Spatio-Temporal Variability of Water Quality in the Upper Chao Phraya River, Thailand, between 2008 and 2018

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ABSTRACT

Variability of water quality in the three largest tributaries of the Upper Chao Phraya River Basin (Ping, Nan, and Chao Phraya rivers) was examined over 11 years (2008-2018) using annual averages of 12 water quality parameters from six surface water stations. We applied two multivariate methods, namely a self-organizing map (SOM) and principal component analysis (PCA) to assess the spatio-temporal variation. The results revealed strong spatio-temporal patterns of water quality conditions, evidenced by three distinct clusters of samples (ANOSIM, $p<0.05$). The PCA explains as much variation as possible in two dimensions, which eigenvalues of two axis is 45.08 %. The graphical PCA shows that cluster B is completely separated, while the cluster A and C overlap. Parameters in cluster A (comprising many of the Ping, Nan, and Chao Phraya samples between 2009-2018, and further separated by drought and floods years) were within the regulated standards for surface water. In cluster B, which only included the Chao Phraya stations during the dry period from 2013-2015, the water quality was affected by community waste, as indicated by high total coliform bacteria and fecal coliform bacteria. Meanwhile, cluster C comprised 2008, 2011, 2012 and 2017 samples from the Ping, Nan, and Chao Phraya rivers in high flood periods, and was further divided into two sub-clusters. It was characterized by high turbidity (121.70±47.59 NTU) and total solids (240.96±30.75 $mg \cdot L^{-1}$), which were caused by heavy rains and flooding. Our analyses show that the variability of water quality in the studied area was largely affected by human activities and seasonal variation.

Keywords: Principal component analysis, Self-organizing map, Water monitoring, Water quality

INTRODUCTION

The goods and services provided by rivers support human livelihoods in various forms and have a close relationship with human societies (i.e., culture and religion) (Khorooshi *et al*., 2016). Increasing population as well as urban and industrial development are among the key factors degrading water quality, altering hydrological cycles and changing the assemblage of aquatic fauna and river ecosystems (Tudesque *et al*., 2008; Altansukh and Davaa, 2011). Monitoring of water quality, hydrological regimes, and aquatic faunal composition is important for assessing river conditions, and can support a precautionary approach that provides time and opportunity for improvement or recovery (Simeonov *et al*., 2010).

The Chao Phraya River Basin is the most important system in central Thailand, with a drainage area of approximately 162,000 km^2 (30 % of the country's total area), and is home to 40 % of the Thai population (Nakamuro *et al*., 1982; Komori *et al*., 2012; Huang *et al*., 2019). The basin can be considered as two parts-upper and lower-which are geographically divided by a narrow section in

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Nakhon Sawan Province (Komori *et al*., 2012). The upper river basin is mountainous with a floodplain along the river, and contains the Ping River (33,900 km^2 of watershed area), the Wang River (10,800 km^2), the Yom River (24,047 km^2), and the Nan River (34,300 km^2) (Komori *et al*., 2012; Wichakul *et al*., 2014). The Chao Phraya River (and the lower basin) originates from the union of these four rivers (i.e., Ping, Wang, Yom, and Nan) in Nakhon Sawan Province. Downstream, the Chao Phraya joins with the Sakae Krang River at Chai Nat Province, then flows through floodplain in the country's central region, which covers 55,290 km^2 (35 % of the total basin area) (Office of Natural Water Resources Committee of Thailand, 2003; Komori *et al*., 2012).

The river supports many activities such as agriculture, fisheries, recreation, industry, and municipal uses (Huang *et al*., 2019; Singkran *et al*., 2019). People living in the riparian area depend on the water resources; for example, in Nakhon Sawan Province, it is estimated that 31 % of GPP is from agriculture and livestock, which rely on water supplies from the Chao Phraya (Nakhon Sawan Statistical Office, 2018). Recently, the area along the river has shown a rapid change due to vast urbanization, economic growth, industry expansion, intensive agriculture development, and other human activities (Molle, 2007). The anthropogenic stressors along the river have inevitably led to a deterioration of water quality. Besides these direct stressors, climate change has also been recognized as a tremendous cause of changes in the timing and intensity of precipitation, and of hydrological characteristics of the river (e.g., flooding and flow) (Naik and Jay, 2011; Singkran *et al*., 2019). Moreover, nutrient transport and eutrophication are affected by the change in river flow, and consequently impact the river's aquatic flora and fauna (Prathumratana *et al*., 2008).

Flood and drought periods, as well as changes in stream flow, can lead to eutrophication and nutrient transport, which affect water quality factors such as DO, BOD, NH_4^+ and turbidity (Senhorst and Zwolsman, 2005; Prathumratana *et al*., 2008). DO represents available oxygen for aquatic animals, while BOD is the collective compounds. The level of pH is critical for the toxicity of heavy metals and their metabolism by aquatic organisms (Sidabutar *et al*., 2017). Nitrogen compounds (ammonia and nitrate) are toxic to aquatic life at high pH, while nitrite is a main cause of eutrophication (MPCA 2008; Sidabutar *et al*., 2017). Furthermore, total coliform bacteria and fecal coliform bacteria are commonly used indicators of water contaminated by the feces of humans and other warm-blooded animals (Huang *et al*., 2019). Turbidity, total solids, and suspended solids, meanwhile, affect the penetration of light into water, which influences both photosynthesis and water temperature (Bidorn *et al*., 2016). Population pressure and environmental phenomena are increasing sediment loads and suspended solids through deforestation for agriculture, water resource development, and heavy floods (Bidorn *et al*., 2016; Sidabutar *et al*., 2017).

