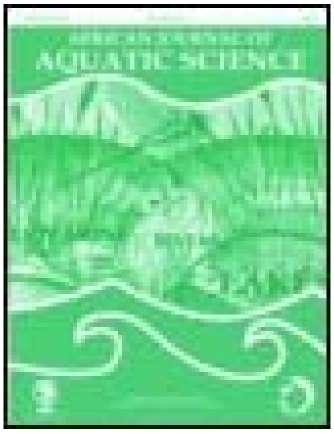

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Ecosystem-specific water quality indices

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Review Paper

Ecosystem-specific water quality indices

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The water quality index (WQI) has emerged as a central tool for analysing and reporting quality trends since 1965. It provides a better overview of water quality variability in a catchment than conventional monitoring programmes that use individual variables. Since water quality is not static, due to point and non-point pollution sources, water managers require tools that are easily adaptable to changing trends. For aquatic environments, different WQIs have been developed to classify specific areas and to determine the fitness of various water resources for specific uses such as drinking. The development of indices poses the challenge of standardising methods for selecting input variables, data transformation and aggregation. Inappropriate input variables may lead to a wrong evaluation of the overall water quality status, possibly resulting in the use of polluted water. This paper reviews methods and aspects to consider when developing ecosystem-specific WQIs – their strengths, limitations and the suitability of the methodologies. These could be applied when developing a water quality index for the uMngeni Basin, KwaZulu-Natal, South Africa, where ecosystem-specific modelling is being done to enhance basin management.

Keywords: aggregation, fitness-for-use, pollution, water quality index, weight factor

Introduction

While humans have developed coping mechanisms for living in polluted environments and for treating water for various uses, these options are unfortunately not available for aquatic animals. This raises a need for the continual monitoring of the Earth's finite and crucial water resources, upon which aquatic organisms depend. As water pollution activities continue to increase, especially in developing countries because of population growth and industrialisation, water managers now, more than ever before, need advice, as well as sound and updated water quality management tools including water quality indices, to assist with assessments and decision making. Bartram and Ballance (1996) highlighted the necessity for water quality monitoring programmes to provide updated information for rational decision making, especially where it concerns the identification of emerging water quality problems in specific ecosystems.

A tool that can translate complex monitoring data into information that is understandable and usable by different non-technical stakeholders should assist in keeping updated databases. Keeping the general public updated regarding water quality and quantity issues motivates them to support policies for the protection of aquatic resources. The water quality index (WQI) has emerged as such a central tool for that purpose (Horton 1965; Walsh and Wheeler 2012).

In South Africa, freshwater resource quality is deteriorating, mainly due to anthropogenic pollution (Ashton 2007). For example, in the Vaal Basin, concerns have been raised regarding the mobilisation of mining pollutants and decanting of acid mine drainage (Dzwairo 2011; Dzwairo et al. 2011; Dzwairo and Otieno 2014). In the uMngeni River, sewage effluent and agricultural runoffs have been documented as the main polluting activities (DWAF 2003; Graham 2004). Such non-standardised human-induced pollution begs for specific WQIs that could provide a clearer overview of a given catchment's pollution sources and management practices.

The literature on WQIs is reviewed with a view to developing an index suitable for assessing water quality in the uMngeni River in KwaZulu-Natal. Various methodologies for developing WQIs, as well as the pros and cons of these indices, are reviewed. The conclusions might assist future researchers in deciding on the most suitable index for a particular ecosystem.

Monitoring and water quality indices

As early as 1848, efforts were made in Germany to associate the quality of water with the presence of certain organisms (Ott 1978; Dojlido and Best 1993). Around that time 616 people died of cholera in the United Kingdom, an occurrence which Snow (1855) linked to impure water. Several countries gradually adopted the idea of determining water quality in reservoirs and also classified their river systems based on pollution levels. This early classification system was basically descriptive, with turbidity and the presence/absence of certain macro- and microorganisms being used as the units for describing the quality of water (Couillard and Lefebvre 1985), resulting in complex numerical reports that made it difficult for politicians, decision-makers and the general public to understand, since they lacked the necessary expertise (Hallock 2002).

