



A Method for Assessing and Predicting Water Quality Status for Improved Decision-Making and Management

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Abstract

In this study, subindex formulations for key water quality parameters were developed and enhanced to incorporate water quality thresholds and criteria. The enhanced subindex formulations were built into the Unweighted Multiplicative Water Quality Index (UMWQI) and tested for suitability, with a focus on the Western Lake Erie Basin (WLEB). The modified UMWQI model integrates water quality criteria and thresholds set forth by the United States Environmental Protection Agency (USEPA) and state-level environmental agencies, to improve the water quality status. Monthly average subindex values for total suspended solids (TSS) ranged between 33 and 80 (ranking from “poor” to “very good”), those for total phosphorus ranged between 31 and 73 (ranking “poor” to “good”), while those for soluble reactive phosphorus ranged between 13 and 78 (ranking “unsuitable for all uses” to “good”). Overall index values ranged from 35 to 80 throughout the basin, indicating that water quality in the basin is generally “poor” to “good”, consistent with existing literature and water quality reports. Of the four sites that were being assessed, the River Raisin site tended to have the highest annual overall water quality index (cleanest system), with the Tiffin and Blanchard sites ranking the worst. All four sites had soluble reactive phosphorus as the worst ranking determinant, indicating that this is the determinant of greatest concern, also consistent with existing literature. Results indicated that UMWQI and associated subindices as developed were suitable for use within the WLEB. Methodologies and approaches developed are applicable in other areas experiencing similar concerns.

Keywords Water quality · Water quality indices · Decision making and management · Water resources

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1 Introduction

With increasing population growth and demand for surface water, it is crucial to be able to assess water quality on a real-time basis. Today, a relatively large amount of water quality data exists that can be harnessed along with much improved computational capacity to provide indications of water quality status. This can be done both in real-time and in a predictive sense to determine when and where issues are likely to arise. Water quality indices (WQIs) provide a simple and reliable method by which water quality parameters can be expressed in common units and aggregated into a composite value (Brown et al. 1972; CCME 2001; USEPA 2009; Poonam et al. 2013; Gitau et al. 2016) without losing the scientific foundation of the assessment of water quality (Sutadian et al. 2016). Existing data can therefore be analyzed more efficiently. Several WQIs exist, each comprised of a manageable number of determinants (5–9) that are reflective of key determinants of water quality status and intended use (Brown et al. 1972; McClelland 1974; Dunnette 1979; Landwehr and Deininger 1976; Hallock 2002).

Water Quality Indices (WQIs) were first proposed in Germany in 1848 (Abbasi and Abbasi 2012); however, the first modern WQI was developed by Horton in 1965 (Horton 1965). Since then, scientists and environmental organizations have been developing WQIs with many proposing WQIs for specific purposes and eco-regions (Abbasi and Abbasi 2012; Gitau et al. 2016; Sutadian et al. 2016). The United States Environmental Protection Agency (USEPA) was amongst the first designers of the index framework that is still in use today (USEPA 2009). Commonly used WQIs include the additive model (AWQI) (Brown et al. 1972; Lumb et al. 2011a, 2011b), the multiplicative model (MWQI) (McClelland 1974; Lumb et al. 2011a, 2011b), the unweighted multiplicative model (UMWQI) (Landwehr and Deininger 1976; Gupta et al. 2003), and the minimum operator model (MOWQI) (Smith 1990; Swamee and Tyagi 2000) as detailed in Gitau et al. (2016). These authors compared the indices to one another to determine their accuracy and suitability and found the multiplicative models (UMWQI, MWQI) rating about the same and ranking the best in terms of consistency, with the UMWQI being more flexible.

The concept of using an aggregated value as a composite indicator of status is common in many disciplines, including economics and ecology (Abbasi and Abbasi 2012). The indices are not meant to replace biological, chemical, or ecological data; rather, they provide an accessible synthesis of compiled information. One example of a commonly used index for environmental management is the Index for Biological Integrity (IBI). This index is used to assess the integrity of the water through the monitoring of fish and other aquatic biological communities and their tolerance and abundance (Karr 1981). Globally, the development and use of biological indicators to communicate and assess the status and trends of aquatic ecosystems has played a major role in environmental conservation and management practices (Poonam et al. 2013).

The purpose of this study was to develop new subindex equations to improve the accuracy and suitability of the Unweighted Multiplicative Water Quality Index (UMWQI). Specifically to: (1) develop a methodology for calculating an improved WQI by redesigning and incorporating flexible, criteria-based subindex formulations; (2) evaluate the impacts of determinant selection and data availability on composite water quality rating; and (3) demonstrate WQI functionalities, including water quality assessment, communication, and prediction. The subindex formulations were designed to be representative of the region's ecological characteristics, considering the intended use of the streams and the determinants that have the largest impacts on water quality. The new subindex equations accommodate ecoregional water quality

thresholds specified based on representative thresholds for the area of interest. The Unweighted Multiplicative Model (Brown et al. 1972; McClelland, 1974; Dunnette 1979) was adopted because of its flexibility and ability to accurately represent water quality status of the area of interest. Thus, in this study, new subindex formulations that incorporate water quality thresholds based on existing standards and criteria were developed for the UMWQI. Index and subindex ratings were also re-defined to more accurately represent water quality status and account for the water’s intended use.

The pilot site for this project, the Western Lake Erie Basin (WLEB, Fig. 1), was selected for several reasons: its value as a water resource to both society and the environment; the severity of its water quality issues including re-eutrophication (Bridgeman et al. 2012; Kane et al. 2014) and poor water clarity (Daloglu et al. 2012); and, the relatively large amounts of water quality data available in this region. Methods and approaches are generalizable and could easily be adapted to other areas with similar water quality concerns.

