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A review of water quality index models and their use for assessing surface water quality

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ABSTRACT

The water quality index (WQI) model is a popular tool for evaluating surface water quality. It uses aggregation techniques that allow conversion of extensive water quality data into a single value or index. Globally, the WQI model has been applied to evaluate water quality (surface water and groundwater) based on local water quality criteria. Since its development in the 1960s, it has become a popular tool due to its generalised structure and ease-of-use. Commonly, WQI models involve four consecutive stages; these are (1) selection of the water quality parameters, (2) generation of sub-indices for each parameter (3) calculation of the parameter weighting values, and (4) aggregation of sub-indices to compute the overall water quality index. Several researchers have utilized a range of applications of WQI models to evaluate the water quality of rivers, lakes, reservoirs, and estuaries. Some problems of the WQI model are that they are usually developed based on site-specific guidelines for a particular region, and are therefore not generic. Moreover, they produce uncertainty in the conversion of large amounts of water quality data into a single index.

This paper presents a comparative discussion of the most commonly used WQI models, including the different model structures, components, and applications. Particular focus is placed on parameterization of the models, the techniques used to determine the sub-indices, parameter weighting values, index aggregation functions and the sources of uncertainty. Issues affecting model accuracy are also discussed.

1. Introduction

Water is a crucial component of the environment; but surface water and groundwater quality have long been deteriorating due to both natural and human-related activities. Natural factors that influence water quality are hydrological, atmospheric, climatic, topographical and lithological factors (Magesh et al., 2013; Uddinet al., 2018). Examples of anthropogenic activities that adversely affect water quality are mining, livestock farming, production and disposal of waste (industrial, municipal and agricultural), increased sediment run-off or soil erosion due to land-use change (Lobato et al., 2015) and heavy metal pollution (Sánchez et al., 2007).

In recent times, developing countries have faced significant problems in protecting water quality when trying to improve water supply and sanitation (Carvalho et al., 2011; Debels et al., 2005; Kannel et al., 2007; Ortega et al., 2016). Even developed nations have been fighting to maintain or improve the status of their water quality in the face of problems such as nutrient enrichment and eutrophication of water resources (Abbasi and Abbasi, 2012; Debels et al., 2005) and the provision of water and wastewater services to increasing populations.

Management of water quality requires the collection and analysis of large water quality datasets that can be difficult to evaluate and synthesise. A range of tools have been developed to evaluate water quality data; the Water Quality Index (WQI) model is one such tool. WQI models are based on an aggregation functions which allow analysis of large temporally and spatially-varying water quality datasets to produce a single value, i.e. the water quality index, that indicates the quality of the waterbody. They are attractive to water management/supply agencies as they are relatively easy to use and convert complex water quality datasets into a single value measure of water quality that is easy to understand.

A WQI typically comprises four processes or components. First, the water quality parameters of interest are selected. Second, the water quality data are read and for each water quality parameter the

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concentrations are converted to a single-value dimensionless sub-index. Third, the weighting factor for each water quality parameter is determined and fourth, a final single value water quality index is calculated by an aggregation function using the sub-indices and weighting factors for all water quality parameters. Many different WQI models have been developed with variations in model structure, the parameters included and their associated weightings, and the methods used for sub-indexing and aggregation (Debels et al., 2005; Jha et al., 2015; Kannel et al., 2007; Sun et al., 2016). Most of the WQI model components have been developed based on expert views and local guidelines (Hsu and Sandford, 2007; Sutadian et al., 2016) and many models are therefore region-specific. Many researchers refer to the uncertainty problems of WQI models (Kannelet al., 2007). While uncertainty is an unavoidable in any mathematical model (Lowe et al., 2017), all four stages of the WQI can contribute to the model uncertainty.

The primary aim of this paper was to critically review the most commonly used WQI models and determine which were the most accurate. This involved a review of 110 published manuscripts from which we identified 21 WQI models used globally (see Fig. 1), which were then individually and comparatively assessed. The review identified seven basic WQI models from which most other WQI models have been developed; these were subjected to a more thorough critical analysis. Section 2 of the paper presents a brief history of WQI model development. Section 3 presents an overview of the basic structure of WQI models and describes in detail the four major structural elements of most models, namely, (1) parameterisation, (2) parameter sub-indexing, (3) parameter weighting and (4) index aggregation. Section 4 describes the seven primary WQI models in detail while Section 5 presents and discusses the major findings of the review. Finally, Section 7 presents the main conclusions from the research.

2. A brief history of WQI models

The development history of the WQI model is presented graphically in Fig. 2. Although WQI models have only been developed over the last 50 years, water quality indices were being used for classification of water quality as far back as the mid-1800 s (Abbasi and Abassi, 2012). Horton developed the first WQI model in the 1960 s which he based on 10 water quality parameters deemed significant in most waterbodies (Horton, 1965). Brown with support from the National Sanitation Foundation, developed a more rigorous version of Horton's WQI model, the NSF-WQI, for which a panel of 142 water quality experts informed the parameter selection and weighting (Abbasi and Abbasi, 2012). Several other WQI models have since been based on the NSF-WQI. In 1973, the Scottish Research Development Department (SRDD) developed their SRDD-WQI which was also somewhat based on Brown's model and used it for assessment of river water quality (reference). The Bascaron Index (1979), House Index (1986) and Dalmatian Index (Štambuk-Giljanović, 2003) are all later derivatives of the SRDD-WQI. Steinhart et al. (1982) later developed the Environmental Quality Index model for the assessment of water quality in the Great Lakes ecosystems.

Another important development was the British Columbia WQI (BCWQI) which was developed by the British Columbia Ministry for Environment, Lands and Parks in the mid-90′s and was used to evaluate the quality status of many waterbodies in the province of Britich Columbia, Canada (Saffran et al., 2001). Said et al. (2004) note that the BCWQI was found to have the highest sensitivity to sampling design and the highest dependency on the specific application of water quality objectives. The Water Quality Guidelines Task Group of the Canadian Council of Ministers of the Environment developed the CCME WQI in 2001 (Saffran et al., 2001) following a review and revision of the BCWQI model (Lumb et al., 2011). The BCWQI model has been recognized since in 1990 by the CCME (Dunn, 1995). In recent times models such as the

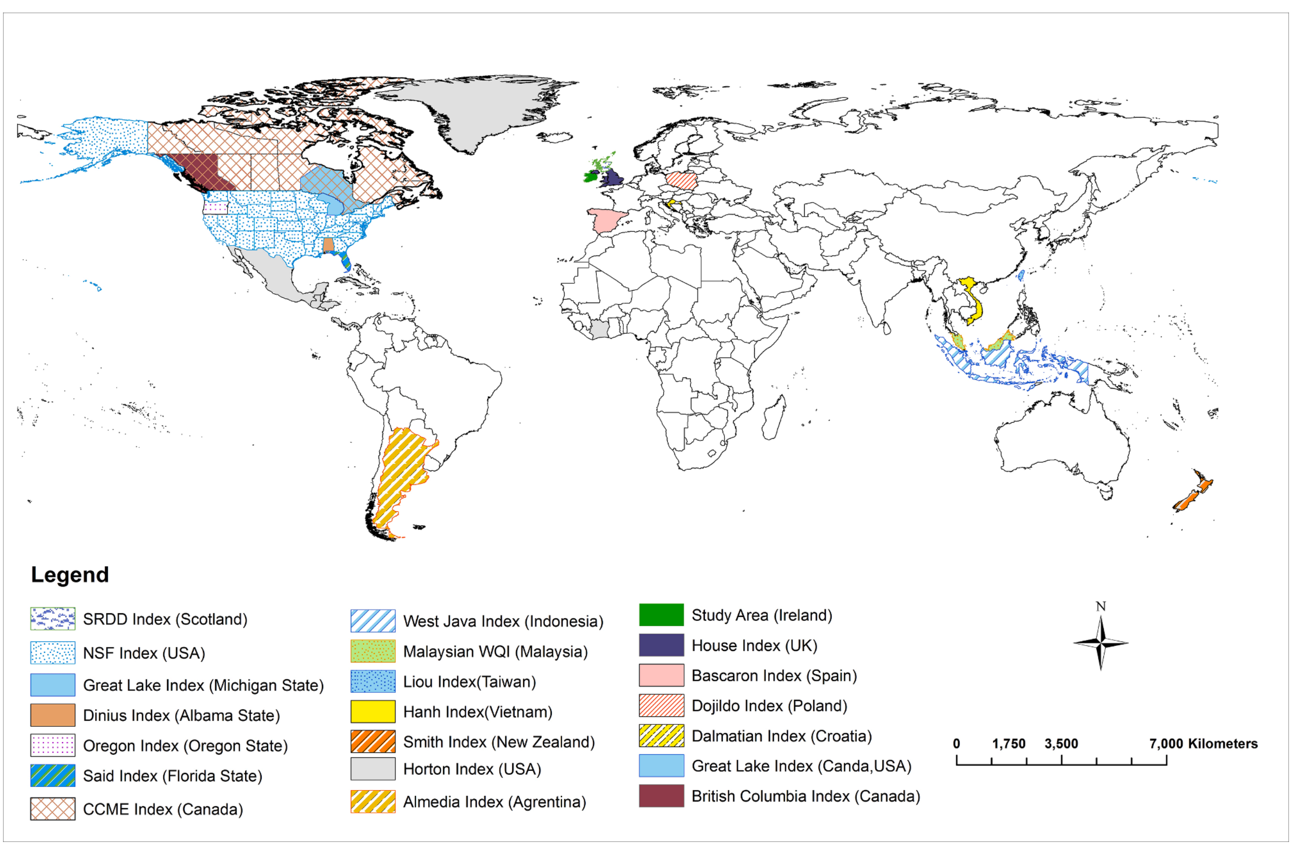

Fig. 1. Most commonly used WQI models and regions of use (1960–2020).

Liou Index, the Malaysian Index and the Almeida Index have also been developed.

To date, more than 35 WQI models have been introduced by various countries and/or agencies to evaluate surface water quality around the world (Abbasi and Abbasi, 2012; Dadolahi-Sohrab et al., 2012; Kannel et al., 2007; Stoner, 1978). As shown in Fig. 3, WQI models have been used in most parts of the world. Table 1 shows that, although WQI models have been applied to all major types of waterbodies, 82% of applications have been to assess river water quality. Additionally, the table shows that the CCME and NSF models have been used 50% of the reviewed studies.

3. WQI model structure

The general structure of WQI models is illustrated in Fig. 4 and shows that most WQIs contain four main steps (Abbasi and Abbasi, 2012; Abrahão et al., 2007; Lumb et al., 2011; Sutadian et al., 2018), namely:

1) selection of the water quality parameters: one or more water quality parameters are selected for inclusion in the assessment
2) generation of the parameter sub-indices: parameter concentrations are converted to unit less sub-indices
3) assignment of the parameter weight values: parameters are assigned weightings depending on their significance to the assessment
4) computation of the water quality index using an aggregation function: the individual parameter sub-indices are combined using the weightings to give a single overall index. A rating scale is usually used to categorise/classify the water quality based on the overall index value.

The details of the components of the primary models are discussed in the following sections and a summary is presented in Table 2.

3.1. Parameter selection

Parameter selection is the initial step of the WQI process and considerable variation was determined between models in the type and number of parameters selected and the reasons for selecting them. Table 2 gives a detailed overview of the parameters included in model studies on a model-by-model basis. The most commonly included parameters (see Fig. 5) were temperature, turbidity, pH, suspended solids (SS), total dissolved solids (TDS), faecal coliforms (FC), dissolved oxygen (DO), biochemical oxygen demand (BOD) and nitrate nitrogen (NH_3-N). Most of the models employed eight to eleven water quality parameters (Table 3 and Fig. 5). A few models used just four which were selected by the user, such as the CCME index , the Roos index and the Said index models (Ferreira et al., 2011; Lumb et al., 2006; Said et al., 2004; Khanet al., 2004; Lumbet al., 2011), while the Bascaron model recommended twenty-six (26) parameters (Fig. 5).

