be seen that there is a small error in prediction in areas where there is a sampled point and those without has large error in prediction. On the other hand, in universal kriging, small error in prediction is evident in areas with sampled points and those that are close to them.

Table7. Cross-validation Results

	Ordinary Kriging	Universal Kriging
RMSE	0.6166	0.5724
Mean Error	0.0465	0.0134
MSDR	1.7961	1.0824

Results of cross-validation for ordinary and universal kriging showed that the performance of universal kriging is better than that of ordinary kriging. This is evident in universal kriging's RMSE which is close to 1, mean error closer to 0, and MSDR closer to 1. These indicates that the estimates from universal kriging are unbiased and represent a good prediction compared to ordinary kriging.

PHOSPHATE

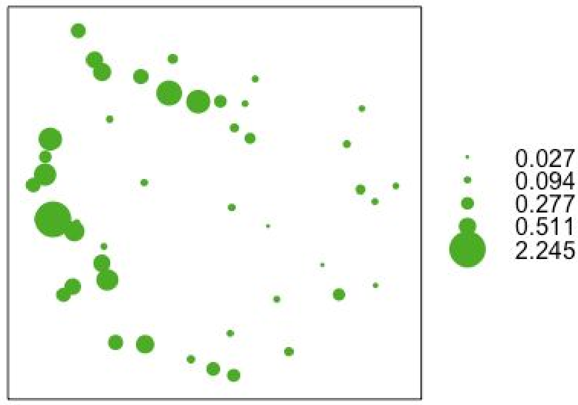


Figure 22. Bubble Plot of Phosphate Concentration

As seen in the bubble plot above, there is a concentration of high phosphate levels in the northwest part of the study area.

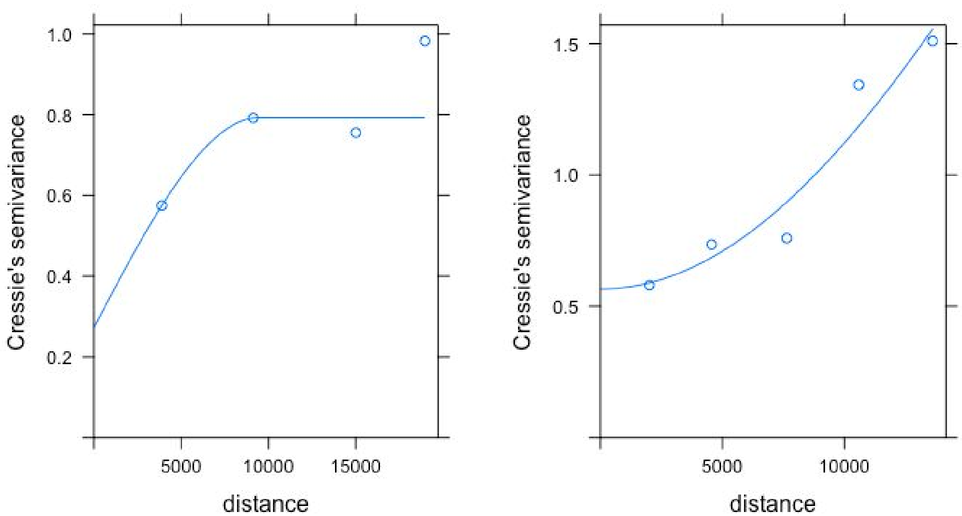


Figure 23. Variogram Models for Ordinary Kriging (left) and Universal Kriging (Right)

As before, variogram was first fitted before performing kriging. The spherical model yields the best fit for ordinary kriging while gaussian model yields the best fit for universal kriging. The spherical model is best represented by the equation $\gamma(h) = 0.3681240 + (0.4162729 - 0.3681240)\left(\frac{3h}{2(8921.636)} - \frac{h^3}{2(8921.636)^3}\right)$ when $0 \le h \le 8921.636$, 0 when $h = 0$, and $\sigma^2 = 0.4162729$, otherwise Furthermore, the *log(amm)* was used as a covariate for in performing universal kriging.

