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QUAL2Kw – A Water Quality Modelling Tool for Rivers and Streams: A Review

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Abstract
The QUAL2Kw is a widely used one-dimensional water quality model designed for rivers and streams under steady-state flow conditions. This review critically assesses the input data requirements, applications, recent advancements, strengths, and limitations of the model. Numerous studies have used QUAL2Kw to model the impacts on water quality of both point and non-point pollution sources, to assess pollution load capacity, and to frame control strategies for water quality management of rivers and streams. Its flexible kinetic structure, genetic algorithm-based calibration, and compatibility with Microsoft Excel make it a preferred tool for researchers and policymakers. However, limitations such as the model's steady-state flow assumption, simplified hydrodynamics, and challenges in representing temporal variability are also addressed. This paper provides an overview of recent enhancements and hybrid approaches that combine QUAL2Kw with other models and tools to enhance prediction accuracy and support informed decision-making. The review aims to enable users to understand the model's compatibility and its various applications in achieving the sustainable management goal of river water sources.

Keywords
WQM, Q2K, one-dimensional steady-state model, integrated use of QUAL2Kw, RMSE

1.0 Introduction:

QUAL2Kw is the water quality model designed for rivers and streams by the United States Environmental Protection Agency (USEPA). It is a one-dimensional model and simulates the transport of water quality constituents assuming a steady-state flow condition. The model is capable of simulating various water quality parameters, including pH, inorganic solids, temperature, dissolved oxygen (DO), carbonaceous biochemical oxygen demand (in two forms slow and fast), phosphorus (in organic and inorganic forms), nitrogen (in the forms of nitrite, nitrate, nitrite, and ammonia), pathogens, detritus, algae and phytoplankton. The model provides a user-friendly interface in the form of Microsoft Excel, integrated with Visual Basic Applications (VBA). The model has a built-in genetic algorithm (GA) that facilitates

users for automatic calibration of the water quality parameters (Chapra & Pelletier, 2003; Pelletier et al., 2006).
Numerous researchers have utilized the QUAL2Kw model to assess river water quality for various purposes, including evaluating assimilative capacity and pollution load from different wastewater discharges, developing strategies by simulating various pollution and flow control conditions, and managing pristine river water sources. Therefore, it has proved as a powerful tool in environmental sustainability (Darji et al., 2022).

This review provides a comprehensive understanding of the QUAL2Kw model, enabling users to understand its input requirements, features, applications, sensitivity, and performance. The paper outlines the models' simulation capability under diverse pollution loads and seasonal climatic conditions. The paper also provides insights into the integrated use of the model with decision support tools such as Water Quality Index (WQI), Geographic Information Systems (GIS), and other hydrological and watershed models for its enhanced applications. This paper synthesizes recent case study findings to identify the model's performance across various environments, best practices, and key challenges such as calibration and data reliance. The review concludes by highlighting the limitations of QUAL2Kw and proposes modifications to increase its usability, such as incorporating real-time data and combining with other tools to handle the complex pollutants beyond standard metrics.

2.0 Model overview and key features:

The United States Environmental Protection Agency (USEPA) has developed a series of QUAL models for water quality simulations in river systems with a network of tributaries, including pollution from both point and non-point sources. These models are mainly one-dimensional and capable of simulating either steady-state or dynamic flow conditions. The initial QUAL models were updated to QUAL2E and ultimately to the QUAL2K series.

The QUAL2E model was amended and developed as QUAL2K by upgrading computer coding and integrating it with the supplementary components, such as the denitrification process, algal growth, and impacts on dissolved oxygen dynamics. The QUAL2Kw, also known as Q2K, was introduced in 2003 by Chapra and Pelletier as an advanced version of the QUAL2K model. The model features automatic calibration, enhanced flexibility, and improved process kinetics, which enable more accurate water quality simulations for rivers (Park & Lee, 2002; Pelletier et al., 2006; Pelletier & Chapra, 2008).

Although QUAL2Kw is essentially a one-dimensional steady-state model, it is capable of performing dynamic simulations for water quality kinetics and heat budgets (Chapra & Pelletier, 2003; Ranjith et al., 2019; Turner et al., 2009). The model simulates the mainstream of a river, whereas tributaries are included as point sources rather than being modeled separately, as depicted in Figure 1.