WQI model parameters were typically selected based on data availability, expert opinion or the environmental significance of a water quality parameter. Debels et al. (2005) reported that many WQI models employed only the basic water quality parameters due to lack of availability of other parameter measured data (Cude, 2001; Banerjee and Srivastava, 2009). Many researchers modified the model parameter lists based on data accessibility and obtainability and sometimes it is not possible to add the crucial water quality parameter into the model for this reason (Ma et al., 2020; Naubi et al., 2016). A number of WQI models did not include suspended solids, microbiological contamination and toxic compounds due to the high analytical cost and lack of modern analytical laboratory facilities. In several studies, the water quality parameters were selected based on the application type, e.g. drinking

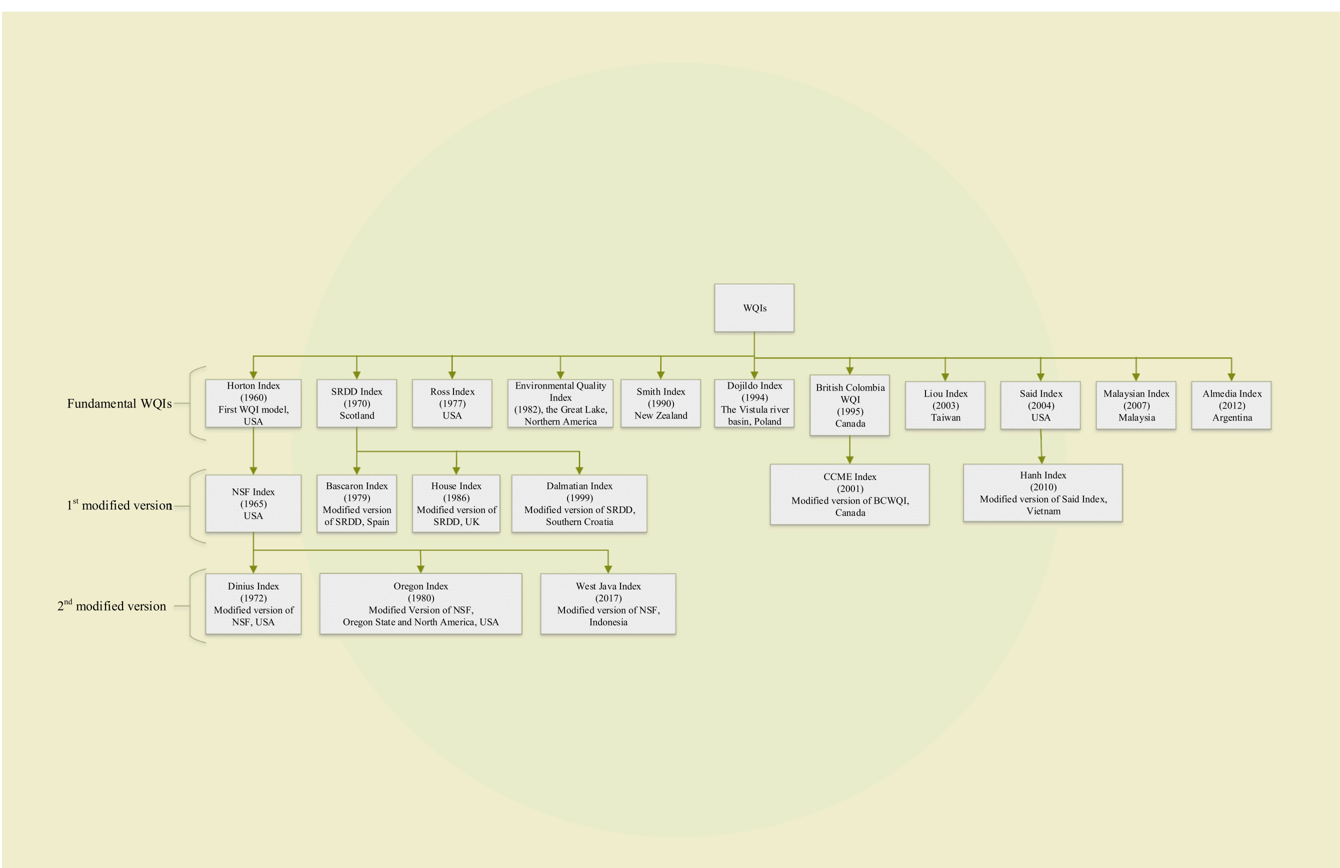

Fig. 2. Historical development of the WQI model.

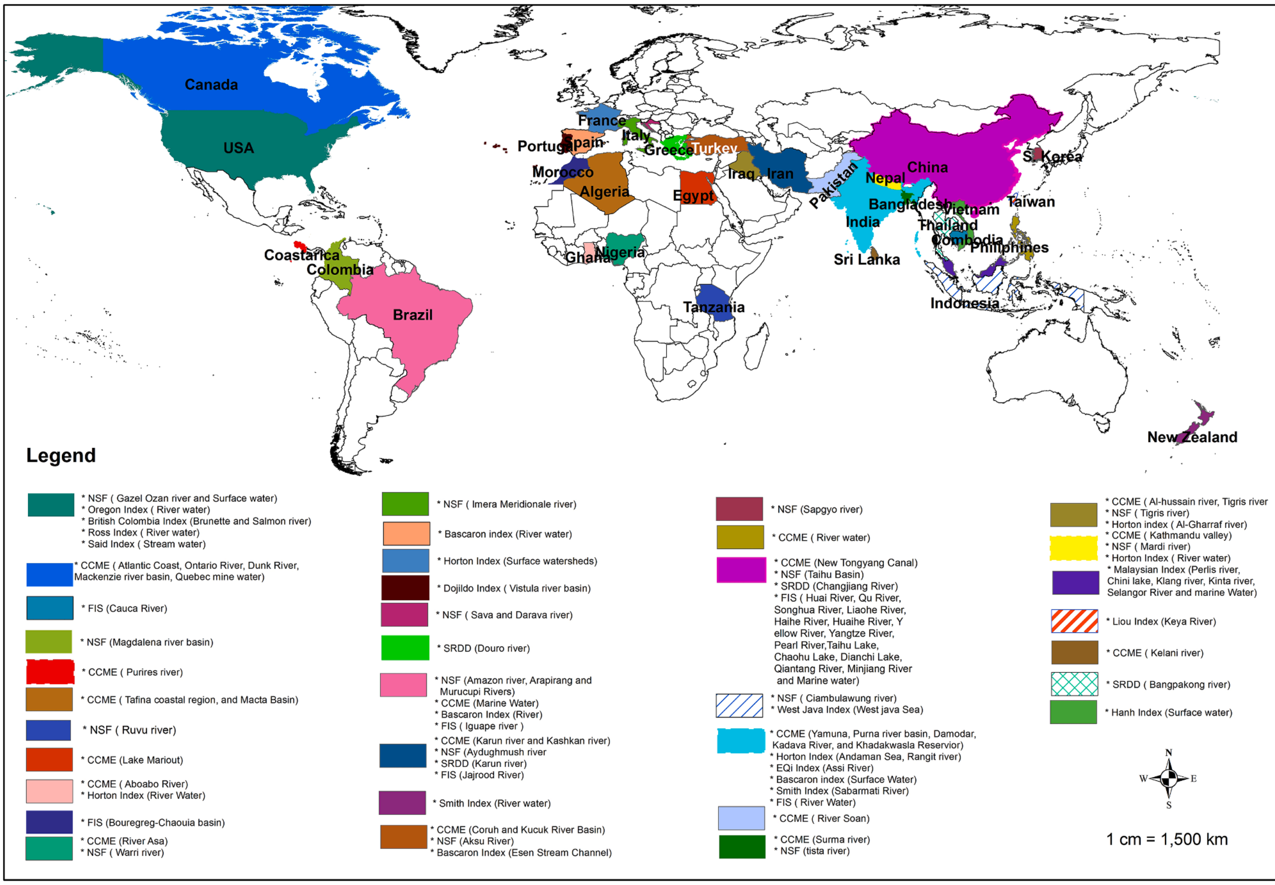

Fig. 3. Countries and types of waterbodies in which WQIs have been applied globally.

water quality assessment or urban environmental impact (Kannelet al., 2007).

The Delphi technique was used for selecting water quality parameters in a number of WQI model applications (Abbasi and Abbasi, 2012; Dunnette, 1979). Here, the important parameters are selected based on gathering expert opinions through interviews or surveys (House, 1989). In general, there are no specific rules or guidelines for selecting the water quality parameter for inclusion in the WQI model. The traditional WQI model does not follow any systematic technique for setting their parameters. It seems that the WQI model parameters were generally chosen based on a few common water quality issues such as oxygen availability, eutrophication, health considerations, physical and chemical phenomena, and dissolved constituents. Even for several new WQI models it was found that they applied only general criteria and they did not employ any hazardous parameters of water quality (Bayati et al., 2017; Bilgin, 2018; Mahmood, 2018; Noori et al., 2019; Verma et al., 2019; Ewaid, 2016). Generally, WQI models did not consider any toxic or radioactive constituents to evaluate water quality. A few models such as the Oregon index, the Dojildo index, the Liou index, the Almeida index and the West-Java WQI recommended to include toxins (detergent, phenols), pesticides and trace variables (Pb, Cu, Zn, Cd, Hg. Mn, Fe, etc.) for evaluating water quality in a water body.

Table 1
Summary of WQI model applications (in total and by study area) found in literature published from 1960 to 2019.

WQImodel	Number of Applications	Type of Study Area		
		River	Lake	Marine/coastal/sea
CCME	36	28	5	3
NSF	18	17	1	–
FIS	12	10	1	1
MWQI	8	6	1	1
Horton	7	6	–	1
SRDD	6	6	–	–
Bascaron	4	3	–	1
EQI	2	1	1	–
Oregon	2	2	–	–
Smith	2	2	–	–
Almedia	1	1	–	–
BCWQI	1	1	–	–
Dalmatian	1	–	–	1
Dojildo	1	1	–	–
Dinius	1	1	–	–
Hanh index	1	1	–	–
House index	1	1	–	–
Liou index	1	1	–	–
Said	1	–	–	1
WJWQI	1	–	–	1

3.2. *Sub-indexing*

The primary goal of the sub-index process is to convert parameter concentrations into unitless values known as the parameter sub-indices (Abbasi and Abbasi, 2012). Several WQI models used standard guideline values of water quality to establish the sub-indices (Liou et al., 2004; Abbasi and Abbasi, 2012; Sutadian et al., 2016). While most of the reviewed models included this step, the CCME model (Nearyet al., 2001) and the Dojildo model omitted the step and performed the final aggregation function using the parameter concentrations directly rather than sub-indices (Dojlido et al., 1994). The following sub-index rules were used by models (see Table 2).

i Parameter concentrations

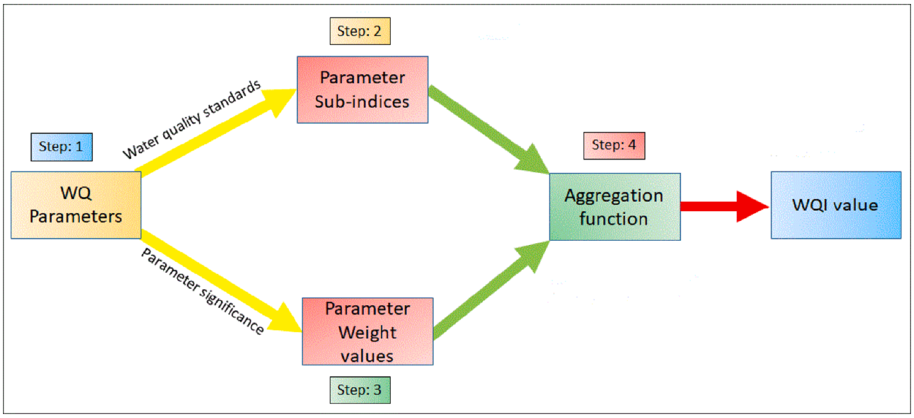

Fig. 4. General structure of WQI model.

The simplest sub-index process, used by the Horton index, the Dinius index, the Dalmatian Index, the Liou index and the Said index, used the measured parameter concentrations directly as the sub-index values without any conversion process.

ii Linear interpolated functions

The NSF model used recommended parameter ranges from water quality standards to compute the sub-index values linearly (Effendi and RomantoWardiatno, 2015; Lobato et al., 2015; Tomas et al., 2017). The sub-index scale ranged between 0 and 100; when parameter concentrations were found below the recommended values, then the sub-index value was assigned 100, otherwise, 0 registered automatically (Hoseinzadeh et al., 2015; Lobato et al., 2015; Misaghi et al., 2017; Medeiroset al., 2017). The West Java WQI model used simple linear interpolation function. In this instance, the sub-index value was calculated using equations (1) and equation (2).

$$S_i = S_1 - \left[(S_1 - S_2)\left(\frac{X_i - X_1}{X_2 - X_1}\right)\right] \tag{1}$$

$$S_i = S_1 - \left[(S_1 - S_2)\left(\frac{X_1 - X_i}{X_1 - X_2}\right)\right] \tag{2}$$

where S_i is the sub-index value for water quality parameter i computed for the measured value X_i. S_1 and S_2 are the maximum and minimum sub-index values for the maximum and minimum guideline values (X_1 and X_2) for parameter i. Eq. (1) is used when the measured parameter value is higher than the upper guideline value otherwise Eq. (2) is used (Dunnette, 1979; Sutadian et al., 2016).

