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Assessing the impact of COVID-19 lockdown on surface water quality in Ireland using advanced Irish water quality index (IEWQI) model ☆

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ABSTRACT

The COVID-19 pandemic has significantly impacted various aspects of life, including environmental conditions. Surface water quality (WQ) is one area affected by lockdowns imposed to control the virus's spread. Numerous recent studies have revealed the considerable impact of COVID-19 lockdowns on surface WQ. In response, this research aimed to assess the impact of COVID-19 lockdowns on surface water quality in Ireland using an advanced WQ model. To achieve this goal, six years of water quality monitoring data from 2017 to 2022 were collected for nine water quality indicators in Cork Harbour, Ireland, before, during, and after the lockdowns. These indicators include pH, water temperature (TEMP), salinity (SAL), biological oxygen demand (BOD_5), dissolved oxygen (DOX), transparency (TRAN), and three nutrient enrichment indicators—dissolved inorganic nitrogen (DIN), molybdate reactive phosphorus (MRP), and total oxidized nitrogen (TON). The results showed that the lockdown had a significant impact on various WQ indicators, particularly pH, TEMP, TON, and BOD_5. Over the study period, most indicators were within the permissible limit except for MRP, with the exception of during COVID-19. During the pandemic, TON and DIN decreased, while water transparency significantly improved. In contrast, after COVID-19, WQ at 7% of monitoring sites significantly deteriorated. Overall, WQ in Cork Harbour was categorized as "good," "fair," and "marginal" classes over the study period. Compared to temporal variation, WQ improved at 17% of monitoring sites during the lockdown period in Cork Harbour. However, no significant trend in WQ was observed. Furthermore, the study analyzed the advanced model's performance in assessing the impact of COVID-19 on WQ. The results indicate that the advanced WQ model could be an effective tool for monitoring and evaluating lockdowns' impact on surface water quality. The model can provide valuable information for decision-making and planning to protect aquatic ecosystems.

1. Introduction

Surface water quality is crucial for environmental and human health, but pollution from human activities such as industrial processes, agriculture, urbanization, and improper waste disposal poses a significant threat (Chakravarty and Gupta, 2021a; Parween et al., 2022; Uddin et al., 2017, 2021, 2018, 2023h; Varol et al., 2022; Goovaerts et al., 2005; Varol and Tokatlı, 2023). Recently several studies have reported that the anthropogenic activities have long been recognized as a key driver of pollution in all spheres of the environment (Diganta et al., 2023; EPA, 2020; Uddin et al., 2023b, 2022b; 2022c, 2021; Varol, 2020; Verma et al., 2022). Chemicals and heavy metals from industrial

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processes contaminate surface waters, while fertilizers and pesticides from agriculture increase nutrient and chemical levels (Asha et al., 2020; EPA, 2021a; Islam Khan et al., 2021; Uddin et al., 2016, 2018). Urbanization and infrastructure development increase impervious surfaces, leading to higher runoff and erosion rates that impact surface water quality (Parween et al., 2022; Uddin et al., 2022b). Improper waste disposal, such as untreated wastewater discharge, spreads water-borne diseases (Chen et al., 2020). Moreover, the agricultural activities and industrial effluents are the primary sources of pollution in surface waterbodies (Chakravarty and Gupta, 2021b; Parween et al., 2022). A few studies have revealed that the urbanization and land use change significantly impact surface water quality (Ataul Gani et al., 2023; Santy et al., 2020).

The COVID-19 pandemic caused by SARS-CoV-2 has affected millions worldwide since its first identification in December 2019 (Ali and Alharbi, 2020; Cheval et al., 2020). The pandemic resulted in the implementation of social distancing measures and travel restrictions globally, causing widespread disruption of normal life (Langone et al., 2021). Alongside its impact on human health and economies, the pandemic has also raised concerns about its impact on water quality (Dobson et al., 2021; Ormaza-Gonzaìlez et al., 2021; Raza et al., 2023). Disinfectants and personal protective equipment usage have increased, leading to potential chemical contamination of water systems (Etim et al., 2022). Studies have detected the presence of the COVID-19 virus in wastewater, suggesting potential transmission through fecal matter (Khan et al., 2021; Kucharski et al., 2020). However, it remains unclear if the virus can be transmitted through water, and the increased use of disinfectants may lead to an increase in chemical byproducts in water systems (Ostadtaghizadeh et al., 2022; Raza et al., 2023, 2022). The decrease in water usage by commercial and industrial sectors during the pandemic may also have disrupted the natural flow of wastewater treatment systems, leading to a decrease in water quality (Chakraborty et al., 2021a,b; Haghnazar et al., 2022; Kakwani et al., 2023; Ormaza-Gonzaìlez et al., 2021; Yunus et al., 2020).

The COVID-19 pandemic and associated lockdown measures have raised concerns about their impact on surface water quality worldwide. A number of studies have investigated the effects of the pandemic-induced societal changes on surface water quality parameters, including chemical contamination, viral presence, and disruptions in wastewater treatment systems (Chakraborty et al., 2021b; Dobson et al., 2021; Haghnazar et al., 2022; Islam et al., 2021; Kakwani et al., 2023). The findings of these research have significant implications for global policymakers and environmental agencies, providing insights into the relationship between the pandemic and surface water quality (Ali and Alharbi, 2020; Dobson et al., 2021; Haghnazar et al., 2022; Maity et al., 2023; Mallik et al., 2022; Raza et al., 2023; Tokatlı and Varol, 2021; Wagh et al., 2021; Yunus et al., 2020).The impact of COVID-19 on water quality is a complex issue that requires further research and monitoring (Chakraborty et al., 2021a; Kakwani et al., 2023; Manoiu et al., 2022). Recently, several studies have revealed that the COVID-19 lockdown have had a significant impact on surface water quality (Chakraborty et al., 2021b; Haghnazar et al., 2022; Kakwani et al., 2023; Mallik et al., 2022; Ormaza-Gonzaìlez et al., 2021). A number of research have reported that during the lockdown phase the water quality have improved significantly (Kakwani et al., 2023; Khan et al., 2021; Ormaza-Gonzaìlez et al., 2021; Yunus et al., 2020). However, the COVID-19 pandemic and subsequent shutdowns of industrial and transportation sectors have led to a significant decrease in pollution levels around the world (Raza et al., 2023).

The COVID-19 pandemic has significantly affected the Republic of Ireland, with the first confirmed case reported on February 29, 2020 ("Cases in Ireland - Health Protection Surveillance Centre," n.d.; "COVID-19 (coronavirus) - HSE.ie," n.d.; Ireland's National). The government responded with strict measures, including a country-wide lockdown from March 12, 2020("COVID-19 (coronavirus) - HSE.ie," n.d.; "Ireland: WHO Coronavirus Disease (COVID-19)," n.d.). The phased reopening began on May 10, 2021, and restrictions on various activities were gradually lifted("gov.ie - The Irish Economy – Recovery from Covid and Beyond in Ireland," n.d.). As the reopening process continues, evaluating its impact on public health, the economy, and society is critical. However, there is a need for continued monitoring and research into the impact of COVID-19 on water quality. To the best of the authors' knowledge, there is no evidence of EU countries investigating COVID-19 impacts on surface water quality. Although, several countries worldwide have conducted studies to assess the impact of COVID-19 on surface water quality (Ali and Alharbi, 2020; Chakraborty et al., 2021b; Dobson et al., 2021; Haghnazar et al., 2022; Islam et al., 2021; Kakwani et al., 2023; Maity et al., 2023; Mallik et al., 2022; Raza et al., 2023; Tokatlı and Varol, 2021; Wagh et al., 2021; Hossain et al., 2022; Rahman et al., 2023; Yunus et al., 2020). This study is the first initiative to investigate the COVID-19 impact on surface water quality in Ireland.

For the purposes of the assessment of water quality, a series of tools and techniques used, the water quality index (WQI) model is a widely used technique for assessing water quality, including the impact of COVID-19 on surface water (Chakraborty et al., 2021a; Kakwani et al., 2023; Islam Khan et al., 2021; Mallik et al., 2022; Yunus et al., 2020). It converts water quality indicator information into a dimensionless value, known as a WQI score. The model typically consists of five components, including indicator selection, sub-index functions, indicator weight estimation, aggregation functions, and classification schemes. However, recent studies have criticized the WQI model for model uncertainty, eclipsing, and ambiguity problems. Details of various WQI models, architectures, applications, and their limitations can be found in Uddin et al. (2021). To address these issues, an improved model called the Irish water quality index (IEWQI) model was developed. The IEWQI model has been reported to significantly reduce model uncertainty, with less than 1% uncertainty reported, compared to other approaches with nearly 12% uncertainty (Uddin et al., 2023a, 2023b, 2023c, 2023i). The IEWQI model has been found to be the most efficient for computing WQI scores accurately (Uddin et al., 2023d). This research utilized the IEWQI model to assess the impact of COVID-19 on surface water quality in Cork Harbour, Ireland. It is noted that the IEWQI model was developed specifically for coastal and transitional waters in Ireland (Uddin et al., 2022a).

In order to assess the impact of COVID-19 on water quality and determine the efficiency of the IEWQI model application, the study considered the following two research hypotheses.

- *Null Hypothesis (H_0):* The COVID-19 lockdown had no significant impact on surface water quality in Cork Harbour, Ireland. There is no statistically significant difference in water quality indicators and overall water quality between the pre-lockdown, during-lockdown, and post-lockdown periods.
- *Alternative Hypothesis (H_a):* Also, the COVID-19 lockdown had a significant impact on surface water quality in Cork Harbour, Ireland. There are statistically significant differences in water quality indicators between the pre-lockdown, during-lockdown, and post-lockdown periods, indicating changes in water quality due to the reduced anthropogenic activities during the lockdown.

