Clark County Long-term Index Site and Salmon Creek Monitoring Projects' Status and Trends Based on Oregon Water Quality Indices

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Introduction

Often there is an interest in local stream's water quality status and whether it is getting better or worse. The purpose of this report is to summarize the latest local streams' water quality and statistically examine data for changes that potentially could signal emerging water quality degradation or improvements. For this analysis the Oregon Water Quality Index (OWQI) was used to help summarize various water quality data.

The OWQI is used as an environmental indicator by the State of Oregon to summarize scientifically based information on the significance of environmental conditions and trends (Cude, 2001, pp. 131-134). The OWQI is used for many applications including: indicating water quality impairment, comparing conditions among reaches of a river or between different watersheds, detecting trends over time, and tracking progress of water quality management practices. The OWQI was developed to provide a simple and concise method for expressing streams' relative water quality for general recreational uses, such as fishing and swimming (Cude, 2001, pp. 125-126). Its use is designed to improve the understanding of water quality issues by integrating complex data and generating water quality status scores that also can be used for trend evaluation.

Background on Statistical Considerations

Statistically, the null hypothesis (H_O) is that there is no trend over time. The outcome of the statistical test is a "decision" to either reject or not reject the null hypothesis. However, failing to reject the null hypothesis does **not** mean that it was "proven" that there is no trend. Rather, it simply means that the evidence available is not sufficient to conclude that there is a trend (Helsel and Hirsch, 1993, pp. 324-325). Similarly, a nonsignificant test result does not mean that there is no trend, but that the null hypothesis of no trend cannot be rejected (at a particular level of significance), and any observed trend could be attributed to chance (New York City Water Protection Program, 2001, Appendix C). The lower the P-value (attained significance level) from a particular statistical test, when compared to a pre-specified alpha (acceptable probability of incorrectly rejecting the H_O when in fact the H_O is true), the more likely the observed trend is not attributable to chance. More generally, the smaller the p-value, the heavier the weight of sample evidence for rejecting the null hypothesis (MiniTab, 2006, Technical Support Document, "Taking the Perplexity out of P-Values").

This report's analysis of monthly data evaluated only approximately 3.5 years which is considerably less than the typical minimum of 5 years of monthly data used for trend analysis (Washington State Department of Ecology, Hallock and Ehinger, 2003, p. 4 and U.S.G.S. Water Resources Investigations Report 91-4040, Schertz et al., 1991, p. 25).

Trend power was also not evaluated in this analysis. A failure to reject the null hypothesis of no trend is often used to improperly conclude that there was no trend (Washington State Department of Ecology, Hallock, 2003, pp. 5 & 11). In reality, there may have simply been insufficient data or too much variance in the data to allow trend detection at the specified level of confidence (1-alpha). Washington State Department of Ecology found that empirically determined minimum detectable trends (MDT) ranged from a low of 2 percent change in the mean over 10 years to a high of 36 percent. Generally, more variable constituents such as fecal coliform bacteria and suspended solids tended to have the greatest MDT, while relatively consistent, normally distributed constituents like oxygen had the lowest MDT. Similar trend power calculations for Clark County's Lacamas Creek data showed that, as percentages of change in means over 5 years of monthly monitoring and assuming Type 1 (alpha) and 2 (beta) error rates of 0.1, predicted MDTs of 10.1%, 36.5%, and 93.0% for Flow, Flow Adjusted Total Phosphorus, and Non-flow Adjusted Total Suspended Solids respectively would be required to detect trends at these error rates (Clark County Water Resources Section, Jeff Schnabel and Bob Hutton, 2004, p.32).

Some common characteristics of water resources data, among others, are that they may contain cycles (for example seasonal cycles) and exhibit serial correlation (Helsel and Hirsch, 1993, pp. 324-325). Both of these could impact the types of and interpretation of statistical analyses. Seasonal variation, a confounding or exogenous effect, must be compensated for or removed in order to better discern or improve the power of statistical tests for trends over time (Helsel and Hirsch, 1993, p. 337). Keeping the number of seasons relatively small, such as the selection of 12 seasons, helps to reduce problems resulting from serial correlations (U.S.G.S. Water Resources Investigations Report 03-4026, Ebbert et al., 2003).

For this report's time trend analysis, no attempt was made to address confounding variables other than seasonality. These confounding or exogenous variables, usually natural random phenomena such as rainfall, temperature, and streamflow could have considerable influence on the water quality response variable (Helsel and Hirsch, 1993, pp. 329-330). The additional background variability or noise created by these exogenous variables may mask the trend signal and reduce the ability or power of the trend test to discern changes in water quality over time.

Nonparametric procedures are well suited to multi-record trend analysis studies (Helsel and Hirsch, 1993, p. 348). Additionally, if a many-station and many-variable trend study is required, without case-by-case checking of assumptions, then nonparametric procedures are often appropriate (Helsel and Hirsch, 1993, p. 329). One potentially applicable robust nonparametric statistical test for trends is the Seasonal Kendall statistic. This statistical test accounts for seasonality by computing the Mann-Kendall test on each of the seasons (e.g. using months where January data is compared only with other January data, etc.) separately then combining the results (Helsel and Hirsch, 1993, pp. 338-339). The Mann-Kendall test generally is a test for whether Y values tend to increase or decrease with time or more typically their central values, such as medians, change over time (Helsel and Hirsch, 1993, pp. 327-328). The test does not assume normality of the data. However, there must be no serial correlation for the resulting p-values to be correct and the spread of the data's distribution (variance) over time must generally remain constant (except for their central location) or addressed through transformations (e.g. log transformations for increasing variance within the data over time). The Mann-Kendall S statistic is computed from Y, T data pairs. The null hypothesis of no change is rejected when S is significantly different from zero and a conclusion of a monotonic (not necessarily linear) trend in Y over time exists. Typically, an estimate of the rate of change over time is desired and tested as the slope coefficient of B1. The nonparametric Theil-Sen rank-based slope estimator is often used to estimate the rate of change but assumes possible trends are linear (Aquatic Informatics Inc., 2006, pp. 48-49). Sen's method, closely related to the Mann-Kendall test, is not greatly affected by data errors or outliers and can be computed when data are missing (Gilbert, 1987, pp. 217-218). Importantly, monotonic trends are considered to be gradual and continuing changes over time (Helsel and Hirsch, 1993, pp. 348-350). This is a different approach than step trends where there are two non-overlapping sets of data such as early and late periods or before and after an event that is likely to have changed water quality. Step trends were determined to not be applicable based on the characteristics of our monitored system.

Methods

This report's analyses are limited to results from locally maintained, dispersed Clark County stream monitoring sites. The data utilized were generated from two long term monitoring projects: Long-term Index Site Project (LISP) and Salmon Creek Monitoring Project (SCMP) (Figures 1 and 2 Maps of LISP and SCMP sites, respectively). The specific field and laboratory procedures used follow standard protocols for attaining high quality data (Clark County Water Resources, Schnabel, 2003, Clark County NPDES Salmon Creek Monitoring Project Quality Assurance Project Plan; and Clark County Water Resources, Schnabel, 2004, Clark County NPDES Long-term Index Site Project Quality Assurance Project Plan). The fifteen sites evaluated in this report were selected to be representative of a wide range of conditions found in Clark County but were not randomly selected for inferences beyond these sites (Table 1 LISP and SCMP station descriptions).

Field methods were held as consistent as possible and certain assumptions were made in order to reduce potential complexities and to realistically limit statistical interpretations possible from the relatively short duration of the monitoring data set. The sampling frequency for both the LISP and SCMP projects was consistently at approximately monthly intervals with no substantial breaks. Additionally, it is assumed that there were no major events (such as dams, diversions, new sources of contamination, or new treatments) that would have suddenly and substantially changed the quality of the monitored water systems. Due to feasibility and the limited time span of the available local data for this initial trend analysis, no attempt was made to statistically address some of the confounding factors, such as the impact of year to year changes in precipitation or streamflow on the trend analysis results.

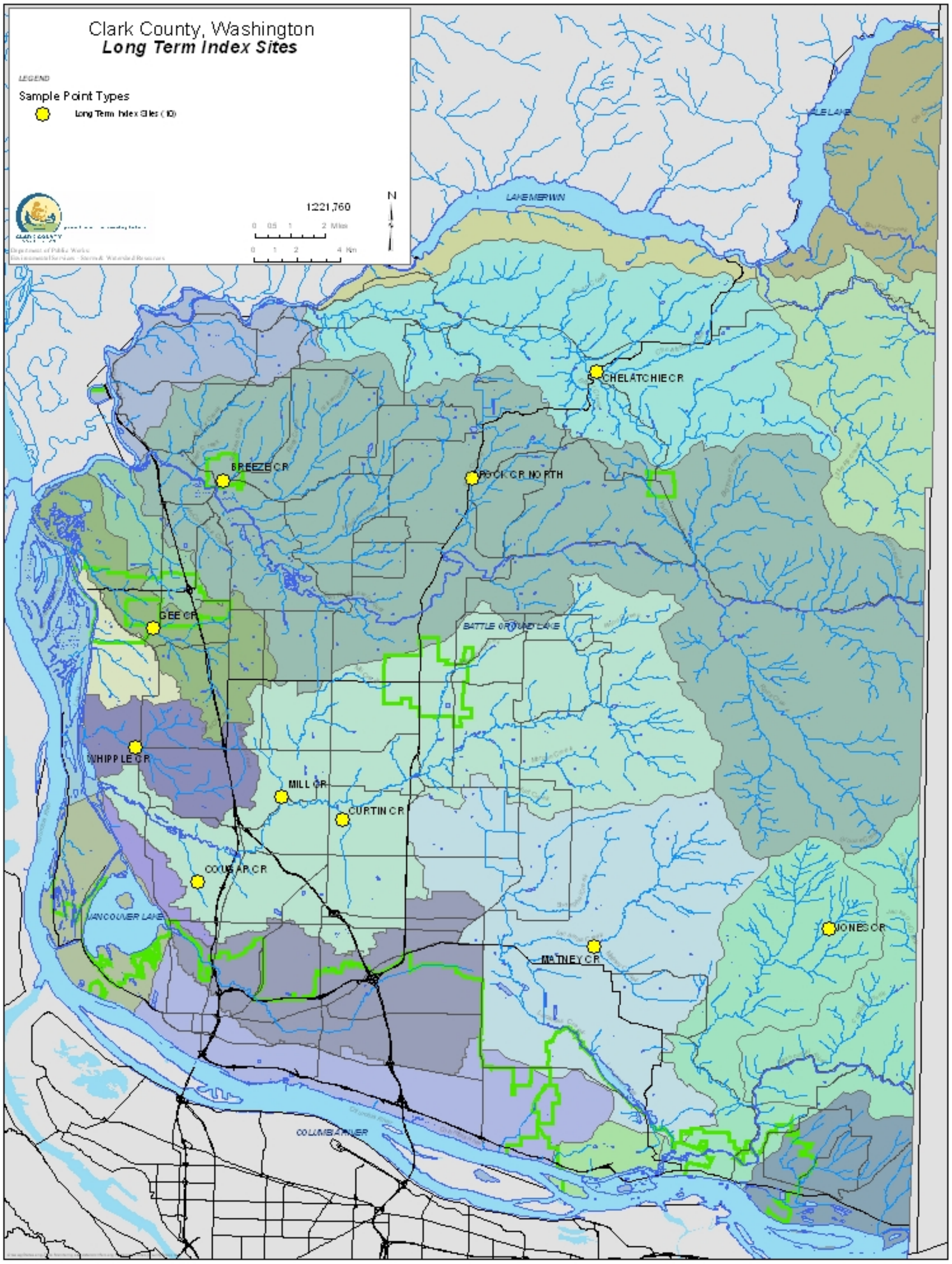


Figure 1. Map of LISP sites (from LISP QAPP).