Liou et al. (2004) recommended equation (3) for obtaining the sub-index value for parameter i:

$$S_i = \frac{P_c}{M_{pl}} \tag{3}$$

where P_c is the measured value and M_{pl} is the maximum permissible guideline limit (mg/L) of the water quality parameter.

iii Rating curve functions

The environmental quality index (EQI) or Great Lakes Nearshore index (GLNI) (Schierow and Chesters, 1988), Malaysia river WQI (MRWQI) (Fulazzaky et al., 2010; Gazzaz et al., 2012; Hasan et al., 2015; Naubi et al., 2016; Othman and Alaa Eldin, 2012; Shuhaimi-Othman et al., 2007; Sim et al., 2015; Amneera et al., 2013) used rating curve functions for transforming measured values of water quality parameters to dimensionless values (Sutadian et al., 2017). The Oregon WQI model applied logarithmic transformations and a nonlinear regression technique to obtain its sub-index values (Dunnette, 1979; Cude, 2001).

Several WQI models, such as the Almeida index (2012), the House index (1989), and the Hanh surface WQI model, applied a rating curve technique to obtain the sub-index value. The rating curve system was developed based on water quality parameter standard guidelines that were formulated by legislative bodies or concerned authorities (HOUSE, 1989; Pham et al., 2011; Sutadian et al., 2016, 2017). The rating curve relates the measured parameter value to a sub-index scale, which must be first specified (HOUSE, 1989). An example is shown in Fig. 6, where the DO values are related to a sub-index scale ranging from 0 to 100 (Smith, 1990).

In instances where it has been applied, the rating curve is usually developed by a panel of experts (Smith, 1990; Sutadian et al., 2016) and taking into account the water body type (e.g. groundwater, surface water, marine water, wastewater, etc.) and the use/application (e.g. drinking, agriculture, ecological perspective, recreational, watershed management, wastewater treatment, etc.) (O'Flaherty and Allen, 2001).

3.3. Parameter weighting

In general, the parameter weight value is estimated based on the relative importance of the water quality parameter and/or the appropriate guidelines of water quality (Sarkar and Abbasi, 2006). The majority of WQI models applied unequal weighting techniques where the sum of all of the parameter weight values was equal to 1 (Table 2 and Table 4). The Horton, Bascaron and Ameida index models also used unequal weighting but the weightings were integers and their totals were greater than 1. Some models, such as the Oregon model, used an equal weighting approach where all parameters were assigned an equal weighting. On the other hand, the CCME index, the Smith index, and the Dojildo index models do not require weight values for estimating the final score.

Through the aggregation function (Step 4), the parameter weight values can strongly influence the final index value. WQI model robustness is therefore best developed by using the unequal parameter weighting system and assigning the most appropriate weighting values. This technique reduces the uncertainty in the WQI model and helps improve model integrity. Conversely, if inappropriate weightings are used, i.e. a parameter is given greater importance than it merits, then it can adversely affect the model assessment. Tables 3 presents the parameter weighting values recommended for use in the most common WQI models. It can be seen that there is significant variation in the values for a given parameter. Depending on the WQI application, weighting values different to the recommended values may be specified to improve the model outputs. Tables 5 and 6 compare parameter weight values used for different applications of the same model in the assessment of river and marine waterbodies, respectively.

Two approaches have been commonly used for obtaining

Table 2
Summary of structures of most common WQI models.

WQI model	Model Components				
	No of parameters and selection process	Sub-indexing procedure	Parameter Weighting	Aggregation techniques	Rating scale
Horton index (1960)[a]	• 8 parameters suggested • parameters significance and data availability	• parameters value used as sub-index value, and sub-index ranges from 0 to 100 assigned	• fixed and unequal system (4 for DO and 1 for other parameters) suggested	• used simple additive mathematical function (Eq. (9)) • another modified function recommended (Eq. (10))	• Five categories - Very good (91–100) - Good (71–90) - Poor (51–70) - Bad (31–50) - Very bad (0–30)
NSF index (1965)[b]	• 11 parameters • Used Delphi technique	• used water quality standard guideline and scale ranged from 0 to 1; When, Parameter value < standard = 1, Parameter value > standard = 0 modified	• the expert panel judgement, and sum of weight value is equal to 1 given	• used two mathematical functions • first one is additive formula (Eq. (4)) • second one is multiplicative formula (Eq. (5))	• Five categories - excellent (90–100) - good (70–89) - medium (50–69) - bad (25–49) - very Bad (0–24)
SRDD Index (1970)[c]	• 10 parameters • Used Delphi	• Used expert opinion, and it ranged from 0 to 100 recommended by SRDD	• panel based and sum of weight value equal to 1 recommended by SRDD	• additive mathematical function adopted (Eq.11) • multiplicative formula that was used for NSF (Eq. (5)),	• seven classification - clean (90–100) - good (80–89) - good with treatment (70–79) - tolerable (40–69) - polluted (30–39) - several polluted (20–29) - piggery waste (0–19)
Dinius index (1972)[d]*modified version of NSF index	• 11 parameters • Delphi technique	• parameters value directly assigned as sub-index value	• used unequal weight • sum of Weighting value is equal to 10	• multiplicative function used (Eq.5)	• Five classification - Purification not required (90–100) - minor purification required (80–90) - treatment required (50–80) - doutful (40–50)
Ross Index (1977)[e]	• 4 general WQ parameters • Delphi method	• Expert panel judgement based sub-index system	• expert based and sum of weight value is equal to 1 given	• used additive mathematical equation, (Eq. (9))	Not specified
Bascaron Index (1979)[f]	• 26 parameters were suggested	• Parameters value directly transformed into sub-index value using liner transformation function • It ranges from 0 to 100	• Used unequal and fixed weighting technique • ranges from 1 to 4 • Sum of weight value is equal to 54	• Used two additive mathematical functions • Subjective based aggregation function (Eq. (19)) • Objective WQI function (Eq. (20))	• Five classes - Excellent (90– 100) - Good (70–90) - Medium (50–70) - Bad (25–50) - Very bad (0–25)
Oregon Index (1980)[g]*refined version of NSF index	• 8 parameters used Delphi process	• Sub-index were estimated using averaging mathematical functions. • Logarithmic transformation and non-liner regression were used for generating sub-index	• Sub-index values directly used as Weighting factors	• the weight arithmetic mean function was recommended by the Oregon department of environment (Eq. (9)) • Dojlido et al., 1994, recommended the unweighted modified harmonic square mean formula as Eq. (6)	• Five classes - excellent (90–100) - good (85–89) - fair (80–84) - poor (60–79) - very poor (<60)
EQ index (1982)[h]	• 9 parameters recommended • Adopted Delphi method	• Fixed system, and used national-international water quality guideline • Used expert opinion	• fixed and unequal (0.1 for physical, chemical and biological parameters, and 0.15 for organic and inorganic r parameters)	• used simple additive mathematical function (Eq. (9))	• Five categories - excellent (90–100) - very good (80–89) - good (70–79) - fair (55–69) - poor (<55)
House index (1986)[i]*refined version of SRDD index	• 9 parameters • Key personnel interview • Expert panel judgement process	• Parameters value directly used as a sub-index • Sub-index scale ranges from 10 to 100	• the expert panel judgement, and sum of weight value is equal to 1	• used SRDD aggregation technique, as (Eq. (11))	• recommended 4 classification - high quality (71–100) - reasonable quality (51–70) - moderate quality (31–50) - polluted (10–30)
Smith Index (1990)[j]	• 7 parameters • Used Delphi technique	• Fixed system and expert based	• Not required	• Used minimum operator function (Eq. (7))	• Not specified
Dojildo Index (1994)[k]	• 26 parameters	• Not required	• Not required	• Adopted square root of the harmonic mean function (Eq. (6))	• Four quality recommended by Dojildo

(continued on next page)

Table 2 (*continued*)

WQI model	Model Components				
	No of parameters and selection process	Sub-indexing procedure	Parameter Weighting	Aggregation techniques	Rating scale
	• Open (additional group) and close system (basic parameters group)				- Very clean (75 – 100) - clean (50–75) - polluted (25–50) - very polluted (0–25)
British Colombia Index(1995)[l]	• Used common monitoring parameters • Open choice system • At least 10 parameters	• Sub-index assigned based on expert opinion	• Unequal and expert based	• Simple specific mathematical formula	• Five classes - excellent (0–3) - good (4–17) - fair (18–43) - borderline (44–59) - poor (60–100)
Dalmatian Index (1999)[m]*modified version of SRDD index	• 8 parameters • Delphi technique	• Parameters value used directly as sub-index	• Fixed and unequal weight fixed by expert panel • Sum of weight value equal to 1.	• Used automatic index formulas	• Categories not specified
CCME (2001)[n]*reformed version of BCWQI index	• 4 WQ parameters • Delphi technique	• Not required	• Not required	• Used fixed mathematical functions (Eq. 12–18)	• Suggested 5 types of WQ - excellent (95 – 100) - Good (80 – 94) - fair (65 – 79) - marginal (45 – 65) - poor (0 – 44)
Liou Index (2004)[o]	• 13 parameters were used • Parameters were selected based on environmental and health significance	• Parameters actual concentration directly used as sub-index	• Equal Weighting system • Weighting factors were generated by the using rating curves that were illustrated based on the standard guideline of WQ variables	• Liou-WQI model proposed hybrid (additive and multiplicative) functions (Eq. (9), 10)	• Not specified
Said Index (2004)[p]	• 5 parameters • Based on environmental significance	• Parameters value used as sub-index	• Not required	• Used simple mathematical function (Eq. (8))	• Three WQ classification and index value ranges from 0 to 3. - highest purity (3) - marginal quality (<2) - poor quality (<1)
Malaysian Index (2007)[q]	• 6 parameters used	• Parameters value directly used as sub-index, and it is ranged from 0 to 100	• Unequal and close system • Expert based • Sum of weight is 1	• Simple additive function used	• Parameter based individual rating scale used
Hanh Index (2010)[r]	• 8 parameters • Based on monitoring data availability	• Rating curve-based sun-indexing system • curve developed based on Vietnamese surface water quality standards	• not required	• Hanh suggested two aggregation techniques for evaluating overall water quality and as well as basic water quality (Eq.4, 5).	• five quality classification - Excellent (91–100) - good (76–90) - fair (51–75) - marginal (26–50) - poor (<25)
Almeida Index (2012)[s]	• 10 WQ parameters • Delphi technique	• Rating curve-based sun-indexing system • Parameters rating curve recommended by expert panel	• Close and unequal system • Weighting factors fixed by expert panel • Sum of weight value is 1	• Multiplicative mathematical function (NSF aggregation formula) used Eq. (5)	• Four categories - Excellent (91–100) - good (81–90) - medium (71–80) - poor (<25) - poor (<70)
West Java Index (2017)[t]	• 13 parameters • Parameters were selected based on monitoring data availability and comparison of standards.	• Used straightforward mathematical function • Adopted guideline value for generating sub-indexing	• Multi decision making tools like as Analytic Hierarchy Process (AHP). • Fixed and unequal weight values • Expert based opinion • The sum of weight values is equal to 1	• Non equal geometric technique as Eq. (5)	• Five classification - Excellent (90–100) - good (90–75) - Fair (75–50) - Marginal (50–25) - poor (25–5)

