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Summarizing Stream Water Quality in Western North Carolina Using Biotic Indices

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Abstract

Various biotic indices are used as indicators in order to evaluate water quality. Impaired waters are waters in which quality samples for a defined parameter of that water body exceed water quality standards. The state of North Carolina uses two indices in their benthic macroinvertebrate water quality assessments: the biotic index (BI) and the Ephemeroptera Plecoptera Trichoptera (EPT) index. The state of North Carolina only samples a given location once every two years. Therefore, it may have problems such as missing impaired sites or sampling a site on an atypical day. A volunteer benthic macroinvertebrate water sampling program, the Stream Monitoring Information Exchange (SMIE) samples more sites more frequently than the state. Because the state data and the SMIE data have some sampling sites in common, the main hypothesis of this study is to examine if combining the state data with the SMIE data would improve estimates of average biotic indices in western NC relative to estimates using only the state data. Using generalized linear models in SAS, trends and other factors that affect water quality are examined using the biotic indices of BI and EPT. Including factors such as site identification, sampling (state or SMIE), and year, it is found that incorporating the more frequently sampled SMIE data with the state analyses provides more precise results than the state data alone in order to summarize water quality in western NC.

1. Introduction

Judging surface water quality can be imprecise if there is infrequent sampling. The state of North Carolina's Division of Water Quality (DWQ) uses benthic macroinvertebrates, primarily aquatic insects, to indicate the biological integrity of North Carolina's streams, rivers, and other water bodies[1]. Benthic macroinvertebrates are advantageous biological monitors because they are found in all aquatic environments, are relatively immobile, and are of a size that makes them easy to collect. Because they are sedentary in nature, benthic macroinvertebrates are ensured to be exposed to pollutants related to local conditions, allowing for the comparison of multiple monitoring sites that are close in proximity. The use of benthic macroinvertebrates has also been shown to be a cost-effective method for monitoring water quality compared to other testing approaches[1].

The state of North Carolina uses two biotic indices in their benthic macroinvertebrate water quality assessments: the biotic index (BI) and the Ephemeroptera Plecoptera Trichoptera (EPT) index. In this study, a "taxa" is a group of one or more populations of an organism or organisms that form a sample unit. The BI for a taxa sample is a measure of the tolerance value of that taxa in regards to pollution. Therefore, a higher BI score indicates that a taxa sample has a higher tolerance to pollution and thus an increased chance of water impairment. Each taxa is assigned a pollution tolerance value and an abundance value. These are the two main factors that are used to equate BI scores. The BI score is calculated using the equation below[1]:

$$Biotic\ Index\ (BI) = \frac{\sum_{i=1}^{n}(TV_i)(K_i)}{N}$$

Where: TV_i is the ith taxa's tolerance value; K_i is the ith taxa's abundance value of either 1,3, or 10; and N is the sum of all of the abundance values.

The Ephemeroptera Plecoptera Trichoptera (EPT) index uses EPT taxa, which are considered the most pollution-sensitive aquatic invertebrates. Ephemeroptera are mayflies, Plecoptera are stoneflies, and Trichoptera are caddisflies[2]. EPT scores are calculated visually by the number of EPT taxa observed. The state considers at least 35 possible EPT taxa, while the Stream Monitoring Information Exchange (SMIE), a volunteer benthic macroinvertebrate water sampling program in Western North Carolina, considers only 19 possible EPT taxa. Because of this, the state should have significantly higher EPT scores. Therefore, adjustments must be applied to the SMIE data in order to compare the EPT scores based on the higher number of EPT taxa that the state considers.

The state's sampling procedure pertinent to this study is called the "Standard Qualitative Method." This technique entails collections from net samples, leaf-pack samples, sand samples, mesh rock samples, and visual collections. The invertebrates are then separated from the samples, preserved in 95% ethanol, and finally assessed using the BI and the EPT indices[1]. This sample collection process has been restricted in budget, causing sampling that takes place as infrequently as once every few years[2].

