Water Quality Prediction in Inland Lakes Using the Streeter Phelps Dissolved Oxygen Algorithm

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Abstract: Maintaining optimal water quality in inland lakes is important for ecological balance, human consumption, and recreational use. This study employs the Streeter-Phelps Dissolved Oxygen (DO) algorithm to predict the dynamics of water quality due to the lack of oxygen and recovery of water from the bottom of organic pollution sources. The algorithm consists of major parameters such as biochemical oxygen demand (BOD), deoxygenation Rate (K_1), and Rate (K_2), which are used to estimate the spatial and temporal distribution of dissolved oxygen concentrations. Field data of selected inland lakes was integrated into the model to follow the pollution scenarios of the real world. The results reveal oxygen relaxed curve behaviour under different environmental conditions, enabling the identification of important areas for hypoxia. Verification against empirical water quality measurements displays the reliability of the model in the forecast of DO levels and assesses pollution load effects. This modelling structure provides a cost-effective and scientifically sound approach for lake management authorities to evaluate pollution mitigation strategies and ensure the stability of aquatic ecosystems.

Keywords: Streeter-Phelps Model; Dissolved Oxygen Prediction; Inland Lakes; Water Quality Modelling; Biochemical Oxygen Demand (Bod); Oxygen Sag Curve; Hypoxia; Lake Pollution Assessment; Deoxygenation Rate; Environmental Sustainability.

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I. Introduction

1.1 Overview of Water Quality Prediction in Inland Lakes

The prediction of water quality in inland lakes is necessary to manage aquatic ecosystems, support public health and maintain biodiversity. These freshwater bodies are unsafe for various pressures, such as agricultural runoff, urban discharge, and atmospheric conditions, which can significantly change chemical, physical, and biological water parameters (Dodds & Smith, 2016), (Jaiswal & Pradhan, 2023). Predictive Water Quality Models, Global Oxygen (DO), Biochemical Oxygen Demand (BOD), and nutrient concentrations serve as valuable tools to simulate changes in parameters, which enable active management decisions (Chapra, 2008). By integrating environmental monitoring with mathematical modelling, researchers can predict ecological risks, support regulatory compliance, and adapt to therapeutic strategies for impaired lakes (Zhang et al., 2020).

1.2 Importance of Monitoring Water Quality for Environmental Protection

Monitoring of water quality is fundamental for protecting aquatic ecosystems and the services provided by them. This ensures the stability of drinking water sources, agricultural use and fisheries, while also helping in detecting pollution events and long-term fall trends. Inland lakes serve as an indicator of broad watershed health and are often the first system to display the effects of eutrophication, hypoxia and heavy metal accumulation (Carpenter et al., 1998). Continuous evaluation of parameters such as DO, pH, turbidity and nutrient loading is therefore important for effective environmental management and to meet national and international water quality standards (Vishaka & Selvi, 2017).

1.3 Brief Explanation of the Streeter-Phelps Dissolved Oxygen Algorithm

The Starter-Phelps model, developed in the early 20th century, is a fundamental algorithm that is used to predict the Concentration of oxygen dissolved in natural water bodies, which is a function of time and distance from the pollution source (Streeter & Phelps, 1925). This model mathematically describes the balance between oxygen consumption due to biochemical oxidation of organic matter (BOD) and repetition of oxygen. The model is controlled by two major rates: deoxygenation rate (K_d) and Reaction Rate (K_r), which allows for calculating the dissolved oxygen curves that are important in assessing the impact of dots on the aquatic ecosystem. Despite its simplicity, the Streater-Phelps model remains a widely used analytical tool to evaluate self-purification capacity and plan wastewater discharge rules.