2 Methodology

2.1 Pilot Study Site Description

The pilot site for this study is the WLEB (Fig. 1), with particular focus on the Maumee River and its tributaries, as these contribute the largest nutrient inputs to Lake Erie due to agricultural practices in the basin (Bridgeman et al. 2012; Daloglu et al. 2012; Kane et al. 2014; Stow et al. 2015; Keitzer et al. 2016). The WLEB spans an area of 2.83 million ha (7 million ac) in the

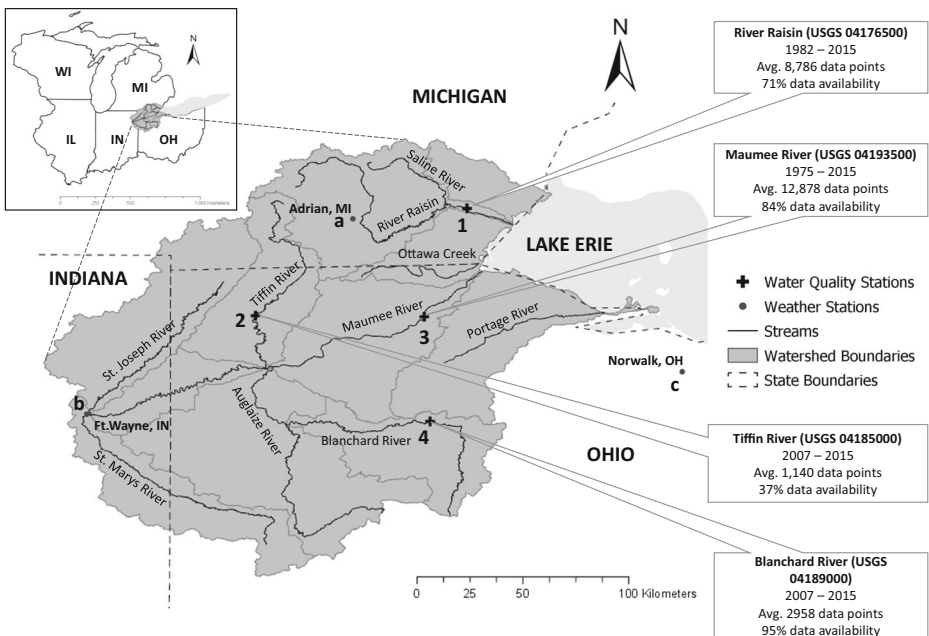


Fig. 1 Pilot site (Western Lake Erie Basin) with selected stream gauge sites and weather stations. Also shown is information on: length datasets; average number of data points available per water quality parameter; and, the average availability (%) over the data length

states of Indiana, Michigan, and Ohio, and has ten sub-basins (NRCS 2015). Nonpoint source pollution due to intense agricultural practices (70% of land usage) in this region is directly linked to the harmful algal blooms in Lake Erie (Stow et al. 2015). The annual precipitation within the WLEB varies from 838 mm to 940 mm (Mehan et al. 2017). Generally, the eastern side of the WLEB receives greater amounts of annual precipitation than the northern and western portions (Gitau et al. 2018).

Determinants that were representative of water quality concerns in the pilot site were Total Suspended Solids (TSS), Total Phosphorus (TP), Soluble Reactive Phosphorus (SRP), and Water Temperature. These are common determinants of concern in other regions within the United States. Seasonal water temperatures have been found important for the tributaries in the WLEB in relation to water quality and harmful algal blooms (HABs) (OEPA 2009a; b; Richards et al. 2010; OEPA 2014; Stow et al. 2015). Thus, water temperature was included as a determinant in this study, though it has been excluded in other WQI formulations (e.g. USEPA 2009) due to concerns about double accounting for the determinant. Four water quality sites from the Heidelberg Tributary Loading Program Dataset (Heidelberg University 2017) were selected for the analysis, as shown in Fig. 1.

2.2 Development of Water Quality Thresholds

Table 1 shows the water quality threshold for each of the determinants considered, their impact on bodies of water, and the water quality standards and established thresholds that were implemented in the water quality index model developed through this study. For this study, 0.1 mg/L of total phosphorus was used as the threshold for standardization purposes. For soluble reactive phosphorus, a maximum level of 0.005 mg/L was adopted, consistent with the Wawasee Area Conservancy Foundation recommendation for lake systems (IDEM 2014).

Table 1 Summary of potential key determinants, their ecological effects, and WQI concentration thresholds

Determinant	Ecological Effects	WQI Threshold	References
Nitrate +Nitrite (NO ₂₋₃)	<ul style="list-style-type: none"> Excessive levels may deplete dissolved oxygen supply, Contribute to cyanobacteria growth 	10 mg/L	Vitousek et al. (2002); Mueller and Spahr (2006); Chaffin et al. (2013)
Soluble Reactive Phosphorus (SRP)	<ul style="list-style-type: none"> 100% SRP from agricultural lands contributes to HABs 86% increase from 1975 to 1995 	0.005 mg/L	Daloglu et al. (2012); Rucinski et al. (2010); Richards et al. (2002)
Total Phosphorus (TP)	<ul style="list-style-type: none"> 25–50% particulate phosphorus from agricultural lands contribute to HABs 	0.1 mg/L	Kerr et al (2016); Richards (2006); Richards et al. (2010); Kane et al. (2014); Stow et al. (2015); Mueller and Helsel 1996
Total Suspended Solids (TSS)	<ul style="list-style-type: none"> Aesthetic degradation Higher costs of treatment Release of toxic/heavy metals May accelerate nitrification process 	60 mg/L	Owens et al. (2005); Bilotta et al (Bilotta and Brazier 2008, Bilotta et al. 2012); Mulligan et al. (2009); Myers et al. (2000)
Water Temperature	<ul style="list-style-type: none"> Biological productivity Closely tied with to available dissolved oxygen supply Controls rate of chemical processes 	N/A	Cude (2001); Chuis (1972); Stefan and Preud'homme (1993); Webb and Nobilis (1997)

Though most of the state standards were based on turbidity, a threshold of 60 mg/L for total suspended sediment was chosen based on an average value from standards from North and South Dakota, New Jersey, Hawaii, and Alaska (USEPA 2015). For nitrates-nitrite, the Clean Water Act establishes a criterion of 10 mg/L (33 U.S.C. § 1251 *et seq.*), which was used as the water quality threshold for the proposed WQI model.