The idea of a WQI was first suggested by Horton (1965) as a theoretical replacement for subjective methods of classifying water quality. This author presented a mathematical method of selecting variables, data transformation and aggregating subindex values in a simple but scientific manner. Since then, many indices have been developed and applied (e.g. Ott 1978; Couillard and Lefebvre 1985; Pesce and Wunderlin 2000; UNEP GEMS/Water 2007). Consequently, a WQI has been widely described as a mathematical equation that incorporates data on multiple water quality variables and gives a single value that rates the overall quality status of a water system (Stambuk-Gijanovic 1999; Cude 2001).

Importance of a WQI

Studies have described a WQI as an important management tool for bridging the gap between reporting and monitoring of water quality results (Richardson 1997; Darapu et al. 2011; Edwin and Murtala 2013). It allows the easy compilation and reporting of complex water quality datasets in a consistent manner to all stakeholders, including the general public. By keeping the public informed, they are motivated to support policies meant to assist in improving water quality.

When the same water quality objectives, variables and methodologies are used, an index can be used to determine the relative differences in water quality among sites in a catchment (Couillard and Lefebvre 1985; Pesce and Wunderlin 2000). Temporal trending of the WQI scores assists in the determination of the evolution tendency of water quality over a period of time. Such findings could assist in the evaluation of a resource as a viable source for a given purpose such as aquatic habitat. Both spatial and temporal trends can also be used to evaluate the successes and failures of management strategies meant to improve water quality.

In consideration of these benefits, time and money could be invested in order to fine-tune the applicability of a WQI for the benefit of both human and aquatic life (Ott 1978; Hallock 2002; Pesce and Wunderlin 2002).

Limitations and concerns of a WQI

As with any index, such as the air quality index, a WQI contains less information than the data it summarises (McClelland 1974; Hallock 2002), due to the limitations of resources, time and complexity. It typically only integrates variables that are deemed significant for one particular use to give an overview of the water quality in a particular catchment. In some cases, this might present a problem; for example, a station receiving a good score might still have impaired water quality as a result of excluded variable(s). Such an example is the six-parameter WQI used in Malaysia to evaluate potable water quality; this WQI does not incorporate coliforms, a critical parameter for measuring the microbiological safety of water (Zainudin 2010). Thus, the use of such an index could present challenges as it could classify water contaminated with pathogenic bacteria as clean when the intake of that water could cause human fatalities.

Due to the problem of the loss of data that are associated with a WQI, a water manager, when making decisions, should crosscheck the prevailing situation with the original water quality data, because a single index value might fail to cover critical issues (Hallock 2002; Parmar and Singh 2011; Tyagi et al. 2013). Furthermore, since indices have pre-identified sets of water quality variables, problems could arise where variables which were not originally incorporated were later detected and found to present detrimental effects. This is expected because water quality is not static and new pollution sources are always emerging in catchments (Meybeck et al. 1996; UNEP GEMS/Water 2008). For example, in the uMngeni River, periodic algae blooms have been reported during rainy seasons, with low levels in winter months (Rangeti 2014). As a result, algae can be regarded as a significant factor that influences habitat modification and treatment cost in the rainy season as compared to the dry winter months. Additionally, nitrogen and phosphorus are measurable in lotic environments but are usually below detectable limits in lentic environments where the slow flow results in uptake by primary producers. Thus, an eutrophic system may be masked by a high biomass of primary producers in which nutrients are trapped within the biomass.

In some cases, WQI computation methods might mask or over-emphasise water quality problems (Wepener et al. 1992). For example, if eight of the variables that make up the US National Sanitation Foundation WQI indicate pristine scores, but pH scores a value of 0, a waterbody might have an index value of 85, which is regarded as a 'good' score. Yet, a waterbody with an extremely high or low pH would not be capable of supporting normal aquatic life and might be unsuitable for recreation, drinking or irrigation (Lieven 2007).

Even although a WQI might be criticised as not being the best method for understanding the quality of large-scale water resources, it is sometimes the most applicable and practical tool. However, once the user has developed a general understanding by applying a WQI to a given location, the user is then encouraged to explore the raw data underlying the index in order to obtain a better understanding of it.

