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A novel machine learning application: Water quality resilience prediction Model

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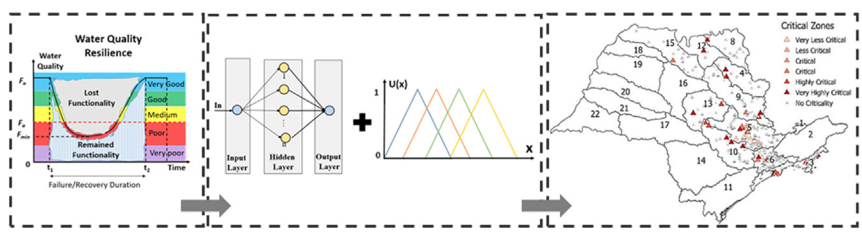
HIGHLIGHTS

- Machine learning methods are effective techniques in predicting systems' resilience.
- Resilience predictive model enables resilience-informed water management.
- Predictive model assists decision-makers with more effective resilience planning.
- Zones criticality show similarities & differences with & without resilience model.
- Resilience-driven interventions can reduce over/underestimation of critical zones.

GRAPHICAL ABSTRACT



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ABSTRACT

Resilience-informed water quality management embraces the growing environmental challenges and provides greater accuracy by unpacking the systems' characteristics in response to failure conditions in order to identify more effective opportunities for intervention. Assessing the resilience of water quality requires complex analysis of influential parameters which can be challenging, time consuming and costly to compute. It may also require building detailed conceptual and/or physically process-based models that are difficult to build, calibrate and validate. This study utilises Artificial Neural Network (ANN) to develop a novel application to predict water quality resilience to simplify resilience evaluation. The Fuzzy Analytic Hierarchy Process method is used to rank water basins based on their level of resilience and to identify the ones that demand prompt restoration strategies. The commonly used 'magnitude * duration of being in failure state' quantification method has been used to formulate and evaluate resilience. A 17-years long water quality dataset from the 22 water basins in the State of São Paulo, Brazil, was used to train and test the ANN model. The overall agreement between the measured and simulated WQI resilience values is satisfactory and hence, can be used by planners and decision makers for improved water management. Moreover, comparative analyses show similarities and differences between the 'level of criticalities' reported in each zone by Environment Agency of the state of São Paulo (CETESB) and by the resilience model in this study.

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1. Introduction

Historically, environmental status of water resources in an area is assessed against pre-defined water quality (WQ) standards. For this purpose, spatial and temporal changes (e.g. monthly or annually) of WQ parameters (or WQ indexes) are collected and used to identify and assess WQ characteristics due to natural and man-made influences (Chounlamany et al., 2017) or for life cycle assessment of geomorphological dynamics (Tooth, 2018). In line with this, risk-based approaches are also commonly used to tackle the sparsity of WQ data and the limitations of statistical methods to reconstruct the time-series for WQ analysis (Maier et al., 2001; Hart et al., 2003; Mondal and Wasimi, 2007; Sarang et al., 2008; Asefa et al., 2014; Hoque et al., 2013, 2016). However, in practice, there are limitations to traditional WQ assessment methods and approaches used due to first, a high degree of uncertainty in emerging threats; second, time blindness of risk measures used; third, complexity of their consequences (Park et al., 2012; Sweetapple et al., 2018). Some latest studies have proposed resilience as a complementary measure to risk for a more robust decision-making in WQ management (Sweetapple et al., 2018). These studies focus on the promotion of key drivers, attributes and role players' adaptive capacities to cope with changing conditions rather than the use of control-based risk management (van den Hoek et al., 2011; Hoque et al., 2012; Mallya et al., 2018). Conventional WQ management relies on the ability to project future change in order to design restoration strategies to well-known and defined problems (Pahl-Wostl et al., 2011). Therefore, the assessment methods used, tend to overlook the collective interaction of magnitude, frequency, and duration of failing periods as long as the overall performance (e.g. annual average) can fairly satisfy the desired standards. This approach can potentially become more difficult to maintain under highly variable future with numerous interconnected stressors leading to failure incidents (Zimmerman et al., 2008; Butler et al., 2016). Resilience-informed water quality management embraces the growing environmental challenges and provides greater accuracy by unpacking the systems' characteristics in response to failure conditions in order to identify more effective opportunities for intervention.

Drawing on the above discussion, resilience-informed WQ assessment requires WQ data and information that are generally expensive and time-consuming to collect, particularly for large-scale and complex catchments (Cumming, 2011; Rowny and Stewart, 2012; Zeng et al., 2013; Li et al., 2014). Building surrogate models and/or methods proved to be effective methods in water quality (WQ) management to evaluate and demonstrate the relationship between different components in a system - particularly the effect of different interventions. Historically, Machine Learning (ML) techniques such as Artificial Neural Network (ANN) have been widely used for prediction and forecasting in water quality studies (Mitrović et al., 2019; Ahmed et al., 2019; Zhu and Heddam, 2020; Antanasijević et al., 2020), especially in WQ predictions (Palani et al., 2008; Singh et al., 2009; Khalil et al., 2011; Khan and See, 2016; Seo et al., 2016) and also in WQ indexes predictions (Gazzaz et al., 2015; Elshemy and Meon, 2017). In addition, there are many advantages of using ANNs for prediction purposes such as: eliminating the need for a priori knowledge of the underlying process and the existing complex relationships of the system elements (Kalin et al., 2010; Sarkar and Pandey, 2015). ANNs are often combined with other AI-based and/or evolutionary techniques to improve quality and accuracy of predictions in various applications for analysis and decision-making (Chau, 2006; Kuo et al., 2006; Zhang and Lai, 2011; Chen and Liu, 2015; Chen et al., 2015; Mahmoudi et al., 2016; Noori et al., 2020). Moreover, there are several studies based on multiple linear regression methods combined with AI methods to develop WQ models (Ji et al., 2017; Slaughter et al., 2017; Tomas et al., 2017; Wu et al., 2018; Antanasijević et al., 2020; Rajaee et al., 2020).

In recent years, advancement and innovations have been made in relation to resilience-informed disasters management (such as flood resilience) but very limited studies are available in the context of WQ management, partly due to non-acute and less visible impacts and consequences. To the date of this paper, WQ resilience has been quantified and analysed in a few studies using adaptive cycle algorithm (Li et al., 2016), functionality loss metrics and evolutionary algorithm-based optimisation (Zhang et al., 2020) and remained functionality metrics (Hoque et al., 2012; Sweetapple et al., 2018). These studies rely on case studies' data sets/archives and physical models to evaluate resilience and validate the results which are quite challenging. Having a resilience predictive model, in conjunction with the existing evaluation methods, can support WQ resilience management by reducing the reliance on physical data/model for evaluation and validation purposes and additionally, it can support future planning for resilience by making predictions. To data of this paper such model is yet to be studied and this is the gap that this study aims to tap in. Hence, the key novelty of this research embeds in development of a new model to predict WQI resilience. It should be noted that this paper will not introduce any new machine learning method or algorithms, rather, it utilises the commonly used algorithms and methods in a new application (i.e. resilience-informed WQ assessment).

In general, three stages can be defined for resilience-informed WQ management at a catchment level: 1. modelling, assessing, evaluating resilience of the catchment; 2. prioritising the areas (e.g. (sub)-catchments) needing restorative intervention on the basis of their resilience level; and 3. determining the appropriate intervention to those most at risk. This paper focuses on the first stage and how it can inform prioritisation process in the second stage.

In this study, the resilience prediction model is set up for the case study of São Paulo city in Brazil to identify vulnerable contaminated areas (so-called critical zones or sub-catchments). Prediction of resilience (spatially/temporally) provides a tool for resilience planning by capturing the trend of resilience fluctuations (e.g. on an annual basis) in order to characterize, design and evaluate adaptation strategies. This predictive model can potentially assist key stakeholders and decision-makers in CETESB in their annual planning for environmental improvement.

In this paper, the study methodology is explained in Section 3 with the discussion of measuring water quality resilience and ANN structure. In this section, the Fuzzy Analytic Hierarchy Process (FAHP) conceptual model with the mathematical representation of that is also explained. In Section 4, we have discussed the procedure of identifying the critical zones based on the developed model. The results and associated discussions based on the outcomes have been described in Section 5. The study limitations have been also critically evaluated in this section. The conclusions with the future direction have been drawn in the last section.

2. Material and methods

The methodology section is twofold: the first part describes the development of WQ resilience evaluation framework (i.e. *stage 1* mentioned above); and the second part focuses on the integration of the ANN model as a surrogate for calculating WQ values (i.e. *stage 2* mentioned above).

