Literature review for the project “Water quality predictions”

# Search approach

Searched in Scopus “machine learning AND surface water” (then added “water quality”) – 119 results. Reviewed these results, very few were about microbial water quality. A lot is written about remote sensing, mapping, spatial analysis (also in the context of water quality), but I did not look at these publications. Then I looked at a relevant publication from 2019 about machine learning and recreational (microbial) water quality and found many relevant citations in its introduction. I looked at these citations, and some of the citations within these as well, then I had identified many relevant articles and stopped the search. The identified articles about microbial water quality and machine learning were organised into the table below.

# Recreational and microbial water quality context

Microbial water quality refers to the presence of microorganisms (bacteria, virus, protozoa) in water. Microbial water quality is often assessed through measuring faecal indicator organisms or groups of organisms, for example, *E. coli*, enterococci, total coliforms, faecal coliforms, coliphages. These are often called FIO (faecal indicator organisms) or FIB (faecal indicator bacteria).

Table 1 Research publications (in reverse chronological order) reporting on implementing machine learning (and other data-based methods) to describe and predict microbial water quality.

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| **Author(s)** | **Target water quality parameter(s)** | **Machine learning method(s)** | **Data used** | **Country** | **Outcomes** |
| (Laureano-Rosario et al., 2019) | culturable enterococci – exceedance of USEPA recreational water quality guidelines (RWQC) | ANN | 10 years of culturable enterococci, satellite-derived sea surface temperature (SST), direct normal irradiance (DNI), turbidity, and dew point, precipitation, mean sea level (MSL) | Puerto Rico (marine beach) | The factors identified as the most relevant for enterococci exceedance predictions based on the U.S. EPA RWQC were DNI, turbidity, cumulative 48 h precipitation, MSL, and SST; they predicted culturable enterococci exceedances with an accuracy of 75% and power greater than 60% based on the Receiving Operating Characteristic curve and F-Measure metrics. Results show the applicability of satellite-derived data and ANNs to predict recreational water quality at Escambron Beach. |
| (Avila et al., 2018) | *E. coli* | The models include naive model, multiple linear regression, dynamic regression, regression tree, Markov chain, classification tree, random forests, multinomial logistic regression, discriminant analysis and Bayesian network. | E. coli levels for the weekly data collected over the summer months from 2006 to 2014. Data used: past values of E. coli counts, accumulated rainfall of a monitored upstream site in the past 48 h and river flow. | New Zealand, the Oreti river in Wallacetown | The results show that Bayesian network was superior to all the other models. Overall, it had a leave-one-out and k-fold cross validation error rate of 21%, while predicting the majority of instances of E. coli levels classified as unsafe. |
| (Zhang et al., 2018) | *E. coli* | nonlinear autoregressive network with exogenous inputs (NARX) method with explanatory variables  Also apply the nonlinear input–output network (NIO) and nonlinear autoregressive neural network (NAR) methods in addition to a hybrid wavelet-NAR (WA-NAR) model and demonstrate their application. | 3 months of observed data | four Lake Michigan beach sites | Results revealed that the NARX models provided the best performance and that the WA-NAR model, which requires no explanatory variables, outperformed the NIO and NAR models; therefore, the WA-NAR model is suitable for application to data scarce regions. |
| (Choi and Bae, 2018) | Total coliform | an artificial neural network, Self-organizing Linear Output (SOLO) | rainfall and streamflow data | Aliso Creek watershed, located in the lower part of Orange County, California. | The results show that the prediction of total coliform concentrations is possible if rainfall events occur. However, poor estimation results are obtained when there is no rain. The model performance improves slightly during periods of no rain if streamflow data are incorporated into the input. However, the model requires more input variables for no-rain periods, because the streamflow data do not enable observed variations to be fully predicted. |
| (Vijayashanthar et al., 2018) | FIB | ANN | Eight input variables were eventually selected from 10 initially proposed variables: water temperature; turbidity; daily, 2-day, and 7-day cumulative rainfall; river flow discharge; distance from the upstream water reclamation plant; and number of upstream combined sewer outfalls. | the Chicago River, USA | Water reclamation plants and combined sewer overflows were found to be critical contributors of microbial pollution in this urban waterway and should be considered in the ANN model. The developed model has an accuracy of 86.5% to predict whether fecal coliform concentration is above or below a regulatory threshold. |
| (Mohammed et al., 2018) | FIB | zero-inflated regression models (ZI), Random Forest regression model (RF) and adaptive neuro-fuzzy inference system (ANFIS) | The ZI, RF and ANFIS faecal indicator bacteria predictive models were built using physico-chemical (pH, temperature, electrical conductivity, turbidity, color, and alkalinity) and catchment precipitation data from 2009 to 2015. | Raw surface water, Norway |  |
| (Mohammed et al., 2017a) (Mohammed et al., 2017b) | norovirus | adaptive neuro-fuzzy inference system (ANFIS) and Gaussian Process for Machine Learning (GPML) | water pH, turbidity, conductivity, temperature and rain | Raw surface water, Norway |  |
| (Mohammed et al., 2017c) | Faecal indicator organisms |  | conductivity, pH, color, turbidity, seasons | Raw surface water, Bergen, Norway |  |
| (Safaie et al., 2016) | Compared statistical (multiple regression) and mechanistic models |  |  | Lake Michigan, USA |  |
| (Thoe et al., 2015) | predicting advisories due to FIB contamination | multiple linear regression model, binary logistic regression model, partial least-squares regression model, artificial neural network, and classification tree |  | 25 beaches along the California coastline, USA | Classification tree and the binary logistic regression model with threshold tuning are consistently the best performing model types for California beaches. Beaches with good performing models usually have a rainfall/flow related dominating factor affecting beach water quality, while beaches having a deteriorating water quality trend or low FIB exceedance rates are less likely to have a good performing model. |
