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Water Quality Index Aggregation and Cost Benefit Analysis

Patrick Walsh and William Wheeler

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Abstract: The water quality index (WQI) has emerged as a central way to convey water quality information to policy makers and the general public and is regularly used in US EPA regulatory impact analysis. It is a compound indicator that aggregates information from several water quality parameters. Several recent studies have criticized the aggregation function of the EPA WQI, arguing that it suffers from "eclipsing" and other problems. Although past papers have compared various aggregation functions in the WQI (usually looking at correlation), this is the first paper to examine these functions in the context of benefit-cost analysis. Using data from the 2003 EPA CAFO rule, the present paper examines four aggregation functions and their impact on estimated benefits. Results indicate that the aggregation method can have a profound effect on benefits, with total benefit estimates varying from $82 million to $504 million dollars. Furthermore, a sensitivity analysis does not find convincing evidence to substitute the current aggregation function, although several changes to the underlying WQI methodology may be warranted.

Keywords: Valuation, Water Quality, Cost Benefit Analysis
JEL Classifications: D61, D62, Q25, Q28, Q51, Q53, Q58

I. Introduction

There are several laws and regulations that require the quantification of water quality changes. For instance, the EPA is required to do benefit-cost analysis on economically significant rules, which requires quantification and monetization. Additionally, section 303(d) of the Clean Water Act requires states to report water quality conditions to the EPA.[1] The quantification of water quality changes is inherently problematic; however, since there are a range of water quality indicators to choose from, which can vary in importance over geographic regions and represent different aspects of quality. Also, it can be difficult to convey relevant water quality information to policy makers and the general public, who do not always have technical knowledge about the components of waterbody health.

To overcome these obstacles, analysts developed a Water Quality Index (WQI) (McClelland, 1974) to transmit complex water quality information in valuation exercises. For the past few decades, EPA has used the WQI to quantify and monetize water quality changes in several of its Regulatory Impact Analyses (RIAs). The WQI is a composite indicator that combines information from multiple water quality parameters into a single overall value (on a 0-100 scale). This indicator has seen widespread use since its inception and is employed by multiple states and countries (Ott, 1978; Pesce and Wunderlin, 2000; Prakirake et al., 2009; Taner et al., 2011). Creating the WQI involves three main steps (US EPA, 2009): (1) obtain measurements on individual water quality indicators (2) transform measurements into "subindex" values to represent them on a common scale (3) aggregate the individual subindex values into an overall WQI value.

Given the widespread use of the WQI over three decades, it is surprising that more attention has not been paid to the construction of the index. A few sources have criticized EPA's

[1] See OMB's Circular A-4 for additional information: http://www.whitehouse.gov/omb/circulars_a004_a-4/

current approach to the third aggregation step (Dojlido et al., 1994; Cude, 2001), where the geometric mean is used to aggregate the subindex values, and others have proposed variations of the WQI (Landwehr and Deininger, 1976; Smith, 1990; Swamee and Tyagi, 2000; Gupta et al., 2003). However, no past papers have examined the impact of WQI variations on benefit-cost analysis. The present paper demonstrates the effect of using four different WQI aggregation functions—the geometric, arithmetic, and harmonic means, and the minimum operator—on a benefit-cost analysis of a past EPA RIA. Data from the EPA CAFO Rule (US EPA, 2003) is used to calculate the national benefits of the rule under the four variations. Results indicate that the aggregation function can have a profound impact on estimated benefits; yielding a range of $82 million to $504 million dollars. Additionally, a sensitivity analysis supports the continued use of the geometric mean, while recognizing that several parts of WQI construction need to be updated.

II. Background

"Accurate and timely information on status and trends in the environment is necessary to shape sound public policy and to implement environmental programs efficiently….one of the most effective ways to communicate information on environmental trends to policy makers and the general public is with indices" (Landwehr and Deininger, 1976). The WQI has become one of the chief ways to communicate information about water quality. It represents a means of distilling information from multiple sources into one easily understood value. There are currently two main types of WQI: relative and absolute. Relative indices focus on the achievement of legislated thresholds or criteria. For example, Carruthers and Wazniak (2004) formulate a WQI based on the achievement of ecosystem criteria. Several binary variables, indicating criteria achieved or not, are averaged together to form their WQI. Absolute indices, on the other hand, are independent of criteria or thresholds, and wholly based on water quality measurements. The present paper focuses on absolute indices, since they can be applied more broadly than relative indices and are more commonly used by the EPA and other environmental agencies.

One of the earliest WQI's appeared in Horton (1965), which developed a compound index of ten water quality variables. This was the first paper to outline the three main steps for WQI construction discussed earlier: [1] select quality characteristics and obtain measurements, [2] establish a rating scale for each characteristic and transform observations into subindex values, and [3] select a weighting method and aggregate individual subindex valuesinto one index number. Horton's approach to steps [1] and [2] was rather arbitrary, so the index was not useful for policy analysis. For step [3], Horton used the arithmetic aggregation function (or mean), but with temperature and "obvious pollution" entering multiplicatively:

$$WQI_{Horton} = WQI_A * T * O \tag{1}$$

Where temperature is T, obvious pollution is O, and WQI_A is the arithmetic weighting of the other water quality variables:

$$WQI_A = \sum_{i=1}^{n} q_i w_i \tag{2}$$

In (2), q_i is the 0-100 rating for each variable and w_i are the weights, where $\sum_{i=1}^{n} w_i = 1$.