Water quality data encompass a large and complex set of parameters, often with multidimensional, non-linear, and non-normal distribution (Ye *et al*., 2015; An *et al*., 2016). Meanwhile, many statistical methods have the weakness of requiring normal distribution of data. The assessment of water quality, especially variation in space and time, is performed by multivariate analysis techniques such as principal component analysis (PCA) and self-organizing maps (SOM), which are powerful tools when applied to these types of data. Both techniques have been widely applied in water quality, aquatic ecology, hydrology and the environment (Kalteh *et al*., 2008; Mishra, 2010; Ye *et al*., 2015; An *et al*., 2016; Chea *et al*., 2016; Sowmiya and Raj, 2016; Orak *et al*., 2020). Although PCA is limited to classification, it is an effective technique to identify important parameters and explain the variance of a large dataset of correlated variables with a smaller set of independent variables (Mishra, 2010; An *et al*., 2016). Meanwhile, SOM can be used for monitoring and determining spatio-temporal variation by clustering and classification (Ye *et al*., 2015). SOM is an unsupervised artificial neural network, which is a powerful method for the analysis of large data sets by reducing high dimensional input data to a low dimensional map in an output layer (Chea

The surface water quality in Thailand is monitored by the Pollution Control Department (PCD). A general water quality assessment is conducted based on the surface water quality standards and water quality index, and is reported every year (Simachaya, 2000; Wongaree, 2019). Most previous studies of water quality in the Chao Phraya River Basin were focused on only one effect on water quality, such as season, flood or drought, climate change, and anthropogenic effects that do not relate to spatio-temporal variation (Komori *et al*., 2012; Wichakul *et al*., 2014; Singkran *et al*., 2019). However, recognizing long-term changes (i.e., over decades) of some important water quality parameters and their patterns of change in space and time is also important for resource managers to better maintain or improve water quality. This paper, therefore, aims to assess the spatio-temporal variation of 12 selected water quality parameters among representative stations over 11 years of sampling in the upper part of Chao Phraya (i.e., Nakhon Sawan Province).

MATERIALS AND METHODS

Water quality parameters considered for this study included physical, chemical, and biological properties that are affected by anthropogenic stress, eutrophication, or climate change. The selected water quality parameters comprised pH, dissolved oxygen (DO, $mg \cdot L^{-1}$), biochemical oxygen demand (BOD, $mg \cdot L^{-1}$), water temperature (WT, °C), turbidity (Tur, NTU), total solids (TS, $mg \cdot L^{-1}$), suspended solids (SS, $mg \cdot L^{-1}$), total coliform bacteria (TCB, $MPN \cdot 100\ mL^{-1}$), fecal coliform bacteria (FCB, $MPN \cdot 100\ mL^{-1}$), ammonia nitrogen (NH_3-N, $mg \cdot L^{-1}$), nitrate (NO^-_3-N, $mg \cdot L^{-1}$), and nitrite (NO^-_2-N, $mg \cdot L^{-1}$). Water quality parameters were obtained from monitoring data used in surface water quality standards and a water quality index (WQI) developed by the Thailand Pollution Control Department, which describes methods for water quality analysis (Simachaya, 2000; Pitakwinai *et al*., 2018). All parameters were obtained from six stations (PI01, PI02, NA01, NA1.1, CH30, and CH32) during 2008-2018 (Figure 1). The abbreviations PI, NA, and CH stand for Ping, Nan, and Chao Phraya rivers, respectively. The PI and CH stations are in community zones, while NA is representative of a rural zone (Table 1). The raw data were supplied by Regional Environmental Office 4, in which the monitoring of surface water quality parameters is conducted four times per year.

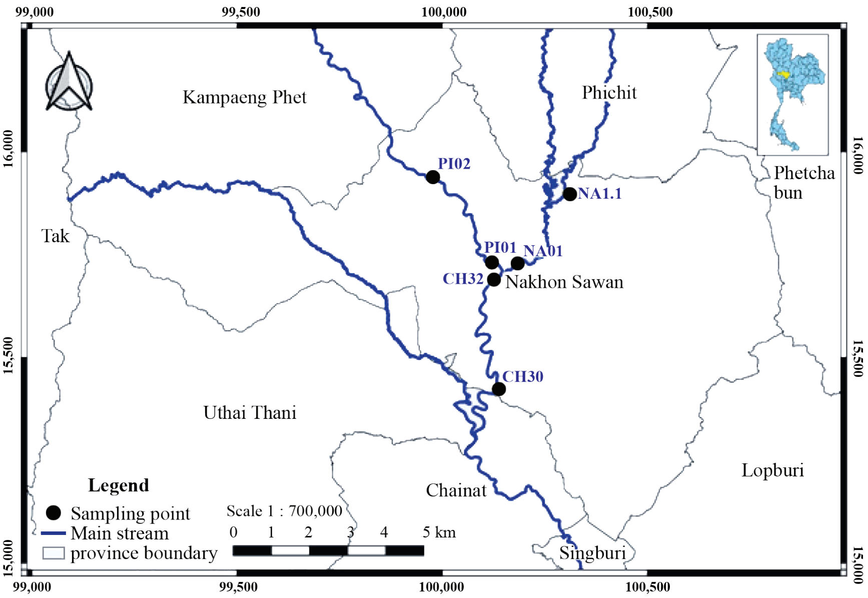

Figure 1. Location of surface water sampling stations in Nakhon Sawan Province (marked yellow in inset).