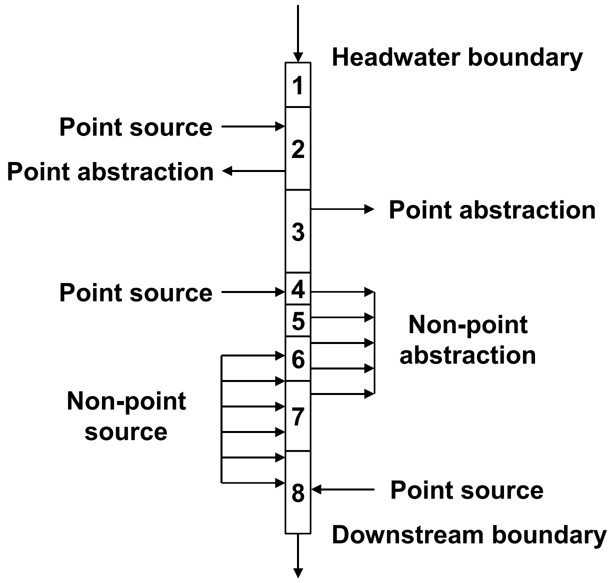

Figure 1 Segmentation of River Reaches in QUAL2Kw (Pelletier & Chapra, 2008)

QUAL2Kw integrates several new features: it employs Microsoft Office programming, including macro and Visual Basic applications, creating a user-friendly interface; it allows for the simulation of river reaches of varying lengths within a single system, accommodating multiple loading input options; and it models organic carbon as carbonaceous biochemical oxygen demand (CBOD) in two forms, slow and fast. Furthermore, it simulates dissolved oxygen and nutrient fluxes internally, resulting from the interactions between sediment and water, while also being capable of simulating parameters such as bottom algae, alkalinity, total inorganic carbon, and pathogens. Additional parameters, including hyporheic exchange, sediment pore water quality, and light extinction, are also incorporated.

The distinguished feature of QUAL2Kw is its ability to simulate diurnal variations in significant parameters, such as dissolved oxygen, temperature, pH levels, and algal activity, representing a notable enhancement over the previous QUAL2E model (Pelletier et al., 2006). The model supports multiple point and non-point source inputs and includes considerations for light extinction processes and sediment oxygen demand, thus making it well-suited for realistic modeling of pollution dynamics (Kannel, Lee, Kanel, et al., 2007; Mummidivarapu et al., 2023). Additionally, the inclusion of the advanced automatic calibration tool utilizing a genetic algorithm helps to optimize parameter calibration effectively. Due to its distinctive features, user-friendly design, and various advantages over competing software, it is widely used for simulating water quality for rivers and streams under various pollution and environmental scenarios.

A sensitivity analysis should be conducted to quantify the errors linked to the simulated parameters. The model reliability can be checked by an uncertainty analysis. Monte Carlo simulation calculates the uncertainty of the parameters. Various statistical tests, such as R^2, Mean Bias Error (MBE), Root Mean Square Error (RMSE), and Standard Deviation Bias Error (SDBE), provide a better judgment of differences between input and simulated data (Moghimi Nezad et al., 2018).

3.0 Comparison with the other water quality models:

A wide variety of water quality models (WQMs) have been available for streams or rivers. Multiple reviews are available highlighting the different features of each model. Costa et al., (2021) reviewed CE-QUAL-W2, SPARROW, AQUATOX, WASP7, and SWAT models and indicated the distinctive features and applications of each model. Ejigu (2021) described an overview of water quality modeling with model classification and selection, and highlighted certain water quality models used at the catchment and for water bodies, including BASINs, AQUATOX, MIKE, Streeter-Phelps, QUAL, CE-QUAL-W2, CE-QUAL-RIV1, DUFLOW, WASP, HSPF, HEC-5Q, TELEMAC, and EFDC. Olowe (Olowe & Kumarasamy, 2018) critically reviewed models such as QUAL2K, WASP, AQUATOX, MIKE11, SWAT, and CEQUALRIV1, focusing on their structural framework, parameter requirements, spatial-temporal resolution, and suitability for various hydrological and ecological conditions. Darji et al., (2022) described six selected widely used water quality models, QUAL2Kw, SWAT, WASP, SIMCAT, CE-QUAL-W2, and MIKE-11, providing a concise summary to assist users in selecting an appropriate model.