| (Tornevi et al., 2014) | turbidity and concentrations of *E. coli*, Clostridium and coliforms | short-term variations in relation with precipitation were analyzed with time series regression and non-linear distributed lag models | Data covering 7 years of daily monitoring of river water turbidity and concentrations of *E. coli*, Clostridium and coliforms were obtained. | the Göta River, Sweden | Rainfall was associated with exponential increases in concentrations of indicator bacteria while the effect on turbidity attenuated with very heavy rainfall. Clear associations were also observed between consecutive days of wet weather and decreased water quality. The precipitation effect on increased levels of indicator bacteria was significant in all seasons. Conclusions: Rainfall elevates microbial risks year-round in this river and freshwater source and acts as the main driver of varying water quality. Heavy rainfall appears to be a better predictor of fecal pollution than water turbidity. |
| (Thoe et al., 2014) | concentrations of summertime fecal coliform and enterococci concentrations | multiple linear regression model, binary logistic regression model, partial least square regression model, artificial neural network, and classification tree | Past measurements of bacterial concentration, storm drain condition, and tide level are found to be critical factors in the predictive models. | California (marine beach) | The classification tree models perform the best; for example they correctly predict 42% of beach postings due to fecal coliform exceedances during model validation, as compared to 28% by the current method. Artificial neural network is the second best model which minimizes the number of incorrect beach postings. The binary logistic regression model also gives promising results, comparable to classification tree, by adjusting the posting decision thresholds to maximize correct beach postings. |
| (Motamarri and Boccelli, 2012) | primary and secondary water quality standards within using. | learning vector quantization (LVQ) - a direct classification approach - for comparison with MLR and ANN approaches with input selection | meteorologic, hydrologic, and microbial explanatory variables | the Charles River Basin, Massachusetts, USA | Integrating input selection into model development showed that discharge variables were the most important explanatory variables while antecedent rainfall and time since previous events were also important. With respect to classification, all three models adequately represented the non-violated samples (>90%). Overall, the use of LVQ as a direct classifier provided the best overall classification ability with respect to violated/non-violated samples for both standards. |
| (Zhang et al., 2012) | enterococci | This study presents and compares three models for nowcasting and forecasting enterococci levels at Gulf Coast beaches in Louisiana, USA. One was developed using the artificial neural network (ANN) in MATLAB Toolbox and the other two were based on the US EPA Virtual Beach (VB) Program. | A total of 944 sets of environmental and bacteriological. The data were collected weekly during the swimming season (May-October) at six sites of the Holly Beach by Louisiana Beach Monitoring Program in the six year period of May 2005-October 2010. The ANN model includes 15 readily available environmental variables such as salinity, water temperature, wind speed and direction, tide level and type, weather type, and various combinations of antecedent rainfalls. | US (Holly Beach) | The predictive models (especially the ANN and the nonlinear VB models) developed in this study in combination with readily available real-time environmental and weather forecast data can be utilized to nowcast and forecast beach water quality, greatly reducing the potential risk of contaminated beach waters to human health and improving beach management. |
| (Stidson et al., 2012) | Faecal indicator organisms (FIO) | “simple relationship between variables” and “decision tree tools” | antecedent rainfall and river flow | Four beach sites are located in the south‐west of Scotland. | Further improvements are anticipated through the inclusion of additional environmental variables, which are known to affect local bathing water quality, e.g. tidal, wind and sunshine data. Additionally, results may be improved by modelling of individual parameters separately and by using spatial and temporal rain radar information for the data input, to augment (or replace) point source rain and river gauges. |
| (Thoe et al., 2012) | *E. coli* | Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) | rainfall, solar radiation, wind speed, tide level, salinity, water temperature and past *E. coli* concentration | Marine beach in Hong Kong | The models are able to track the dynamic changes in *E. coli* concentration and predict compliance/exceedance with an overall accuracy of 70-96%. Both the MLR and ANN models are superior to the current beach advisories in capturing water quality variations, and in predicting exceedances. The MLR and ANN models have similar performances; ANN model tends to be better in predicting the high-end concentrations, with however a greater number of false positive predictions (false alarms). |
| (He and He, 2008) | faecal indicator bacteria (FIB) | ANN | temperature, conductivity, pH, turbidity, channel water flow, rainfall, and/or time lapse after a rainstorm | California (marine beach) | With the test dataset, concentrations were correctly predicted at 100% for TC (total coliforms), 93% for FC 8faecal coliforms), and 97% for EN (enterococci). With the validation dataset, concentrations were correctly predicted at 97% for TC, 94% for FC, and 89% for EN. |
| (Mas and Ahlfeld, 2007) | Faecal coliforms | Ordinary least squares (OLS) and binary logistic regression methods, and artificial neural networks (ANNs) | precipitation and temperature data, as well as instantaneous measurements of streamflow and conductivity | mixed land-use watershed in France? | The ANNs are able to correctly classify 69% and 85% of faecal coliform concentrations relative to 20 and 200 cfu/100 mL water quality standards, respectively, results moderately better than those observed for the regression models. The ANN models using only meteorological inputs were able to correctly classify 72% and 81% of the observations relative to the 20 and 200 cfu/ 100 mL standards, respectively. The ANN models are notably better at predicting when the 200 cfu/100 mL standard is violated. In addition, the ANN models have lower percentages of false negatives, a characteristic desirable for protection of public health. |
| (Lin et al., 2003) | the compliance of bathing waters, faecal coliforms | ANN | Water quality data collected at 7 locations during 1990-2000. Rainfall, river discharge, sunlight and tidal condition were used as input. | Scotland, UK | River discharge and tidal ranges were found to be the most important parameters that affect the coliform concentration levels. For compliance points close to the meteorological station, the influence of rainfall was found to be relatively significant to the concentration levels. |