Table 1. Location and characteristics of surface water stations used for water quality study of the Upper Chao Phraya River.

Station Name	Geographical co-ordinates	Characteristics
PI01	100.1208° N 15.7257° E	This reach of Ping River receives water from agricultural areas and riparian communities. The topography of the river is shallow and narrow.
PI02	99.9790° N 15.9294° E	This reach of Ping River receives water from agricultural areas and community areas in Banphot Phisai District, Nakhon Sawan Province. The topography of the river is shallow and narrow.
NA01	100.1897° N 15.7270° E	This reach of Nan River receives water from agricultural areas and riparian communities. The topography of the river is narrow and deep.
NA1.1	100.3102° N 15.8979° E	This reach of Nan River receives water from agricultural areas and community areas in Chum Saeng District, Nakhon Sawan Province. The topography of the river is narrow and deep.
CH30	100.1385° N 15.4226° E	This reach of Chao Phraya River receives water from agricultural areas, community and market areas in Phayuha Khiri District, Nakhon Sawan Province. The topography of the river is wide and deep.
CH32	100.1260° N 15.6857° E	This reach of Chao Phraya River receives water from the community and market area in Muang District, Nakhon Sawan Province. The topography of the river is narrow and deep.

The data were then prepared as a matrix of samples in columns (i.e., observation at surface water station x year, for example CH32_08 is the observation from station CH32 in year 2008) and annual average values for water quality parameters (12 variables) in rows.

A self-organizing map (SOM) was used to investigate spatio-temporal variation by clustering the samples according to differences in water quality data. The SOM is an unsupervised algorithm of an artificial neural network (ANN) (Kohonen, 1982). It has been applied to studies of water resources and ecology, and is capable of clustering and classification. SOM is a powerful method for the analysis of complex data with non-linear relationships; it classifies similar elements from high dimensional input data into a low dimensional map in an output layer (Kalteh *et al*., 2008; Orak *et al*., 2020). The SOM consists of two layers (input and output) that are connected by weight vectors (An *et al*., 2016). The input layer in our case contained 12 neurons (water quality parameters), which connected 66 input vectors (i.e., samples) to the output layer. The output layer comprised 42 neurons, which was represented by a lattice map with six rows and seven columns. The number of neurons on the map was calculated from the equation $C = 5\times\sqrt{n}$, as proposed by the laboratory of Computer and Information Science (CIS), Helsinki University, where C is the number of cells and n is the number of observations, and which guarantees a minimum of quantization and topographic errors. The hierarchical cluster analysis (Ward's method) was used to help in decisions on cluster classification. Significant differences among clusters were determined by the analysis of similarity (ANOSIM), which uses occurrence probability from the connection intensity during the learning process in SOM at α = 0.05.

The interrelationship among samples and the 12 water quality parameters was determined by principal component analysis (PCA). All parameters have different units of measurement, which creates substantial variance. The data were standardized by a covariant matrix with a mean of 0 and a standard deviation of 1 (Souza *et al*., 2020). The Monte Carlo method was used to test significance of results with 1,000 random permutations. Differences among clusters of each water quality parameter was also tested by Kruskal-Wallis, and Wilcoxon's post-test was applied if a significant difference was found at α = 0.05. All statistical methods were performed by Program R (R Core team, 2020) with kohonen (Wickham, 2016), factoextra (Wehrens and Kruisselbrink, 2018) and ggplot2 packages (Kassambara and Fabian, 2020).

RESULTS AND DISCUSSION

Self-organizing map (SOM)

The SOM categorized the samples into 42 cells, with each cell representing a different suite of water quality parameter values (i.e., samples within a cell have similar values for all parameters). As similar samples are mapped close together and dissimilar ones farther apart, SOM cells were grouped into three clusters, based on the hierarchical dendrogram results (Figure 2 and Figure 3). ANOSIM indicated significant dissimilarity among the three clusters ($p<0.05$). Cluster A samples were mostly from the Ping (PI01 and PI02) and Nan (NA01 and NA1.1) rivers between 2013 and 2016. Cluster Bincluded only Chao Phraya River samples (CH30 and CH32), which clearly separated it from the other clusters. Samples in this cluster were exclusively taken between 2013 and 2015, a notably dry period. Cluster C contained the remaining samples and could be divided into two sub-clusters.