2.3 Subindex Equations Development

Initial subindex formulations were developed based on modifications of the formulations proposed by USEPA (2009), as well as the methodology developed by Dunnette (1979) and Cude (2001). In this study, the development of the subindex transformation curves was based on the statistical distribution of the key determinants to account for variability in natural characteristics of streams.

In our subindex approach, data for TSS, TP, SRP, and NO₂₋₃ were rated as follows. First, observed historical data was filtered for each day *i* and determinant *p* ($Q_{i,p}$) to a subset of only the observations below the threshold ($P_{\text{threshold}}$) for that determinant. Determinant values equal to the 10th percentile (P_{10}) value in the filtered dataset were given a rating of 80, and the 90th percentile (P_{90}) values were rated 50. Concentrations below the 10th percentile value were scored between 80 and 89 on a linear scale, decreasing in rating with increased concentrations; ratings of 90–100 were reserved for pristine waters that require no treatment. The lowest concentration observation of data (P_{min}) received a score of 89. Similarly, concentrations above the 90th percentile of passing observations were rated from 40 to 49, also decreasing linearly. Determinant values between the 10th and 90th percentile values in the observed historical data were fitted to ratings from 50 to 79, using an exponential function based on USEPA (2009).

Observations from the unfiltered data set with concentrations above the maximum threshold were rated 39 or below, with a rating of 0 assigned to the maximum failing observation in the data (P_{max}). This was done because a water body could potentially find alternative uses, up to a point, even with one or more determinants failing to meet their respective water quality thresholds. The index of 0 captures the point beyond which water was no longer suitable for any uses. This method was used in the same way across determinants regardless of the thresholds or measurement units, thus, allowing severity to be comparable across determinants.

2.4 Water Temperature Subindex Equation

Water temperature, being the only potential key determinant that is not a contaminant, required a different set of subindex equations. Unlike TSS, TP, SRP, and NO₂₋₃, this potential key determinant is directly tied to the bioproductivity of a water body. As available water temperature data at individual stations were insufficient for subindex development, the data from eight United States Geological Survey (USGS) gauges and twenty weather stations from the National Oceanic and Atmospheric Administration (NOAA) Climate Data Online were aggregated to assess the data availability of observed water temperature. Since air temperature data are generally more accessible and available than water temperature, a linear relationship between the aggregated air and the aggregated water temperatures based on Cluis (1972), Stefan and Preud'homme (Stefan and Preud'homme 1993), and Webb and Nobilis (Webb and Nobilis 1997) was developed:

$$T_w(t) = 17.532 + 0.8264 \cdot T_a(t) \quad (1)$$

where T_w is the water temperature in Celsius ($^{\circ}\text{C}$), and T_a is the air temperature in Celsius ($^{\circ}\text{C}$) for day t . According to the distribution of the temperature data, water temperature varied from 0°C to 20°C . The lower limit was potentially due to the difficulty in assessing water temperature when approaching the triple point of water (the air temperature at which water can exist as liquid, solid, and gas), which could cause difficulty with measuring the temperature if some water was frozen. Performance analysis gave values of $R^2 = 0.84$, $\text{NSE} = 0.83$, and $p\text{-bias} = -2.04$. Through trial and error, it was found that the optimal value for the R^2 and NSE value could be obtained by removing air temperature values less than -24.2°C . This removal resulted in relatively small changes in performance statistics, though the $p\text{-bias}$ value dropped below zero (taking on a value that was worse than before). Based on criteria in Moriasi et al. (2015), this method of estimating water temperatures was suitable for use in the pilot site since both R^2 and NSE were above 0.75. Once a means of estimating water temperatures had been developed, the temperature subindex equation (Eq. 2) from Cude (2001) was adopted for use. The equation was evaluated using back-calculations and existing literature to determine its suitability for use in the WLEB.

$$Q_{\text{temp},t} = \begin{cases} \text{Temp} \leq 11^{\circ}\text{C} & 100 \\ 11^{\circ}\text{C} < \text{Temp} \leq 29^{\circ}\text{C} & 76.54 + 4.172 \cdot T - 0.1623T^2 - 2.0557 \cdot 10^{-3} \cdot T^3 \\ 29^{\circ}\text{C} < T & 10 \end{cases} \quad (2)$$

where $Q_{\text{temp},t}$ is the subindex value for water temperature of day t , and T is temperature in degrees Celsius.

2.5 Water Quality Index Computation

The overall water quality index used in this study (Eq. 3) is an adaptation of the works by Harkins (1974) and Hallock (2002), which utilize an unweighted multiplicative model and implement a nonparametric multivariate ranking procedure (Kendall 1957; Harkins 1974; Landwehr and Deininger 1976; Hallock 2002):

$$\text{UMWQI}_i = \left(\prod_{i=1}^p Q_{i,p} \right)^{\frac{1}{p}} \quad (3)$$

Where Q_i is the subindex value from 0 to 100, p is the number of key determinants within the WQI, all with data availability on day i , and UMWQI is the geometric mean of the subindex values.

