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Water Quality Assessment of Mananga River Using Principal Component Analysis

Mary Julia N. Mercado[1], Wesly T. Cai[1], Cybelle Concepcion M. Futalan[2], Mayzonee Ligaray[3,4]*, and Angelo Earvin Sy Choi[1]*

[1]Department of Chemical Engineering, Gokongwei College of Engineering, De La Salle University, Manila 0922 the Philippines
[2]Institute of Civil Engineering, College of Engineering, University of the Philippines Diliman, Quezon City 1101 the Philippines
[3]Institute of Environmental Science and Meteorology, College of Science, University of the Philippines Diliman, Quezon City 1101 the Philippines
[4]Natural Sciences Research Institute, College of Science, University of the Philippines Diliman, Quezon City 1101 the Philippines

The Mananga River in the Philippines has been classified as a Class A river in 1997. Since then, the river has significantly deteriorated due to pollution, especially in the downstream area around Talisay in the Cebu region. In this study, the water quality parameters – namely, dissolved oxygen (DO), biological oxygen demand (BOD), and total suspended solids (TSS) – were assessed using principal component analysis (PCA). Water quality data were obtained from the Department of Environmental and Natural Resources–Environmental Management Bureau Region 7. The water samples were collected on a quarterly basis from 2016–2019. The effect of weather conditions on water quality and significant relationships between the water quality parameters were determined. In addition, the comparison of water quality in each sampling station was investigated. Results show that about 84.3% of the total variance in water quality can be attributed to two significant principal component scores. Evident correlations were observed such as DO and BOD are negatively correlated, whereas a positive correlation exists between DO to RH and wind speed, BOD to temperature, and TSS to wind speed. Furthermore, negative correlations are observed between DO to temperature and wind direction, BOD to rainfall, and TSS to wind direction and rainfall. In the overall analysis of the results, the heavier the influence of a variable, the more likely it is to contribute to affecting the water quality. Therefore, this can alter the overall distribution within the plots and the correlations among the variables. The findings are a predictive measure of future changes and trends in the Mananga River. Therefore, the results of the present work will be used in environmental monitoring, environmental management, and assistance for the rehabilitation of the Mananga River using PCA.

Keywords: Cebu City, Mananga River, principal component analysis, water quality, weather

*Corresponding author: angelo.choi@dlsu.edu.ph
mligaray@iesm.upd.edu.ph

INTRODUCTION

Cebu, which is the seventh most populous city in the Philippines, has one of the fastest economic growths in the region (World Population Review 2022). The dense population in combination with urban development gave rise to the increase in commercial establishments and industries to meet the needs of the people. The discharges from these establishments affect a massive portion of the rivers in the province, one of which is the Mananga River (Flores and Zafaralla 2012). In 1997, the Mananga River was classified as a Type A river, and the quantity of water flow was sufficiently large enough to supply its surroundings. A freshwater body is categorized as Class A for its use as a public water supply Class II, which is a source of water supply that is required to undergo conventional treatment (coagulation, sedimentation, filtration, *etc.*) to meet the Philippine National Standards for Drinking Water. The following criteria are provided for Class A water: maximum biological oxygen demand (BOD) is 3 mg/L, minimum dissolved oxygen (DO) is 5 mg/L, and maximum total suspended solids (TSS) is 25 mg/L. Unfortunately, the recent sampling of the river proved that it no longer possesses the requirements of a Class A river based on the Water Quality Guidelines and General Effluent Standards of 2016, otherwise known as the Department of Environment and Natural Resources (DENR) Administrative Order No. 2016-08. The water quality decline of the rivers increased from upstream to downstream, which could be attributed to the high amount of organic matter present from both unmonitored discharges from natural and anthropogenic sources. Similarly, the study of Amper *et al.* (2019) investigated the effect of land use and practices on the physicochemical parameters of the Muleta watershed. Results show that optimal conditions in water quality were observed in the upstream section of the Muleta River in Bukidnon. A decline in water quality was observed in both the midstream and downstream segments of the river, which was attributed to a combination of abiotic and biotic factors present in the surrounding environment and within the river itself (Amper *et al.* 2019). In another study on Muleta Watershed in Bukidnon, similar results were found where a decline in the water quality of the river was observed in the downstream watershed. In this case, the deterioration of the water quality is due to the land use and land cover of the river (Dumago *et al.* 2018). Moreover, other causes of the decline of the river were attributed to runoff pollution from sewage, improper solid waste disposal, and agricultural matter (Flores and Zafaralla 2012). The assessment of a high number of variables and water quality parameters has proven to be often difficult, especially data interpretation. To address this, various statistical models have been utilized in the reliable measurement and evaluation of water quality parameters and their corresponding changes (Mohamed 2008).