Moreover, to determine the efficiency of the IEWQI model application and assess the impact of COVID-19, the study also considered the following hypothesis.

- *Null Hypothesis (H_0):* The IEWQ model is not effective for assessing the impact of the COVID-19 lockdown on surface waters in Cork Harbour.
- *Alternative Hypothesis (H_a):* The IEWQ model is effective for assessing the impact of the COVID-19 lockdown on surface waters in Cork Harbour.

However, the study aimed to assess the impacts of the COVID-19 pandemic lockdown on surface water quality in Cork Harbour, Ireland, using the advanced IEWQI model. The research also analyzed and interpreted the water quality data through appropriate statistical tests and model evaluations to determine whether the lockdown measures had a measurable effect on surface water quality. Additionally, the efficiency and reliability of the IEWQI model were assessed to understand its effectiveness in evaluating water quality dynamics during the COVID-19 lockdown period.

2. Description of the study area

This study was conducted in Cork Harbour, a Special Protection Area (SPA) located on the southwest coast of Ireland. For the purpose of reporting the environmental setting of the Harbour, it is divided into three regions for spatial assessment: Upper Harbour, Lower Harbour, and Outer Harbour. Fig. 1 shows the Cork Harbour, monitoring sites including divisions. The region is known for its unique geological patterns, which play a vital role in the area's ecosystem and freshwater quality. Cork Harbour, the deepest and longest surface waterbody in Ireland, has been designated as an SPA under the 1979 Wild Birds Directive (79/409/EEC) (Uddin et al., 2023a, 2022b; 2022a, 2020b). Additionally, this region is heavily populated and industrialized, with extensive agricultural activities impacting water quality. Cork City, an industrial hub, lies at the River Lee's mouth, which contributes approximately 75% of the freshwater to the Harbour (Hartnett et al., 2012; Olbert et al., 2023; Uddin et al., 2023b, 2023c). Furthermore, several large wastewater treatment plants (WWTPs) discharge significant amounts of wastewater into the Harbour, further affecting water quality (Hartnett et al., 2012; Uddin et al., 2023b, 2023c; 2023d, 2023e; 2022b, 2020b). The EPA has reported a continuous decline in the Harbour's water quality (EPA, 2021a; 2021b, 2020; 2019, 2018).

3. Methods and materials

3.1. Data description

Water quality data was collected from the EPA monitoring database for a period of six years, from 2017 to 2022, at 29 out of the 37 available monitoring sites. Fig. 1 shows the geographical location of the monitoring sites. Details of the site attributes can be found in Table S1. The data is publicly accessible at https://www.catchments.ie/data/. The EPA has implemented a thorough quality control and quality assurance system to ensure the reliability, accuracy, and precision of the data generated by the national monitoring program (refer to EPA (2021) for further details). These sites were selected based on the availability of comprehensive water quality indicator data and their distribution across the entirety of the Harbour. To ensure consistency in the analysis, only samples obtained from a depth of 1 m below. For the calculation of the IEWQI, nine water quality indicators were taken into account, following the methodology proposed by Uddin et al. (2023d). These indicators include pH, dissolved oxygen (DOX), salinity (SAL), biological oxygen demand (BOD_5), water temperature (TEMP), transparency (TRAN), total organic nitrogen (TON), molybdate reactive phosphorus (MRP), and dissolved inorganic nitrogen (DIN). It is noted that, the EPA measured

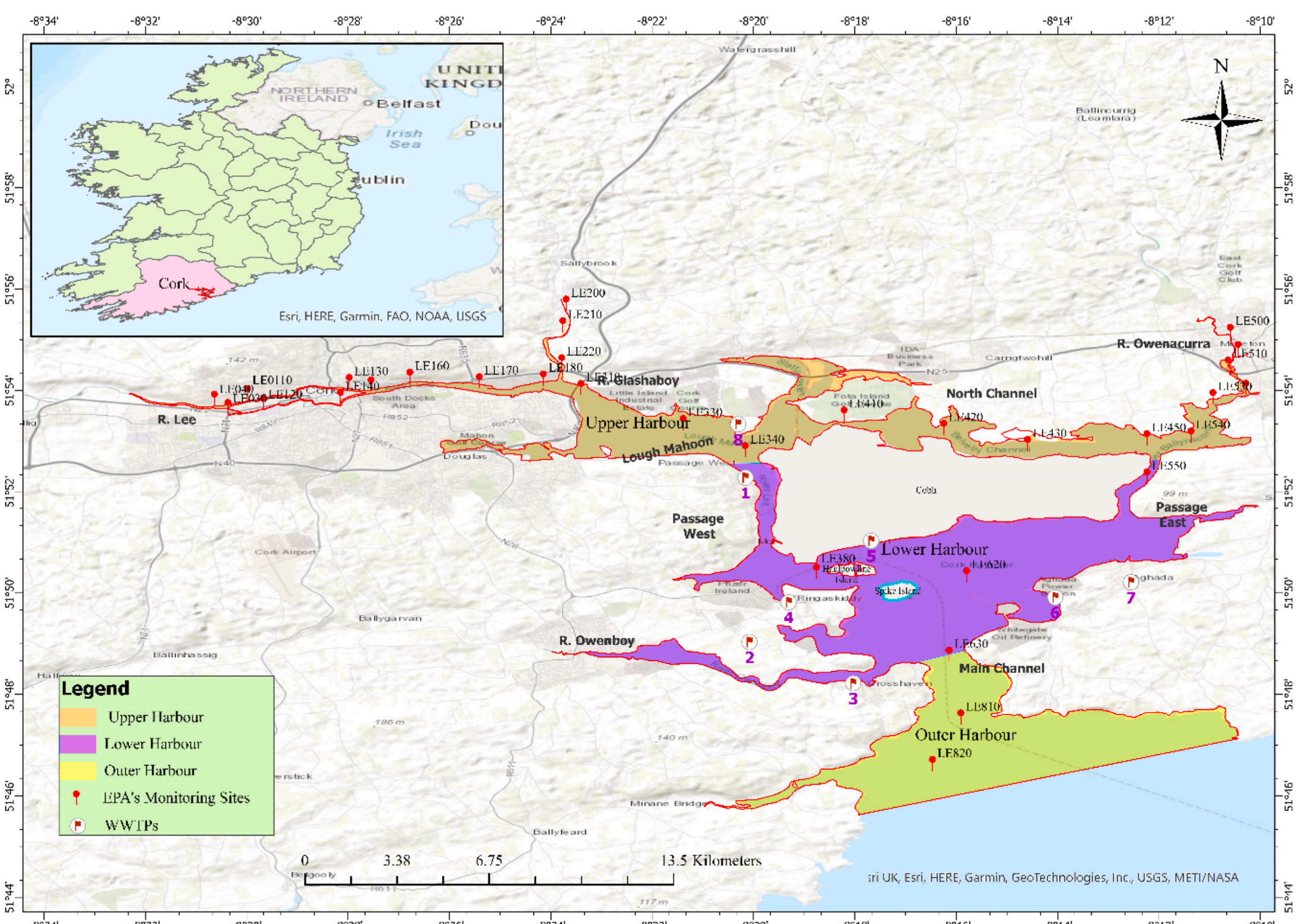

Fig. 1. Study area and water quality monitoring sites in Cork harbour, Ireland.

water quality indicators according to the standard methods for the examination of water and wastewater, American Public Health Association (2005). Depth-averaged concentrations of these water quality indicators were determined by computing the annual mean of the measurements for each respective indicator. Salinity (SAL) used for moving thresholds of nutrient enrichment indicators only. Table S1 contains information about the water quality monitoring sites and attributes of water bodies, while Table S2 provides the selected water quality (WQ) indicators along with their units and corresponding guideline values, respectively.

3.2. Computation of IEWQI scores

In the computation of the Water Quality Index (WQI) score, various techniques have been widely used (Parween et al., 2022; Sutadian et al., 2018; Uddin et al., 2023b; Uddin et al., 2022b, 2021). However, many recent studies have reported that existing models produce significant uncertainty due to model eclipsing and ambiguity issues, leading to inconsistent results in the final water quality assessment(Ataul Gani et al., 2023; Georgescu et al., 2023; Talukdar et al., 2023; Uddin et al., 2023c, 2022b; 2021). Detailed limitations of existing models can be found in Uddin et al. (2021). Recently, the authors developed a sophisticated model for rating transitional and coastal (TrC) waters, specifically focusing on Ireland's TrC waters(Uddin et al., 2023b). The IEWQI model is reliable and efficient in reducing model uncertainty (Ataul Gani et al., 2023; Georgescu et al., 2023; Talukdar et al., 2023; Uddin et al., 2023d, 2023e; 2023b; 2023i). In comparison to widely used techniques such as the Canadian Council of Ministers of the Environment (CCME) index and the National Sanitation Foundation (NSF) index, the IEWQI model produces less than 1% uncertainty, while other models contribute around 12% uncertainty(Uddin et al., 2023d, 2023b). Furthermore, several recent studies have utilized this model for assessing rivers, lakes, and TrC waters. As a result, this research employs the IEWQI model to compute the WQI according to the approaches outlined in Uddin et al. (2023a).

Similar to other typical models, the IEWQI model consists of five components: (i) indicator selection technique, (ii) sub-index function(s), (iii) weight generation processes, (iv) aggregation function, and (v) classification scheme. Details of the IEWQI model and its architecture are briefly presented in Uddin et al. (2023a). The IEWQI model can be defined as follows:

$$IEWQI = \sqrt{\sum_{i}^{n} w_i s_i^2} \tag{1}$$

where s_i is the sub-index value for parameter i; w_i is weight value of respective variables and n is the number of parameters.