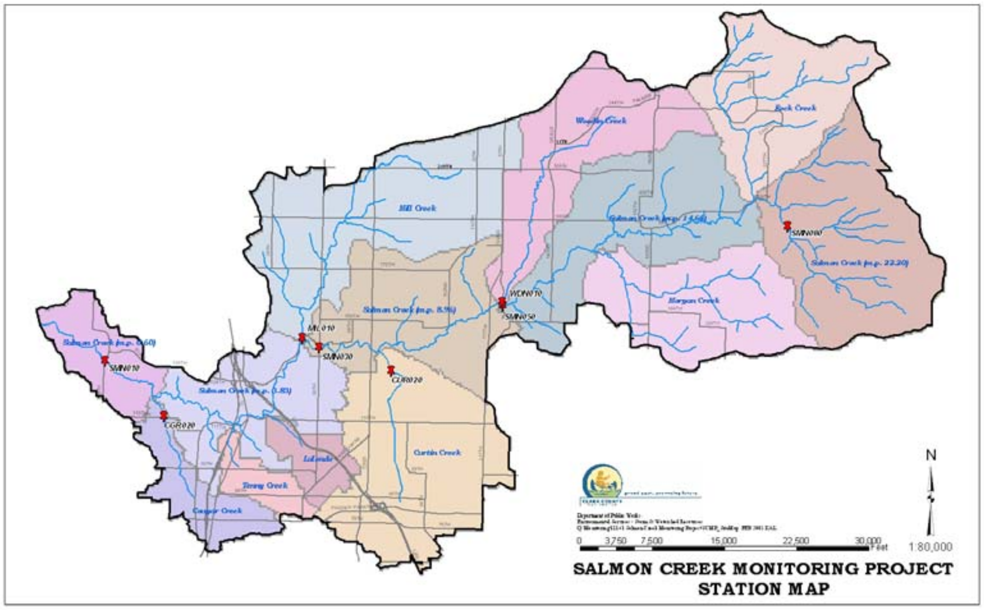


Figure 2. Map of SCMP sites (from SCMP QAPP).

Long Term Monitoring Project	Station Symbol	Station Description
LISP	BRZ010	Brezee Creek upstream of La Center Bottoms trail bridge
LISP (& SCMP)	CGR020	Cougar Creek upstream of NW 119th Street
LISP	CHL010	Chelatchie Creek upstream of State Route 503
LISP (& SCMP)	CUR020	Curtin Creek downstream of NE 139th Street
LISP	GEE050	Gee Creek downstream of Royle Road
LISP	JNS060	Jones Creek upstream of Camas water intake
LISP	MAT010	Matney Creek upstream of NE 68th Street
LISP (& SCMP)	MIL010	Mill Creek upstream of Salmon Creek Avenue
LISP	RCN050	Rock Creek North upstream of Gabriel Road
LISP	WPL050	Whipple Creek upstream of NW 179th Street
SCMP	SMN010	Salmon Creek at NW 36th Avenue
SCMP	SMN030	Salmon Creek at NE 50th Avenue
SCMP	SMN050	Salmon Creek at Caples Road
SCMP	SMN080	Salmon Creek at NE 199th Street
SCMP	WDN010	Woodin Creek at Caples Road

Table 1. LISP and SCMP station descriptions.

This study's response or dependent variable tested for significant trends over time is a slightly modified OWQI, by integrating 7 of its 8 water quality variables, based on monthly subindex scores. The explanatory or independent variable of interest is time and not spatial such as for studying changes related to downstream order of stream sections (Helsel and Hirsch, 1993, pp. 323-327). It is assumed that any potential changes in water quality over time were gradual and continuing as opposed to step changes resulting from a known event impacting water quality.

Monthly LISP and SCMP water quality field and laboratory results were converted/transformed into parameter specific subindex scores and then combined into monthly index values based on the Oregon Water Quality Index (OWQI) technique. This involved an iterative process of editing, sorting, filtering, and applying formulas to fields of data in spreadsheet worksheets with results from one analysis as input for successive sheets (Appendix A: OWQI Spreadsheet Calculation Methods). Monthly water quality values were analyzed using seven of the eight parameter specific OWQI subindex formula (Cude, 2001, pp. 134-136). The variables evaluated included: Temperature, Dissolved Oxygen (both concentrations and saturation), pH, Total Solids, Inorganic Nitrogen (ammonia and nitrate), Total Phosphorus, and Fecal Coliform; but not Biochemical Oxygen Demand. The individual subindex scores for each month were then combined into an overall monthly OWQI value utilizing an unweighted harmonic square mean calculation which allows the most impaired variable to impart the greatest influence on the water quality index (Cude, 2001, p. 130). Since the primary water quality values were already transformed to calculate the OWQI subindex scores no further transformations (e.g. log transformations to achieve equal variance across variables) were utilized because such transformation results would not be compatible with OWQI calculations. Additionally, time series plots of all the parameters did not show any obvious nonlinear trends such as exponential relationships that would suggest a need for transformations.

WQSTAT PLUS, an environmental data statistical software package, was utilized for preparatory data manipulation, evaluating assumptions, computing descriptive statistics, and inferential statistical analyses of the monthly OWQI scores. Inferential statistical analyses involved evaluating the data for serial correlation and trends; both of which can be impacted by the confounding influence of seasonality.

It was assumed that seasonality existed in the original monthly OWQI values based on patterns in the time series plots and previous experience with water quality data analysis. Therefore, prior to statistical testing, the monthly OWQI data were first transformed into an alternative deseasonalized series by subtraction of seasonal means and adding back the overall mean to each observation (Intelligent Decision Technologies, Ltd., 1998, p. 37). Additionally, in order to run the robust nonparametric Seasonal Kendall test within WQSTAT PLUS, a prerequisite is to have at least 4 data points (e.g. 4 years of monthly data) to define seasons (Intelligent Decision Technologies, Ltd., 1992-2003). Since our current data set was shorter than this, an alternative trend analysis approach was utilized within WQSTAT PLUS. Thus it was decided to run the Sen's Slope and Mann Kendall trend test on the deseasonalized (Alt.) OWQI values. This would allow addressing, as best as possible given the very limited duration of Clark County's existing data set (approximately 3.5 years), the confounding effects of seasonality.

An important assumption evaluated was serial correlation or dependence. The presence of serial correlation may increase the chance for false positive test results or incorrectly rejecting the null hypothesis of no trend (Aquatic Informatics Inc., 2006, Appendix on Mann-Kendall and Thiel-Senn Trend Analysis). To address the question of the presence of serial correlation, the Rank von Neumann test for serial correlation was run for each station's data. However, this test will also reflect the presence of trends or cycles, such as seasonality (Intelligent Decision Technologies, Ltd., 1998, p. 69). Therefore, this test was also run on the monthly deaseasonalized data and its results for stations with trends may need to be interpreted with caution.

Results and Discussion

Primary metered and laboratory data from May 2002 through February 2006 was analyzed for this report. This monthly data was derived from Clark County's 10 long term monitoring sites (LISP) and Clark Public Utilities' 5 (SCMP) sites. Note that three of the depicted LISP sites (CGR020, CUR020, and MIL010) technically are also considered SCMP sites but were analyzed and presented here as exclusively LISP sites. These 15 stations' primary data were utilized to calculate site specific OWQI subindex and final scores. The OWQI classification scheme, based on research by Oregon (Cude, 2001, p. 131), interprets scores into the following five qualitative categories: <60 very poor, 60-79 poor, 80-84 fair, 85-89 good, and 90-100 excellent.

Each of the 15 monitored sites' overall water quality was ranked (with 1 being the worst and 15 being the best). Additionally, each was assigned to one of five possible relative quality classes, from very poor to excellent, based on the lower of the two seasonal average OWQI scores (Table 2 Seasonal low flow [summer] and higher flow [fall, winter, and spring] average OWQI values with seasonal minimums in bold [including ties] for the period May 2002 - February 2006).

Station	**CUR 020**	**CGR 020**	**WPL 050**	**GEE 050**	**SMN 010**	**SMN 030**	**BRZ 010**	**MIL 010**
F. W. S. Average	42	55	71	68	79	82	78	79
Summer Average	**31**	**36**	**60**	**63**	**73**	**73**	**75**	**75**
Site Rank	1	2	3	4	5.5	5.5	7.5	7.5
Quality	Very Poor	Very Poor	Poor	Poor	Poor	Poor	Poor	Poor
Station	**WDN 010**	**RCN 050**	**MAT 010**	**SMN 050**	**CHL 010**	**SMN 080**	**JNS 060**	
F. W. S. Average	81	**79**	**85**	**86**	**87**	**92**	**95**	
Summer Average	**77**	88	88	**86**	88	94	**95**	
Site Rank	9	10	11	12	13	14	15	
Quality	Poor	Poor	Good	Good	Good	Excellent	Excellent	

Table 2. Seasonal low flow (summer) and higher flow (fall, winter, and spring) average OWQI values with seasonal minimums in bold (including ties) for the period May 2002 - February 2006.

The pattern of these overall OWQI scores reflects relative location, general land use or land cover, and seasonal impacts on water quality. The two very poor sites are located in urbanizing to established urbanized areas where polluted runoff may reduce scores. Curtin Creek's very poor rating appears to be driven especially by its groundwater derived high inorganic nitrogen values. The poor sites generally are found in suburban to rural residential areas where both development and hobby to commercial farm impacts occur. The good sites are found in more rural areas where more protective forest cover exists. The two excellent sites are closer to headwater areas in the foothills of the Cascades with very little development and generally the most forest cover. Interestingly, no monitoring sites fell into the fair (80-84) class of OWQI scores. This relative dichotomy of the sites' very poor to poor versus the good to excellent classes may partly result from the overall differences in the watersheds' general land use patterns. Additionally, the overall pattern of the stations' seasonal minimums (bold scores in Table 2) suggests issues associated with relative flow levels and/or temperature may be consistently impacting water quality. More specifically, the lowest nine ranked stations, from very poor to poor, had the lower of their two seasonal average OWQI scores during the low flow summers. Whereas, the five higher ranked stations, from good to excellent, had the lower or ties of their seasonal minimums during the wetter and cooler fall, winter, spring defined season. Also, the relative differences between each station's summer versus fall, winter, spring averages generally diminishes from the worst to the best ranked stations. This would imply stronger seasonal impacts on the water quality variability of the lower ranked sites and more consistency in seasonal water quality for the higher ranked sites.