Multivariate statistical models are utilized to determine patterns of variability in random variable samples. There are multiple statistical models that were used in the investigation of the water quality of surface waters and groundwater such as the cyclostationary processes (Boudou and Viguier-Pla 2021), soil and water assessment tool (Kim and Kim 2021), positive matrix factorization (Rahman *et al.* 2021), water quality index (WQI) (Uddin *et al.* 2021), exploratory factor analysis (Kim *et al.* 2017), and principal component analysis (PCA) (Karamizadeh *et al.* 2013). Among these tools, PCA is commonly utilized over the other statistical models. PCA is a dimension-reducing technique extensively used to assess seasonal variation in large and complicated water quality data sets. It is a powerful multivariate analytic method for selecting the most notable features in a dataset. This is commonly used to provide qualitative information on contaminated sources in a system (Rahman *et al.* 2021). PCA reduces the multidimensionality of data to small proportions while maintaining most of the information of the original data and its variability (Karamizadeh *et al.* 2013). In addition, it can transform the original multi-index into independent comprehensive indexes, which could also be applied in the analysis of meteorological studies or weather dynamics (Ling *et al.* 2021). A study on the Marrecas stream in Brazil applied a PCA algorithm that reduced the number of variables for easier testing of each sampling site in the stream (Teixeira de Souza *et al.* 2020). Meanwhile, a study of the Ganga River successfully employed PCA for complex water quality datasets to determine which parameter is responsible for the deteriorating river (Maji and Chaudhary 2019). The study of Chounlamany *et al.* (2017) investigated the water quality of a segment of the Marikina River in terms of spatial and temporal fluctuations. Results of PCA show that 83% of the overall variance in the data set can be attributed to three latent factors (Chounlamany *et al.* 2017). A similar study utilized PCA in the long-term investigation of the water quality and weather trends linked to fish kills at Taal Lake. The application of PCA was set after the authors identified large variations within the data set (Mendoza *et al.* 2019).

Several rivers in the Philippines need to be tested and reclassified, one of which is the Mananga River. However, there is difficulty in analyzing a large amount of gathered data. Some of the rivers that are tested applied tools that make it more complex to identify the classification of the river. PCA is a statistical tool that is seldom used in examining the water quality of rivers in the Philippines. The assessment of the rivers in the Philippines has not yet included the Mananga River. Moreover, no sufficient analysis has been done to re-classify and rehabilitate the Mananga River to date.

Despite being a Class A river, the water quality of the Mananga River continuously deteriorates, which has a detrimental effect on its surrounding environment, ecosystems, and the livelihood of the community. Based on previous literature, there are no reports on the assessment of the Mananga River using multivariate statistical methods in the evaluation of the relationship between water quality parameters and weather conditions. In this study, the water quality of the Mananga River was evaluated using PCA. The significant water quality parameters such as DO, BOD, and TSS, as well as the possible sources of pollution were examined. The study also determined the effects of weather conditions on river water quality. Moreover, the main factors that affect the water quality of the river were determined that could be utilized as a guideline for proper water management and improvement.

MATERIALS AND METHODS

Study Area

The upstream part of the Mananga River originates at the center of Cebu Island and flows south over the steep mountain range located on the eastern side of the province. The river empties into the southwest region of several watersheds such as Mananga, Kotkot, and Lusaran before passing through Talisay City (Flores and Zafaralla 2012). The Mananga River and the location of monitoring stations are shown in Figure 1.

The Ambient Monitoring and Technical Services Section of the Department of Environment and Natural Resources–Environmental Management Bureau (DENR-EMB) Region 7 Office (RO7) defined the five monitoring stations in Mananga River, where the samples for this study were collected. Figure 1 shows the location of the five sampling stations where water samples were collected by the DOST-EMB-RO7 in the Mananga River. Stations 1–5 refer to the Lawaan II Bridge with a position of 10.25°C latitude and 123.83° longitude, SRP Bridge with coordinates 10.26° latitude and 123.84° longitude, Mananga Bridge with 10.26° latitude and 123.84° longitude, Jaclupan with a latitude of 10.28° and longitude of 123.82°, and Camp IV Bridge with latitude 10.32° and longitude of 123.82°.

Mananga River Data Collection

Water samples were collected from 2016–2019 on a quarterly basis by the Ambient Monitoring and Technical Services Section of the DENR-EMB-RO7 using the ambient standard water quality monitoring method. Three water quality parameters (DO, BOD, and TSS) from five