Water as an indicator of river ecosystem quality

While there is no simple solution to many of the existing environmental problems, a commitment to monitor changes in an ecosystem is a necessary step towards addressing them. To this end, ecologists have developed various methods of monitoring ecosystems. However, the main challenge is developing a simple but effective indicator for evaluating the overall health status of any aquatic ecosystem (Dale and Beyeler 2001), which is one of the major reasons for having many WQIs for various local, regional and international settings.

In South Africa, as part of the River Health Programme, several indices have been developed to monitor and assess the status of aquatic ecosystems. For example, the EcoClassification methodologies of Kleynhans and Louw (2007) have produced several indices including the fish response assessment index (FRAI), geomorphological driver assessment index (GAI), physico-chemical driver assessment index (PAI) and the riparian vegetation response assessment index (VEGRAI). The overall status of an ecosystem is then determined by integrating these indices. However, integration of a range of diverse indicators such as plants and animals can pose some problems in that populations of organisms in such an ecosystem are also influenced to various extents by other factors such as community climax, disease, parasitism and natural habitat competition (Chapman et al. 1996; Holt and Miller 2011). This is as a result of the diversity of aquatic ecosystems in which both living and non-living components exist, which makes it difficult to determine an indicator that could represent overall health status.

A good ecological indicator should be able to quantify the magnitude of stress, degree of exposure to the stress, and/or degree of ecological response to the exposure (Hunsaker and Carpenter 1990; Suter 1993). The indicator should be made up of a set of variables that give a general impression of the state of the ecosystem. For these reasons, water quality can be recommended as a good indicator for determining a river ecosystem's overall health, since water quality variables such as turbidity and nitrate are easily quantifiable (Simões et al. 2008).

Specific water quality indices

Some studies have highlighted that the choice of a WQI depends on three aspects: the specific pollution problem in the catchment, the intended use of the water, and the possibility of accomplishing analysis (Abrahão et al. 2007; Rangeti 2014). These factors, however, present limitations for the application of general or specific indices, leading researchers to develop a specific index that applies to a particular site or region. In addition, because pollution sources vary with time and space, WQIs are found to be specific and not directly used for different settings without incorporating the background values of those target areas. For example, the Oregon WQI was developed to assess the water quality status of the rivers in Oregon State, USA (Cude 2001).

In the case of South Africa, for example, Dzwairo (2011) developed a WQI to profile the variability of water quality in the upper and middle reaches of the Vaal Basin. This particular ecosystem is mainly impacted by mine effluent and acid mine drainage, thus the WQI cannot be used directly in, for example, the uMngeni Basin, where the major source of pollution is effluent from sewage treatment plants (DWAF 2003; Graham 2004). However, the same approach and methodology that were developed by Dzwairo (2011) could be applied to develop any other index, for example, by using the same aggregation method. Additionally, the variables would have to change in order to suit the objectives of the index for the target spatial and temporal settings in a specific ecosystem.

Furthermore, some indices are ecosystem- or objective-specific. For example, the CCME–WQI (Canadian Council of Ministers of the Environment – Water Quality Index) incorporates different objectives for assessing that region's water quality, allowing for the definition of different objectives for different water uses. Objectives for irrigation water are thus different from those for protecting sensitive aquatic life forms. This means that an index value is calculated and compared specifically to the set objective of specified user.

With regard to fitness-for-use, Walski and Parker (1974) presented a WQI to determine the suitability of water for recreational activities. The index included 11 pollution indicator variables grouped under four general headings: appearance; odour and taste; effect on aquatic life; and effect on human health. O'Connor (1971) developed the fish and wildlife index (FAWL) to determine the fitness of water for fish and wildlife habitats. In Taiwan, the river pollution index (RPI), composed of four variables – dissolved oxygen, biochemical oxygen demand, suspended solids, and ammonia nitrogen (NH_3-N) – was developed to monitor pollution trends for both planning and day-to-day management of surface water quality (Liou et al. 2004).