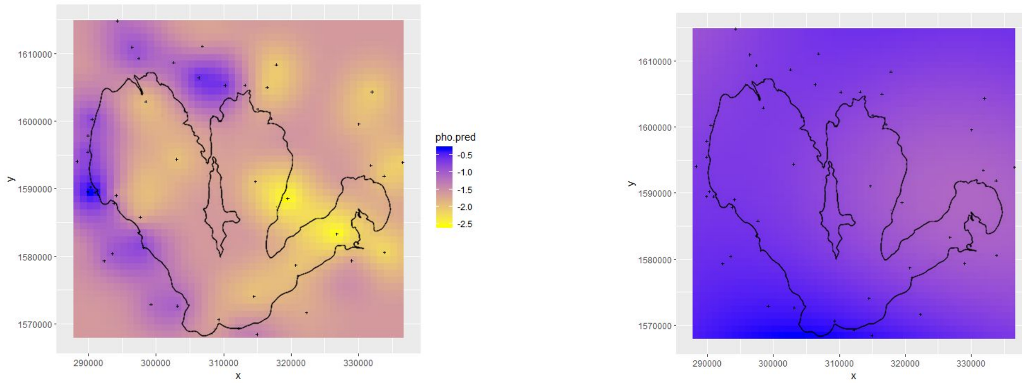


Figure 24. Estimates of Log-phosphate Concentration from Ordinary (left) and Universal Kriging (right)

Figure 24 shows the prediction maps obtained from the interpolation methods. The maps above show different estimates of log-phosphate concentration. For ordinary kriging, it can be seen that the log-phosphate concentration is high at the northwest part outside the study region and it is low at the southeast part. Furthermore, there is mild log-phosphate concentration inside the whole study region. For universal kriging, the whole study region together with the areas outside it have a log-phosphate concentration of -1 and higher towards the positive direction.

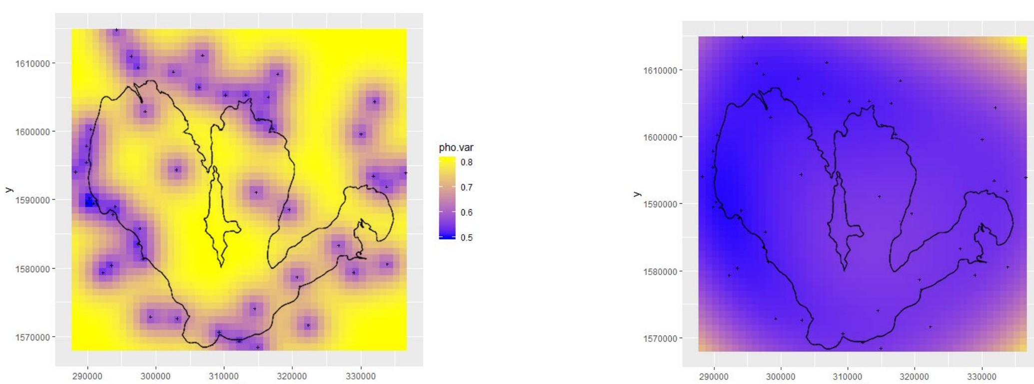


Figure 25. Prediction Variances from Ordinary (left) and Universal Kriging (right)

Figure 25 shows the prediction variances obtained from the two interpolation methods performed. In ordinary kriging, it can be seen that there is a small error in prediction at areas where there is a sampled point and those without has large error in prediction. On the other hand, the whole study region has small error in prediction but comparing it to that of the ordinary kriging, it is way larger.

Table 8. Cross-validation Results

	Ordinary Kriging	**Universal Kriging**
RMSE	0.8690	0.5088
Mean Error	-0.0502	-0.0046
MSDR	1.1518	0.3567

Results of cross-validation for ordinary and universal kriging showed that the performance of ordinary kriging is better than that of universal kriging. This is evident in ordinary kriging's RMSE which is closer to 1, mean error close to 0, and MSDR closer to 1. These indicates that the estimates from ordinary kriging are unbiased and represent a good prediction compared to universal kriging.

V. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

Cross-validation of the results obtained from the two most common spatial interpolation methods showed that universal kriging works best in interpolating most of the water quality parameters considered in the study.