# Other search results that may be relevant, simulated various non-microbial water quality parameters

The points highlighted in yellow have higher priority.

* Used process-based model to train machine learning techniques to simulate runoff and pollutant transport (Liang et al., 2019)
* An improved method that incorporates an artificial neural network (ANN) into the MCS to enhance the computational efficiency of conventional risk assessment. Training and test data sets for the model were obtained from FEM (finite element model) calculations of the water quality model equation. The ANN model was then connected to the MCS to assess the water quality risk. China, the Lanzhou section of the Yellow River. (Jiang et al., 2013)
* Aquifers, nitrate contaminations, SWAT (process-based model) and ANN (Jang et al., 2020)
* About thermal stratification of lakes using machine learning (Butcher et al., 2017)
* Simulated discharge using process-based models and using several machine learning methods (but probably did not connect the process-based and data methods with each other) (Khwairakpam et al., 2018)
* Tested different machine learning methods to predict water quality parameters in China (not microbial) (Chen et al., 2020)
* Secchi depth and chlorophil-a under conditions of monsoon were predcited in many water sources using different machine learning methods (Mamun et al., 2020)
* Predict water quality index (based on temperature, turbidity, pH and total dissolved solids) using different supervised machine learning methods (Ahmed et al., 2019)
* Some review, but does not seem to be good (Kiran Relangi et al., 2019)
* Assess impact of wastewater discharges (Di et al., 2019)
* Tested different machine learning tools to select which water quality variables could predict algae (Hussein et al., 2019)
* Studied the factors that impact formation of disinfection by-products (Bagheban et al., 2019)
* Internet of things for water quality in Pakistan (Shafi et al., 2018)
* Ph, dissolved oxygen(DO), Potassium permanganate index (CODMn) and ammonia-nitrogen(NH3-N) the Extreme Learning Machine algorithm optimized by Dolphin Swarm Algorithm (DSA-ELM) was used (Yan et al., 2017)
* Temperature, pH conductivity, turbidity and ANN and SVM (Ladjal et al., 2016)
* 4 water quality parameters and ANN (Khan and See, 2016)
* Extreme learning machine and ANN to predict streamflow (Deo and Şahin, 2016)
* Predicted Chl-a (algal blooms) using SVM and ANN 7 day ahead (Park et al., 2015)
* SVM and normalized water quality indices (Li and Zhang, 2013)
* From my earlier literature review: (Asheri Arnon et al., 2019; Samanipour et al., 2019; Speight et al., 2019; Stevenson and Bravo, 2019)