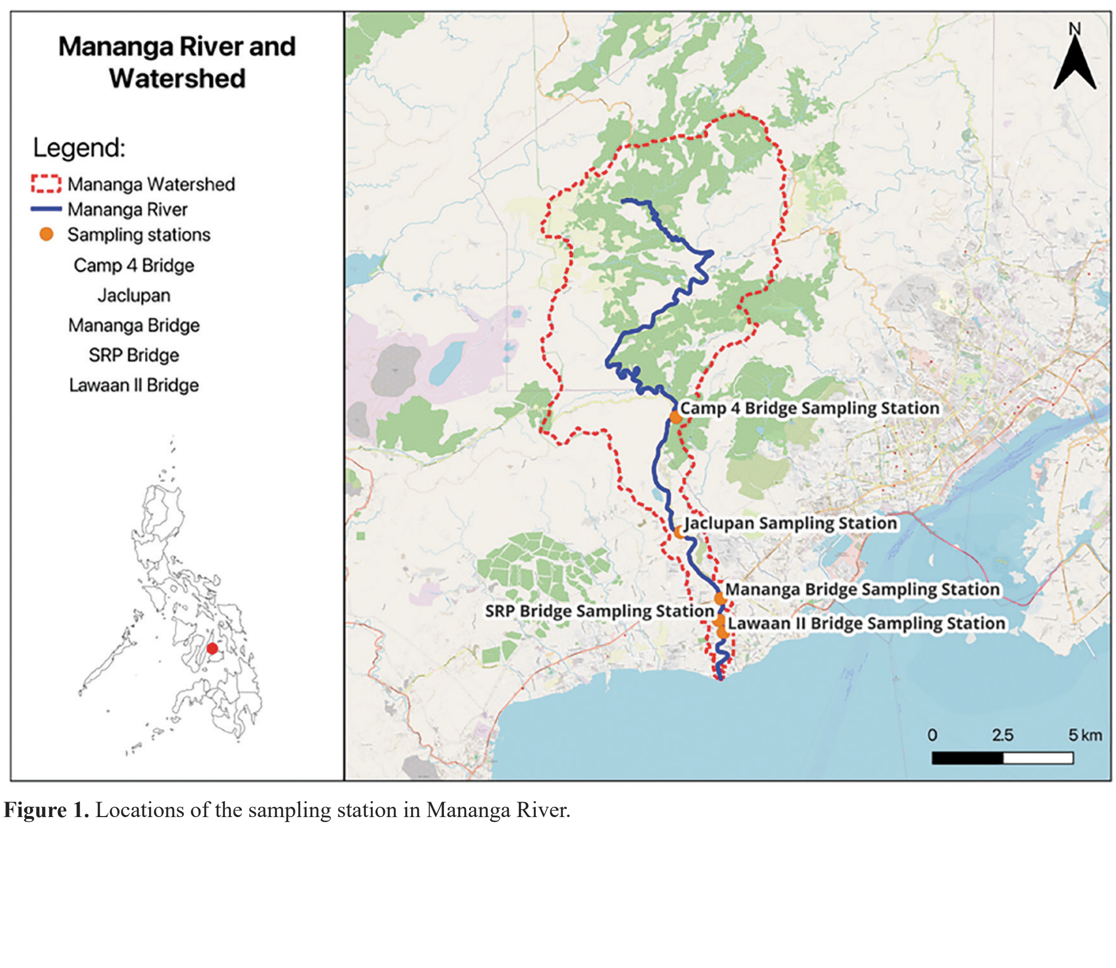

Figure 1. Locations of the sampling station in Mananga River.

monitoring stations were examined. There are other water quality parameters measured but were not included in the present work since there was a significant number of missing values from 2016–2019. The incompleteness of the data can compromise the reliability of the results of the study by interfering with the accuracy and consistency of the findings.

The monthly weather data from 2016–2019 was requested and obtained from the Climate and Agrometeorological Data Section (CADS) of the Department of Science and Technology–Philippine Atmospheric, Geophysical, and Astronomical Services Administration (DOST-PAGASA), which includes the minimum temperature (T_{min}), maximum temperature (T_{max}), wind speed, wind direction, relative humidity (RH), and rainfall. Preprocessing was done to transform the monthly data to a quarterly basis to ensure similarity to the quarterly collection of the water quality parameters. The statistical methods used to convert the data assisted by CADS were the summation of three consecutive months for rainfall, the average of three consecutive months for temperature, RH, and windspeed, and, lastly, the mode of three consecutive months for wind direction. It was recorded at the Mactan Cebu station with a position at 123°58' longitude and 10°18' latitude. The land use, vegetation map, slope map, geomorphological map, and soil series map were acquired from the Bureau of Soils and Water Management. A total of nine variables were inputted into the JMP Pro 11 software to be analyzed.

Principal Component Analysis (PCA)

In this study, the interrelationship and variability of water quality parameters and weather parameters were examined using PCA. The JMP Pro 11 software was utilized to carry out the PCA. Principal components (PCs) were generated as new, uncorrelated variables, which are linear combinations of the original water quality parameters. For ease of interpretation, the PCs produced were rotated using varimax rotation. PCA was performed using the following steps: [a] measurements were standardized, [b] covariance matrix was computed, [c] eigenvalues and eigenvectors were determined, and [d] rejection of components that had little contribution toward variation.

RESULTS AND DISCUSSION

Water Quality in Mananga River

As of 1997, the Mananga River is classified as a Class A freshwater body. Figure 2 shows the average concentration of BOD and TSS from 2016–2019 has exceeded the maximum contaminant level for a Class A river. Meanwhile, annual DO values were within the standard. The highest and lowest DO concentrations were observed in 2016 and 2018, respectively. Figure 2b shows the lowest level of BOD occurred in 2017, whereas the highest level of BOD was observed in 2019. Figure 2c