Box and whisker plots, graphically summarizing descriptive statistics, depict how the central tendencies and dispersion of the monthly deseasonalized OWQI values varied across the monitoring stations (Figures 3 and 4 Box and Whisker plots of LISP and SCMP sites' deseasonalized monthly OWQI values, respectively). These box and whisker plots present site statistics utilizing: the ends of the boxes as interquartile ranges (IQRs or 25th through 75th percentiles), the horizontal centerlines as the medians, the plus signs as means, and whiskers extending from the box ends to the minimums or maximums (Intelligent Decision Technologies, Ltd., 1998, p. 67). In more symmetric distributions the medians and means may overlap. In very asymmetric distributions, the mean is “pulled” away from the median and toward the longer whisker. Note, for this report, that the range of values depicted on some graphs’ y-axes differs from the original OWQI range because the data have been deseasonalized to reduce its confounding effect. Therefore, the y-axes should be considered as relative scales.

Patterns found in the box and whisker plots of the monthly deseasonalized OWQI scores are similar to the briefer findings presented in the above rankings. Curtin and Cougar Creeks had the lowest median OWQI values and the largest IQR, reflecting their poor and variable water quality. In fact, even though their IQRs were much wider, they still were much lower than and did not overlap with any other sites. The extent of Curtin and Cougar Creeks’ vertical whiskers were symmetric indicating a fairly balanced distribution of their more extreme high and low OWQI scores. The second worst water quality group of sites, with many OWQI scores in the 60’s, was for Gee and Whipple Creeks. These two stations had very similar patterns for their medians, IQRs, and the extent of their asymmetric whiskers. All of which probably indicate their somewhat parallel water quality. Conversely, Jones Creek and Salmon Creek at NE 199th Street (SMN080) had the highest median OWQI values and narrower IQRs than any other sites. This reflects the higher central tendency of their water quality. Interestingly, SMN080’s very long lower whisker indicates some very low OWQI scores yet it is still the second highest ranked site. The central tendency and especially the distribution of OWQI values for Chelatchie and Matney Creeks were the next highest and most similar to Jones Creek’s very good water quality. Mill and Woodin Creeks’ central tendencies and distributions were fairly similar but with Woodin having some lower OWQI values. Although Rock Creek North and Brezee Creeks had similar medians, Brezee had a wider IQR and asymmetric whiskers with a shorter upper and longer lower whisker indicating lesser high values and lower lows. This is reflected in Brezee Creek’s slightly lower ranking above. In general, the main stem Salmon Creek sites’ (SMN010, SMN030, SMN050, and SMN080) OWQI medians gradually improved and their IQRs typically narrowed depicting improved water quality with increasing distance upstream. This general pattern of improving upstream OWQIs may result from less adverse land use impacts, improving riparian shading, and elevation benefited water temperatures. However, all of the main stem Salmon Creek sites were somewhat asymmetric with more relatively extreme low than high OWQI scores possibly due to low flow impacts on water quality. In fact, the most upstream site, SMN080 had the lowest main stem Salmon Creek OWQI score.

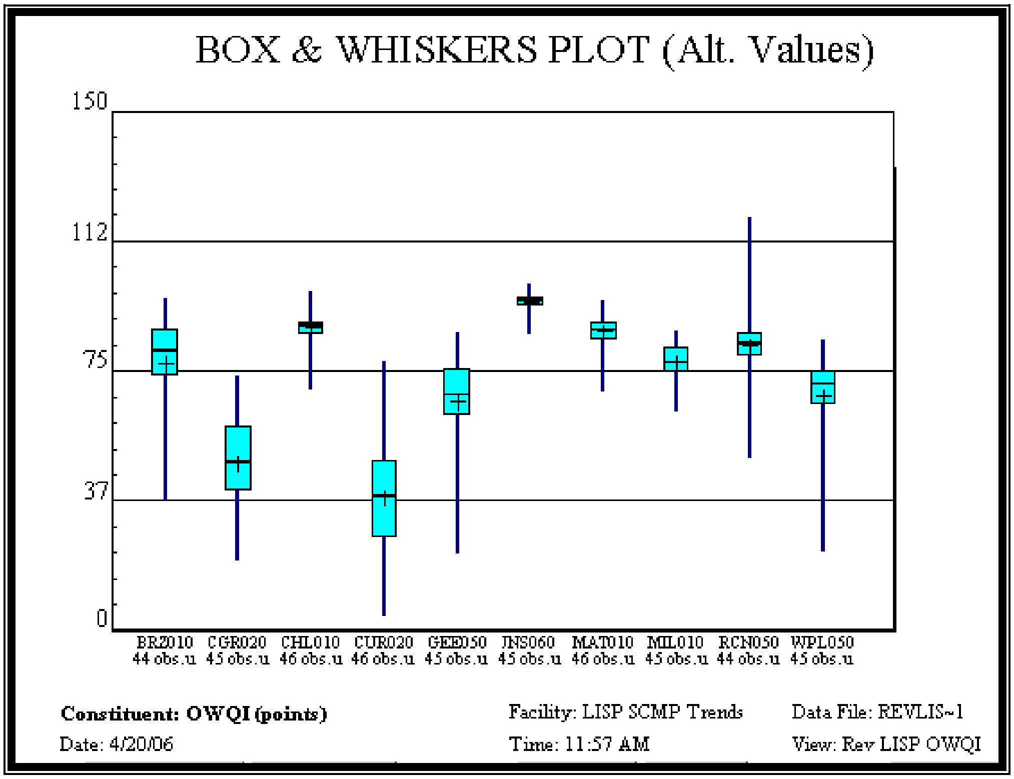


Figure 3. Box and whisker plot of LISP deseasonalized monthly OWQI values.

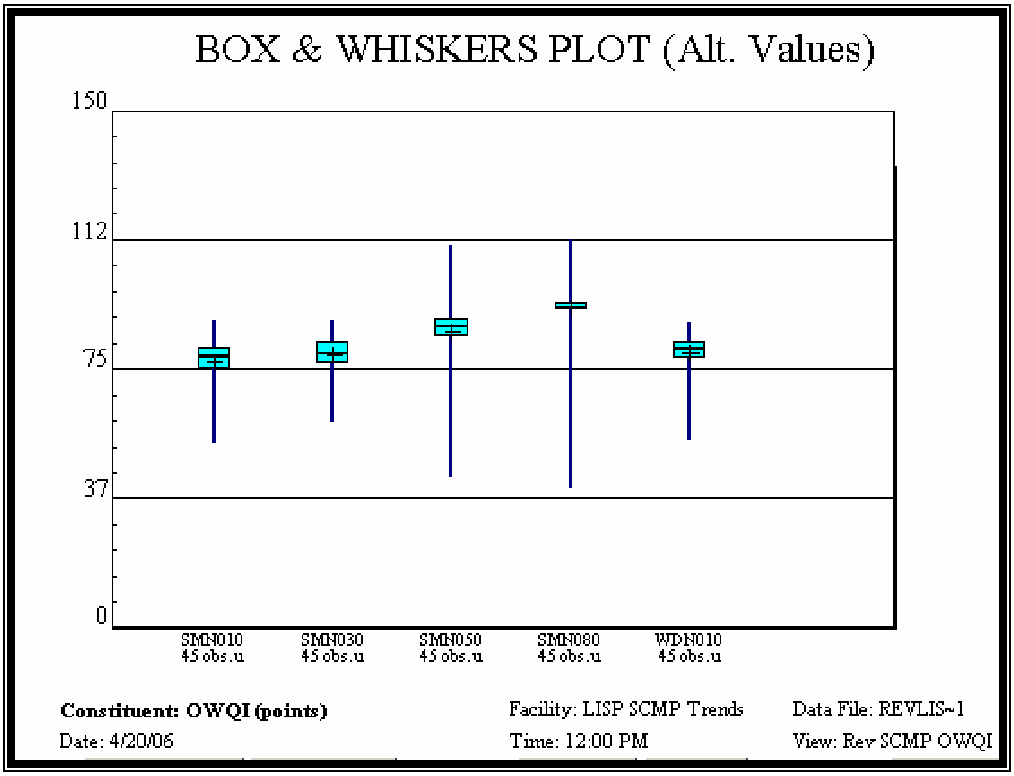


Figure 4. Box and whisker plot of SCMP deseasonalized monthly OWQI values.

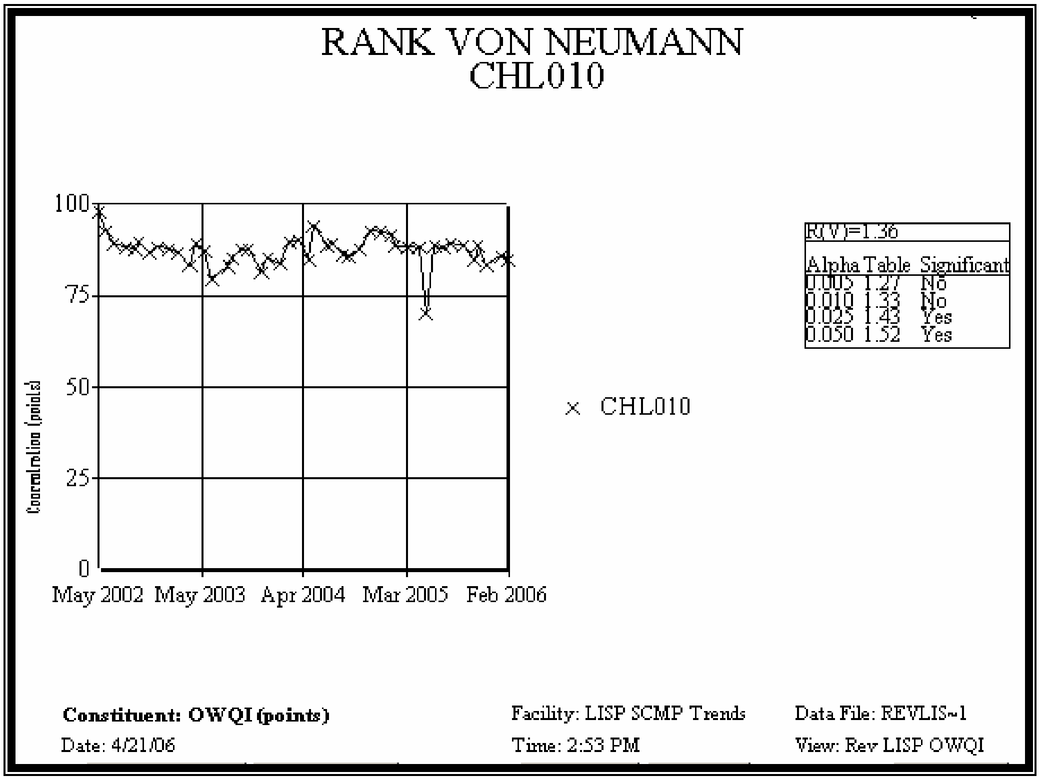
Similar to the patterns of the above box and whisker plots, the descriptive statistics for the monitoring station's monthly deseasonalized OWQI scores indicate distributions that are asymmetric (Table 3. Descriptive statistics for LISP and SCMP deseasonalized monthly OWQI values May 2002 - February 2006). However, this reinforces this report's use of nonparametric analyses because they do not assume symmetric normal distributions.