3.2.1. Determination of WQ status

The primary objective of the WQI model is to classify water bodies based on the guidelines for specific indicators (Georgescu et al., 2023; Parween et al., 2022; Uddin et al., 2023b, 2023c; Uddin et al., 2021). Until now, different index models have used various classification schemes (Uddin et al., 2021). Some recent studies have reported that existing classification schemes are influenced by metaphoring problems, which may result in different water quality classes for similar indicators (Uddin et al., 2021, 2022a; 2022b, 2023c; 2023d). Consequently, the index may produce inaccurate classifications. The authors have recently introduced and validated a new rating scale suitable for any transitional and coastal water (Uddin et al., 2022b, 2023c). This study utilizes this scale to determine water classes using the IEWQI model. In supplementary material, Table S3 presents the water quality rating scale according to Uddin et al. (2023b). Detailed information on the development methodology of the rating scale can be found in Uddin et al. (2022b).

3.3. Model sensitivity analysis - prediction approaches

3.3.1. Input preparation for developing ML models

Input preparation is a crucial step in machine learning (ML) model development, as the quality and structure of the input data significantly impact the accuracy and effectiveness of the model. Data preprocessing techniques, such as cleaning, normalization, and feature selection, can improve the quality and relevance of the input data, leading to better model performance (Mamun et al., 2020; Moreno-Rodenas et al., 2019; Urbanowicz et al., 2018; Wang et al., 2021; Rahman and Harding, 2016). Feature engineering is another essential aspect of input preparation, which involves selecting and transforming relevant features that capture the underlying patterns in the data (Gao and Wu, 2020; Islam Khan et al., 2021; Uddin et al., 2023c). However, this process can help reduce the dimensionality of the data and improve the model's accuracy and generalization ability.

3.3.1.1. Data standardization. Standardization is an essential step in machine learning model development and can improve model performance, reduce overfitting, and increase the interpretability of the model (Aldhyani et al., 2020; Bui et al., 2020; Uddin et al., 2022a, 2023c). It is a crucial preprocessing step in machine learning model development. It involves scaling the features of the dataset to have a mean of 0 and a standard deviation of 1, making them comparable and preventing features with larger scales from dominating the model. This step ensures that the model can effectively learn from all features in the dataset and improve its performance. Standardization can be performed using various techniques, including z-score scaling, min-max scaling, and robust scaling. The research used the Z-score scaling technique to standardize the input features of ML model(s) according to the approaches of Uddin et al. (2022a). Details of the methodology are provided in Uddin et al. (2022a).

3.3.2. Optimize model(s) architecture

Hyperparameter optimization is a critical step in machine learning model development, involving tuning the hyperparameters to achieve optimal performance (Belete and Huchaiah, 2021). Grid search is a popular and systematic technique for hyperparameter optimization, which evaluates the performance of the model for each combination of values defined in a grid of hyperparameter values (Elgeldawi et al., 2021). While grid search is computationally expensive due to its exhaustive search, it remains widely used due to its effectiveness in finding optimal hyperparameters. In a study by Uddin et al. (2023d), the grid search technique was applied to optimize the hyperparameters of the ML models for predicting WQI in Cork Harbour.

3.3.3. Machine learning (ML) models

ML is commonly used to identify patterns and make predictions based on big data generated from various scenarios (Islam Khan et al., 2021; Kadam et al., 2019; Uddin et al., 2022a, 2022b; 2023b, 2023d). It has grown rapidly in recent years in the context of data analysis and computing, enabling applications to function intelligently (Bui et al., 2020). This study utilizes seven ML algorithms including (1) liner regression (LR) models, (2) regression trees (RT), (3) support vector machines (SVM), (4) Gaussian process regression (GPR) models, (5) kernel approximation regression (KAR) models, (6) ensembles of trees, and (7) neural networks (NN) to predict water quality in Cork Harbour. Several previous studies have used ML techniques to predict water quality to avoid the complexity of the WQI model (Bui et al., 2020; Rezaie-Balf et al., 2020; Uddin et al., 2022a). The limitations of the WQI model are described in Uddin et al. (2021) and (2022b). Recent studies have demonstrated that ML models are more effective than conventional methods in predicting water quality using WQI approaches (Aldhyani et al., 2020; Bui et al., 2020; Grbčić et al., 2021; Kadam et al., 2019; Uddin et al., 2022a, 2022b; 2023a, 2023c). In this study, the regression learner app in MATLAB R2022b was used to identify the best-fitted ML algorithm. The best-fitted ML model was selected from seven models using the trial-and-error approach according to the methodology of Uddin et al. (2023a), with details of the various ML models available in Uddin et al. (2022a). Based on training performance, the exponential GPR model was selected to predict the WQ input dataset. To compare the performance of different models, this study employed cross-validation approaches, following the methodology of Uddin et al. (2022a). Although, a number of recent studies have reported that the GPR model could be more reliable and effective to predict WQI score in terms of reducing the prediction uncertainty (Tiyasha Tung and Yaseen, 2021; Uddin et al., 2023a). The model hyperparameters were optimized using grid search technique according to the methodology of Uddin et al. (2023a), with the optimized values/parameters for the GPR model provided in Uddin et al. (2023a).

3.3.3.1. Performance evaluation of the prediction model(s). The performance evaluation of prediction models is critical in determining their accuracy, precision, and reliability. Various metrics are available for assessing the performance of prediction models, including Nash-Sutcliffe Efficiency (NSE), Mean Error Factor (MEF), Root Mean Square Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2) metrics. The NSE metric compares the model predictions to the observed data, where a value of 1 indicates perfect agreement between the two. The MEF metric calculates the ratio of the mean observed values to the mean predicted values and provides information on how well the model predicts the mean values (Uddin et al., 2023e). Details of the MEF approach can be found in Uddin et al. (2023d). The RMSE, MSE, and MAE metrics measure the differences between predicted and observed values, with lower values indicating better model performance, whereas the R^2 metric provides a measure of the proportion of the variance in the observed data that is explained by the model. The use of these metrics enables researchers to identify areas for improvement in prediction models and to determine the most effective approach for optimizing model performance (Chen et al., 2020; Suvarna et al., 2022; Uddin et al., 2023e).

3.3.4. Model(s) deployed for prediction IEWQI score

In order to predict IEWQI scores for six years, it is essential to deploy the ML model(s) for practical use involves several steps, including preparing the model for production, integrating it with the application or system, and validating its performance. One approach is to package the model as a web service or REST API, which can be accessed over the internet. The model can be deployed on a cloud platform like Google Colab, AWS, or Azure or on a local server. The deployed model can be used to predict IEWQI scores for new water quality data inputs. To deploy the optimized ML model for IEWQI score prediction using Google Colab, the trained model can be saved as a serialized object using the pickle library. The saved model can then be loaded into a new Python script, and new water quality data inputs can be pre-processed and fed into the model for IEWQI score prediction. Google Colab provides a scalable and efficient environment for model deployment and access to powerful hardware resources, such as GPUs and TPUs, which can speed up prediction for large datasets. Regular monitoring and updating of the model may also be necessary to maintain its accuracy and relevance. Deploying the optimized ML model for IEWQI score prediction using Google Colab can facilitate efficient and scalable prediction for new water quality data inputs.

3.4. Evaluation of IEWQI eclipsing and ambiguity problems

Since the development of Water Quality Index (WQI) models, they have faced criticism due to inconsistencies in assessment results for specific indicators when using various techniques. Several recent studies have shown that this can occur due to the eclipsing and ambiguity issues within the models. Detailed information on these problems can be found in Uddin et al. (2021), and the corresponding assessment techniques are provided in Uddin et al. (2022b). To the best of the authors' knowledge, this is the first approaches for addressing these issues in WQI models. Consequently, this research employs the methodology outlined in Uddin et al. (2022b) to assess model eclipsing and ambiguity problems. Several recent research have utilized this techniques for assessing the eclipsing and ambiguity problems (Ataul Gani et al., 2023; Georgescu et al., 2023; Manna and Biswas, 2023; Uddin et al., 2023b, 2023c; 2023e). Further details of the approach can be found in Uddin et al. (2022b).

3.5. Spatio-temporal analysis of water quality

Empirical Bayesian Kriging (EBK) is an advanced geostatistical technique used for spatial prediction and interpolation (Uddin et al., 2023a, 2020a; 2018). It utilizes a Bayesian approach to estimate the unknown parameters of the underlying statistical model, which provides a more accurate and reliable estimate of the water quality parameters compared to traditional kriging methods (Amini et al., 2019). In addition, it incorporates additional information from the observed data and prior knowledge to improve the accuracy and reliability of the predictions by estimating the hyperparameters of the kriging model from the observed data and prior knowledge, instead of assuming fixed values for these parameters (Belete and Huchaiah, 2021; Elgeldawi et al., 2021; Verma et al., 2019). Several recent studies has been successfully applied this approach in various fields, including environmental monitoring and management, hydrology, and agriculture (Antal et al., 2021; Elgeldawi et al., 2021; Hoque et al., 2015). The research utilized this technique for analyzing the spatio-temporal analysis of IEWQI in Cork Harbour over the six years according to the methodology of Uddin et al. (2020a). Details of the methodology can be found in similar research. Spatio-temporal analysis using EBK can provide valuable insights into the variations in water quality over time and space, enabling the identification of hotspots and trends in water quality (Uddin et al., 2023a). The technique has been applied in various studies to assess water quality in different regions and water bodies, including rivers, lakes, and coastal waters. Recently, the authors applied this technique for analysing the spato-temporal attributes of water quality in various waterbodies in Ireland (Uddin et al., 2023a, 2020a).