The UMWQI model minimizes ambiguity between the overall index and the subindex values and provides flexibility by allowing removal and addition of determinants (Gitau et al. 2016). As configured in this study, the UMWQI does not calculate the overall index for any one day unless all the key determinants have data points available for that given day. To ensure the accuracy of development of the subindex equations for TSS, TP, SRP, and NO_{2-3} , it was necessary to verify that excluding a portion of the data would not cause the piecewise subindex equation to be substantially different than when an entire dataset was used. The Maumee River dataset (USGS 04193500) was used to validate the subindex equations. It had the longest and most consistent data, hence the most appropriate dataset to validate the equations. For this assessment, the dataset (1975–2015) was broken up into two portions: data from the years 1975 to 2005 and data from the years 2006 to 2015. The earlier dataset was used to calculate the subindex curve parameters,

while the second portion was used to verify the subindex curve parameters, checking that they did not change drastically when this latter section of the data was removed.

3 Results

3.1 Subindex Formulations and Verification

Figure 2 shows the subindex equations and associated classifications and ranges as developed through this study and in relation to ecological associations based on Dinius (1972). Associated water quality ratings as derived through this study are shown in the footnote for Fig. 2. Based on the analysis, the only substantially different curve parameters once the data were separated into two portions (1975–2005 and 2006–2015) were the subindex curve parameters describing the data that would be ranked 40–49 — *f* and *g* (Fig. 2) — for the TP subindex curve. This was because there was only a small difference between the $P_{\text{threshold}}$ and P_{90} values, yet the corresponding index values covered the range between 40 and 49. The percent change is the difference between $P_{\text{threshold}}$ and the maximum filtered value, $P_{\text{max},f}$, and P_{90} , P_{min} , and P_{10} , which play crucial roles in the linear portion of the subindex pairwise equations for each of the potential key determinants. It should be noted that for this portion of the analysis, $P_{\text{max},f}$ was given a value of 40 (rather than the $P_{\text{threshold}}$) which, in the final formulations, represents the lower limit for “passing” values. This was because the verification was conducted during the development process before the subindex equations were finalized.

3.2 Temperature Subindex

Because the WLEB is more susceptible to algal blooms in the summer when the air temperature is higher, it was expected that the Cude (2001) equation (Eq. 2) would give an accurate

	Index Range	Subindex Curve	Data Range	Ecological Associations [†] Based on Intended Use		
				Public Water Supply	Recreation	Fish, Shellfish, Wildlife
Passing Water Quality Threshold ($P_{i,t} < P_{\text{threshold}}$)	90-100	$Q = c(P) + d$	$P_{\text{min}} < P_{i,t} < P_{10}$	Purification not necessary	Acceptable for all water sports	Acceptable for all fish
	80-89			Purification required		
	70-79	$Q = ae^{b(P)}$	$P_{10} < P_{i,t} < P_{90}$	Necessary treatment becoming more extensive	Becoming polluted; bacteria count still acceptable	Marginal for trout
	60-69					Doubtful for sensitive fish
	50-59					
40-49	$Q = f(P) + h$	$P_{90} < P_{i,t} < P_{\text{threshold}}$	Doubtful	Doubtful for water contact	Hardy fish	
Failing Water Quality Threshold	30-39	$Q = j(P) + h$	$P_{i,t} > P_{\text{threshold}}$	Not acceptable	Boating only, no water contact	Coarse fish only
	20-39				Obvious pollution appearing	Not acceptable
	0-19					

[†] Adopted from Dinius (1972). Ratings: 90-100 Pristine; 70-89 Good; 50-69 Fair; 40-49 At Risk; 30-39 Poor; 0-29 Unsuitable for all uses.

Equations for Subindex Curve Parameters

$$a = \frac{50}{e^{b(P_{90})}} \quad b = \frac{\ln\left(\frac{8}{5}\right)}{P_{10} - P_{90}} \quad c = \frac{80 - d}{P_{10}} \quad d = \frac{\left(89 - 80\left(\frac{P_{\text{min}}}{P_{10}}\right)\right)}{1 - \frac{P_{\text{min}}}{P_{10}}} \quad f = \frac{\left(40 - 50\left(\frac{P_{\text{max}}}{P_{90}}\right)\right)}{1 - \frac{P_{\text{max}}}{P_{90}}} \quad g = \frac{50 - f}{P_{90}} \quad h = \frac{(40)}{1 - \frac{P_{\text{threshold}}}{P_{\text{max}}}} \quad j = \frac{-h}{P_{\text{max}}}$$

* P_{max} = maximum value, 100th percentile

Fig. 2 Subindex formulations and classifications as developed and in relation to ecological associations based on Dinius (1972)

representation of the water quality status in the basin with respect to water temperature. According to the Michigan Department of Environmental Quality (MDEQ 2009; 2015), warm-water habitats (WWH) should have summer water temperatures of 60–70 °F (15.6–21 °C). Though it was originally developed for cold-water habitats, Eq. 2—with a warm water temperature threshold of 29 °C—could be considered conservative with respect to the range of values provided by the MDEQ. This is because it would rank values about 21 °C at about the maximum value of the acceptable range for summer water temperatures based on the exponential equation, rather than assigning them a flat value of 10. The water temperature threshold obtained by back-calculating from Eq. 2 and finding the water temperature at which the subindex equation gave a ranking of 40 (consistent with the lower limit for “passing” values for the other key determinants) was 25.9 °C (78.6 °F). Based on values for climate conditions and maximum water temperature tolerance of 57 different American fish species (Eaton and Scheller 1996) sampled throughout the U.S., the 29 °C water temperature threshold in Eq. 2 was indicative of fish species living under extreme stress and was, thus, considered a suitable threshold for maximum tolerance of water temperature. Consequently, Eq. 2 was adopted without change for this study.

3.3 Western Lake Erie Basin Case Study

To determine which water quality determinants were most crucial with respect to the water quality status of the WLEB, the concentrations of total suspended solids (TSS), total phosphorus (TP), soluble reactive phosphorus (SRP), and nitrate-nitrite (NO_{2-3}) were assessed based on the thresholds listed in Table 1. Out of the four determinants, nitrate-nitrite (NO_{2-3}) was the only determinant for which >90% of the data met its respective threshold. In comparison to the rest of the determinants across all four sites (SRP ranged from 0.3–19.8%, TP from 6 to 51%, and TSS from 62.9–84.9%), nitrate-nitrite concentrations in the WLEB tributaries were consistently lower, and the majority of the NO_{2-3} subindex values were thus ranked above 39.