LISP Station	**BRZ 010**	**CGR 020**	**CHL 010**	**CUR 020**	**GEE 050**	**JNS 060**	**MAT 010**	**MIL 010**	**RCN 050**	**WPL 050**
Observations	44	45	46	46	45	45	46	45	44	45
Maximums	94	82	97	78	82	98	97	88	94	85
Minimums	25	23	69	23	18	82	64	64	23	21
Means	77.05	48.31	87.26	38.46	66	94.89	86.13	77.44	82.11	67.49
Std. Dev.	16.1	17.96	4.519	20.32	15.41	2.979	5.826	6.203	15.58	15.05
Skewness	-1.667	-0.2274	-1.324	0.9025	-2.006	-2.526	-1.336	-0.377	-2.656	-1.489
SCMP Station	**SMN 010**	**SMN 030**	**SMN 050**	**SMN 080**	**WDN 010**					
Observations	45	45	45	45	45					
Maximums	88	89	93	98	88					
Minimums	50	52	26	24	46					
Means	77.07	79.18	86	92.87	79.64					
Std. Dev.	8.438	8.755	10.89	10.69	7.364					
Skewness	-1.096	-1.491	-4.022	-6.141	-2.621					

Table 3. Descriptive statistics for LISP and SCMP deseasonalized monthly OWQI values for period May 2002 - February 2006.

Inferential statistical test results for various LISP and SCMP long term monitoring stations are depicted in the following graphics. All the graphics include a plot and a table of test results for calculated deseasonalized monthly OWQI scores (points). The plots include deseasonalized OWQI on the y-axis and time along the x-axis. To the right of each plot are test statistic results and associated tables to help in their interpretation including the significance of test results at various levels of alpha. Alpha represents the specified significance level which is the tolerable error (probability) for incorrectly rejecting the null hypothesis (Kleinblaum et al., 1988, pp. 26-32). This is equivalent to the probability of making Type I error or False Positive decision associated with hypothesis testing. Only calculated statistical test results which are larger or smaller, depending on the specific test, than the corresponding table's critical value at a particular alpha would be significant.

Initially, deaseasonalized monthly OWQI data were analyzed using the rank Von Nuemann statistical procedure to test for serial correlation at each station. The null hypothesis is that there is no serial correlation present in the data (Intelligent Decision Technologies, Ltd., 1998, pp. 69-70). Three monitored stations (i.e., CHL010, CUR020, and RCN050) were found to have significant serial correlation at some level of alpha even after deseasonalized their monthly OWQI values (Figures 5 through 7 Serial Correlation test for stations deseasonalized monthly OWQI values). Therefore, the p-values for these three stations' Mann-Kendall trend tests should be interpreted conservatively.

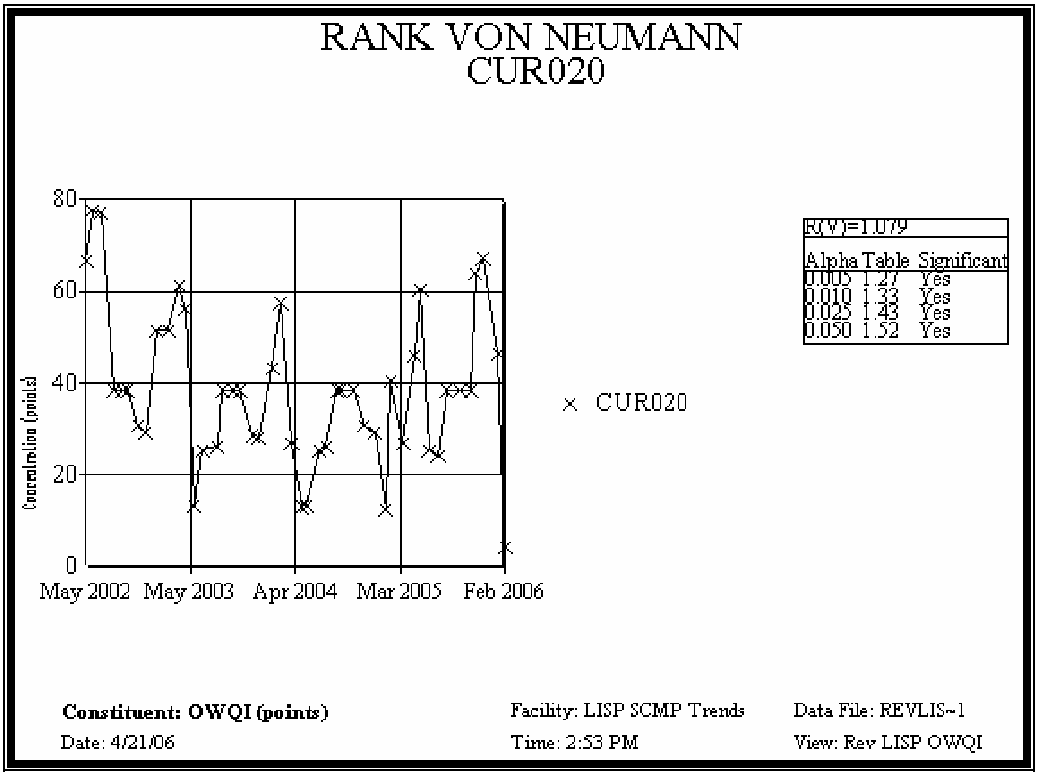


R(V)=1.36

Alpha	Table	Significant
0.005	1.27	No
0.010	1.33	No
0.025	1.43	Yes
0.050	1.52	Yes

Constituent: OWQI (points)
Date: 4/21/06
Facility: LISP SCMP Trends
Time: 2:53 PM
Data File: REVLIS~1
View: Rev LISP OWQI

Figure 5. Serial correlation test for Chelatchie Creek deseasonalized monthly OWQI values.

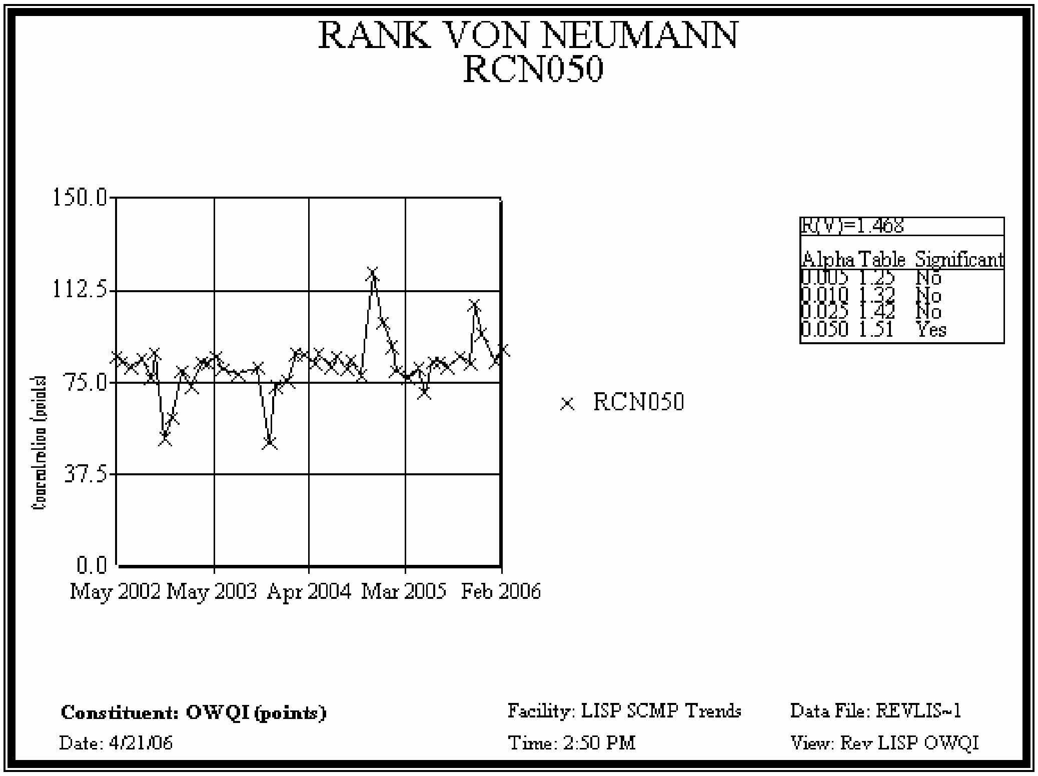


RANK VON NEUMANN
CUR020

R(V)=1.079		
Alpha	Table	Significant
0.005	1.27	Yes
0.010	1.33	Yes
0.025	1.43	Yes
0.050	1.52	Yes

Constituent: OWQI (points)
Date: 4/21/06
Facility: LISP SCMP Trends
Time: 2:53 PM
Data File: REVLIS~1
View: Rev LISP OWQI

Figure 6. Serial correlation test for Curtin Creek deseasonalized monthly OWQI values.



RANK VON NEUMANN
RCN050

R(V)=1.468		
Alpha	Table	Significant
0.005	1.25	No
0.010	1.32	No
0.025	1.42	No
0.050	1.51	Yes

Constituent: OWQI (points)
Date: 4/21/06
Facility: LISP SCMP Trends
Time: 2:50 PM
Data File: REVLIS~1
View: Rev LISP OWQI

Figure 7. Serial correlation test for Rock Creek North deseasonalized monthly OWQI values.

Subsequently, deseasonalized monthly OWQI scores were tested for significant trends over time using Mann-Kendall trend analysis. Statistically significant trends over time were found for the four stations: JNS060, RCN050, SMN010, SMN030 (Figures 8 through 11 Mann Kendall trend test for stations deseasonalized monthly OWQI values). Nonsignificant trend test results are presented in Appendix B.

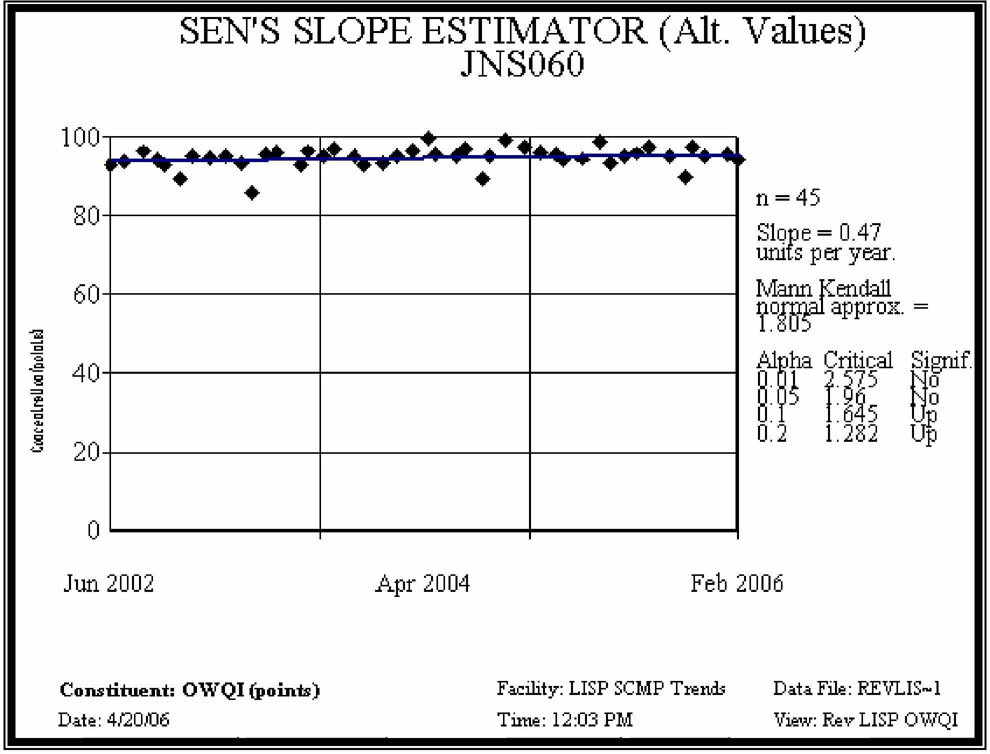


Figure 8. Mann Kendall trend test for Jones Creek deseasonalized monthly OWQI values.