Despite the availability of a wide range of water quality models, the Qual2Kw model has emerged as an important tool and has been successfully applied in various research studies. Numerous studies have reported its widespread applications in countries like India and Iran. (Ghorbani et al., 2022; Mulla et al., 2024; Patel & Jariwala, 2024; Sarafaraz et al., 2024; Verma et al., 2024)

4.0 Model input requirement:

To run the QUAL2Kw model effectively, a range of physical, chemical, biological, and hydraulic input data is required. These data are typically organized reach-wise (i.e., for each river segment) and help in accurate water quality simulations (Pelletier & Chapra, 2008). The inputs can be categorized into the following major groups:

Headwater data: Flow and water quality at the headwater; downstream water quality, if a prescribed boundary exists at the downstream end, are required for assessment of its effect on the simulation.

Water quality data (Headwater and Boundary Conditions): These are required both at the Headwater and for model calibration: temperature, conductivity, inorganic suspended solids (ISS), dissolved oxygen (DO), CBOD slow, CBOD fast, organic nitrogen, NH_4-nitrogen, NO_3-nitrogen, organic phosphorus, inorganic phosphorus, phytoplankton, detritus, pathogen, alkalinity and pH

Sediment Parameters (Optional but recommended): sediment oxygen demand (SOD), nutrient fluxes from sediments, benthic algae properties.

Reach data: Reach label (Optional), reach label at the downstream end (optional), Downstream location, upstream and downstream elevation, downstream latitude and longitude, length of each reach.

Hydraulic model: Q2K provides two alternatives for computing velocity and depth based on flow: (1) rating curves or (2) the Manning formula. It is required to select one of the options and leave the other blank or zero. If the model detects a blank or zero value for the Manning n, it will implement the rating curves. Otherwise, the Manning formula will be solved. For the rating curve method, the data, including the Velocity coefficient and exponent, the depth or width coefficient, and the depth or width exponent, are required. For manning's formula, bottom width, side slopes, channel slope, manning's roughness coefficient (n), prescribed dispersion if known at the reach downstream end, weir height (optional), prescribed reaeration if known for the reach, bottom algae coverage, bottom SOD coverage, prescribed SOD, prescribed CH_4 (Methane) flux, prescribed inorganic phosphorus flux, prescribed NH_4 (Ammonium), sediment thermal conductivity (suggested default value 1.6 W/(m °C), sediment thermal diffusivity (suggested default value 0.0064 cm^2/sec) , sediment thickness (Typically about 10 cm if there is negligible hyporheic exchange and approximately 20-100cm if there is substantial hyporheic exchange), hyporheic exchange flow if hyporheic exchange is simulated, hyporheic sediment porosity (Typical porosity of cobble, gravel, sand, silt sediments ranges from about 35% to 50%. A default value of 40% is suggested), sky opening for longwave (recommended default value is 100% for no adjustment of the longwave radiation terms)

Meteorological Data: air temperature, dew point temperature, wind speed, cloud cover, or solar radiation

Light and heat rate parameters: QUAL2Kw allows users to enter and select the model for light and heat rate parameters.

Point and non-point source data: The sources of inflow and outflow and their location; temperature and water quality constituents of the inflow are required to be entered.

Kinetic and process rate parameters: These govern the transformation of pollutants and biological processes: reaeration coefficients, BOD decay rate, nitrification rate, denitrification rate, algal growth and death rates, settling and resuspension rates for solids. Default values are provided in QUAL2Kw, but site-specific calibration is recommended.

5.0 Model calibration and Validation:

Calibration and validation are required to ensure the model's accuracy. Calibration includes optimizing model parameters to match observed data, while validation compares the calibrated model against a separate dataset to confirm its reliability. These processes are important for building confidence in the model's simulation ability under various conditions and for supporting informed management decisions. This ensures that the model accuracy of the simulation in the specific river or stream being studied. Validating the model provides confidence in the calibrated model to predict various water scenarios. The step-by-step procedure of the model's calibration and validation is described below and shown in Figure 2.