A Western North Carolina volunteer benthic macroinvertebrate water sampling program, the Stream Monitoring Information Exchange (SMIE), samples more water quality sites at a much more frequent rate than the state sampling[2]. Like the state method, the SMIE sampling method involves group-led collections of kicknets (mesh bags), leaf packs, and visual search methods. The primary habitat for benthic macroinvertebrate collection is called a "riffle." Riffles are defined as areas that are larger than 15 square feet with shallow water (5-40 cm) and a visible current. Samplers are instructed by the group-leader to overturn stones for one minute within a 15 square foot distance upstream of the kicknets. The macroinvertebrates are then collected from the nets, identified, and recorded. The leaf pack collection method instructs samplers to collect a certain volume of leaf material in a leaf pack sample, wash the pack several times, pour it through a kicknet, and then collect the organisms for recording. The visual search method instructs samplers to visually survey "searchable habitats" for organisms to be collected and recorded[2].

With the greater sampling frequency provided by the SMIE, it is possible to use statistical summaries of resulting data to make decisions about the impairment of sites. According to the state, a body of water is impaired/poor if its macroinvertebrates provide an EPT score between 0-10 or a BI score greater than 7. In the past, impaired waters have been statistically evaluated using the EPA's 305(b) guidelines based on parameters that are typically sampled much more than is typical with benthic sampling[3]. These guidelines state that no more than 10% of the samples obtained from a specific water body are allowed to exceed a regulatory standard without being considered impaired.

Using site identifications that are shared by both the state DWQ and the SMIE, it is hypothesized that combining the state and the SMIE data will provide a better estimation of the true water quality of the state's infrequently sampled sites. Specifically in Western North Carolina, this increase in sampling iterations will provide estimates of median BI and EPT index levels that can then be compared to the infrequent state water quality assessment cutoffs in order to predict a more accurate water quality evaluation of these sites.

2. Methodology

The North Carolina State Division of Water Quality and the Stream Monitoring Information Exchange (SMIE) provided the raw data used in this study. The data provided by the state was collected between the years of 2000 and 2012. The data provided by the SMIE was collected between the years of 2005 and 2013. In order to properly assess the data, the raw state and the raw SMIE datasets were combined using only the testing sites that sampled BI and EPT for both the state and the SMIE.

Using the mixed model procedure in SAS (Statistical Analysis System), multiple factors were tested for significance with response variables of BI and EPT. Factors tested included season, year, site identification, and sampling (SMIE or state). Interactive effects from each pair of factors were investigated, but because there were no significant interactive factors, they were dropped from the model.

The combined raw dataset provided BI and EPT score residual plots that had positively skewed distributions for both parameters. In order to make the distributions more symmetric, the natural log (ln) of the BI and EPT scores were taken. The distribution of the residuals for ln(EPT) were negatively skewed; therefore, a value of 10 was added to each EPT score to make the residuals symmetric. The residuals in the ln(BI) and ln(EPT) scores provided a relatively symmetric distribution but had positive kurtosis. In order to adjust for the positive kurtosis of the distributions, a transform was performed on the ln(BI) and ln(EPT) scores.

For both ln(BI) and ln(EPT), mean values were calculated based on sampling (state or SMIE) and were transformed using the following equations where "y*" is our transformed value based off of a power of .5, which was found to work well using trial and error:

For:

$$y^{*} = m - (m - \ln(y))^{p}, for \ \ln(y) < m$$
$$y^{*} = m + (\ln(y) - m)^{p}, for \ \ln(y) \geq m,$$

Table 1. Transform (y*) equation values

Where:

Sample Type	*Variable (y)*	*Mean of the Natural Logged Values (m)*	*Value of p*
State Data	*BI*	*1.3*	*.5*
	EPT + 10	*3.681*	*.5*
SMIE Data	*BI*	*1.328*	*.5*
	EPT + 10	*2.844*	*.5*

After having adjusted for positive kurtosis in the ln(BI) and ln(EPT) residual distributions, the mixed models procedure in SAS was utilized in order to estimate mean transformed (y*) values for both BI and EPT. 95% confidence intervals for these mean values were also calculated. The models took into account site identification as a random effect.