Subindices for Soluble Reactive Phosphorus (SRP), Total Phosphorus (TP), Total Suspended Solids (TSS), and Water Temperature (°C), and the overall water quality index were calculated for all four selected sites in the WLEB. Figure 3 shows the monthly and annual averages of the overall daily WQIs, respectively. Monthly average subindex values for total suspended solids (TSS) ranged between 33 and 80 (ranking from “poor” to “good”). Those for total phosphorus ranged between 31 and 73 (“poor” to “good”). Soluble reactive phosphorus had the largest range, between 13 and 78 (ranking “unsuitable for all uses” to “good”). Overall index values ranged from 35 to 80 throughout the basin, indicating that water quality in the basin is generally “poor” to “good”, consistent with results from Sekaluvu et al. (2017) and USEPA (2017).

To provide a more accurate assessment of the trends, a nonparametric trend analysis using Kendall’s τ was conducted. All four sites had an increase in the monthly mean subindex for TSS with significant increases seen at Maumee River ($\tau = 0.2138$; $p < .0001$), River Raisin ($\tau = 0.0968$; $p = 0.0051$), and Tiffin River ($\tau = 0.1843$; $p = 0.0061$). For the River Raisin, Maumee River, and Tiffin River sites, there were increases in monthly mean TP subindex values, although trends in the Tiffin River were not significant. Monthly TP subindex values declined significantly at the Blanchard River site ($\tau = -0.1586$; $p = 0.0165$). Significant negative trends in SRP subindex values for the River Raisin ($\tau = -0.0889$; $p = 0.0102$) were consistent with results in Sekaluvu et al. (2017). The positive trends in TP subindex values at the Maumee River site ($\tau = 0.2257$; $p < .0001$) were contrary to results in Sekaluvu et al. (2017) which showed that TP levels remained mostly stable but high. The Maumee River SRP

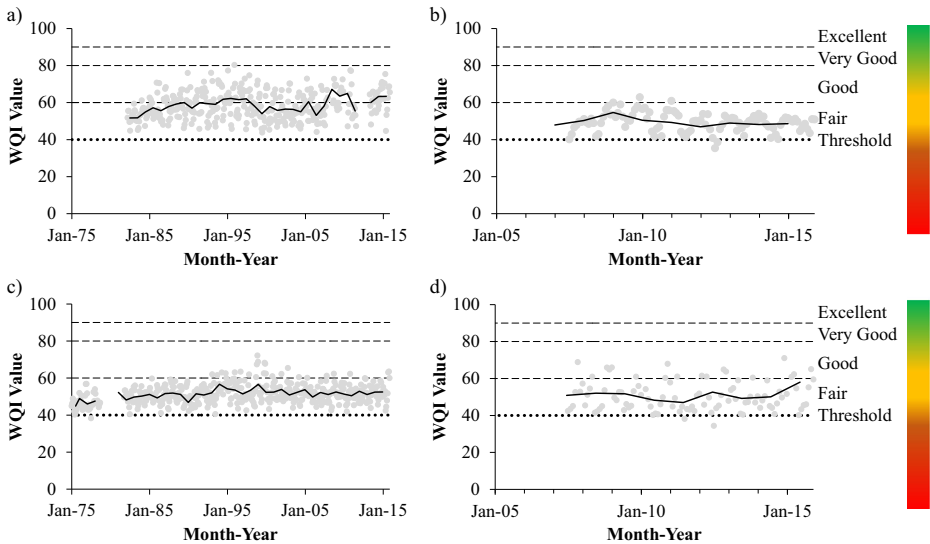


Fig. 3 Long-term WQIs for the four selected USGS gauge sites. The solid lines are annual averages and the markers show monthly values. Stations represented are: (a) River Raisin (USGS 04176500); (b) Blanchard River (USGS 04189000); (c) Maumee River (USGS 04193500); and, (d) Tiffin River (USGS 04185000). Dotted lines represent pass/fail threshold while the dashed lines show the boundaries for the different classifications

subindex trends implied improvement in associated water quality status, contrary to the findings of Sekaluvu et al. (2017) of increasing SRP concentrations.

4 Discussion

Water quality thresholds and criteria were incorporated in subindex formulations developed for key water quality determinants. The enhanced subindex formulations were built into the UMWQI and tested for suitability, with the WLEB serving as a pilot site. Based on the modified WQI, the River Raisin and Maumee River sites showed statistically significant trends of increasing overall WQI values, while the Blanchard River site showed a trend of declining WQIs. The Tiffin River showed no significant trends in overall WQI. For all four sites, there was a positive trend for monthly mean subindex values for TSS. All but the Blanchard site showed a positive trend for the monthly mean TP subindices. The Maumee River site was the only one that showed a positive, albeit not statistically significant, trend in SRP monthly mean subindices. This result was contrary to findings in Sekaluvu et al. (2017) and was potentially reflective of periods of improvements than of current trends.

The Western Lake Erie Basin is a warm-water habitat, and rising air temperatures due to climate change play a role in the prevalence of HABs (Paerl and Huisman 2008, 2009; Paerl et al. 2011). The statistically-estimated water temperature dataset developed in this study did not necessarily capture the extremes that could occur; since the dataset was based upon median values of the daily averages for the USGS gauge sites and the NOAA weather stations, it could underestimate water temperatures during warmer periods. Furthermore, the equation does not account for temperature effects of industrial discharges and reduced tree canopy, both of which present water temperature-related concerns. It would be ideal if more water temperature data

were collected. Dissolved oxygen may be an appropriate substitute to water temperature in the UMWQI model when water temperature measurements are not feasible, given its ties to the well-being of aquatic life (USGS 2017) and that it is amongst the most common key determinants in other WQIs (Gitau et al. 2016; Sutadian et al. 2016; Lumb et al. 2011a).