Variables considered for WQIs

The composition of WQIs in terms of the water quality variables provides uniqueness to the indices (Couillard and Lefebvre 1985; Wepener et al. 2006). This means that even if different ecosystems are given the same score using the same methodology, it does not necessarily imply that the different catchments have the same water quality, unless the indices contain the same variables. The number of variables may also vary from one upwards, depending on the degree of importance that is placed on variable(s) within that particular setting. With the CCME–WQI, it is recommended that a minimum of four variables, sampled at least four times, be used to calculate index values, depending on the objective of monitoring (CCME 2001; Hallock 2002).

For river water quality monitoring, a major challenge is the selection of variables that describe fitness-of-water for the habitat of freshwater organisms. For example, small amounts of nutrients such as nitrates and phosphorus are required for plant growth, but if these are in excess they may cause eutrophication (Ryther and Dunstan 1971; Stow et al. 2014). A bloom of algae in a catchment influences the type and quantity of animals and plants that can be supported, in addition to its negative effects on water treatment processes (NSW DEC 2005). In the uMngeni Basin, which experiences algal blooms, algae were singled out as one of the significant drivers of potable water treatment cost (Rangeti 2014). Thus the inclusion of nutrient variables such as nitrates and phosphorus in a river WQI is logical, as it has been established that these variables alter the structure of an ecosystem to a large extent (Cude 2001; Graham 2004). The 2010 environmental performance WQI aggregated nutrient-measuring parameters, namely, total nitrogen, total phosphorus and dissolved oxygen, as well as two chemical-measuring variables, namely, pH and electrical conductivity (Emerson et al. 2010). The major reason for using these particular variables was that they cover issues of global relevance such as eutrophication, acidification and salinisation (Emerson et al. 2010). With regard to an index for the uMngeni Basin, nutrient variables may be included, among other pollution indicators, because sewage effluent is mainly composed of nutrient variables.

Temperature can also be considered, since it causes shifts in ecosystem structure (Poff et al. 2002). For example, it is noted that chemical and bacteriological activities generally increase as temperature increases. This is because, generally, high rates of reaction are experienced at temperatures >25 °C as compared to those at <15 °C. For dissolved oxygen (DO), cold water has a higher DO-holding capacity than warm water, while the density of water decreases with an increase in water temperature (Dallas 2009).

Turbidity is of interest because it reduces light penetration and ultimately affects photosynthesis (Telesnicki and Goldberg 1995). According to Kutty (1987), turbidity affects fish production. However, Lieven (2007) used DO and dissolved oxygen deficit (DOD), along with a WQI, to evaluate the quality of water in various reservoirs and watersheds. The latter study noted that DO had a major influence on physical, chemical and biological characteristics of streams. Additionally, it was suggested that oxygen demand could provide an overall pollution status of a catchment by making it a surrogate for determining the level of various oxygen demanding substances like algal biomass, other dissolved organic matter, ammonia, volatile suspended solids, and sediment, among others.

For specific ecosystems, such as freshwater, Dunnette (1979) recommended the selection of variables from five impairment categories most ordinarily recognised as: (1) oxygen concentration, (2) eutrophication, (3) health aspects, (4) physical characteristics, and (5) dissolved substances. Among the 36 variables that were reviewed by Bharti and Katyal (2011), 35 had been frequently used. Among these, dissolved oxygen appeared in 15 indices, pH in 11, biological oxygen demand in 11, total phosphorus and phosphates in 11, nitrates in 10, total dissolved solids in 8 and total hardness in 5.

For the monitoring of drinking water quality, priority should be placed on health-impacting microbiological contaminants such as *Escherichia coli* (Berg et al. 1978; DWAF 1996; Boyacioglu 2007). Where microbiological data are very limited or unavailable, Dzwairo (2005) suggested the use of surrogates such as nitrate as crude indicators of faecal pollution in the environment.

When aggregating water quality variables for an index, one should avoid double-counting (Hallock 2002). This occurs when variables that exhibit a combined effect, for example, nitrates and phosphates, are included in an index, resulting in an overemphasis of the effect. The harmonic mean method has been recommended as a better approach for avoiding double-counting (Hallock 2002). An example is given in Equation 1, for turbidity (Turb) and total suspended solids (TSS), which are highly correlated:

$$x = \frac{2}{\frac{1}{\mathrm{TSS}} + \frac{1}{\mathrm{Turb}}} \qquad \text{(Eqn 1)}$$

Due to the complexity of variable variation, it has been difficult to develop a generalised universal model (Steel et al. 1996). Rather, researchers have continued to develop water quality indices that are specific for assessing various catchments.