The first stage (Section 2.4) explores the feasibility of integrating historical data and conventional machine learning techniques (ANNs) to develop a novel resilience predictive model for WQ without the need of costly physical models. In the second stage (Section 2.5), the widely studied Analytical Hierarchy Process (AHP) (Saaty, 1982; Saaty, 1977) is adopted for the prioritisation process adopting a fuzzy approach due to its simplicity and effectiveness in this kind of problem (Kahraman et al., 2004; Moktadir et al., 2017).

This predictive model can assist key stakeholders and decision-makers in two possible ways; first, in creating effective long-term actions to promote regional water resources resilience; second, in developing strategies that focus on desirable priorities such as environmental compliance, social equity or economic prosperity. The predictive model is particularly useful to overcome the challenges of costly and time-consuming manual data collection. In addition to being costly, manual data collection has its own challenges such as significant accessibility and safety issues particularly in the case study used. Also, data quality is critical in improving model accuracy and reducing uncertainty; and it can significantly be affected by the lack of automated monitoring systems. It should be noted that this is a feasibility study and not a comprehensive evaluation of the approach.

2.1. Case study

Surface water resources in the state of São Paulo (SP) in Brazil have been used as a case study in this research. SP is located southeast of Brazil with a state area of 248,000 km^2 and is the most populous state in Brazil (IBGE, 2014). It is divided into 22 Hydrographic Units of Water Resources Management (UGRHI) (Instituto Socioambiental, 2009) with three river basin districts and seven distinct climates. Surface water and groundwater resources together account for about 80% and 20% of water supply in SP, respectively. It has benefited from rapid economic and urban growth over recent decades which has come at the cost of compromising the quality of local water resources. This reduction in WQ has occurred for various reasons, mainly water management conflicts and the absence of clear long-term sustainable development plans for both urban areas and wastewater infrastructure. Environment Agency of the state of São Paulo (CETESB) operates 425 manual and 44 automatic freshwater quality monitoring stations (in total: 469 stations) and the number of collected WQ samples could vary from one season to another in each station depending on climatic conditions. These data are used by CETESB for WQ management in the state of SP.

2.2. Water quality data

Decision makers in CETESB and the imposed environmental and social concerns of unsustainable developments in the state of SP have created the need for a great deal of information to be collected in response to public policies and the monitoring of their effects. To aid this data collection and analysis, CETESB has developed water quality indexes (WQI) that process increasing quantities of information, in a systematic and accessible way for decision makers. The main advantages of the indexes are the ease of communication with the lay public, the status greater than the isolated variables and the fact that it represents an average of several variables in a single number by combining different units of measure into a single unit (CETESB-Appendix C, 2017).

This study will focus on the impairment of surface WQ due to organic substances (mainly arisen from the lack of sufficient and efficient sewage collection and treatment systems) and in relation to aquatic life. Therefore, Table 1 in Supplementary Information (SI) outlines CETESB's three relevant WQIs (IQA, IET, and IVA) for decision-making on WQ policies and in line with the focus of this paper.

This study uses the average monthly values of CETESB's WQI (shown in Table 2 in SI) from 2001 to 2017 (in total 17 years of data) (CETESB, 2000–2017) to develop the predictive WQ resilience model, which provides a consistent and long-term data set ideal for ANN calibration and validation. As the data published by CETESB from 2010 onwards were more comprehensive, it was necessary to use data sets from latter years i.e. the first 16 years in this study, to develop a more accurate predictive model. The 2017 data set was then used for prediction validation purpose. The data used are publicly available in CETESB's annual reports and published after rigorous evaluations in terms of quality and accuracy. The data sets are of high quality, resolution, coverage and are used for policy and decision-making, on environmental matters in the region; therefore, no significant data pre-processing was needed (further details can be found in Section 2 in SI). The water quality data used in this study are collected by CETESB from 469 automatic and manual monitoring stations across the State of São Paulo and WQIs are evaluated. These stations are spatially wide-spread, well-representing the whole study area. The quality of the monitoring stations is continuously monitored and improved by CETESB. The data collected represent temporal changes in wet and dry seasons. The collection sites cover the surface water resources such as rivers, streams, lakes, branches, and places of transposition to reservoirs. WQI time series are used to calculate the annual resilience values that are used for ranking of the zones using a fuzzy algorithm which will be discussed in section 2.5 in the paper.

In addition to that, to evaluate resilience in terms of locally-defined acceptable levels of WQ, CETESB has introduced service thresholds and descriptive classification ranges for WQIs as shown in Table 2 in SI (CETESB, 2017). The greater IQA value indicates a better quality of surface water resources while this is opposite for IET and IVA (the lower, the better). These thresholds are used throughout the study for resilience evaluation. It should be noted that in this study the lower limits of the 'average quality class' in Table 2 in SI (i.e. 36 for IQA, 3.4 for IVA and 52 for IET), are used as the standard threshold (i.e. P_0 in Eq. (2) in SI) for each WQI. This is in line with CETESB's approach to 'average quality' as an acceptable threshold.

2.3. Water quality resilience formulation

In this study, WQ resilience is defined as the capacity of a surface water resource system to cope with, and recover from contamination in order to maintain the required level of service and comply with predefined WQ standards to protect people and the environment.

It is important to make a distinction between the emerging concept of resilience and the commonly used assimilative capacity in WQ assessment. Traditionally, assimilative capacity utilises process-based modelling to build a relationship between WQ and quantity to assess whether a waterbody can meet pre-determined criteria for its ecological function and designated use. In other words, assimilative capacity tends to be reliability-driven (i.e. 'Fail-Safe' approach) aiming to avoid/prevent failures. On the other hand, resilience embraces assimilative capacity to improve its resistance capacity (one of the characteristics of resilience), but it also takes a 'Safe-Fail' approach in order to maximise its adaptation capacity to tackle emerging challenges (and their uncertainties) and to minimise adverse impacts (Butler et al., 2016). Further information about some potential differences between traditional environmental assessment method and resilience-based assessment methods have been provided in section 1 in the enclosed SI.

Several metrics/measures have been developed and introduced in literature to quantify resilience for different contexts in different water systems (Hashimoto et al., 1982; Fowler et al., 2003; Matrosov et al., 2012; Jung, 2013; Paton et al., 2014; Butler et al., 2016). This study inspired by the 'volume-based resilience metrics' method, introduced in the study by Roach et al. (2018), and formulated by Hasan et al. (2019) and McClymont et al. (2020), to encapsulate a suitable resilience-based performance metric for WQ evaluation. Details about formulation of WQR can be found in Section 3 in SI. Additionally, details have been provided on data preparation and pre-processing in Section 2 in SI.

2.4. Stage 1 - predictive water quality resilience model

As mentioned above, *Stage 1* focuses on development of the predictive WQ resilience model and its output can be the resilience value predicted in a zone (or a station in a zone) in the study area. The predictive WQ resilience model integrates the WQ resilience evaluation method (section 2.3) and the ANN. This model can be used to assess water resource adaptive capacity in order to identify the most vulnerable/critical contaminated UGRHIs (so-called zones in this paper) without the need for a great deal of costly data collection and time-consuming system modelling. Additionally, it can enable water and environment sectors

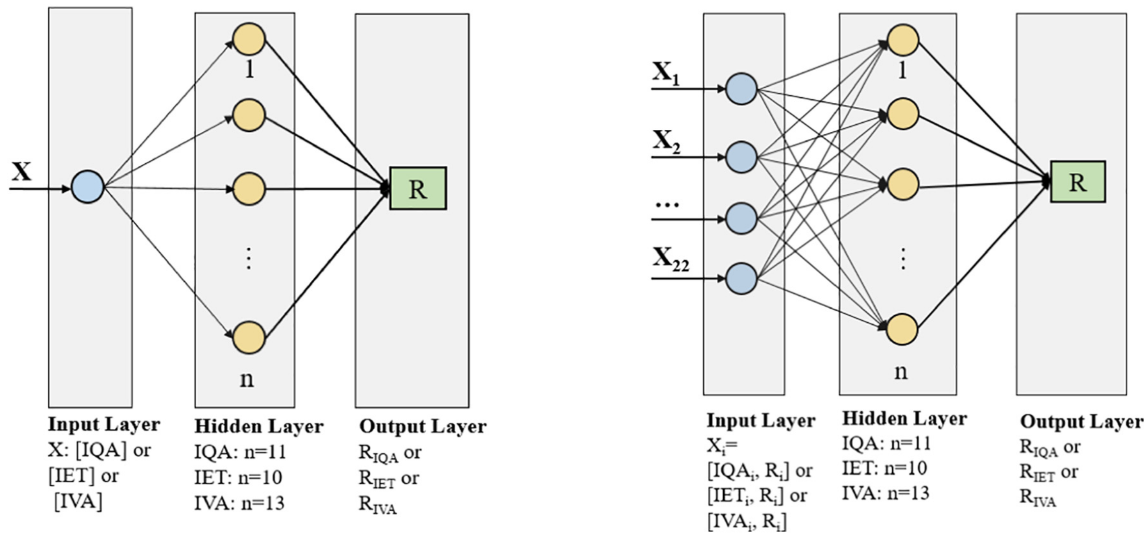

Fig. 1. ANN predictive model; a) Architecture of the predictive network and b) Predictive network architecture in the 'training phase'.