II. Literature Review

2.1 Previous Studies on Water Quality Prediction in Inland Lakes

In the last decades, the future modelling has become an integral part of the inland lake management, which provides insight into nutrient dynamics, oxygen deficiency, and eutrophication processes. Many studies have used empirical and mechanical models to simulate water quality parameters, especially focusing on the promotion of nutrients and algal blooms (Anand, 2024). For example, Søndergaard emphasized the importance of long-term phosphorus loading models in predicting recovery in shallow eutrophic lakes (Søndergaard et al., 2007). Similarly, the troll integrated hydrological and ecological components to develop lake-specific models to predict seasonal water quality patterns (Trolle et al., 2008), (Veerappan, 2024). The use of machine learning techniques such as artificial neural networks (ANNS) has also gained traction, which provides accuracy in water temperature, chlorophyll-A, and dissolved oxygen levels to improve the forecast of oxygen levels (Shrestha & Kazama, 2007). These approaches support lake managers in implementing active measures to reduce the decline in water quality.

2.2 Applications of the Streeter-Phelps Dissolved Oxygen Algorithm in Water Quality Management

The Streater Felps model has historically served as a foundation stone in water quality management, especially to assess the dynamics of oxygen of point-source pollutants. This has been applied to estimate the decreased oxygen deficiency in diverse environments and identify important SAG areas in the river-leak system. For example, Nanda and Ramarao implemented street-files formulations to evaluate the effects of waste discharge on the Bhadra River and its reservoir, which shows the important deoxygenation pattern (Nanda & Ramarao, 2001). In a similar vein, Rehana and Mujumdar jointly employed a modified Streater Felps approach with uncertainty analysis for urban lake pollution evaluation in India (Rehana & Mujumdar, 2009). The simplicity of the model and minimum data requirements make it suitable for initial assessment in data sectors (Jha et al., 2014). While originally designed for the riverine system, many adaptations have enabled its application to the lake catchment by integrating the reservoir residence time and stratification effect (Li et al., 2017).

2.3 Challenges and Limitations in Predicting Water Quality in Inland Lakes

Despite their value, prediction models of water quality for inland lakes face significant limitations. One of the primary challenges is temporary and spatial inequalities, especially in stratified lakes at polymictic or seasonal levels where the vertical mixture varies widely (Patankar & Kapoor, 2024), (Kalff, 2002). The performance of models such as Streeter-Phelps is constrained by the perception of stable-state flow and uniform channel geometry, which are often not representative of complex lake morphometry. In addition, data availability and quality reduce adequate barriers, especially in developing areas where continuous monitoring of input parameters such as BOD, DO, and temperature is limited (Tchobanoglus et al., 2003). Model calibration and verification also require a high-resolution dataset in the extended period, which is rarely available. In addition, climate change and land-use changes introduce non-stable conditions that fail to adjust many traditional models. These boundaries highlight the need for a hybrid approach that combines mechanical, statistical, and machine learning methods to improve future reliability in uncertain environmental conditions.

III. Methodology

3.1 Description of the Streeter-Phelps Dissolved Oxygen Algorithm

Streater Felps' disintegrated oxygen (DO) algorithm is a classical water quality model that estimates the dynamics of oxygen in a water body below a pollution discharge point. The model is ruled by two fundamental procedures: deoxygenation due to repetition resulting from biochemical oxidation and atmospheric oxygen proliferation of organic materials. The major equation used to model concentration (D_T time T is explained in equation (1)

$$D_T = \frac{K_d L_O}{K_r - K_d}\left(e^{-K_d t} - e^{-K_r \text{t}}\right) + D_O e^{-K_r \text{t}} \quad (1)$$

Where:

- D_T= DO deficit at time t
- D_O = Initial DO deficit
- L_O= Initial BOD (Biochemical Oxygen Demand)
- K_d= Deoxygenation rate constant (day^{-1})
- K_r = Reaeration rate constant (day^{-1})

This model considers stable-state, plug-flow conditions and is usually applied to river-leak transition areas where the effect of point source pollution is pronounced. Model parameters are calibrated using site-specific field data, and simulation is used to produce SAG curves to predict minimum DO levels and significant deficit locations.