# References

Ahmed, U., Mumtaz, R., Anwar, H., Shah, A.A., Irfan, R., García-Nieto, J., 2019. Efficient water quality prediction using supervised machine learning. Water (Switzerland) 11. https://doi.org/10.3390/w11112210

Asheri Arnon, T., Ezra, S., Fishbain, B., 2019. Water characterization and early contamination detection in highly varying stochastic background water, based on Machine Learning methodology for processing real-time UV-Spectrophotometry. Water Res. 333–342. https://doi.org/10.1016/j.watres.2019.02.027

Avila, R., Horn, B., Moriarty, E., Hodson, R., Moltchanova, E., 2018. Evaluating statistical model performance in water quality prediction. J. Environ. Manage. 206, 910–919. https://doi.org/https://doi.org/10.1016/j.jenvman.2017.11.049

Bagheban, M., Baghdadi, M., Mohammadi, A., Roozbehnia, P., 2019. Investigation of the effective factors on the mutagen X formation in drinking water by response surface methodology. J. Environ. Manage. 251. https://doi.org/10.1016/j.jenvman.2019.109515

Butcher, J.B., Zi, T., Schmidt, M., Johnson, T.E., Nover, D.M., Clark, C.M., 2017. Estimating future temperature maxima in lakes across the United States using a surrogate modeling approach. PLoS One 12. https://doi.org/10.1371/journal.pone.0183499

Chen, K., Chen, H., Zhou, C., Huang, Y., Qi, X., Shen, R., Liu, F., Zuo, M., Zou, X., Wang, J., Zhang, Y., Chen, D., Chen, X., Deng, Y., Ren, H., 2020. Comparative analysis of surface water quality prediction performance and identification of key water parameters using different machine learning models based on big data. Water Res. 171. https://doi.org/10.1016/j.watres.2019.115454

Choi, S.-W., Bae, H.-K., 2018. Daily prediction of total coliform concentrations using artificial neural networks. KSCE J. Civ. Eng. 22, 467–474. https://doi.org/10.1007/s12205-017-0739-y

Deo, R.C., Şahin, M., 2016. An extreme learning machine model for the simulation of monthly mean streamflow water level in eastern Queensland. Environ. Monit. Assess. 188, 1–24. https://doi.org/10.1007/s10661-016-5094-9

Di, Z., Chang, M., Guo, P., Li, Y., Chang, Y., 2019. Using real-time data and unsupervised machine learning techniques to study large-scale spatio-temporal characteristics of wastewater discharges and their influence on surface water quality in the Yangtze River Basin. Water (Switzerland) 11. https://doi.org/10.3390/w11061268

He, L.-M. (Lee), He, Z.-L., 2008. Water quality prediction of marine recreational beaches receiving watershed baseflow and stormwater runoff in southern California, USA. Water Res. 42, 2563–2573. https://doi.org/https://doi.org/10.1016/j.watres.2008.01.002

Hussein, A.M., Abd Elaziz, M., Abdel Wahed, M.S.M., Sillanpää, M., 2019. A new approach to predict the missing values of algae during water quality monitoring programs based on a hybrid moth search algorithm and the random vector functional link network. J. Hydrol. 575, 852–863. https://doi.org/10.1016/j.jhydrol.2019.05.073

Jang, W.S., Engel, B., Yeum, C.M., 2020. Integrated environmental modeling for efficient aquifer vulnerability assessment using machine learning. Environ. Model. Softw. 124. https://doi.org/10.1016/j.envsoft.2019.104602