to map the spatial and temporal dynamics of resilience fluctuations across the study area and time (Hasan et al., 2019), without direct characterisation of the influential factors (e.g. land use pattern, hydrological parameters, etc.). The proposed predictive model can be utilised to make predictions of future WQ resilience and therefore, enables proactive resilience planning. The key advantage of the predictive model is that it can be integrated into complex process-based models, for example as a surrogate to assess WQ resilience in ungauged catchments or for a fast resilience evaluation to enhance resilience-informed land-water system planning. It should be noted that resilience thresholds (how much resilience is needed, feasible, good enough, acceptable, low, high, etc.) have been recognised as playing a key role in resilience planning strategies and to the best of the authors' knowledge, these thresholds are yet to be developed due to the complexity and challenges involved. The predictive model can assist and facilitate in the development of these resilience thresholds.

2.4.1. ANN structure

ANN and its algorithms have played a crucial role in predicting, modelling and classifying WQ parameters. The predictive model developed in this study is a multilayer perceptron neural network (MLPNN). This ANN model is formed in three layers: input layer that contains WQI values in a zone (IQA or IET or IVA), hidden layers and output layer having the dependent variable (i.e. the predicted resilience value associated with each WQI in a zone). It should be noted that, in this study, separated networks for each WQI have been produced (i.e. three separated networks). This reflects CETESB' approach to distinct remedial planning for surface water protection as defined in Table 1 in SI.

A log-sigmoid function widely used as a transform function to update weights and biases in the hidden layer and a linear transfer function for the output layer. All these layers contain a number of interconnected neurons (i.e. processing units). The optimal number of neurons in the hidden layer is proceeded by trial and error using the backpropagation (BP) algorithm and the mean square error (MSE). In this study, the best network training results were achieved with 11, 10 and 13 neurons in the hidden layer for IQA, IET and IVA datasets, respectively.

Fig. 1a demonstrates the overall architecture of the predictive model in this study with WQI as the input neuron (IQA or IET or IVA) and its associated resilience value predicted, in output layer. Fig. 1b demonstrates the network architecture in 'training phase'. In training phase, the input layer has 22 input neurons representing annual WQI (i.e. IQA or IET or IVA) in each of 22 UGRHIs (or zones) and their associated resilience values (using Eq. (3) in Section 3 in SI). Hence, the total number of input neurons adds up to 44 for each WQI in this phase. Table 1 summarises the details of the network in training phase and also illustrates the number of epochs, gradient and Mu values for each input dataset in training phase and also illustrates the number of epochs, gradient and Mu values for each input dataset.

In this study, a feed-forward back propagation ANN (i.e. ANN trained using the Levenberg-Marquardt (LM) method), which has been widely used in developing predictive models for water systems (Sarkar and Pandey, 2015), is set to approximate WQ resilience. For this purpose, LM algorithm is used in the curve fitting process, Bayesian Regularization (BR) algorithm is used for nonlinear regression conversions during training process, and Scaled Conjugate Gradient (SCG) algorithm is used for batch learning method while computing the errors. These are commonly well-performed ANN algorithms in a wide range of applications (including WQ evaluations) (Xiang et al., 2006; Palani et al., 2008; Singh et al., 2009; Najah et al., 2013; Sarkar and Pandey, 2015; Seo et al., 2016).

The BR back propagation method is used for its accurate predictions in training (Alvisi and Franchini, 2011; Ha and Stenstrom, 2003; Malekmohammadi et al., 2009). A batch mode of training is applied to enter the inputs to the network before the weights to be updated utilising SCG algorithm. The network training is finished when the specified number of epochs or training accuracy is achieved. The number of epochs represents the time needed for training of the network. If the training time is shorter, the network architecture is more efficient. Similarly, the fewer number of weights indicate that the net will better

Table 1
Structure of the predictive model in 'training phase' for each WQI.

Input datasets	Total number of input neurons	Hidden neurons	Transfer functions for Hidden layers	Output dataset	Total number of output neurons	Transfer function for output layer	Epochs	Gradient	Mu
[IQA, R_{IQA}]	44	11	Log-Sigmoid	R_{IQA}	1	Linear	60	9.6178	0.1
[IET, R_{IET}]	44	10		R_{IET}	1		22	0.1977	0.01
[IVA, R_{IVA}]	44	13		R_{IVA}	1		30	0.0025	0.0001

Table 2
'Significance intensity' of WQI by AHP and TFN (Kahraman et al., 2004).

IQA resilience			IVA/IET resilience		
Significance intensity	FAHP scale (λ)	TFN scale (l, m, n)	Significance intensity	FAHP scale (σ)	TFN scale (l, m, n)
Very low resilience (very poor WQ)	1	(0.1,0.2,0.3)	Very high resilience (very high WQ)	6	(0.9, 1.0,1.0)
Low resilience (poor WQ)	2	(0.3,0.4,0.5)	High resilience (high WQ)	5	(0.8,0.9,1.0)
Average resilience (average WQ)	3	(0.5,0.6,0.7)	Good resilience (good WQ)	4	(0.7,0.8,0.9)
Good resilience (good WQ)	4	(0.7,0.8,0.9)	Average resilience (average WQ)	3	(0.4,0.5,0.6)
High resilience (high WQ)	5	(0.9,1.0,1.0)	Low resilience (poor WQ)	2	(0.0,0.1,0.2)
			Very low resilience (very poor WQ)	1	(0.0,0.1,0.2)

generalize to validation, test, and new data with the same statistical attributes.

Given the ANN structure, each input dataset (Table 1) was randomly distributed into a 70% set for training, 15% set for validation and 15% set for testing, using the 469 WQ monitoring stations collected data across the 22 zones in São Paulo state.

It should be noted that authors are aware of further studies that could be conducted to identify the most suitable ANN algorithms and functions in a more systematic way. However, this is a feasibility study aiming to explore the possibility of developing a reliable model for resilience prediction in a water system application.

2.5. Stage 2 - predictive model application: to identify the critical zones

Stage 2 embraces CETESB's approach in prioritisation of zones most in need for interventions. This could be easily implemented by evaluating the resilience of each zone. However, due to the existing conflicting interactions among the three WQIs, identification and prioritisation of critical zones can be quite challenging. Hence, this study has developed a multi-criteria ranking method by integrating predicted resilience in each zone (i.e. the outcomes of the Stage 1) and Fuzzy Logic to overcome the abovementioned challenge. In line with this, FAHP method has been utilised in this study for its proven robustness and flexibility in resolving multi-criteria decision-making problems. It should be noted that, there are several approaches available in AHP methods such as weighted linear optimisation approach, ABC clustering approaches (Lolli et al., 2014) and triangular fuzzy number (TFN). In the context of this application and using TFN, there are several approaches that have been explored such as distance-based trapezoidal fuzzy number, graded mean integration representation and pairwise comparison matrix (Zhang et al., 2014). The step-by-step process is illustrated in Fig. 6 in SI.

2.5.1. Step 1: set the geometric fuzzy

In this step, a fuzzy algorithm is used to measure the importance of each WQI for each monitoring station based on its overall resilience value (from Stage 1) over the time period of study. Fuzzy analysis has been used in this study because of its inherent ability and flexibility in solving multi-criteria decision-making problems with embedded vagueness and uncertainties. Fuzzy linguistic labels are particularly great assets in the methodology to represent significant intensity in the context of resilience levels/thresholds.

TFN has been utilised in this study because of its proven simplicity and suitability to scale the 'significance intensity' (i.e. importance) of each WQI (in each station) based on its evaluated resilience value; and the multi-criteria system required (IET, IQA, IVA) to create the perception of different alternatives according to the criterion (Wang et al., 2016). It should be noted that TFN is used in this study based on the pairwise comparison matrix. The TFN scales shown for each WQI in Table 2, have been widely used for group assessment and approximation (Dagdeviren and Yüksel, 2008; Wang et al., 2008). A set of membership functions have been defined and used by the triplet (l, m, n), as shown in Section 4, Eq. (6) and Fig. 3 in SI, in relation to the required fuzzy algorithm.

