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

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Summary

Two long-term water quality monitoring projects, Long-term Index Site Project (LISP) and Salmon Creek Monitoring Project (SCMP), are operated by Clark County. These projects help track the water quality of 15 streams spanning diverse watersheds from urban to very rural settings. This report presents the latest status and trend analysis results for these stream monitoring sites from August 2002 through December 2006. One analysis approach used a slight variant of the regionally appropriate Oregon Water Quality Index (OWQI) to help summarize the sites' overall water quality. The OWQI integrates seven separate water quality parameters into monthly, seasonal, and an overall score for each site. Additionally, monthly fecal coliform OWQI subindex scores and turbidity values were also examined because of their potential health and environmental importance.

The status of the fifteen streams was evaluated based on the ranks and ranges of their overall OWQI scores, fecal coliform subindex scores, and their relative turbidity levels. Graphical summaries of the sites' statistics visually grouped them and tended to parallel their site rankings. As expected based on their overall OWQI scores, the more urban and agricultural watersheds' streams (i.e., Curtin, Cougar, Whipple, and Gee Creeks) ranked lower in the very poor to poor categories whereas the more rural forested ones ranked higher as good to excellent (i.e., Salmon Creek at Caples Rd. and 199th St., Matney, Chelatchie and Jones Creeks). Several streams in transitional watersheds ranked in the middle with higher poor to fair ratings (i.e., Salmon Creek at NW 36th Ave. and 50th Ave.; Mill, Brezee, and Woodin Creeks; and Rock Creek North). The streams' rankings changed substantially when only their fecal coliform OWQI subindex scores were evaluated. The most dramatic changes in rankings were large improvements for Curtin and to a lesser extent for lower Salmon Creek locations versus substantial drops for Brezee Creek. This suggests potential bacteria problems for Brezee and different causes of degradation for the lower Salmon Creek and Curtin Creek. The turbidity rankings separate Whipple and Gee Creeks and sometimes Brezee and Cougar Creeks into lower quality groups probably due to soil and urban runoff. The more rural upper Salmon Creek, Chelatchie and Jones Creeks, and somewhat surprisingly Curtin Creek fall into the best rankings based on just turbidity. The remaining streams fall into the middle turbidity rankings probably also due to transitional watersheds.

A total of nine significant trends were found. All of which indicated degradation over the 4.5 year monitoring period. Salmon Creek at NE 199th Street's overall OWQI was trending downward with a projected change in its current OWQI class status from excellent to good in approximately 2 years. Mill Creek's fecal coliform OWQI subindex also trended downward with a projected change from its current fair status to poor in approximately 2 years based solely on fecal coliform data. Seven streams had significant upward trends in their turbidity values indicating degrading water quality: Brezee Creek, Matney Creek, Mill Creek, Rock Creek North, and the three upper main stem Salmon Creek locations at NE 50th Avenue, Caples Road, and NE 199th Street. No projected change in status for these seven locations was possible based solely on turbidity.

Several limitations need to be kept in mind when interpreting these latest findings. First, the programs'4.5 year monitoring period is relatively short for trend analysis. Most trend analyses of monthly water quality data require at least five years and more often ten years of results. A shorter period decreases the sample size and substantially reduces the ability to statistically detect subtle water quality changes over time. Also, the August 2002 to December 2006 monitoring period was drier than average. Additionally during this monitoring period, the sampling days' flows for the nearby free-flowing East Fork of the Lewis River were mostly lower and trended upward when compared to their long term U.S.G.S. flow record. This mostly drier period, that happened to be observed during this relatively short monitoring time span, is emblematic of smaller samples. A longer data set would hopefully be more typical and representative by capturing a greater portion of the full range of flow and water quality values. The degraded water quality trends found may also be complicated by the apparent trend in the field days' flows. Additionally, the laboratory method used to measure fecal coliform levels changed during the monitoring period. All of these factors complicate or confound the latest findings, especially those for trend analysis, so the current results should be considered provisional until a longer, more representative data set has been analyzed in the future.

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 over time that potentially could signal emerging water quality degradation or improvement. The Oregon Water Quality Index (OWQI) and other selected parameters were analyzed for this report.

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.

Additionally, two other specific water quality parameters, fecal coliform and turbidity, were analyzed because of their potentially important impact on water body users or stream health. The nearby free-flowing East Fork of the Lewis River's extensive flow record was also briefly examined to place the water quality results in the context of influences from the monitoring period's relative drought or wetness.

Appendix A contains detailed background on statistical considerations taken into account for this report. It is presented to assist those unfamiliar with water quality trend analysis.

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 relatively consistent at approximately monthly intervals with no substantial breaks.

This study's response or dependent variables used to evaluate status or test for significant trends over time are: a slightly modified overall OWQI (by integrating 7 of its 8 water quality variables), fecal coliform OWQI subindex, and turbidity. 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. For example, it is assumed for this study 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. Therefore, due to these considerations, step trend analysis is not applicable.

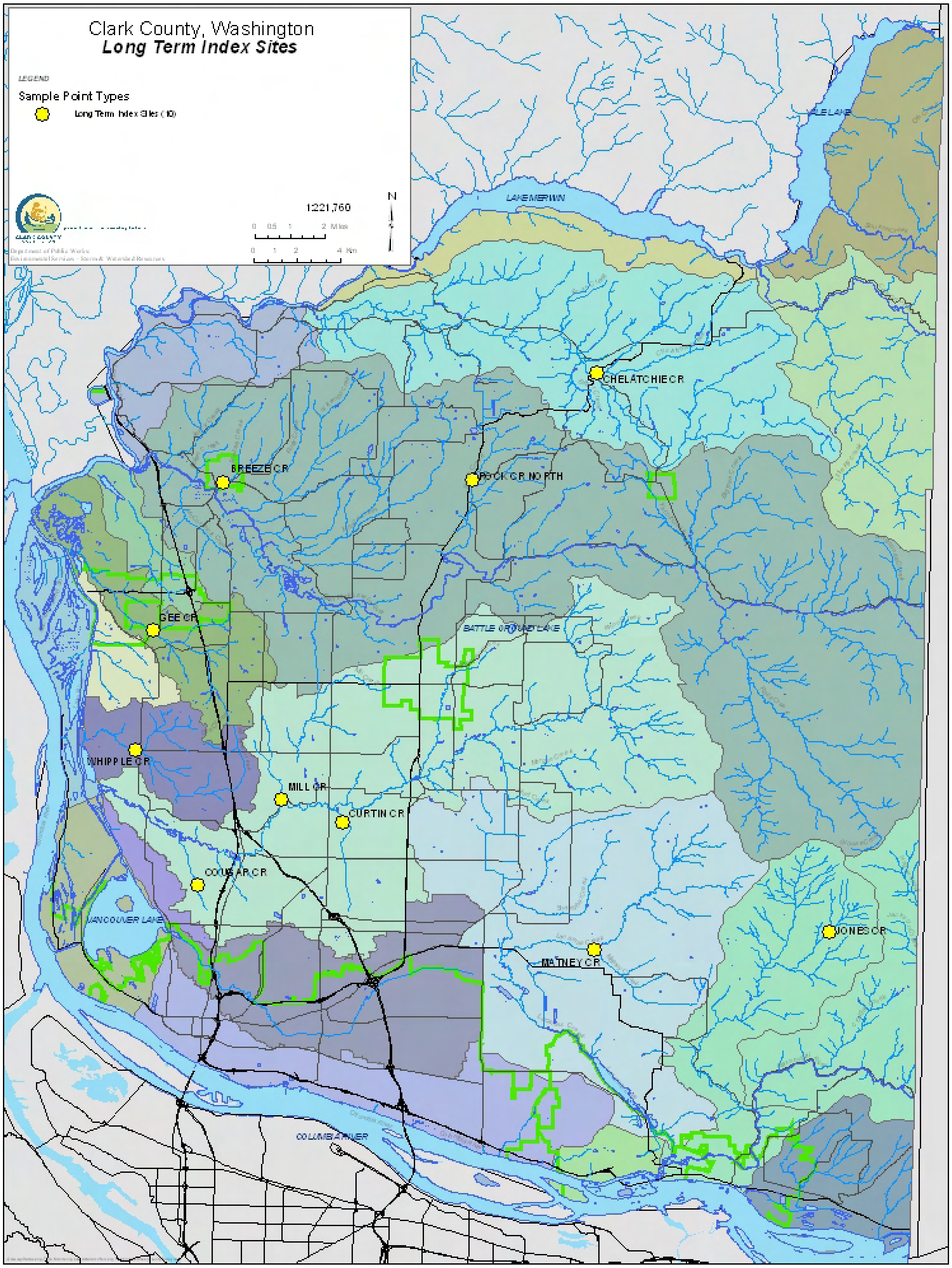


Figure 1. Map of LISP sites (from LISP QAPP).

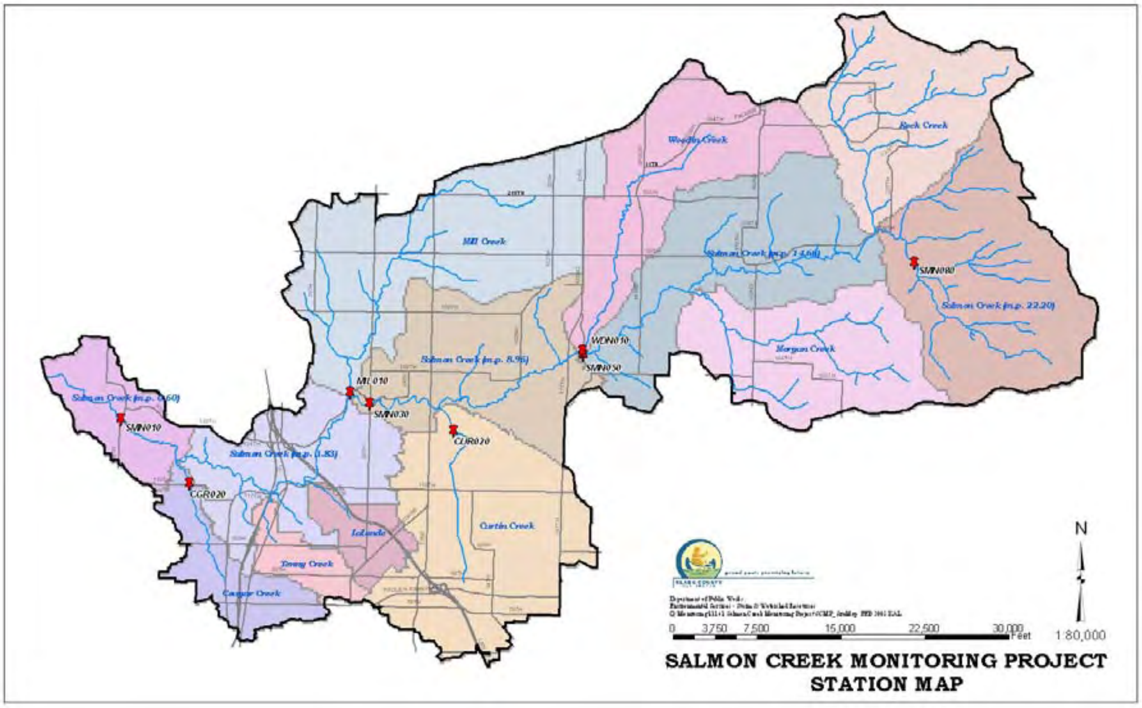


Figure 2. Map of SCMP sites (from SCMP QAPP).