Models were implemented for the state data only, for the SMIE data only, and for the state and SMIE data combined (including an effect for the type of sampling). For the state data only and for the combined data, the fitted model was used to come up with an estimated mean of all possible state samples at the time of the last year for the transformed response, along with 95% confidence intervals. These values were reverse transformed in order to calculate expected lower confidence levels for the medians, estimated medians, and estimated upper confidence levels for the medians for the original data. This is because the mean of the transformed data will be reverse transformed into the medians of the original data, which is assumed to approximately follow the lognormal distribution. This is so that the hypothesis of increased state iterations improving the accuracy of water quality evaluations among sites could be tested using both the state data and the SMIE data, but only be reverse transformed in relation to state standards. Utilizing the state mean cutoff levels, the following reverse transform model was used for both BI and EPT. A power of 2 was utilized because it is the inverse of the previously used power of .5 in the original transform:

For:

$$\widehat{m}(y) = e^{m-(m-y^{*})^{1/p}}, when \ \ y^{*} < m$$
$$\widehat{m}(y) = e^{m+(m-y^{*})^{1/p}}, when \ \ y^{*} \ \geq m$$

Note that in these equations: $\widehat{m}(y)$ denotes the estimated median lower confidence levels, the estimated medians, and the estimated upper confidence levels for the given y (BI or EPT); y^* denotes the mean transform lower confidence levels, the mean transform estimates, and the mean transform upper confidence levels for the given y (BI or EPT); m denotes the mean cutoff values for the state (1.3 for BI, 3.681 for EPT); and p denotes a power of .5 ($1/p = 1/.5 = 2$). For the $\widehat{m}(EPT)$ calculations for lower confidence levels, estimated medians, and estimated upper confidence levels, a value of 10 was subtracted from each $\widehat{m}(EPT)$ value in order to properly reverse transform the estimates due to the previous addition of 10 to each EPT value before taking the log to make the distribution of the residuals of ln(EPT) symmetric.

This reverse transform procedure provides estimated medians with 95% confidence intervals of the combined SMIE and state data. BI and EPT scores were calibrated by adding significant state effects to all of the SMIE scores and then calculating the estimates. The resulting data will more specifically provide estimates of median BI and EPT index levels that would occur with increased state iterations that can be compared to those based only on infrequent state water quality assessments.

3. Results

3.1 Raw Data

Figure 1 represents the BI scores of the raw data from both the SMIE sampling and the state sampling. The red lines designate the cut-offs for water quality ranks based off of the state's criteria. There are cut-offs at 4.05, 4.88, 5.74, and 7. Any state BI score below 4.05 is considered to be representative of "excellent" water quality. Any state BI score between 4.06 and 4.88 is considered to be representative of "good" water quality. Any state BI score between 4.89 and 5.74 is considered to be representative of "good-fair" water quality. Any state BI score between 5.75 and 7 is considered to be representative of "fair" water quality. Any state BI score greater than 7 is considered to be representative of "poor" water quality[1].