Indices application Domains	References materials
[a]Focus based on the North America	Gupta et al., 2017; Kannel et al., 2007; Oni and Fasakin, 2016; Panda et al., 2016; Sánchez et al., 2007; Yidana and Yidana, 2009; Alobaidy et al., 2010; Banerjee and Srivastava, 2009; Ewaid and Abed, 2017; Gupta et al., 2016; Singh et al., 2018; Sánchez et al., 2007; Yidana and Yidana, 2009; Singh et al., 2018
[b]Application domain in USA	Bakan et al., 2010; Mladenović-Ranisavljević and Žerajić, 2018; Mojahedi and Attari, 2009; Ortega et al., 2016; Babaei Semiromiet al., 2011; Sánchez et al., 2007; Tomas et al., 2017; Zeinalzadeh and Rezaei, 2017
[c]Surface water, Soctland	Bordalo, 2001; Bordalo et al., 2006; Carvalho et al., 2011; Dadolahi-Sohrab et al., 2012; Ionuş, 2010
[d]This model developed based on the cost-effective approaches	Dinius, 1987
[e]Evaluation of general water quality	References missing
[f]Model developed based on Spain	Pesce and Wunderlin, 2000; Koçer and Sevgili, 2014
[g]Oregon streams water, USA	Cude, 2001; Dunnette, 1979

(continued on next page)

Table 2 (*continued*)

Indices application Domains	References materials
[h]The Great lakes nearshore area, North America	Schierow and Chesters, 1988; Steinhurt and Somogniz, 1982
[i]The European community directives of specific uses purposes	House, 1980
[j]Surface water, New Zealand	Shah and Joshi, 2015; Smith, 1990
[k]The Vistula river basin, Poland	References missing
[l]Surface water bodies, Colombia state, USA	Zandbergen and Hall, 1998
[m]River water, southern Croatia	Nives, 1999; Štambuk-Giljanović, 2003
[n]Surface water, Canada	Saffranet al., 2001
[o]Keya river, Taiwan	Liou et al., 2004
[p]Streams water, USA	
[q]River water, Malaysia	Fulazzaky et al., 2010; Othman and Alaa Eldin, 2012; Amneera et al., 2013; Hasan et al., 2015; Naubi et al., 2016
[r]Surface water Vietnam	Pham et al., 2011
[s]The Potrero de los Funes river, Argentina	Almeida et al., 2012
[t]Java Sea, Indonesia	Sutadian et al., 2017

appropriate parameter weight values. Many WQI models used expert opinion to inform the parameter weighting process (Sarkar and Abbasi, 2006). The House index adopted the key personnel interview technique to establish the appropriate parameter weight values (HOUSE, 1989), where participants completed questionnaires. The Horton, NSF, SRDD, Ross, EQ, House, Dalmatian and Almeida indices all used the Delphi technique to develop their parameter weightings. Expert panels typically comprise key stakeholders such as water quality experts, policy-makers or practitioners, government representatives and non-governmental organizations or authorities responsible for managing water resources quality.

The analytic hierarchy process (AHP) method was developed by Thomas Saaty in the 1970 s. It is a technique for decision making in complex environments in which many variables or criteria are considered in the prioritization and selection of alternatives. In the context of WQI parameter weightings, it allows one to determine the most appropriate weightings for given parameters that are reflective of their influence on overall water quality. The parameter pairwise comparisons criteria are employed for generating weight values. This helps to check the reliability of the decision maker's assessments, and it also reduces preconceptions in the decision-making process. The West-Java WQI model applied the AHP technique for formulating parameter weight values (Sutadian et al., 2017). Ocampo-Duque et al., (2006) and Gazzaz et al., (2012) successfully applied the AHP technique for establishing weight values which highlighted the relative significance of the parameters (Sutadian et al., 2017). Several scientists have noted that AHP is an effective method that can minimize model uncertainty and increase the accuracy of the weighting procedure (Sarkar and Abbasi, 2006).

3.4. *Aggregating functions*

The aggregation process is the final step of the WQI model. It is applied to aggregate the parameter sub-indices into a single water quality index score (Sutadian et al., 2016). Most models have used either additive functions or multiplicative functions or a combination of the two (see Table 2). The different aggregation functions are discussed briefly here.

(1) Additive functions

Several WQI models (e.g. Horton model, SRDD model, NSF index (earlier version), House index, Malaysian and Dalmatian index models) employed a simple additive aggregation function expressed as:

$$WQI = \sum_{i=1}^{n} s_i w_i \quad (4)$$

where s_i is the sub-index value for parameter i, w_i (which ranges from 0 to 1) is the corresponding parameter weight value and n is the total number of parameters.

(2) Multiplicative functions

Some models (e.g. the NSF, West Java index and Lious index model)

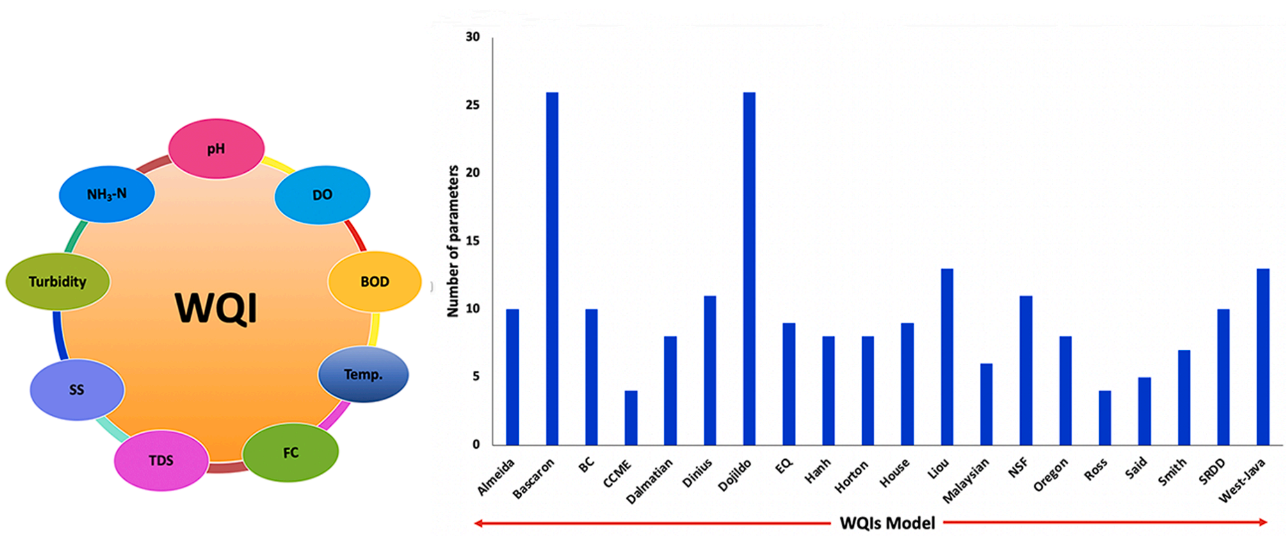

Fig. 5. Most frequently used water quality parameters and number of parameters per model.

Table 3
Water quality parameters included in WQI models.

WQI	Common WQ parameters															Additional Parameters					Toxics, pesticides and trace metal								
	Physical					Chemical								Biologic.															
	Temperature	Color or App.	Turbidity	SS	Total Solids	pH	DO	BOD	COD	Specific Con.	Alkalinity	Cl-	NH3-N	F. Coliforms	T. Coliforms	T. Phosphate	T. Sulfate	Nitrates	T. hardness	Total Nitrogen	Cd	Mn	Zn	Cu	Hg	Pb	Phenols	Detergent	Others
Horton (8)						Y	Y			Y	Y	Y		Y															• Sewage treatment • carbon chloroforms extract • Pesticides • Toxic components
NSF (11)	Y		Y		Y	Y	Y	Y						Y		Y		Y											
SRDD (10)	Y			Y		Y	Y	Y		Y			Y	Y		Y				Y									
Dinius (11)	Y	Y				Y	Y	Y		Y	Y	Y		Y	Y				Y										
Ross (4)				Y			Y	Y					Y																
Bascaron (26)	Y	Y	Y			Y	Y	Y		Y		Y	Y		Y		Y	Y	Y									Y	• Permanganate reduction, • Pesticides, oil and grease, • CN^-, Na^+, free CO2, • Mg^{2+}, P, NO_2^-, Ca^{2+} • visual appearance
Oregon (8)	Y				Y	Y	Y	Y					Y	Y		Y		Y		Y									
EQI (9)		Y		Y						Y		Y		Y		Y					Y				Y	Y	Y		• Chlorophyll *a* • Toxaphene, Polychlorinated Biphenyls, and Chloroform • Arsenic, Nickel
House (9)	Y			Y		Y	Y	Y				Y	Y		Y			Y											
Smith (7)	Y		Y	Y			Y	Y					Y	Y															
Dojildo (26)				Y		Y	Y	Y	Y			Y	Y			Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		• Nickel • Free CN • Cr (VI) • Total Cr • Fe • COD-Cr • Dissolved solids
BCWQI																													• Parameters are not specified
Dalmatin (8)	Y						Y	Y							Y	Y				Y									• mineralization corrosion coefficient • protein nitrogen
CCME (4)																													• any four parameters
Liou (13)	Y		Y	Y		Y	Y	Y					Y	Y							Y		Y	Y		Y			• Cr
Said (5)			Y				Y			Y				Y		Y													
Malaysia (6)				Y		Y	Y	Y	Y				Y																
Hanh (8)			Y	Y			Y	Y	Y				Y		Y														• Orthophosphate
Almeida (10)			Y			Y			Y					Y	Y	Y		Y										Y	• enterococci, • *Escherichia coli*
WJWQI (13)	Y				Y		Y		Y			Y		Y		Y		Y					Y		Y	Y	Y	Y	

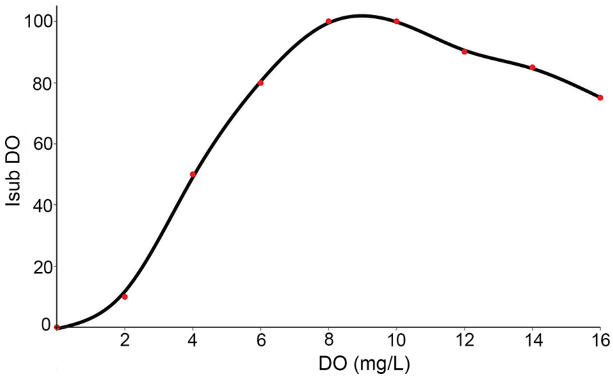

Fig. 6. Example of sub-index rating curve for dissolved oxygen (Source: Smith, 1990, pp. 1240).

have used a multiplicative aggregation function expressed as:

$$WQI = \prod_{i=1}^{n} s_i^{w_i} \tag{5}$$

(3) Combined aggregating functions

Several researchers tried to apply combined aggregation (a mix of additive and multiplicative functions) for obtaining the final WQI score (Abbasi and Abbasi, 2012; Swamee and Tyagi, 2000). Liou et al., (2004), Ewaid and Abed, (2017) and Alobaidy et al., (2010) successfully applied a combined aggregation function when evaluating water quality in Taiwan. The NSF model uses both additive and multiplicative functions.

(c) Square root of the harmonic mean function

Cude (2001) and Dojlido index (1994) recommended the square root of the harmonic mean function (Eq.6) for the aggregation process. Dojildo et al. (1995) proposed it as a modified aggregation function for the Oregon WQI model (Cude, 2001). Pham et al. (2011) also applied the harmonic mean function in the Hanh model. The square root of the harmonic mean function is expressed as:

$$WQI = \sqrt{\frac{n}{\sum_{i=1}^{n} \frac{1}{s_i^2}}} \tag{6}$$

(4) Minimum operator function

Smith (1990) applied the minimum operator function (Eq.7), in which the minimum sub-index values for parameters are taken as the total water quality index values. Smith developed this index to assess the water quality of the rivers and streams in New Zealand. In mathematical terms this is expressed as:

$$WQI = Min(s_i, s_{i+1}, s_{i+2} \cdots\cdots .. I_{sub_n}) \tag{7}$$

Shah and Joshi (2015) also applied the Smith index for evaluating surface water quality in India - the first application of the Smith index in the South Asia region although it was recommended only for application in New Zealand (Smith, 1990).

(5) Unique linear/non-linear aggregation functions

A few WQI models applied unique linear or non-linear aggregation functions for aggregation. For instance, the Said index (Eq. (8)), which uses the parameter concentrations as the sub-index values, aggregates the final WQI using the following unique logarithmic function (Said et al., 2004):

Table 4
A comparison study of the common water quality parameters weight values applying different WQI model.