Following the work of Horton, the National Sanitation Foundation (NSF) created a seminal WQI several years later, as published in Brown et al. (1970). To accomplish steps [1] and [2] in a less arbitrary way than Horton, a Delphi survey of 142 water quality experts was performed, with the composition of this group appearing in Table 1. The experts were asked to evaluate the importance of a wide variety of water quality indicators, with chances to re-evaluate their scores in a second round (after viewing general results from the first round). Once the expansive list of indicators was reduced to nine, respondents were asked to create graphs that translated variable concentrations into 0-100 values, with higher values indicating healthy water. The final versions of these graphs were used to produce the subindex values used in step [3] of the WQI construction—the focus of the present paper. An example of the DO graph appears in Figure 1. The subindex curves from Brown et al. (1970) are still used in current EPA analysis, as well as in other studies that use the WQI (Johnston et al., 2005). Also, the weights in current six-parameter WQI's used in recent EPA RIA's were derived directly from the nine-parameter weights in Brown et al. (1970), illustrating the lasting impact of the paper.

Similar to Horton (1965), Brown et al. (1970) also employed basic arithmetic weighting (WQI_A), although without the multiplicative *T* and *O* variables. The arithmetic weighting is the most transparent, and is still used today in several countries as the official method, including Turkey (Taner et al., 2011) and Argentina (Pesce and Wunderlin, 2000). The full NSF WQI developed in Brown et al. (1970) was adopted by the Thai Ministry of Natural Resources and Environment in 1995 as the main tool for water assessment (Prakirake et al., 2009).

Several years after Brown et al.'s (1970) study, McClelland (1974) introduced a different form of weighting to the WQI: the geometric mean. McClelland was concerned that the arithmetic mean lacked sensitivity to low value parameters, a characteristic later deemed "eclipsing." McClelland instead proposed the weighted geometric mean appearing in (3):

$$WQI_G = \prod_{i=1}^{n} q_i^{w_i} \tag{3}$$

To compare the arithmetic WQI to the geometric WQI, McClelland obtained survey responses from over 100 water quality experts—with 30 of them having participated in the original Brown et al. (1970) survey. The experts were given data from actual stream samples and asked to rate them in three iterations similar to a Delphi procedure. When compared to the experts' ratings of waterbodies, on a scale of 0-100, the arithmetic WQI was on average 10 to 15 units higher than the WQI using the experts' evaluation, whereas the geometric WQI averaged only 6 units different, distributed above and below the experts. Using a similar process, Landwehr and Deininger (1976) also found that the geometric mean matched experts' ratings better than several other WQI variations. The geometric mean has been used in all EPA RIAs that use a water quality index, including: the CAFO rule (U.S. EPA 2003a), the Concentrated Aquatic Animal Production rule (U.S. EPA 2004), the Meat and Poultry Processing Rule (U.S. EPA 2004), the Construction and Development Rule (U.S. EPA 2009), and the Florida Numeric Nutrient Criteria Rule (U.S. EPA 2010).

The third WQI aggregation method explored in this paper, the harmonic mean, was first popularized in Dojlido et al. (1994). This mean, appearing in (4), does not use weights for the individual indicators.[2] The number of subindices used (or, the number of water quality variables aggregated) is represented by *n*. Dojlido (1994) found that it was more sensitive to the most impaired indicator than the arithmetic or harmonic means—reducing eclipsing—while still accounting for the influence of other indicators.

$$WQI_H = \sqrt{\frac{n}{\sum_{i=1}^{n} 1/q_i}} \tag{4}$$

One concern with the harmonic mean, however, is that it may result in "ambiguity," a situation where all subindices indicate good water quality but the overall indicator does not (Swamee and Tyagi, 2000). The harmonic mean was also recommended by Cude (2001), which developed a WQI for the State of Oregon. Drawing from Dunnette (1979), Cude (2001) also popularized

[2] Note that $WQI_H = 0$ if $q_i = 0$ for any *i*.

ecoregion-specific subindex curves, allowing the WQI to be tailored to local conditions. This regional approach the subindex curves was used in the analyses for EPA's Construction and Development Rule (U.S. EPA 2009) and The Florida Numeric Nutrients Rule (U.S. EPA 2010). However, the harmonic mean has not been used in EPA regulatory analysis.

The final subindex aggregation method is the minimum operator, which has been proposed as another method to eliminate eclipsing. As shown in (5), the overall WQI in this variation is simply the lowest subindex value:

$$WQI_M = \min(q_1, q_2, ..., q_n) \tag{5}$$

(Smith, 1990) established widespread interest in this method; arguing that the limiting indicator is critical information hidden by other aggregation methods. It has been popular with government environmental organizations in New Zealand (Nagels et al., 2001) and Canada (Khan et al., 2003). Nagels et al. (2001) argue that it is particularly important for certain designated uses, like primary contact recreation. However, the minimum operator is totally insensitive to changes in the other variables, and so is not useful for monitoring purposes or for comparing two waterbodies (Swamee and Tyagi, 2000). Other papers that use or support the minimum operator include Pesce and Wunderlin (2000), Flores (2002), Parparov et al. (2006), Simoes et al. (2008), and Prakirake et al. (2009). For reference purposes, all 4 aggregation functions are summarized in Table 2.

Other, more exotic, aggregation methods have been proposed. For instance, Kung et al. (1992) and Change et al. (2001) support the use of "fuzzy" evaluation tools to account for uncertainty in data and decision-making. Also, Walski and Parker (1974) and Bhargava (1983) use "sensitivity functions" along with parameter weights to aggregate variables. However, these indicators have not gained as much traction in the literature or in applied policy settings as the four methods discussed above.