Jiang, Y., Nan, Z., Yang, S., 2013. Risk assessment of water quality using Monte Carlo simulation and artificial neural network method. J. Environ. Manage. 122, 130–136. https://doi.org/https://doi.org/10.1016/j.jenvman.2013.03.015

Khan, Y., See, C.S., 2016. Predicting and analyzing water quality using Machine Learning: A comprehensive model, in: 2016 IEEE Long Island Systems, Applications and Technology Conference, LISAT 2016. https://doi.org/10.1109/LISAT.2016.7494106

Khwairakpam, E., Khosa, R., Gosain, A., Nema, A., Mathur, S., Yadav, B., 2018. Modeling simulation of river discharge of Loktak Lake catchment in Northeast India. J. Hydrol. Eng. 23. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001674

Kiran Relangi, N.D.S.S., Chaparala, A., Sajja, R., 2019. Perspectives in water quality assessment. Int. J. Recent Technol. Eng. 8, 7–11. https://doi.org/10.35940/ijrte.B1002.0782S419

Ladjal, M., Bouamar, M., Djerioui, M., 2016. Application of ANN and SVM multiclass models used for multi-sensor monitoring and measurement of surface water quality. Mediterr. J. Meas. Control 12, 627–635.

Laureano-Rosario, A.E., Duncan, A.P., Symonds, E.M., Savic, D.A., Muller-Karger, F.E., 2019. Predicting culturable enterococci exceedances at Escambron Beach, San Juan, Puerto Rico using satellite remote sensing and artificial neural networks. J. Water Health 17, 137–148. https://doi.org/10.2166/wh.2018.128

Li, Z.-Y., Zhang, Z.-J., 2013. Model of water quality evaluation with normalized indexes values based on regression support vector machines. Zhongguo Huanjing Kexue/China Environ. Sci. 33, 1502–1508.

Liang, J., Li, W., Bradford, S.A., Šimůnek, J., 2019. Physics-informed data-driven models to predict surface runoffwater quantity and quality in agricultural fields. Water (Switzerland) 11. https://doi.org/10.3390/w11020200

Lin, B., Kashefipour, S.M., Falconer, R.A., 2003. Predicting near-shore coliform bacteria concentrations using ANNS. Water Sci. Technol.

Mamun, M., Kim, J.-J., Alam, M.A., An, K.-G., 2020. Prediction of algal chlorophyll-a and water clarity in monsoon-region reservoir using machine learning approaches. Water (Switzerland) 12. https://doi.org/10.3390/w12010030

Mas, D.M.L., Ahlfeld, D.P., 2007. Comparing artificial neural networks and regression models for predicting faecal coliform concentrations. Hydrol. Sci. J. 52, 713–731. https://doi.org/10.1623/hysj.52.4.713

Mohammed, H., Hameed, I.A., Seidu, R., 2018. Comparative predictive modelling of the occurrence of faecal indicator bacteria in a drinking water source in Norway. Sci. Total Environ. 628–629, 1178–1190. https://doi.org/10.1016/j.scitotenv.2018.02.140

Mohammed, H., Hameed, I.A., Seidu, R., 2017a. Comparison of adaptive neuro-fuzzy inference system (ANFIS) and gaussian process for machine learning (GPML) algorithms for the prediction of norovirus concentration in drinking water supply. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics). https://doi.org/10.1007/978-3-662-56121-8\_4

Mohammed, H., Hameed, I.A., Seidu, R., 2017b. Adaptive neuro-fuzzy inference system for predicting norovirus in drinking water supply, in: 2017 International Conference on Informatics, Health and Technology, ICIHT 2017. https://doi.org/10.1109/ICIHT.2017.7899134

Mohammed, H., Hameed, I.A., Seidu, R., 2017c. Random forest tree for predicting fecal indicator organisms in drinking water supply, in: Proceedings of 4th International Conference on Behavioral, Economic, and Socio-Cultural Computing, BESC 2017. pp. 1–6. https://doi.org/10.1109/BESC.2017.8256398

Motamarri, S., Boccelli, D.L., 2012. Development of a neural-based forecasting tool to classify recreational water quality using fecal indicator organisms. Water Res. 46, 4508–4520. https://doi.org/10.1016/j.watres.2012.05.023

Park, Y., Cho, K.H., Park, J., Cha, S.M., Kim, J.H., 2015. Development of early-warning protocol for predicting chlorophyll-a concentration using machine learning models in freshwater and estuarine reservoirs, Korea. Sci. Total Environ. 502, 31–41. https://doi.org/10.1016/j.scitotenv.2014.09.005