In this study, *l*, *m* and *n* are the representatives for the upper, middle and lower values in a fuzzy AHP, adopted from TFN by Kahraman et al. (2004). A knowledge contrivance is created by utilising AHP (Saaty, 1977), which is a technique to solve multi-criteria-based complex systems. To facilitate the decision-making process in this study, linguistic variables (e.g. high quality, poor quality, etc.) (Zadeh, 1975) are created and scaled to categorise resilience as presented in Table 2 (high resilience, low resilience, etc.).

In this study, the 'criticality' (of the zones) is set using TFN and scaled between 0 (resilient) and 1 (critical).

2.5.2. Step 2: set the global index of monitoring stations

In this step, a fuzzy-based global index is developed to measure the overall importance of each zone. The global index will be used to identify the critical zones based on their overall resilience value. Eq. (1) calculates the aforementioned global index using FAHP and TFN scales shown in Table 3.

$$\delta_k^z = \lambda_j \times \sigma_j \tag{1}$$

where, δ_k^z denotes the fuzzy global index associated to a zone ($z = 1,..,22$); λ and σ are the significance intensity of each monitoring station in a zone (Table 3); and *k* denotes the number of monitoring stations in a zone.

2.5.3. Step 3: set the fuzzy weight of each WQI

In this step, the weight of each WQI is determined by fuzzy mean using TFN scale (in Table 3), indicating the 'significance intensity (importance)' of that WQI, in its zone (as shown in Eq. (2)):

$$\underline{w_z} = \left[\frac{l_i}{\sum_{i=1}^{k} l_i}, \frac{m_i}{\sum_{i=1}^{k} m_i}, \frac{n_i}{\sum_{i=1}^{k} n_i}\right] \tag{2}$$

where, *w* denotes the fuzzy mean; *l*, *m* and *n* are the membership functions (as shown in Table 2); *k* represents the number of stations in a zone; and *z* represents the zone number. w_z is then used to evaluate the total weight of each WQI, across the 22 zones, by combining the entire upper and lower values and dividing them by the sum of the α-cut values as shown in Eq. (3).

$$W_{idx} = \left(\frac{\alpha\left(W_{Z_{lower}}\right)}{\sum_{i=1}^{z}\alpha_i}, \frac{\alpha\left(W_{Z_{upper}}\right)}{\sum_{i=1}^{z}\alpha_i}\right) \; z = 1, \ldots, 22 \tag{3}$$

where, W_{idx} denotes the fuzzy weight of each WQI; α denotes the cut values in the crisp values; *z* presents the number of zones; $W_{\underline{Z}\,lower}$

Table 3
Average RMSE values of the applied algorithms.

Algorithm	RMSE for IQA	RMSE for IET	RMSE for IVA
LM	0.651	0.722	0.031
BR	0.670	0.076	0.011
SCG	4.635	3.479	0.227

and $W_{Z_{upper}}$ are the upper and lower bounds of the α-cut values, respectively, using the weighting average method (Kim and Park, 1990; Klir and Yuan, 1995). It should be noted that the factors belonging to the IQA have five α-cut values and IET have IVA, six cut values.

2.5.4. Step 4: defuzzify the total weight of each WQI

In this step, W_{idx} is defuzzified using Eq. (4). This process interprets membership degrees into a specific decision.

$$W_{idx_T} = \left[\gamma\left(W_{idx\left(w_{z_{lower}}\right)}\right) \times (1-\gamma)\left(W_{idx\left(w_{z_{upper}}\right)}\right)\right];\gamma \in [0,1] W_{id} = \left[\gamma\left(\frac{\alpha(w_{in})}{\sum_{i=1}^{z}\alpha_i}\right) \times (1-\gamma)\left(\frac{\alpha(w_{il})}{\sum_{i=1}^{z}\alpha_i}\right)\right];\gamma \in [0,1] \quad (4)$$

where, W_{idxT} denotes the total weight of each WQI in a zone; γ represents optimism index (i.e. reflects risk-taking attitude of decision makers); z presents the number of zones.

2.5.5. Step 5: fine-tune the parameters

In this step, the ANN parameters are fine-tuned until the minimum errors are obtained. The root mean square error (RMSE) method is used to calculate the errors.

2.5.6. Step 6: identify and rank the critical zones

Generally, the critical zones are determined using δ_k and W_{idxT} as shown in Eq. (3). To identify the most critical zones, initially all zones are ranked based on their W_{idxT} (for each WQI). The higher W_{idxT}values represent more criticality (lower resilience) and the lower ones represent less criticality (higher resilience).

The ranking process follows the 'stack principle' in a standard data structure for a given list. In other words, the 'stack' contains the most critical zones. For example, if the stack contains a lower W_{idxT} for IQA (i.e. less critical) in one zone and a higher W_{idxT} for IQA in the next one (i.e. more critical), then the stack pops that zone and pushes the new one. In this study, it includes the highest values for IET and IVA and the lowest values for IQA in a monitoring station (see Eq. (5)). Eq. (5) illustrates the critical monitoring stations based on the combined WQI importance. This study only considers a zone with more than two critical stations for each WQI. Drawing on these, each monitoring station can be expressed by Eq. (3):

$$CS_i^k = Maximise : \sum_{i=1}^{n}\left[\left(W_{idx_T}|IVA_z|, \sum_{i=1}^{z}\delta_i^k\right)\left(W_{idx_T}|IET_z|, \sum_{i=1}^{z}\delta_i^k\right)\right] + Minimise : \left(W_{idx_T}|IQA_z|, \sum_{i=1}^{z}\delta_i^k\right) \quad (5)$$

where, CS_i^k denotes the identified critical monitoring stations in each zone (based on combined WQI); n denotes the number of monitoring stations (it varies for each WQI); z and k present the number of zones and monitoring stations in that zone, respectively; δ denotes the global index value.

Drawing on Eq. (5), Eq. (6) is finally used to identify the most critical zones in the case study area using W_{idxT} and CS_i^k.

$$Z = [CS_z]; \forall_{stations} W_{id} = \left[\gamma\left(\frac{\alpha(w_{in})}{\sum_{i=1}^{z}\alpha_i}\right) \times (1-\gamma)\left(\frac{\alpha(w_{il})}{\sum_{i=1}^{z}\alpha_i}\right)\right];\gamma \in [0,1] \quad (6)$$

where, Z denotes the critical zones across the case study area (i.e. 22 zones); CS_z is the number of critical stations in each zone.

3. Results and discussion

In this study, the network training stops as soon as any of the following conditions occur: (i) model performance in validation dataset decreases abruptly in successive iterations; (ii) the maximum number of epochs of 100 is reached.

Fig. 2 depicts the overall performance of the neural network based on the training, validation and testing dataset for IQA and IET and IVA. In this figure, the best validation performance occurred at epoch 54, 16 and 24 for IQA, IET and IVA, respectively, showing Mean Squared Error (MSE) trend during the learning procedure. The decreasing trend of the validation set confirms that there is no over-fitting in the model.

Fig. 3 demonstrates the scatter plots of the calculated WQI resilience values using Eq. (2) in SI and their corresponding ANN-based resilience prediction model. The observations demonstrate that there is a reasonable approximation by the ANN model across the spectrum of the evaluated WQI resilience values. Therefore, the overall agreement between the measured and simulated WQI resilience values (R values for IQA: 0.98814; IET: 0.99228; and IVA: 0.9999) are satisfactory. Similarly, a set of error histograms using student's *t*-test have been presented in Fig. 4 in SI. Further details about the test can be found in the study by Hasan (2020).

Fig. 4 illustrates the *MSE* and *R* values of different algorithms for IQA, IET and IVA resilience predictions. It is noticeable in Fig. 4 that LM has performed better than BR and SCG for IQA and IET training. However, BR has performed significantly better with the testing dataset in the ANN model. Moreover, in all cases, SCG has shown the weakest performance. A possible reason is the poor convergence due to the adjustments of the weights and eigenvalues.

Table 3 shows the RMSE for the IQA, IET and IVA resilience, where it measures the differences between the resilience values predicted by the developed ANN-based resilience prediction model and the calculated WQI resilience values using Eq. (2) in SI. In other words, it shows the goodness-of-fit of generalization of the model. For the IET and IVA resilience, the BR performs significantly better compared to the LM and SCG in training, validation and testing purposes. Similarly, SCG performs poorest in all three WQIs. As a result, the SCG is not a suitable choice for predicting WQ resilience due to its poor accuracy in training, validation and testing phases. In terms of accuracy, the BR is preferable than LM for IET and IVA resilience. However, the average RMSE is slightly better for LM in the dataset of IQA.