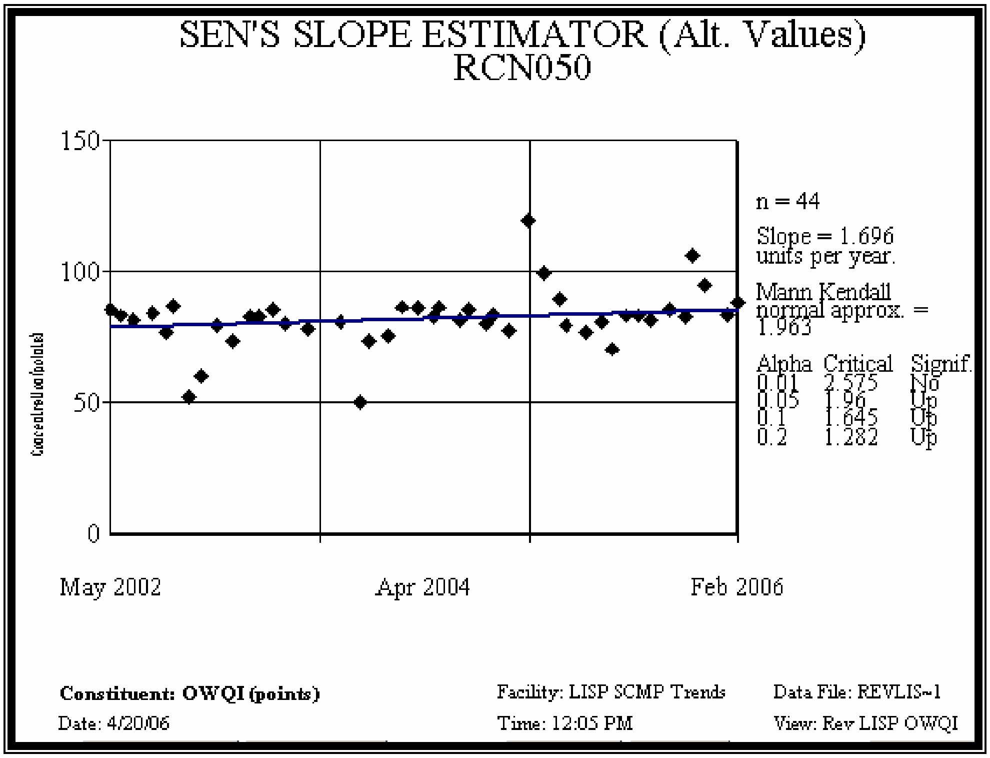


Figure 9. Mann Kendall trend test for Rock Creek North deseasonalized monthly OWQI values.

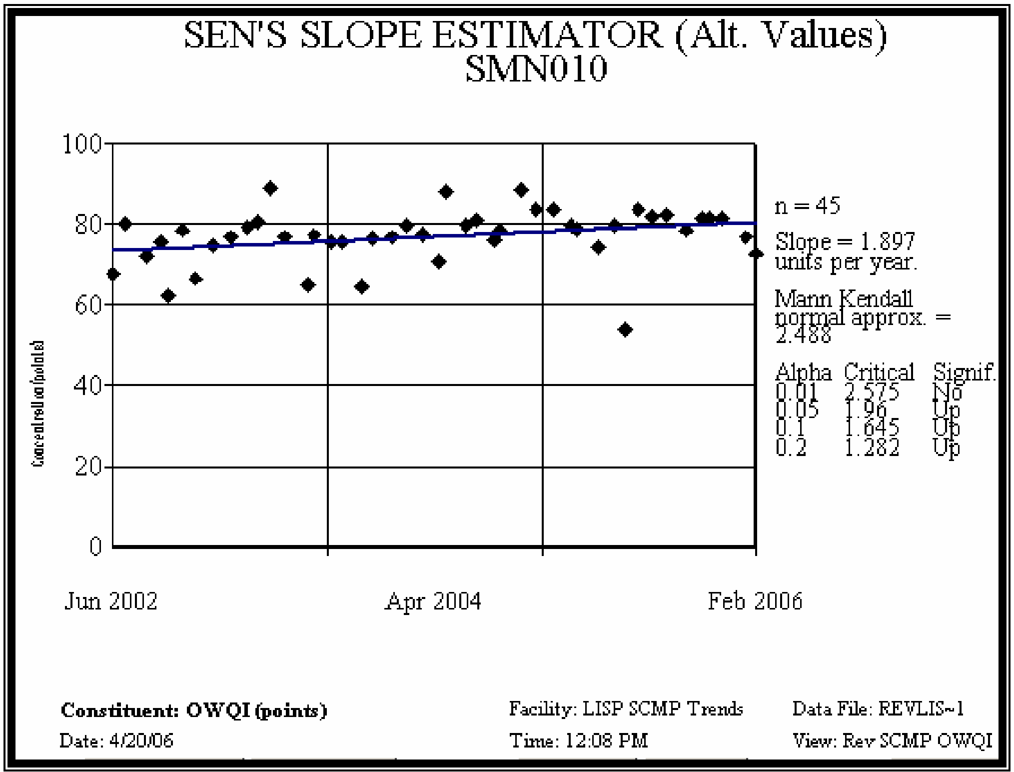


Figure 10. Mann Kendall trend test for Salmon Creek at NW 36th Ave deseasonalized monthly OWQI values.

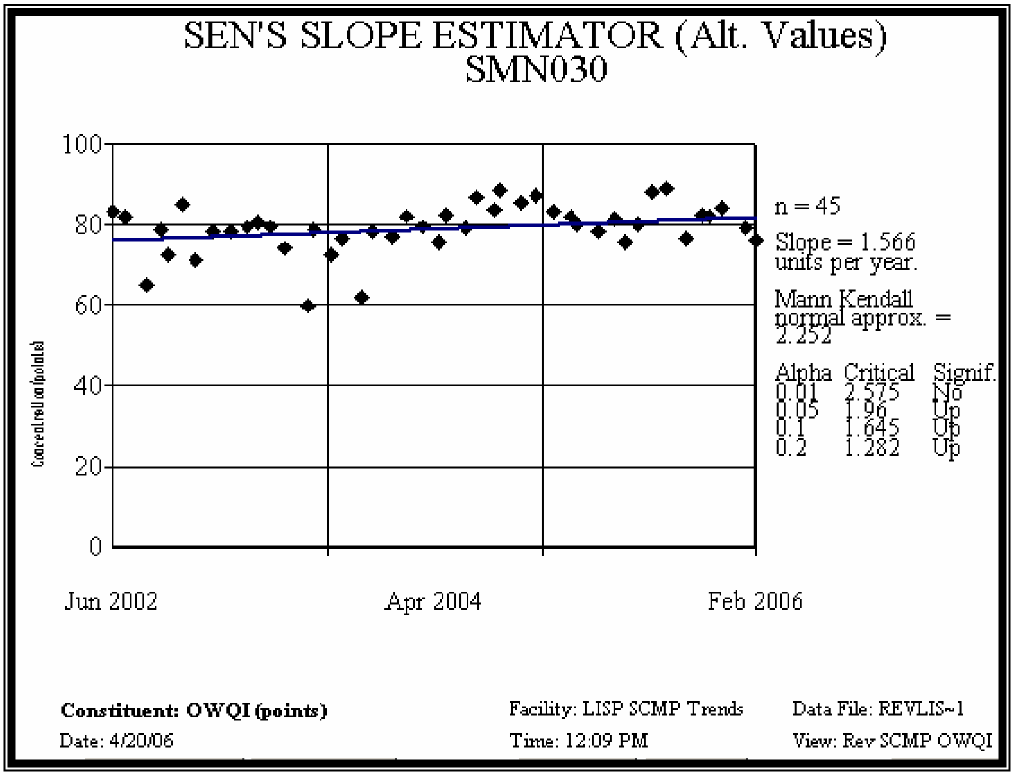


Figure 11. Mann Kendall trend test for Salmon Creek at NE 50th Ave deseasonalized monthly OWQI values.

Interestingly, all four stations with significant trends over time (i.e., JNS060, RCN050, SMN010, and SMN030) in their deseasonalized monthly OWQI values were positive and trending upward (Table 4. Summary of significant Mann-Kendall trend analyses tests and projections at current rates of change). This would suggest improvements in water quality at these stations over the limited duration of the existing monitoring data. Jones Creek's (JNS060) upward trending of 0.47 OWQI points per year was significant at an alpha as small as of 0.1. Rock Creek North's (RCN050) upward trending of 1.696 OWQI points per year was significant at an alpha as small as 0.05. Salmon Creek at NW 36th Avenue's (SMN010) upward trending of 1.897 OWQI points per year was significant at an alpha as small as 0.05. Salmon Creek at NE 50th Avenue's (SMN030) upward trending of 1.566 OWQI points per year was significant at an alpha as small as 0.05. Of these four upward trending stations, only Rock Creek North had significant serial correlation. Therefore the p-values associated with Rock Creek North's results may be suspect and the significance of its trend test may be suspect at these alpha levels. Also, Rock Creek North has periodically dried up during the summer which limits how representative the monitoring may be from this station for trend analysis. More specifically, during some summer months there was no sampling due to very low flow for Rock Creek North. This could bias comparisons against corresponding months of other years when there was flow especially if these were periods of low OWQI scores.

Additionally, estimates were made of the future time required for a change or shift in the OWQI class status for each of the monitored stations with significant Mann-Kendall trends over time (Table 4. Summary of significant Mann-Kendall trend analyses tests and projections at current rates of change). These projected times range from less than a year for Rock Creek North to approximately four years for SMN10 and SMN30. Since Jones Creek is already at the highest OWQI ideal class, it can not shift to a higher class. These time estimates are based on the assumed appropriateness of a linear Sen's slope estimate of a constant rate of change over time and the more precise current overall OWQI scores for these stations.