3.6. Trend analysis of water quality

For the purposes of the trend analysis, a range of statistical tools and techniques used, the Mann-Kendall test is one of them most widely used method (Kisi and Ay, 2014; Mozejko, 2012). It is a non-parametric statistical test used to assess whether there is a monotonic trend in a time series data set (Chiew and McMahon, 1993; Stevenson et al., 2010). The test is widely used in various scientific fields, including environmental science, hydrology, and geology, to detect trends in the data over time (Chaudhuri and Ale, 2014; Mozejko, 2012; Yürekli, 2015). Several recent water research studies have utilized this technique for determining the water quality trend in a time series data attributes (Beck et al., 2022, 2018; Chaudhuri and Ale, 2014; Mahmoodi et al., 2021). The test is particularly useful in cases where the underlying distribution of the data is not normal, and conventional parametric tests may not be appropriate (V. Z. Antonopoulos et al., 2001; Chiew and McMahon, 1993). The Mann-Kendall test is based on the calculation of the Kendall's tau statistic, which is a measure of the correlation between the rankings of the data points in the time series. The test statistic is calculated as follows:

$$\tau = \left(\frac{2}{n(n-1)}\right) \sum (i,j) sign\left(y_i - y_j\right) \quad (2)$$

where n is the number of data points in the time series, y_i is the value of the ith data point, and sign is a function that returns 1 if $y_j > y_j$, −1 if $y_i <$

y_j, and 0 if $y_i = y_j$.

The significance of the test statistic is then evaluated using a two-tailed test, with the null hypothesis that there is no monotonic trend in the data. If the calculated test statistic is significant, the alternative hypothesis is accepted, and a monotonic trend is present in the data.

4. Results and discussion

4.1. Statistical summary of the IEWQI model' input

Nine WQ indicators were used to compute IEWQI, following Uddin et al. (2023d), with SAL concentration determining moving thresholds for nutrient enrichment indicators (DIN, DOX, MRP). Methodology details are in Uddin et al. (2022b) and (2023d). Fig. 2 presents the statistical summary of nine WQ indicators (2017–2022) compared to guideline values. Most indicators were within permissible limits, except TRAN, DIN, and TON during pre-, during, and post-COVID-19 periods (see Tables S4–S9). Maximum and minimum values were generally within guideline ranges, barring outliers for breached indicators, except MRP post-COVID-19, whereas small standard deviations indicate consistency (Fig. 2f). While water quality was generally acceptable, a few monitoring sites exhibited deviations in TRAN, DIN, and TON (see Tables S4–S9). The observed phenomenon may arise from the substantial anthropogenic pressures exerted on Cork Harbour, aligning with comparable findings previously reported by the EPA, Ireland (EPA, 2018; 2022; Uddin et al., 2022b; 2023b). Z-statistical results suggest updating management strategies to address these deviations of WQ indicators concentration over the years in Cork Harbour (Fig. 2).

The study also used Pearson correlation analysis to assess the relationship between WQ indicators and IEWQI scores in Cork Harbour. Fig. S1 shows significant correlations between IEWQI and various indicators. Water pH, SAL, and TRAN displayed strong positive correlations with IEWQI, except in 2018, suggesting that increasing these indicators could decrease water quality. Conversely, nutrient enrichment indicators (DIN, TON, MRP) showed strong negative correlations, indicating that lower concentrations signify better water quality. TEMP, DOX, and BOD exhibited weaker correlations, suggesting less influence on water quality. Similar results have reported in literature across in the world (Chakraborty et al., 2021a,b; Cherif et al., 2020; Haghnazar et al., 2022; Kakwani et al., 2023; Manoiu et al., 2022; Muduli et al., 2021; Patterson Edward et al., 2021; Sharma and Gupta, 2022; Yunus et al., 2020). However, these findings can guide monitoring and management of key performance indicators to improve Cork Harbour's water quality.

4.2. IEWQI results

For the purposes of the computation of IEWQI score, the research utilized the approaches of Uddin et al. (2023d). Fig. 3 presents the IEWQI scores at each monitoring site in Cork Harbour over six years, with summary statistics in Fig. 4. Spatial distribution of the IEWQI scores are presented in Fig. S2. The IEWQI scores varied significantly over time and across sites in Cork Harbour (Fig. 3). Average scores ranged from 70.31 ± (SD = 10.96) to 75.48 ± (SD = 16.86), with a Harbour-wide mean of 72.43 ± (SD = 14.33). Higher scores were in the outer Harbour, and lower scores in the upper Harbour (Fig. 3). Temporal variations showed highest scores during COVID-19 (2020) and lowest in 2021 (Fig. 3). Several recent studies have revealed that the similar results of the temporal variations for the IEWQI scores in Cork Harbour in literature (Uddin et al., 2023d, 2023b; 2022b, 2022a; 2020b).

On the other hand, the spatial distribution of IEWQI scores were performed in the research using the approaches of Uddin et al. (2020a). Details of the methodology can be found in Uddin et al. (2020a). The spatio-temporal analysis of IEWQI scores in Cork Harbour also revealed significant differences in water quality across the study period (2017–2022) and between monitoring sites. The overall trend (Spatio-temporal) showed a slight improvement in water quality, with the mean IEWQI score increasing from 75.48 ± 16.27 in 2020 (Fig. 3;

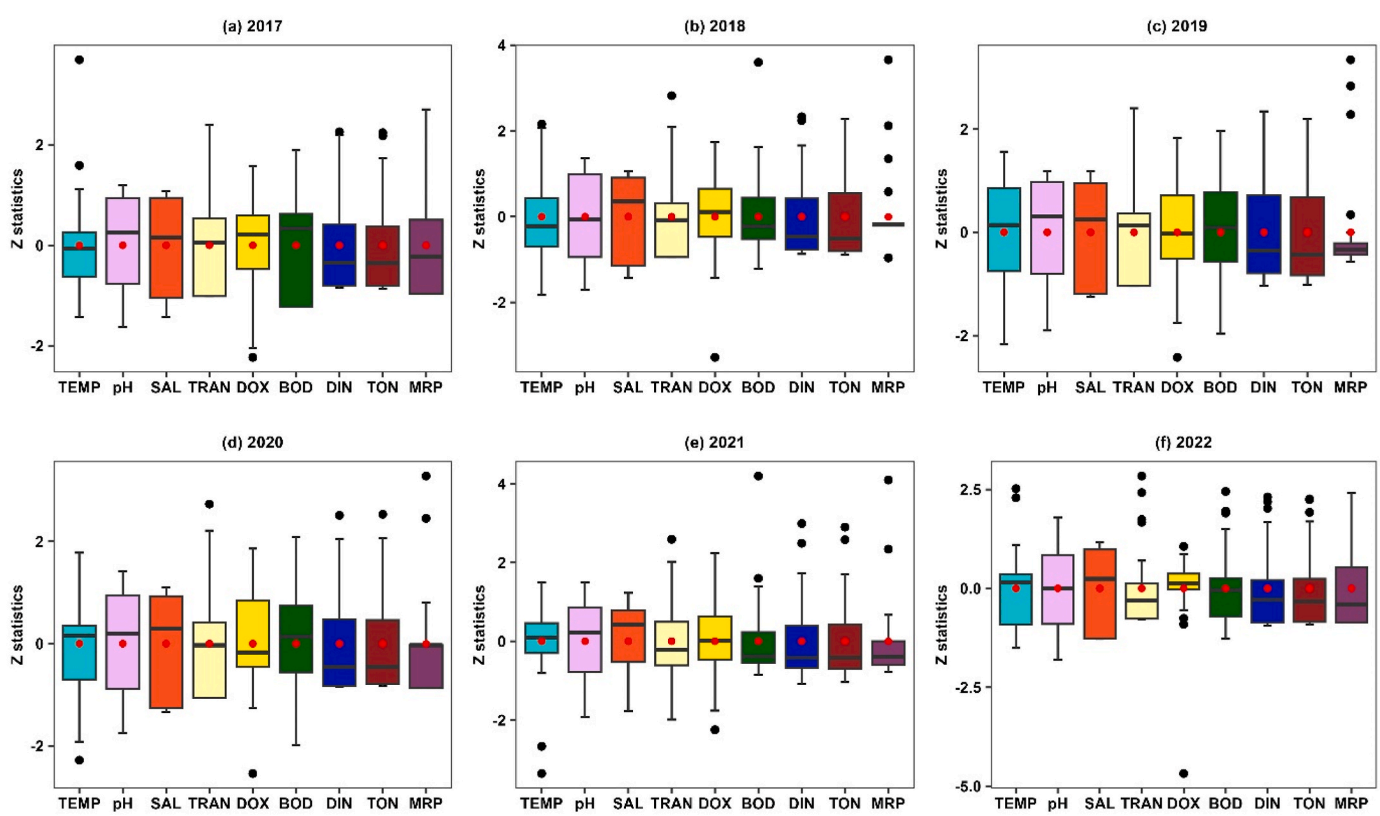

Fig. 2. Statistical summary of various water quality indicators in Cork Harbour [2017–2022].