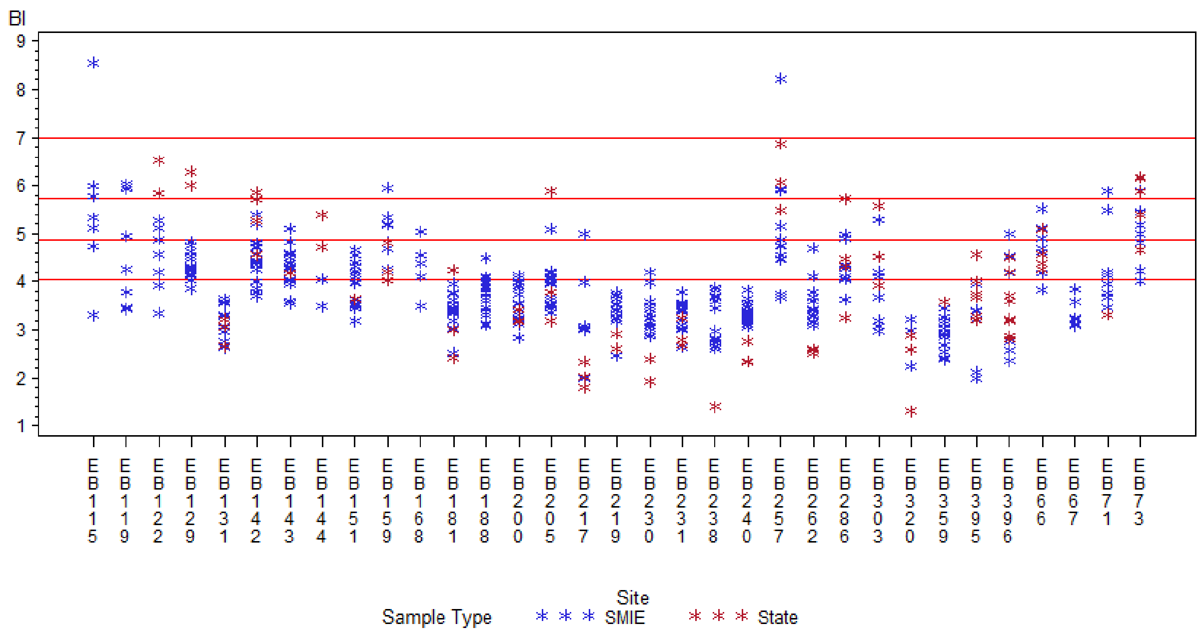

Figure 1. Raw biotic index (BI) scores

Figure 2 represents the EPT scores of the raw data from both the SMIE sampling and the state sampling. The red lines designate the cut-off levels for water quality ranks based off of the state's criteria. There are cut-offs at 10, 18, 27, and 35. Any state EPT score above 35 is considered to be representative of "excellent" water quality. Any state EPT score between 28 and 35 is considered to be representative of "good" water quality. Any state EPT score between 19 and 27 is considered to be representative of "good-fair" water quality. Any state EPT score between 11 and 18 is considered to be representative of "fair" water quality. Any state EPT score between 0 and 10 is considered to be representative of "poor" water quality[1]. Note that the SMIE EPT scores tend to be lower because there are fewer taxa involved, as discussed earlier.

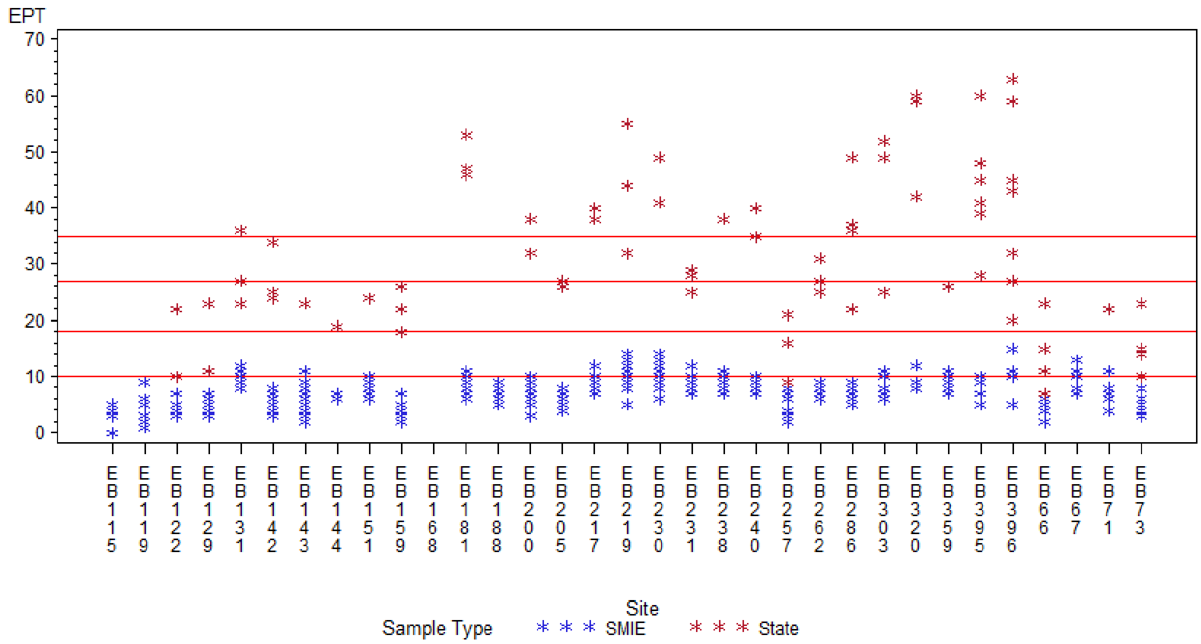

Figure 2. Raw EPT scores

3.2 Transformed Data (y*)

Represented in the table below (Table 2) are the variables from the outputs of the transformed (y*) mixed models procedures run in SAS for the state only transformed BI and transformed EPT, SMIE only transformed BI and transformed EPT, and combined SMIE and state transformed BI and transformed EPT, along with their corresponding coefficients and P-values. A common P-value of .05 is used as a cutoff to show the statistical significance of each variable. Any variable with a P-value less than .05 is considered statistically significant.