WQI	Weight value of the water quality parameters																		
	Tem.	Color	Turb.	SS	TS	pH	DO	BOD	COD	SC	Alk.	Cl-	NH_3-N	FC	TC	TP	NO_3^-	TON	Hard.
Horton						4	4			1	1	1		1					
NSF	0.10		0.08		0.07	0.11	0.17	0.11						0.16		0.10	0.10		
SRDD	0.05			0.07		0.09	0.18	0.15		0.06			0.12	0.12		0.08		0.08	
House	0.02			0.11		0.09	0.2	0.18				0.04	0.16		0.11		0.09		
Bascaron	1	2	4			1	4	3		4		1	3		3		2		
Dalmatian	0.07						0.16	0.1							0.16	0.12		0.16	
WJWQI	0.034			0.044			0.10		0.10			0.077		0.179		0.058	0.065		
Dinius						0.077	0.109	0.097			0.063	0.074		0.090				0.090	0.065
EQI	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1		0.15	0.15	0.15	0.1
Said			0.15				1.5			0.5				15		3.8			
Oregon						0.167	0.167	0.167				0.167		0.167			0.167		
MWQI				0.16		0.12	0.22	0.19	0.16				0.15						
Almeida			3			1			3					1	2	3	3		
Ave.	0.196	1.050	1.466	0.097	0.085	0.675	0.909	0.455	0.840	1.132	0.388	0.351	0.706	1.980	1.318	1.044	0.796	0.120	0.083
SD	0.329	0.950	1.691	0.039	0.015	1.163	1.431	0.900	1.247	1.474	0.433	0.412	1.147	4.617	1.234	1.506	1.111	0.035	0.018
Min	0.020	0.100	0.080	0.044	0.070	0.077	0.100	0.097	0.100	0.060	0.063	0.040	0.100	0.090	0.110	0.058	0.065	0.080	0.065
Max	1	2	4	0.16	0.1	4	4	3	3	4	1	1	3	15	3	3.8	3	0.16	0.1

Table 5
Variation of parameter weight values for different applications of the NSF and SRDD models for assessing surface water (river) quality.

WQI	WQ parameters	Modelrecommended weight values	Researchers defined parameters weight values for the rive water					
			Effendi et al., 2015	BabaeiSemiromi et al., 2011	Shah, 2014	Hoseinzadeh et al., 2015	Ewaid, 2016	Tomas et al., 2017
NSF	DO	0.17	0.2	0.129	0.17	0.17	0.17	0.2857
	pH	0.11	0.11	0.133	0.11	0.12	0.11	0.0714
	BOD	0.11	0.13	–	0.11	0.1	0.11	0.2142
	tem	0.1	0.12	–	0.1	0.1	0.1	–
	TP	0.1	0.12	–	0.1	0.1	0.1	0.1429
	Nitrate	0.1	0.12	0.128	0.1	0.1	0.1	0.1429
	Turbidity	0.08	0.1	0.155	0.08	0.08	0.08	–
	TS	0.07	0.08	0.1	0.07	0.08	0.07	–
	FC	0.16	–	0.182	0.16	0.15	0.16	–
	*TON	–	–	–	–	–	–	0.1429
	*SS	–	–	0.173	–	–	–	–
	Total	**1**	**0.98**	**1**	**1**	**1**	**1**	**1**
			Bordalo et al., 2006	Oana, 2010	Carvalho et al., 2011			
SRDD	Tem.	0.05	0.05	0.1	0.05			
	SS	0.07	0.07	0.07	0.07			
	pH	0.09	0.09	0.11	0.09			
	DO	0.18	0.18	0.17	0.19			
	BOD	0.15	0.15	0.11	0.15			
	SC	0.06	0.06	–	0.06			
	NH_3-N	0.12	0.12	–	0.12			
	FC	0.12	0.12	–	0.12			
	TP	0.08	0.08	0.1	–			
	TON	0.08	0.08	–	–			
	*NO3–	–	–	0.1	–			
	*COD				0.15			
	Total	**1**	**1**	**0.76**	**0.85**			

*researchers modified WQ parameters.

$$WQI = \log\left[\frac{(DO)^{1.5}}{(3.8)^{TP}(Turbi)^{0.15}(15)^{fecal/10000}+0.14(SC)^{0.5}}\right] \tag{8}$$

where DO, Turbi, TP, fecal and SC are the parameter sub-index values for dissolved oxygen (% oxygen saturation), turbidity (nephelometric turbidity units [NTU]), total phosphates (mg/L), fecal coliforms (counts/100 mL) and specific conductivity (S/cm at 25 °C), respectively.

4. Major WQI models

The review identified twenty-one different WQI models; the primary characteristics of all of these models are summarized in Table 2. From Table 1 it is seen that seven models have been used in four or more applications and together they account for 85% of the 107 WQI applications reviewed. These seven models were therefore selected for a more detailed analysis of their structures i.e. the parameter selection procedures, the sub-index techniques, the parameter weighting systems and the aggregation functions. The West Java Index model, although used in only one study to date, was also selected for a more detailed analysis as it is one of the most recent models published and it purports to have addressed some of the known issues of earlier WQI models. The key features of these eight WQI models are described in the following sections.

4.1. The Horton index

The Horton model has been used by many researchers (Appendix 1) in many different countries (Fig. 3) for the assessment of fresh surface waters. It contains the four standard WQI components, i.e. parameter selection, sub-index calculation, parameter weighting and sub-index aggregation (Alobaidy et al., 2010; Ewaid and Abed, 2017).

(1) Parameter selection

The original Horton model employed eight physicochemical parameters of water quality including DO, pH, coliforms, specific conductance (specifically measured exact total dissolved solids), carbon chloroforms extract, alkalinity, and chlorides (Abbasi and Abbasi, 2012; Shah and Joshi, 2015). The model also included sewage treatment as an assessment parameter based on entry of the percentage of population upstream served by treatment. The model parameters were determined based on important environmental considerations such as parameter significance, relative influence of other parameters, and authentication and reliability of data (Abbasi and Abbasi, 2012).

(2) Sub-index Generation

To convert parameter values to the sub-index, Horton applied a linear scaling function where sub-index values were assigned based on concentration level or condition of pollution. Sub-index values ranged from 0 to 100; 0 is assigned for conditions of the worst quality and 100 is recommended for excellence. For the sewage treatment sub-index, a value of 100 is assigned when treatment plants are in operation serving pretty much the entire upstream population (95 to 100%) with a direct, measurable influence at the point being considered. If<50 per cent of the population is being served a zero value is applied. Rating values between those limits are then graded according to the amount of population served (Horton, 1965).

(3) Parameter weighting

The parameter weight values were established by using the Delphi technique. Environment significance and relative impacts were considered for giving weight values. The expert panel assigned weight values between 1 and 4 to the various water quality parameters. Horton proposed 1 for four parameters (special conductivity, chlorides, alkalinity and carbon chloroform extract), 2 for one parameter (faecal coliforms) and 4 for three parameters (DO, sewerage treatment and pH).

(4) Aggregation

Table 6
Parameters weight values used in model applications for assessment of marine ecological status.

WQI	WQ parameters	Model recommended weights values	Researchers defined parameters weight values for marine and coastal water Jha et al., 2015	Application Domains
Horton WQI	[a]DO	4	0.01556	*Andaman Sea, India*
	[a]pH	4	0.00972	
	[b]BOD	–	0.02593	
	[a]S. Con.	1	–	
	[b]Ammonia	–	0.77797	
	[b]Nitrate	–	0.07780	
	[a]Cl-	1	–	
	[b]TP	1	0.07780	
	[a]FC	1	0.00016	
	[b]Chl-a	–	0.01074	
	[a]Alkalinity	1	–	
	[a]Sewage treatment	1	–	
	[a]Carbon chloroforms extract	1	–	
	[b]TSS	–	0.00432	
	Total	**15**	**1**	
			Aminah et al., 2017	
Malaysian Index	[b]TSS	–	0.14	*Port Dickson coast belt*
	[a]SS	0.16	–	
	[a]pH	0.12	–	
	[a]DO	0.22	0.2	
	[a]BOD	0.19	–	
	[a]COD	0.16	–	
	[a]NH_3-N	0.15	0.16	
	[b]FC	–	0.14	
	[b]TP	–	0.11	
	bNO3-	–	0.12	
	[b]O & G	–	0.13	
	Total	**1**	**1**	
			Nives, 1999	
Dalmatian Index	[a]Temperature	0.07	0.07	*Dalmatian Coast, Split, Croatia*
	[a]Mineralization	0.07	0.07	
	[a]Corrosion coefficient	0.06	0.06	
	[a]DO	0.16	0.16	
	[a]BOD	0.1	0.1	
	[a]Total Nitrogen	0.16	0.16	
	[a]Protein nitrogen	0.1	0.1	
	[a]Total phosphorus	0.12	0.12	
	[a]Total coliform	0.16	0.16	
	Total	**1**	**1**	
Said Index			Said et al., 2004	*Streams waterbodies, Florida, USA*
	[a]DO	1.5	1.5	
	[a]TP	3.8	3.8	
	[a]Turbidity	0.15	0.15	
	[a]FC	15	15	
	[a]SC	0.5	0.5	
	Total	**20.95**	**20.95**	
			Sutadian et al., 2018	
WJWQI	Temperature	0.034	0.034	*Water bodies, coastal area of the west Java sea, Indonesia*
	SS	0.044	0.044	
	COD	0.1	0.1	
	DO	0.1	0.1	
	Nitrite	0.065	0.065	
	TP	0.058	0.058	
	Detergent	0.079	0.079	
	Phenol	0.085	0.085	
	Chloride	0.077	0.077	
	Zinc	0.038	0.038	
	Lead	0.061	0.061	
	Mercury	0.079	0.079	
	Faecal coliforms	0.179	0.179	
	Total	**0.99**	**0.99**	

[a] model recommended paramters; [b]researcher's modified WQ parameters

An additive function is used to aggregate the final WQI value as follows:

$$WQI = \left[\frac{w_1s_1 + w_2s_2 + w_3s_3 + \cdots. + w_ns_n}{w + w_2 + w_3\cdots\cdots + w_n}\right]m_1m_2 \tag{9}$$

where m1 and m_2 are the coefficients of temperature and obvious pollution, respectively. If the temperature is lower than 34 °C then $m_1 = 0.5$ is used and when the temperature is greater than 34 °C then $m_1 = 1.0$ is used. The obvious pollution applies to factors that make sight and smell offensive. Such conditions include, but are not limited to, the creation of sludge deposits, the presence of oil, debris, foam, scum or other liquid materials, and waste discharge causing a disturbance of colour or odour. When the apparent signs of emissions are present, then m_2 is taken as 0.5 otherwise 1.0.

In 1970, Brown completed a critical study on the Horton index (Brown et al., 1970). This study concluded that since the two additional parameters temperature and obvious pollution used in the aggregation function were not rated, the index only shows gradations in water quality. Brown also reviewed the model parameters taking into account the expert opinions and their recommended weight values and proposed a weighted average index formula for stream water as follows:

$$BrownWQI = \sum_{i=1}^{n} w_is_i \tag{10}$$

where the weight values summed to 1. Brown concluded that this index function worked well if all water quality parameters were considered independent of each other.

(5) WQI evaluation

The Horton model recommends the following five water quality classes for the value of the final water quality index:

1) Very good (WQI = 91–100)
2) Good (WQI = 71 – 90)
3) Poor (WQI = 51 – 70)
4) Bad (WQI = 31 – 50)
5) Very bad (WQI = 0 – 30)

4.2. National sanitation Foundation WQI (NSF-WQI)

The NSF WQI was developed by Brown in 1965 (Abrahão et al., 2007) as a modified version of the Horton model (Lumb et al., 2011). It has been used to evaluate surface water quality in various domains (see Appendix 1 and Fig. 3 for details). Like the Horton model, it contains the four basic WQI components.

(1) Parameter selection

The Delphi technique was used to select the water quality parameters (Ewaid, 2016; Lobato et al., 2015; Rocha et al., 2015; Tomas et al., 2017). The NSF index proposed eleven water quality parameters divided into five groups: (1) the physical parameters (temperature, turbidity and total solids), (2) the chemical parameters (pH and dissolved oxygen), (3) the microbiological parameters (faecal coliforms and BOD), (4) the nutrient parameters (total phosphate and nitrates) and (5) the toxic parameters (pesticides and toxic compounds) (Abbasi and Abbasi, 2012; Sutadian et al., 2016; Lumbet al., 2011). Brown et al. (1970) recommended that the toxic parameters group be added where most other WQI models omitted toxic elements.

(2) Sub-index generation

The parameter sub-indexing was developed based on expert panel judgement. Sub-index values ranged from 0 to 1 where the sub-index value was considered 1 when the measured value was found to be within the recommended guideline values and 0 otherwise (Sutadian et al., 2016; Lumbet al., 2011).