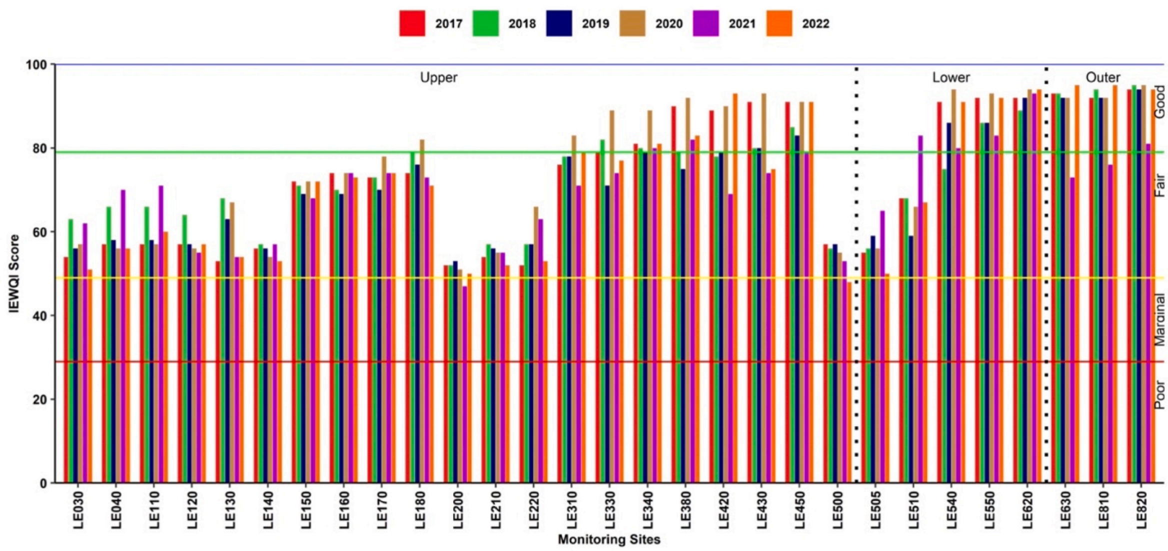

Fig. 3. Computed IEWQI scores at each monitoring sites in Cork Harbour over the study period [2017–2022].

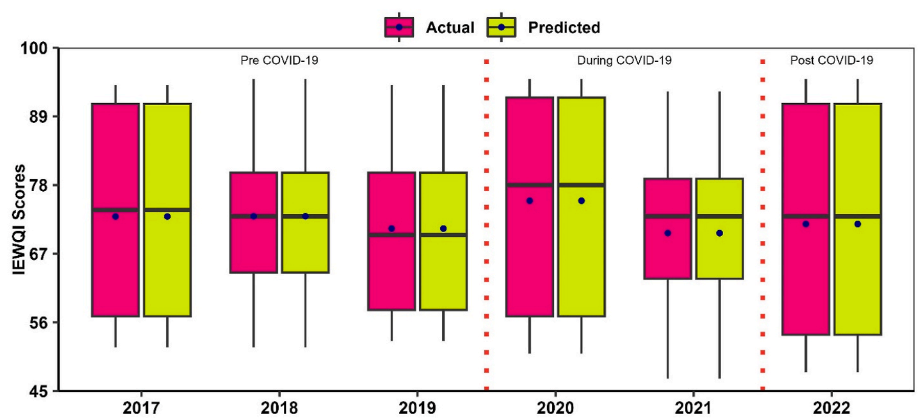

Fig. 4. Comparison between actual and predicted IEWQI scores over the study periods from 2017 to 2022.

Fig. S2). However, spatio-temporal differences were observed, with some monitoring sites exhibiting consistently high or low IEWQI scores, while others showed more variability over time. The upper harbour area had the lowest mean IEWQI score (67.8) and the highest variability, while the outer harbour had the highest mean IEWQI score (87.3) and the lowest variability. These results suggest that water quality management strategies should be tailored to the specific spatio-temporal patterns observed in each area, taking into account the various environmental pressures (like domestic wastes, industrial wastes and agricultural), sources of pollution (points and non-points), and the local environmental conditions (EPA, 2021; 2017; Uddin et al., 2022a, 2022b; 2022c, 2023a; 2023d).

5. IEWQI prediction results

5.1. Performance of prediction models

This study utilized seven ML algorithms to predict IEWQI scores, with performance evaluated using commonly used metrics such as RMSE, MSE, and MAE. Results in Table 1 show that the GPR model had the lowest error during both the training and testing periods. Advanced metrics such as NSE and MEF were used for further verification, revealing that the GPR model had the highest accuracy with NSE and MEF values of 0.99 and 0.01, respectively. The low MSE, RMSE, and MAE values also indicate the models' ability to accurately predict IEWQI scores at each monitoring site. Moreover, the comparison between actual and predicted IEWQI scores for six years from 2017 to 2022 in Cork Harbour showed that the developed GPR-ML model performed well in predicting the IEWQI scores. The model had a high correlation coefficient ($R^2 = 1.0$, see Fig. 5) between the actual and predicted IEWQI scores, indicating a strong linear relationship. Overall, the developed models showed high accuracy and performance in predicting water quality data inputs' IEWQI scores.

Table 1
10-fold cross-validation results of the GPR model for predicting IEWQI scores in Cork Harbour.

ML Models	Model training errors			Model testing errors		
	RMSE	MSE	MAE	RMSE	MSE	MAE
GPR	**3.91**	**15.34**	**3.03**	**4.09**	**17.40**	**3.33**
SVM	4.99	25.29	3.76	5.52	31.31	4.51
LR	6.44	41.43	4.39	5.97	35.87	5.08
DT	8.07	72.27	6.73	11.65	141.59	9.87
ANN	10.64	114.63	7.67	6.30	43.25	5.27
XGBoost	6.68	44.67	5.03	8.11	65.79	7.21
KAR	9.21	88.57	7.69	146.90	11.98	10.17

5.2. Comparison between actual and predicted IEWQI scores

Fig. 4 displays a statistical summary of the actual and predicted IEWQI scores for Cork Harbour over six years, while Fig. S3 presents a point-wise comparison of the actual and predicted IEWQI scores at each monitoring site in Cork Harbour. In Fig. 4, the boxplots illustrate the median, quartiles, and outliers of the actual and predicted IEWQI scores for each year. The figure shows a strong agreement between the predicted and actual IEWQI scores for each year, with no outliers observed. The statistical attributes (mean and standard deviation) indicate that the optimized ML model is effective in predicting the IEWQI scores for Cork Harbour and can be utilized for monitoring and managing water quality in the area.

Moreover, the Tukey test was performed to validate the comparison results among years in Cork Harbour according to the approaches of Uddin et al. (2023a). Details of the methodology can be found in Uddin et al. (2023a). Significant differences in the means of the groups were observed in the results of the Turkey pair-wise ANOVA analysis. The post-hoc analysis indicated significant differences in the means between years 2020 and 2019 ($p < 0.001$), and years 2021 and 2020 ($p < 0.001$) (Fig. S4). These findings suggest that the years are not equal, and there are significant differences between the means of the IEWQI scores. Additionally, the F-statistic was utilized to validate the variation of IEWQI scores. The research found $F = 0.945$ at a 95% confidence interval (CI) for five degrees of freedom, indicating a relatively small difference between the means of the years being compared. However, further analysis and validation of the model may be necessary to ensure its accuracy and reliability in the long term.

5.3. IEWQI sensitivity and uncertainty

Fig. 5 presents the IEWQI model sensitivity results in Cork Harbour for six years water quality. The sensitivity analysis of the optimized GPR-ML model for IEWQI score prediction over a six-year period (2017–2022) in Cork Harbour showed that the model's performance was stable and consistent, with an R^2 value of 1.0 indicating a strong correlation between the predicted and actual IEWQI scores. Similar, results have reported for the IEWQI model in a number of earlier studies (Ataul Gani et al., 2023; Georgescu et al., 2023; Uddin et al., 2023f, 2023g).

For the purpose of uncertainty analysis, the study employed four statistical measures, including mean, minimum, maximum, and standard deviation (SD), which is widely used to estimate the uncertainty level in measures(Moreno-Rodenas et al., 2019; Uddin et al., 2020b, 2020a). Fig. 6 presents a comparative analysis of various statistical attributes of IEWQI scores (actual and predicted). The results of the uncertainty analysis indicated that the predicted IEWQI scores had a low level of uncertainty over the six-year period (Fig. 6). Furthermore, the comparison between actual and predicted IEWQI scores showed no significant differences. These findings indicate that the model's predictions were reliable and could be effectively used for water quality management and decision-making. Several studies in the literature have reported similar results to those obtained in this research (Ataul Gani et al., 2023; Manna and Biswas, 2023; Uddin et al., 2023d, 2023c; 2023e, 2023b; 2023f, 2022b; 2022a). Overall, the sensitivity and uncertainty analyses offer valuable insights into the performance and reliability of the ML model for predicting IEWQI scores.

5.4. Assessment of model eclipsing and ambiguity

In determining the performance of the IEWQI model with respect to addressing model eclipsing and ambiguity problems, this study utilized the methods outlined by Uddin et al. (2022b). Table 2 summarizes the results of eclipsing and ambiguity issues. From the data, it is evident that the calculated IEWQI scores are free from eclipsing problems, although ambiguity issues were observed at several monitoring sites. On average, 45% of sampling sites were affected by overestimation problems, but there were no significant changes in water quality status due to ambiguity issues (Table 2). The outcomes of the eclipsing and ambiguity