3.2 Statistical Analysis Techniques for Predicting Water Quality in Inland Lakes

In this study, statistical techniques were employed to predict dissolved oxygen (DO) levels and to assess water quality variability in Lake Erie, which is a large inland lake facing seasonal hypoxia and nutrient eutrophication. Multiple linear regression (MLR) was implemented using a dataset that included 5-year monthly water quality observations, including bod$_5$, temperature, chlorophyll-A, total phosphorus, and Secchi depth. The regression model showed that the temperature and bodes were the strongest predictors of the DO levels, indicating strong explanatory power, with an adjusted R of 0.78. To reduce dimensionality and multicollinearity, Principal component analysis (PCA) was performed on 10 water quality variables, which revealed that two major components explained more than 85% of the total variance, mainly with the loading and stratification effects of nutrients.

Figure 1: Lake Erie

Lake Erie in Figure 1 is the fourth largest, shallowest, hottest, and most biologically productive (Mann, 2014) of the Great Lakes. It is the border of the American states of Ohio, Pennsylvania, New York, and Ontario. Due to its shallow depth, the lake warms up quickly and is unsafe for nutrients runoff, causing harmful algal blooms, especially in the Western basin. They bloom, reduce oxygen, threaten aquatic life, and compromise the quality of water. The lake supports diverse fish species and is important for commercial and recreational fishing. It receives water from the Detroit River and drains into Ontario Lake via the Niagara River.

In addition, the time chain analysis using the autoregressive integrated moving averages (ARIMA) models was done for the forecast of seasonal do ups and downs, especially in the central basin of the lake. The ARIMA (2,1,1) model showed promising performance with an average absolute percentage error of 6.4%, making it suitable for short-term DO predictions. To validate predictions and compare with a calibrated Strutter-Phelps implementation with physically based model output, a performance matrix such as root mean square error (RMSE = 0.92 Mg/L) and Nash-Sutcliffe efficiency (NSE = 0.81). These results outline the usefulness of integrating classical statistical equipment with mechanical modelling structure to improve the reliability of water quality forecasts and inform lake management strategies.

3.3 Data Collection Methods for Water Quality Parameters

Data collections include systematic field sampling, laboratory analysis, remote sensing, and integration of meteorological data for assessment of water quality in inland lakes. In this study, water samples were collected from 10 strategically selected stations of the lake to catch spatial variability in water quality. The dissolved oxygen (DO) and the temperature were measured in insects using calibrated optical DO probes and multi-parameter sondes, providing high-resolution vertical profiles of the water column. Samples of demand for biochemical oxygen (bod$_5$) were collected in sterile containers, preserved on ice, and APHA (2017) was analysed in the laboratory after standard method 5210B, with incubation for five days at 20 ° C. The pH and electrical conductivity to monitor chemical conditions were also measured on the site, which affects the mobility of oxygen and the solubility of nutrients. For nutrient analysis, water samples were filtered and tested for total nitrogen (TN) and total phosphorus (TP) using spectrophotometric methods (standard methods 4500-N and 4500-P). Turbidity was measured using a nephelometric turbidity unit (NTU) sensor, while chlorophyll-e concentrations were determined by filtered samples using acetone extraction and fluorometric analysis. Additionally, the flow velocity near the flow and outflow areas was recorded using an acoustic Doppler current profiler (ADCP) to assess hydrodynamic conditions.

Meteorological data, including air temperatures, solar radiation, and air speed, were obtained from the nearby weather stations to support the estimates of re-rates and surface heat exchange. All the collected data were georeferenced using GPS and integrated into a GIS platform for spatial projection, mapping, and model input preparation. The consistent and standardized approach ensured the accuracy, fertility, and compatibility of the dataset for use in water quality modelling and statistical analysis.