Safaie, A., Wendzel, A., Ge, Z., Nevers, M.B., Whitman, R.L., Corsi, S.R., Phanikumar, M.S., 2016. Comparative Evaluation of Statistical and Mechanistic Models of Escherichia coli at Beaches in Southern Lake Michigan. Environ. Sci. Technol. 50, 2442–2449. https://doi.org/10.1021/acs.est.5b05378

Samanipour, S., Kaserzon, S., Vijayasarathy, S., Jiang, H., Choi, P., Reid, M.J., Mueller, J.F., Thomas, K. V, 2019. Machine learning combined with non-targeted LC-HRMS analysis for a risk warning system of chemical hazards in drinking water: A proof of concept. Talanta 195, 426–432. https://doi.org/10.1016/j.talanta.2018.11.039

Shafi, U., Mumtaz, R., Anwar, H., Qamar, A.M., Khurshid, H., 2018. Surface Water Pollution Detection using Internet of Things, in: 2018 15th International Conference on Smart Cities: Improving Quality of Life Using ICT and IoT, HONET-ICT 2018. pp. 92–96. https://doi.org/10.1109/HONET.2018.8551341

Speight, V.L., Mounce, S.R., Boxall, J.B., 2019. Identification of the causes of drinking water discolouration from machine learning analysis of historical datasets. Environ. Sci. Water Res. Technol. 5, 747–755. https://doi.org/10.1039/c8ew00733k

Stevenson, M., Bravo, C., 2019. Advanced turbidity prediction for operational water supply planning. Decis. Support Syst. 119, 72–84. https://doi.org/10.1016/j.dss.2019.02.009

Stidson, R.T., Gray, C.A., Mcphail, C.D., 2012. Development and use of modelling techniques for real-time bathing water quality predictions. Water Environ. J. 26, 7–18. https://doi.org/10.1111/j.1747-6593.2011.00258.x

Thoe, W., Gold, M., Griesbach, A., Grimmer, M., Taggart, M.L., Boehm, A.B., 2015. Sunny with a chance of gastroenteritis: Predicting swimmer risk at California beaches. Environ. Sci. Technol. 49, 423–431. https://doi.org/10.1021/es504701j

Thoe, W., Gold, M., Griesbach, A., Grimmer, M., Taggart, M.L., Boehm, A.B., 2014. Predicting water quality at Santa Monica Beach: Evaluation of five different models for public notification of unsafe swimming conditions. Water Res. 67, 105–117. https://doi.org/https://doi.org/10.1016/j.watres.2014.09.001

Thoe, W., Wong, S.H.C., Choi, K.W., Lee, J.H.W., 2012. Daily prediction of marine beach water quality in Hong Kong. J. Hydro-Environment Res. 6, 164–180. https://doi.org/10.1016/j.jher.2012.05.003

Tornevi, A., Bergstedt, O., Forsberg, B., 2014. Precipitation effects on microbial pollution in a river: Lag structures and seasonal effect modification. PLoS One 9. https://doi.org/10.1371/journal.pone.0098546

Vijayashanthar, V., Qiao, J., Zhu, Z., Entwistle, P., Yu, G., 2018. Modeling Fecal Indicator Bacteria in Urban Waterways Using Artificial Neural Networks. J. Environ. Eng. (United States) 144. https://doi.org/10.1061/(ASCE)EE.1943-7870.0001377

Yan, H., Liu, Y., Han, X., Shi, Y., 2017. An evaluation model of water quality based on DSA-ELM method, in: ICOCN 2017 - 16th International Conference on Optical Communications and Networks. pp. 1–3. https://doi.org/10.1109/ICOCN.2017.8121280

Zhang, J., Qiu, H., Li, X., Niu, J., Nevers, M.B., Hu, X., Phanikumar, M.S., 2018. Real-Time Nowcasting of Microbiological Water Quality at Recreational Beaches: A Wavelet and Artificial Neural Network-Based Hybrid Modeling Approach. Environ. Sci. Technol. 52, 8446–8455. https://doi.org/10.1021/acs.est.8b01022

Zhang, Z., Deng, Z., Rusch, K.A., 2012. Development of predictive models for determining enterococci levels at Gulf Coast beaches. Water Res. 46, 465–474. https://doi.org/10.1016/j.watres.2011.11.027