The WQI was first applied in water quality valuation studies by Mitchell and Carson (1989) and Smith and Desvousges (1986) in stated preference surveys administered in 1980 and 1981, respectively. Both of these studies relied on the transformation of the WQI created by Vaughan (1981), known as the water quality ladder. The WQL is based on "designated use" classifications and was designed to better convey water quality information to the public. The WQL divides the (0-100) WQI scale into five designated use groups.[3] The WQL was calibrated using five water quality parameters which already had designated uses assigned to them by various national, state, or local government agencies. Both Mitchell and Carson (1989) and Smith and Desvousges (1986) used the ladder as an aid to respondents in their surveys. Since these surveys, the ladder has continued to be used in valuation studies to organize meta-analyses (Johnston et al. 2003; van Houtven et al 2007) and benefit transfers (van Houtven et al. 2011).

The WQI was first applied by the EPA in U.S. EPA (2000), in a study examining the value of reductions in conventional pollutants (BOD, TSS, DO, and fecal coliform) arising from the Clean Water Act. It has since been used by EPA in several rules,[4] as recently as 2010 (U.S. EPA 2010). Originally, EPA applied the Mitchell and Carson (1989) (or the later version, Carson and Mitchell, 1993) values directly to modeled changes in WQI, but now relies on meta-analyses of valuation studies (U.S. EPA 2009). The next two sections present a more thorough examination of past EPA approaches.

III. Data

[3] The five designated uses are: (1) acceptable for boating, (2) acceptable for rough fishing, (3) acceptable for game fishing, (4) acceptable for swimming, and (5) acceptable for drinking water treatment.
[4] See Griffiths et al. (2011) for more background on the approaches to benefits estimation in EPA water rules.

This paper uses water quality data from the EPA RIA for the 2003 CAFO rule (US EPA, 2003). The rule uses National Pollutant Discharge Elimination System (NPDES) permits, effluent limitations, and technology standards to protect water quality from manure, wastewater, and other process waters generated by CAFO's. The data contain baseline and projected measures of six water quality variables: biological oxygen demand (BOD), dissolved oxygen (DO), fecal coliform bacteria (FCB), total suspended solids (TSS), nitrogen (NO_3), and phosphorous (PO_4).[5] These six variables were used by U.S. EPA (2003) to create a six parameter WQI, with weights rescaled from the nine-variable McClelland (1974) WQI.[6] The water quality data are geocoded using the RF1 river network, augmented with some RF3 reaches, and includes 1,817,988 reaches totaling 2,655,437 miles within the contiguous 48 states.[7] The projected values were obtained through several water quality models, based on local conditions and projected impacts of the policy.[8]

IV. Analysis

This exercise is aimed at measuring the sensitivity of estimated benefits to the specification of the aggregation function. In the first step, the baseline and forecast water quality parameters are transformed into subindex values. Next, the subindex values are fed to the four different aggregation functions to calculate WQI's. The weights for the geometric and arithmetic

[5] Note that these are the baseline and projected values at the time of the rule, so have not been updated or changed since the rulemaking.
[6] Three variables from McClelland's analysis were therefore omitted: pH, temperature, and total solids. The weights are rescaled so that the ratios of the weights are retained and the weights still sum to one.
[7] Technically the model used RF3 lite, or Reach File 3 lite, which is a subset of the Reach File 3 hydrologic database. The Reach File databases contain data on US surface waters, and are inputs to several large scale hydrologic models. The RF3 lite subset contains streams longer than 10 miles, as well as the small streams needed to connect those (> 10 mile) segments. For additional information, see US EPA (2003c).
[8] For additional information about the 2003 CAFO rule, see http://www.epa.gov/npdes/regulations/cafo_fedrgstr.pdf and for the water quality benefits estimation in particular, http://cfpub.epa.gov/npdes/docs.cfm?view=allprog&program_id=7&sort=name#cafofinalrule_nationaleconbenefits_2003.

functions are directly from US EPA (2003), and appear in Table 2. Figure 2- Figure 5 contain graphs of the baseline distribution of national water quality for each WQI variation. The graphs exhibit considerably different pictures of water quality, illustrating the importance of the aggregation function to the WQI. For instance, the distributions of the harmonic mean (Figure 4) and minimum index (Figure 5) in portray a much bleaker state than the arithmetic and geometric WQI variations. The forecast of the change in water quality is also heavily influenced by the aggregation function. Table 3 contains summary statistics on the change in WQI from baseline to policy forecast for each WQI variation. The harmonic mean, which is designed to be most sensitive to the lowest parameter, shows the greatest change, while the arithmetic WQI shows a smaller change that is more concentrated around zero.

The next step in the analysis is the monetization of the WQI changes. Following the CAFO RIA, the projected change in water quality is valued for each state using the following benefit transfer function from Carson and Mitchell (1993).[9] [10] [11]

$$\begin{aligned}\Delta TOTWTP = &\exp[0.8341 + 0.819 * \log(WQI_1/10) + 0.959 * \log(Y)] \\ &- \exp[0.8341 + 0.819 * \log(WQI_0/10) + 0.959 * \log(Y)]\end{aligned} \tag{6}$$

Where WQI_1 is final WQI, WQI_0 is baseline WQI, and Y is statewide annual household income.[12] The state values are aggregated to obtain the national estimate of benefits.