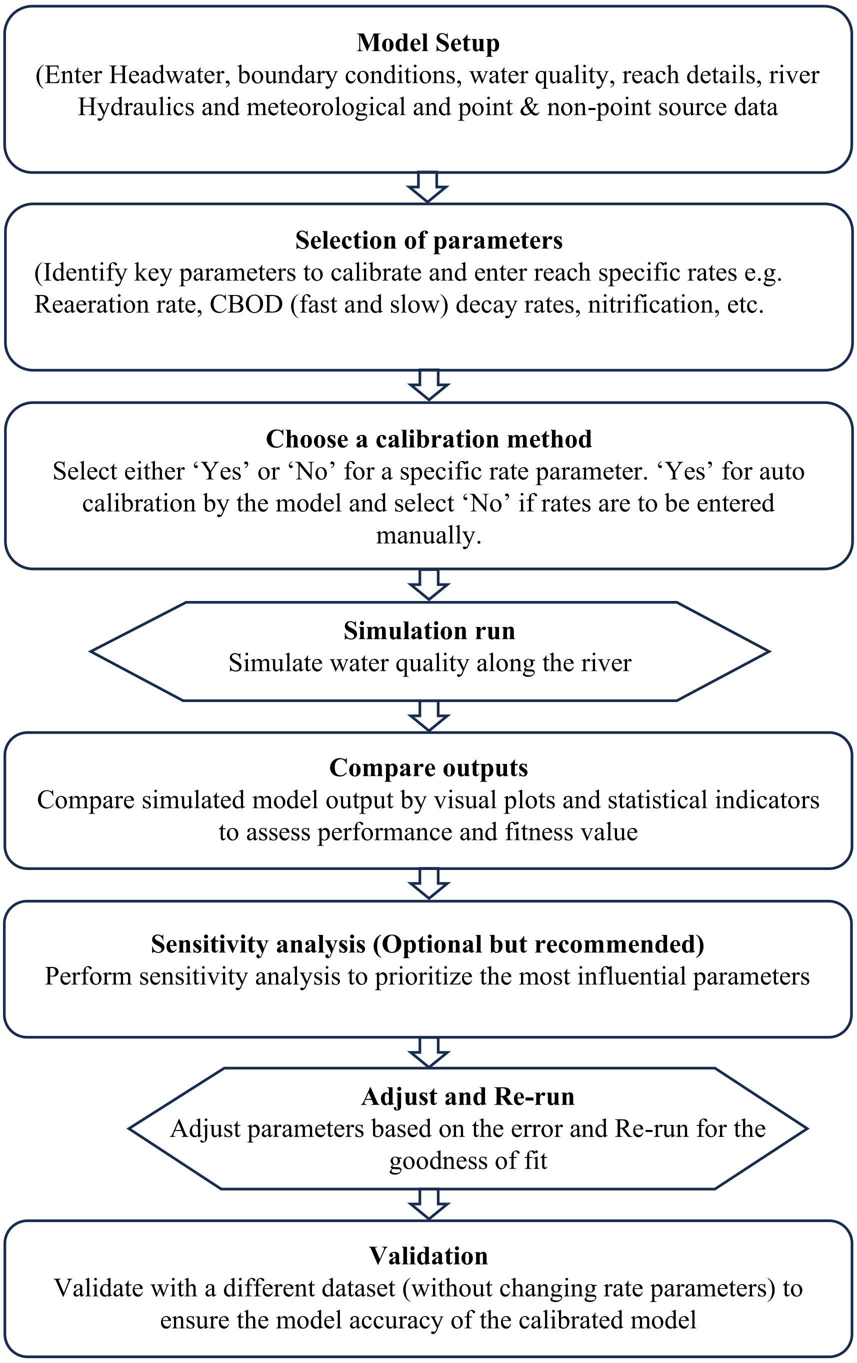

Figure 2 Step-by-step procedure of QUAL2Kw model calibration and validation

Model calibration:

Calibration in QUAL2Kw refers to the process of adjusting the model's parameters to optimize the difference between input and output water quality data. The built-in genetic algorithm allows for the automatic calibration of the water quality parameters. The user needs to specify manual or automatic calibration of the selected rate parameter by selecting the 'Yes' or 'No' option. 'No' option allows manual calibration of the selected rate parameters i.e. the values entered by the users will be used for the calibration. While the 'Yes' option undergoes the automatic calibration of the selected rate parameters.

Raeisi et al., (2022) indicated the best model optimization with the calibrated values obtained through automatic calibration by GA.

Sensitivity analysis:

The sensitivity analysis needs to be performed to measure the error related to the key parameters. Some parameters have a larger influence than others; uncalibrated sensitive parameters may cause poor predictions. The sensitivity analysis helps optimize model performance. Recent sensitivity analyses of QUAL2Kw stream water quality models have reported that the model performance is significantly affected by reaeration rate and flow dynamics. Khonok et al., (2022) found that electrical conductivity, biochemical oxygen demand, and pH are the key parameters in the Sefid Rud River model most affected by changes in flow, whereas total nitrogen and phosphorus were less sensitive. Mulla et al., (2024) reported that dissolved oxygen in the Kabini River is significantly influenced by the reaeration rate, point-source discharge, and total nitrogen, with a lesser impact from the channel slope, width, and total phosphorus.