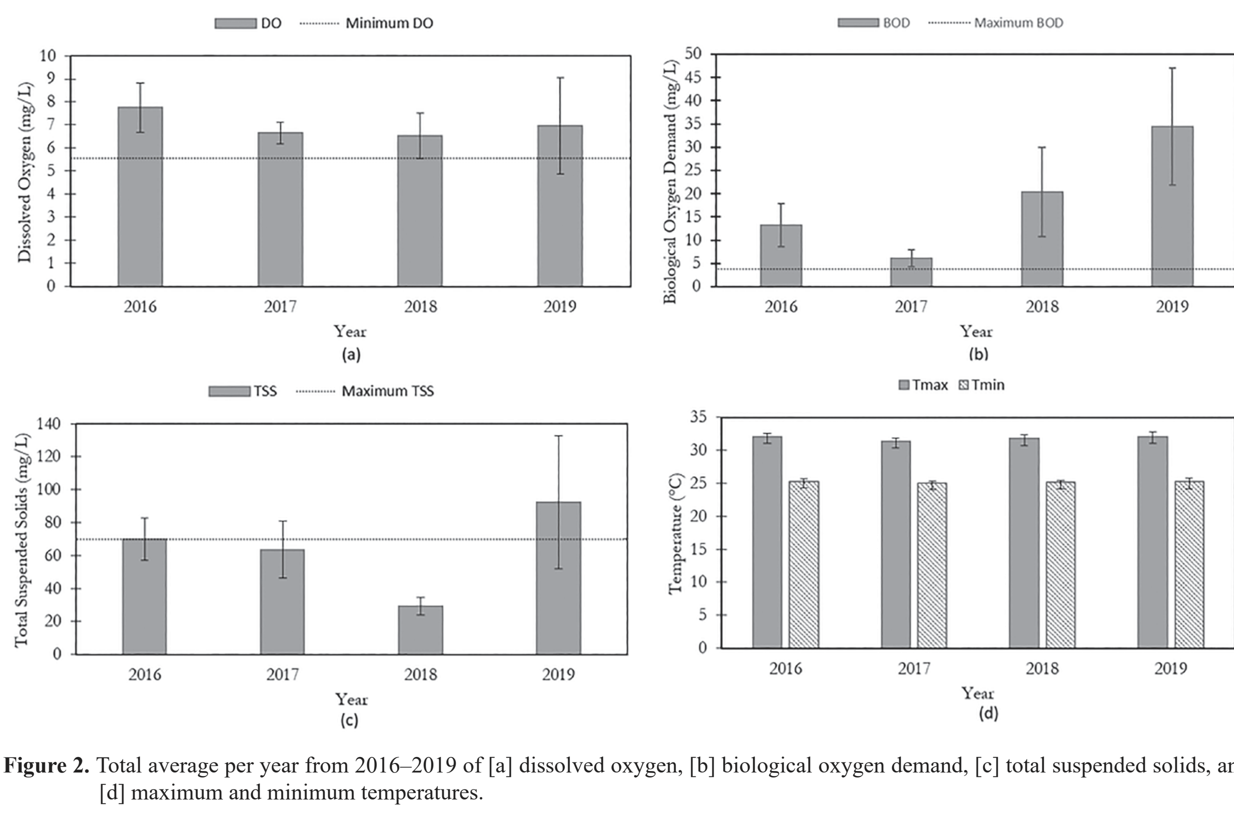

Figure 2. Total average per year from 2016–2019 of [a] dissolved oxygen, [b] biological oxygen demand, [c] total suspended solids, and [d] maximum and minimum temperatures.

shows the TSS concentration to be the highest in 2019. The highest concentrations for BOD (35 mg/L) and TSS (90 mg/L) in Mananga River were observed in 2019. The observed BOD concentration in 2019 does not even conform to the Philippines' water quality guidelines of Class D waters. Lastly, the high concentration of TSS in 2019 is comparable to that of the Class D standard with a concentration of 110 mg/L. Meanwhile, the DO level from 2016–2019 has been within the recommended standard, whereas the values of BOD and TSS in 2019 were not in accordance with the set standard of DENR.

Table 1 illustrates the basic statistics for the three water quality parameters and weather data. Each variable had a total of 63 values in the data set. The standard deviation of the water quality parameters and weather data were determined to assess the deviations with respect to the mean. A low standard deviation value means that data are clustered around the mean, and a high standard deviation indicates data are more spread out making it less reliable. A standard deviation close to zero indicates that data points are close to the mean, whereas a high or low standard deviation indicates data points are respectively above or below the mean. The mean is a description of the usual value within the dataset that is for general comprehension and comparison. Meanwhile, the standard deviation shows how much an individual value deviates from the mean (Smith 2006). Clustering or a higher divergence from the central tendency indicates a greater spread in the data set. Therefore, PCA is a suitable choice to employ for dimensionality reduction and noise reduction with minimal loss from the original information.

Figure 3 displays the result of the PCA from 2016–2019 of water quality parameters such as BOD, DO, and TSS of the Mananga River. A total of three PCs were generated, as shown in Figure 3A, in the eigenvalue Pareto plot. However, only two PCs were considered significant with their eigenvalue greater than 1. PC1 had a cumulative percent of 44.4%, and PC2 had 39.9%. This implies that 84.3% of the total variance in the water quality of the river can be attributed to PC1 and PC2. In Figure 3B, most of the data were clustered on the negative side of PC1 and PC2, whereas the rest were scattered in the other quadrants. TSS was positively correlated to both BOD and DO, whereas the DO and BOD were negatively correlated to one another. The positive correlation between TSS and BOD is attributed to some part of TSS being organic in content that would require oxygen for degradation, whereas the BOD refers to the oxygen demand needed by bacteria in order to break down the substrate present in the water body (Gerardi and Lytle 2015).

To maintain the aquatic life of water bodies, a certain concentration of DO should be maintained. The presence of BOD in waters would imply organic contamination and would require the consumption of oxygen in the water. This shows that BOD is negatively correlated to DO since a high-level BOD would indicate a decrease in DO (USGS 2018). There are several possible sources of BOD such as poultry farms, sanitary landfills, open dump sites, residential areas, and healthcare facilities that surround the river.

Results show that TSS had a positive correlation to DO. During the time of sampling, the temperature of the water was low, which corresponded to a high DO concentration. In addition, the discharge flow of the river may have been strong enough to affect the movement of sediments within the river (Bilotta and Brazier 2008). The major sources of TSS included sand mining, glass and aluminum cutter shops, sanitary landfills, and open dump sites, which are the industries and establishments around the river. However, the study of Gaona *et al.* (2011) determined that TSS was negatively correlated to DO since a high amount of suspended solids would lower the DO content. DO is

Table 1. Descriptive statistics of water quality parameters and weather parameters from 2016–2019.