The following are the insights obtained from the interpolation:

1. Under universal kriging, the whole Laguna de Bay as well as those outside it have log-ammonia concentration about 2.5 which is approximately equivalent to 12.18. It is also noteworthy that tributary rivers in Angono, Cainta, Jala-jala, Taytay, Marikina, Taguig, Pagsanjan, Pangil, and Sta. Rosa have even higher ammonia concentration. Furthermore, the value of 12.18 fails the DENR Water Quality Guidelines for Classes A to D waters. Ammonia concentration of this value is toxic to freshwater organisms so necessary actions must be done to treat it in order not to cause damage especially to the livelihood of fishermen.

2. Under ordinary kriging, the whole Laguna de Bay as well as those outside has log-BOD concentration about 1 which is approximately equivalent to 2.72. This value conforms with the DENR Water Quality Guidelines for Class A waters. In terms of BOD concentration, the Laguna de Bay and its tributary rivers can be sources of water supply requiring conventional treatments. However, those tributary rivers found in Cainta, Taytay, Marikina, Muntinlupa, Taguig, Cabuyao, Calamba, San Pedro, and Sta. Rosa have BOD concentration values that fail the DENR Water Quality Guidelines for Classes A to D waters. This means that organic pollution is present in these areas. Attention must be given to these areas since they are at risk of water contamination.

3. Under universal kriging, there is almost 0 dissolved oxygen concentration both for the Laguna de Bay and areas outside it. This value fails the DENR Water Quality Guidelines for Classes A to D waters. The body of water is not healthy enough to sustain many aquatic species in it.

4. Under universal kriging, there is log-nitrate concentration about -3 in Laguna de Bay and those tributary rivers found in Manila area. This value is approximately equivalent to 0.050. This value conform with the DENR Water Quality Guidelines for Classes A, B, and C waters. In terms of nitrate concentration, the waters can be a source of water supply requiring conventional treatment. They are also safe for primary contact recreation such as bathing and swimming. Furthermore, the waters can be used for propagation and growth of fish and other aquatic resources as well as for boating, fishing, agriculture, irrigation, and livestock watering. Furthermore, those tributary rivers in Laguna and Rizal have higher nitrate concentration but they also passed the DENR Water Quality Guidelines for Classes A, B, and C waters.

5. Under universal kriging, most of Laguna de Bay has a pH level of 8.4 while the far northeast area outside it has a pH level of 8. The rest has a pH concentration ranging from 7 to 7.6. These values conform with the DENR Water Quality Guidelines for Classes A and B waters. In terms of pH level, the waters can be a source of water supply requiring conventional treatment. They are also safe for primary contact recreation such as bathing and swimming.

6. Under ordinary kriging, Laguna de Bay and most of its tributary rivers has log-phosphate concentration ranging from -2.5 to -1.0. Taking the anti-log of these yields to values that conform with the DENR Water Quality Guidelines for Classes A, B, and C waters. In terms of phosphate concentration, the waters can be a source of water supply requiring conventional treatment. They are also safe for primary contact recreation such as bathing and swimming. Furthermore, the waters can be used for propagation and growth of fish and other aquatic resources as well as for boating, fishing, agriculture, irrigation, and livestock watering. However, tributary rivers found in Morong, Muntinlupa, and San Pedro have log-phosphate concentration about -0.5. Taking the anti-log of this yields a value

that conforms with DENR Water Quality Guidelines for Class D waters. The waters in these areas are navigable waters.

Since half of the physicochemical parameters considered in the study failed the DENR Water Quality Guidelines, this only means that the life of Laguna de Bay is in danger. The national government as well as the local governments of municipalities around Laguna de Bay must do a collaborative effort in cleaning Laguna de Bay. Rehabilitation of the said lake just like the one done in Boracay can also be done in order to save it from further damage.

For future researchers, it is important to include other physicochemical parameters cited by DENR such as fecal and total coliform concentration in order to look at the overall quality of water at Laguna de Bay. Data gathered in a recent year should also be considered so as to see the progress of lake sustainability. Furthermore, computation of a water quality index from the interpolated values can be done in order to have a single statistic that can best describe the water condition in the said lake.