The following sections review the basic steps of developing a WQI.

Methodology for developing a WQI

WQIs are basically designed using the following four steps: (1) selecting the water quality variables; (2) transforming the variables to a common scale; (3) weighting the significant variables; and (4) computing the overall water quality index (Brown et al. 1970; Liou et al. 2004; Aslhashemi and Taghipour 2010; Dzwairo 2011).

Selecting the water quality variables

The first step is to choose an appropriate set of variables. Since it is generally impossible to monitor all water quality variables due to time constraints and lack of resources, the most important variables should be considered. This stage can be regarded as challenging because exclusion of some variables may lead to loss of important information. The composite variables selected make each index unique for a given purpose or specific ecosystem. Hence, variables considered insignificant for an agricultural WQI, such as turbidity, might be significant for inclusion in a WQI for determining the fitness of water for drinking purposes.

Horton (1965) used a committee to debate whether or not to include a chosen variable. Joung et al. (1979), however, criticised that approach, pointing out that it incorporated subjective opinions. Experts frequently disagree on the relative importance of variables, and this failure to attain consensus makes it difficult for an administrator to make a decision that could be challenged by another panel of experts. On the other hand, the Delphi Technique used questionnaires to gather water experts' opinions in order to develop a list of variables according to their importance (Brown et al. 1970). Both the above approaches (i.e. using a committee or questionnaires) were criticised by Lohani and Todino (1984), who argued that experts' judgements were biased by their professional backgrounds. Lohani and Todino (1984) further argued that this made it almost impossible to construct an acceptable water quality index.

Factor analysis is an alternative method that expresses a large number of variables in terms of a smaller, more manageable number of factors, based on linear relationships among the original variables (Lohani and Todino 1984; Jolliffe 2005). The method is mainly used in studies to evaluate a specific ecosystem's water quality, such as a river basin, and it is recommended because it reduces large datasets into small groups that reflect pollution characteristics and source (Boyacioglu et al. 2005; Dzwairo et al. 2011).

Principal component analysis has been suggested as a better approach for selecting variables to include in an index than the above-mentioned methods (Lohani and Todino 1984; Richardson 1997; Jolliffe 2005). The technique reduces large datasets of dimensionality without loss of information. Since the method converts possible correlated variables into a set of linearly uncorrelated variables, called principal components, it reduces collinearity among variables (Ouyang 2005). The removal of collinearity tends to enhance the performance of an index since only significant uncorrelated variables are aggregated.

However, even although principal component analysis and factor analysis have been suggested as plausible approaches, their use remains uncommon possibly due to their associated complicated statistical procedures. As a result, many studies still continue to use expert opinion along with literature findings when selecting variables. Artificial intelligent methods like artificial neural networks (ANNs) and evolutionary algorithms may also be explored for selecting variables to use in indices (Maier and Dandy 2000; Juahir et al. 2004; Singh et al. 2009). These techniques have been reported to be highly accurate for learning data (data that are used for modelling scenarios) and thus could be useful in variable selection (May et al. 2011). However, their complexity tends to limit their wide use.

Transforming variables to a common scale

Water quality variables occur in different ranges and scales and are expressed in different units, such as counts per volume or parts per million. For example, pH is always given within the range 0–14 units, while most chemicals and nutrients are presented in mg l^{-1} or in parts per million (ppm). For this reason, simple aggregation becomes impossible and common knowledge dictates that all indicators be transformed to the same dimensionless scale.