Fig. 5 maps the identified critical (so-called vulnerable) zones utilising the predictive ANN-based resilience model and the FAHP method results for the case study area over the collective study period. The zones have been characterised descriptively by colour codes, varying from dark to light colours (most critical to least critical OR low resilience to high resilience). The observations illustrate that the Zones 5, 6, 7 and 9 have the lowest level of water resources resilience and therefore, in critical condition in São Paulo state. These zones are the most populated zones with rapid urban creeps and unsustainable developments leading to deteriorated WQ in the absence of sufficient and efficient wastewater collection and treatment infrastructures. However, prioritisation for intervention in critical Zones 5, 6, 7 and 9, where resources are limited, is required and according to the resilience-driven predictive model, Zone 5 has the most priority and Zone 7, the least.

It is important to investigate the ranking of critical zones using the resilience–driven ranking method proposed in this study with CETESB's traditional approach in order to gain a better understanding of paradigm shift in WQ assessment. Details of these investigation can be found in Section 6 and Fig. 5 in SI.

3.1. Limitations

This is a feasibility study to investigate the potential and suitability of using machine learning methods for resilience predictions in water engineering applications. Machine learning methods, and particularly artificial neural networks, have been commonly and successfully used in water systems management. On the other hand, resilience is a fast-growing concept proved to be an effective approach in preparing

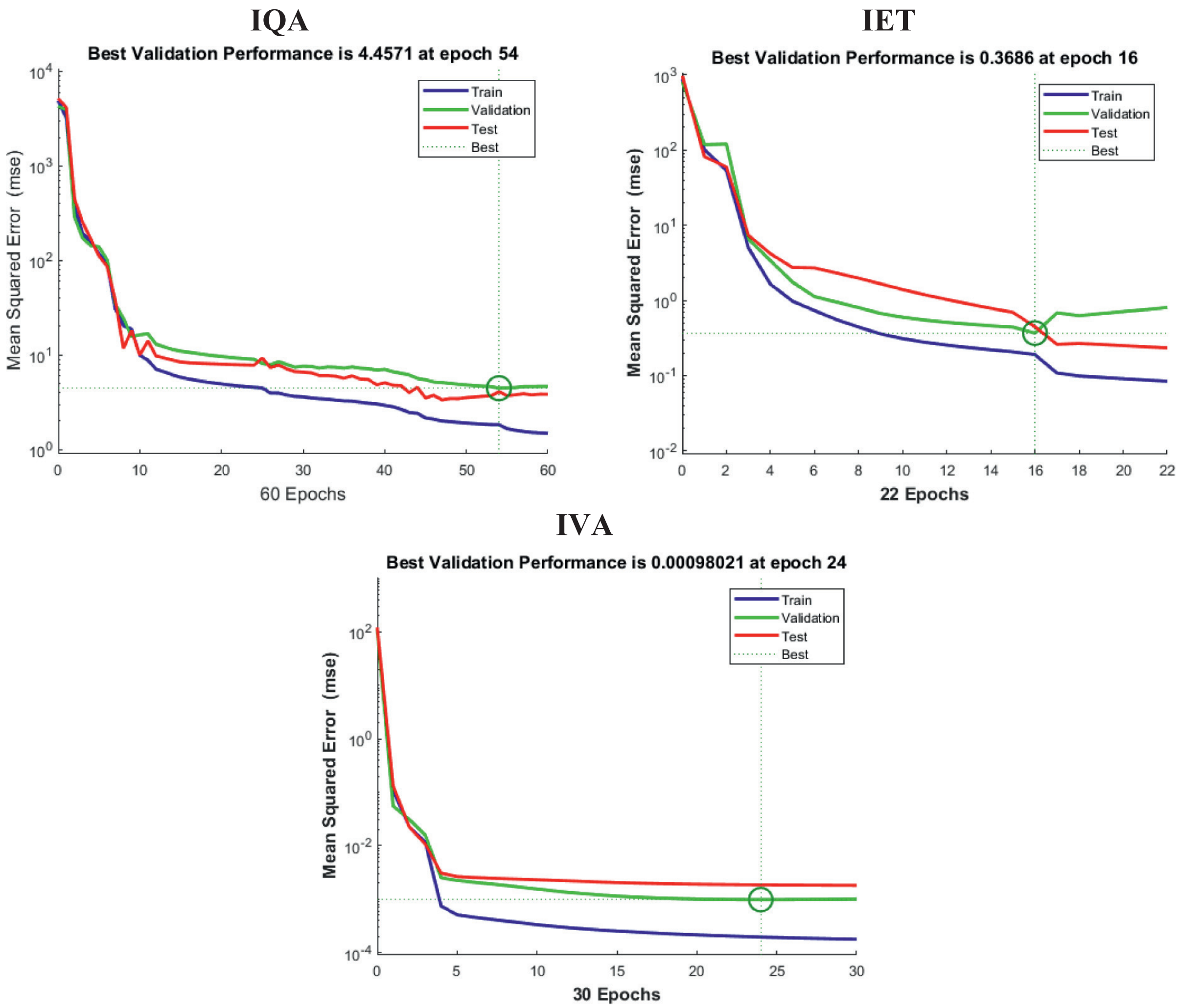

Fig. 2. ANN performance.

engineering systems to tackle and cope with emerging challenges. Authors believe that the integration of machine learning techniques to predict water quality resilience can provide an opportunity for more effective adoption of resilience to tackle the emerging challenges. This study is currently at its early stages and will be furthered in future studies. One potential improvement in horizon will be using more effective machine learning methods such as deep learning or deep reinforcement learning.

4. Conclusions

Planning water resources and related systems that are resilient in terms of delivering water of sufficient quality despite potential contamination that may occur in the catchment requires complex and integrated physical models that are challenging to build, characterize, and calibrate/validate. Moreover, these models rely on datasets that are costly and time consuming to collect. This study has focused on the

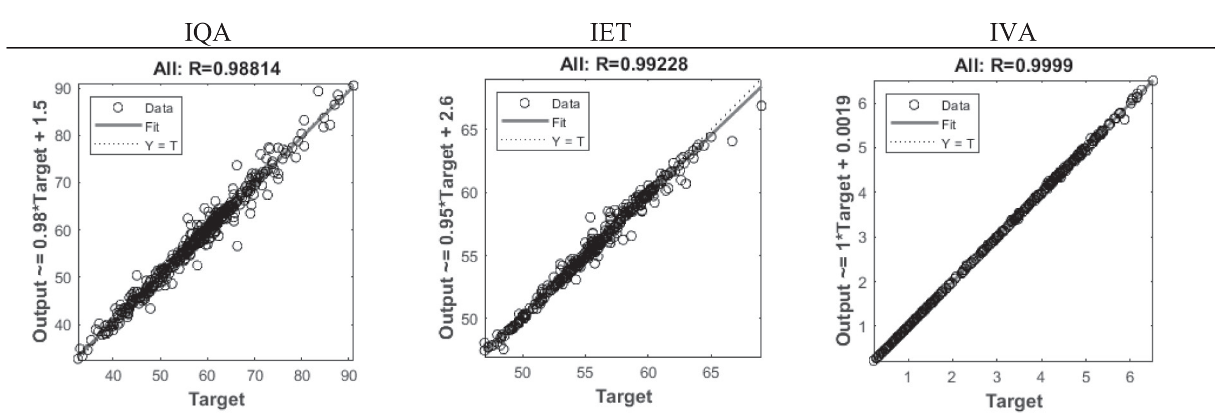

Fig. 3. ANN model validation results.