VI. REFERENCES

Andrews, G. (2018). Resolving the Water Pollution Crisis in the Philippines: the Implications of Water Pollution on Public Health and the Economy. *Pepperdine Policy Review*, *10*(1), 2.

Bailey, T. C., & Gatrell, A. C. (1995). *Interactive spatial data analysis* (Vol. 413). Essex: Longman Scientific & Technical.

Chang, H. (2008). Spatial analysis of water quality trends in the Han River basin, South Korea. *Water research*, *42*(13), 3285-3304.

De Guzman, S. S. (2018). Save Laguna Bay. *Philstar*. Retrieved May 26, 2019, from https://www.philstar.com/opinion/2018/05/28/1819194/save-laguna-de-bay

Food and Agriculture Organization of the United Nations. (2014). Fishery and aquaculture country profiles - The Republic of the Philippines. Retrieved May 26, 2019, from http://www.fao.org/fishery/facp/PHL/en

Goher, M. E. M. (2002). Chemical studies on the precipitation and dissolution of some chemical elements in Lake Qarun. *SA HABIB, AMAS SAMAH*.

Jakubek, D. J., & Forsythe, K. W. (2004). A GIS-based kriging approach for assessing Lake Ontario sediment contamination. *The Great Lakes Geographer*, *11*(1), 1-14.

Kimleang, Chum & Sok, Ty & Ratboren, Chan & Bunmanut, Heng & Siev, Sokly & Heejun, Yang & Yoshimura, Chihiro & Song, Layheang & Oeurng, Chantha. (2017). Assessment of Spatial Interpolation Methods to Map Water Quality in Tonle Sap Lake.

Laguna Lake Development Authority. (n.d.). *Laguna de Bay*. Retrieved May 26, 2019, from http://llda.gov.ph/laguna-de-bay/

Luo, W., Taylor, M. C., & Parker, S. R. (2008). A comparison of spatial interpolation methods to estimate continuous wind speed surfaces using irregularly distributed data from England and Wales. *International journal of climatology*, *28*(7), 947-959.

Maruyama, S., & Kato, H. (2017). Identification of waters incorporated in Laguna Lake, republic of the philippines, based on oxygen and hydrogen isotopic ratios. *Water*, *9*(5), 328.

NSCB (2005). *The Philippine countryside in figures*. National Statistical Coordination Board, Philippines

Oliver, M. A., & Webster, R. (2015). Basic steps in geostatistics: the variogram and kriging (Vol. 106). New York: Springer.

Patil, P. N., Sawant, D. V., & Deshmukh, R. N. (2012). Physico-chemical parameters for testing of water-A review. *International Journal of Environmental Sciences*, *3*(3), 1194.

Qureshimatva, U. M., Maurya, R. R., Gamit, S. B., Patel, R. D., & Solanki, H. A. (2015). Determination of physico-chemical parameters and water quality index (WQI) of Chandlodia lake, Ahmedabad, Gujarat, India. *J Environ Anal Toxicol*, *5*(288), 2161-0525.

Shahid, S. U., Iqbal, J., & Khan, S. J. (2017). A comprehensive assessment of spatial interpolation methods for the groundwater quality evaluation of Lahore, Punjab, Pakistan. *NUST Journal of Engineering Sciences*, *10*(1), 1-13.

Solanki, H. (2012). *Status of Soils and Water Reservoirs near Industrial Areas of Baroda: Pollution and Soil; Water Chemistry*. Lap Lambert Academic Publishing.

Solanki, H. A. (2015). Physico-chemical parameters of water in Bibi Lake, Ahmedabad, Gujarat, India. *Journal of Pollution Effects & Control*, 1-5.

Solanki, H. A., & Pandit, B. R. (2006). Trophic status of lentic waters of ponds water of Vadodara, Gujarat state, India. *Inernational Journal of Bioscience Reporter*, *4*, 191-198.