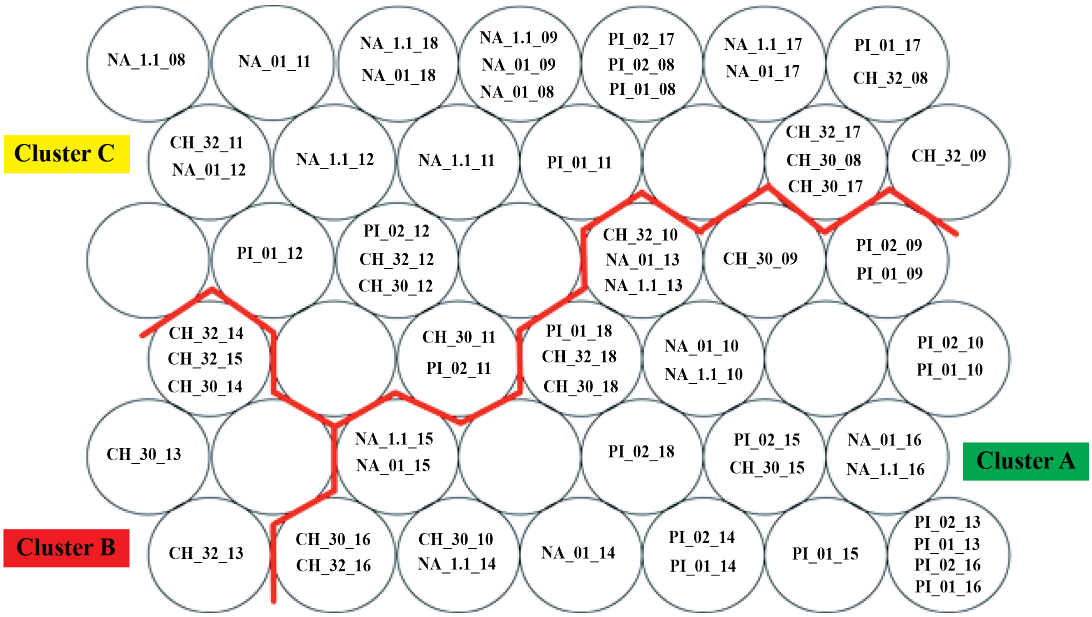

Figure 2. Output layer of 42 neurons as clustered by self-organizing map (SOM).

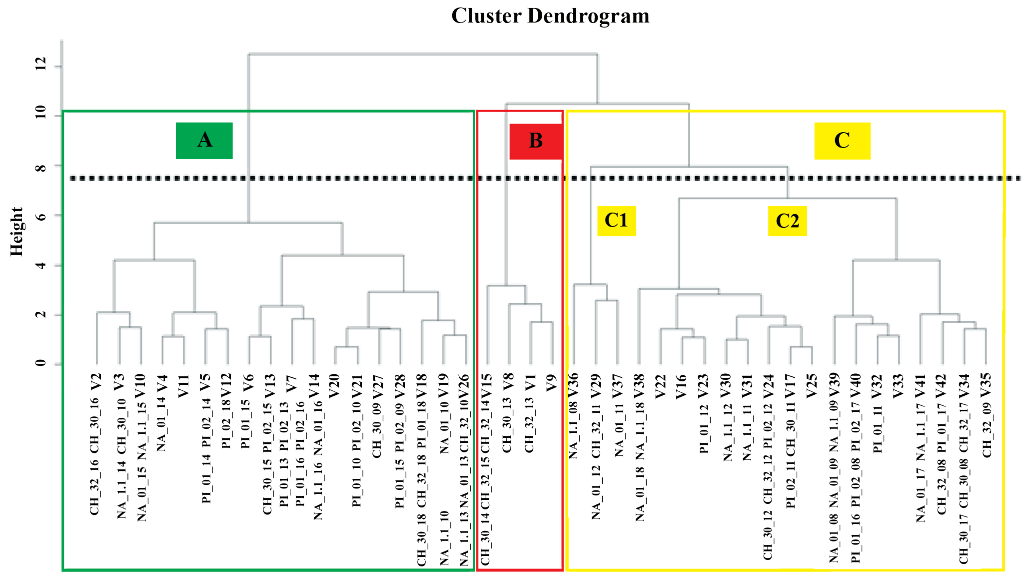

Figure 3. Hierarchical dendrogram produced by SOM.

Principal component analysis (PCA)

The PCA represents the relationship and direction of water quality parameters among stations (Figure 4). The PCA explains as much variation as possible in two dimensions (i.e., along two axes). The eigenvalues of principal component axis 1 (PC1) and axis 2 (PC2) show that they explain 28.57 % and 16.51 % of variance, respectively (together they explain 45.08 %). DO, Tur, and TS had the highest loading scores in PC1, and reflect contamination by study area and season. The second axis (PC2) had strong loading scores from BOD, TCB, and FCB, which indicate contamination by human or animal feces. The diagrams clearly show correlation and direction among water parameters and samples (Figure 4), and the Monte Carlo test was significant (1,000 permutations, p-value<0.001). Meanwhile, the variable loadings >|0.25| were considered important in structuring samples, implying high influence during the study period (Table 2) (Fischer and Paukert, 2008). The graphical PCA shows that only observations belonging to cluster B are completely separated, while the observations for clusters A and C overlap. This indicates that the water quality in cluster B was explicitly different from the two remaining clusters.

Cluster characteristics

By combining the SOM and PCA results, the characteristics of each cluster can be further explored.