Evaluating model performance:

Model performance can be evaluated by various statistical indicators such as coefficient of determination R^2, mean bias error (MBE), Root Mean Square Error (RMSE), Normalized RMSE, Nash-Sutcliffe Efficiency (NSE), standard deviation bias error (SDBE), and percent bias. These indicators are commonly used in environmental modeling to estimate the accuracy of calibration and validation, and assist in determining the suitability of a model for predictive purposes in river water quality management.

Moriasi et al., (2007) established guidelines for interpreting the performance of water quality and hydrological models, including Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), R^2, and RMSE, indicating that lower RMSE and NRMSE values signify better accuracy, and R^2 values closer to 1 signify a strong correlation between the simulated data and observed data. Pelletier et al., (2006) utilized RMSE as an objective function in the model's built-in genetic algorithm for auto calibration in QUAL2Kw development. A lower value of the NRMSE indicates a better match between the model's predictions and the actual data, implying greater accuracy and dependability in the model's performance. Chai & Draxler, (2014) highlighted the significance of utilising both RMSE and MBE to identify systematic errors and overall model bias. Sharma et al., (2017) utilized coefficient of determination (R^2), mean bias error (MBE), root mean square error (RMSE), normalized RMSE, and standard deviation bias error (SDBE) for assessing statistical variations between model input and output water quality parameters. Table 1 depicts statistical indicators commonly used to estimate the model's performance.

Table 1 Statistical indicators utilized for the model's performance

Metric	Full Form	Ideal Value	Interpretation	Reference
RMSE	Root Mean Square Error	less than half of the standard deviation of measured data is considered low <0.7RSR (Satisfactory) < 0.6RSR (good) <0.5 RSR (very good)	Measures average magnitude of prediction error; sensitive to large errors.	(Chai & Draxler, 2014; Moriasi et al., 2007; Sarafaraz et al., 2024)
NRMSE	Normalized RMSE	< 20% (acceptable) < 10% (good)	Normalized form of RMSE; enables comparison across parameters or datasets.	(Kori et al., 2013; Moriasi et al., 2007; Sharma et al., 2017)
R^2	Coefficient of Determination	> 0.5 (Acceptable)	Indicates the strength of linear correlation between observed and predicted values.	(Kannel, Lee, Kanel, et al., 2007; Khonok et al., 2022; Sharma et al., 2017)
NSE	Nash–Sutcliffe Efficiency	>0.5 (Satisfactory), >0.65 (good)	Describes predictive skill; 1 is perfect, 0 means same as the mean of the observed.	(Cho & Lee, 2019; Moriasi et al., 2007)
MBE	Mean Bias Error	Close to 0	Shows average bias; positive means overestimation, negative means underestimation.	(Khonok et al., 2022; Moriasi et al., 2007; Sharma et al., 2017)
SDPE	Standard Deviation of Prediction Error	Low	Assesses variability in prediction error; lower values indicate consistent accuracy.	(Sharma et al., 2017)
PBIAS	Percent Bias	< ±10% (excellent), <±25% (satisfactory)	Indicates model tendency to under- or over-predict; low absolute value is preferred.	(Cho & Lee, 2019; Moriasi et al., 2007; Van Liew et al., 2007)

Model fitness:

In the QUAL2Kw model, calibration is driven by a fitness function that takes the reciprocal of a weighted average of normalized RMSE values (NRMSE) across all simulated water quality constituents (Pelletier et al., 2006).

$$f(x) = \left[\sum_{i=1}^{n} w_i\right]\left[\sum_{i=1}^{n} \frac{1}{w_i}\left[\frac{\frac{\sum_{j=1}^{m} O_{ij}}{m}}{\left[\frac{\sum (P_{ij}-O_{ij})^2}{m}\right]^{1/2}}\right]\right]$$

where $O_{i,j}$ = observed values, $P_{i,j}$ = predicted values, m=number of pairs of predicted and observed values, w_i : weighting factors, and n= number of different state variables used in the reciprocal of the weighted normalized RMSE.