UN Environment. (2017). *Battling pollution in the Philippines' largest lake*. Retrieved May 26, 2019, from https://www.unenvironment.org/news-and-stories/story/battling-pollution-philippines-largest-lake

United Nations. (n.d.). Sustainable development goals: Sustainable development knowledge platform. Retrieved May 26, 2019, from https://sustainabledevelopment.un.org/?menu=1300

Velasquez, I. B., Jacinto, G. S., & Valera, F. S. (2002). The speciation of dissolved copper, cadmium and zinc in Manila Bay, Philippines. *Marine Pollution Bulletin*, *45*(1-12), 210-217.

Wetzel, R. G. (2001). *Limnology: lake and river ecosystems*. gulf professional publishing.

Yadav, P., Yadav, V. K., Yadav, A. K., & Khare, P. K. (2013). Physico-chemical characteristics of a fresh water pond of Orai, UP, Central India. *Octa Journal of biosciences*, *1*(2).

VII. APPENDIX

APPENDIX A

MONITORING STATIONS

Table A.1 Station Names and Numbers

Station No	Station	Station No	Station
I	Central West Bay	11	San Juan River (Calamba)
II	East Bay	12	Molawin Creek (Los Baños)
IV	Central Bay*	13	Bay River
V	Northern West Bay	14	Pila River
VIII	South Bay	15	Sta. Cruz River*
XV	San Pedro*	16	Pagsanjan River
XVI	Sta. Rosa	17	Pangil River - Downstream*
XVII	Sanctuary	17U	Pangil River -Upstream*
XVIII	Pagsanjan	18	Siniloan River*
1	Marikina River	19	Sta. Maria River - Downstream
2	Bagumbayan River (Taguig)	19U	Sta. Maria River - Upstream*
3	Buli Creek (Taguig)	20	Jala-jala River*
4	Mangangate River - Downstream (Muntinlupa)	21	Pililla River*
4U	Mangangate River - Upstream (Muntinlupa)*	22A	Tanay River - Brgy. Wawa*
5	Tunasan River - Downstream (Muntinlupa)	22B	Tanay River - Midstream*
5U	Tunasan River - Upstream (Muntinlupa)*	22C	Tanay River - Daranak*
6	San Pedro River	23	Baras River
7	Biñan River	24	Morong River - Downstream
8	Sta. Rosa River - Downstream	24U	Morong River - Upstream*
8M	Sta. Rosa River - Midstream*	25	Manggahan Floodway
8U	Sta. Rosa River - Upstream*	26	Sapang Baho River
9	Cabuyao River	27	Angono River*
10	San Cristobal River (Calamba and Cabuyao)	28	Teresa River*

*Stations with estimated coordinates

APPENDIX B

VARIOGRAM MODEL AND ESTIMATES

For Ammonia:

	Ordinary Kriging				Universal Kriging			
Model	***Nugget***	***Range***	***Sill***	***SSError***	***Nugget***	***Range***	***Sill***	***SSError***
Exponential	1.021855	175822	61.895831	$6.534856e^{-07}$	0	3342.379	1.225608	$7.975832e^{-09}$
Gaussian	1.120995	11152.95	7.811759	$1.249803e^{-15}$	0.2925229	2798.785	0.8804467	$1.549527e^{-07}$
Spherical	0.817105	93049.9	26.5129108	$7.553088e^{-07}$	0.3908356	7709.193	0.7705539	$3.655089e^{-08}$

For Biochemical Oxygen Demand:

	Ordinary Kriging				Universal Kriging			
Model	***Nugget***	***Range***	***Sill***	***SSError***	***Nugget***	***Range***	***Sill***	***SSError***
Exponential	0.4480383	5388.079	0.8587912	$2.045443e^{-08}$	0.2312038	7441.523	0.1409128	$3.550943e^{-10}$
Gaussian	0.6401654	5343.719	0.6401654	$2.979494e^{-08}$	0.25076868	4478.54	0.07334218	$4.366684e^{-10}$
Spherical	0.5631601	12867.47	0.6902750	$2.56224e^{-08}$	0.2428541	16626.16	0.1250860	$3.856684e^{-10}$

For Dissolved Oxygen:

	Ordinary Kriging				Universal Kriging			
Model	***Nugget***	***Range***	***Sill***	***SSError***	***Nugget***	***Range***	***Sill***	***SSError***
Exponential	1.711768	9833.878	6.855187	$3.847005e^{-07}$	1.674693	574246	45.452800	$1.690027e^{-07}$