Cluster A includes samples from the Ping, Nan and Chao Phraya rivers between 2009 and 2018, and is further divided into two periods, i.e., dry years (2013 to 2016) and flood years (2009, 2010 and 2018). DO was highest in this cluster, whereas TCB, FCB, Tur, NH_3-N, and NO^-_2-N were lower than in clusters B and C (Figure 5). This cluster was also characterized by slightly higher BOD, TCB, and FCB in dry periods. DO concentration is related to flow conditions, for which there is a seasonal effect (Voutsa *et al*., 2001). The high water in the rainy season causes dilution and general improvement of water quality along with increasing the DO level (Qadir *et al*., 2008; Huang *et al*., 2019). This phenomenon of water fluctuation, which is created by alternate dry and flood periods, dilutes water pollution and moves it downstream (Simachaya *et al*., 2000). This process is a form of natural self-purification, and is reflected by the seasonal effect on water quality (Zubaidah *et al*., 2019). Water quality in cluster A was thus better than in clusters B and C.

Table 2. Principal component (PC) loading scores for water quality parameters at six sites in the Upper Chao Phraya River Basin during 2008-2018.

Water quality parameter	PC1	PC2
pH	0.16	**-0.16**
Dissolved Oxygen (DO, mg·L^{-1})	0.36	-0.06
Biochemical Oxygen Demand (BOD, mg·L^{-1})	0.19	-0.48
Water Temperature (WT, °C)	**0.23**	**-0.22**
Turbidity (Tur, NTU)	-0.46	-0.09
Total solids (TS, mg·L^{-1})	-0.46	0.05
Total Coliform Bacteria (TCB, MPN·100 mL^{-1})	-0.10	-0.51
Fecal Coliform Bacteria (FCB, MPN·100 mL^{-1})	-0.09	-0.56
Ammonia nitrogen (NH_3-N, mg·L^{-1})	-0.13	-0.28
Nitrate (NO^-_3-N, mg·L^{-1})	**-0.23**	**-0.13**
Nitrite (NO^-_2-N, mg·L^{-1})	**-0.14**	**-0.01**

Note: Bold text indicates variable loadings <|0.25|.

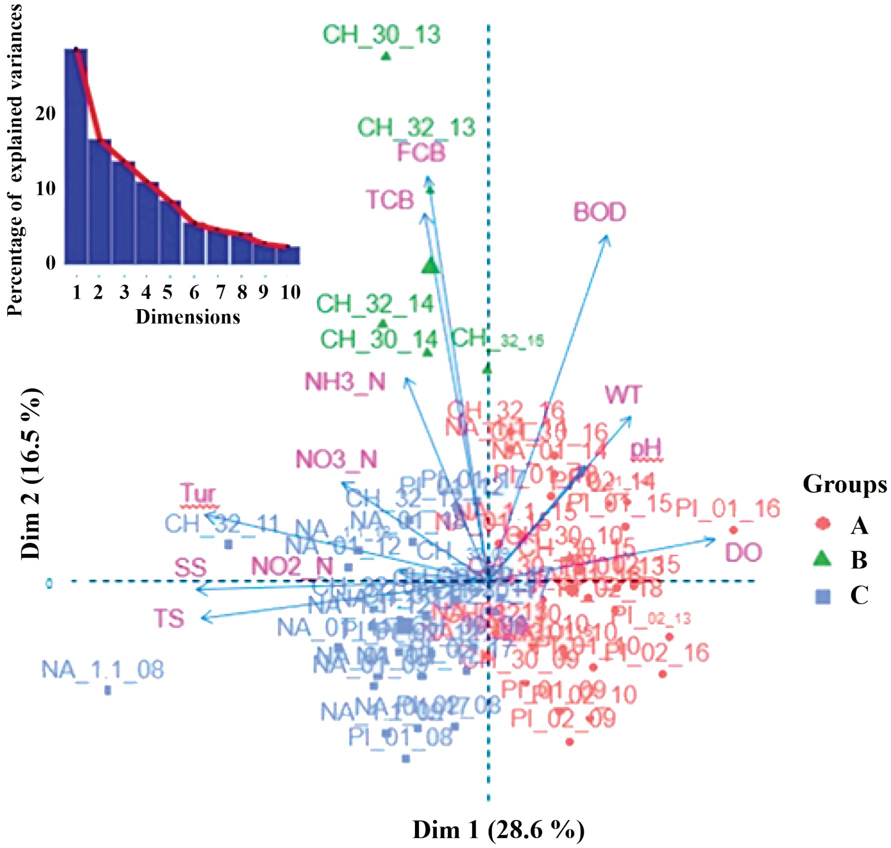

Figure 4. PCA of 12 water quality parameters for three clusters of surface water samples from the Upper Chao Phraya River.