Table 4 contains the total estimated benefits of the CAFO rule for each WQI variation. These benefits vary from a low of $82 million for the arithmetic WQI to a high of $504 million for the harmonic WQI, exhibiting a six-fold difference. The geometric mean actually has the

[9] As in the CAFO RIA, the WQI for each state is calculated by weighting each reach by its length as a proportion of the total reach miles in the state.
[10] More recent RIA's use meta analyses to monetize benefits, instead of Carson and Mitchell (1993).
[11] Note that the Carson and Mitchell (1993) equation has two extra terms, W_r and A_e, which are dummy variables that indicate respondent recreational activities and attitudes about pollution. Following Mitchell and Carson (1993), the CAFO rule inserted mean values for these variables, and they are subsumed into the 0.8341 constant term.
[12] The approach follows the CAFO analysis, with figures inflated to 2001 dollars using the CPI.

second-smallest estimated benefits, although the ordinal relationships in magnitudes might not hold in different places on the marginal benefit curve. Although only the geometric mean was considered in the CAFO RIA, these results indicate that the aggregation function has a surprisingly large impact on estimated benefits, which could have a large impact on policy recommendations arising from the benefit-cost analysis. Although previous papers have shown differences in the calculated WQI values as a result of the aggregation function, this paper is the first to estimate the impact on estimated benefits.

Sensitivity Exercise

To further investigate the four aggregation methods, a hypothetical sensitivity analysis is performed on the Ohio water quality data from the CAFO Rule. Ohio is used because the state has relatively good monitoring data covering the majority of waterbodies in the state.[13] Concentrating on one state should isolate subindex aggregation issues from other concerns with population, income, and heterogeneity in water quality monitoring.

A hypothetical water quality improvement is instituted in all waterbodies in the state to gauge the impact on estimated benefits for the four versions of WQI. Two different changes are analyzed for each water quality variable: a five percent increase and a five point increase in the subindex value.[14] The change in WQI is then monetized using the benefit transfer function from equation (6).

Figure 6 shows the change in benefits from increasing each variable by five points. The graph is dominated by the improvement in fecal coliform, valued at a maximum of over $160

[13] Furthermore, the state has a diverse set of waterbodies. "Ohio is a water-rich state with more than 25,000 miles of streams and rivers, a 451 mile border on the Ohio River, more than 5,000 lakes, ponds, and reservoirs (>1 acre), and 236 miles of Lake Erie shoreline. Ohio has 10 scenic rivers comprising more than 629 river miles, the fourth largest total of any state in the nation," from http://www.epa.ohio.gov/dsw/general.aspx.

[14] Each variable is increased individually, not compounded on top of the changes in other variables. Other changes in magnitude were also analyzed. However, the results were qualitatively similar to the 5% and 5 point changes, so are not presented.

million using the harmonic WQI. The exaggerated benefits of fecal coliform occur because it is the most impaired indicator in most waterbodies, with an average subindex value of around two (out of 100). A five point jump is therefore a comparatively large improvement. Since the harmonic mean was designed to better account for the lowest value indicator, it is expected to value this change highly. The eclipsing problem can also be seen in this Figure with the arithmetic function. While the geometric, harmonic, and minimum WQI's experience a large jump in Figure 6, the arithmetic response is much more muted. Note that the geometric WQI does not appear to be particularly susceptible to eclipsing in this graph.

The more realistic five percent changes appear in Figure 7. The harmonic and minimum WQI are still quite sensitive to the improvement in FEC, and the arithmetic WQI still exhibits eclipsing. However, the minimum and harmonic WQI's do not appear to be particularly responsive to improvements in variables other than FEC. For example, since there were no reaches with nitrogen and phosphorous as the most impaired variable, the minimum WQI assigns their improvement a value of zero. This is an unattractive quality for benefit cost analysis, since efforts to reduce nutrient pollution would not be represented by corresponding increases in the WQI.

Not only does the arithmetic mean WQI eclipse the change in FEC, it places a much larger value on the change in DO. Figure 8 contains a graph of the distribution of DO subindex values in Ohio. The DO variable has the most right-skewed distribution of all indicators in the data, with most reaches containing subindex values above 90. This highlights a particularly undesirable property of the arithmetic function; the level of the subindex value matters. This issue is further magnified for DO, since its subindex value is assigned the highest weight (Table 2), at 0.24.

The geometric WQI is the one function that does not suffer from either of the eclipsing problems in Figure 7. In fact, the ordering of the benefit values in the Figure aligns exactly with the parameter weights from Table 2. DO has the highest weight (0.24), so increases in it produce the greatest benefits—although only slightly higher than FEC (with a weight of 0.23). So if the goal is to have a WQI that most accurately represents the parameter weights, whereby improvements in parameters that are deemed most important for waterbody health yield higher benefits, then the geometric WQI best satisfies that goal.

V. Conclusion

The WQI has become a central part of many EPA RIAs and is also widely used by environmental agencies in other countries (Nagels et al., 2001; Khan et al., 2003; Liou et al., 2004). However, the specification of the WQI and its impact on policy analysis has previously received scant attention. The present paper analyzes an important step in WQI construction, where several water quality variables are standardized and then aggregated into an overall value. Several recent studies (Dojlido et al., 1994; Cude, 2001) have criticized the use of the geometric mean—which is currently used in EPA RIAs—as the aggregation function. Although other papers have previously compared the properties of different aggregation functions, this is the first paper to analyze the problem in the context of benefit-cost analysis.