Parameter	**Mean**				**Standard deviation**
	2016	2017	2018	2019	
Rainfall	1987.30	2134.83	1616.60	1317.60	99.52
T_{max}	32.04	31.40	31.77	32.02	1.10
T_{min}	25.32	25.03	25.21	25.23	0.75
RH	77.43	80.50	77.92	75.08	3.41
Wind speed	3.00	3.00	3.67	3.25	0.99
Wind direction	40.00	40.00	40.00	50.00	78.54
DO	7.76	6.65	6.53	6.96	3.83
BOD	13.23	6.10	20.37	34.48	27.34
TSS	69.8	63.6	29.37	92.44	64.26

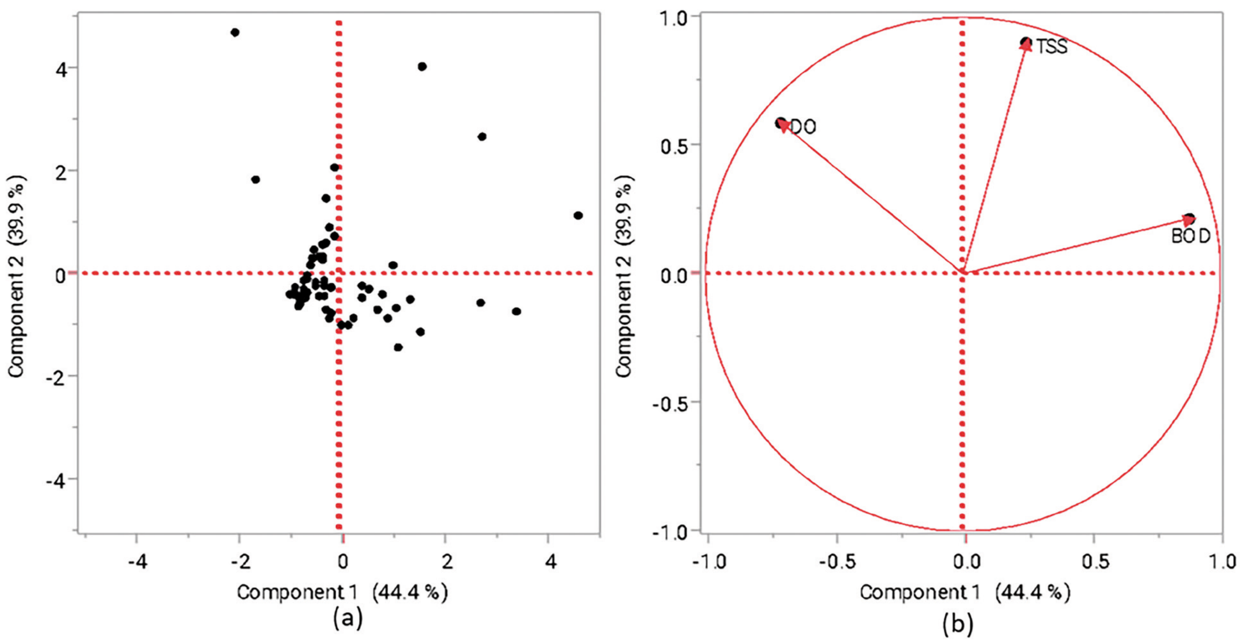

Figure 3. The PCA result of 2016–2019 of BOD, DO, and TSS parameters throughout the whole Mananga River as [a] score plot and [b] loading plot.

consumed by the microbes during the degradation of the organic matter component of TSS.

There are no available studies that correlate each sampling site of the Mananga River, but it can be determined through the flow of the river itself – from the upstream at Camp IV bridge until it flows down to the downstream at Lawaan II bridge. The dynamics of the Mananga River and the effect of each sampling site on one another can be inferred according to the findings made from the study on the Mun River Basin in Thailand, wherein the results show that agricultural activities are the primary cause of pollution in water (Zhao *et al.* 2018). Therefore, this can be deduced that agricultural activities or land use surrounding the river may have affected the water quality. Furthermore, the same study determined that the upper stream during the dry season has better water quality than the lower stream during the wet season. The amount of precipitation varies between the dry and wet seasons, and its dilution of contamination concentrations and conveyance of water flow has an impact on the distribution of the quality of water throughout the river. The spatial distribution of soil nutrients varies significantly between both seasons, and both the amount of soil nutrients present and surface runoff have a direct impact on the quality of water. Human activities have an impact on soil nutrients, which may contribute to nonpoint source pollution in this river basin. Appropriate agricultural practices must be put in place to enhance the water quality (Zhao *et al.* 2018). Hence, the distribution of contaminants such as those that originated from weather and human activities is based on water flow. This is because the movement of water such as in the Mananga River serves as a conduit for pollutants allowing transport and dissemination along the course of the water. As a result, the water quality is lower downstream because it is highly saturated with contaminants.

Results of Weather Data against Water Quality Parameters

Figure 4 shows the relationship between weather data and water quality parameters such as BOD, DO, and TSS of the Mananga River. The eigenvalue Pareto plot for Figure 4A shows that nine PCs were created from the original variables. However, only the first two components (PC1, PC2) were used for the score plot and loading plot. PC1 had the highest cumulative percentage, which was 31.2%, whereas PC2 had 21.2%. The score plot in Figure 4B features the score value (point) for each observation (row) from the input data set. The placement of the points shows how they correlate to the PCs and how they make up the first two PCs. The distribution is observed to be evenly spread out. The clustered points were negatively correlated to PC1 but positively correlated to PC2. The points that are farther apart were positively correlated to PC1 and negatively correlated to PC2. The further apart these points are from the origin and the axis, the more that these points contribute to the making of the PC. The nearer the points are to the origin the less it will likely be contributing to either PC1 or PC2.