Table 2. Mixed model results for transformed (y*) data

Variable	*Coefficient*	*P-value*
State only Transformed BI		
Season		0.1546
Year	-0.03484	0.0159
SMIE only Transformed BI		
Season		< 0.0001
Year	-0.00665	0.2633
SMIE and State Combined Transformed BI		
Sampling		< 0.0001
Year	- 0.00292	0.4913
State only Transformed EPT		
Season		0.2215
Year	0.02408	0.0110
SMIE only Transformed EPT		
Season		0.0002
Year	0.003252	0.5547
SMIE and State Combined Transformed EPT		
Sampling		< 0.0001
Season		0.0004
Year	0.01195	0.0090

For the state only transformed BI mixed model and the state only transformed EPT mixed model, the variable "Year" is the only statistically significant variable. For the SMIE only transformed BI mixed model and the SMIE only transformed EPT mixed model, the variable "Season" is the only statistically significant variable. For the combined SMIE and state transformed BI mixed model, the variable "Sampling" is the only statistically significant variable. For the combined SMIE and state transformed EPT mixed model, the variables "Sampling," "Season," and "Year" are all statistically significant.

3.3 Reverse Transformed Median Outputs

Graphed below are the reverse transformed Median BI and Median EPT scores with their corresponding 95% confidence levels. The state only median BI estimates (Figure 3), the combined SMIE and state median BI estimates (Figure 4), the state only median EPT estimates (Figure 5), and the combined SMIE and state median EPT estimates (Figure 6) are graphed respectively. Boxes were utilized to show the lower 95% median confidence levels for BI or EPT at the bottom of each box, the estimated medians for BI or EPT as the single line within each box, and the upper 95% median confidence levels for BI or EPT at the top of each box. The cut-offs for water quality ranks, as mentioned above, are graphed in red.