Four aggregation functions were analyzed, which were selected because they have been used or supported in regulatory analysis for national or state entities. They include the arithmetic, geometric, and harmonic means, as well as the minimum operator. Data from the EPA CAFO Rule (US EPA, 2003) was used to estimate the benefits of a proposed water quality change for all four WQI variations. Additionally, two hypothetical changes in water quality were instituted to further examine the behavior of the four aggregation functions.

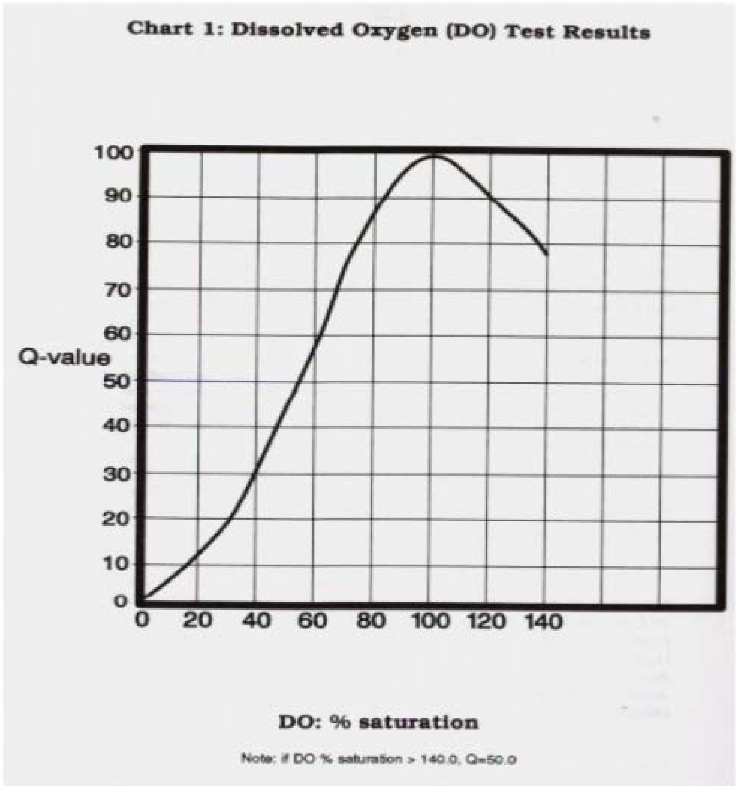
From the CAFO data, it is clear that estimated benefits are quite sensitive to the subindex aggregation function. Over the four different functions, benefits range from $82 million to $504 million. The geometric mean, which is used in EPA RIAs, sits near the middle of that range at $287 million. Although these monetized benefits need to be added to other monetized benefits, such as the value of reduced nitrification of private wells ($30.9 – $45.7 million), reduced public water treatment costs ($1.1 - $1.7 million), and reduced livestock mortality ($5.3 million), they represent the lion’s share of monetized benefits. Since the total social costs of the rule were estimated to be $335 million (US EPA, 2003b), the choice of the aggregation function could move the rule from positive monetized net benefits to negative. Policy recommendations from the benefit-cost analysis could vary drastically depending on the aggregation function used.

The sensitivity analysis did not support a switch from the geometric mean. With the geometric WQI, the importance of individual parameters to estimated benefits is a good reflection of the weights provided by a panel of hydrology experts. Also, the geometric mean does not inflate high valued indicators or eclipse the most impaired indicator as much as the other aggregation functions. The harmonic and minimum functions were found to be extremely sensitive to the most impaired variable, while the arithmetic mean was subject to eclipsing and is dependent on the level of water quality..

Although this paper does not support a move from the geometric mean, the results highlight another pressing issue: an updating of the WQI weights and subindex curves. The weights had a relatively strong influence on estimated benefits in the sensitivity analysis. Since the weights presently used by the EPA are based on a survey from the 1970’s (McClelland, 1974); an update may be in order. The biology, ecology, and limnology underlying water quality analysis have all improved in the last 40 years and expert opinion has likely evolved as well. Furthermore, most state and national water quality criteria have become more refined to different uses and there are now additional criteria for different pollutants.[15] Some of the criticism of the current WQI may be assuaged by developing new weights and subindex curves. A regional approach to the subindex curves, popularized by Cude (2001), represents a promising future path. That approach has already been used in the Construction and Development (2009) and Florida Numeric Nutrients (2010) rules, and has been met with widespread approval.

[15] It may also be desirable to convene a more diverse set of experts for a Delphi survey, since the previous panel represented in Table 1 is heavily influenced by regulatory officials.

Figure 1: Subindex Curve for DO



Source: (US EPA, 2003)

Figure 2: National Arithmetic WQI (n=577,068)