(3) Parameter weighting

The model uses unequal parameter weight values which sum to 1. The original weight values were obtained by employing an expert panel but subsequent applications of the model have used modified weight values for evaluating surface water quality (Lobato et al., 2015; Noori et al., 2019; Tomas et al., 2017). The original NSF model prescribed weight values for DO (0.17), FC (0.16), pH (0.11), BOD (0.11), temperature (0.10), total phosphate (0.10), nitrates (0.10), turbidity (0.08) and total solids (0.07). Similarly, this model also considered the environmental significance of water quality parameters to allocate the parameter weight value (Harkins, 1974).

(4) Aggregation

The original NSF model used a simple additive aggregation function like equation (4). In 1973, Brown proposed an alternative aggregation function (Brown et al., 1973) – the multiplicative function shown in equation (5).

(5) WQI evaluation

The model outputs a WQI that ranges from 0 to 100. 0 indicates the worst water quality and 100 indicates excellent water quality. The model proposed five water quality classes:

1) excellent (WQI = 90–100)
2) good (WQI = 70–89)
3) medium (WQI = 50–69)
4) bad (WQI = 25–49)
5) very bad quality (WQI = 0–24)

4.3. Scottish Research development Department (SRDD) index

The SRDD model has been continually developed by the Scottish Research Development Department since 1970 to evaluate surface water quality (Bordalo, 2001; Dadolahi-Sohrab et al., 2012; Sutadian et al., 2016). Most temperate and tropical-sub-tropical countries apply the SRDD model due to its flexibility and regional convenience. For example, it has been used to assess surface water quality in Iran (Dadolahi-Sohrab et al., 2012), Romania (Ionuş, 2010), and Portugal (Carvalho et al., 2011). A modified SRDD model has also been used for evaluating river water quality in Eastern Thailand (Bordalo, 2001 Bordalo et al., 2006).

(1) Parameter selection

The SRDD model also applied the Delphi technique for selecting water quality parameters. It recommended eleven water quality parameters (Ionuş, 2010). The model parameters and categorized in four water quality groups (Bordalo et al., 2006). There were: (1) the physical group (temperature, conductivity and suspended solids), (2) the chemical group (DO, pH and free and saline ammonia), (3) the organics group (total oxide, nitrogen, phosphate), and (4) the microbiological group (BOD) and *Escherichia coli* (*E. coli*).

(2) Sub-index generation

The model parameter sub-index values were obtained using the Delphi technique (Bordalo, 2001). Sub-index values range from 0 to 100. The rating curve technique was applied to calculate sub-indices; the curves were developed based on expert opinions (Dadolahi-Sohrabet al., 2012). The model also employed the EU water quality standard guidelines to generate the sub-index values (Carvalho et al., 2011).

(3) Parameter weighting

The Delphi process was used to obtain the parameter weight values taking consideration of regional guidelines and characteristics of water quality (Bordalo et al., 2006). The model uses fixed, unequal weightings that must sum to 1. The SRDD recommended weight values were for DO (0.18), BOD (0.15), free and saline ammonia (0.12), pH (0.09), total oxidized nitrogen (0.08), phosphate (0.08), suspended solids (0.07), temperature (0.05), conductivity (0.06) and E. Coli. (0.12). The highest weight values were assigned for DO, BOD and E. coli. to reflect their importance and influence (Carvalho et al., 2011; Dadolahi-Sohrab et al., 2012).

(4) Model aggregation function

The SRDD model uses the following modified additive function for aggregation:

$$SRDD - WQI = \frac{1}{100}\left(\sum_{i=1}^{n} S_i W_i\right)^2 \tag{11}$$

The model also recommended a multiplicative aggregation method (Eq. (5)) to aggregate the parameters sub-index and weight values. The modified aggregation function of SRDD was developed based on the NSF WQI (Lumb et al., 2011).

(5) WQI Evaluation

The computed WQI can range from 0 to 100 and the model proposed a seven-category rating scale for evaluating water quality:

1) clean (WQI = 90 – 100)
2) good (WQI = 80 – 89)
3) good without treatment (WQI = 70 – 79)
4) tolerable (WQI = 40 – 69)
5) polluted (WQI = 30 – 39)
6) several polluted (WQI = 20 – 29)
7) piggery waste (WQI = 0 – 19)

4.4. Canadian Council of Ministers of the Environment (CCME) WQI

The CCME model was developed from the British Colombia WQI Model (BCWQI) in 2001 (Lumbet al., 2011). Worldwide, the CCME WQI model has been applied to a wide range of surface water bodies (Abbasi and Abbasi, 2012; Uddin et al., 2017). Relatively, it is widely used due to its ease of application and because it provides flexibility in choosing the water quality parameters to be included in the model. The review found a range of CCME model applications for the assessment of surface (river or marine) water quality in various regions of the world (see Appendix 1 and Fig. 3).

(1) Parameter selection

The CCME WQI model requires the use of a minimum of four water quality parameters but does not specify which ones – this is left to the user to decide (Saffran et al., 2001). To order to pick model parameters, the developers suggest using the expert panel evaluation processes.

(2) Sub-index calculation

The CCME model does not include a sub-index calculation component. Comparatively, this is a major deficiency of this model.

(3) Parameter Weightings

Parameter weight values are not required to obtain the final WQI.

(4) Aggregation

The aggregation function used by the CCME is quite different to other models. It is expressed as:

$$WQI = 100 - \left[\frac{\sqrt{{F_1}^2 + {F_2}^2 + {F_3}^2}}{1.732}\right] \tag{12}$$

The three factors, F_1, F_2 and F_3 are defined as:

(a) F_1: termed the 'scope', this is the percentage of the total parameters that do not meet with the specified objectives. It is expressed as:

$$F_1 = \left[\frac{number\ of\ failed\ parameters}{total\ number\ of\ parameters}\right] \times 100 \tag{13}$$

(b) F_2: termed the 'frequency', this is the percentage of individual tests values that do not meet with the objectives values (failed tests). It is expressed as:

$$F_2 = \left[\frac{number\ of\ failed\ tests}{total\ number\ of\ tests}\right] \times 100 \tag{14}$$

(c) F_3: termed the 'amplitude', this is a measure of the amount by which which test values fail to meet their objectives. The amplitude is calculated by an asymptotic function that scales the normalized sum of the excursions (*nse*) of the test values from the objectives to yield a value between 0 and 100 using:

$$F_3 = \left[\frac{nse}{0.01(nse) + 0.01}\right] \tag{15}$$

If a test value falls below the objective value, the excursion for that test value is calculated as:

$$excursion_i = \left[\frac{failed\ test\ value_i}{Objective_j}\right] - 1 \tag{16}$$

Conversely, if the test value exceeds the objective value, the excursion value is calculated as:

$$excursion_i = \left[\frac{Objective_j}{failed\ test\ value_i}\right] - 1 \tag{17}$$

The *nse* then is the collective amount by which individual test values are out of compliance and is calculated by summing the excursions of individual tests from their objectives and dividing by the total number of tests (both those meeting objectives and those not meeting objectives). This is expressed mathematically as:

$$nse = \left[\frac{\sum_{i=1}^{n} excursion_j}{total\ number\ of\ test}\right] - 1 \tag{18}$$

The divisor of 1.732 in equation (12) is used as a normalizing factor to ensure the resultant WQI is in the range of 0 to 100 where 0 denotes the "worst" water quality and 100 the "best" (Saffranet al., 2001). The factor of 1.732 arises because each of the three individual index factors (F_1, F_2 and F_3) can have a maximum value of 100 giving a maximum value for the numerator of 173.2 (Neary et al., 2001).

(5) WQI evaluation

The CCME model proposed four water quality classes as follows:

(1) excellent (WQI = 95 – 100) - natural water quality
(2) Good (WQI = 80 – 94) - water quality is departed from natural or desirable levels.
(3) fair (WQI = 65 – 79) - water quality condition sometimes departs from natural or desirable levels
(4) marginal (WQI = 45 – 64) - water quality is frequently threatened or impaired; conditions often depart from natural or desirable level
(5) poor (WQI = 0 – 44) - water quality is not suitable for using purposes at any level.

4.5. Bascaron index (BWQI)

This model was developed by Bascaron in 1979 to assess water quality based on Spanish water quality guidelines (Abrahão et al., 2007; Sun et al., 2016). The Bascaron model considered the highest water quality parameter to assess surface water quality (Abrahão et al., 2007; Kannel et al., 2007; Nong et al., 2020). As shown in Fig. 3, many South American countries adopted the Bascaron model to evaluate surface water quality such as Brazil (Abrahão et al., 2007), Argentina (Pesce and Wunderlin, 2000) and Chile (Debels et al., 2005). There have been a few applications in the southern Asian region such as Nepal (Kannel et al., 2007) and India (Banerjee and Srivastava, 2009). Several countries have also tried to develop a modified WQI model based on the Bascaron index model, for example, (Central Chili), and Sun et al., 2016 (China).

(1) Parameter selection

The model proposed 26 water quality parameter representing different groups of water quality characteristics (Abrahão et al., 2007; Pesce and Wunderlin, 2000; Sun et al., 2016). Model parameters were pH, BOD_5, DO, temperature, total coliform (TC), colour, turbidity, permanganate reduction, detergents, hardness, DO, pesticides, oil and grease, sulphates (SO_4^-), nitrate (NO_3^-), cyanides, sodium, free CO_2, ammonia nitrogen (ammonia NH_3-N), chloride (Cl^-), conductivity, magnesium (Mg^{2+}), phosphorus (P), nitrites (NO_2^-), calcium (Ca^{2+}) and the visual appearance of water.

(2) Sub-index Generation

The linear transformation function is applied to convert measured parameter values into sub-index values (Abbasi and Abbasi, 2012; Kannel et al., 2007) which range from 0 to 100 (Pesce and Wunderlin, 2000; Sun et al., 2016). The sub-index values are determined based on local water quality guideline values (Abrahão et al., 2007).

(3) Parameter weightings

The model uses an unequal and fixed weighting system where weight values range from 1 – 4. The sum of the weight values of all 26 parameters is 54.

(4) Aggregation

Bascaron proposed two modified additive functions to aggregate sub-indices. The objective aggregation function is defined as:

$$Bascaron - WQI_{obj} = \frac{\sum w_i s_i}{\sum w_i} \tag{19}$$

The subjective aggregation function incorporates a subjective assessment of the visual appearance of the water and is expressed as:

$$WQI_{sub} = k\frac{\sum_{i=1}^{n} w_i s_i}{\sum_{i=1}^{n} w_i} \tag{20}$$

where *k* is a constant which is obtained by visual assessment of the water (Pesce and Wunderlin, 2000). For river water, it takes one of the following values depending on the condition:

(a) 1.00 = clear water without apparent contamination of natural solids suspended.
(b) 0.75 = light contaminated water, indicated by light non-natural colour, foam, light turbidity for no natural reason.
(c) 0.50 = contaminated water, indicated by non-natural colour, light to moderate odour, high turbidity (non-natural), suspended organic solids, etc.
(d) 0.25 = highly contaminated water, indicated by blackish colour, hard odour, visible fermentation, etc.

(5) WQI Evaluation

This index adopted five quality classes for assessing the quality of river water.

1) Excellent (WQI = 90–100)
2) Good (WQI = 70–90)
3) Medium (WQI = 50–70)
4) Bad (WQI = 25 – 50)
5) Very bad (WQI = 0 – 25)

4.6. Fuzzy interface system (FIS)

Fuzzy logic emerged in the 1960 s and many researchers and scientists have applied FIS in the environmental risk assessment field (Peche and Rodríguez, 2012). In recent decades, several researchers have adopted FIS-based WQI models to assess river water quality (see Fig. 5). Examples include Canada (Lu et al., 2014), Brazil (Lermontov et al., 2009), China (Li et al., 2016; Xia and Chen, 2014; Yan et al., 2010), Spain (Ocampo-Duque et al., 2006; Peche and Rodríguez, 2012), Mexico (Carbajal-Hernández et al., 2012), Iran (Nikoo et al., 2011; Sami et al., 2014), India (Mahapatra et al., 2011), Malaysia (Bai Varadharajan et al., 2009; Che Osmi et al., 2016), Sri Lanka (Ocampo-Duque et al., 2013) and Morocco (Mourhir et al., 2014). FIS based WQI models contain four steps which are analagous to the typical WQI components: (1) fuzzy sets and membership function; (2) fuzzy set operations; (3) fuzzy logic; and (4) inference rules (Lermontov et al., 2009).