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.

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 B: 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/nitrite), 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) of these scores 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 other transformations.

Two software programs were used for data manipulation and analysis. Microsoft EXCEL, a spreadsheet program, was used for initial data manipulation, calculations, and preparation for further statistical analyses. WQSTAT PLUS, an environmental data statistical software package, was then utilized for further 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.

The nonparametric Seasonal Kendall Trend test was performed on the overall OWQI scores, fecal coliform OWQI subindex scores, and turbidity values to help address the data's non-normal distribution and potential confounding effects of seasonality. 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). Our current data set just met this threshold allowing use of this statistical tool to address the confounding effects of seasonality.

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. One method for addressing the confounding effects of flow on trend analysis is by using flow-adjusted concentrations. However, flow adjusted concentrations were not used for this report's trend analysis because direct flow measurements were not yet available for the water quality monitoring sites.

Therefore, indirect methods were used to evaluate potential confounding impacts from flow. Flow from a nearby unaffected station which could be expected to be correlated with natural flow at the site of interest (Helsel and Hirsch, 1993, p. 331-332) could be used to examine potential impacts from exogenous flow variables. However, when removing the effect of one or more exogenous variables (e.g. flow); their probability distributions are assumed to be unchanged over the period of record. Also, trend analysis of flow observations may be used to determine whether the time series of flow has undergone change with time (U.S.G.S. Water Resources Investigations Report 91-4040, Schertz et al., 1991, p. 25). Thus, concurrent flows from the nearby East Fork of the Lewis River were briefly examined for relative flows and trends in this study (Appendix C).

This report's analysis of monthly data evaluated only approximately 4.5 years; which is 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, pp. 5, 13, and 25). The reported levels of statistical significance become more accurate as the sample size (number of values per season) becomes larger than 10 (e.g. 10 years of monthly data). Oregon analyzed ten water years of ambient water quality data for their water quality index work (Cude, 2001, p. 132) to attenuate the effects of drought cycles and ensure sufficient data to analyze trends. Our data set was shorter so a brief examination of possible drought impacts was made by evaluating the concurrent relative flow levels from the nearby East Fork Lewis River's long flow record (Appendix C). This allowed a brief qualitative indirect assessment of how representative the monitoring period's limited time span was relative to this nearby stream's longer term hydrologic period of record.

An important trend 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 (Appendix D). However, this test will also reflect the presence of trends or cycles, such as seasonality (Intelligent Decision Technologies, Ltd., 1998, p. 69). Therefore, the Rank von Neumann test was run on sequentially deseasonalized and detrended data but results for stations with trends may still need to be interpreted with caution.

Results and Discussion

Primary metered and laboratory data from August 2002 through December 2006 was analyzed for this report except where noted otherwise. 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.

Rankings

These 15 stations' primary data were utilized to calculate, rank, and interpret site specific OWQI scores, subindex scores, and turbidity results. The OWQI classification scheme, based on research by Oregon (Cude, 2001, p. 131), groups applicable scores into the following five qualitative categories: <60 very poor, 60-79 poor, 80-84 fair, 85-89 good, and 90-100 excellent.

OWQI Station Rankings

Each of the 15 monitored sites' overall water quality was ranked (1 = worst and 15 = best). Additionally, each was assigned to one of the five possible relative quality classes, from very poor to excellent, based on the lower of the two seasonal average OWQI scores (Table 2A Seasonal low flow and higher flow average overall OWQI values with seasonal minimums in bold, site rankings, and quality categories).

Station	CUR020	CGR020	WPL050	GEE050	SMN010	SMN030	MIL010	BRZ010
F. W. S. Average	40	55	67	66	77	82	78	77
Summer Average	**25**	**33**	**62**	**64**	**73**	**73**	**74**	**76**
Site Rank	1	2	3	4	5.5	5.5	7	8.5
Quality	Very Poor	Very Poor	Poor	Poor	Poor	Poor	Poor	Poor
Station	**WDN010**	**RCN050**	**SMN050**	**MAT010**	**CHL010**	**SMN080**	**JNS060**	
F. W. S. Average	79	**80**	86	**86**	**87**	**92**	**95**	
Summer Average	**76**	82	**85**	89	88	93	**95**	
Site Rank	8.5	10	11	12	13	14	15	
Quality	Poor	Fair	Good	Good	Good	Excellent	Excellent	

Score	<60	60-79	80-84	85-89	90-100
Quality	Very poor	Poor	Fair	Good	Excellent

Table 2A. Seasonal low flow (summer) and higher flow (fall, winter, and spring) average overall OWQI values with seasonal minimums in bold (including ties), site rankings, and categories (Aug '02-Dec '06).

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. Rock Creek North is the only fair site and its watershed has transitional characteristics between those found for the poor and good quality sites. 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, only one monitoring site fell into the fair 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 2A and 2B) 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 four highest 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.

<u>Fecal Coliform OWQI Subindex Station Rankings</u>

Table 2B shows that the pattern of station scores and ranks changed when just fecal coliform OWQI subindex scores were calculated compared to the overall OWQI summary in table 2A. Based on fecal coliform subindex versus the overall OWQI, the most dramatic relative improvement was for Curtin Creek which went from the lowest overall rank to 8.5 (Very Poor to Good). This probably mostly reflects the negative impact of high nitrate levels on this site's overall OWQI score. Brezee Creek's rank, dropping from 8.5 to 3, was the second largest change but stayed in the poor category. This indicates that this station probably has a significant bacteria water quality issue possibly from the growing urbanizing area around La Center. Woodin, Rock Creek North, Salmon Creek at Caples Road, and Matney Creek all declined moderately for their fecal coliform ranking from their overall OWQI ranks; but only Woodin changed qualitatively from poor to fair. Cougar and Whipple Creeks' rankings only changed slightly while only Whipple switched from poor to very poor based solely on bacteria. Gee Creek remained unchanged in its ranking and category. There were moderate to large improvements in ranking for Mill Creek and Salmon Creek at 36th and 50th Avenues, with all three switching from poor to good categories based solely on fecal coliform. Finally, there were only minor or no changes in ranking for Salmon Creek at 199th Street, Jones and Chelatchie Creeks with only the later changing from good to excellent.

Station	**CGR 020**	**WPL 050**	**BRZ 050**	**GEE 050**	**WDN 010 ***	**RCN 050**	**SMN 050**	**MAT 010**
F. W. S. Average	77	72	77	**78**	86	91	92	88
Summer Average	**53**	**56**	**62**	**78**	**81**	**82**	**86**	**87**
Site Rank	1	2	3	4	5	6	7	8.5
Fecal Coliform OWQI Subindex Quality	Very Poor	Very Poor	Poor	Poor	Fair	Fair	Good	Good
Overall OWQI Site Rank & Quality	2 Very Poor	3 Poor	8.5 Poor	4 Poor	8.5 Poor	10 Fair	11 Good	12 Good
Station	**CUR 020**	**MIL 010**	**SMN 030**	**SMN 010**	**SMN 080**	**CHL 010**	**JNS 060**	
F. W. S. Average	94	**88**	92	**88**	98	**95**	**98**	
Summer Average	**87**	90	**88**	94	**95**	96	**98**	
Site Rank	8.5	10	11.5	11.5	13	14	15	
Fecal Coliform OWQI Subindex Quality	Good	Good	Good	Good	Excellent	Excellent	Excellent	
Overall OWQI Site Rank & Quality	1 Very Poor	7 Poor	5.5 Poor	5.5 Poor	14 Excellent	13 Good	15 Excellent	

Table 2B. Seasonal low flow (summer) and higher flow (fall, winter, and spring) average OWQI Fecal Coliform Subindex and Overall OWQI values with seasonal minimums in bold (including ties) for the period August 2002 - December 2006. WDN010 was extended to February 2007 for equal sample size.*

<u>Turbidity Station Rankings</u>

Results from the evaluation of the sites based solely on their average turbidity values are summarized below (Table 2C Average Monthly Turbidity (NTU) and Overall OWQI values and site rankings from August 2002 – December 2006). Since turbidity is not a parameter included in the OWQI analysis only relative comparisons to changes in ranking are possible. The largest decreases in ranking were for Brezee Creek, Rock Creek North, and Matney Creek which all dropped approximately five places from their overall OWQI rankings. This would indicate that, in relative terms, turbidity may be impacting these streams but its overall impact is difficult to gage. Whipple, Gee, and Salmon Creek at both Caples Road and 199th Street all experienced a moderate drop of two or three in their rankings relative to their OWQI rankings. Whipple and Gee had the lowest ranked sites, based on their chronic turbidity issues especially during the wet season, probably from a combination of land use impacts, erodible soils, and bank erosion. Salmon Creek at 36th Avenue, Woodin, Chelatchie, and Jones Creeks changed by one or less in their relative rankings based on turbidly with the later two remaining among the highest ranks. Cougar, Mill, and Salmon Creek at 50th Avenue experienced moderate improvements in rankings of 2 to 4.5 above their overall OWQI ranks. Curtin Creek had the largest improvement in rankings, a gain of 12 places based solely on turbidity, which probably again reflects the negative impact of high nitrate values on its overall OWQI score.

Station	**WPL 050**	**GEE 050**	**BRZ 010**	**CGR 020**	**RCN 050**	**SMN 010**	**MAT 010**	**SMN 050**
Turbidity Average (NTU)	19.4	10.4	10.1	8.76	6.97	6.87	6.68	6.33
NTU Site Rank	1	2	3	4	5	6	7	8
OWQI Site Rank & Quality	3 Poor	4 Poor	8.5 Poor	2 Very Poor	10 Fair	5.5 Poor	12 Good	11 Good
Station	**WDN 010**	**SMN 030**	**MIL 010**	**SMN 080**	**CUR 020**	**CHL 010**	**JNS 060**	
Turbidity Average (NTU)	6.20	6.01	6.00	3.65	3.12	2.41	0.73	
NTU Site Rank	9	10	11	12	13	14	15	
OWQI Site Rank & Quality	8.5 Poor	5.5 Poor	7 Poor	14 Excellent	1 Very Poor	13 Good	15 Excellent	

Table 2C. Average Monthly Turbidity (NTU) and Overall OWQI values and site rankings from August 2002 – December 2006.

Box and Whisker Plots

Box and whisker plots, graphically summarizing descriptive statistics, depict how the central tendencies and dispersion of the monthly calculated index scores and turbidity values varied across the monitoring stations. 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.

The box and whisker plots, due to software limitations for showing the relative water quality within and between the monitoring sites, are presented in pairs based on the feature evaluated (Figures 3 through 8; Box and Whisker plots of LISP and SCMP sites’ monthly: Overall OWQI, Fecal Coliform OWQI subindex; and Turbidity values, respectively). Generally they depict similar results as the briefer findings presented in the above rankings. Also similar to the patterns depicted in the box and whisker plots, the descriptive statistics for the monitoring stations’ overall monthly OWQI scores, fecal coliform subindex scores, and turbidity values indicate distributions that are asymmetric (Appendix D, [Tables D1 through

D3] Descriptive statistics and Assumptions Checked for LISP and SCMP monthly results, August 2002 - December 2006). However, this reinforces this report's use of nonparametric analyses because they do not assume symmetric normal distributions. Except where noted otherwise, all statistics are based on the monthly results over the August 2002 through December 2006 monitoring period.