Gaussian	2.704378	6305.264	3.756726	6.362986e^{-07}	1.857170	38394.46	4.928672	1.075515e^{-10}
Spherical	2.235758	18284.05	5.241491	4.721533e^{-07}	1.787578	194254.4	8.001983	1.348148e^{-07}

For Nitrate:

	Ordinary Kriging				**Universal Kriging**			
Model	***Nugget***	***Range***	***Sill***	***SSError***	***Nugget***	***Range***	***Sill***	***SSError***
Exponential	0.5276479	542935.8	42.8597675	1.452723e^{-07}	0.5795448	529176.4	36.1073169	1.248634e^{-07}
Gaussian	0.5764216	13752.24	1.4969034	4.627906e^{-08}	0.6058362	13501.87	1.3820096	5.21137e^{-08}
Spherical	0.510299	171608.9	7.392100	6.748241e^{-08}	0.5207859	192731.9	9.0765564	7.496609e^{-08}

For pH:

	Ordinary Kriging				**Universal Kriging**			
Model	***Nugget***	***Range***	***Sill***	***SSError***	***Nugget***	***Range***	***Sill***	***SSError***
Exponential	0	7645.816	0.5441016	2.956241e^{-09}	0.05345183	20900.61	0.6287710	7.701822e^{-07}
Gaussian	0.07252904	4511.81	0.38527464	1.884454e^{-08}	0.672322	1322845	54659.564	6.463404e^{-06}
Spherical	0	12124.25	0.4529646	1.551528e^{-09}	0.1450426	27494.26	0.4602812	5.935727e^{-07}

For Phosphate:

	Ordinary Kriging				**Universal Kriging**			
Model	***Nugget***	***Range***	***Sill***	***SSError***	***Nugget***	***Range***	***Sill***	***SSError***
Exponential	0	3225.028	0.8231256	5.700641e^{-09}	0.5934489	263916.1	18.2293525	2.6319e^{-07}

Gaussian	0.00636559	2614.65	0.78647381	$7.0779e^{-08}$	0.5656131	32072.28	6.0062518	$3.628345e^{-08}$
Spherical	0.3681240	8921.636	0.4162729	$5.147909e^{-09}$	0.5393616	144505.3	8.2230492	$3.331737e^{-07}$

APPENDIX C

DENR WATER QUALITY GUIDELINES (EXTENDED)

For Ammonia:

CLASS	REMARKS
A	Concentration of less than and up to 0.05 mg/L
B	
C	
D	Concentration of more than 0.05 mg/L and up to 0.75 mg/L
Failed the WQG	Concentration of more than 0.75 mg/L

For Biochemical Oxygen Demand:

CLASS	REMARKS
A	Concentration of less than and up to 3 mg/L
B	Concentration of more than 3 mg/L and up to 5 mg/L
C	Concentration of more than 5 mg/L and up to 7 mg/L
D	Concentration of more than 7 mg/L and up to 15 mg/L
Failed the WQG	Concentration of more than 15 mg/L

For Dissolved Oxygen:

CLASS	REMARKS
A	Concentration of more than and equal to 5 mg/L
B	
C	
D	Concentration of more than 2 mg/L and up to less than 5 mg/L
Failed the WQG	Concentration of less than 2 mg/L

For Nitrate:

CLASS	REMARKS
A	Concentration of less than and up to 7 mg/L
B	
C	
D	Concentration of more than 7 mg/L and up to 15 mg/L
Failed the WQG	Concentration of more than 15 mg/L

For pH:

CLASS	REMARKS
A	Acceptable range = 6.5 to 8.5
B	
C	Acceptable range = 6.5 to 9.0
D	Acceptable range = 6.0 to 9.0
Failed the WQG	Less than 6 and more than 9

For Phosphate:

CLASS	REMARKS
A	Concentration of less than and up to 0.5 mg/L
B	
C	
D	Concentration of more than 0.5 mg/L and up to 5 mg/L
Failed the WQG	Concentration of more than 5 mg/L