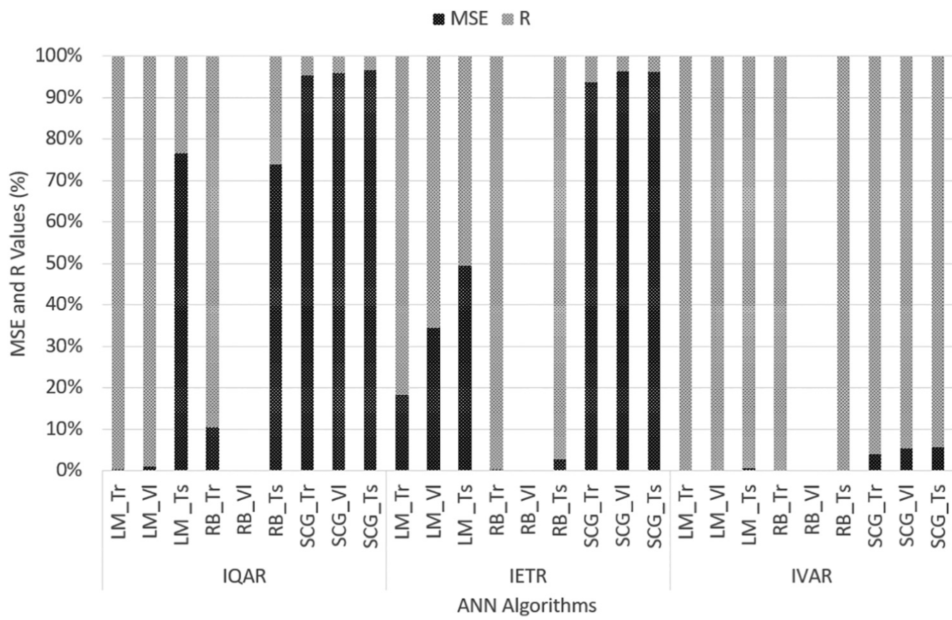

Fig. 4. Performance evaluation of the utilised algorithms.

application of a machine learning method (i.e. Artificial Neural Network), to develop a predictive model to evaluate resilience using readily available local data. This predictive model can support the key stakeholders and decision makers for targeted investments to improve resilience. The key advantage of the predictive model is that it can be integrated into complex process-based models to enhance resilience-informed land-water system planning. The predictive model can assist and facilitate in the development of the resilience thresholds.

This study has inspired by a 'volume-based resilience metrics' method for water quality resilience evaluation. It has also utilised a fuzzy-based algorithm to measure the criticality of water quality parameters with conflicting interactions. Additionally, the Fuzzy Analytical Hierarchy Process was used to develop a multi-criteria rating method to identify and rank the critical areas based on predicted resilience values.

The model was applied to and tested, using real data, for a case study in São Paulo state in Brazil. The results are satisfactory and demonstrate that the predictive model can make accurate predictions of resilience. In this model, Bayesian Regularization algorithm offered better performance as compared to the Levenberg-Marquardt and Scaled Conjugate Gradient in making water quality resilience predictions and Scaled Conjugate Gradient showed the poorest performance. Additionally, the results indicated the low resilience identified in 45% of the 22 zones mainly located on the east and south east of the São Paulo state. These zones are the most populated zones with rapid unsustainable developments and climate change-induced risks leading to the deterioration of water resources quality in the absence of sufficient and efficient wastewater collection and treatment infrastructures.

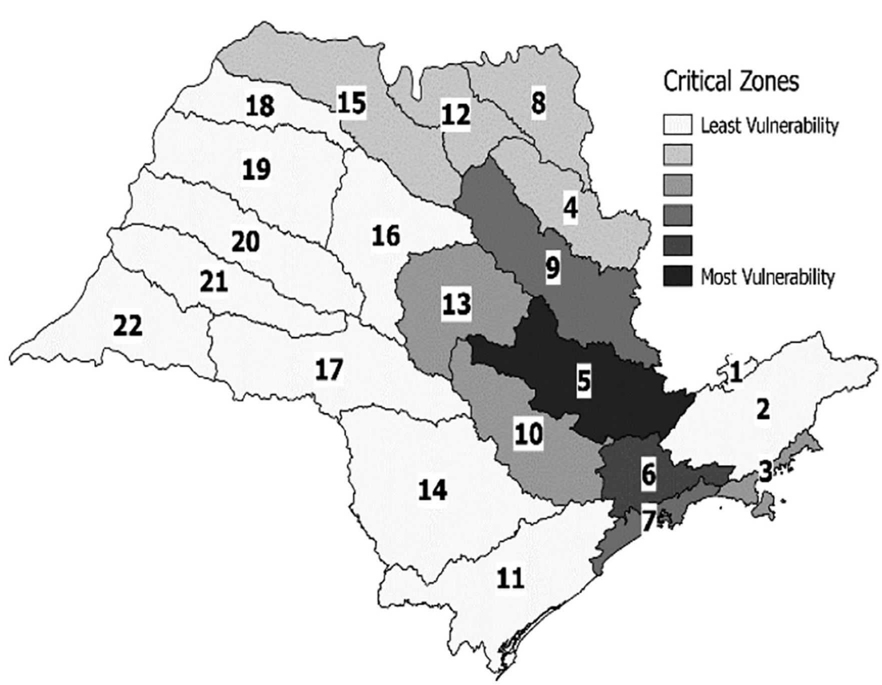

Fig. 5. Mapped critical zones.

The São Paulo state's environment agency (CETESB) publishes an annual report on the conditions of water resources quality across the whole region. There is a desire to incorporate 'resilience mapping' into this annual report for more effective resilience-informed planning. This can create an opportunity for adoption of the developed predictive model to assist decision makers' in CETESB in the future. Additionally, the integration of different machine learning techniques (e.g. deep reinforcement learning, recurrent neural network, convolutional neural network, etc.) with resilience-based methods could be further explored in order to create new techniques/methods for more effective adoption of 'resilience' in complex systems (e.g. integration of the resilience predictive model with physical models). Moreover, this study can potentially support reactive and planned maintenance for water supply. It also shows a direction for the researchers to implement the proposed model in various water reservoirs to measure water quality resilience, which may help to reduce the efforts of manual data collection. Therefore, the successful implementation of various machine learning algorithms in predicting water quality resilience is a new paradigm and can enrich the implementation of Artificial Intelligence and machine learning technologies to study the hydroinformatics and hydrodynamics arena. Furthermore, this model can be promoted and expanded by integration of real-time data monitoring systems for a more dynamic resilience prediction system.

CRediT authorship contribution statement

Maryam Imani: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Md Mahmudul Hasan:** Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Luiz Fernando Bittencourt:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Kent McClymont:** Software. **Zoran Kapelan:** Formal analysis, Writing – review & editing, Supervision.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.144459.

References

Ahmed, A.N., Othman, F.B., Afan, H.A., Ibrahim, R.K., Fai, C.M., Hossain, Md.S., Ehteram, M., Elshafie, A., 2019. Machine learning methods for better water quality prediction. J. Hydrol. 578, 124084. https://doi.org/10.1016/j.jhydrol.2019.124084.

Alvisi, S., Franchini, M., 2011. Fuzzy neural networks for water level and discharge forecasting with uncertainty. Environ. Model. Softw. 26, 523–537. https://doi.org/10.1016/j.envsoft.2010.10.016.

Antanasijević, D., Pocajt, V., Perić-Grujić, A., Mirjana, R., 2020. 2020. Multilevel split of high-dimensional water quality data using artificial neural networks for the prediction of dissolved oxygen in the Danube River. Neural Comput. & Applic. 32, 3957–3966. https://doi.org/10.1007/s00521-019-04079-y.

Asefa, T., Clayton, J., Adams, A., Anderson, D., 2014. Performance evaluation of a water resources system under varying climatic conditions: reliability, resilience, vulnerability and beyond. J. Hydrol. 508, 53–65. https://doi.org/10.1016/j.jhydrol.2013.10.043.

Butler, D., Ward, S., Sweetapple, C., Astaraie-Imani, M., Diao, K., Farmani, R., Fu, G., 2016. Reliable, resilient and sustainable water management: the safe & sure approach. J. Glob. Chall. 1, 63–77. https://doi.org/10.1002/gch2.1010.

CETESB, 2000–2017. Companhia Ambiental do Estado de São Paulo (São Paulo State Environmental Company). Relatórios de Qualidade das Águas Superficiais do Estado de São Paulo (Reports on Surface Water Quality from São Paulo State). Secretaria de Estado do Meio Ambiente (State Secretary for the Environment). https://cetesb.sp.gov.br/aguas-interiores/publicacoes-e-relatorios/.

CETESB, 2017. Qualidade das Águas Superficiais no Estado de São Paulo, Apêndice C - Índices de Qualidade das Águas. Accessed:. https://cetesb.sp.gov.br/aguas-interiores/wp-content/uploads/sites/12/2013/11/Apêndice-C-Índices-de-Qualidade-das-Águas-2.pdf.

Chau, K.W., 2006. A review on integration of artificial intelligence into water quality modelling. Mar. Pollut. Bull. 52, 726–733. https://doi.org/10.1016/j.marpolbul.2006.04.003.

Chen, W.B., Liu, W.C., 2015. Water quality modeling in reservoirs using multivariate linear regression and two neural network models. Adv. Artif. Neural Syst, 1–12 https://doi.org/10.1155/2015/521721.

Chen, X.Y., Chau, K.W., Busari, A.O., 2015. A comparative study of population-based optimization algorithms for downstream river flow forecasting by a hybrid neural network model. Eng. Appl. Artif. Intell. 46 (Part A), 258–268. https://doi.org/10.1016/j.engappai.2015.09.010.