Overall OWQI Box Plots

The LISP and SCMP sites' relative water quality, as graphically summarized by the central tendencies and distributions of their OWQI index scores, are shown in Figures 3 and 4. Curtin and Cougar Creeks generally have the poorest water quality. Their OWQI scores have the lowest medians as well as the lowest and largest interquartile range (IQR). Both statistics reflect their poor and variable water quality. Almost 75% of their scores fall in the very poor category. In fact, even though their IQRs are much wider, they still are much lower than and do not overlap with any other sites. The extent of Curtin and Cougar Creeks' vertical whiskers are asymmetric indicating a wider high than low range in their more extreme OWQI scores. Cougar Creek had the lowest OWQI score of all the monitoring stations as shown by the extent of its lower whisker. Interestingly, Curtin Creek's mean is pulled toward the shorter tail indicating more lower than higher scores that probably are contributing to its lowest overall OWQI rank. Gee and Whipple Creeks are the second worst water quality group of sites, with more than 75% of their OWQI scores in the poor or very poor categories. These two stations have 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's and Salmon Creek's at NE 199th Street (SMN080) high ranks are reflected in the pattern of their OWQI scores. Their very good overall water quality is shown by both their highest median OWQI values as well as the narrowest and highest IQRs. More than three-quarters of Jones Creek's scores are excellent. Interestingly, SMN080's very long lower whisker attributed to one very low OWQI score (also see Figure 9) indicates sporadic water quality problems yet it is still the second highest ranked site. The central tendency and especially the distribution of OWQI values for Chelatchie and Matney Creeks are the next highest and most similar to Jones Creek's very good water quality.

Salmon Creeks' at 36th and 50th Avenues as well as Woodin, Mill and Brezee Creeks' middle rankings are reflected in their distribution of scores. Most of their IQRs span from near the good-fair boundary into the poor categories with these site's lowest scores in the very poor category. Rock Creek North and Brezee Creeks have similar asymmetric ranges with some low values but Rock's somewhat higher IQR contributes to its better ranking.

Parallel to their respective rankings, 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.

Fecal Coliform OWQI Subindex Box Plots

Figures 5 and 6 depict how the distribution of the fecal coliform OWQI subindex scores differs substantially from the overall OWQI pattern. The relative water quality for almost all stations improved when the evaluation was limited to just the fecal coliform OWQI subindex rather than the overall OWQI. This improvement compared to the overall OWQI would be expected, given that none of the other potentially low water quality parameter results have been included in this single subindex. Almost all of the fecal subindex means, medians, and 75th percentiles, and maximums increased compared to their equivalent statistics for the overall OWQI (also see Appendix D, Tables D1 and D2). The only exceptions were for minor decreases in Brezee Creek's means and medians and no changes in the maximums for Jones Creek and Salmon Creek at 199th Street. On average, the stations' fecal subindex means improved more than 10 points from their OWQI means while some stations' mean scores improved substantially. Curtin and Cougar Creeks', the two lowest OWQI ranked stations, means increased by 57 and 21 points, respectively, which contributed to improving Curtin Creeks rank by 8 places. Compared to their equivalent

25th percentile statistics for OWQI, four stations decreased, two remained about the same, and nine increased. However, relative to their OWQIs', the fecal subindex's minimums decreased for eight, stayed approximately equal for two (within 5 points), and increased for 5 respective stations. Curtin, Jones, and the three upper main stem Salmon Creek stations minimums increased by at least 7 points with the two upper main stem stations minimums improving the most. This would suggest impacts other than fecal coliform are pulling down the overall OWQI scores for the upper main stem Salmon Creek.

The general pattern for fecal coliform subindex values coincides with their rankings and what would be expected for their watershed's predominant land uses. Jones and Chelatchie Creeks and Salmon Creek at 199th Street, the three highest subindex ranked stations, also have the highest IQRs reflecting their mostly rural watershed character. Conversely, Cougar, Whipple, Brezee, and Gee Creeks (the four lowest fecal subindex ranked stations) have the lowest 25 percentiles and the most urbanized and agricultural watersheds. The fact that only Brezee Creek's mean fecal coliform subindex score was lower than its overall OWQI score and that it has the widest subindex IQR suggest that it may have substantial periodic bacterial contamination. Whereas, Jones Creek consistently and Salmon Creek at 199th Street mostly have few bacteria problems. As evidenced by their relatively high IQR but low minimum subindex scores, Chelatchie Creek and Salmon Creek at 36th, 50th and Caples have sporadic bacteria issues.

Turbidity Box Plots

The turbidity box plots results presented in figures 7 and 8 also parallel their station rankings (also see Appendix D Table D3). Since these box plots are based on actual measured values, as opposed to calculated index or subindex scores, higher values represent poorer water quality (opposite to those depicted in the OWQI and fecal coliform subindex box plots). Whipple Creek, as expected for the lowest ranked station based on turbidity, has the highest maximum, minimum, average, and IQR turbidity values. Gee and Brezee Creeks, the second and third lowest ranked stations, also have relatively high turbidity maximums over 65 NTU, means over 10, and IQRs that taken together point to ongoing turbidity problems for these streams. Cougar Creek's second highest maximum turbidity value of 194 but third lowest minimum suggest that this stream has sporadic severe turbidity problems commonly associated with flashy urban watersheds. Once again at the other end of the spectrum, the highest ranked Jones Creek has the lowest maximum, minimum, and mean turbidity values. The next highest ranking stations, Chelatchie and Curtin Creeks and Salmon Creek at 199th Street also have the lowest mean turbidities that are all less than 3.5 NTU. Chelatchie Creek also has the second lowest maximum turbidity while Salmon Creek at 199th Street has substantially lower maximum and mean turbidity values than the other main stem Salmon Creek stations. All of the main stem Salmon Creek stations' IQR turbidity values are less than 7.5.

Compared across stations, the turbidity box and whisker plots show some substantial differences and spatial patterns. Gee, Brezee, Cougar, and especially Whipple Creeks generally have higher turbidities and lower water quality. Whereas, Chelatchie and especially Jones Creeks have the best water quality based on just turbidity. The remaining stations have substantial overlap in their turbidities. Salmon Creeks' turbidities generally decrease with upstream distance.

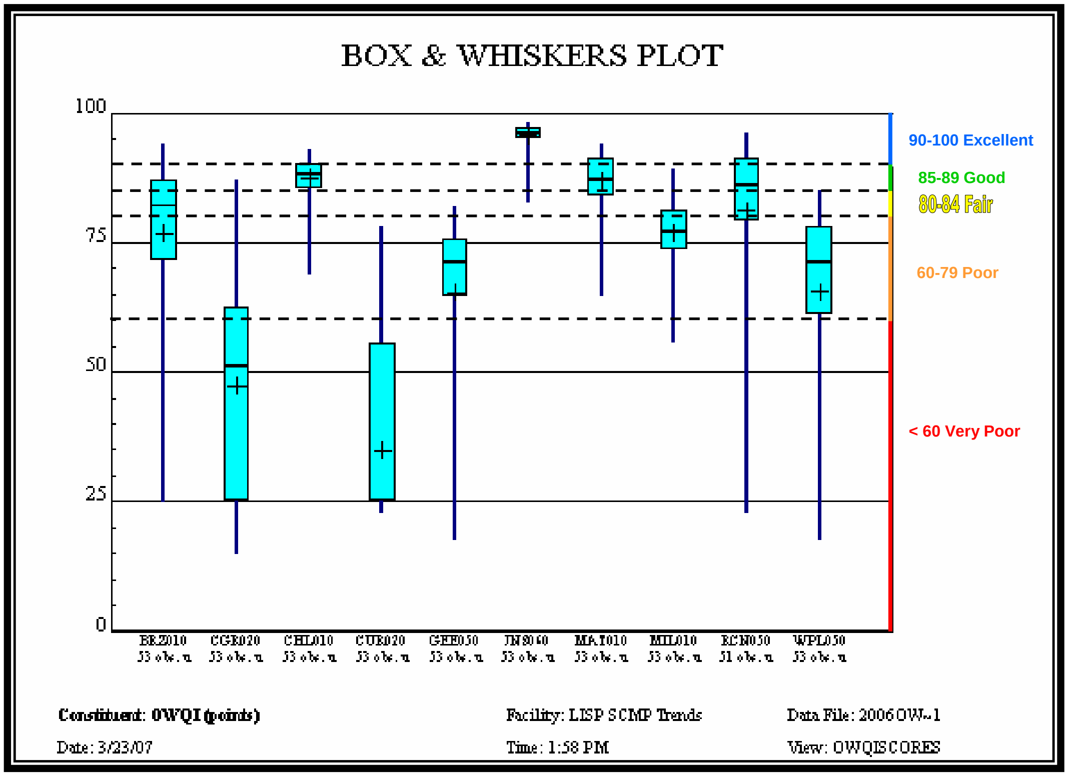


Figure 3. Box and whisker plot of LISP monthly OWQI values.