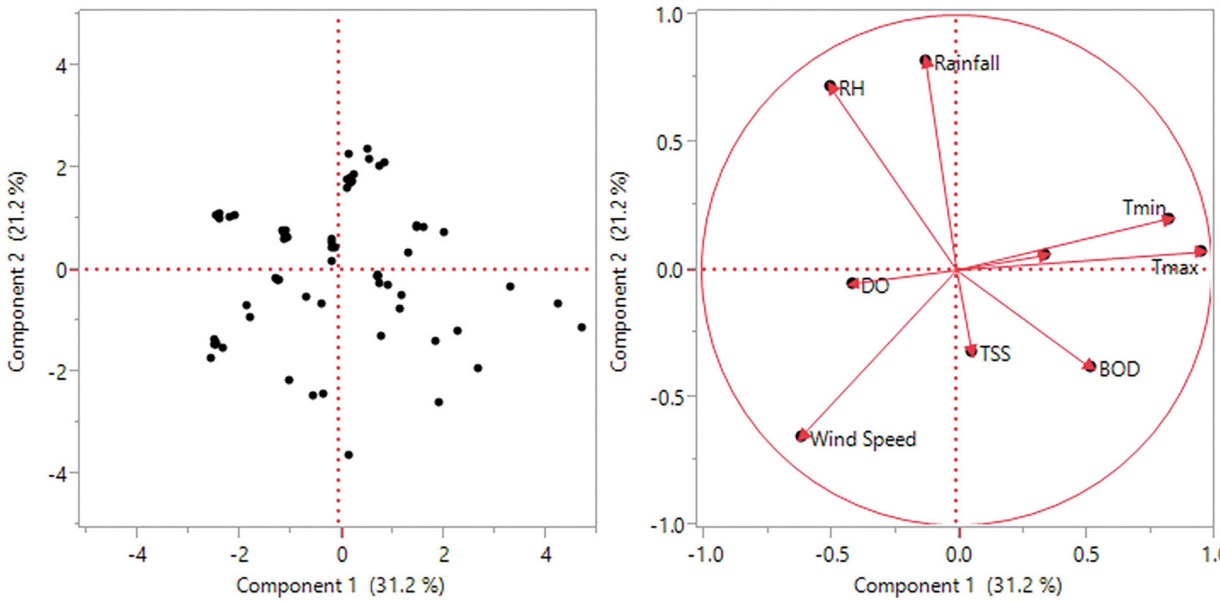

Figure 4. [a] Scatter plot and [b] component loading of the weather data against BOD, DO, and TSS parameters for Mananga River from 2016–2019.

In Figure 4B, the DO, RH, wind speed, and rainfall were negatively correlated to PC1, whereas the rest have a positive correlation. As for PC2, the negatively correlated to it were DO, wind speed, TSS, and BOD. This, then, left the others as positively correlated. TSS, BOD, and wind direction still have a significant intake in creating PCs. However, it does not weigh as much in comparison with the other variables since these variables are near the origin. Moreover, the loading plot specifies the correlation of variables. Wind speed was positively correlated with both TSS and DO. This implies that increasing the wind speed can also increase TSS and DO. A high wind speed facilitated sediment resuspension, which corresponded to a rise in TSS (Du *et al.* 2022). Therefore, the positive correlation between TSS and wind speed proved to be significant, as consistently seen in the results of Figure 4. Additionally, the wind speed also had an influence over the DO concentration. An increase in DO concentration could be attributed to an increase in the rate of re-aeration caused by an increase in wind speed (Elbaradei and Alsadeq 2019). Re-aeration occurs when bubbles develop on the surface of the water; oxygen from the air bubbles dissolves into the water, and the DO concentration is resupplied. Moreover, RH and DO were also positively correlated. An increase in humidity causes the partial pressure of oxygen to rise, which consequently leads to a higher DO level. On the other hand, BOD was positively correlated to T_{max} and T_{min}, which signifies the correlation of BOD to temperature. High temperature indicates an increase in microbial activity, which would lead to high oxygen consumption (de Matos *et al.* 2014). Another positive correlation is the wind direction to BOD. Tidal factors affect BOD concentration since wind direction affects the tides. The concentration increases when the tide flows towards the land lagoon and decreases when the tide flows toward the sea (Rizki *et al.* 2021). The findings in Figure 4 deviate from the previous study due to the water body of a river in this research has a larger surface area as opposed to a lagoon. The larger an area of water over which the wind blows, the greater its effect on the body of water. In this case, since a river has a smaller surface area, it is less affected by the wind. Therefore, the results of this research may deviate from those found in studies conducted in other type of water bodies. There were also negatively correlated variables among the plots. According to Figure 4, the RH is negatively correlated to TSS and BOD. This finding serves as the correlation result for this research. However, there were no other similar recorded relationships found to support the relationship of RH to TSS and BOD. Rainfall was negatively correlated to TSS and BOD. Based on Figure 4, the TSS was negatively correlated to rainfall. Pollutants undergo dissolution during rainfall, which would lower TSS. Some part of the TSS is dissolved and converted as total dissolved solids (Gong *et al.* 2016). Thus, an increase in rainfall activity would decrease TSS due to it breaking down into smaller particles. Moreover, rainfall was negatively correlated with BOD. The effect of high rainfall produces more surface runoff, which results in higher inflow of water into the river. The high discharge of surface runoff would result in the dilution of pollutants in the river, which would result in lower BOD concentration. Furthermore, Figure

4 illustrates the negative correlation of DO concentration to T_{min} and T_{max}. Thus, DO was negatively correlated with temperature. A study stated that oxygen solubility is highly dependent on water temperature; as temperature rises, oxygen solubility decreases, hence resulting in a decrease in DO concentration (Rajwa-Kuligiewicz *et al.* 2015). As a result, cold water has a higher concentration of DO, whereas hot water has a lower DO count. Lastly, wind direction was negatively correlated with DO. In a study of the Changjiang Estuary, strong winds reduce DO levels due to algal bloom caused by wind mixing. When the direction of such strong winds is directed to the Mananga River, it is possible that algal blooms form, which results in decreasing amounts of DO (Ni *et al.* 2016). Therefore, wind direction does affect the DO count negatively. The more wind is present in an area, the more likely DO amounts are to be reduced.