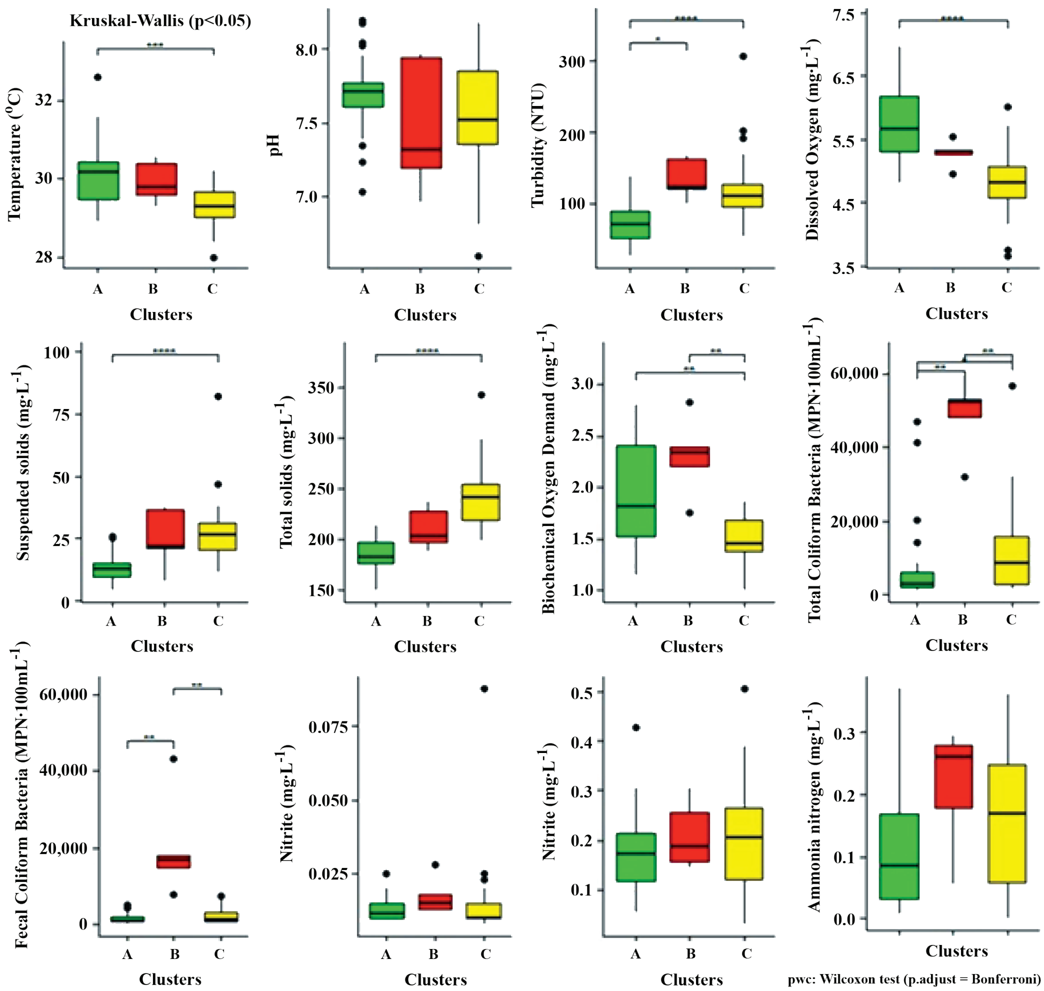

Figure 5. Boxplot showing distribution of values for each parameter in three clusters of water quality monitoring samples from the Upper Chao Phraya River Basin.

Cluster B is limited to only samples from CH30 and CH32 (Chao Phraya River), and only during a period of low water volume between 2013 and 2015 (drought period). Significantly high loadings of TCB and FCB were found in this cluster (Figure 4 and 5), which implied effects from human activities, domestic wastewater, and livestock waste (Campos and Cachola, 2007). In addition, TCB and FCB are used as indicators of the sanitary quality of water and to detect contamination by feces of humans and other warm-blooded animals (Huang *et al*., 2019). The Thai surface water quality standards prescribe TCB and FCB levels of not more than 20,000 and 4,000 MPN·100 mL^{-1}, respectively; higher values imply that water quality is poor (Simachaya, 2000). Meanwhile, average BOD, NH_3-N, and NO^-_2-N were higher than in clusters A and C (Figure 5). Stations CH30 and CH32 are located in municipal and central plain areas with high densities of population, industry, and livestock. Wastewater from these land uses is the main cause of decreased DO and increased BOD (Kunacheva *et al*., 2011). Moreover, NH_3-N and NO^-_2-N are harmful to humans and animals, especially aquatic animals. These pollutants are discharged into the river via animal feed lots, agricultural fertilizers, manure, industrial waste, and garbage dumps (MPCA , 2008; Thongdonphum *et al*., 2011).

Cluster C includes samples from the Ping, Nan, and Chao Phraya rivers, but only in high flood periods. It was divided into two sub-clusters (C1 and C2). Sub-cluster C1 was represented by only the Nan and Chao Phraya rivers in high flood years (2008, 2011 and 2012). Notably, Nan River samples had high Tur, SS, and TS, whereas Chao Phraya samples had high FCB and TCB. Sub-cluster C2 included samples from all three rivers during high flood years (2008-2012). The parameters Tur, SS, and TS were high for this sub-cluster, but FCB and TCB showed fluctuation. The differences in average TS and SS compared to clusters A and B were highly significant (Figure 5). Heavy rainfall increases surface runoff, which carries and deposits both sediment and warm-blooded animal feces into the river (An *et al*., 2016; Bidorn *et al*., 2016; Huang *et al*., 2019; Singkran *et al*., 2019). Furthermore, the transported soil particles can bring pollutants such as fertilizers, pesticides, and heavy metals into the river, which may lead to algal blooms, oxygen decline, and impaired health of aquatic life (Khatri and Tyagi, 2015). In addition, seasonal variation and long-term anthropogenic factors impact turbidity (Zhou *et al*., 2021). Turbidity blocks light penetration, and thus reduces photosynthesis and transparency (Sidabutar *et al*., 2017; Shen *et al*., 2019).