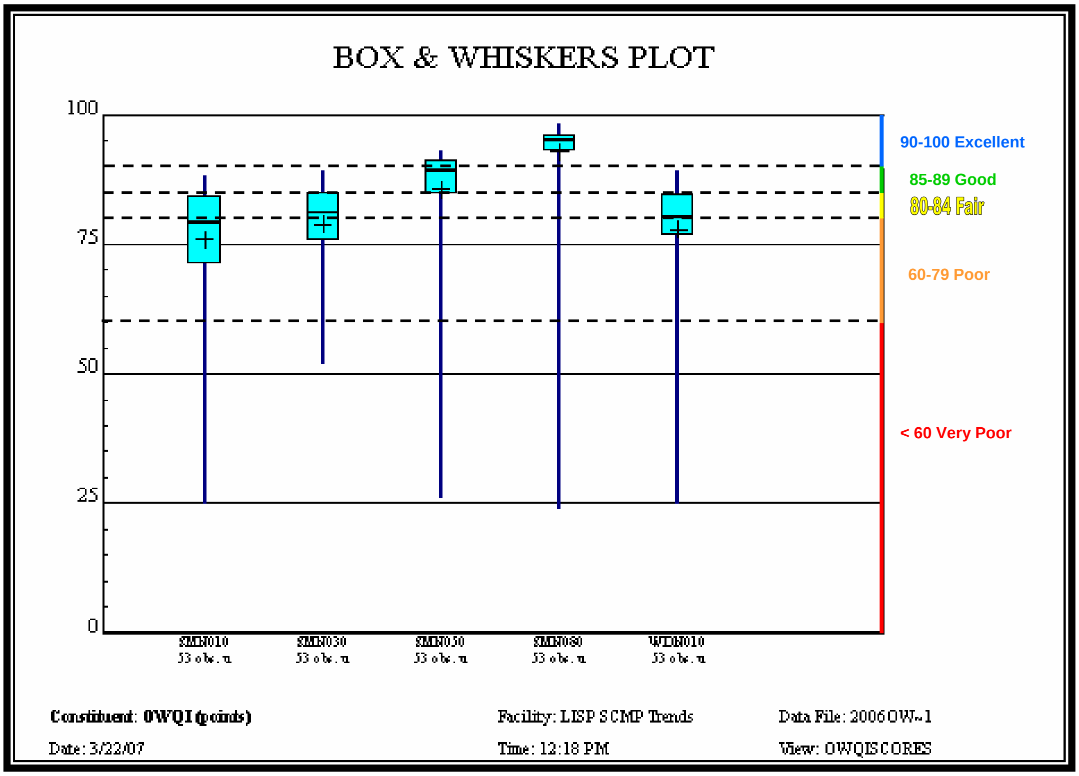
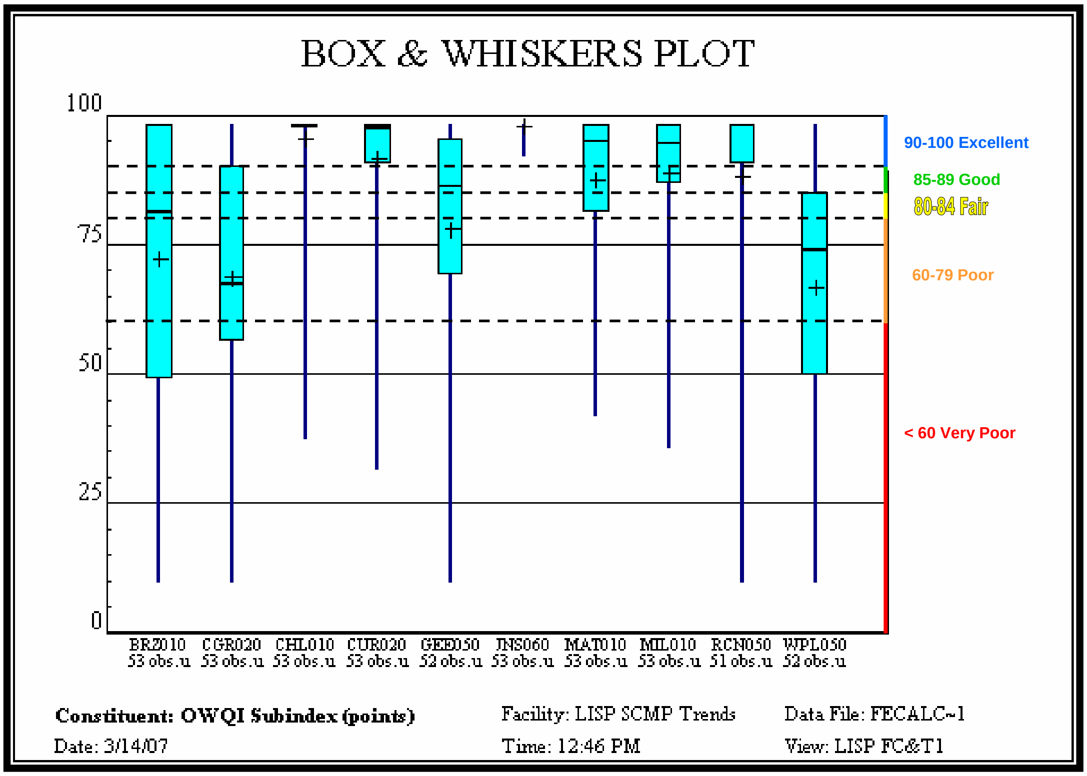


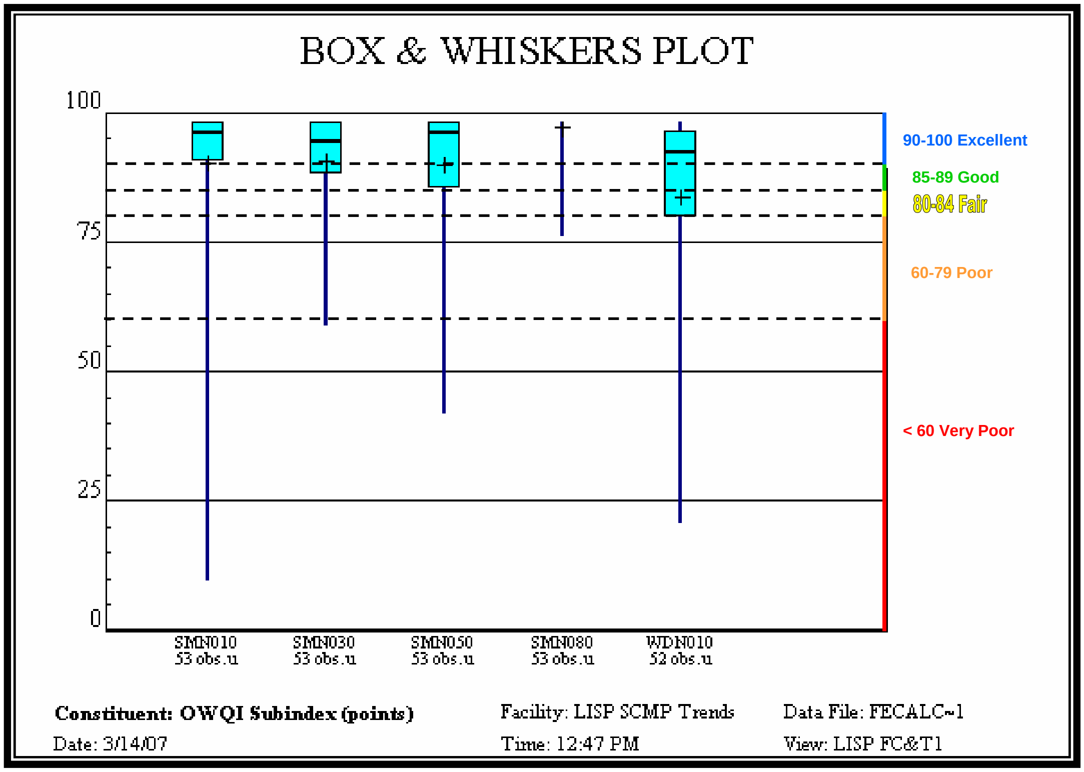
Figure 4. Box and whisker plot of SCMP monthly OWQI values.



Constituent: OWQI Subindex (points) Facility: LISP SCMP Trends Data File: FECALC~1

Date: 3/14/07 Time: 12:46 PM View: LISP FC&T1

Figure 5. Box and whisker plot of LISP monthly Fecal Coliform OWQI subindex values.



Constituent: OWQI Subindex (points) Facility: LISP SCMP Trends Data File: FECALC~1

Date: 3/14/07 Time: 12:47 PM View: LISP FC&T1

Figure 6. Box and whisker plot of SCMP monthly Fecal Coliform OWQI subindex values.

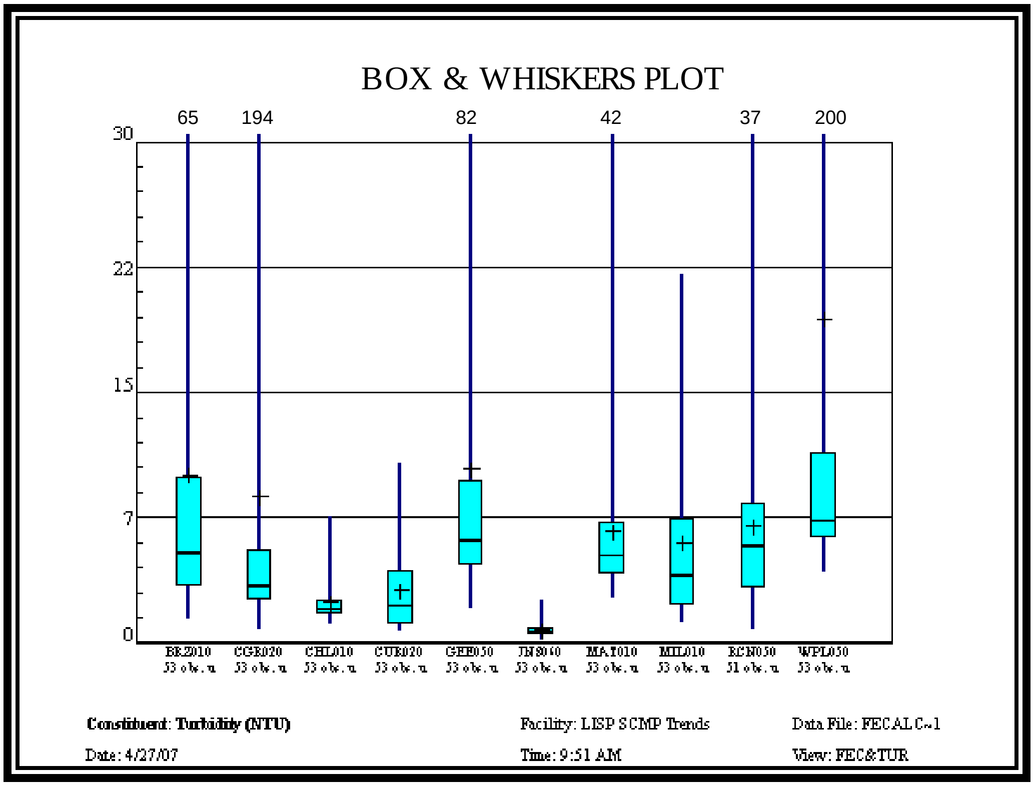


Figure 7. Box and whisker plot of LISP monthly Turbidity values.

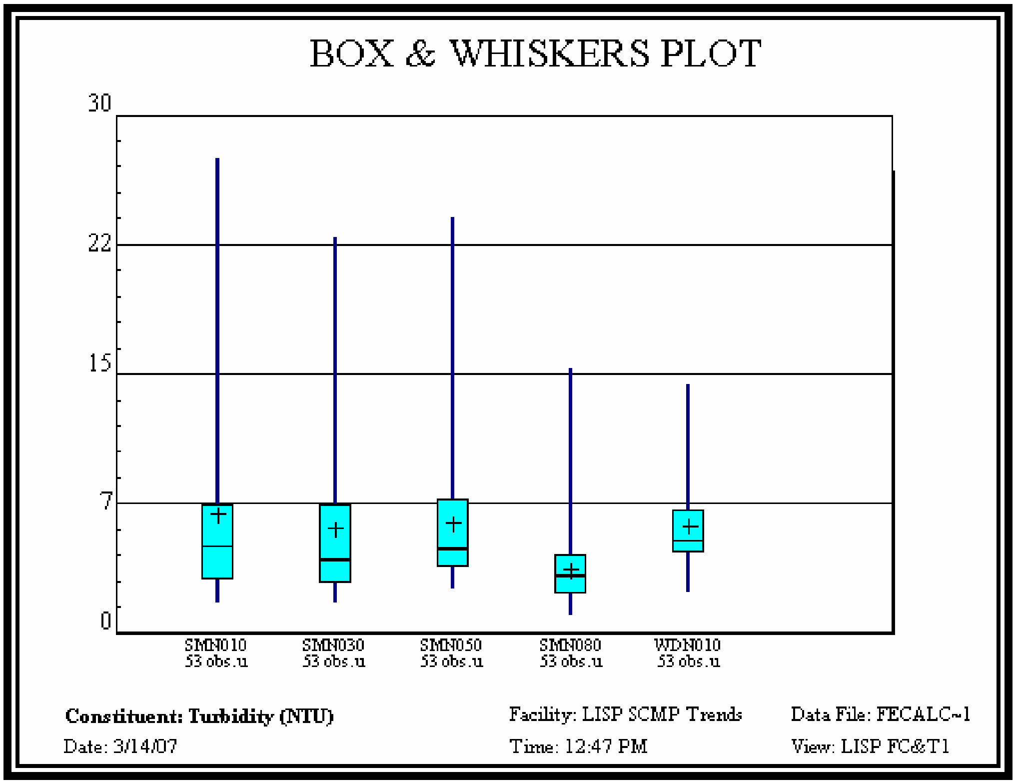


Figure 8. Box and whisker plot of SCMP monthly Turbidity values.