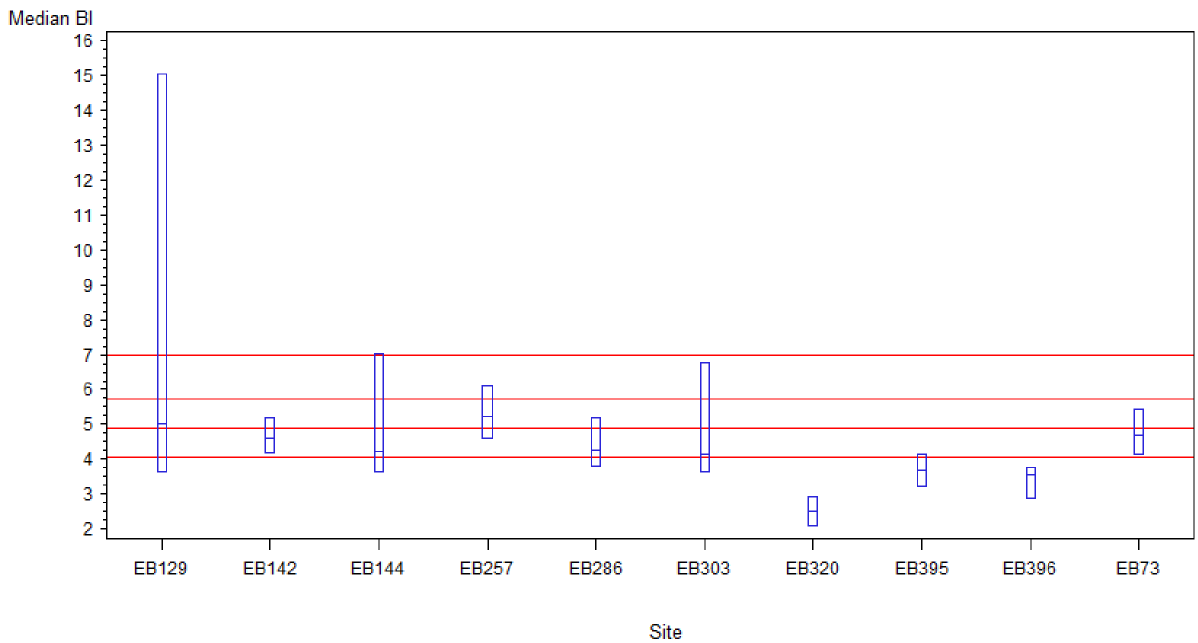

Figure 3. State only estimated median BI scores

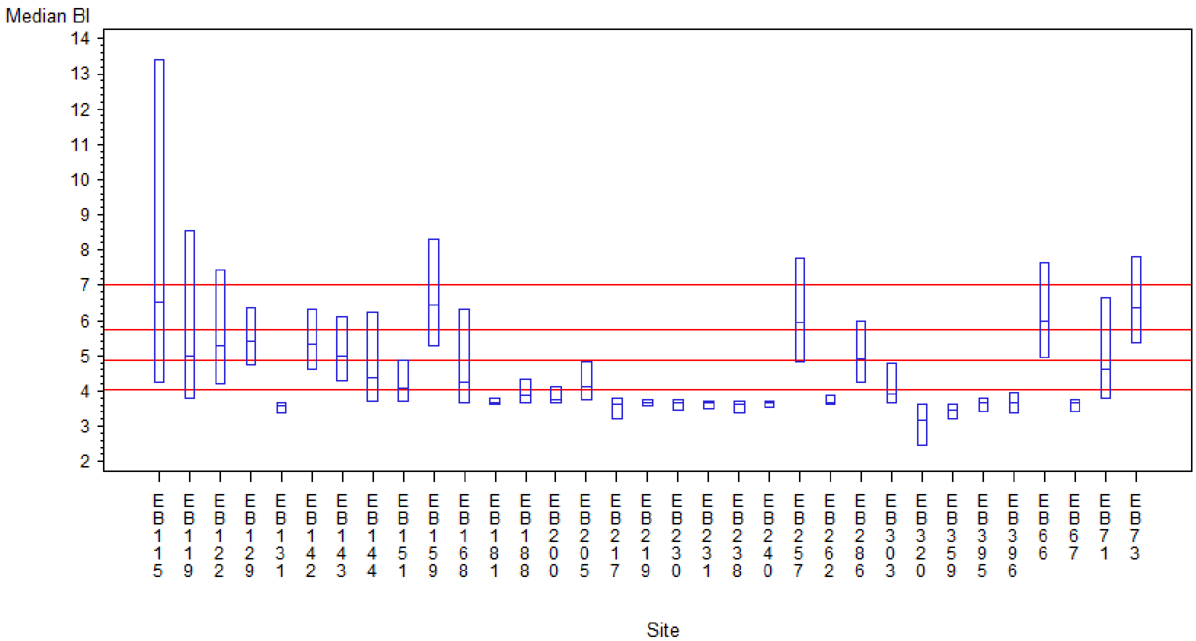

Figure 4. Combined SMIE and state estimated median BI scores

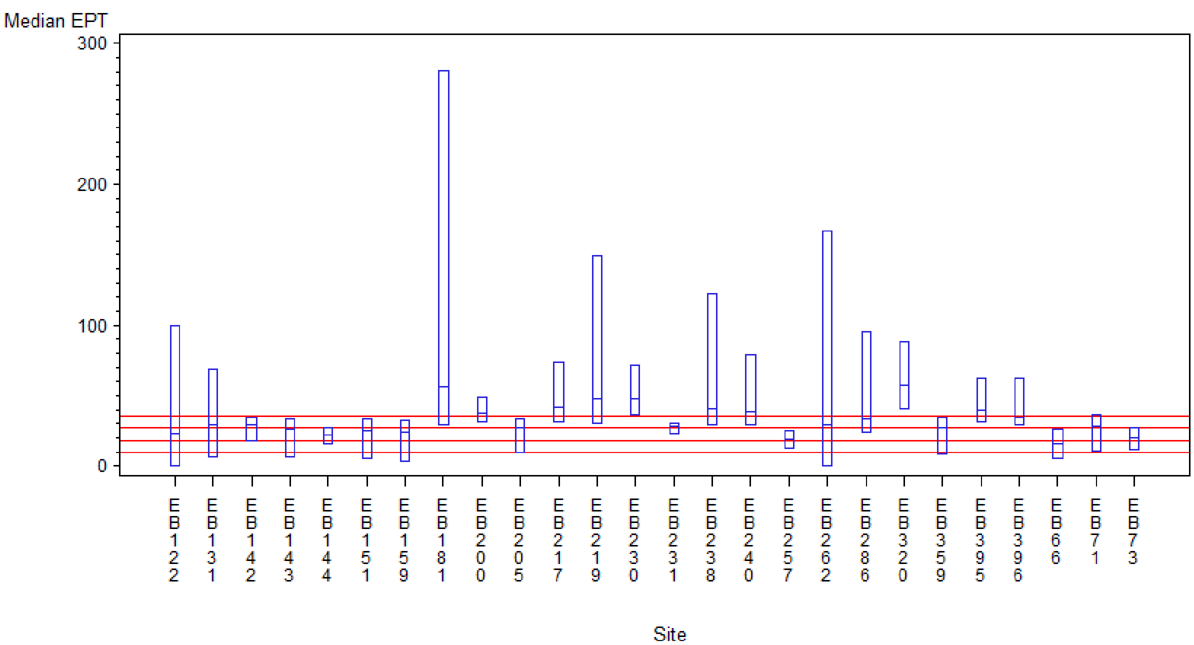

Figure 5. State only estimated median EPT scores

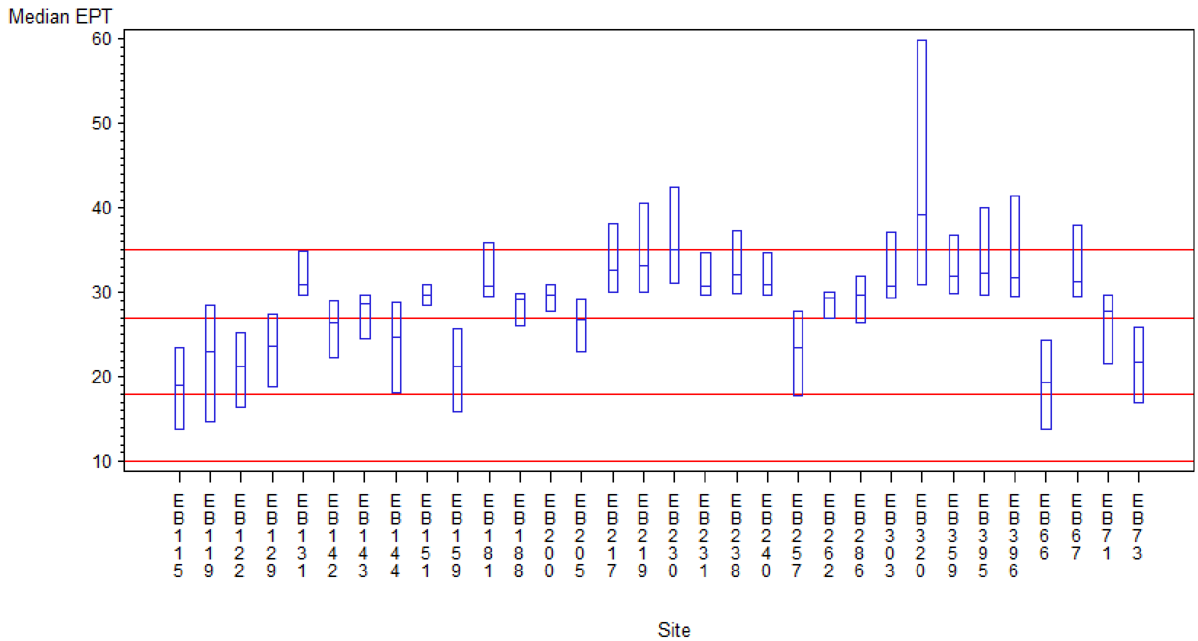

Figure 6. Combined SMIE and state estimated median EPT scores

4. Discussion

4.1 Significance of Variables in Transformed Data (y*)

Because the variable "Year" is statistically significant with a negative estimated coefficient for the state only BI data, this suggests that the BI scores are decreasing over time. However, "Year" is not significant for the SMIE only BI data or the combined SMIE and state BI data.

For the SMIE only transformed BI mixed model, the variable "Season" is the only statistically significant variable. Because the variable "Season-Fall" is statistically significant with a positive estimated coefficient for the SMIE only BI data, this suggests that the BI scores are higher in the Fall than they are in the Spring.

For the combined SMIE and state transformed BI mixed model, the variable "Sampling" is the only statistically significant variable. Because the variable "Sampling-SMIE" is statistically significant with a negative estimated coefficient for the combined SMIE and state BI dataset, this suggests that the BI scores are lower when the sample type is SMIE as opposed to state.

Because the variable "Year" is statistically significant with a positive estimated coefficient for the state only EPT data, this suggests that the EPT scores are increasing over time.

For the SMIE only transformed EPT mixed model, the variable "Season" is the only statistically significant variable. Because the variable "Season-Fall" is statistically significant with a negative estimated coefficient, this suggests that the EPT scores are lower in the Fall than they are in the Spring.