The most challenging part of developing the WQI was accurately representing the water quality status in terms of thresholds or water quality targets—some of which are regulatory, while some may be deemed arbitrary as they may not necessarily indicate the ecological threshold of a contaminant. Because ecological thresholds of contaminants generally differ by location, regulatory thresholds may not be the most accurate for assessing water quality status. In this study, nitrate-nitrite, or more commonly nitrate-N data, were removed from the assessment due to the indication that the associated water quality status was at least fair based on the 10 mg/L threshold set for drinking water through the Clean Water Act. However, this threshold may be too high, considering that nitrogen could affect the prevalence and toxicity of harmful algal blooms (Gobler et al. 2016; Anderson et al. 2002), implying a need for more stringent environmental thresholds. Further research is necessary to better determine more appropriate environmental thresholds that may be incorporated in subindex equation development.

An important consideration pertaining to the water quality index is the use of concentration levels of key determinants rather than their loads. Surface water quality guidelines are developed based on concentrations considering the need to protect aquatic life and agricultural uses, as well as recreation and aesthetics (El-Sadek et al. 2005; Koltun, 2012). For Lake Erie (USEPA 2017), spring seasonal thresholds were developed both in terms of loads and flow-weighted mean concentrations (FWMC). The FWMC are a form of flow-adjusted concentrations. Concentrations are useful measures based on which to assess water quality, as they play a critical role in biological productivity (Cahn and Hartz 2010). Loads are typically related to the accumulation of mass or volume, and/or gauging the effect of Best Management Practices (BMPs) on reducing pollutant delivery (Koltun, 2012). Both measures are important when assessing the effects of contaminants in a watershed; the choice of data depends on the framework of the study.

The subindex computations for this study were based on statistical distributions. Because the overall index was based upon the distribution of the data, one concern is that the WQI may change as new data are added, depending on their impact on the statistical distribution. To prevent this from occurring and from favoring poor performing streams in the “failing” portion of the subindex, a “maximum” threshold could be created such that anything surpassing this would receive a value of 0. In the case of TP and SRP, for example, the “maximum” threshold for the data could be concentrations associated with hypereutrophic states for streams. However, most of the science and literature around hypereutrophic water bodies is for lakes; the concentrations that could be found in literature would be for lakes and not for streams.

Another option to consider is the possibility of bounding a “failing” standard using an exponential decay. This would standardize the bottom portion of the subindex equation and not favor lower-performing systems due to the distribution of the data being more concentrated in the “failing region.” This would keep the subindices from reaching zero and shift the focus to how quickly the decay would occur and how this could be assessed based on site-specific data. Though the ranking did not differ as greatly for the “passing” data, it is possible to set an optimal value which gets ranked at 100. As developed, the WQI in this study does not rank anything higher than 89 based on the assumption that there are very few water sources that would qualify as pristine.

The WQI that was developed in this study has great potential throughout the water quality decision-making process and offers several functionalities. Because varying concentrations of contaminants can indicate different water quality status, the WQI provides the ability to standardize how determinants affect the water quality status. Furthermore, WQIs can provide a method with which to efficiently communicate water quality concerns based on the common ranking system proposed. Finally, WQI can be used for predictive purposes based on short- and long-term trend analysis to establish overall water quality status and to pinpoint key determinants that need to be addressed in management initiatives.

5 Conclusion

This study was aimed at creating criteria-based and flexible subindex equations for the UMWQI, using the WLEB as a pilot site. The UMWQI was selected due to its flexibility and applicability beyond the WLEB. The subindex equations were developed by incorporating water quality thresholds based primarily on criteria and targets for Indiana, Ohio, and Michigan, and using statistical distributions to assign specific subindex values. The overall WQI values were calculated by taking the geometric mean from the subindex values for the Soluble Reactive Phosphorus (SRP), Total Phosphorus (TP), Total Suspended Solids (TSS), and Water Temperature (T, °C). Subindex equations developed for the respective determinant were found suitable based on the results from the River Raisin, Tiffin River, Blanchard River, and Maumee River stations. Water quality indices provide a way to report and assess large amounts of water quality data in an efficient manner. They have been tested and verified for their usefulness and effectiveness. The UMWQI provides flexibility, so that it can be applied to different sites with water quality data. Though the WQIs provide a “snapshot” of the water quality status by summarizing large amounts of water quality data, by no means do they replace water quality and environmental data. This study was conducted considering WLEB tributaries and results might not be directly applicable elsewhere. The methodology as developed is, nonetheless, applicable to other sites with similar water quality challenges.

Compliance with Ethical Standards

Conflict of Interest None.

References

- Abbasi T, Abbasi SA (2012) Water quality indices. Elsevier, Oxford, UK 978-0-444-54304-2
- Anderson DM, Glibert PM, Burkholder JM (2002) Harmful algal blooms and eutrophication: nutrient sources, composition, and consequences. *Estuaries* 25(4):704–726
- Bilotta G, Brazier R (2008) Understanding the influence of suspended solids on water quality and aquatic biota. *Water Res* 42(12):2849–2861
- Bilotta G, Burnside N, Cheek L, Dunbar M, Grove M, Harrison C, Joyce C, Peacock C, Davy-Bowker J (2012) Developing environment-specific water quality guidelines for suspended particulate matter. *Water Res* 46(7): 2324–2332