This approach enables researchers to give different weights to each parameter based on its ecological significance or modeling goals. The researchers should identify the significant variables influencing the water quality of a river or stream within the study area, which helps users in applying a water quality model to achieve the specific goal of the study. Multivariate statistical analysis helps researchers to identify significant water quality variables (Darji & Lodha, 2025; Kannel et al., 2011; Noori et al., 2010). As reported by the various studies, dissolved oxygen or nutrients have a more significant impact on model calibration results. For instance, more weights can be assigned to DO when water quality management is a key goal, whereas lower weights are allocated to less important parameters (Darji et al., 2022; Kannel, Lee, Kanel, et al., 2007; Pelletier et al., 2006).

Various studies utilized different weighting strategies for water quality parameters to tailor the calibration process toward specific environmental or management objectives. For instance, Kannel, Lee, Lee, et al., (2007) gave a significantly high weight of 50 to dissolved oxygen (DO), highlighting its significance in evaluating river health and model accuracy. Kannel, Lee, Kanel, et al., (2007) assigned varying weights to represent the relative significance of water quality parameters to frame management strategies of the Bagmati River, Nepal: a weight of 10 was given to dissolved oxygen (DO), while parameters including BOD_5, Total nitrogen, pH, temperature, and total phosphorus were given weights of 2. A default weight of 1 was assigned to the other parameters. According to Kori et al., (2013) the weight for dissolved oxygen was given as 50, being the most influential parameter. Weight 5 was given for BOD, and weight 1 was given to the other parameter for simulating the water quality of the Karanaja River, India. This hierarchical weighting strategy guarantees that calibration efforts concentrate on enhancing parameters that are most indicative of ecological health and regulatory compliance. Weight-based methods enable modelers to more accurately model the behaviour of key pollutants while preserving computational efficiency and model reliability (Pelletier et al., 2006).

Model validation:

To ensure the accuracy of the calibrated model beyond the calibration dataset, model validation is essential. Validation in QUAL2Kw involves using a separate dataset, collected at a different time or location, to assess the model's ability to predict water quality. This step is critical for ensuring that the calibrated model is not just fitting the specific data used for calibration, but can also generalize to other conditions (Kannel, Lee, Kanel, et al., 2007; Sharma et al., 2017).

6.0 Application of QUAL2kw in River water quality management:

Numerous studies have applied QUAL2Kw for river pollution load assessment, policy formulation, and water quality management. Various applications of the model are described below and summarized in Table 2.

Assessment of Pollution load and self-purification of the river

Researchers have utilized the model to quantify the impact of point and non-point sources of pollution on industrial effluents and agricultural runoff on river water quality. For instance, Rizky et al., (2024) evaluated the pollution load carrying capacity of the Garuda River, impacted by tofu industry effluents. They used QUAL2Kw under three scenarios to compute carrying capacities for TSS, BOD, and COD, finding critical exceedances particularly for TSS and BOD (e.g., 233–259 kg TSS/day; 12.9–15.6 kg BOD/day). Darajati Setiawan et al., (2018) applied QUAL2Kw to the Bedog River in Indonesia to evaluate BOD and COD loading from domestic and non-point sources, concluding that the river was operating within its assimilative limits. Hoseini & Hoseini, (2018) used QUAL2Kw to assess the assimilative capacity of Gharehsou River. Simulated DO, BOD, NO_3, temperature, and pH showed good optimization with observed data (e.g., R^2 up to 0.75 for BOD). Similarly, Lestari et al.(Lestari et al., 2019) assessed the carrying capacity of the Musi River, estimating a daily BOD_5 load of over 25,000 kg and highlighting the need for effective load management. Sharma et al., (2017) applied QUAL2Kw to assess pollution in the Yamuna River, India. The results showed sharp declines in DO and rises in BOD levels near major sewage outfalls.

Scenario development for pollution control strategies

QUAL2Kw has been widely used model for simulating different management strategies such as flow augmentation, treatment efficiency improvement, and pollution load reduction. Patel & Jariwala, (2023) estimated the carrying capacity of the Tapi River (India) with different pollution load scenarios and reported higher capacity at the downstream segment compared to the upstream and middle stream segments. Waturu et al., (2022) applied QUAL2Kw to the Athi River basin in Kenya to model pollutant trajectories up to 2030, revealing a projected decline in water quality under business-as-usual conditions.