Station	Direction Of Significant Trend	Sample Size (n = # of months)	Significance at Alphas * of:	Estimated Sen's Slope (OWQI points / yr.)	Current OWQI Quality Overall Precise Score & Class	At Current Rate of Change, Projected Time to Shift Class (years)
JNS060	Upward	45	0.1, 0.2	+0.47	94.72-Excellent	n/a
RCN050	Upward	44	0.05, 0.1, 0.2	+1.696	79.36 - Poor	0.38 to Fair
SMN010	Upward	45	0.05, 0.1, 0.2	+1.897	72.87 –Poor	3.76 to Fair
SMN030	Upward	45	0.05, 0.1, 0.2	+1.566	73.38 - Poor	4.23 to Fair

Table 4. Summary of significant Mann-Kendall trend analyses tests and projections at current rates of change. The significance of Rock Creek North results may be impacted by serial correlation.

Conclusion

Long-term monitoring at fixed stations followed by periodic statistical trend analysis and interpretive reporting provide the most efficient and sensitive means for the early detection of emerging water quality problems (Washington State Department of Ecology, Hallock and Ehinger, 2003, p. 4). This "early warning" approach was the main reason for this initial evaluation of the limited duration LISP and SCMP data sets through trend analysis. In the future, as the monthly data sets increase in duration, the application of more powerful statistical analyses will be able to detect potentially more subtle changes.

The value of the long term monthly monitoring data set for statistical analyses will continue to improve into the near future. The longer data set will gradually increase the power of the statistical analyses, especially for trend analysis. The availability of four complete years of monthly monitoring data will allow us to better define seasons and perform the Seasonal Kendall Trend test within WQSTAT PLUS. This will, in turn, keep the trend plots' y-axes in the original OWQI ranges. In general, a longer, high quality data set will provide more confidence in all statistical analyses by improving how representative the analyses samples are of the diverse population of stream water quality values.

Additionally, future evaluation of the water quality parameters or characteristics contributing to OWQI scores would be helpful in fine tuning the potential sources of impairment or improvement. For streams with significant upward or downward trends over time, the specific subindexes contributing to them can be examined in more detail. Possible confounding factors or exogenous variables (natural random phenomena such as rainfall, temperature, or streamflow) that may be impacting significant trends could be compensated for by reducing their contribution to background variability or noise (Helsel and Hirsch, 1993, pp. 329-330). For example prior to trend analyses, flow or rainfall exogenous variables could be addressed through calculations of flow-adjusted concentrations.

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Appendix A. OWQI Spreadsheet Calculation Methods

(Revised from original Water Resources OWQI calculations spreadsheet instructions by Ron Wierenga.)

1. This is not a template that runs on its own. It requires many manual steps.
2. Reduce dataset to only characteristics used for OWQI calculations (but include both Dissolved Oxygen and Dissolved Oxygen Saturation). Be sure any duplicate characteristics-start date-location rows are deleted (e.g. replicate sample or measurement values).
3. Calculate, if possible, estimates for any missing OWQI variables (e.g. Dissolved Oxygen Saturation, Total Solids using rough estimate from Conductivity and Total Suspended Solids).
4. Paste your data into the appropriate columns on the calculations sheet.
5. Sort the data set by characteristic with the one exception of keeping together pairs of Dissolved Oxygen and Dissolved Oxygen Saturation matched by start date-location-characteristic.
6. Calculate the subindex scores for the characteristics. Use formulas in the subindex formulas sheet for the characteristics you have in your data set. Manually copy and paste the formula. Then delete subindex calculation rows for Dissolved Oxygen Saturation (otherwise duplicates DO subindexes).
7. After copying calculation sheet and converting all subindex formula results into values, sort the data set by station, date, and characteristic to get it back into original shape.
8. Calculate the OWQI for each date. Copy the formula from the formulas sheet and paste it in your data set. Modify the formula to reference the characteristics that you have and the number of characteristics (n). You may find that if your dataset is consistent you'll be able to construct the OWQI calculation once, filter the dataset on characteristic for the top cell's value, paste the formula all the way down and then unfilter. If the dataset has an inconsistent number of characteristics used, filter for sample run start dates with same # of characteristics and insert each with customized OWQI formula based on # of characteristics used.
9. Convert the OWQI formula results into values then filter the OWQI column and select for non-blank cells. Copy the filtered dataset over to the summary sheet and delete columns between date and OWQI.
10. Manually construct formulas to calculate the FWS and SUM averages and minimums after sorting by location-season-OWQI and customizing formula range based on the number of rows with the same station and season.
11. Confirm that the minimum average season and status formulas have worked.

Appendix B. Non-significant Mann-Kendall Trend Tests Results

The following graphs show non-significant trends over time for LISP and SCMP stations.

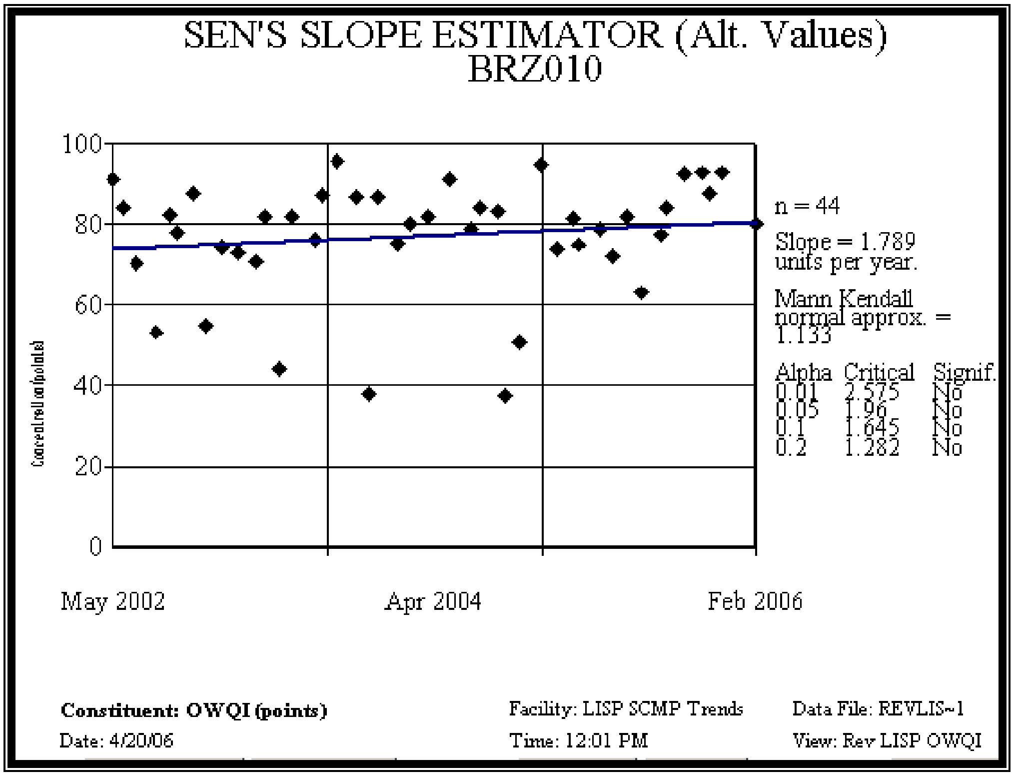

Figure B1. Mann Kendall trend test for Brezee Creek deseasonalized monthly OWQI values.

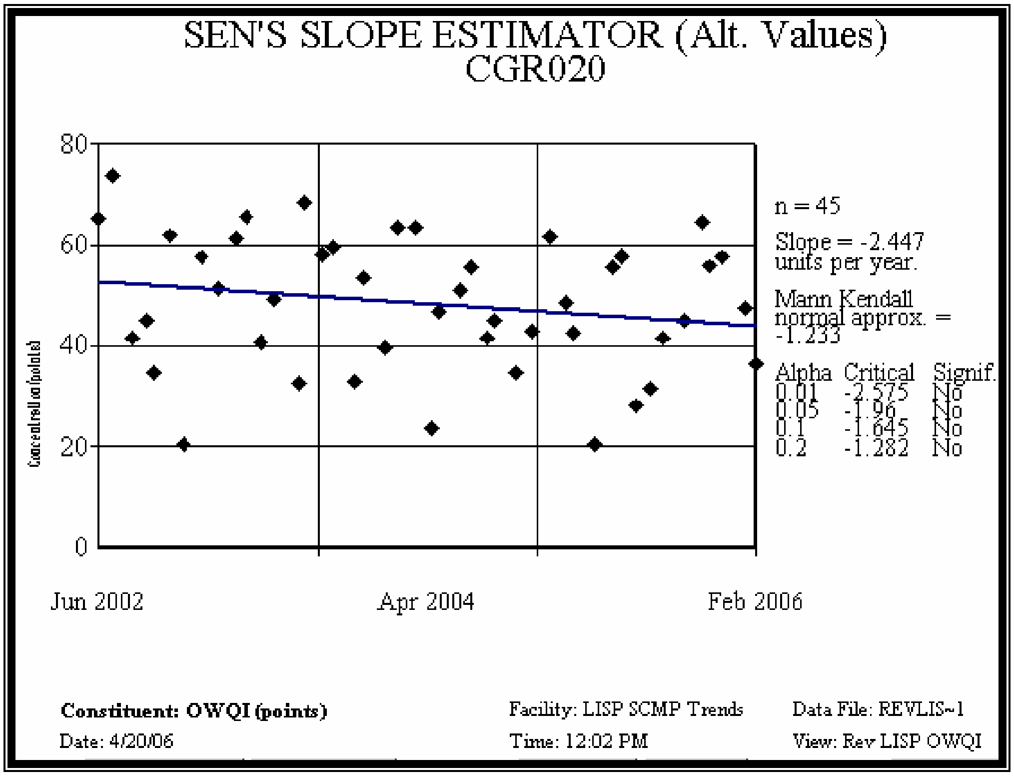

Figure B2. Mann Kendall trend test for Cougar Creek deseasonalized monthly OWQI values.

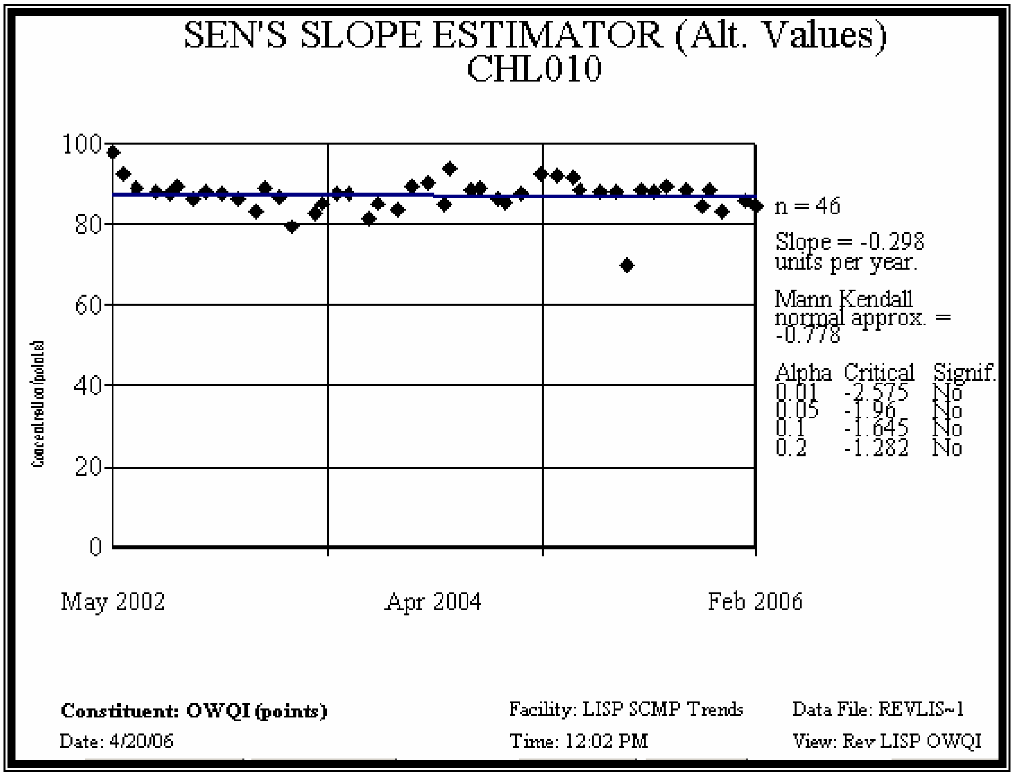

Figure B3. Mann Kendall trend test for Chelatchie Creek deseasonalized monthly OWQI values.