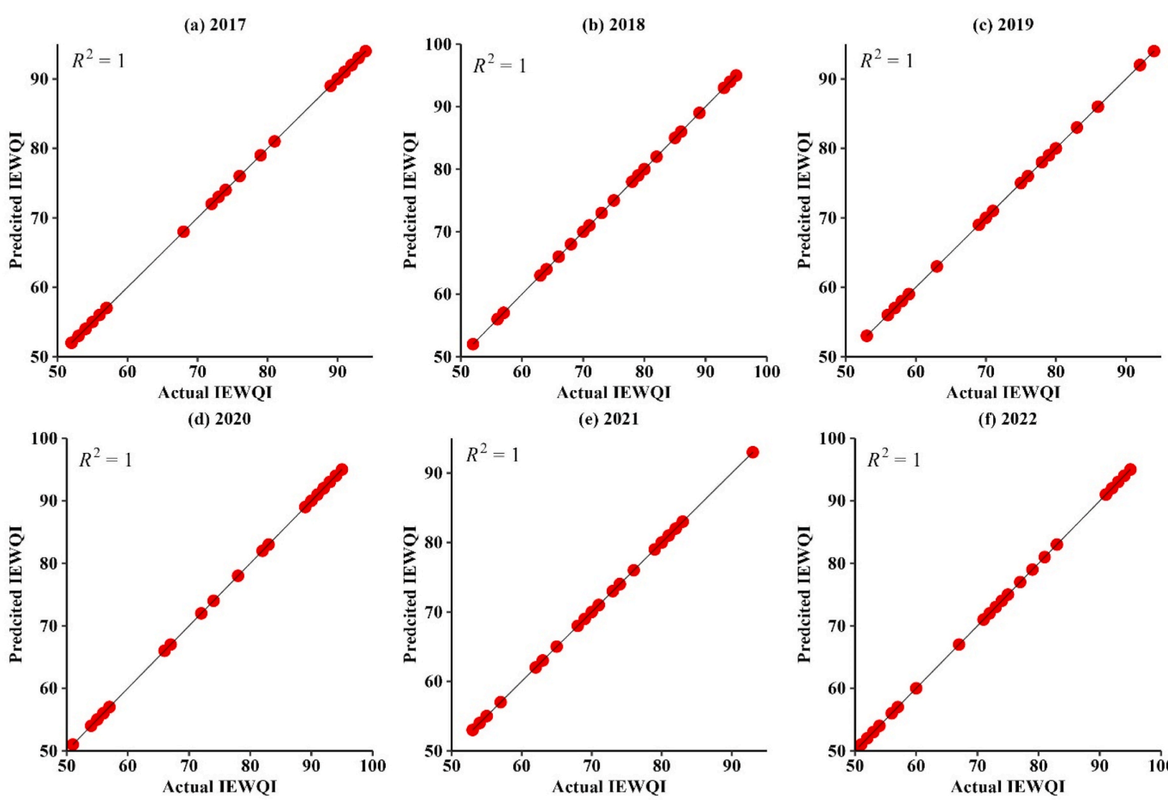

Fig. 5. IEWQI model sensitivity for predicting WQI scores in Cork Harbour over the six years.

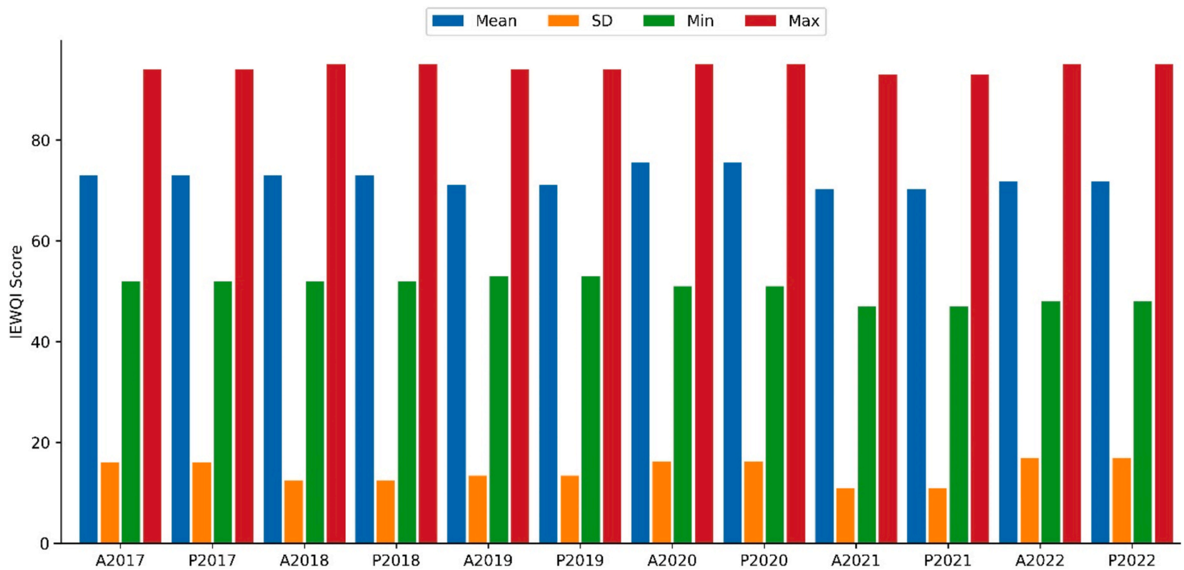

Fig. 6. Comparison of different statistical measures between actual and predicted IEWQI scores in Cork Harbour during the research ["A" represents the actual IEWQI scores, while "P" refers to the predicted scores for the monitoring year].

Table 2
The summary of statistics for the results of the IEWQI model's eclipsing and ambiguity effects.

Attributes	Years					
	2017	2018	2019	2020	2021	2022
Eclipsing	0	0	0	0	0	0
Ambiguity	15 (52%)	10 (34%)	13 (45%)	14 (48%)	13 (45%)	13 (45%)
Total monitoring sites	29	29	29	29	29	29

analysis indicate that the IEWQI model could be an effective and efficient approach for computing WQI scores. Several recent studies have reported the similar findings of the model eclipsing and ambiguity issues across various waterbodies application of the IEWQI model.

6. Assessment of water quality in Cork Harbour

6.1. Results of trend analysis

6.1.1. Temporal changes of selected water quality indicators

For the purposes of the temporal trends in various water quality indicators in Cork Harbour, the study was utilized the Mann-Kendall test. Fig. S5 presents the results of temporal variations of selected WQ indicators across monitoring sites in Cork Harbour over a six-year period, with a focus on the COVID-19 pandemic period. Table 3 provides the Mann-Kendall test results. The results showed that the WQ indicators varied significantly over the six-year period, with some indicators exhibiting clear temporal trends. The results reveals that water pH, TRAN, BOD, and TEMP shows positive trends, while TON shows the negative trend over the years (Table 3; Fig. S5). The results of the positive trend of the TRAN and trend of TON indicates that the water quality is improved over the research period. Interestingly, DIN, DOX, and MRP showed no significant trends over the study period, suggesting stable conditions of these indicators in Cork Harbour (Fig. S5). It is noted that most monitoring sites DOX and MRP were found to be within the permissible limit (See Tables S2–S9). But, it is highlighted that the BOD_5 shows a significant increasing trend, in particular, it has increased significantly post COVID-19, suggesting that various anthropogenic pressures like domestic wastewater, industrial wastewater, effluent treatment plants' discharges. Overall, the trends analysis results indicate that the a particularly BOD_5 should be take care of most carefully for improving water quality in Cork Harbour. The results indicate a rejection of the null hypothesis as the study revealed a significant impact of the COVID-19 lockdown on water quality indicators in Cork Harbour over the years.

Table 3
The Mann-Kendall test results of various water quality indicators in Cork Harbour over six years.

Indicator	Trend	Tau	p-value	Z-score	Sen's slope
pH	increasing	0.140	0.006	2.740	0.001
TRAN	increasing	0.144	0.005	2.840	0.003
DIN	no trend	−0.068	0.181	−1.338	−0.001
TON	decreasing	−0.105	0.040	−2.054	−0.002
DOX	no trend	−0.089	0.080	−1.748	−0.024
BOD_5	increasing	0.106	0.037	2.080	0.002
TEMP	increasing	0.155	0.002	3.041	0.006
MRP	no trend	0.060	0.234	1.190	0.000

Similarly, to analyse the trend of overall water quality in Cork Harbour over the years, the Mann-Kendall test was employed to detect changes in the IEWQI scores. Fig. 7 illustrates the six-year temporal trend of IEWQI and water quality states in Cork Harbour. Based on the Mann-Kendall test results, the trend analysis of water quality in Cork Harbour is as follows.

- A Z-score of 1.2 suggests a minor positive trend, but it lacks the strength to be considered significant (Fig. 7b).
- With a P-value of 0.23, there is insufficient evidence to conclude a significant trend in IEWQI water quality under the null hypothesis (no trend) (Fig. 7b).
- A Tau value of 0.06 reveals a weak positive correlation over the years, implying a slight improvement in water quality, but the relationship is weak (Fig. 7b).
- On the other hand, a Sen's Slope of 0.02 indicates a marginal increase in water quality over time, which may not be practically significant (Fig. 7b).