Trends

Seasonal Kendall trend test results for various LISP and SCMP long term monitoring stations are depicted in the following graphics. They include tables and plots of test results for overall OWQI scores, fecal coliform OWQI subindex scores, or turbidity on the y-axis and time along the x-axis. To the right of each plot are test statistic results and associated tables to aid interpretation including significance of test results at various confidence levels. 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.

Nine statistically significant trends over time were found based on using monthly defined seasons. There was only one significant trend result each for the overall OWQI scores (at Salmon Creek at 199th Street) and the fecal coliform OWQI subindex scores (at Mill Creek) (Figures 9 and 10 Seasonal Kendall trend test for monthly OWQI and fecal coliform subindex values, respectively). However, seven significant trend test results were found for turbidity (Figures 11 – 17 Seasonal Kendall trend test for monthly turbidity). Nonsignificant trend results are not presented. Additionally, none of the stations with significant trends also had significant serial correlation or lack of independence when using monthly defined seasons.

Interestingly, all the stations' significant water quality trends were worsening for the monitoring period (Table 3. Summary of significant Seasonal Kendall trend analyses tests and as applicable projections at current rates of change). Salmon Creek at 199th Street's declining overall OWQI scores were significant at up to the 90% confidence level. Mill Creek's declining fecal coliform OWQI subindex scores were significant at up to 95% confidence. Seven stations were found to have significant increasing trends for turbidity: Brezee (steepest trend slope), Matney, Mill, Rock Creek North, and main stem Salmon Creek at 50th Avenue, Caples Road, and 199th Street. All seven stations were trending towards higher turbidity levels and more degraded water quality. Confidence levels for the seven significant turbidity trends were as high as 80 % for Rock Creek North, 90% for Matney Creek, and 95% for the remaining five stations.

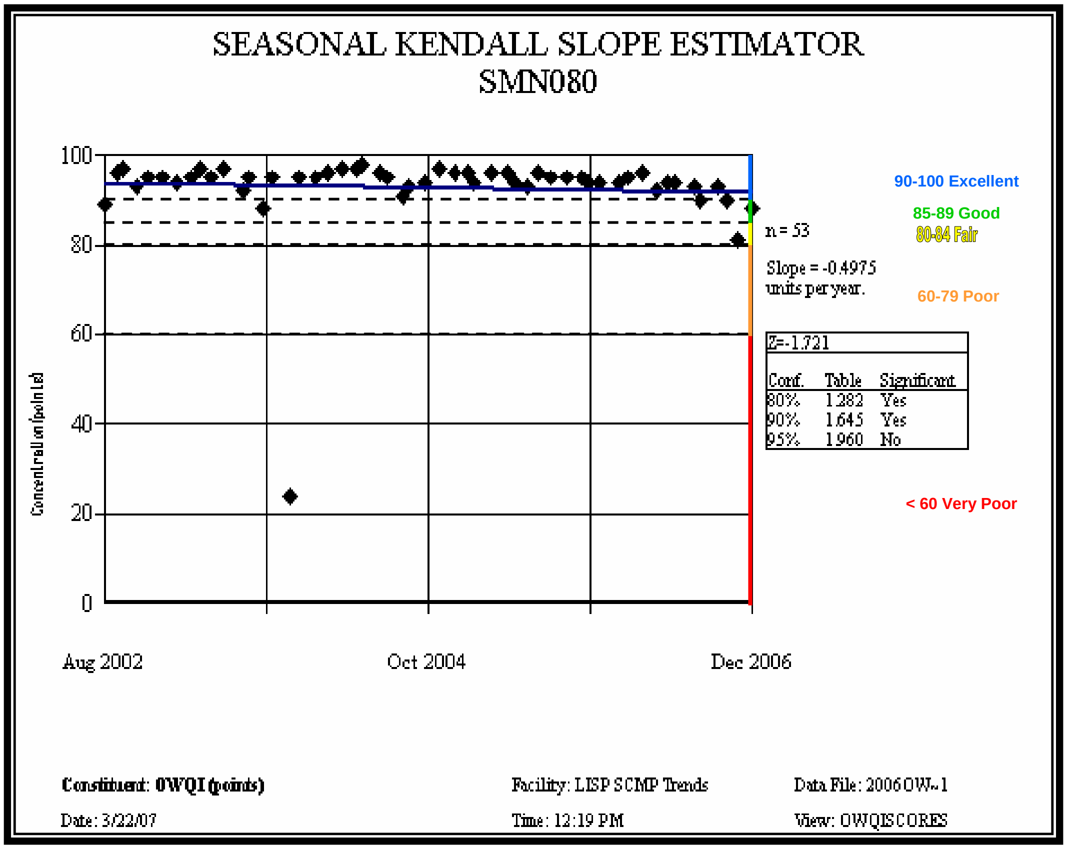


Figure9. Seasonal Kendall trend test for Salmon Creek at 199th Street monthly OWQI values.

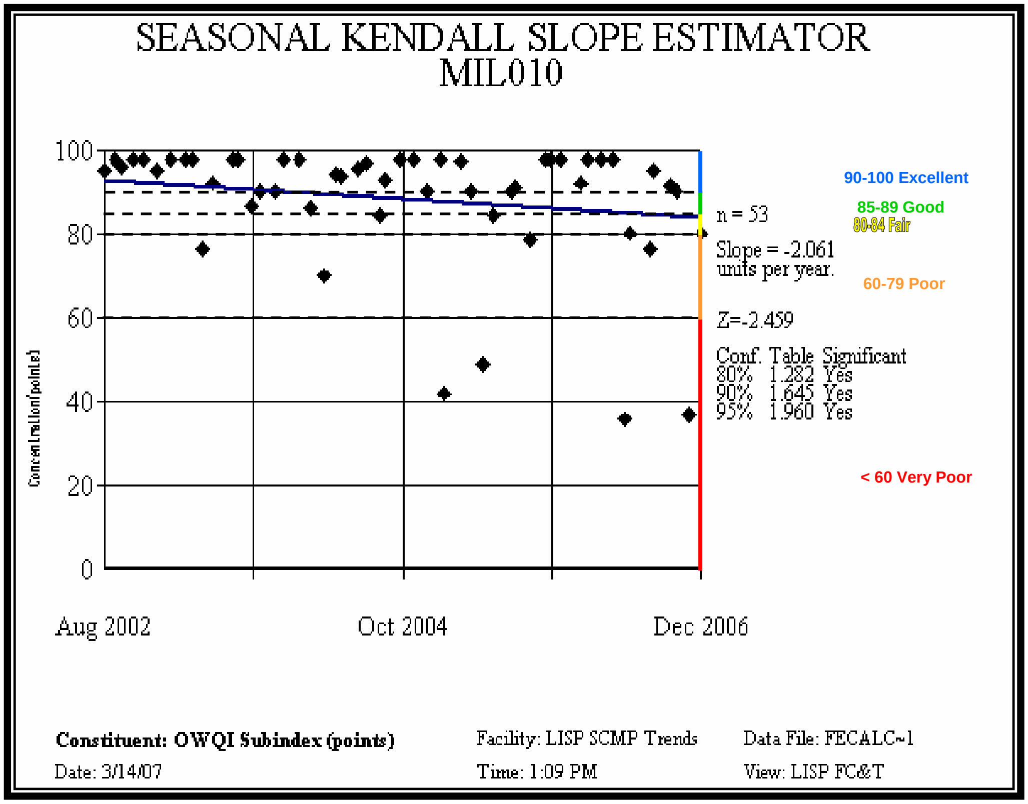


Figure10. Seasonal Kendall trend test for Mill Creek monthly fecal coliform OWQI subindex values.

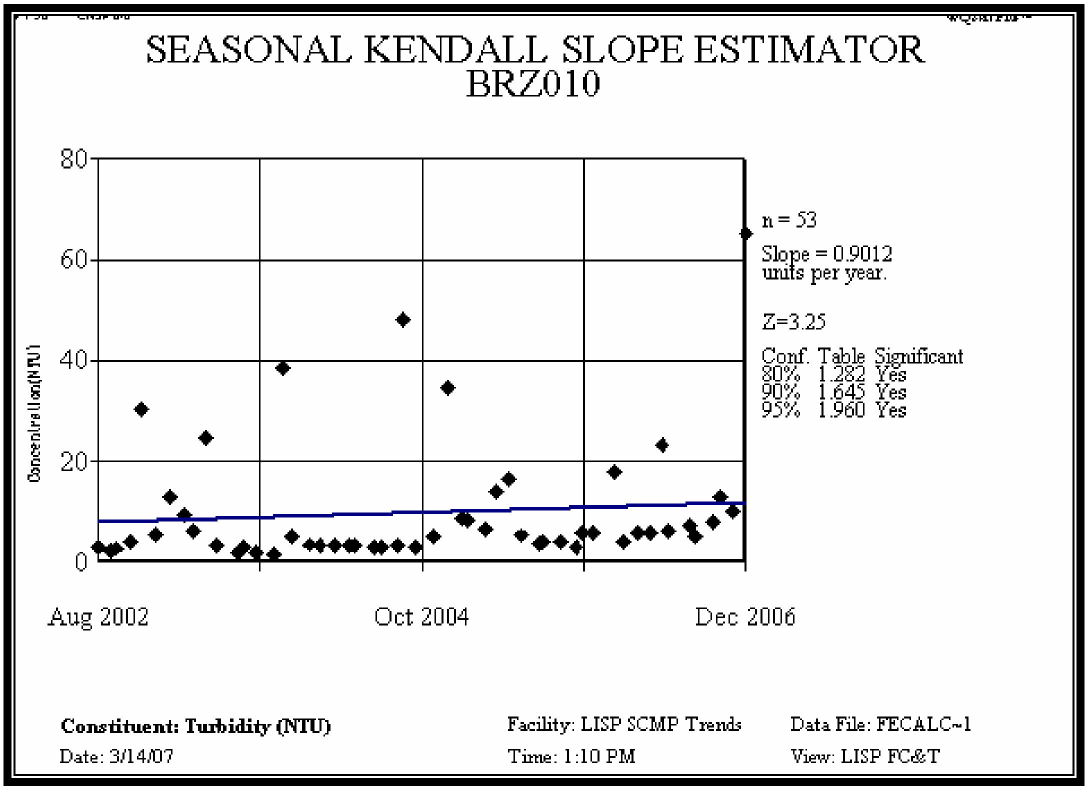


Figure11. Seasonal Kendall trend test for Brezee Creek's monthly turbidity values.