(1) Fuzzy sets (i.e. parameter selection)

Set functions theory and logical rules are applied to select model parameters but the FIS approach does not recommend any specific water quality parameters for evaluation of the water quality. The FIS model employs correlation studies of the parameters for setting the model parameters. Theoretical and statistical approaches are followed to build a correlation between parameters. A few studies used expert panel opinions for setting water quality parameters (Nikoo et al., 2011).

(2) Fuzzy set operation process (i.e. sub-index generation)

Water quality parameters are normalized by adopting FIS, which allows a numerical value as input, that is then converted to a qualitative value stated by a few FIS functions (member functions, rules, sets and operators) (Lermontovet al., 2009).

(3) Fuzzy logic function (i.e. parameter weightings)

The weight values of the parameters are generated using FIS logic function.

(4) Interface rules (i.e. aggregation)

A range of fuzzy logic interface rules are applied to aggregate the WQ parameters. The final water quality score is obtained by the defuzzification processes of FIS (Ocampo-Duque et al., 2013, 2006).

4.7. Malaysian water quality index (MWQI)

In 1974, the MWQI was developed by the Department of Environment, Malaysia to evaluate the surface water quality and its classification locally. It is also known as the Department of Environment WQI (DOE-WQI) framework. Malaysian national water quality criteria were applied to define the local water quality and their characteristics (Gazzaz et al., 2012). This model comprises the four common components of WQI models.

(1) Parameter selection

Six typical physicochemical water quality parameters - pH, Dissolved Oxygen (DO), Biological Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Ammonical Nitrogen (NH_3-N), Suspended Solid (SS) - were used by the Malaysian WQI model to estimate the surface water quality and its classification. The model parameters were selected based on expert panel opinion (Gazzaz et al., 2012; Khuan et al., 2002)

(2) Sub-index generation

For each selected parameter, a unique quality function (curve) was developed which transforms the measured value to a non-dimensional sub-index value. (Gazzaz et al., 2012). Parameter thresholds and their best fitted sub index equations (i.e. the quality curves) are given in table 7.

Table 7
Parameter thresholds range and their sub-index functions for calculation the sub-index value (Department of Environment (Malaysia), 2005).

WQ parameter	Thresholds value	Best fitted Sub- index Equations
DO	for × ≤ 8	$SI_{DO} = 0$
	for × ≤ 92	$SI_{DO} = 100$
	for $8 < x < 92$	$SI_{DO} = -0.395 + 0.030x^2 - 0.00020x^3$
BOD	for × ≤ 5	$SI_{BOD} = 100.4–4.23x$
	for × greater than 5	$SI_{BOD} = 108^* \exp(-0.055x) - 0.1\ x$
COD	for × ≤ 20	$SI_{COD} = -1.33x + 99.1$
	for × greater than 20	$SI_{COD} = 103^*\exp(-0.01\ 57x) - 0.04x$
NH_3-N	for × ≤ 0.3	$SI_{AN} = 100.5 - 105x$
	for $0.3 < x < 4$	$SI_{AN} = 94^*\exp(-0.573x) - 5^*\ I \times -\ 2\ I$
	for × ≥ 4	$SI_{AN} = 0$
SS	for × $\leq 1\ 00$	$SI_{SS} = 97.5^* \exp(-0.00676x) + 0.05x$
	for $100 < x < 1000$	$SI_{SS} = 71\ ^* \exp(-0.0061\ x) + 0.01\ 5x$
	for × ≤ 100	$SI_{SS} = 0$
pH	for × < 5.5	$SI_{pH} = 17.02–17.2x + 5.02x^2$
	for $5.5 \leq x < 7$ for	$SI_{pH} = -242 + 95.5x - 6.67x^2$
	For $7 \leq x < 8.75$	$SI_{pH} = -1\ 81 + 82.4x - 6.05x^2$
	for × ≥ 8.75	$SI_{pH} = 536–77.0x + 2.76x^2$

(3) Parameters weightings

An unequal weighting technique was used to determine parameter weight values by taking into consideration the expert panel opinions (Khuan et al., 2002). The sum of the weight values of the parameters is equal to 1. The highest weight value was assigned for the DO (0.22) and BOD (0.19) separately. The same weight value (0.16) was used for COD and SS, respectively. A weighting of 0.15 was determined for ammonical nitrogen while the lowest weight value was given for pH (0.12) (Gazzaz et al., 2012; Amneera et al., 2013)

(4) Aggregation

The WQI score was determined using a simple additive aggregation formula where the products of the parameter sub-index values (SI) and their weightings are summed as follows:

$$WQI = 0.22\times SI_{Do} + 0.19\times SI_{BOD} + 0.16\times SI_{COD} + 0.15\times SI_{AN} + 0.16\times SI_{ss} + 0.12\times SI_{pH} \tag{21}$$

(5) WQI evaluation

The DOE, Malaysian (2005) Index proposed three water quality classes to evaluate the surface water quality. There are

(1) Clean (81 – 100)
(2) Slightly polluted (60 – 80)
(3) Polluted (0 – 59)

4.8. West Java WQI (WJ-WQI)

Sutadian et al. (2018) developed the West-Java WQI model in 2017. It is the most recently developed WQI model in the literature. This model tried to reduce the uncertainty present in other WQI models by following specific and systematic processes in each step.

(1) Parameters selection

The West-java WQI model prescribes thirteen crucial water quality parameters including six water quality groups (Table 2). These are (1) temperature and suspended solids (physical parameters), (2) Chemical Oxygen Demand (COD) and DO (Oxygen depletion parameters), (3) NO_2^- and total phosphate (nutrients), (4) detergent and phenols (organics parameters), chloride (Minerals), (5) Zn, Pb and Hg (heavy metals) and (6) faecal coliforms (microbiological parameters). Model parameters should be selected by first using two screening steps using statistical assessment to determine parameter redundancy, and then using a final step to identify common parameters across all sampling stations (Sutadian et al., 2018).

(2) Sub-index calculation

The linear scaling method is applied for producing the sub-index of temperature while the linear mathematical function of equation (1) – (2) is used to obtain the sub-index for other water quality parameters.

(3) Parameter weighting

Model parameter weight value were allocated based on expert opinions. The expert panel's opinions were evaluated using the Analytic Hierarchy Process (AHP). Parameters weight values are presented in Table 4, they are fixed and unequal values where the sum of the total weight value is equal to 1.

(4) Aggregation

The model uses the same multiplicative aggregation function (see equation (5)) as the NSF WQI model.

(5) WQI evaluation

The West-Java WQI model recommended five water quality classes based on the final model output:

(1) Excellent (WQI = 90–100)
(2) Good (WQI = 75–90)
(3) Fair (WQI = 50–75)
(4) Marginal (WQI = 25 – 50)
(5) Poor (WQI = 5 – 25)

5. Discussion

5.1. Model eclipsing problems

One of the main problems with WQI models is that they are not able to deal with the eclipsing problem. The eclipsing term was first used by Ott (1978) is used to describe how the final model output hides the true nature of the water quality (Ott, 1978). The eclipsing problem can be caused by inappropriate sub-indexing rules, parameter weightings that do not reflect the true relative influences of parameters, or inappropriate aggregation functions. For instance, consider a WQI model with two parameters whose sub-index values are $I_1 = 50$ and $I_2 = 110$, and weight values W_1, W_2 are both equal to 0.5. Using a simple additive aggregation function, the final WQI would be 80. This index value (I = 80) might indicate acceptable water quality, even though one or other of the parameters may not meet with its guideline value. In this situation, the parameter failure is hidden or "eclipsed" by the aggregation process.

Many scientists have acknowledged that crucial water quality information might be destroyed during the aggregation process (Abbasi and Abbasi, 2012). Otte (1978) and Smith (1990) explain eclipsing problems in detail. Several researchers have identified eclipsing issues in WQI models (Smith, 1990; Steinhart et al., 1982; Sutadian et al., 2016). They note that it is produced due to the use of extensive mathematical functions in the aggregation stage (Smith, 1990).

Many researchers have tried to avoid eclipsing issues; for example, the Smith index recommended using the minimum operator index aggregation function to minimize eclipsing problems (Abbasi and Abbasi, 2012). If a single determinant's multiple sub-index values are used to implement the different aggregation functions, then the final WQI score is adjusted (Smith, 1990). Smith (1990) argued that the maximum and lowest weight values of 0.30 and 0.12 are the dissolved oxygen and faecal coliform determinants provided for the test. Using different aggregation function, when applying these weighting values, they produce the different WQI scores for the same determinant to calculate the final WQI score (Fig. 7). That variation is known as the eclipsing problem. Throughout this circumstance, Smith (1990) prescribed that the final WQI score be accomplished without eclipsing the minimal operator function (Eq. (7)). The minimum operator function not only solves the eclipsing fundamental issue but still produces that much uncertainty during the aggregation process.

5.2. Model uncertainty issues

An analysis of index uncertainty focuses on how the variation of the parameter threshold could affect the respective sub-index and end index values. Uncertainty is the fundamental feature of any model and may be correlated with specific parameters of the model. Studies have found that uncertainty in the final indices of WQI models are linked to various sources of the WQI model (Juwana et al., 2016; Seifi et al., 2020). The model uncertainty was contributed by the selection of parameters, the

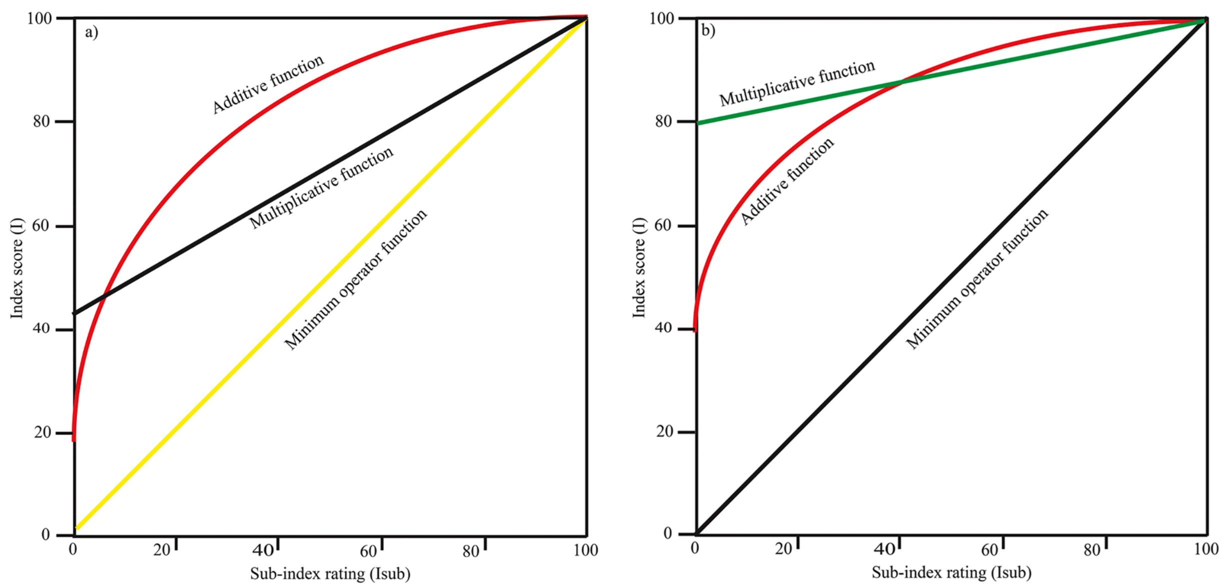

Fig. 7. Transition of the final WQI score when applying three different aggregation functions and changing just one sub-index rating (I_{sub}) (all others being fixed at their maximum value) for (a) dissolved oxygen concentration changing and (b) faecal coliform concentration changing.

sub-indexing technique and the weighting of parameters (Juwana et al., 2016; Sutadian et al., 2016). The key sources of WQI system eclipses and uncertainty are shown in Table 8. The aggregation function has been shown to be a major source of uncertainty (Smith, 1990). Functional uncertainty of the WQI model aggregation was illustrated by Smith (Fig. 7). Juwana et al. (2016) analyzed the uncertainty and sensitivity of different aggregation functions that applied different weight schemes and found that the final index values were most sensitive to the aggregation function (arithmetic and geometric) used. Several studies have been carried out to identify the sources of uncertainty and to quantify uncertainty. Such studies have used a range of statistical approaches to eliminate ambiguity in parameter selection processes such as correlation analysis, main component analysis, cluster analysis, and discriminant analysis. Some WQI models used expert opinion to mitigate uncertainty in the selection and weighting process of the parameters. Juwana et al. (2016) used the Monte Carlo Simulation method for the coefficient of variation and correlation to estimate the uncertainty and sensitivity of the various aggregation functions. Designing a WQI model should involve defining and quantifying uncertainty so that the final WQI scores can be treated with confidence and used to take proper initiative in water resource management and maintain its good health.