Variable transformation eliminates the different variable units and produces a dimensionless scale with two end-points (Ott 1978; Dunnette 1979; Pesce and Wunderlin 2002). The highest end-point shows acceptable quality while the lowest represents unacceptable values (Richardson 1997). Transformation of variables to an approximate score is usually done using either a graphical or mathematical function (Boyacioglu 2007; Dzwairo et al. 2012). Numerous ranges have been suggested including 10 to 100, 0 to 25, 0 to 14, 0 to 5 and 0 to 1, while 0 to 100 dominates (Wepener et al. 2006). Dzwairo (2011) used the range 1 to 5, as suggested by House and Ellis (1980), who argued that water always has some economic value, such as for transportation, even if it is polluted, and thus should always have a value greater than 0.

Although several transforming methods have been suggested for use when developing the ranges, the rating curve method has been widely applied (Smith 1990; Stambuk-Gijanovic 1999; Liou et al. 2004). A rating curve generally links a variable's concentration with the quality of water. Variable transformation can also be done using rating tables, non-parametric multivariate ranking procedures or multiple regression analysis (Harkins 1974; Lohani and Todino 1984).

Weighting the significant variables

The third step in developing a WQI is to assign a weight factor (WF) to each variable in accordance with its perceived relative importance as an indicator of water quality for a given use (Pesce and Wunderlin 2000; Dzwairo et al. 2012). Dzwairo et al. (2012) described a WF as a barometer that signals the level of harmful exposure to cause negative effects.

To rate the relative importance of a given variable, one must have some background knowledge about it – for example, toxicity and permissible levels. Variables that have higher permissible limits are generally less harmful, and their WFs are thus inversely related to the variables' permissible limits (Kumar and Dua 2009). With respect to toxicity, in developing an index for the determination of the suitability of water for drinking purposes, faecal coliforms are assigned a higher WF than dissolved oxygen, due to their detrimental effect on human health. However, in a WQI for determining the health status of a freshwater ecosystem, dissolved oxygen is assigned a higher weight compared to faecal coliforms.

Since variable weighting is normally either subjective or objective, its scale tends to vary depending on the methodology employed (Pesce and Wunderlin 2000). In some cases the proportional weight may be calculated as a percentage or any other numerical range. However, some studies prefer scaling down WFs to a fraction of 1 for easy comparison (e.g. Dornbusch and Barrager 1973; Dzwairo et al. 2012).

Computing the overall water quality index (aggregation)

Several formulae have been developed and applied in order to provide a single value that represents an approximate overall value of individual components (Wepener et al. 2006; Abbasi and Abbasi 2012; Fu and Wang 2012). In general, aggregation functions can be classified as additive, multiplicative, minimum, or maximum operator forms (Ott 1978). The process of aggregating a subindex is considered to be a crucial step in the overall procedure due to the potential loss of information. The most common types of data distortion are ambiguity, eclipsing and rigidity (Ball and Church 1980; Couillard and Lefebvre 1985).

Ambiguity or overestimation occurs when the value of an index exceeds a limit value when none of the individual quality scores do (Liou et al. 2004; Abbasi and Abbasi 2012). This is particularly true for non-standardised indices. This inconvenience can be avoided by standardising the index, which is done by dividing by the number of variables involved. Eclipsing or underestimation occurs when an overall index score is acceptable but one or more of the variables exceeds acceptable limits (Ott 1978; Singh et al. 2005; Swamee and Tyagi 2007). Rigidity exists when additional variables are included in the index to address specific water quality concerns (Swamee and Tyagi 2007).

Aggregation methods

Weighted arithmetic mean

This method is widely used to aggregate water quality variables (Landwehr and Deininger 1976; Pesce and Wunderlin 2000). In order to calculate the overall index, water quality components are multiplied by a weight factor and then aggregated using Equation 2. The weighted arithmetic mean method, like other additive forms of aggregating subindices, has been criticised for lacking sensitivity (Liou et al. 2004).

$$\mathrm{WQI} = \sum_{i=1}^{n} \mathrm{SI}_i \times W_i \qquad \text{(Eqn 2)}$$

where SI_i = subindex i, n = number of subindices, and W_i = weight given to SI_i.

With this aggregation method, eclipsing can be reduced by considering a large number of variables.