Chounlamany, V., Tanchuling, M.A., Inoue, T., 2017. Spatial and temporal variation of water quality of a segment of Marikina River using multivariate statistical methods. Water Sci. Technol. 76 (6), 1510–1522. https://doi.org/10.2166/wst.2017.279.

Cumming, G.S., 2011. Spatial resilience: integrating landscape ecology, resilience, and sustainability. Landsc. Ecol. 26, 899–909. https://doi.org/10.1007/s10980-011-9623-1.

Dagdeviren, M., Yüksel, I., 2008. Developing a fuzzy analytic hierarchy process (AHP) model for behavior-based safety management. Inf. Sci. 178, 1717–1733. https://doi.org/10.1016/j.ins.2007.10.016.

Elshemy, M., Meon, G., 2017. Water quality assessment of Aswan high dam reservoir. In: Negm, A.M. (Ed.), The Nile River. Springer International Publishing, Cham, pp. 105–143.

Fowler, H.J., Kilsby, C.G., O'Connell, P.E., 2003. Modeling the impacts of climatic change and variability on the reliability, resilience, and vulnerability of a water resource system. Water Resour. Res. 39 (8), 1222. https://doi.org/10.1029/2002WR001778.

Gazzaz, N.M., Yousoff, M.K., Ramli, M.F., Juahir, H., Aris, A.Z., 2015. Artificial neural network modeling of the water quality index using land use areas as predictors. Water Environ. Res. 87 (2), 99–112. https://doi.org/10.2175/106143014X14062131179276.

Ha, H., Stenstrom, M.K., 2003. Identification of land use with water quality data in storm water using a neural network. Water Res. 37, 4222–4230. https://doi.org/10.1016/S0043-1354(03)00344-0.

Hart, B.T., Lake, P.S., Webb, J.A., Grace, M.R., 2003. Ecological risks to aquatic systems from salinity increases. Aust. J. Bot. 51 (6), 689–702. https://doi.org/10.1071/BT02111.

Hasan, M., 2020. An Intelligent Decision-Making Scheme in a Dynamic Multi-Objective Environment Using Deep Reinforcement Learning.

Hasan, M.M., Lwin, K., Imani, M., Shabut, A., Bittencourt, L.F., Hossain, A., 2019. Dynamic multi-objective optimisation using deep reinforcement learning: benchmark, algorithm and an application to identify vulnerable zones based on water quality. Eng. Appl. Artif. Intell. 86, 107–135. https://doi.org/10.1016/j.engappai.2019.08.014.

Hashimoto, T., Loucks, D.P., Stedinger, J., 1982. Reliability, resilience and vulnerability for water resources system performance evaluation. Water Resour. Res. 18 (1), 14–20.

Hoque, Y.M., Tripathi, S., Hantush, M.M., Govindaraju, R.S., 2012. Watershed reliability, resilience and vulnerability analysis under uncertainty using water quality data. J. Environ. Manag. 109, 101–112. https://doi.org/10.1016/j.jenvman.2012.05.010.

Hoque, Y.M., Raj, C., Hantush, M.M., Chaubey, I., Govindaraju, R.S., 2013. How do land-use and climate change affect watershed health? A scenario-based analysis. Water Qual Expo Health 6, 19–33. https://doi.org/10.1007/s12403-013-0102-6.

Hoque, Y.M., Tripathi, S., Hantush, M.M., Govindaraju, R.S., 2016. Aggregate measures of watershed health from reconstructed water quality data with uncertainty. J. Environ. Qual. 45, 709–719. https://doi.org/10.2134/jeq2015.10.0508.

IBGE, 2014. Estimativas da população residente no Brasil e Unidades da Federação com data de referência em 1° de julho de 2014. [Accessed: file://anglia.local/fs/StaffHome/ma72/My%20Documents/My%20Downloads/nota_metodologica_2014.pdf].

Ji, N., Wang, S., Zhang, L., 2017. Characteristics of dissolved organic phosphorus inputs to freshwater lakes: a case study of Lake Erhai, Southwest China. Sci. Total Environ. 601-602, 1544–1555. https://doi.org/10.1016/j.scitotenv.2017.05.265.

Jung, D., 2013. Robust and resilient water distribution systems. PhD Thesis. University of Arizona, USA.

Kahraman, C., Cebeci, U., Ruan, D., 2004. Multi-attribute comparison of catering service companies using fuzzy AHP: the case of TURKEY. Int. J. Prod. Econ. 87, 171–184. https://doi.org/10.1016/S0925-5273(03)00099-9.

Kalin, L., Isik, S., Schoonover, J.E., Lockaby, B.J., 2010. Predicting WQ in unmonitored watersheds using artificial neural networks. J. Environ. Qual. 39, 1429–1440. https://doi.org/10.2134/jeq2009.0441.

Khalil, B., Ouarda, T.B.M.J., St-Hilaire, A., 2011. Estimation of WQ characteristics at ungauged sites using ANN and canonical correlation analysis, J. Hydrology 405 (3–4), 277–287. https://doi.org/10.1029/2006WR005142.

Khan, Y., See, C.S., 2016. Predicting and analyzing water quality using machine learning: a comprehensive model, IEEE Long Island systems, applications and technology conference (LISAT), 1-6. DOI https://doi.org/10.1109/LISAT.2016.7494106.