Integration with Decision Support Systems:

QUAL2Kw has been combined with GIS, remote sensing, and multi-criteria decision analysis in several studies to improve visualization and policy relevance. Pramaningsih et al., (2020) demonstrated how integration of QUAL2kw with GIS enhances spatial analysis and helps in identifying critical pollution hotspots in the Karang Mumus River. Ahmad Kamal et al., (2020) conducted a study of the QUAL2Kw model integrated with the Geographic Information Systems (GIS) to evaluate the spatial and temporal distribution of water quality in the Langat River Basin, Malaysia. The study found that this approach was very effective in identifying pollution hotspots and provided a clearer spatial understanding of the impact of land use and point source discharges on river water quality

Evaluating Seasonal and Climatic Influence

The QUAL2Kw model is particularly well-suited for evaluating the influence of seasonal and climatic variability on river water quality due to its ability to simulate dynamic changes in flow, temperature, and pollutant transformation processes under varying environmental conditions. Hoseini & Hoseini, (2018) assessed the Gharehsou River in Iran during both January (winter) and July (summer). The model revealed notable differences in DO and BOD patterns due to changes in temperature-dependent reaction kinetics and flow volumes, with higher BOD degradation rates during warmer months. Similarly, Waturu et al., (2022) used QUAL2Kw to evaluate long-term seasonal trends in Kenya's Athi River, incorporating time series forecasts under different climate scenarios, which indicated deteriorating water quality during extended dry periods.

By integrating seasonal datasets and climatic inputs, QUAL2Kw serves as a valuable decision-support tool for developing adaptive pollution control strategies, particularly in regions where water quality is highly sensitive to hydrological and meteorological fluctuations.

Combination of QUAL2kW with composite indices:

In recent years, an integrated approach combining process-based modeling (QUAL2Kw) with composite indicators (Water Quality Index, WQI) has gained traction for comprehensive river health assessment. This dual-method strategy leverages the dynamic simulation capabilities of QUAL2Kw—used for predicting the spatial and temporal variation of pollutants such as DO, BOD, NH_3-N, and nutrients—with the simplicity and communicative strength of WQI, which consolidates multiple parameters into a single numeric value for easy interpretation.

Iqbal et al., (2018) applied the QUAL2Kw model in conjunction with the Water Quality Index (WQI) to evaluate river water quality across different climatic zones. The study revealed that climatic variations significantly influence dissolved oxygen (DO) dynamics, including reaeration rates, oxygen solubility, and reoxygenation capacity. Results indicated that tropical, temperate, and arid zones exhibited a clear decline in DO levels and WQI along the river stretch, whereas the cold climate zone showed relatively stable conditions with minimal longitudinal variation. The combined QUAL2Kw-WQI approach proved effective in identifying climate-specific water quality trends, providing valuable insights for developing tailored and sustainable water quality management strategies.

Mummidivarapu et al., (2023) implemented an integrated modeling framework combining QUAL2K, GIS mapping, and Water Quality Index (WQI) analysis to assess river water quality under diverse hydro-climatic and pollution scenarios in the Bhadravati stretch of the Bhadra River, India. Their calibrated QUAL2K model simulated key parameters—temperature, pH, conductivity, DO, BOD, nitrates, ammonia, and alkalinity—and these were processed via a weighted-arithmetic WQI to generate spatial water-quality maps. The study demonstrates that the QUAL2K–WQI–GIS approach offers a powerful tool for spatially and scenario-based water quality management, highlighting how maintaining flow regimes and reducing pollution loads can markedly improve river health.

Integration with other tools:

Combining Qual2kw with the other models enhances its simulation capacity under different environmental conditions for complex river water quality. Chen et al., (2023) combined QUAL2kw with the watershed hydrological model, Soil and Water Assessment Tool (SWAT) for the study of Daitou Creek. The proposed framework resulted in efficient stream flow and nutrient dynamics with an optimal reclaimed water supplement scheme and a feasible solution for water quality degradation. Bui et al., (2019) utilized the hydrological process output of SWAT as an input to the QUAL2Kw to simulate water quality of the Cau River basin to support water quality and watershed management. Fan et al., (2009) conducted a study integrating the QUAL2K model with the HEC-RAS hydraulic model to evaluate the water quality of a river located in northern Taiwan, influenced by tidal effects. The study demonstrated that coupling hydrodynamic modeling with water quality simulation provided a more accurate representation of pollutant transport and transformation processes, particularly in tidal-influenced systems. Chaudhary et al., (2018) applied the QUAL2K water quality model in combination with MATLAB to enhance the model's computational efficiency and enable automated calibration. This approach improved the model's accuracy in simulating pollutants such as dissolved oxygen and biochemical oxygen demand. Farokhi et al., (2025) demonstrated coupling WEAP (Water Evaluation and Planning System) for upstream watershed processes with QUAL2K for in-stream water quality dynamics and found an improvement in the accuracy of predictions related to nutrient transport, dissolved oxygen levels, and pollutant dispersion.