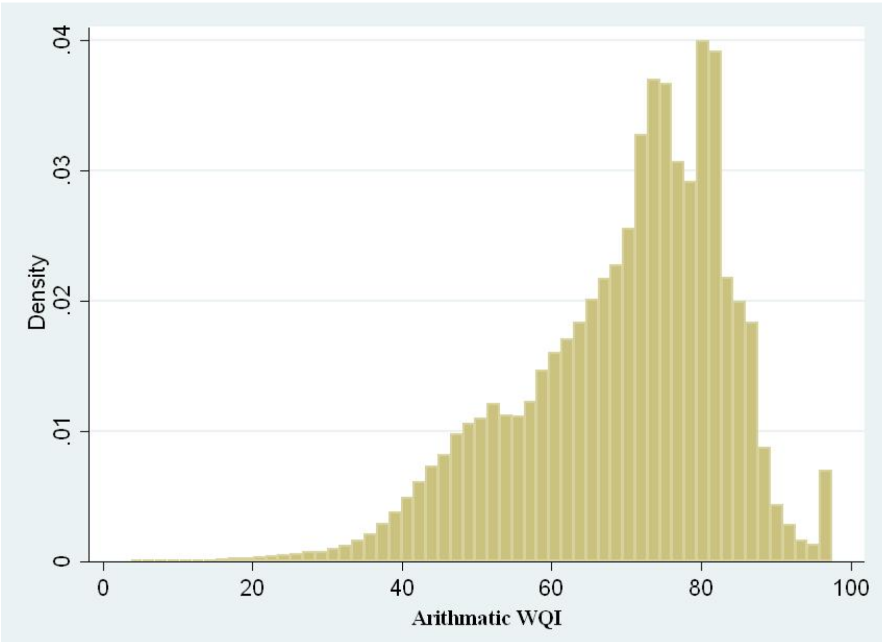


Figure 3: National Geometric WQI (n=577,068)

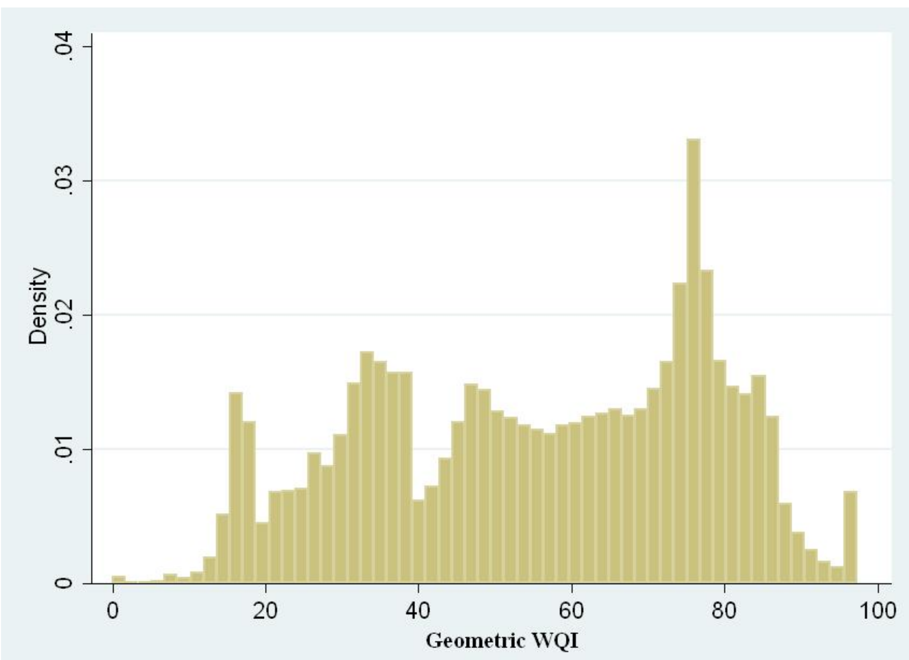


Figure 4: National Harmonic WQI (n=577,068)

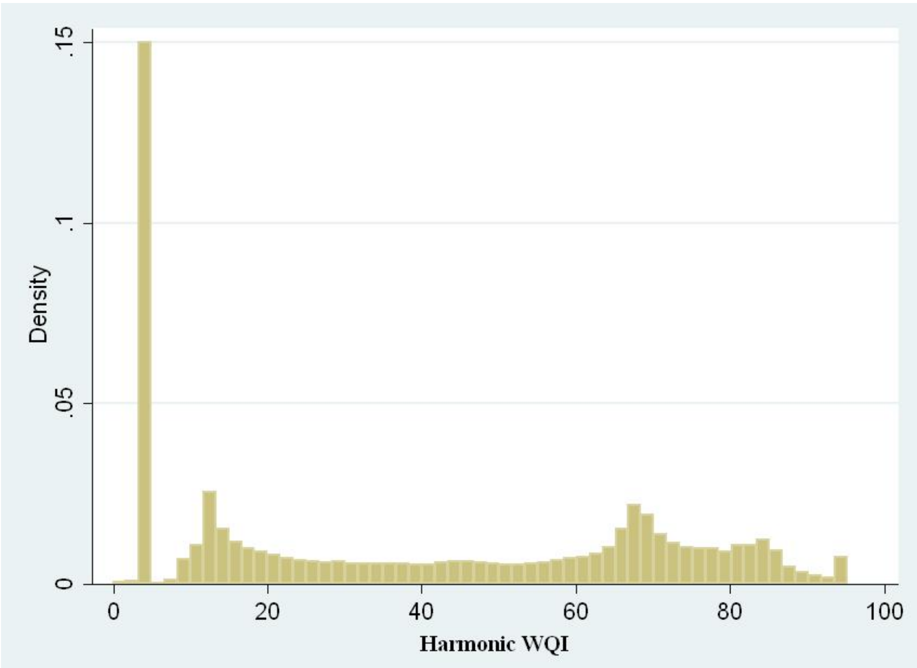


Figure 5: National Minimum WQI (n=577,068)