- Bridgeman TB, Chaffin JD, Kane DD, Conroy JD, Panek SE, Armenio PM (2012) From river to Lake: phosphorus partitioning and algal community compositional changes in Western Lake Erie. *J Great Lakes Res* 38(1):90–97
- Brown RM, McClelland NI, Deiningner RA, O'Connor MF (1972) A water quality index—crashing the psychological barrier. *Ind Environ Qual Springer*:173–182
- Cahn M, Hartz T (2010) Load vs. concentration: implications for reaching water quality goals. CEM County. In: University of California
- Canadian Council of Ministers of the Environment, CCME (2001) CCME water quality index 1.0 technical report. Available at: <http://www.ccme.ca/files/Resources/calculators/WQI%20Technical%20Report%20%28en%29.pdf>. Last accessed 1/31/2018, Canadian Council of Ministers of the Environment, Canada
- Chaffin JD, Bridgeman TB, Bade DL (2013) Nitrogen constrains the growth of late summer cyanobacterial blooms in Lake Erie. *Adv Microbio* 2013
- Cluis DA (1972) Relationship between stream water temperature and ambient air temperature. *Hydrol Res* 3(2): 65–71
- Cude CG (2001) Oregon water quality index a tool for evaluating water quality management effectiveness. *J Am Water Res Assoc* 37(1):125–137
- Daloglu I, Cho KH, Scavia D (2012) Evaluating causes of trends in long-term dissolved reactive phosphorus loads to Lake Erie. *Environ Sci Techno* 46(19):10660–10666
- Dinius SH (1972) Social accounting system for evaluating water resources. *Water Resour Res* 8(5):1159–1177
- Dunnette D (1979) A geographically variable water quality index used in Oregon. *J Water Pol Control Fed*:53–61
- Eaton JG, Scheller RM (1996) Effects of climate warming on fish thermal habitat in streams of the United States. *Limnol Oceanogr* 41(5):1109–1115
- El-Sadek A, Radwan M, Abdel-Gawad S (2005) Analysis of load versus concentration as water quality measures. *Nat Water Res Center Cairo, Egypt*
- Gitau MW, Chen J, Ma Z (2016) Water quality indices as tools for decision making and management. *Water Resour Manag* 30(8):2591–2610
- Gitau MW, Mehan S, Guo T (2018) Weather generator effectiveness in capturing climate extremes *Environ Proc*, 1–13
- Gobler CJ, Burkholder JM, Davis TW, Harke MJ, Johengen T, Stow CA, Van de Waal DB (2016) The dual role of nitrogen supply in controlling the growth and toxicity of cyanobacterial blooms. *Harmful Algae* 54: 87–97
- Hallock D (2002) A water quality index for ecology's stream monitoring program, Washington State Department of ecology Olympia. Publication no. 02-03-052. Olympia WA. Available at <https://fortress.wa.gov/ecy/publications/documents/0203052.pdf>
- Harkins RD (1974) An objective water quality index. *J Water Pol Control Fed* 46(3):588–591
- Heidelberg University (2017) Tributary Data Download. from <https://www.heidelberg.edu/academics/research-and-centers/national-center-for-water-quality-research>, from <https://www.heidelberg.edu/tributary-data-download>. Last accessed 11 Jan 2018
- Horton RK (1965) An index number system for rating water quality. *J Water Pol Control Fed* 37(3):300–306
- Indiana Department of Environmental Management, IDEM (2014) Indiana state nonpoint source management plan. Office of Water Quality. Indianapolis, IN. Available at https://www.in.gov/idem/nps/files/nps_management_plan_2014_only.pdf. Last accessed 31 Jan 2018
- Kane DD, Conroy JD, Richards RP, Baker DB, Culver DA (2014) Re-eutrophication of Lake Erie: correlations between tributary nutrient loads and phytoplankton biomass. *J Great Lakes Res* 40(3):496–501
- Karr JR (1981) Assessment of biotic integrity using fish communities. *Fisheries* 6(6):21–27
- Keitzer SC, Ludsin SA, Sowa SP, Annis G, Arnold JG, Daggupati P, Froehlich AM, Herbert AM, Johnson MVV, Sasson AM (2016) Thinking outside of the lake: can controls on nutrient inputs into Lake Erie benefit stream conservation in its watershed? *J Great Lakes Res* 42(6):1322–1331
- Kendall MG (1957) A course in multivariate statistics. Charles Griffin and Company, London
- Landwehr JM, Deiningner R (1976) A comparison of several water quality indexes. *J Water Pol Control Fed*:954–958
- Lumb A, Sharma T, Bibeault JF (2011a) A review of genesis and evolution of water quality index (WQI) and some future directions. *Water Qual Expo Health* 3(1):11–24
- Lumb A, Sharma T, Bibeault J, Klawunn P (2011b) A comparative study of USA and Canadian water quality index models. *Water Qual Expo Health* 3(3–4):203–216
- Mehan S, Guo T, Gitau MW, Flanagan DC (2017) Comparative study of different stochastic weather generators for long-term climate data simulation. *Climate* 5(2):26
- Moriasi DN, Gitau MW, Pai N, Daggupati P (2015) Hydrologic and water quality models: performance measures and evaluation criteria. *Trans ASABE* 58(6):1763–1785