CONCLUSION

The study investigates the water quality of the Mananga River from 2016–2019. Moreover, the effects of weather parameters on the water quality of the river were also examined. Results show some parameters vary throughout the year and most of the time, the water quality of the Managa River does not meet the Class A standards, especially during 2019. Results show the deteriorating water quality of the river and its temporal variations, which prompts the implementation of an effective environmental and water resource management plan.

PCA was applied to determine the significant relationship between the water quality parameters and weather conditions. BOD was positively correlated to TSS and negatively correlated to DO, which are similar to the results of other studies. PCA was also used to compare the stations by means of the parameters. A correlation was found between each station. However, it does not specify the in-depth connection between them. The only connection between sampling stations that were analyzed is through the flow of the river, whereby the water quality of the river is better during the dry season than in the wet season. It was also observed that the upstream had a better water quality than the downstream of the river.

Results of the PCA also show that weather has a significant effect on the water quality of the Mananga River. The most significant correlations observed were that of the positively correlated variables such as DO to RH and wind speed, BOD to temperature, and TSS to wind speed. Meanwhile, the significantly negatively correlated variables include DO to temperature and wind direction, BOD to rainfall, and TSS to rainfall. The component loading plot shows that BOD is seen to be most negatively correlated to rainfall and temperature when compared to other water quality parameters.

The present study analyzed the water quality data (DO, BOD, and TSS) of the Mananga River from 2016–2019 due to full representation. However, there are limitations to the dataset obtained from the DOST-EMB-RO7. Other water quality parameters were excluded due to the incompleteness of the dataset, which would prevent the utilization of PCA. To ensure the integrity of the data set and for a more accurate analysis using PCA, the variables with a lack of data were omitted.

Water quality assessment involves the measurement of multiple parameters, whereby these parameters contribute to a high-dimensional dataset. Therefore, the use of PCA simplifies the analysis and focuses on the most significant factors. PCA is a guide into which variable has the most impact on water quality, thus capturing the need to produce monitoring programs around these specific parameters. Furthermore, PCA reveals patterns and trends within the data set and could further identify relationships and correlations between variables that would assist in determining which parameter affects another. Furthermore, the PCA plots are influenced by the variables; the more influential a variable is, the more likely it is to contribute to the creation of the PCs. An influential variable can alter and change how PCs are created. Thus, the correlation of variables can also be affected.

RECOMMENDATION

The pre-assessment of the water quality of the Mananga River was performed in this study. Results show the degradation of the river and it is recommended for reclassification. The use of PCA assisted in determining the variations in water quality parameters and analysis of an extensive dataset. In future studies, it is highly encouraged to analyze all nine water quality parameters taken over a long period of time. Most importantly, there should be constant monitoring to be able to identify necessary actions that can be taken to avoid further deterioration of the Mananga River.

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REFERENCES

AMPER RAL, PUNO GR, PUNO RCC. 2019. Rapid assessment of the riparian zone habitat of river. Global Journal of Environmental Science and Management 5(2): 175–190. https://doi.org/10.22034/gjesm.2019.02.04

BILOTTA GS, BRAZIER RE. 2008. Understanding the influence of suspended solids on water quality and aquatic biota. Water Research 42(12): 2849–2861. https://doi.org/10.1016/J.WATRES.2008.03.018

BOUDOU A, VIGUIER-PLA S. 2021. Principal components analysis and cyclostationarity. Journal of Multivariate Analysis [104875]. https://doi.org/10.1016/J.JMVA.2021.104875

CHOUNLAMANY V, TANCHULING MA, INOUE T. 2017. Spatial and temporal variation of water quality of a segment of Marikina River using multivariate statistical methods. Water Science and Technology 76(6): 1510–1522. https://doi.org/10.2166/WST.2017.279

DE MATOS MP, BORGES AC, DE MATOS AT, DA SILVA EF, MARTINEZ MA. 2014. Effect of time-temperature binomial in obtaining biochemical oxygen demand of different wastewaters. Engenharia Agricola 34(2): 332–340. https://doi.org/10.1590/S0100-69162014000200014

DU Y, SONG K, WANG Q, LI S, WEN Z, LIU G, TAO H, SHANG Y, HOU J, LYU L, ZHANG B. 2022. Total suspended solids characterization and management implications for lakes in East China. Science of the Total Environment 806: 151374. https://doi.org/10.1016/j.scitotenv.2021.151374

DUMAGO SWL, PUNO GR, INGOTAN SS. 2018. Water quality assessment in various land use and land cover of Muleta Watershed Bukidnon, The Philippines. Journal of Biodiversity and Environmental Sciences 12(3): 201–209. http://www.innspub.net

ELBARADEI SA, ALSADEQ MAIW. 2019. Effect of wind speed on water quality parameters. IJASEAT 1(4): 16–20.