CONCLUSION

A self-organizing map (SOM) was applied to analyze a large array of data on the water quality of the Ping, Nan, and Chao Phraya rivers from sites in Nakhon Sawan Province. The results showed three main clusters based on the similarity of water quality parameters among samples taken from 2008-2018. In cluster B, water quality was poorer than in the other clusters, and this corresponded with low water levels at the sites. This study indicates that water quality is affected by anthropogenic sources, especially domestic wastewater (Cluster B). Meanwhile, the natural effects of heavy rainfall and drought on water quality are also evident (Clusters A and C). These results can illustrate basic information about water quality to authorities responsible for water management. In addition, sufficient sewage systems and other forms of treatment are necessary for domestic, agricultural, and commercial sources of wastewater, as they have the greatest effect on water quality in the Chao Phraya River.

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LITERATURE CITED

Altansukh, O. and G. Davaa. 2011. Application of index analysis to evaluate the water quality of the Tuul River in Mongolia. **Journal of Water Resource and Protection** 3(6): 398-414.

An, Y., Z. Zou and R. Li. 2016. Descriptive characteristics of surface water quality in Hong Kong by a self-organizing map. **International Journal of Environmental Research and Public Health** 13(1): 1-13.

Bidorn, B., S.A. Kish, J.F. Donoghue, K. Bidorn and R. Mama. 2016. Sediment transport characteristic of the Ping River Basin, Thailand. **Procedia Engineering** 154: 557-564.

Campos, C.J.A. and R.A. Cachola. 2007. Faecal coliforms in bivalve harvesting areas of the Alvor Lagoon (Southern Portugal): influence of seasonal variability and urban development. **Environmental Monitoring and Assessment** 133: 31-41.

Chea, R., G. Grenouillet and S. Lek. 2016. Evidence of water quality degradation in Lower Mekong Basin revealed by self-organizing map. **PLoS ONE** 11(1): e0145527. DOI: 10.1371/journal.pone.0145527.

Fischer, J.R. and C.P. Paukert. 2008. Habitat relationships with fish assemblages in minimally disturbed great plains regions. **Ecology of Freshwater Fish** 17: 597-609.

Huang, G., H. Xue, H. Liu, C. Ekkawatpanit and T. Sukhapunnapha. 2019. Duality of seasonal effect and river bend in relation to water quality in the Chao Phraya River. **Water** 11(4): 656. DOI: 10.3390/w1104 0656.

Kalteh, A.M., P. Hjorth and R. Berndtsson. 2008. Review of the self-organizing map (SOM) approach in water resources: Analysis, modelling and application. **Environmental Modelling and Software** 23(7): 835-845.

Kassambara, A. and M. Fabian. 2020. **Factoextra: Extract and visualize the results of multivariate data analyses.** https://CRAN.R- roject.org/package=factoextra. Cited 2 Feb 2022.

Khatri, N. and S. Tyagi. 2015. Influences of natural and anthropogenic factors on surface and groundwater quality in rural and urban areas. **Frontiers in Life Science** 8(1): 23-39.

Khorooshi, S., R. Mostafazadeh, A. Esmaliouri and M. Raoof. 2016. River health, importance and applications. **Extension and Development of Watershed Management** 4(13): 1-7.

Kohonen, T. 1982. Self-organized formation of topologically correct feature maps. **Biological Cybernetics** 43(1): 59-69.

Komori, D., S. Nakamura, M. Kiguchi, A. Nishijima, D. Yamazaki, S. Suzuki, A. Kawasaki, O. Kazuo and T. Oki. 2012. Characteristics of the 2011 Chao Phraya River flood in central Thailand. **Hydrological Research Letters** 6: 41-46.

Kunacheva, C., S. Tanaka, S. Fujii, S. Boontanon, C. Musirat and T. Wongwattana. 2011. Determination of perfluorinated compounds (PFCs) in solid and liquid phase river water samples in Chao Phraya River, Thailand. **Water Science and Technology** 64(3): 684-692.

Minnesota Pollution Control Agency (MPCA). 2008. nutrients: phosphorus, nitrogen sources, impact on water quality. **Water Quality/ Impaired Waters** 3(22): 1-2.

Mishra, A. 2010. Assessment of water quality using principal component analysis: a case study of the River Ganges. **Journal of Water Chemistry and Technology** 32(4): 227-234.

Molle, F. 2007. Scales and power in river basin management: the Chao Phraya River in Thailand. **Geographical Journal** 173(4): 358-373.

Naik, P.K. and D.A. Jay. 2011. Distinguishing human and climate influences on the Columbia River: Changes in mean flow and sediment transport. **Journal of Hydrology** 404 (3-4): 259-277.

Nakamuro, K., D. Kisananuwat, M. Tabucanon and W. Sukasem. 1982. A study on water quality evaluation of the Chao Phraya River. **Journal of the Science Society of Thailand** 8: 175-191.

Nakhon Sawan Statistical Office. 2018. **Nakhon Sawan one minute. National statistical office, Thailand 2018.** http://nksawan.nso.go.th. Cited 27 Mar 2022.

Office of Natural Water Resources Committee of Thailand. 2003. **Chao Phraya River Basin, (Thailand).** In: UN World Water Development Report 1: Water for People, Water for Life (ed. World Water Assessment Program), pp. 387-400. UNESCO, Paris, France.