Overall, the results of the Mann-Kendall test indicate a weak positive trend in water quality, but it is not statistically significant (Fig. 7a). Consequently, it cannot be confidently stated that the water quality in

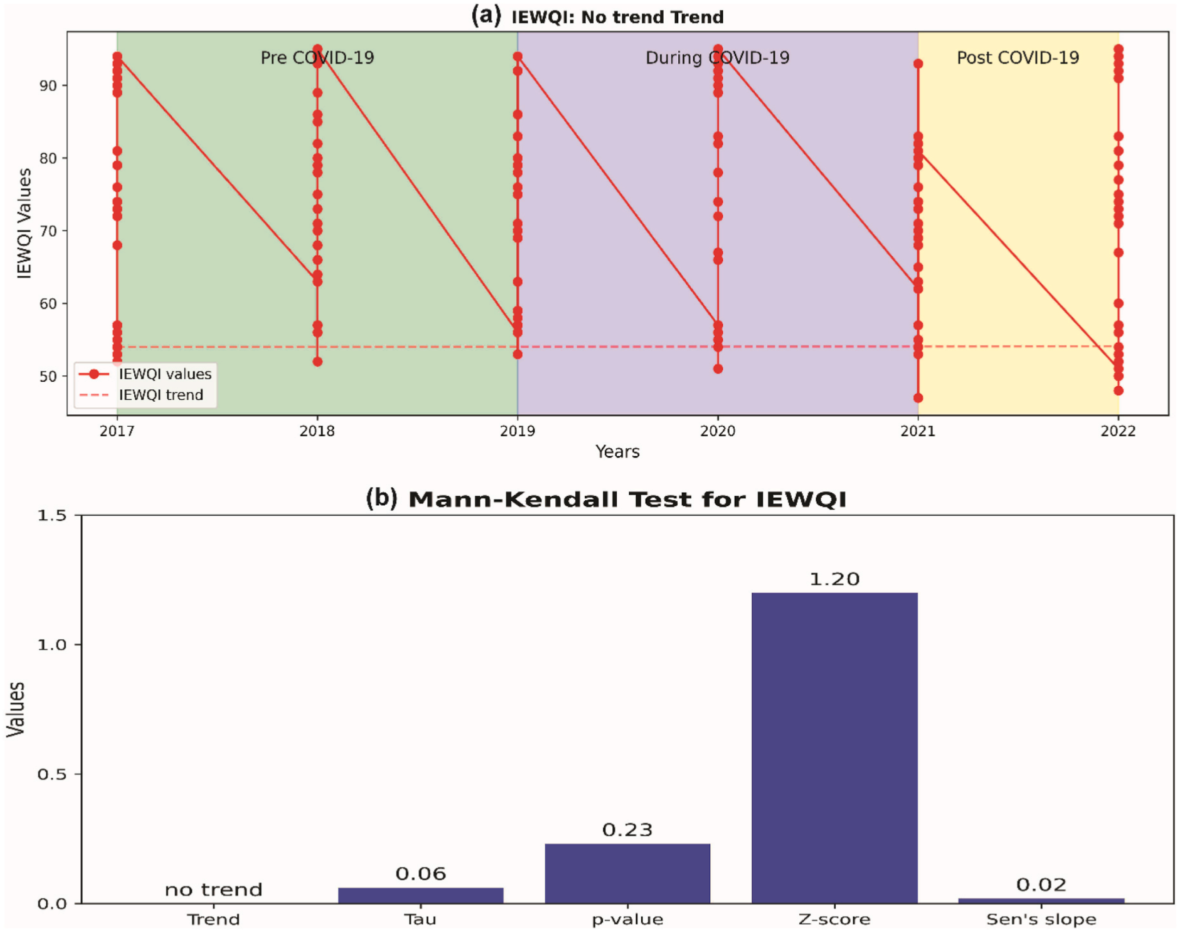

Fig. 7. Temporal variation of IEWQI scores in Cork Harbour over the 2017–2022.

Cork Harbour is improving over time.

6.1.2. *Water quality states in Cork Harbour over the years*

Fig. 8 presents the WQ status in Cork Harbour over the study years. The water quality status analysis in Cork Harbour for six years (2017–2022) using the IEWQI model showed that the overall water quality was classified as "fair," with some variations in different years. The marginal quality status was observed in 2017, 2018, and 2019, indicating that the water quality was poor during those years. In 2020, the water quality improved and was classified as "fair," which may be due to the COVID-19 lockdowns and reduced anthropogenic activities. However, in 2021, the water quality deteriorated again, and the status was classified as "marginal." The year 2022 showed a slight improvement, but the water quality status remained "fair" (Fig. 8). In addition,

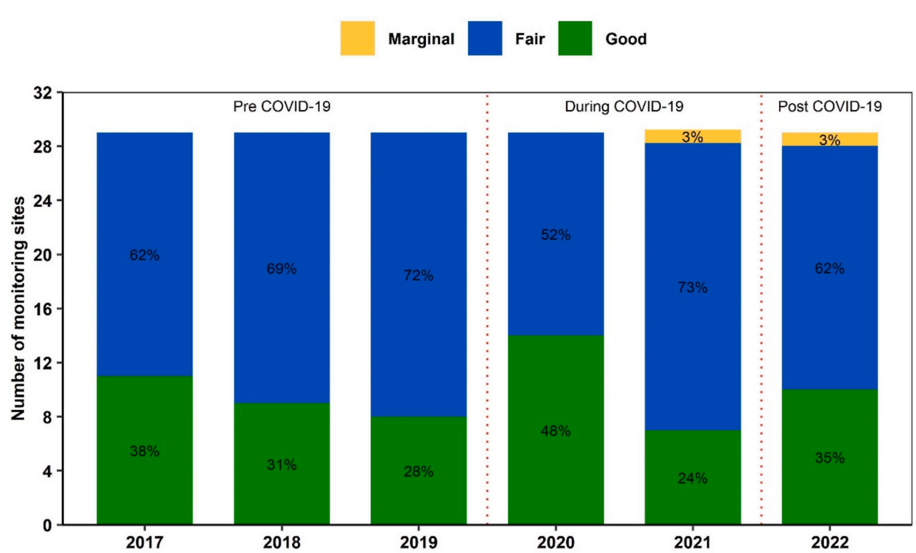

Fig. 8. A statistical summary of water quality status in Cork harbour during study period [2017–2022].

Fig. S6 presents the spatial distribution of water quality status in Cork Harbour. As depicted in the figure, significant spatial variations in water quality can be observed across different regions (upper, lower, and outer). Details of the spatiotemporal variability of water quality presented in supplementary martial as a continuation of section 6.1.2. Overall, the results suggest that the water quality in Cork Harbour has been affected by various factors, including anthropogenic activities and natural processes. The IEWQI model provides a useful tool for monitoring and assessing water quality and can aid in the development of targeted and effective management strategies to improve the water quality in Cork Harbour.

7. Discussion

The research was carried out for assessing the COVID-19 lockdown impacts on surface water quality using improved water quality model. Recently the authors critically reviewed more thirteen WQI models for assessing the suitability of coastal waters (Uddin et al., 2021). The study identified seven fundamental WQI models whereas the most models are modified. Details of the findings are discussed in Uddin et al. (2021). In terms of model reliability, the recent several studies have revealed that the IEWQI approaches effective to assess surface water quality (Ding et al., 2023; Georgescu et al., 2023; Uddin et al., 2023a, 2023f). Therefore, the study utilized this technique for assessing the COVID-19 lockdown impact on surface water quality in Cork Harbour using the recently developed tool IEWQI approaches. In addition, the Study also considered the model reliability in terms of evaluating model uncertainty and spatio-temporal sensitivity. To the best of author's knowledge, this is the first initiative to the application of the IEWQI model for assessing COVID-19 lockdown effect on water quality in Ireland.

For the purposes of the assessment of various water quality indicators, the study utilized the WFD guidelines (Table S2). The present study revealed that most water quality indicators with the exception of the TRAN, DIN, and TON in Cork Harbour remained within permissible limits throughout the years across different monitoring sites (Table S4 – Table S9), aligning with global trends. Similar findings were reported in other regions during the pandemic. For instance, studies in different parts of the world, such as China (Meng and Zhang, 2023), India (M. Balamurugan et al., 2021; Chakraborty et al., 2021a; Dobson et al., 2021; Islam Khan et al., 2021; Ali P. Yunus et al., 2020), Turkey (Tokatlı and Varol, 2021; Varol, 2020; Varol et al., 2022), Iran(Haghnazar et al., 2022), UK (Dobson et al., 2021), and Italy (Balacco et al., 2020; Binda et al., 2021), indicated that water quality parameters generally met regulatory standards during the COVID-19 lockdown periods.

The analysis indicated a significant increase in the concentrations of dissolved inorganic nitrogen (DIN) and total organic nitrogen (TON), whereas the water TRAN considerable decreased during the COVID-19 lockdown period in Cork Harbour (Table S4 – Table S9). Moreover, similar investigations were carried out by the EPA, Ireland (EPA, 2022). In the global context, studies investigating the impact of the COVID-19 pandemic lockdown on water quality have demonstrated mixed results. Some studies have reported improvements in water quality indicators during lockdown periods (M. Balamurugan et al., 2021; Chakraborty et al., 2021a; Islam Khan et al., 2021, 2021b; Meng and Zhang, 2023; Tokatlı and Varol, 2021; Varol et al., 2022; Ali P. Yunus et al., 2020), while others have indicated negative effects due to increased domestic wastewater discharge and inadequate treatment facilities (Hartnett et al., 2012). These variations highlight the importance of considering local conditions, including infrastructure and population density, when assessing the pandemic's influence on water quality. In addition, several recent studies carried out for similar purposes. These findings align with studies conducted globally, including research in the Ganges River (Singh et al., 2022), Damodar River (Chakraborty et al., 2021a), and the Yangtze River (Qiao et al., 2021), which reported improvements in water quality indicators during lockdowns due to reduced human activities. In that case, a few indicators such as DIN, and TON increased and TRAN decreased may due to the extensive industrial activities over the COVID-19 lockdown periods (EPA, 2022). Because, the Cork Harbour is a densely populated and industrialized area in Ireland (Uddin et al., 2023b, 2022b), and complex dynamics characteristic water bodies (Hartnett et al., 2012).

However, the ultimate goal of the IEWQI model is to rank water quality based on the particular indicators using their guidelines. In order to the assessment of the overall water quality, the IEWQI ranked water quality "good" and "fair" categories over the pre-COVID-19, whereas the water quality into classified three categories- "good", "fair", and "marginal" over the during-post COVID-19 across different monitoring sites (Fig. S6). There were a significant differences found of water quality states between pre-COVID-19 and during-post COVID-19 in Cork Harbour (Fig. S4). It could be happed due to the inconsistence of the DIN, TON and TRAN over the monitoring years (EPA, 2020; 2022; Hartnett et al., 2012; Uddin et al., 2023g). Similar findings of the research reported a number of recent studies by the authors (Uddin et al., 2020b, 2022a; 2022b, 2023a; 2023b, 2023d; 2023e, 2023f). In addition, these findings are consistent with global observations, as studies in various countries in literature (Aman et al., 2020; M Balamurugan et al., 2021; Chakraborty et al., 2021a; Haghnazar et al., 2022; Islam Khan et al., 2021, 2021b; Tokatlı and Varol, 2021; Varol et al., 2022; Vijay Prakash et al., 2021; Ali P Yunus et al., 2020), whereas (Liang et al., 2020; Wan Mohtar et al., 2019; Xiong et al., 2021)have reported spatial heterogeneity in water quality, indicating the need for localized management strategies.