5.3. Parameter selection

The number of parameters used by WQIs to assess water quality varies significantly between models. A few models, such as the CCME index and Said index employed only four parameters to assess water quality. It would seem that this is too few to be able to express the complete picture of the water quality since water quality depends on many different natural and anthropogenic factors. On the other extreme, the WJ index requires 26 parameters and it is unlikely that measured data for all 26 would be easily available. Most WQI model parameter lists are selected based on the judgements of expert panels while one must also consider the availability and quality of the monitoring data.

Some models offer user-flexibility in parameter selection while others do not. In open systems, e.g. the CCME model, users can easily select WQ parameters using their own justification. In fixed systems such as the NSF, SRDD, Ross and Bascaron models users can only considering the model-recommended parameters. Mixed systems such as the Dojildo index (1994) allow some flexibility. Expert knowledge and experience should be used for selecting parameters. Some researchers applied statistical tools to analyse the opinions of expert panels. The Delphi technique is a popular tool to obtain the best parameter selection from an expert panel, but a few studies found this technique produced data uncertainty and reduced model accuracy. Local water quality guideline should also be used when selecting parameters and the purpose of the assessment (e.g. to assess for drinking water quality, bathing water quality, shellfish cultivation, etc.) should be taken into account. Recently, the use of statistical approaches to aid parameter selection has become popular. Ma et al. (2020), for example, used Spearman's rank correlation coefficient to measure the interaction between parameters and excluded those parameters that showed no significant correlation with the others.

Data availability is a major concern in the parameter selection process. Some WQI models need comprehensive water quality data on physical, chemical, biological, toxic and pesticide parameters (Ongley and Booty, 1999). This is particularly difficult for developing countries because of the cost and labour intensity of water quality monitoring programs. Recent studies have recognized the monitoring program as a main source of errors and uncertainty through improper site selection and planning, inaccurate measurement due to poorly calibrated equipment or sample contamination, poor sampling techniques, inconsistent recording and data transcription, management and storage capability (Department of Water, 2009). Many developing countries are also unable to construct modern advanced laboratory facilities due to their lack of adequate capital, such as economic support, skilled human resources and effective water management boards (Debels et al., 2005).

Models should be updated when new data or new evidence of parameter importance becomes available. The Oregon WQI model has been updated repeatedly and temperature and total phosphorus were incorporated to improve the model (Cude, 2001). Many researchers have used principal component analysis (PAC) to determine parameter importance (Abrahão et al., 2007; Debels et al., 2005; Gazzaz et al., 2012; Sun et al., 2016; Wu et al., 2018) while others have used cluster analysis (CA). Traditionally, faecal coliforms have been used as an indicator organism for faecal contamination and microbiological water quality; this is reflected in the inclusion of faecal coliforms in many of the reviewed WQI models (Odonkor and Ampofo, 2013). Nowadays, it is commonly accepted that *E-coli* are a better indicator of faecal contamination and microbiological water pollution than faecal coliforms and international bodies such as the World Health Organization (Ashbolt et al., 2001) and the EU, via the Water Framework Directive (WFD,

Table 8
Comparative analysis of WQI model sources of eclipsing and uncertainty.

WQI Model	Factors contributing to eclipsing	Sources of uncertainty
Oregon Index	(a) Complex parameter selection process that was contributed to eclipsing in WQI	- Aggregation function contributes to uncertainty (Swamee and Tyagi, 2000).
Horton Index	(a) No nutrient elements for the parameter group were included in the model	- The key source of uncertainty is the aggregation function, since the coefficient factors are not well defined (Brown et al., 1970).
House Index	(a) The eclipsing problem arises through the procedure for parameter selection of the model	- Aggregation function is the main sources of Instability (Sutadian et al., 2016)
NSF Index	(a) Parameter selection phase contributes to the eclipsing of the model	- Brown et al. (1973) introduced a new multiplicative aggregation function due to the lack of original function sensitivity (Lumb et al. 2011).
CCME Index	(a) Model does not specified the WQ parameters (b) Weighting value does not required, both are responsible for eclipsing problems	- The CCME model uses a number of complex aggregation functions, which could lead to the ambiguity of the end index ranking (Sutadian et al., 2016; Lumbet al., 2011).
Smith Index	(a) Number of required WQ parameters does not specified (b) Complicated subindex equations used for the subindex resulting from the eclipsing problems (c) Parameters weight values does not required	- Not referenced
Malaysian Index	(a) Model only used very common WQ parameters (b) Not included any oxic and biological indicators	- Not referenced
Said Index	(a) Literature based parameter selection process (b) parameter standardization not required	- Not referenced
Hanh Index	(a) complex parameter selection procedures (mixed) (b) equal weight assigned for all selected parameters	- Hybrid aggregation methods produce the uncertainty in the final score (Sutadian et al., 2016).
Dojildo Index	(a) Number of required WQ parameters does not specified (b) Parameter selection processes were based on the intent of the end user	- Aggregated index does not reflect the overall quality of water (Smith, 1990).
Almeida Index	(a) There is no scope for incorporating other essential WQ parameters for the potential implication of closed parameter selection processes. (b) Actual WQ concentration values used explicitly as a sub-index	- The key source of uncertainty is the aggregation process (Swamee and Tyagi, 2000).
Liou Index	(a) The eclipsing problem is a form of fixed-parameter selection that arises due to the lack of other critical parameters.	- The aggregation function leads to uncertainty since the final value is not correlated with the lowest sub-index ranking (Smith, 1990; Sutadian et al., 2016; Swamee and Tyagi, 2000).
West Java WQI	(a) Model parameter selection process is mainly source of eclipsing due to the model parameters were selected based on availability of monitoring data	- Not referenced
FIS	(a) The technique of parameter selection can help to enhance the eclipsing of data into the model	- Fuzzy logic rules are the main origin of uncertainty at final index

2000), recommend the use of *E. coli* over faecal coliforms. Newly developed WQI models should therefore include *E. coli* as well as, or instead of, faecal coliforms, particularly if their purpose if for assessment of drinking or bathing waters.

5.4. Parameter Sub-index calculation

Although sub-index calculation would appear to be a crucial component of the WQI model system given its influence on the final WQI, it is omitted by a small number of WQI models, such as CCME index , while some WQI models such as the Oregon, British Colombia, House, SRDD, Stoner's and Smith Index used the measured parameter values directly as sub-index values. Of those who do calculate sub-indexes, many have used experts' opinions to develop the sub-index rule for parameters and some of the sub-index generating procedures are quite complex. When developing the techniques to obtain the sub-index values, care must be taken so that the generated values do not conceal the parameter's importance / influence. According to Swamee and Tyagi (2000), a major limitation of sub-indexing strategies is that they bury the original knowledge of water quality. The local guideline values for water quality can, and should, be used to develop appropriate sub-indexing rules; these should be aligned where possible with international guideline values (e.g. WHO and EU Water Framework Directive) to provide more uniformity across WQI models.

5.5. Parameter weighting

The parameter weighting attributes the relative influence of a water quality parameter on the final WQI and is therefore another crucial component in the WQI model. However, some models, e.g. the CCME, Smith and Dojildo models, do not apply weightings at all. Unequal weightings are most popular as they can distinguish between the influence of different parameters. Many models obtained parameter weight values based on expert panel opinion (e.g. the NSF, House and SRDD models). The expert panels have generally based their weightings on the environmental significance of the parameter, recommended guideline values and the applications/uses of the water body. The weightings used for the same parameters vary significantly between models – thus demonstrating the difficulty in assigning appropriate weight values and the variation in the influence of a parameter depending on the purpose of the assessment. An example is dissolved oxygen which has been attributed the following range of weight values by different models: 4, 0.17, 0.18, 0.2, 4, 0.16, 0.10, 8, 0.167 and 0.22. The AHP technique has been used to determine parameters significance and therefore reduces uncertainty resulting from inappropriate weighting of parameters.

5.6. Aggregation function

A large range of aggregation techniques have been applied by researchers. Simple additive or multiplicative functions have been most popular. However, they have been identified as a major source of uncertainty in WQI models and as contributing to the eclipsing problem. As discussed earlier, Smith proposed the minimum operator function to minimize eclipsing problems while Stambuk Giljanovic recommended an automated aggregation function for treating this problem (Eq. (8)). Many researchers have proposed modified aggregation techniques to aggregate parameter sub-index with less uncertainty and have had some success (Hurley et al., 2012; Şener et al., 2017; Wu et al., 2018; Hallock, 2002; Khanet al., 2004). Computer-based aggregation techniques using fuzzy interface systems and artificial neural networks have also has some success here (Kloss and Gassner, 2006; Lermontov et al., 2009; Li et al., 2016; Mahapatraet al., 2011; Nikooet al., 2011; Ocampo-Duqueet al., 2006; Ocampo-Duqueet al., 2013; Peche and Rodríguez, 2012; Ross, 1995; Sami et al., 2014; Xia and Chen, 2014; Gazzaz et al., 2012).

Furthermore, for identical water quality data different aggregation functions formulate different index ratings. A range of variations in the water quality classes were observed as a result. The water quality classes does not match the output score for the WQI model. Thus, it is difficult to identify what the accurate water quality scenarios are. The weakness of the aggregation process in the WQI model reflects these types of uncertainty. Specific guidelines for the development of an ideal WQI model for assessing real surface water quality scenarios are therefore crucial. After that, an effective WQI model could be obtained to evaluate the quality of the surface water without any uncertainty.

6. Conclusions

Given the relative simplicity and easily relatable output, WQI models have been widely used for water quality assessment but many different versions have been developed to date. This review was conducted to investigate the structures and mathematical techniques used in WQI models. The study found that while most models had broadly similar structures, the finer details of the four main components varied greatly. The study also highlighted the issues of eclipsing and uncertainty due to the process of model development. The following are the main conclusions from the review:

- Most WQI models involve four stages: (1) selection of water quality parameters, (2) determination of parameter sub-indices, (3) determination of parameter weightings and (4) aggregation of the sub-indices to compute the overall water quality index. Although most models have been developed in a generic manner such that they are easily transferrable to other sites, model applications are quite region/site-specific. Selection of parameters, sub-indexing rules and weightings are all very dependent on the waterbody type (river / lake / estuary / groundwater), its current / intended uses (e.g. drinking water, industrial use, bathing, fisheries, etc.), local water quality guidelines / assessment protocols and data availability.
- There is significant variability in the number and type of water quality parameters that have been included in WQI models, the weightings attributed to particular parameters and the criteria (e.g. guideline values) used to develop sub-index values. As such, there is very little uniformity between models making it difficult to compare applications to different study areas. Some streamlining of the structure and processes of WQI models, such as incorporation of international guideline values (e.g. WHO, EU WFD or similar) may make them more attractive tools for water quality assessment. Updating of models considering new parameters of interest is also crucial for increased use; for example, the inclusion of *E. Coli* as the preferred indicator (by WHO and EU WFD) of faecal contamination and a measure of microbiological water quality, nutrients (e.g. nitrogen and phosphorous) that are important for eutrophication and toxins. For new studies, care must be taken to determine which model suits best, whether a new/modified model is needed and to ensure that the model is applied in the most appropriate manner.
- Eclipsing and uncertainty are two of the key issues which affect the accuracy of model outputs. All four stages of WQI models can contribute here. Model development to date has relied heavily on expert panel opinions with regard to parameter selection, development of sub-indexing rules and determination of appropriate weightings. While this is preferable to reliance on a single person's opinions, it can still introduce uncertainty into the models. More recently, mathematical techniques like principal component analysis and cluster analysis have been used to better inform the selection of parameters and their weightings and computer-based techniques like fuzzy interface systems and artificial neural networks have been used to reduce uncertainty resulting from the final aggregation process. The use of these techniques should be pursued in order to provide more certainty around the accuracy of the final computed indices. At the very least, model uncertainty should be assessed and quantified for any WQI application.

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

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