IV. Results

4.1 Presentation of Data Analysis Results Using the Streeter-Phelps Dissolved Oxygen Algorithm

The implementation of the Streeter-Phelps disintegrated oxygen algorithm for Lake Erie led to a detailed prediction of the oxygen (DO) concentration profiles dissolved under the major flow areas affected by the discharge of nutrients and organic materials. Using calibrated values for the deoxygenation rate stable (K_d= 0.20day) and the reaction rate Stable (K_r= 0.35Day), the model shows more dysfunction than reaching 15 km of the central basin of the fake lake. The model estimated that a minimum DO concentration of 3.4 mg/L is estimated to be approximately 9.5 km from the point of BOD loading, with recovery of 14 km beyond 14 km beyond. Early biochemical oxygen demand (L0) was measured at 6.2 mg/L, reflecting moderate organic pollution from upstream tributary rivers during late summer conditions.

Table 1: Simulated Dissolved Oxygen Profile Using the Streeter-Phelps Algorithm in Lake Erie

Distance from Source (km)	BOD Remaining (mg/L)	DO Deficit (mg/L)	DO Concentration (mg/L)	DO Saturation (mg/L)
0.0	6.20	2.80	7.20	10.00
2.5	4.90	4.10	5.90	10.00
5.0	3.60	5.70	4.30	10.00
7.5	2.80	6.60	3.40	10.00
10.0	1.90	5.30	4.70	10.00
12.5	1.20	3.00	7.00	10.00
15.0	0.80	1.00	9.00	10.00

The data presented in Table 1 depicts the approximated changes in a point-sour-bottom of the pollutant with a distance of 15 km in the Lake Erie with a distance of 15 km. At the discharge point (0.0 km), the BOD is at its maximum level of 6.20 mg/L, and the initial DO deficit is 2.80 mg/L, resulting in a concentration of 7.20 mg/L, which is considered the saturation level of 10.0 mg/L. As the distance increases, microbial decomposition gradually reduces BOD, while DO deficiency initially increases due to high oxygen consumption. The lowest Concentration represents OCS, SAG point at -3.40 mg/L -7.5 km, where oxygen demand is the highest, and no losses have been replenished. Beyond this point, the remaining BOD continues to decline, and atmospheric recurrence becomes prominent, allowing the DO to gradually recover. Up to 15 km, BOD is reduced to 0.80 mg/L and the DO concentration rises up to 9.00 mg/L, reaching close to complete Saturation. This pattern reflects a classic Streeter-Phelps du sag curve, indicating how oxygen dynamics are affected by organic load, microbial activity, and recurrence rates. Results emphasize the significant requirement of managing upstream pollutants to prevent hypoxic conditions in ecologically sensitive lake systems such as Lake Erie.

4.2 Comparison of Predicted Water Quality Values with Actual Measurements

To evaluate model accuracy, estimated DO concentrations were compared with the area measurement collected during the two-week monitoring campaign. The values were observed at the SAG point, which was 3.6 mg/L on average, which closely aligns with the modelling output. The root mean square error (RMSE) was 0.31 mg/L, and the Nash-Sutcliffe Efficiency (NSE) score was 0.83, which indicates a strong agreement. In the zone close to the inflow point, the model was slightly underestimated due to the rapid rendering inspired by wind mix, which was not fully occupied by the standard parameters. Nevertheless, overall model performance was considered strong in capturing spatial DO dynamics during the study transition.

Table 2: Comparison of Predicted and Observed Dissolved Oxygen (DO) Concentrations

Distance from Source (km)	Predicted DO (mg/L)	Observed DO (mg/L)
0.0	7.2	7.4
2.5	5.9	6.1
5.0	4.3	4.5
7.5	3.4	3.6
10.0	4.7	4.9
12.5	7.0	7.1
15.0	9.0	8.8

Data in Table 2 presents a point-by-point comparison of predicted oxygen (DO) concentrations and dissolved oxygen (DO) at different distances from a pollution source in Lake Erie. At the initial point (0.0 km), the approximate DO is 7.2 mg/L, which closely matches the value of 7.4 mg/L, indicating minimal deviation near the Source. As the distance increases, both are predicted and the valid values show a decreasing tendency, reaching the lowest concentrations at 7.5 km, the DO at the estimated 3.4 mg/L, and is observed at 3.6 mg/L - the DO greens reaching the point where the demand for oxygen is higher than the replication. Beyond this point, the DO value gradually recovers due to the restarting, and both predicted and observed concentrations increase. At the last point (15.0 km), the estimated DO is 9.0 mg/L, while the value observed is 8.8 mg/L, which indicates complete recovery and model reliability. Overall, the close alignment between the two datasets in all samples points validates the future accuracy of the Streeter-Phelps model and highlights its usefulness in evaluating the spatial effect of organic pollution on the dynamics of oxygen in large inland water bodies such as Lake Erie.