Before the COVID-19 pandemic, studies reported varying water quality conditions worldwide. Factors such as industrial activities, agricultural practices, and urbanization influenced water quality parameters, leading to spatial and temporal variations. For instance, research conducted in rivers, lakes, and coastal areas in different countries(Chakraborty et al., 2021a; Dobson et al., 2021; Haghnazar et al., 2022; Islam Khan et al., 2021, 2021b; Kutralam-Muniasamy et al., 2022; Meng and Zhang, 2023; Tokatlı and Varol, 2021; Vijay Prakash et al., 2021; Ali P. Yunus et al., 2020) identified pollutants such as nutrients, metals, and microplastics exceeding regulatory thresholds in certain regions, highlighting ongoing water quality challenges.

During the COVID-19 lockdown periods, a few studies have shown mixed trends in water quality. Some regions experienced improvements in water quality indicators due to reduced anthropogenic activities (Chakraborty et al., 2021b; Islam Khan et al., 2021; Tokatlı and Varol, 2021; Vijay Prakash et al., 2021; Ali P Yunus et al., 2020). For example, studies conducted in urban areas (Haghnazar et al., 2022) and river basins (Chakraborty et al., 2021a; Dobson et al., 2021; Haghnazar et al., 2022b; Islam Khan et al., 2021; Kutralam-Muniasamy et al., 2022; Meng and Zhang, 2023; Pant et al., 2021; Tokatlı and Varol, 2021; Varol and Tokatlı, 2023), lake waters (Yunus et al., 2020), and coastal waters (Lotliker et al., 2021; Ormaza-Gonzaìlez et al., 2021; Vijay Prakash et al., 2021)observed decreases in pollutant concentrations, attributed to reduced industrial discharges, transportation emissions, and tourism-related activities. These findings suggest that temporary restrictions on human activities had positive short-term effects on water quality. The present research findings also align with these results (Fig. S5).

Post-pandemic trends in water quality remain an area of ongoing research. Initial findings from studies conducted in different regions have indicated mixed outcomes. Some areas have experienced a return to pre-pandemic water quality conditions as human activities resumed (Chakraborty et al., 2021b, 2021a; Meng and Zhang, 2023; Vijay Prakash et al., 2021; Ali P. Yunus et al., 2020). On the other the present study investigated there is no significant differences trend of water quality over the study period (Fig. S5). However, localized improvements have also been reported in regions where policy changes and awareness campaigns have led to sustained behavioral shifts towards environmentally friendly practices (Manoiu et al., 2022; Pacaol, 2021). These findings highlight the importance of long-term monitoring and adaptive management approaches to sustain and build upon the positive changes witnessed during the pandemic.

However, contrasting trends were observed in other regions during the pandemic. Studies conducted in areas heavily impacted by domestic wastewater discharges reported deteriorations in water quality indicators (EPA, 2022). Increased household water usage, improper waste management practices, and overwhelmed treatment facilities contributed to elevated pollutant levels (M. Balamurugan et al., 2021; Randazzo et al., 2020; Zhu et al., 2021). These findings underscore the need for effective wastewater treatment and management strategies, particularly during periods of increased domestic activities and limited resources. It is crucial to consider the global variations in water quality trends during the COVID-19 pandemic. Factors such as local infrastructure, population density, and regional environmental regulations contribute to the observed differences. Additionally, the duration and severity of lockdown measures, vaccination rates, and socioeconomic factors influence water quality trends in different regions.

In terms of assessing water quality reliability, this study stands out as the first documentation to include the model uncertainty and sensitivity results, along with the 95% confidence interval of the model outcomes. The performance results of the IEWQI model demonstrate its superiority in assessing surface water quality across various monitoring sites in Cork Harbour. The model evaluation metrics reveal that the IEWQI model could be reliable to evalute the surface water quality. The model demonstrated the lowest uncertainty and higher sensitivity for assessing surface water quality in terms of spatiotemporal resolution while avoiding eclipsing issues. However, it was observed that the model faced challenges of ambiguity at certain monitoring sites in Cork Harbour (Table S4-Table S9), a phenomenon recognized globally (Ataul Gani et al., 2023; Ding et al., 2023; Georgescu et al., 2023; Uddin et al., 2023), underscoring the need for ongoing efforts to refine water quality indexing approaches. Notably, most recent studies only employed WQI approaches to evaluate water quality during the COVID-19 period, and no evidence was found to address the model's limitations, including eclipsing, ambiguity, and uncertainty (Aman et al., 2020; Chakraborty et al., 2021a; Islam Khan et al., 2021; Tokatlı and Varol, 2021; Varol and Tokatlı, 2023; Ali P Yunus et al., 2020a; 2020b).

Several recent studies have highlighted inconsistent assessment results of water quality when using WQI approaches due to these limitations (Burić et al., 2023; Ding et al., 2023; Georgescu et al., 2023; Manna and Biswas, 2023; Uddin et al., 2022a, 2023b; 2023d, 2023e). To the best of the author's knowledge, the present study considered the existing limitations of WQI approaches. The research findings suggest that they can effectively contribute to improving WQI approaches, thereby enhancing the model's reliability for future applications.

In conclusion, global recent studies have provided insights into the trends in water quality before, during, and after the COVID-19 pandemic. The findings highlight the complex and nuanced nature of water quality dynamics, with improvements observed in some regions during the lockdown period, while other regions faced challenges due to increased domestic wastewater discharges. Post-pandemic water quality trends are influenced by a range of factors, necessitating ongoing monitoring, adaptive management, and targeted interventions. These findings emphasize the importance of holistic approaches to water resource management that consider both natural and anthropogenic influences, ensuring sustainable water quality for future generations.

8. Conclusion

This study investigates the impact of the COVID-19 lockdown on surface water quality in Cork Harbour, Ireland, by employing advanced IEWQI (Irish Water Quality Index) approaches and six years of water quality data spanning from 2017 to 2022. Additionally, the research evaluates the newly developed model's performance in terms of reliability for water quality assessment, considering existing limitations. A range of statistical tools, including machine learning (ML) approaches, were utilized to determine the spatiotemporal changes in water quality and evaluate the IEWQI model's performance in assessing surface water. From the findings of the research, the following conclusions were drawn.

- Most water quality (WQ) indicators remained within permissible limits over the years, except for DIN and TON in 2021. Notably, during the COVID-19 lockdown period, the concentrations of these indicators decreased significantly, indicating a slight improvement in water quality during the lockdown.
- The study identifies various anthropogenic pressures, such as domestic waste, industrial wastewaters, and extensive agricultural activities, which might have influenced the water quality indicators over time.
- Over the entire study period, Cork Harbour displayed "good," "fair," and "marginal" categories of water quality, with the outer Harbour exhibiting relatively "good" water quality, while the upper Harbour had "marginal" quality.
- The IEWQI model demonstrated excellent performance throughout the years in terms of model sensitivity and uncertainty, with no eclipsing issues. However, there were instances of model ambiguity at a few monitoring sites.
- Overall, no significant trend in water quality was observed in Cork Harbour during the six-year period, suggesting that the COVID-19 lockdown had no substantial impact on water quality.
- The results of the model performance evaluation revealed that the IEWQI model accurately computed the impact of the COVID-19 lockdown on water quality, highlighting its effectiveness for such assessments.
- The study demonstrates that the IEWQI model is effective in evaluating the impact of various anthropogenic pressures on water quality in Cork Harbour.

This study presents a comprehensive analysis of water quality trends in Cork Harbour during the pre-during-post COVID-19 periods. The findings shed light on the influence of the COVID-19 pandemic on surface water quality and offer valuable insights into the effects of pathogenic events on water resources management and monitoring programs. Our research underscores the significance of considering both anthropogenic and natural events when evaluating water quality in the region. However, it is essential to note that the study's scope was limited to the Cork Harbour area and may not be directly generalizable to other regions with distinct environmental conditions. Additionally, the research focused on a select few water quality indicators as suggested by the IEWQI model. However, it is essential to consider incorporating other indicators such as chemically priority substances (e.g., benzene, lead, dichloromethane) and biological and hydrodynamic components of waters in future research. Expanding the scope to include these additional indicators will provide a more comprehensive understanding of water quality dynamics and further enhance the model's applicability in assessing surface water quality. Moreover, the study only considered short-term impacts of the COVID-19 pandemic lockdown on water quality, and further research is needed to assess its long-term effects.

Credit authors statement

Md Galal Uddin: Conceptualization, Methodology, Investigation, Formal analysis, ML and AI performed, Data curation, Visualization, Writing – original draft, Writing – review & editing. Azizur Rahaman: Data curation, Methodology, statistical and ML analysis, Writing – review & editing. Mir Talas Mahammad Diganta: ML and AI performed, Data curation, Writing – review & editing. Abdul Majed Sajib: ML and AI performed, Data curation, Writing – review & editing. Stephen Nash: Conceptualization, Methodology, Investigation, Writing – review & editing. Tomasz Dabrowski: Writing – review & editing. Reza Ahmadian: Writing – review & editing. Michael Hartnett: Writing – review &

editing. Agnieszka I. Olbert: Conceptualization, Methodology, Investigation, Supervision, Data curation, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2023.122456.

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