- Mueller DK, Helsel DR (1996) Nutrients in the nation's waters: too much of a good thing? Circular 1136. United States Geological Survey, USGS. Denver, CO. <https://pubs.er.usgs.gov/publication/cir1136>. Last accessed 31 Jan 2018
- Mueller DK, Spahr NE (2006) Nutrients in streams and Rivers across the nation—1992–2001. SIR 2006-5107. United States geological survey, USGS. Reston, VA <https://pubs.usgs.gov/sir/2006/5107/>. Last accessed 31 Jan 2018
- Mulligan CN, Davarpanah N, Fukue M, Inoue T (2009) Filtration of contaminated suspended solids for the treatment of surface water. *Chemosphere* 74(6):779–786
- Myers DN, Metzker KD, Davis S (2000) Status and trends in suspended-sediment discharges, soil erosion, and conservation tillage in the Maumee River basin—Ohio, Michigan, and Indiana, US Dept. of the interior, US geological survey; branch of information services [distributor]
- Natural Resource Conservation Service, NRCS (2015) NRCS Investments in the Western Lake Erie Basin Report USDA. https://www.nrcs.usda.gov/wps/PA_NRCSCConsumption/download?cid=nrcseprd402611&index=pdf. Last accessed 31 Jan 2018
- Ohio Environmental Protection Agency, OEPA (2009a) Total Maximum Daily Loads for the Blanchard River Watershed Division of Surface Water Columbus, OH. http://www.epa.state.oh.us/portals/35/tmdl/blanchardrivertmdl_final_may09_wo_app.pdf. Last accessed 31 Jan 2018
- Ohio Environmental Protection Agency, OEPA (2009b) Blanchard River Watershed TMDL Report Fact Sheet Division of Surface Water Columbus, OH. http://www.epa.state.oh.us/portals/35/tmdl/blanchardrivertmdl_factsheet_jul09.pdf. Last accessed 31 Jan 2018
- Ohio Environmental Protection Agency, OEPA (2014) Biological and Water Quality Study of the Maumee River and Auglaize River 2012–2013. Technical report EAS/2014-05-03. Division of Surface Water Columbus, OH Available at http://www.epa.ohio.gov/Portals/35/documents/MaumeeTSD_2014.pdf
- Owens P, Batalla R, Collins A, Gomez B, Hicks D, Horowitz A, Kondolf G, Marden M, Page M, Peacock D (2005) Fine-grained sediment in river systems: environmental significance and management issues. *River Res App* 21(7):693–717
- Paerl HW, Hall NS, Calandrino ES (2011) Controlling harmful cyanobacterial blooms in a world experiencing anthropogenic and climatic-induced change. *Sci the Tot Environ* 409(10):1739–1745
- Paerl HW, Huisman J (2008) Blooms like it hot. *Science* 320(5872):57–58
- Paerl HW, Huisman J (2009) Climate change: a catalyst for global expansion of harmful cyanobacterial blooms. *Environ Microbio Rep* 1(1):27–37
- Poonam T, Tanushree B, Sukalyan C (2013) Water quality indices—important tools for water quality assessment: a review. *Int J Adv Chem* 1(1):15–28
- Richards RP (2006) Trends in sediment and nutrients in major Lake Erie tributaries, 1975–2004 Lake Erie. *Lakewide Management Plan*: 22
- Richards RP, Baker DB, Crumrine JP, Stearns AM (2010) Unusually large loads in 2007 from the Maumee and Sandusky Rivers, tributaries to Lake Erie. *J Soil Water Conserv* 65(6):450–462
- Richards RP, Baker DB, Eckert DJ (2002) Trends in agriculture in the LEASEQ watersheds, 1975–1995. *J Environ Qual* 31(1):17–24
- Rucinski DK, Beletsky D, DePinto JV, Schwab DJ, Scavia D (2010) A simple 1-dimensional, climate based dissolved oxygen model for the central basin of Lake Erie. *J Great Lakes Res* 36(3):465–476
- Sekaluvu L, Zhang L, Gitau MW (2017) Evaluation of constraints to water quality improvements in the Western Lake Erie Basin. *J Environ Man* 205:85–98
- Stefan HG, Preud'homme EB (1993) Stream temperature estimation from air temperature. *J Am Water Res Assoc* 29(1):27–45
- Stow CA, Cha Y, Johnson LT, Confesor R, Richards RP (2015) Long-term and seasonal trend decomposition of Maumee River nutrient inputs to western Lake Erie. *Environ Sci Technol* 49(6):3392–3400
- Sutadian AD, Muttill N, Yilmaz AG, Perera B (2016) Development of river water quality indices—a review. *Environ Mon Assess* 188(1):58
- Swamee PK, Tyagi A (2000) Describing water quality with aggregate index. *J Environ Eng-ASCE* 26:451–455. [https://doi.org/10.1061/\(ASCE\)0733-9372\(2000\)126:5\(451\)](https://doi.org/10.1061/(ASCE)0733-9372(2000)126:5(451))
- United States Environmental Protection Agency, USEPA (2009) Environmental Impact and Benefits Assessment for Final Effluent Guidelines and Standards for the Construction and Development Category. Report Number EPA-821-R-09-012 Office of Water (4303T) Washington, D.C. https://www.epa.gov/sites/production/files/2015-06/documents/cd_envir-benefits-assessment_2009.pdf. Last accessed 31 Jan 2018
- United States Environmental Protection Agency, USEPA (2015) Appendix 3: sediment-related criteria for surface water quality for developing water quality criteria for suspended and bedded sediments (SABs) draft. Office of Water, Office of Science and Technology. <https://www.epa.gov/sites/production/files/2015-10/documents/sediment-appendix3.pdf>. Last accessed 31 Jan 2018

- United States Environmental Protection Agency, USEPA (2017) U.S. Action Plan for Lake Erie: Comments and Strategy for Phosphorus Reduction August 2017 Draft Great Lakes National Program Office Washington , D.C. https://www.epa.gov/sites/production/files/2017-08/documents/us_dap_preliminary_draft_for_public_engagement_8-10-17.pdf. Last accessed 31 Jan 2018
- United States Geological Survey, USGS (2017) Water properties: Dissolved oxygen The USGS Water Science School. <https://water.usgs.gov/edu/dissolvedoxygen.html>. Last accessed 31 Jan 2018
- Vitousek PM, Hättenschwiler S, Olander L, Allison S (2002) Nitrogen and nature. *AMBIO J Human Environ* 31(2):97–101
- Webb B, Nobilis F (1997) Long-term perspective on the nature of the air–water temperature relationship: a case study. *Hydrol Process* 11(2):137–147