Orak, E., A. Akkoyunlu and Z.C. Semra. 2020. Assessment of water quality classes using self-organizing map and fuzzy C-mean clustering methods in Ergene. **Environmental Monitoring and Assessment** 192(10): 1-10.

Pitakwinai, P., W. Khanitchaidecha and A. Naaruk. 2018. Spatial and seasonal variation in surface water quality of Nan river, Thailand. **Nareuan University Engineering Journal** 14(1): 1-10.

Prathumratana, L., S. Sthiannopkao and K.W. Kim. 2008. The relationship of climatic and hydrological parameters to surface water quality in the lower Mekong River. **Environment International** 34(6): 860-866.

Qadir, A., R.N. Malik and S.Z. Husain. 2008. Spatio-Temporal Variations in Water Quality of Nullah Aik-Tributary of the River Chenab, Pakistan. **Environmental Monitoring and Assessment** 140: 43-59.

R Core Team. 2020. **R: A language and environment for statistical computing.** https://www.R-project.org/. Cited 1 Jan 2022.

Senhorst, H.A.J. and J.J.G. Zwolsman. 2005. Climate change and effects on water quality: a first impression. **Water Science and Technology** 51(5): 9-53.

Shen, X., T. Sun, M. Su, Z. Dang and Z. Yang. 2019. Short-term response of aquatic ecosystem metabolism to turbidity disturbance in experimental estuarine wetlands. **Ecological Engineering** 136: 55-61.

Sidabutar, N.V., I. Namara, D.M. Hartono and T.E.B. Soesilo. 2017. **The effect of anthropogenic activities to the decrease of water quality.** Proceedings of the 7th International Conference on Environment and Industrial Innovation 2017: 1-7.

Simachaya, W. 2000. **Water Quality Management in Thailand.** Water Quality Management Division, Pollution Control Department, Bangkok, Thailand. 13 pp.

Simachaya, W., P. Watanamahart, V. Kaewkrajang and A. Yenpiem. 2000. **Water quality situation in the Chao Phraya Delta.** Proceedings of the International Conference: The Chao Phraya Delta: Historical Development, Dynamics and Challenges of Thailand's Rice Bowl 2000: 1-21.

Simeonov, V., P. Simeonova, S. Tsakovski and V. Lov-chinov. 2010. Lake water monitoring data assessment by multivariate statistics. **Journal of Water Resource and Protection** 2(4): 353-361.

Singkran, N., P. Anantawong, N. Intharawichian and K. kunta. 2019. The Chao Phraya River Basin: Water quality and anthropogenic influences. **Water Supply** 19(5): 1287-1294.

Souza, A.T.D., L.A.T.X. Carneiro, O.P.D.S. Junior, S.L.D. Carvalho and J.H.P. Américo-Pinheiro. 2020. Assessment of water quality using principal component analysis: A case study of the Marrecas stream basin in Brazil. **Environmental Technology** 42(14): 1-10.

Sowmiya, B. and A. Raj. 2016. Review of the self-organizing map (SOM) approach in the field of environmental engineering. **International Journal of Soft Computing and Engineering** 6(4): 32-37.

Thongdonphum, B., S. Meksumpun and C. Meksumpun. 2011. Nutrient loads and their impacts on Chlorophyll *a* in the Mae Klong River and estuarine ecosystem: An approach for nutrient criteria development. **Water Science and Technology** 64(1): 178-188.

Tudesque, L., M. Gevrey, G. Grenouillet and S. Lek. 2008. Long-term changes in water physicochemistry in the Adour-Garonne hydrographic network during the last three decades. **Water Research** 42(3): 732-742.

Voutsa, D., E. Manoli, C. Samara, M. Sofoniou and I. Stratis. 2001. A Study of surface water quality in Macedonia, Greece: speciation of nitrogen and phosphorus. **Water Air and Soil Pollution** 129: 13-32.

Wehrens, R. and J. Kruisselbrink. 2018. Flexible self-organizing maps in kohonen 3.0. **Journal of Statistical Software** 87(7): 1-18.

Wichakul, S., Y. Tachikawa, M. Shiiba and K. Yorozu. 2014. Prediction of water resources in the Chao Phraya River Basin, Thailand. **Hydrological Sciences Journal** 363: 151-157.

Wickham, H. 2016. **ggplot2: Elegant Graphics for Data Analysis.** Springer, New York, USA. 213 pp.

Wongaree, M. 2019. Water quality assessment by using of water quality index for Mak Khaeng Canal, Udon Thani Province, Thailand. **Environment Asia** 12(2): 96-104.

Ye, C., S. Li, Y. Yang, X. Shu, J. Zhang and Q. Zhang. 2015. Advancing analysis of spatio-temporal variations of soil nutrients in the water level fluctuation zone of China’s Three Gorges Reservoir using self-organizing map. **PLoS ONE** 10(3): e0121210. DOI: 10.1371/journal.pone.0121210.

Zhou, Q., J. Wang, L. Tian, L. Feng, J. Li and Q. Xing. 2021. Remotely sensed water turbidity dynamics and its potential driving factors in Wuhan, an urbanizing city of China. **Journal of Hydrology** 593: 125893. DOI: 10.1016/j.jhydrol.2020.125893.

Zubaidah, T., N. Karnanigroem and A. Slamet. 2019. The self-purification ability in the rivers of Banjarmasin, Indonesia. **Journal of Ecological Engineering** 20(2): 177-182.