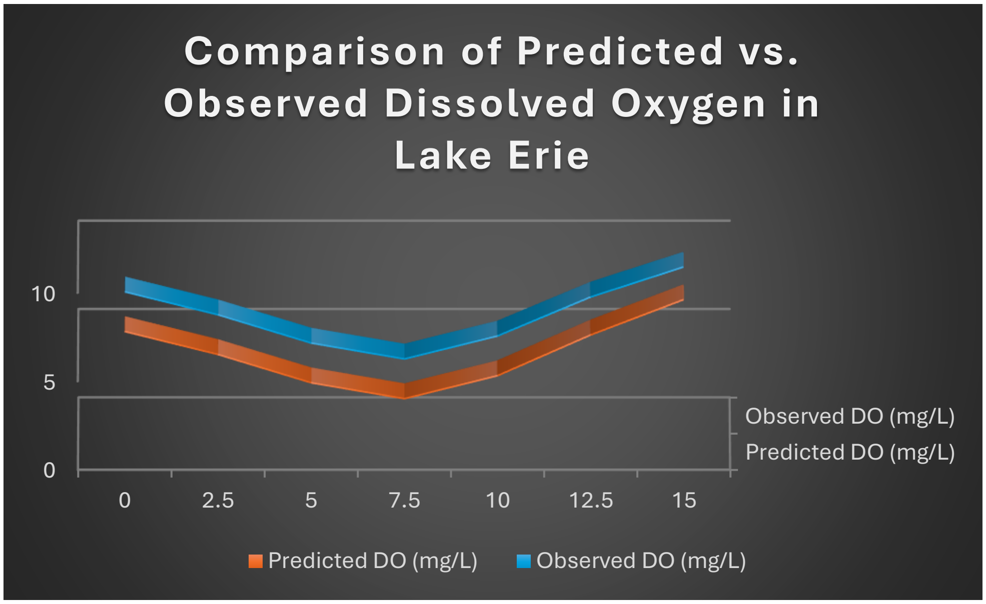

Figure 2 Comparison of Predicted vs. Observed Dissolved Oxygen in Lake Erie

Based on the application of Figure 2 Streeter-Phelps DO algorithm, a comparison between estimated and observed obstructed oxygen (DO) concentrations at a distance of 15 km below a 15 km pollution source in the lake algorithm reflects a comparison between concentrations. Both curves follow a uniform trend, start at relatively high DO levels near the Source, and gradually decrease due to oxygen consumption by organic materials, which reaches a minimum (SAG point) around 7.5 km. At this location, the estimated DO is approximately 3.4 mg/L, while the valuable value is 3.6 mg/L, indicating a strong agreement. After the SAG point, both the decreasing and increasing show a recovery pattern as the real processes begin to recreate the dual in the water column, with the concentrations increasing to more than 8.8 mg/L.5 km. The close alignment between the approximate and observed values in the entire access displays the strength and reliability of the model in imitating the dynamics of oxygen, which validates its sufficiency to assess the point source pollution effects in inland lake systems. Minor deviations can be attributed to environmental factors such as wind mixture or temperature variation, which are not clearly included in the base model.