Weighted geometric mean

Some researchers have proposed using the weighted geometric mean method (Equation 3), since the arithmetic mean method lacks sensitivity, causing eclipsing (McClleland 1974; Walski and Parker 1974). The weighted geometric mean has been described as an unbiased and viable aggregation method (Landwehr and Deininger 1974; McClelland 1974; Joung et al. 1979). This index became known as the NSF-WQI after being recommended and adopted by the National Sanitation Foundation of the United States of America. It was developed to provide a standardised method for comparing quality of water from various sources:

$$\mathrm{WQI} = \prod_{i=1}^{n} \mathrm{SI}_i^{W_i} \qquad \text{(Eqn 3)}$$

where, as above, SI_i = subindex *i, n* = number of subindices, W_i = weight given to SI_i.

Unweighted harmonic square mean and other methods

Gray (1996) criticised the weighted geometric mean as being inadequate because a poor quality score for any of the variables would cause the WQI to become zero. This limitation led to the development of other methods such as the unweighted harmonic square mean (Equation 4; Wepener et al. 2006), minimum operator (Equation 5; Couillard and Lefebvre 1985), Solway-modified unweighted sum (Equation 6; Landwehr and Deininger 1974) and baseline comparative model (CCME) (Equation 7; UNEP GEMS/Water 2007).

$$\mathrm{WQI} = \sqrt{\frac{n}{\sum_{i=1}^{n} \frac{1}{\mathrm{SI}_i^2}}} \qquad \text{(Eqn 4)}$$

$$\mathrm{WQI} = \min(q_1 \times q_2 \,............ q_n) \qquad \text{(Eqn 5)}$$

$$\mathrm{WQI} = \frac{1}{100}\left(\frac{1}{n}\sum_{i=1}^{n} q_i\right)^2 \qquad \text{(Eqn 6)}$$

$$\mathrm{WQI} = 100 - \left(\frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732}\right) \qquad \text{(Eqn 7)}$$

Baseline comparative model (CCME) (Equation 7)

F_1 = Scope

This is the percentage of variables with values that exceed the freshwater ecosystem guidelines (e.g. DWAF 1996) (Equation 7a). 'Failed parameters' are the parameters considered in the indicator, which exceed the guidelines, while 'failed tests' are the samples tested for each parameter considered in the indicator that exceed the guidelines (Rickwood and Carr 2009).

$$F_1 = \left[\frac{\#\ \text{Failed parameters}}{\text{Total}\ \#\ \text{of parameters}}\right] \times 100 \qquad \text{(Eqn 7a)}$$

F_2 = Frequency

This is the percentage of individual tests for each parameter that exceeds the guidelines (Equation 7b):

$$F_2 = \left[\frac{\#\ \text{Failed tests}}{\text{Total}\ \#\ \text{of tests}}\right] \times 100 \qquad \text{(Eqn 7b)}$$

F_3 = Amplitude

This is the extent (excursion) to which the failed test exceeds the guidelines (Equation 7c):

$$F_3 = \left[\frac{\text{nse}}{0.01\text{nse} + 0.01}\right] \qquad \text{(Eqn 7c)}$$

Calculating F_3 involves two steps that determine the excursion and normalised sum of excursion (nse).

Conclusions

While choosing a single WQI that all will find satisfactory is virtually impossible, efforts should be made to avoid or minimise the concerns of indexing methods such as eclipsing and ambiguity. Such caution will enhance the accuracy and robustness of the index. Adopting or developing ecosystem-specific indices has a number of advantages over the traditional methods of water quality monitoring and reporting of results. One advantage is packaging monitoring information that is specific to an ecosystem and in a format that is not too technical to use. This encourages the participation of various stakeholders in decision-making regarding the management of the crucial but finite water resource.

Considering that an index gives a false picture if developed without much caution and understanding of the overall goal, its accuracy can be increased by minimising data loss at all stages of the developmental process, by selecting variables, transforming data and computing the WQI. For indices intended for the evaluation of specific systems such as freshwater ecosystems, efforts should be made to select variables that best represent the pollution sources as incorporation of inappropriate variables could result in the wrong evaluation of the water resources. For complex river basins such as the uMngeni and Vaal, South Africa, recent research suggests that futuristic systems thinking and tools such as ecosystem-specific water quality indices may be applied to manage or mitigate the growing threat of environmental pollution.

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