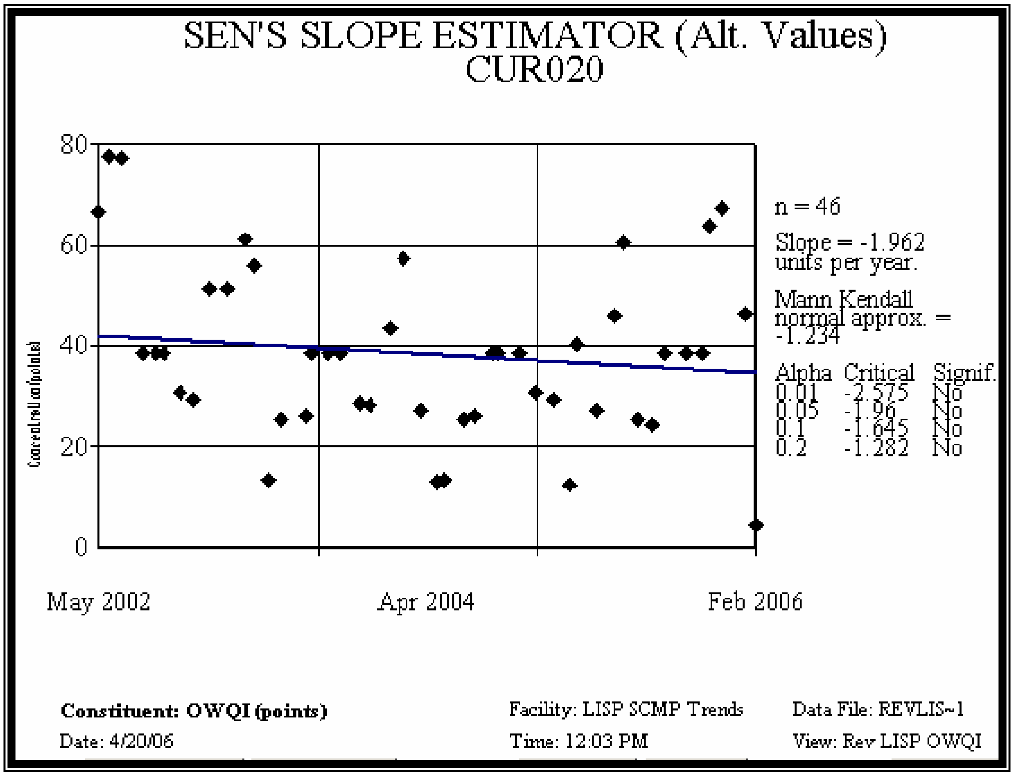

Figure B4. Mann Kendall trend test for Curtin Creek deseasonalized monthly OWQI values.

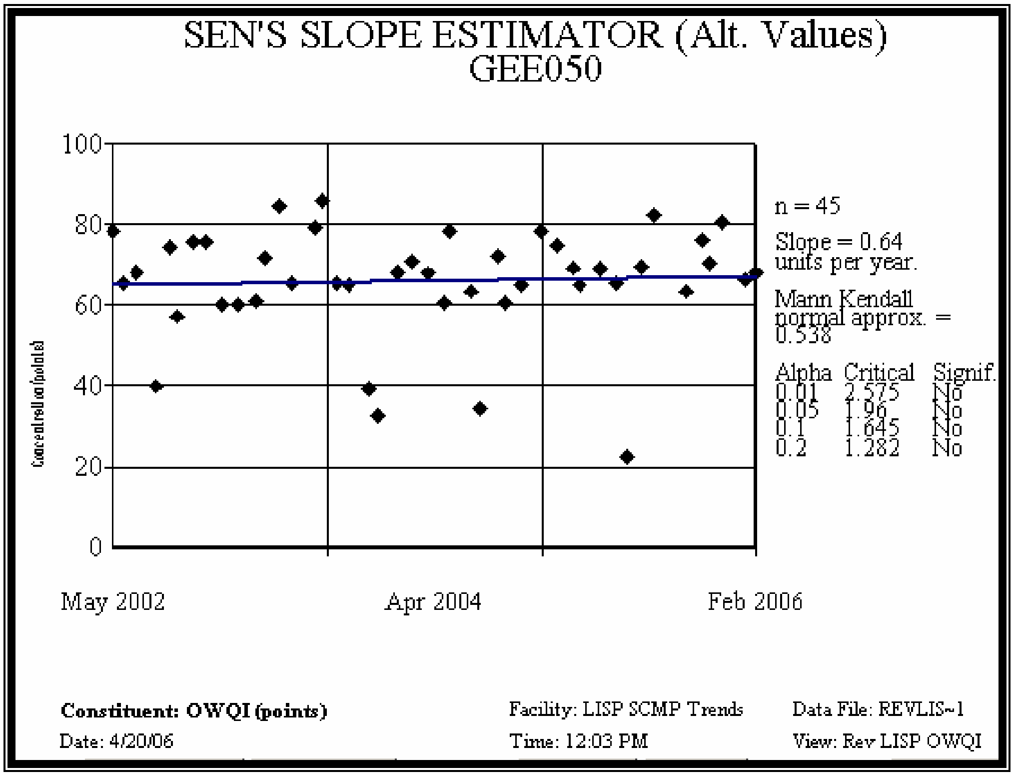

Figure B5. Mann Kendall trend test for Gee Creek deseasonalized monthly OWQI values.

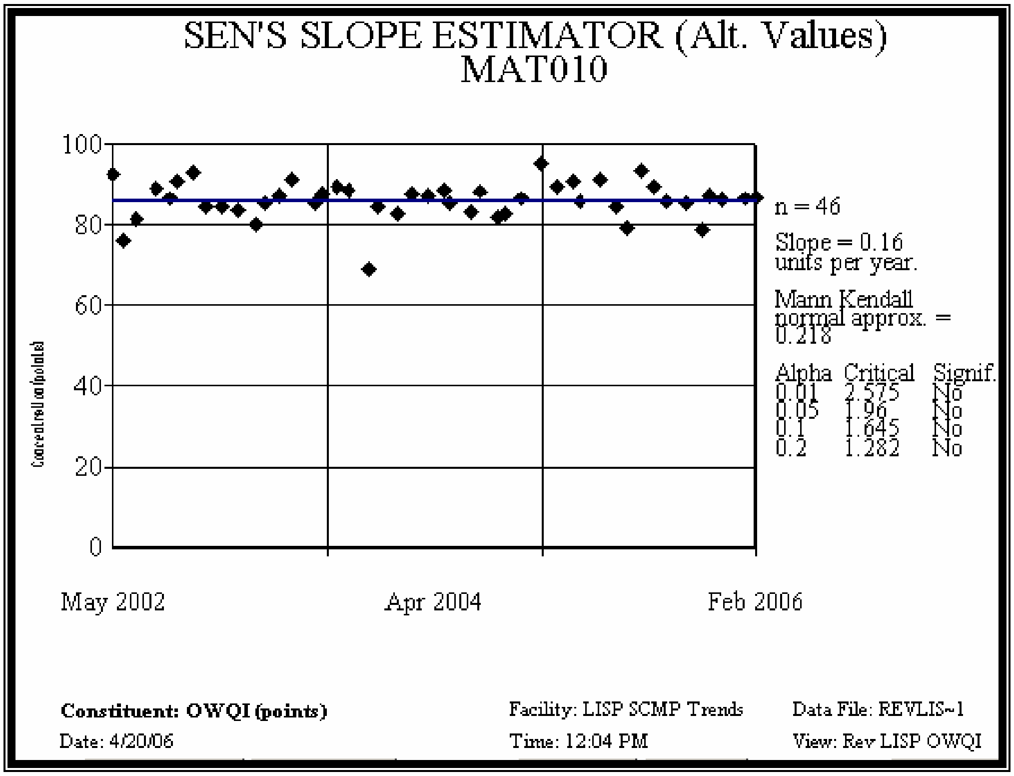

Figure B6. Mann Kendall trend test for Matney Creek deseasonalized monthly OWQI values.

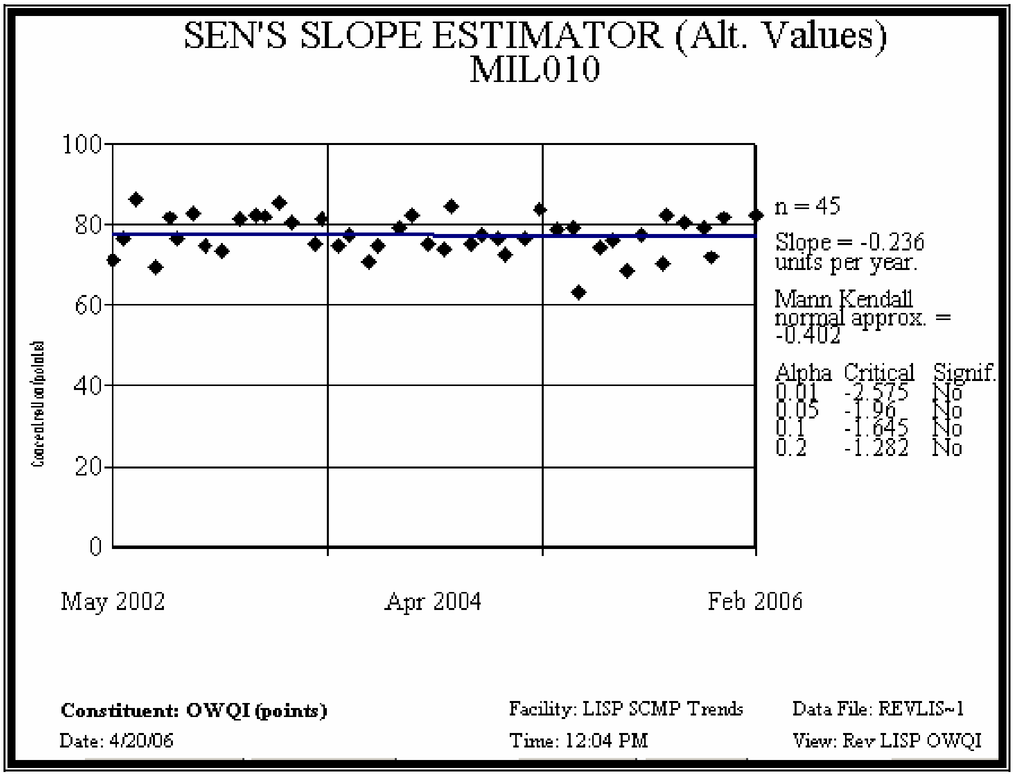

Figure B7. Mann Kendall trend test for Mill Creek deseasonalized monthly OWQI values.