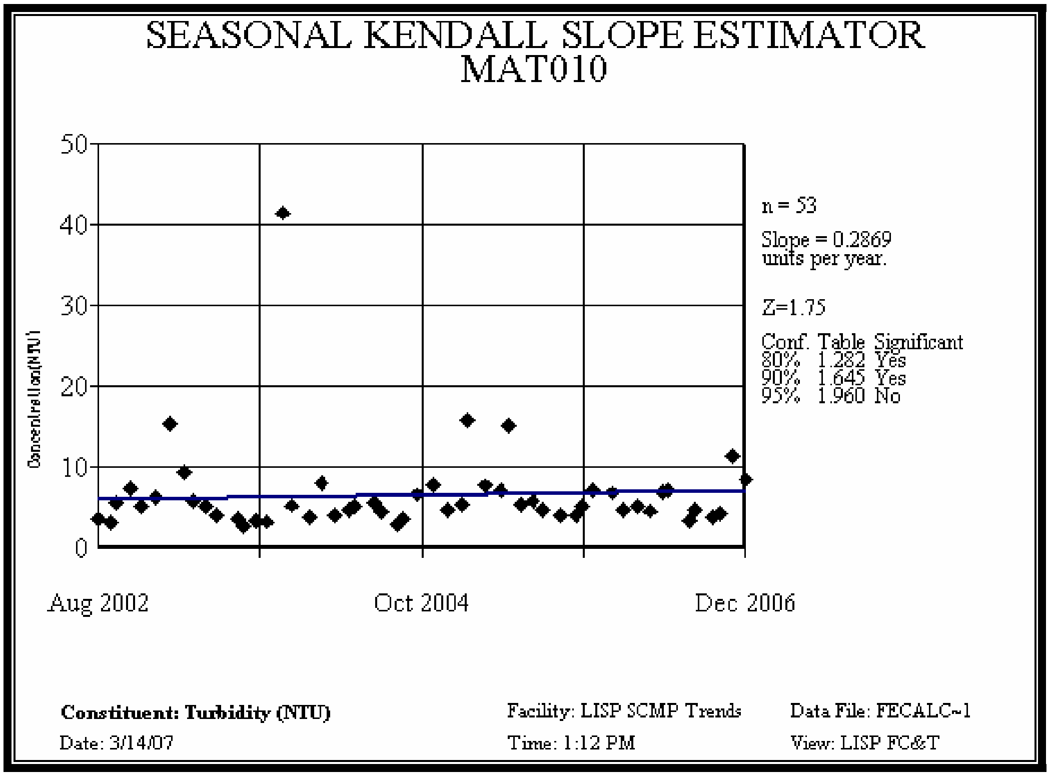


Figure12. Seasonal Kendall trend test for Matney Creek's monthly turbidity values.

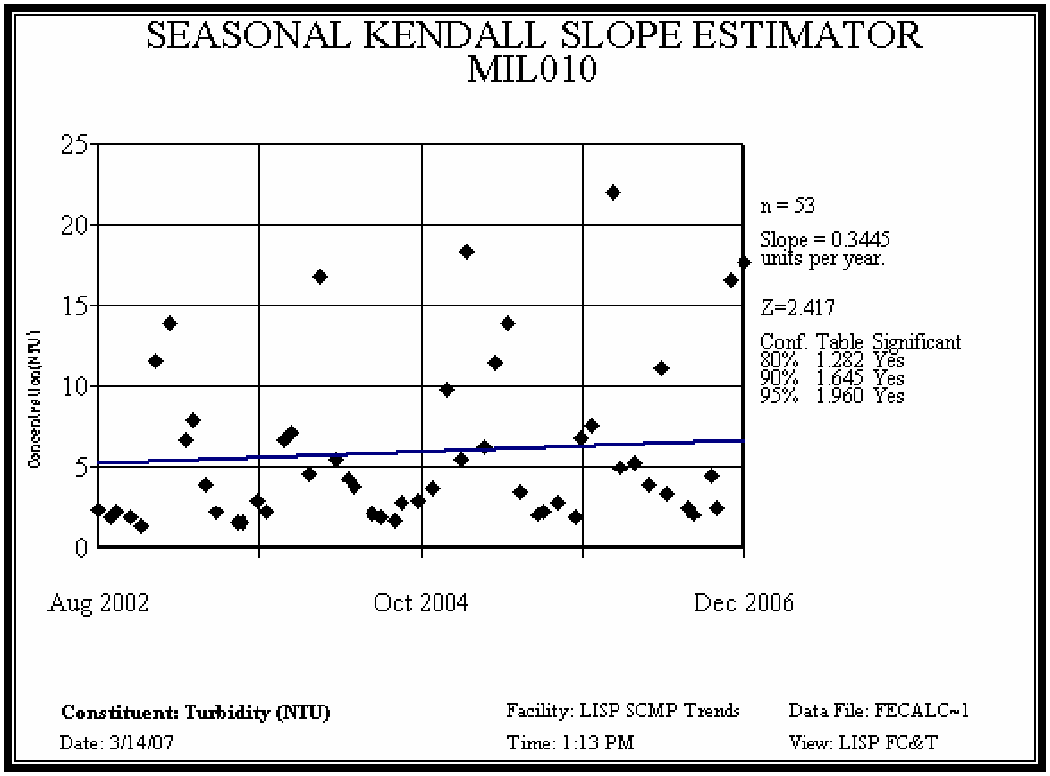


Figure13. Seasonal Kendall trend test for Mill Creek's monthly turbidity values.

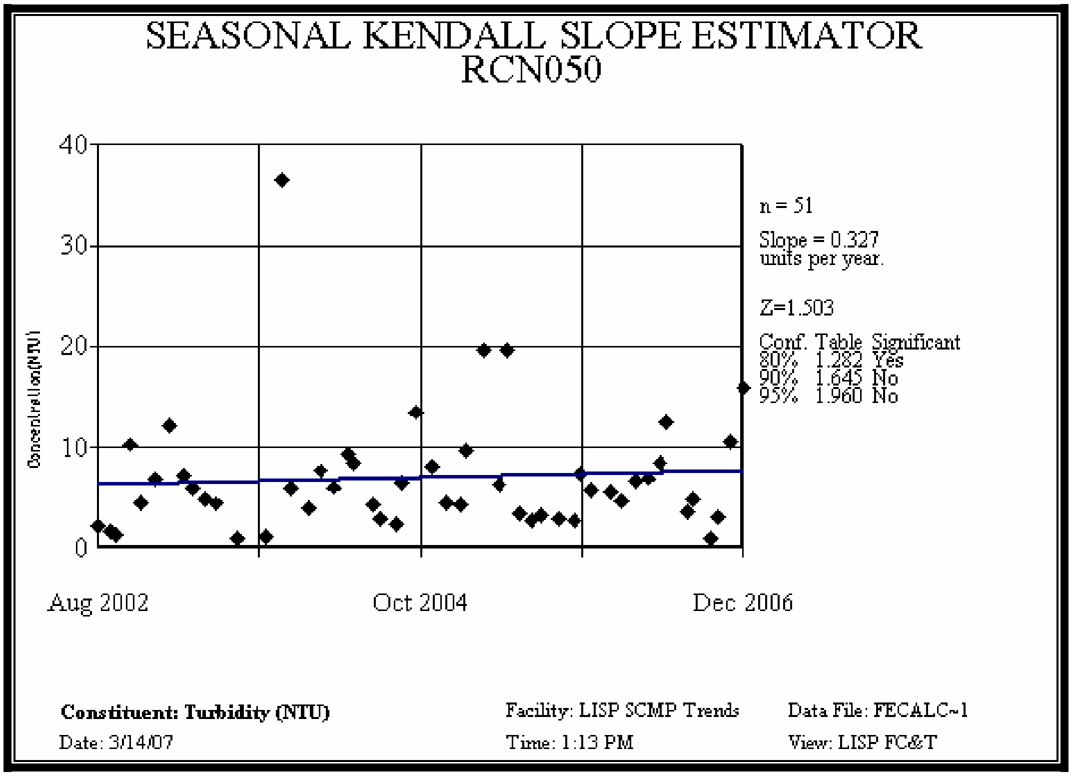


Figure14. Seasonal Kendall trend test for Rock Creek North's monthly turbidity values.

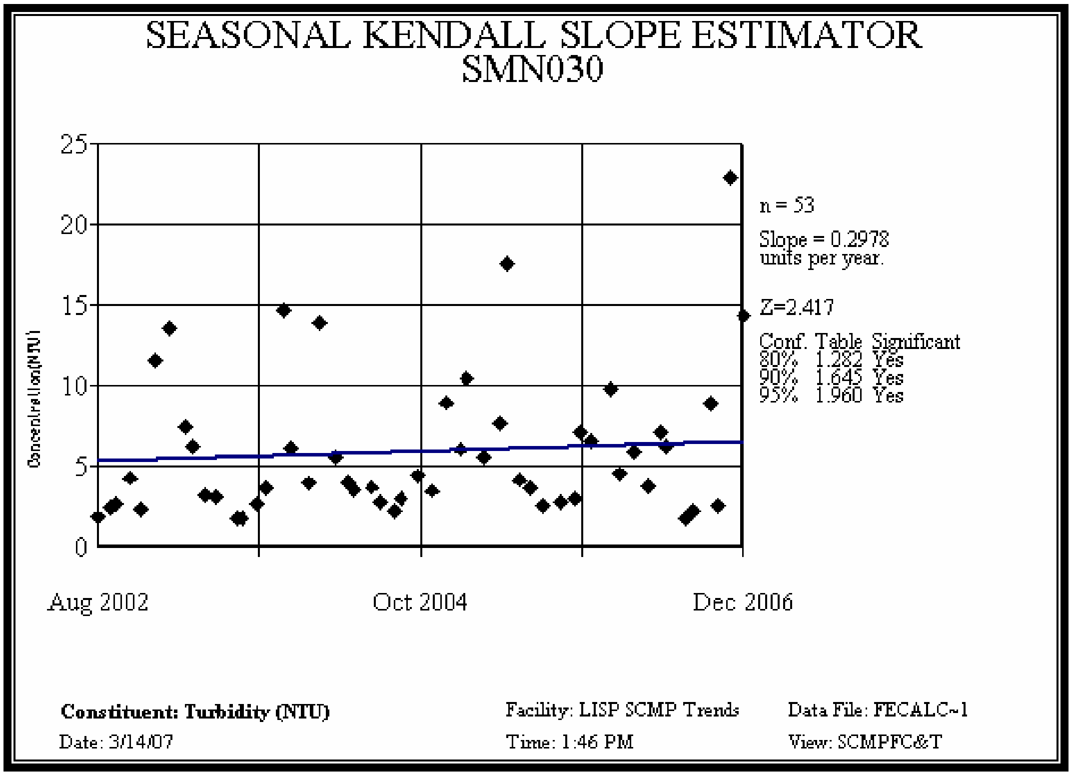


Figure15. Seasonal Kendall trend test for Salmon Creek at NE 50th Avenue's monthly turbidity values.