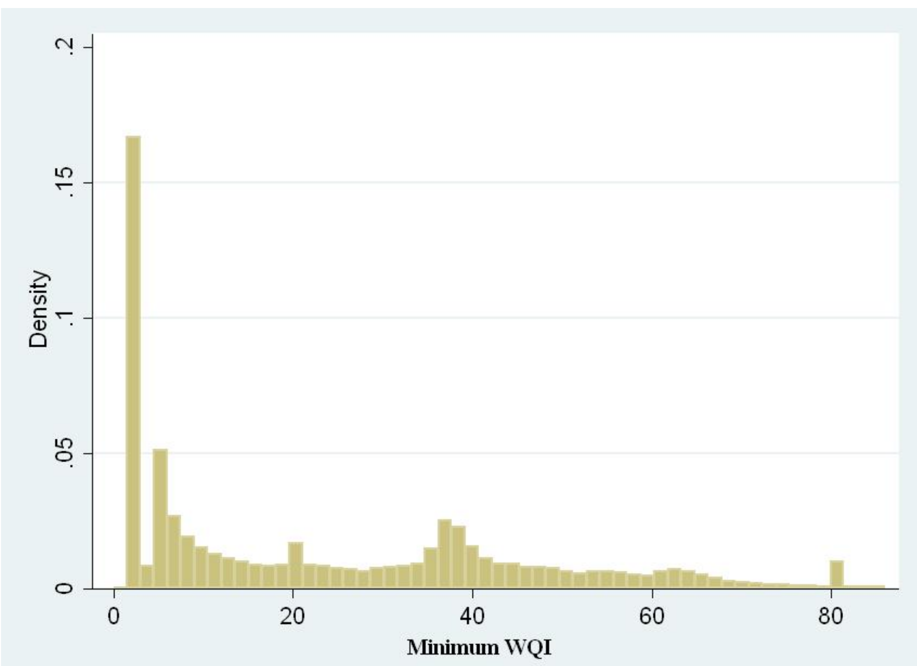


Figure 6: Five Point Increase in Each Variable

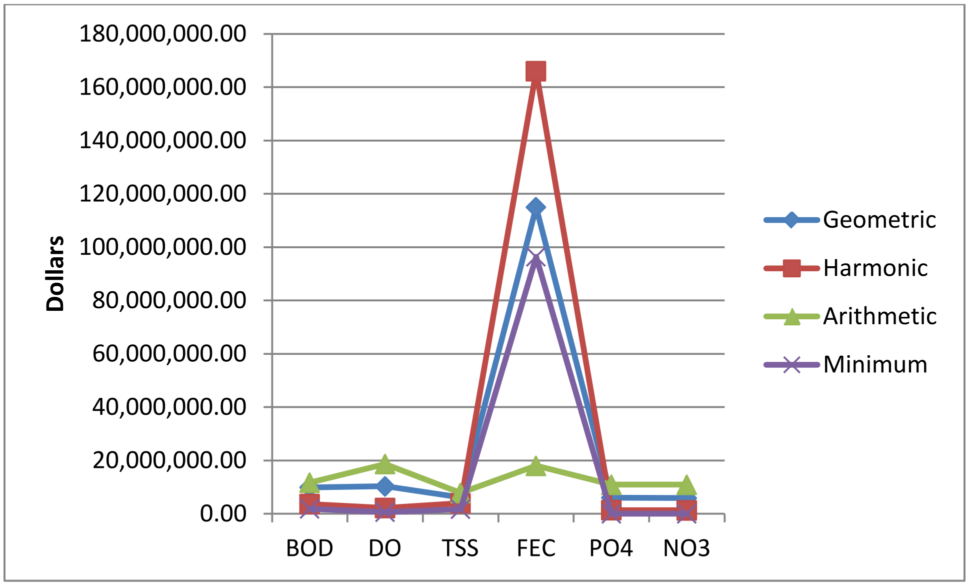


Figure 7: Five Percent Increase in Each Variable

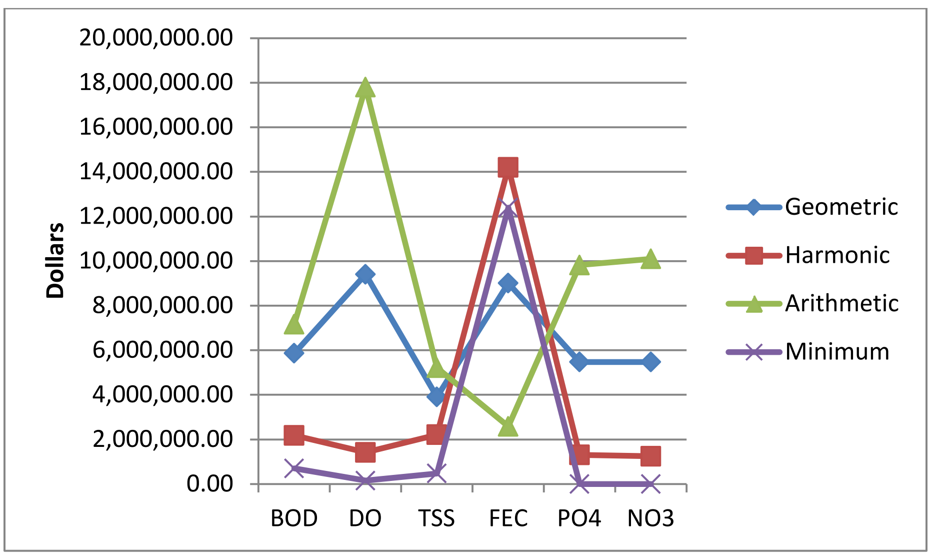


Figure 8: Ohio DO Subindex Value Distribution

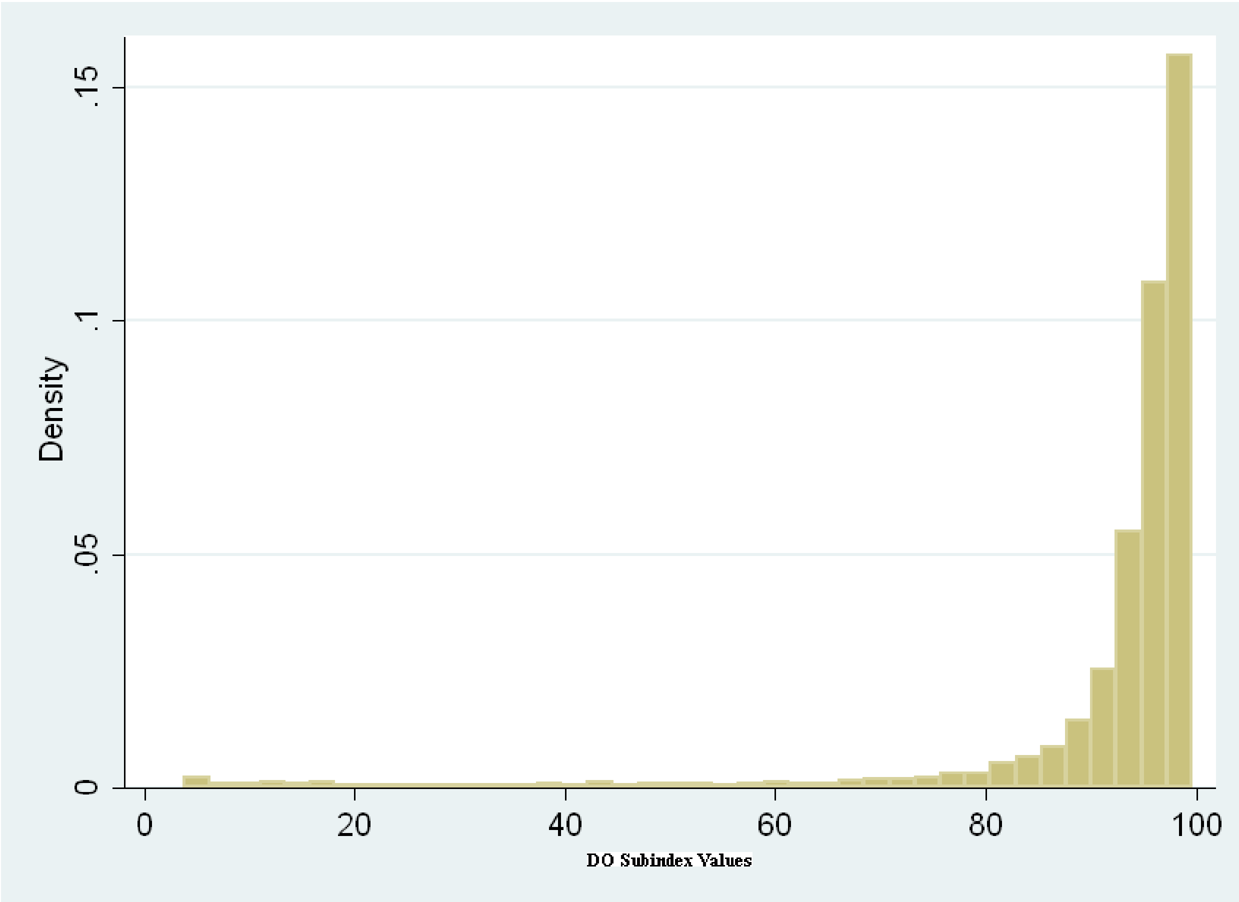


Table 1: Professional Fields of Invited Panelists for NSF WQI

Regulatory officials (federal, interstate, state, territorial and regional)	101
Local public utilities managers	5
Consulting engineers	6
Academicians	26
Others (industrial waste control engineers and representatives of professional organizations)	4
Total	142

Source: (Brown et al., 1970)

Table 2: Summary of Aggregation Functions

Aggregation Function	Formula	Notes
Arithmetic mean	$WQI_A = \sum_{i=1}^{n} q_i w_i$	$\sum_{i=1}^{n} w_i = 1$
Geometric mean	$WQI_G = \prod_{i=1}^{n} q_i^{w_i}$	q_i is the 0-100 subindex rating for each variable.
Harmonic mean	$WQI_H = \sqrt{\frac{n}{\sum_{i=1}^{n} 1/q_i}}$	n is the number of subindices aggregated.
Minimum operator	$WQI_M = \min(q_1, q_2, \ldots, q_n)$	

Table 3: WQI Weights

Parameter	Weight
BOD	0.15
DO	0.24
FEC	0.23
TSS	0.1
NO_3	0.14
PO_4	0.14

Table 4: Policy Forecast for Change in WQI

WQI	Mean	Std. Dev.	Min	Max
Geometric	0.2983	1.4793	-46.4499	52.0442
Harmonic	0.4577	2.5227	-75.0607	77.2153
Arithmetic	0.1004	0.5325	-25.8412	23.2690
Minimum	0.3072	1.9282	-69.1100	65.9200

(n=577,068)

Table 5: National Benefits

WQI	Benefits
Geometric	$287,400,162.45
Harmonic	$503,741,769.09
Arithmetic	$81,913,882.61
Minimum	$358,633,241.42

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