FLORES MJL, ZAFARALLA MT. 2012. An Assessment of the Physicochemical Parameters of Mananga River, Cebu, the Philippines. IAMURE International Journal of Ecology and Conservation 4(1). https://doi.org/10.7718/ijec.v4i1.363

GAONA CAP, POERSCH LH, KRUMMENAUER D, FOES GK, WASIELESKY WJ. 2011. The Effect of Solids Removal on Water Quality, Growth, and Survival of *Litopenaeus vannamei* in a Biofloc Technology Culture System. International Journal of Recirculating Aquaculture 12(1): 54–73. https://doi.org/10.21061/IJRA.V12I1.1354

GERARDI MH, LYTLE B. 2015. BOD and TSS. The Biology and Troubleshooting of Facultative Lagoons. p. 195–198. https://doi.org/10.1002/9781118981771.CH27

GONG Y, LIANG X, LI X, LI J, FANG X, SONG R. 2016. Influence of rainfall characteristics on total suspended solids in urban runoff: a case study in Beijing, China. Water 8(7): 278.

KARAMIZADEH S, ABDULLAH SM, MANAF AA, ZAMANI M, HOOMAN A, KARAMIZADEH S, ABDULLAH SM, MANAF AA, ZAMANI M, HOOMAN A. 2013. An Overview of Principal Component Analysis. Journal of Signal and Information Processing 4(3): 173–175. https://doi.org/10.4236/JSIP.2013.43B031

KIM J, KIM Y. 2021. Statistical interpolation method for water quality data to improve water quality calibration and validation in watershed models. Ecohydrology & Hydrobiology 21(1): 67–78. https://doi.org/10.1016/J.ECOHYD.2020.08.002

KIM SE, SEO IW, CHOI SY. 2017. Assessment of water quality variation of a monitoring network using exploratory factor analysis and empirical orthogonal function. Environmental Modelling & Software 94: 21–35. https://doi.org/10.1016/J.ENVSOFT.2017.03.035

LING Z, GAO Y, CHEN Q. 2021. Application of principal component analysis in meteorological forecast. IOP Conference Series: Earth and Environmental Science 631(1). https://doi.org/10.1088/1755-1315/631/1/012019

MAJI KJ, CHAUDHARY R. 2019. Principal Component Analysis for Water Quality Assessment of the Ganga River in Uttar Pradesh, India. Water Resources 46(5): 789–806. https://doi.org/10.1134/S0097807819050129

MENDOZA MU, DUR G, ROSANA MR, SANTOS MD, MUTIA MTM, KAWIT NS, ITE MO, VILLANUEVA LS, ANNEVILLE O, SOUISSI S, PAPA RDS. 2019. Water quality and weather trends preceding fish kill occurrences in Lake Taal (Luzon Is., the Philippines) and recommendations on its long-term monitoring. https://scienggj.org/2019/PSL%202019-vol12-no02-p147-156-Papa%20et%20al.pdf

MOHAMED M. 2008. Water Quality Models in River Management. 1st Technical Meeting of Muslim Water Researchers Cooperation (MUWAREC). p. 14–26.

NI X, HUANG D, ZENG D, ZHANG T, LI H, CHEN J. 2016. The impact of wind mixing on the variation of bottom dissolved oxygen off the Changjiang Estuary during summer. Journal of Marine Systems 154: 122–130. https://doi.org/10.1016/J.JMARSYS.2014.11.010

RAHMAN K, BARUA S, IMRAN HM. 2021. Assessment of water quality and apportionment of pollution sources of an urban lake using multivariate statistical analysis. Cleaner Engineering and Technology 5: 100309. https://doi.org/10.1016/J.CLET.2021.100309

RAJWA-KULIGIEWICZ A, BIALIK RJ, ROWIŃSKI PM. 2015. Dissolved oxygen and water temperature dynamics in lowland rivers over various timescales. Journal of Hydrology and Hydromechanics 63(4): 353–363. https://doi.org/10.1515/johh-2015-0041

RIZKI N, MASLUKAH L, SUGIANTO DN, WIRASATRIYA A, ZAINURI M, ISMANTO A, PURNOMO AR, NINGRUM AD. 2021. Distribution of DO (Dissolved Oxygen) and BOD (Biological Oxygen Demand) in the Waters of Karimunjawa National Park Using Two-dimensional Model Approach. IOP Conference Series: Earth and Environmental Science 750(1). https://doi.org/10.1088/1755-1315/750/1/012014

SMITH L. 2006. A tutorial on PCSA. Department of Computer Science, University of Otago. p. 12–28.

TEIXEIRA DE SOUZA A, CARNEIRO LATX, DA SILVA JUNIOR OP, DE CARVALHO SL, AMÉRICO-PINHEIRO JHP. 2020. Assessment of water quality using principal component analysis: a case study of the Marrecas stream basin in Brazil. Environmental Technology 42(27): 4286–4295. https://doi.org/10.1080/09593330.2020.1754922

UDDIN MG, NASH S, OLBERT AI. 2021. A review of water quality index models and their use for assessing surface water quality. Ecological Indicators 122: 107218. https://doi.org/10.1016/J.ECOLIND.2020.107218

[USGS] US Geological Survey. 2018. Biological Oxygen Demand (BOD) and Water. Retrieved from https://www.usgs.gov/special-topics/water-science-school/science/biochemical-oxygen-demand-bod-and-water

WORLD POPULATION REVIEW. 2022. Population of Cities in The Philippines. Retrieved from https://worldpopulationreview.com/countries/cities/the Philippines

ZHAO Z, LIU G, LIU Q, HUANG C, LI H. 2018. Studies on the Spatiotemporal Variability of River Water Quality and Its Relationships with Soil and Precipitation: a Case Study of the Mun River Basin in Thailand. International Journal of Environmental Research and Public Health 15(11). https://doi.org/10.3390/IJERPH15112466