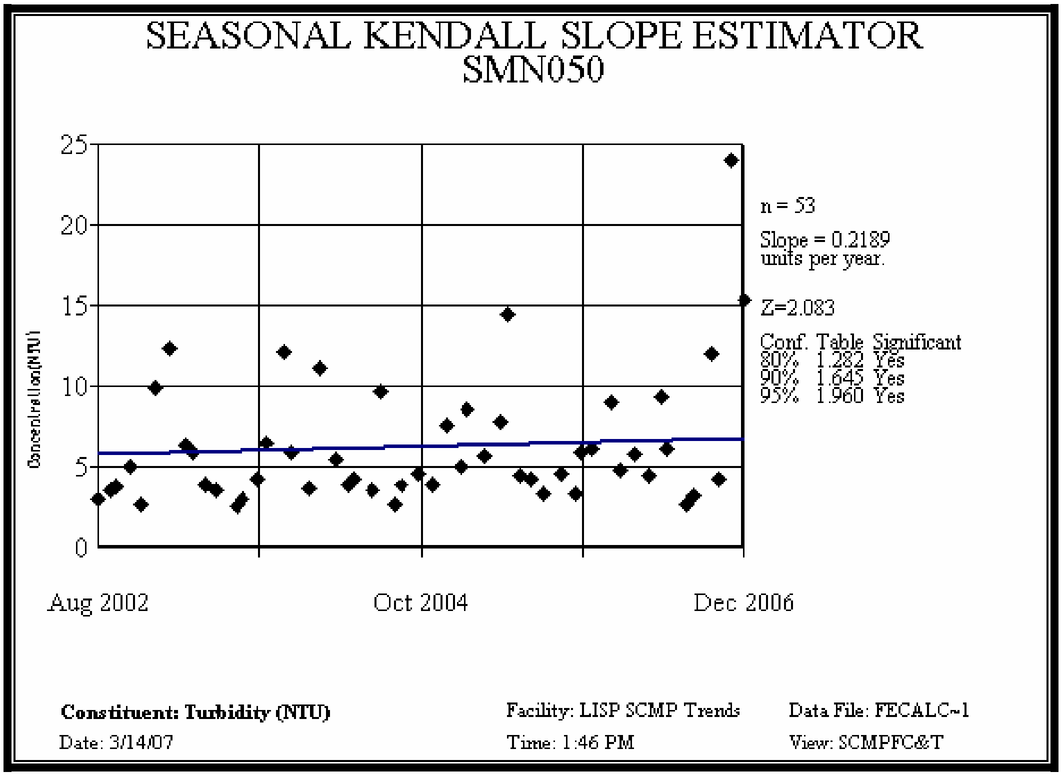


Figure16. Seasonal Kendall trend test for Salmon Creek at Caples Road's monthly turbidity values.

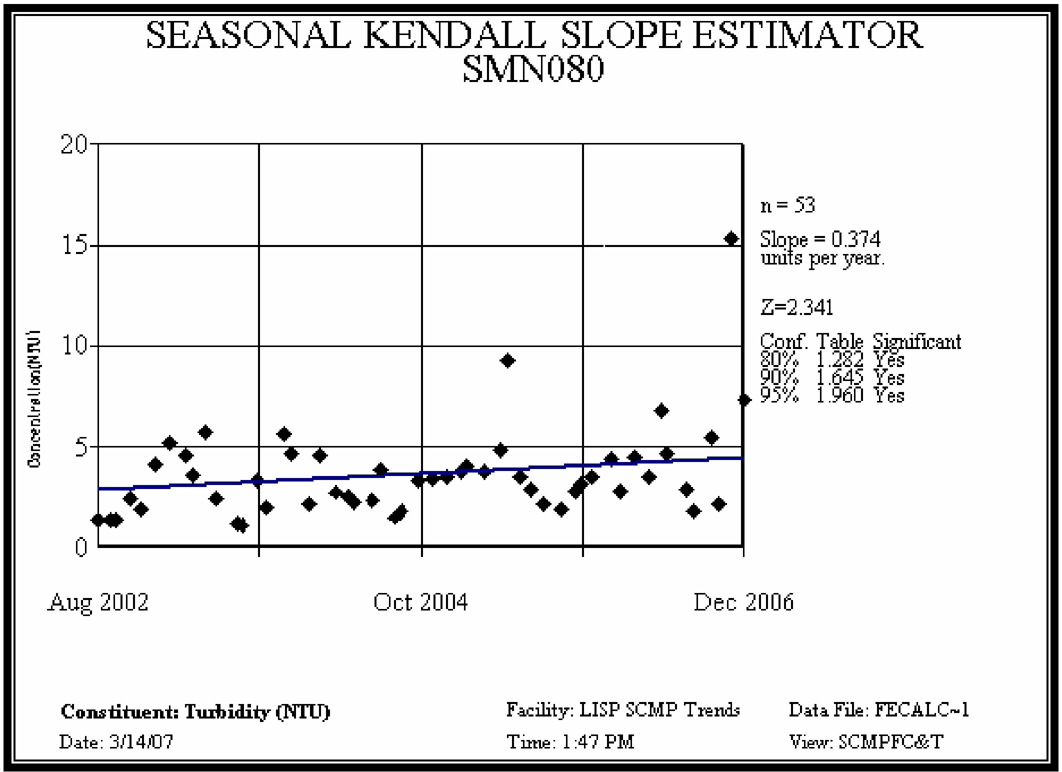


Figure17. Seasonal Kendall trend test for Salmon Creek at NE 199th Street's monthly turbidity values.

Additionally, as applicable, estimates were made by projecting the future time required for a change or shift in the OWQI class status for each of the monitored stations with significant Seasonal Kendall trends (Table 3. Summary of significant Seasonal Kendall trend analyses tests and projections at current rates of change). The projected time for Salmon Creek at 199th Street to degrade from its current Excellent OWQI classification to Good is approximately 2 years. The projected time for Mill Creek to degrade from its current Fair OWQI classification to Poor is approximately 2 years based on using just the fecal coliform OWQI subindex for trend analysis. These projected times are based on the assumed appropriateness of a linear Sen's slope that utilizes a constant rate of change over time and a visual estimate of the applicable scores for these stations at the end of the 2006 calendar year.

Water Quality Indicator	Station	Significant Trend Direction and Quality Change	Sample Size (n = # of months)	Confidence Levels of Trend Result	Estimated Sen's Slope (units / yr.)	Current OWQI or Subindex Score and Quality Class	At Current Rate of Change, Projected Time to Shift Class (years)
OWQI	SMN080	Downward (Worse)	53	90%, 80%	-0.4975	91 = Excellent	2 years to Good
Fecal Coliform Subindex	MIL010	Downward (Worse)	53	95%, 90% 80%	-2.061	84 = Fair	2 years to Poor
Turbidity*	BRZ010	Upward (Worse)	53	95%, 90% 80%	0.9012	N/A	N/A
Turbidity*	MAT010	Upward (Worse)	53	90%, 80%	0.2869	N/A	N/A
Turbidity*	MIL010	Upward (Worse)	53	95%, 90% 80%	0.3445	N/A	N/A
Turbidity*	RCN050	Upward (Worse)	51	80%	0.327	N/A	N/A
Turbidity*	SMN030	Upward (Worse)	53	95%, 90% 80%	0.2978	N/A	N/A
Turbidity*	SMN050	Upward (Worse)	53	95%, 90% 80%	0.2189	N/A	N/A
Turbidity*	SMN080	Upward (Worse)	53	95%, 90% 80%	0.374	N/A	N/A

Table 3. Summary of significant Seasonal Kendall trend analyses tests and projections at current rates of change. The significance of turbidity trend may be impacted by relative changes in flows during the monitoring period.*

Interpretation Limitations

The methods used to collect, preserve, handle, ship, and analyze samples and report data values should remain constant during the period of study for a trend analysis (U.S.G.S. Water Resources Investigations Report 91-4040, Schertz et al., 1991, p. 5). Changes in these methods may confound the detection of trends in ambient water quality or may even directly cause trends to appear in water-quality records. Accordingly, changed laboratory methods for most of the stations in February 2004 may be confounding this report's fecal coliform OWQI subindex trends (also see Appendix C).

The results of the Rank von Neumann statistical test for serial correlation (lack of independence) showed that none of the water quality monthly data had significant serial correlation. Prior to running the test, the monthly water quality data were first detrended and deseasonalized using monthly defined seasons.

Rock Creek North periodically dries up during the summer which may limit how representative its data is 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.
The current LISP and SCMP data sets only extend approximately 4.5 years which is less than the typical minimum of 5 years needed for trend analysis. This relatively short period of record places inherent limitations on the practical interpretations from the trend analyses. Changes in water quality over time could simply be due to changes in an exogenous variable during a portion of the trend analyzed period such as wetter latter years (Helsel and Hirsch, 1993, p.323). So far, this study's sampling period probably is not long enough to be representative of the overall variability present. Our results may only be observing a biased portion of the population. A brief analysis of the historical record for the nearby free-flowing East Fork Lewis River showed that, on a water year basis and generally for the specific LISP field dates, it was substantially drier than average during the time generally coinciding with the August 2002 – December 2006 LISP and SCMP monitoring period (Appendix C).

Trend analysis of flow observations may be used to determine whether the time series of flow has undergone change with time (U.S.G.S. Water Resources Investigations Report 91-4040, Schertz et al., 1991, p. 25 and Helsel and Hirsch, 1993, p. 332). Therefore, a brief analysis of trends in the daily mean flow for the free-flowing East Fork Lewis River was made using both the raw and "normalized" daily mean flow records for the LISP field monitoring dates (SCMP dates were not evaluated because they were within one day of LISP dates). The "normalized" flow data (as a percentage of the historical daily mean flow for those field dates) did have a significant upward trend at the 80%, 90% and 95% confidence levels over the monitoring period's field dates (Appendix C). These results suggest that compared to historical daily mean flows, the actual daily mean flows on the field days of the LISP monitoring runs were on average increasing over the monitoring period of this report. This flow trend increases the potential for confounding effects on any non-flow adjusted water quality trend results because they could be driven by increasing flows over the monitoring period. A great deal of the variance in streamflow concentrations is usually a function of river discharge as a result of dilution or wash-off from overland flow (Helsel and Hirsch, 1993, p. 333). With wash-off, concentrations and fluxes tend to rise with increasing discharge. For the current study, much of the increasing trends found for turbidity could be driven by the increasing trend in the "normalized" flows and associated increases in wash-off sediments over the field dates of the LISP monitoring.

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 current 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. Typically, at least 5 years of monthly data are needed for a trend study (U.S.G.S. Water Resources Investigations Report 91-4040, Schertz et al., 1991, p. 5). The continuation of a longer data set will gradually increase the power of the statistical analyses, especially for trend analysis. The recent availability of four complete years of monthly monitoring data allowed better definition of seasons and use of the Seasonal Kendall Trend test within WQSTAT PLUS. This keeps applicable trend plots' y-axes in the original OWQI ranges for better interpretation. 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. Longer monitoring data sets will also aid long-term trend analysis by reducing potential confounding impacts from drought cycles (also see Appendix C).

Additional 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 statistically calculated flow-adjusted concentrations. The detection of water quality trends may be complicated by the presence of flow-related variability in water-quality records (U.S.G.S. Water Resources Investigations Report 91-4040, Schertz et al., 1991, p. 20). Flow-related variability may be large relative to the magnitude of change in water quality resulting from human activities. If the interest is in evaluating the effect of changes in human activities on water quality then focus on tests for trend in flow independent water quality concentrations (flow adjusted concentrations). This will reduce the total variability in water quality and increase the power of the test or the chance of detecting a trend that is a result of some influence other than stream flow. If trends in the actual ambient concentrations of water quality are of interest (e.g., for comparison with water quality standards) then trends in the raw (non-flow adjusted) concentrations should be examined.

As the LISP and SCMP monthly data sets extend beyond the minimum 5 year period their sample size could increasingly justify more detailed trend analyses than has been done so far. These longer data sets will allow more thorough evaluation of possible impacts of confounding factors (see Appendix C). Evolving specific project goals will also help clarify and direct all future potential trend analyses.