Table 2 Applications of the QUAL2Kw model in simulating river water quality

Sr. No.	Purpose of Application	Benefits	References
1.	Assessment of Pollution load and self-purification of the river	• Impacts of pollution sources can be quantified (point and non-point sources) • Assists in evaluating the river's operating capacity within assimilative capacity and its health • Highlights the requirement of pollution load management	(Darajati Setiawan et al., 2018; Hoseini & Hoseini, 2018; Lestari et al., 2019; Rizky et al., 2024; Sharma et al., 2017)
2.	Development of pollution control strategies	• Different management strategies, such as amendments in pollution load, river inflow, and wastewater flow, and improvement in treatment efficiency, can be simulated	(Patel & Jariwala, 2023; Waturu et al., 2022)
3.	Integration with Decision Support Systems	• Combining with GIS and remote sensing helps identify critical pollution hotspots • Provides a clear understanding of the spatial impacts of point and nonpoint sources	(Ahmad Kamal et al., 2020; Pramaningsih et al., 2020)
4.	Analysing Seasonal and Climatic Influence	• Supports in evaluating the impacts of seasonal and climatic variability on the water quality and long-term seasonal trends • Highly sensitive regions to the seasonal fluctuations can be supported with the adaptive pollution control strategies	(Hoseini & Hoseini, 2018; Waturu et al., 2022)
5.	Predicting spatial and temporal variations of pollutants	• Combining with WQI helps predict variations (spatial and temporal) of pollutants and develop sustainable water quality management strategies	(Iqbal et al., 2018; Mummidivarapu et al., 2023)
6.	Integration with other tools	• QUAL2Kw with SWAT, the watershed hydrological model, provides efficient streamflow and nutrient dynamics for a complex river system	(Bui et al., 2019; Chen et al., 2023)
		• Integration with the HEC-RAS hydraulic model can able to evaluate water quality in a tidal river	(Fan et al., 2009)
		• The researcher used QUAL2Kw in combination with MATLAB to enhance the model's computational efficiency and enable automated calibration.	(Chaudhary et al., 2018)
		• The study demonstrated a coupled modeling approach, integrating QUAL2Kw for water quality simulation of a stream with WEAP (Water Evaluation and Planning System) to account for watershed-scale hydrological processes and pollutant loadings.	(Farokhi et al., 2025)

7.0 Assumptions and limitations

QUAL2Kw is a one-dimensional (1D) water quality model that simulates the longitudinal transport of water, which limits its application to reservoirs or wide rivers with substantial stratification caused by vertical and lateral mixing. The model assumes steady-state flow conditions that limit its application for rivers with diurnal flow conditions (Pelletier et al., 2006).

The model requires manual segmentation of river reaches, which needs to be defined carefully based on the site characteristics and pollution sources of the river. The model is capable of simulating the mainstream of the river, and the tributaries are represented as point sources (Pramaningsih et al., 2020). The reliability of the model is highly dependent on the data. The model requires large data inputs for the simulation of river reaches. Some of which are difficult to specify and depend on the assumptions. This may lead to ambiguity in the calibration and validation output and the model performance (Sharma et al., 2017). The coliforms are simulated up to the primary level, but the complete simulation of the toxic or emerging compounds is not possible (Waturu et al., 2022).

8.0 Conclusion:

The QUAL2Kw model is a widely adopted water quality model for river water quality simulation and assessing different scenarios under various environmental and hydrological conditions. The model is capable of simulating the maximum number of water quality parameters. The model is easily accessible and has a user-friendly interface. The built-in autocalibration facilitates the user in achieving the optimized simulation output. The model can work under diverse environmental conditions and is capable of simulating various scenarios.

The model’s steady-state flow condition, data reliance, and user-defined segmentation limit its application to complex river systems. However, its combined applications with decision support tools and hydrological and watershed models have shown its enhanced applications in complex river systems. The application of a calibrated and validated model with reliable datasets helps in formulating management strategies to restore the river’s health and achieve sustainable management goals.

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