Kim, K., Park, K.S., 1990. Ranking fuzzy numbers with index of optimism. Fuzzy Sets Syst. 35 (2), 143–150. https://doi.org/10.1016/0165-0114(90)90189-D.
Klir, G.J., Yuan, B., 1995. Fuzzy Sets and Fuzzy Logic : Theory and Applications (Prentice Hall PTR).
Kuo, J.T., Wang, Y.Y., Lung, W.S., 2006. A hybrid neural–genetic algorithm for reservoir water quality management. Water Res. 40, 1367–1376. https://doi.org/10.1016/j.watres.2006.01.046.
Li, Y., Shi, Y., Qureshi, S., Bruns, A., Zhu, X., 2014. Applying the concept of spatial resilience to socio-ecological systems in the urban wetland interface. Ecol. Indic. 42, 135–146. https://doi.org/10.1016/j.ecolind.2013.09.032.
Li, Y., Degener, J., Gaudreau, M., Li, Y., Kappas, M., 2016. Adaptive capacity-based water quality resilience transformation and policy implications in rapidly urbanizing landscapes. Sci. Total Environ. 569–570, 168–178. https://doi.org/10.1016/j.scitotenv.2016.06.110.
Lolli, F., Ishizaka, A., Gamberini, R., 2014. New AHP-based approaches for multi-criteria inventory classification. Int. J. Prod. Econ. 156, 62–74. https://doi.org/10.1016/j.ijpe.2014.05.015.
Mahmoudi, N., Orouji, H., Fallah-Mehdipour, E., 2016. Integration of shuffled frog leaping algorithm and support vector regression for prediction of water quality parameters, water Resour. Manag. 30, 2195–2211. https://doi.org/10.1007/s11269-016-1280-3.
Maier, H.R., Lence, B.J., Tolson, B.A., Foschi, R.O., 2001. First-order reliability method for estimating reliability, vulnerability and resilience. Water Resour. Res. 37 (3), 779–790. https://doi.org/10.1029/2000WR900329.
Malekmohammadi, B., Kerachian, R., Zahraie, B., 2009. Developing monthly operating rules for a cascade system of reservoirs: application of Bayesian networks. Environ. Model. Softw. 24, 1420–1432. https://doi.org/10.1016/j.envsoft.2009.06.008.
Mallya, C., Hantush, M., Govindaraju, R.S., 2018. Composite measures of watershed health from a water quality perspective. J. Environ. Manag. 214, 104–124. https://doi.org/10.1016/j.jenvman.2018.02.049.
Matrosov, E.S., Padula, S., Harou, J.J., 2012. Selecting portfolios of water supply and demand management strategies under uncertainty —contrasting economic optimisation and "robust decision making" approaches. Water Resour. Manag. 27 (4), 1123–1148. https://doi.org/10.1007/s11269-012-0118-x.
McClymont, K., Cunha, G.F., d Maidment, C., Ashagre, B., Vasconcelos, A.F., de Macedo, Batalini, Fernanda Nóbrega Dos Santos, M., Nóbrega Gomes Júnior, M., Mendiondo, E.M., Barbassa, A.P., Rajendran, L., Imani, M., 2020. Towards urban resilience through sustainable drainage systems: a multi-objective optimisation problem. J. Environ. Manag. 275, 111173. https://doi.org/10.1016/j.jenvman.2020.111173.
Mitrović, T., Antanasijević, D., Lazović, S., Perić-Grujić, A., Ristić, M., 2019. Virtual water quality monitoring at inactive monitoring sites using Monte Carlo optimized artificial neural networks: a case study of Danube River (Serbia). Sci. Total Environ. 654, 1000–1009. https://doi.org/10.1016/j.scitotenv.2018.11.189.
Moktadir, M.A., Rahman, T., Sultana, R., 2017. Selection of best supplier by using AHP tool for managing risk factors in logistics: a case of leather products industry. Ind. Eng. Manag. 6 (232), 2169–2316. https://doi.org/10.4172/2169-0316.1000232.
Mondal, M.S., Wasimi, S.A., 2007. Evaluation of risk-related performance in water management for the Ganges delta of Bangladesh. J. Water Resour. Plann. Manag. 133, 179–187. https://doi.org/10.1061/(ASCE)0733-9496(2007)133:2(179).
Najah, A., El-shafie, A., Karim, O.A., El-shafie, A.H., 2013. Application of artificial neural networks for water quality prediction. Neural Comput. & Applic. 22 (Suppl. 1), S187–S201. https://doi.org/10.1007/s00521-012-0940-3.
Noori, N., Kalin, L., Isikb, S., 2020. Water quality prediction using SWAT-ANN coupled approach. J. Hydrol. 590, 125220. https://doi.org/10.1016/j.jhydrol.2020.125220.
Pahl-Wostl, C., Jeffrey, P., Isendahl, N., Brugnach, M., 2011. Maturing the new water management paradigm: progressing from aspiration to practice. Water Resour. Manag. 25 (3), 837–856.
Palani, S., Liong, S., Tkalich, P., 2008. An ANN application for WQ forecasting. Mar. Pollut. Bull. 56 (9), 1586–1597. https://doi.org/10.1016/j.marpolbul.2008.05.021.
Park, J., Seager, T.P., Rao, P.S., Convertino, M., Linkov, L., 2012. Integrating risk and resilience approaches to catastrophe Management in Engineering Systems. Risk Anal. 33 (3), 356–367. https://doi.org/10.1111/j.1539-6924.2012.01885.x.
Paton, F.L., Dandy, G.C., Maier, H.R., 2014. Integrated framework for assessing urban water supply security of systems with non-traditional sources under climate change. Environ. Model. Softw. 60, 302–319. https://doi.org/10.1016/j.envsoft.2014.06.018.
Rajaee, T., Khani, S., Ravansalar, M., 2020. Artificial intelligence-based single and hybrid models for prediction of water quality in rivers: a review. Chemom. Intell. Lab. Syst. 200, 103978. https://doi.org/10.1016/j.chemolab.2020.103978.
Roach, T., Kapelan, Z., Ledbetter, R., 2018. Resilience-based performance metrics for water resources management under uncertainty. Adv. Water Resour. 116, 18–28. https://doi.org/10.1016/j.advwatres.2018.03.016.
Rowny, J.G., Stewart, J.R., 2012. Characterization of non- point source microbial contamination in an urbanizing watershed serving as a municipal water supply. Water Res. 46, 6143–6153. https://doi.org/10.1016/j.watres.2012.09.009.
Saaty, T.L., 1977. A scaling method for priorities in hierarchical structures. J. Math. Psychol. 15, 234–281. https://doi.org/10.1016/0022-2496(77)90033-5.
Saaty, T. L., 1982. Decision making for leaders: the analytical hierarchy process for decisions in a complex world. Belmont, California: Wadsworth. ISBN 0-534-97959-9; paperback, Pittsburgh: RWS. ISBN 0-9620317-0-4.
Sarang, A., Vahedi, A., Shamsai, A., 2008. How to quantify sustainable development: a risk-based approach to water quality management. Environ. Manag. 41 (2), 200–220. https://doi.org/10.1007/s00267-007-9047-5.
Sarkar, A., Pandey, P., 2015. River WQ Modelling using artificial neural network technique, international conference on water resources, coastal and ocean engineering (ICWRCOE 2015). Aquatic Procedia 4, 1070–1077.
Seo, I.W., Yuna, S.H., Choia, S.Y., 2016. Forecasting WQ parameters by ANN model using preprocessing technique at the downstream of Cheongpyeong dam, 12th international conference on Hydroinformatics, HIC 2016. Procedia Engineering 154, 1110–1115.
Singh, K.P., Basant, A., Malik, A., Jain, G., 2009. ANN modelling of the river WQ – a case study. Ecol. Model. 220 (6), 888–895. https://doi.org/10.1016/j.ecolmodel.2009.01.004.
Slaughter, A., Hughes, D., Retief, D., Mantel, S., 2017. A management-oriented water quality model for data scarce catchments. Environ. Model. Softw. 97, 93–111. https://doi.org/10.1016/j.envsoft.2017.07.015.
Instituto, Socioambiental, 2009. De Olho Nos Mananciais (Keep an Eye on Water Sources) - A Campaign for Conserving Sao Paulo's Water Sources: Water Sources in Sao Paulo.
Sweetapple, C., Astaraie-Imani, M., Butler, D., 2018. Design and operation of urban wastewater systems considering reliability, risk and resilience. Water Res. 147, 1–12. https://doi.org/10.1016/j.watres.2018.09.032.
Tomas, D., Čurlin, M., Marić, A.S., 2017. Assessing the surface water status in Pannonian ecoregion by the water quality index model. Ecol. Indic. 79, 182–190. https://doi.org/10.1016/j.ecolind.2017.04.033.
Tooth, S., 2018. The geomorphology of wetlands in drylands: resilience, non-resilience, or …? Geomorphology 305, 33–48. https://doi.org/10.1016/j.geomorph.2017.10.017.
van den Hoek, R., Fabiana Brugnach, M., Hoekstra, A.Y., 2011. Toward Resilience Based Water Management: Understanding Uncertainty and Policy Evaluation, Resilience 2011 Conference. Tempe, Arizona, USA.
Wang, J.Y., Da, L.J., Song, K., Li, B.L., 2008. Temporal variations of surface water quality in urban, suburban and rural areas during rapid urbanization in Shanghai, China. Environ. Pollut. 152, 387–393. https://doi.org/10.1016/j.envpol.2007.06.050.
Wang, Q., Wang, H., Qi, Z., 2016. An application of nonlinear fuzzy analytic hierarchy process in safety evaluation of coal mine. Saf. Sci. 86, 78–87. https://doi.org/10.1016/J.SSCI.2016.02.012.
Wu, Z., Wang, X., Chen, Y., Cai, Y., Deng, J., 2018. Assessing river water quality using water quality index in Lake Taihu Basin, China. Sci. Total Environ. 612, 914–922. https://doi.org/10.1016/j.scitotenv.2017.08.293.
Xiang, S.L., Liu, Z.M., Ma, L.P., 2006. Study of multivariate linear regression analysis model for ground WQ prediction. Guizhou Sci 24 (1), 60–62.
Zadeh, L.A., 1975. Fuzzy logic and approximate reasoning. Synthese 30, 407–428. https://doi.org/10.1007/BF00485052.
Zeng, S., Zeng, L., Dong, X., Chen, J., 2013. Polycyclic aromatic hydrocarbons in river sediments from the western and southern catchments of the Bohai Sea, China: toxicity assessment and source identification. Environ. Monit. Assess. 185, 4291–4303. https://doi.org/10.1007/s10661-012-2869-5.
Zhang, N., Lai, S., 2011. Water quantity prediction based on particle swarm optimization and evolutionary algorithm using recurrent neural networks. The 2011 International Joint Conference on Neural Networks, pp. 2172–2176 https://doi.org/10.1109/ijcnn.2011.6033497.
Zhang, X., Ma, W., Chen, L., 2014. New similarity of triangular fuzzy number and its application. Sci. World J., 215047 https://doi.org/10.1155/2014/215047.
Zhang, Q., Zheng, F., Kapelan, Z., Savic, D., He, G., Ma, Y., 2020. Assessing the global resilience of water quality sensor placement strategies within water distribution systems. J. Water Res. 172, 115527. https://doi.org/10.1016/j.watres.2020.115527.
Zhu, S., Heddam, S., 2020. Prediction of dissolved oxygen in urban rivers at the three gorges reservoir, China: extreme learning machines (ELM) versus artificial neural network (ANN). Water Qual. Res. J. 55 (1), 106–118. https://doi.org/10.2166/wqrj.2019.053.
Zimmerman, J.B., Mihelcic, J.R., Smith, J., 2008. Global stressors on water quality and quantity. Environ. Sci. Technol. 42 (12), 4247–4254.