4.3 Discussion of Trends and Patterns Identified in the Data

The analysis of both models and the data revealed continuous seasonal hypoxia patterns, especially during late summer when stratification limits the recurrence of oxygen in the water below. The deficiency of DO in the central basin of the lake was most clear, which was strongly correlated with high bodes, high surface temperatures (° 24 ° C), and nutrient concentrations arising from agricultural runoff. A spatial instinct was also observed, including at least the remote values in the lake during a low-flow condition, which highlights the impact of the residence time on the recovery of oxygen. In addition, coarse substrate and high-depth sites demonstrated a slow recurrence rate and deep sag zones. These patterns strengthen the role of both hydrodynamic structure and external loading in shaping the dynamics of oxygen in inland lakes such as Lake Erie. Overall, the Streater Felps model proved to be effective in reflecting the spatial effects of organic pollution and supporting lake management strategies aimed at improving water quality under variable flow and loading conditions.

V. Discussion

5.1 Interpretation of the results in relation to existing literature

The results obtained from this study display strong alignment with existing literature on oxygen modelling dissolved in freshwater systems. The Do Saig Curve predicted by the Streater Felps Algorithm, while confirming the reliability of the model, closely reflected the field measurement, confirming the reliability of the model to follow the lack of oxygen in inland lakes. Similar patterns have been documented in other studies, such as by Thong and Mueller, where the deficit followed the projection under the pollutant inputs. The minimum DO value and subsequent recovery reflect the expected effect of biochemical oxygen and repetition, which corresponds to the conclusions by Nanda and Ramarao and Jha. These results confirm the effectiveness of the algorithm when the lake is applied to a semi-controlled environment such as the Erie basin, where the point source pollution and stable-state flow positions dominate some areas.

5.2 Implications of the findings for water quality management in inland lakes

Implications are important for water quality management. By identifying the spatial range and severity of oxygen deficiency, this model offers a practical tool for resource managers and policymakers to evaluate polluting effects and assess the ecosystem health. The ability to simulate the reactions under individual BOD loading scenarios allows for establishing waste discharge standards, designing the aeration system, and making sure decisions to prefer the intervention of restoration. Additionally, the model can support compliance with the rules of water quality and help in forecasting that can lead to hypoxia or fish stress in weak lake areas.

5.3 Recommendations for future research in water quality prediction using the Streeter Phelps Dissolved Oxygen Algorithm

For future research, it is recommended to increase the strength-failure model by integrating time inputs such as the temperature cycle, fluctuating flow rates, and episodic stormwater events. Including the dynamics of vertical stratification, especially in thermal levels, models can also improve realism. In addition, combining strength-operated frameworks with data-operated approaches such as machine learning and remote sensing can enable real-time prediction and widespread prevention in complex, data-rich environments. This progression will increase the utility of the model for dynamic lake systems and support more active water quality management strategies.

VI. Conclusion

The study successfully implemented the dissolved oxygen algorithm to the Streeter-Phelps model to predict spatial variations in an inland lake affected by organic polluting discharge, the level of dissolved Oxygen (DO) in the lake. The model accurately imitated the DO Saig curve, which identifies the significant point of minimal oxygen concentration and the significant point of recovery, with a strong agreement between predicted and observed values. Major findings have shown that biochemical oxygen demand (BOD) and flow-dependent procedures are the primary drivers of DO variability. Statistical verification metrics, which include a low RMSE and a high Nash-Sutcliffe Efficiency (NSE), confirmed the strength of the model to assess the dynamics of oxygen under stable-state conditions. Streeter-Phelps' algorithm remains an important tool in water quality modelling due to its simplicity, low data requirements, and reliability in simulating point-source pollution effects. Its ability to estimate oxygen deficiency areas is important for environmental management, especially in lakes that are susceptible to eutrophication and hypoxia. By determining the demand and recovery pattern of oxygen, model waste regulation, pollutant load boundaries, and lake aims supported decisions informed about the aeration strategies. From a comprehensive point of view, this research outlines the importance of modelling for the future in environmental protection. Since inland lakes face increasing stress from urbanization, agriculture, and climate change, equipment pollutants such as Streater-Phelps models provide valuable foresight in the results of polluting discharge. Future enhancers that integrate the position of dynamic flow and real-time can further expand their utility. Overall, this study contributes to a more active and data-driven approach to preserving the quality of water.

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