For the combined SMIE and state transformed EPT mixed model, the variables "Sampling," "Season," and "Year" are all statistically significant. Because the variable "Sampling-SMIE" is statistically significant with a negative estimated coefficient, this suggests that the EPT scores for the combined dataset are lower when the sample type is SMIE as opposed to state. Because the variable "Year" is statistically significant with a positive estimated coefficient, this suggests that the EPT scores for the combined dataset increase over time. Because the coefficient for the variable "Season-Fall" is -0.1828, and the coefficient for the variable "Season-Spring" is -0.08599, this suggests that the EPT scores are lower in the Spring than in the Summer, and even lower in the Fall than in the Summer.

The SMIE only datasets strictly compare the seasons of Fall and Spring because the SMIE data was sampled mostly during the Fall and Spring months. The state only datasets use state data which was mostly sampled in the Summer months. This is why the combined dataset for EPT compares the seasons of Fall, Spring, and Summer.

All of the EPT datasets have positive coefficients for the variable "Year," while all BI datasets have negative coefficients for the variable "Year." This suggests that in general over time, EPT scores are increasing and BI scores are decreasing. As previously stated, higher EPT scores indicate better water quality and lower BI scores indicate better water quality. Therefore, this suggests that water quality is improving over time.

4.2 Reverse Transformed Median BI Estimates: Combined SMIE and State vs. State Only

Combining the SMIE BI data with the state BI data results in much greater precision in estimating median water quality values. For example, upper 95% confidence levels for the state only estimated median BI of sites EB129 and EB144 could be used to indicate that it is possible that these sites have "poor" water quality. Since the state sampled fewer sites less frequently than the SMIE sampled, it is expected that the 95% estimated confidence intervals for the medians of the state only dataset will be much wider than that of the combined SMIE and state dataset. This is exemplified in comparing site EB129 in Figure 3 and Figure 4. The range in the confidence interval in Figure 3 for site EB129 is greater than 11, while the range in the confidence interval in Figure 4 for site EB129 is less than 2. No part of the box for site EB129 in Figure 4 indicates "poor" water quality, unlike the upper 95% confidence level in Figure 3. This shows that more frequent sampling, i.e. the combined SMIE and state data in Figure 4, could change the state's water quality assessment of this specific site if the state's assessment also used confidence intervals. More generally, comparing Figure 3 with Figure 4 shows that the state only estimated medians for BI scores is in fact changed when combined with the SMIE data.

4.3 Reverse Transformed Median EPT Estimates: Combined SMIE and State vs. State Only

Combining the SMIE EPT data with the state EPT data also results in much greater precision in estimating median water quality values. All estimated median lines indicate water quality ranks of "good-fair," "good," or "excellent" at all sites, except at site EB66 which indicates "fair" water quality. As stated before, since the state sampled fewer sites less frequently than the SMIE, Figure 5 has much wider 95% confidence intervals for the estimated medians than those in Figure 6. Site EB181 has a range of over 200 within its confidence interval in Figure 5. In Figure 6, site EB181 has a range of about 6 within its confidence interval. Figure 5 also represents site EB181 to have "excellent" water quality everywhere except its lower confidence limit where it ranks as "good." Figure 6 represents site EB181 to have "good" water quality everywhere except its upper confidence limit where it ranks as "excellent." This is further evidence that combining the SMIE data with the state data creates more precise confidence intervals.

5. Conclusion

In summary, it is shown that over time BI scores are decreasing and EPT scores are increasing. This means that over time it appears that water quality is improving. It is also shown that EPT scores seem to be lower in the Fall than in the Spring, while BI scores seem to be higher in the Fall than in the Spring. This means that water quality tends to be worse in the Fall than it is in the Spring. Also, sampling type is shown to be statistically significant in the combined datasets, meaning that SMIE BI and EPT scores differ from state BI and EPT scores. It is important to remember that all EPT and BI scores were calibrated by adding the state effects to all of the SMIE scores and then calculating the estimates of each site. By adding state effects to the SMIE data when constructing these estimates, the procedure does not change the overall median estimate of BI and EPT, but it does change the median estimates at each individual site. Therefore, the higher frequency of sampling contained in the combined SMIE and state datasets does provide tighter confidence intervals and thus more precise estimates of surface/stream water quality at each individual site.

6. References

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