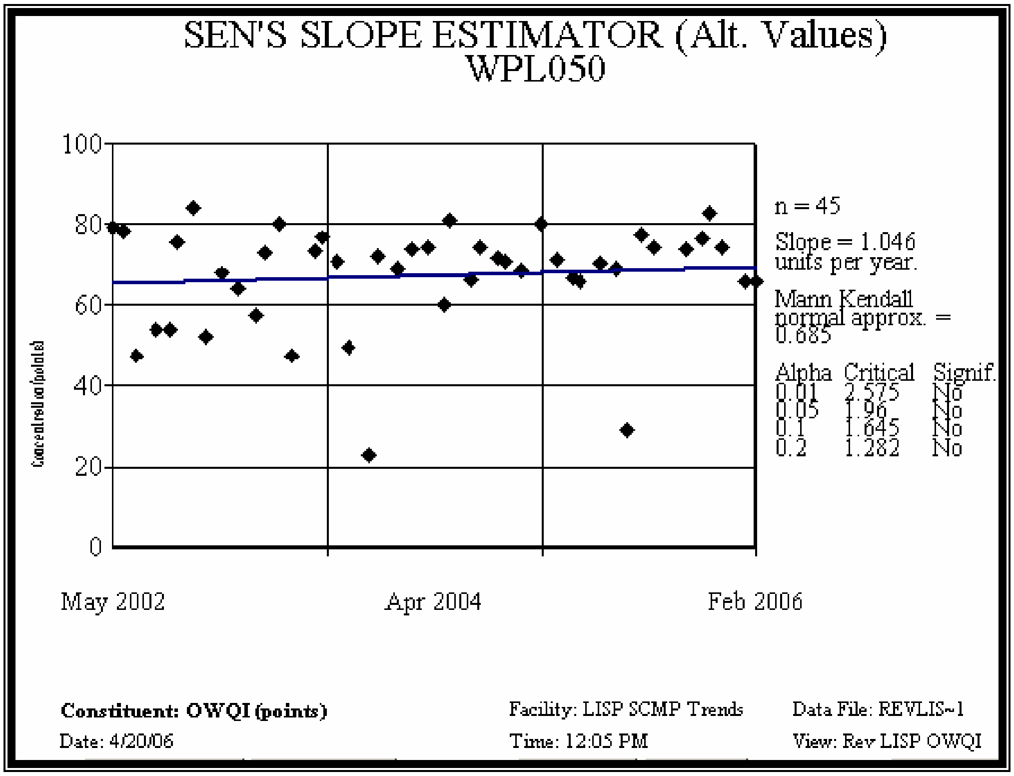

Figure B8. Mann Kendall trend test for Whipple Creek deseasonalized monthly OWQI values.

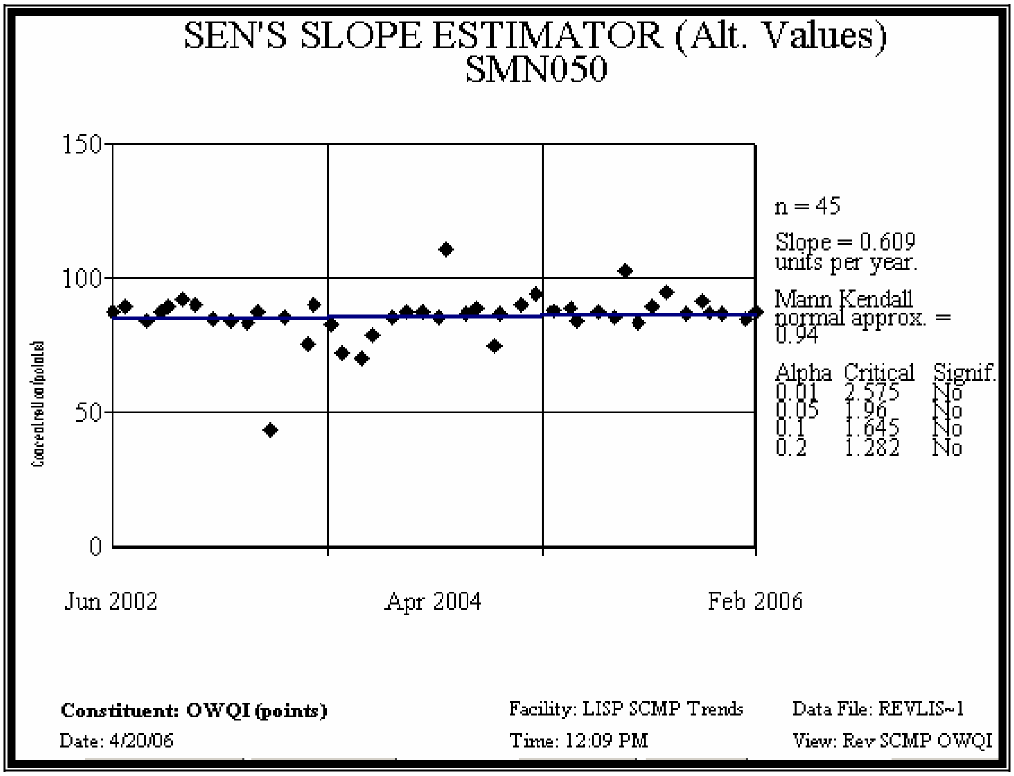

Figure B9. Mann Kendall trend test for Salmon Creek at Caples Road deseasonalized monthly OWQI values.

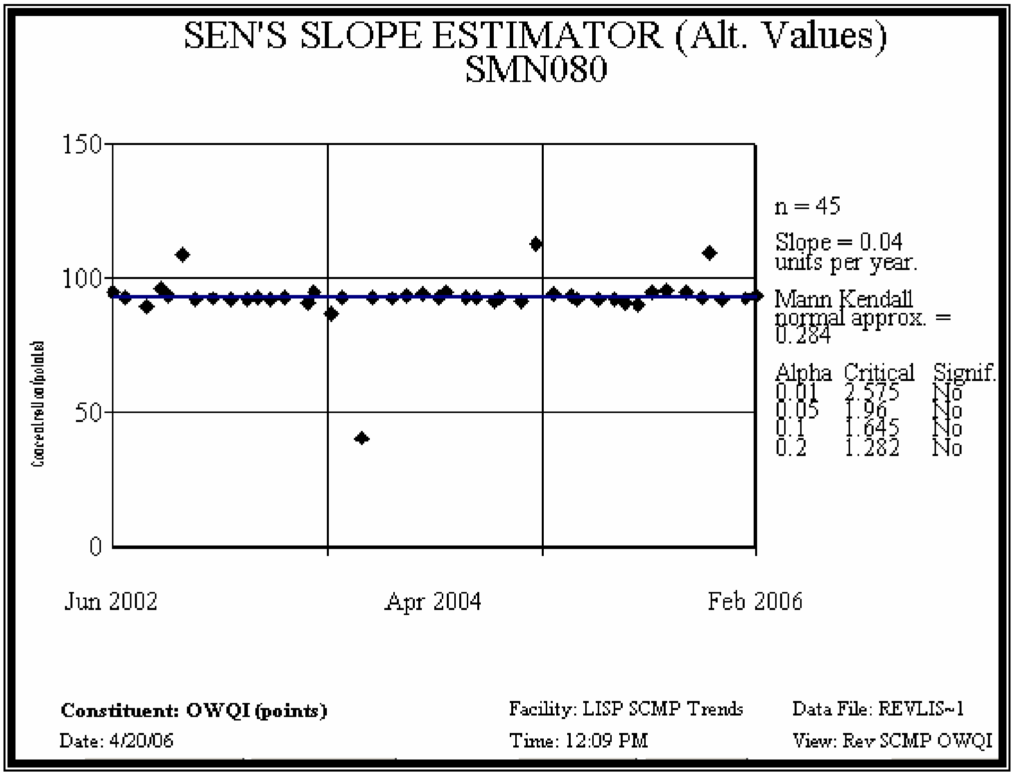

Figure B10. Mann Kendall trend test for Salmon Creek at NE 199th Street deseasonalized monthly OWQI values.

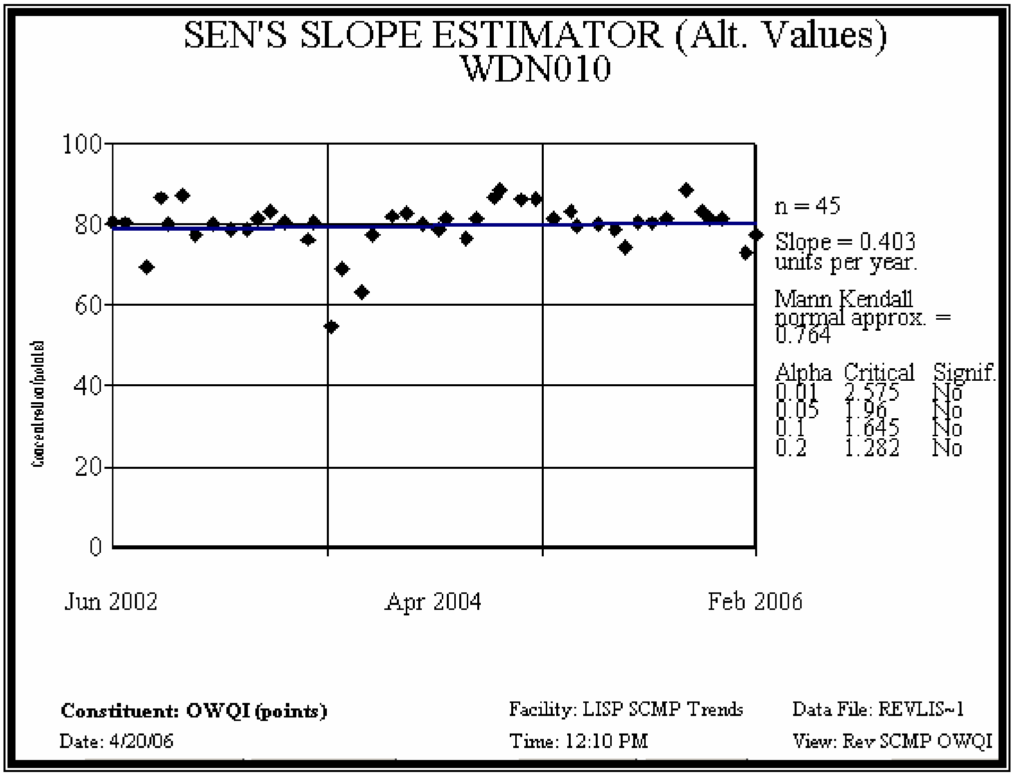

Figure B11. Mann Kendall trend test for Woodin Creek at Caples Road deseasonalized monthly OWQI values.