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Appendix A. Background on Statistical Considerations

Statistically, in trend analysis 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").

Although trend power was also not evaluated in this analysis, it has been in other regional reports. Equivalently to that noted above, 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). Also, 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).

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 (though 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.

The probability that an interval does include the true value is called the confidence level of the interval (Helsel and Hirsch, 1993, p. 67-68). The probability that this interval will not cover the true value is called the alpha level (1- confidence level). Confidence intervals consist of two boundary points between which we have a certain specified level of confidence that the population parameter lies. So at the 95% confidence interval for a parameter, in repeated sets of samples of the same size, 95% of all such intervals would be expected to contain the parameter. Alpha represents the specified significance level; which is the tolerable error (probability) for incorrectly rejecting the null hypothesis (Kleinblaum et al., 1988, pp. 24-32). This is equivalent to the probability of making Type I error or False Positive decision associated with hypothesis testing.

Appendix B. OWQI Spreadsheet Calculation Methods

(Version 3 - Revised from original Water Resources OWQI calculations spreadsheet instructions.)

1. This is not a template that runs on its own. It requires many manual steps and several quality control checks to ensure the completion of a robust dataset.
2. Initially using Access, customize and export a query from the WQDB to include the following water quality parameters as applicable; Ammonia as N, Nitrite as N, Nitrate as N, and Nitrate-Nitrite as N, Dissolved Oxygen mg/L and Dissolved Oxygen % saturation, Total Phosphorous, Water Temperature, Total Solids, pH, Fecal Coliform, Conductivity, and Turbidity.
3. From this point, utilize Excel for data manipulation and calculations. Reduce dataset to only characteristics used for OWQI calculations. These characteristics included Inorganic Nitrogen (Ammonia as N, Nitrite as N, Nitrate as N, and Nitrate-Nitrite as N), Dissolved Oxygen (Dissolved Oxygen mg/L and Dissolved Oxygen % saturation), Total Phosphorous, Water Temperature, Total Solids, pH, and Fecal Coliform. Keep all Inorganic Nitrogen parameters together as well as both Dissolved Oxygen parameters.
4. As a quality control step, be sure any duplicate characteristics-start date-location rows are deleted (e.g. replicate sample or measurement values). Also eliminate all data values with an R? or REJ Data Qualifier, as these data are unreliable and thus unusable.
5. 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 to applicable column of calculation worksheet. Most calculations of subindex scores will be straightforward. However, several characteristics may require additional preparation steps prior to calculating their monthly subindex values. These characteristics include Dissolved Oxygen, Inorganic Nitrogen, Total Phosphorous, and possibly Total Solids (for these characteristics, see steps 6 - 15).
6. Total Phosphorus values are recorded in the WQDB in one of two ways; as a detected value or as a non-detect (ND) value at or above the Method Reporting Limit (MRL) with a Data Qualifier “U” (The analyte was not detected at or above the reported limit). If a value is reported by the laboratory as an ND for Total Phosphorus, it will have a “U” Data Qualifier in the WQDB. The result value recorded in the WQDB is the MRL value. Use one half of the MRL as the new result value for all OWQI calculations.
7. Paste the Total Phosphorus formula into the appropriate column on the calculations sheet and calculate subindex values.
8. For Dissolved Oxygen (DO mg/L and DO % sat.), sort by Location ID_code, Start Date, and then by Parameter. As a quality control step, use “IF” statements to make sure each Location ID_code and Start Date are the same for each collection date and has both a Dissolved Oxygen mg/L and Dissolved Oxygen percent saturation value paired together. For example see below.
   BRZ010 04/26/2006 Dissolved Oxygen mg/L = 11.2
   BRZ010 04/26/2006 Dissolved Oxygen % = 98.3
9. Calculate, if possible, any missing Dissolve Oxygen values using the following equations to calculate Dissolved Oxygen % Saturation. Dissolved Oxygen % Saturation = (Dissolved Oxygen mg/L / (100% saturation value * correction factor)). (100% saturation value = (0.0043 * temperature^2) – (0.03573 * temperature) + 14.76)) and (Correction Factor = 760 – (elevation/100) * 2.5). (\\Nt05\waterresources\PROJECT\011134, mon support, training\MONITORING\Data\Analysis\Tools\OWQI\diss oxygen sat calculator.xls)
10. Paste the Dissolved Oxygen formula into the appropriate column on the calculations sheet and calculate subindex values.
11. Then delete subindex calculation rows for Dissolved Oxygen Saturation (otherwise duplicates DO subindexes).
12. For Total Solids, sort data by Location ID_code and Start Date. Scan data for any missing start dates. Calculate, if possible, any missing Total Solids values using the following equations; (conductivity * 0.65 = Total Dissolved Solids) and (Total Dissolved Solids + Total Suspended Solids = Total Solids) (\\Nt05\waterresources\PROJECT\011134, mon support, training\MONITORING\Data\Analysis\Tools\OWQI\readme.txt).
13. Paste Total Solids formula data into the appropriate column on the calculations sheet and calculate subindex values.

14. Calculate Inorganic Nitrogen values by the adding Ammonia as N values to Nitrate-Nitrite as N values or by the adding Ammonia as N values to both Nitrite as N and to Nitrite as N values. This can be done by filtering and then sorting the data by Location_code, Start Date, and then by Characteristic Name to view all Inorganic Nitrogen component values per Site/Start Date. These values are reported in one of three ways; as a detected value, as a non-detect (ND) value at or above the Method Reporting Limit (MRL), or as a non-detect (ND) value at or above the Method Detection Limit (MDL). All ND values will have a Data Qualifier “U” (The analyte was not delectated at or above the reported result limit) or “UJ” for ammonia (The analyte was not delectated at or above the reported estimate result limit). The result value listed in the WQDB is the MDL or MRL (whichever detection limit the laboratory reported). Use one half of the MDL or MRL as the new result value for all I further OWQ calculations.
15. Paste the summed Inorganic N data into the appropriate column within the calculations sheet and calculate subindex values.
16. Copy calculation sheet containing all applicable processed characteristics then convert all subindex formula results into values into a new worksheet. Sort the data set by station, date, and characteristic to get it back into original shape.
17. Once all characteristics are recombined onto a single sheet containing the subindex values (not formulas), conduct a quality control step. Sort by Location_code and Start Date and utilize a Logic statement (example is =IF(I8>I9,I8+1,"")) to count the number of matching dates per site (should have a result value of 5, 6, or 7 OWQI subindex values per same Location sites and date).
18. Calculate the OWQI for each combination of Location_code and Start Date.
    - a.) If the data set is very consistent in the number of subindex values across months: Copy the OWQI 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 completely 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.
    - b.) If the dataset has an inconsistent number of subindex values across months: Utilize the “OWQI Calculator for Inconsistent Characteristic Dataset.xls” spreadsheet tool (includes its own instructions).
19. Convert the OWQI formula results into values (via copy and paste special onto themselves) 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.
20. 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.
21. Confirm that the minimum average season and status formulas have worked.

Appendix C. Potential Confounding Factors Affecting Trend Results

Changes in Methods

This study's laboratory method used to analyze fecal coliform was changed for most stations as of February of 2004 from Most Probable Number to Colony Forming Units (Figure D1). Additionally, volunteer collected samples since this date continue to be analyzed by the Most Probable Number method. These changes may be confounding trend analyses and contributing to the apparent significant downward trend found in the fecal coliform OWQI subindex scores. After more data become available in the future, it may be necessary to limit the statistical analysis to the period after January 2004 in order to have more reliable trend test results.

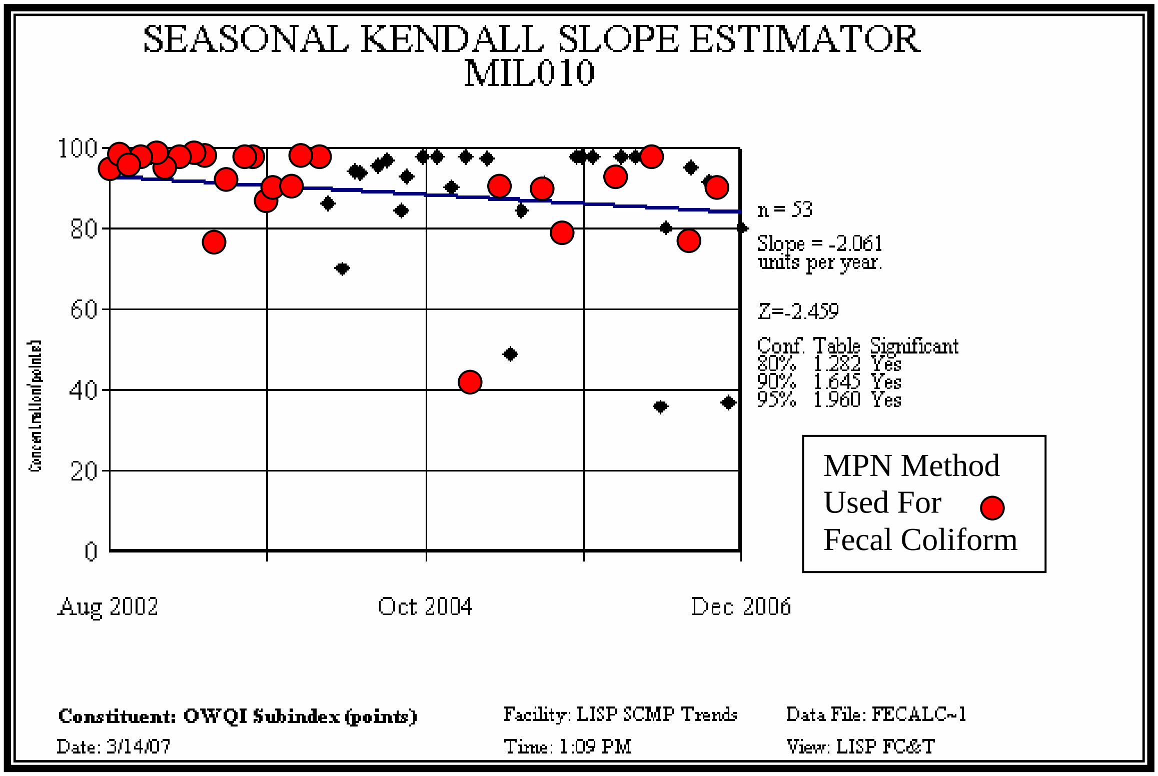


Figure C1. Mill Creek fecal coliform samples analyzed by Most Probable Number laboratory method.

Impacts of Drought and Wet Periods

The current LISP and SCMP data sets only extend approximately 4.5 years which is less than the typical minimum of 5 years needed for trend analysis. This relatively short period of record places inherent limitations on the practical interpretations from the trend analyses. For example, published trend analyses on OWQI scores by Oregon examine a ten year period of ambient water quality data to attenuate the effects of drought cycles and ensure that sufficient data are available to analyze for trends (Cude, 2001, p. 132). Changes in water quality over time could simply be due to changes in an exogenous variable during a portion of the trend analyzed period such as wetter latter years (Helsel and Hirsch, 1993, p.323).

The following is a brief evaluation of how the current monitoring period fits into the overall long term cycle of droughts and wet periods. The nearby East Fork of the Lewis River was chosen because it has a fairly extensive flow period of record extending continuously from September 1929 to the current year (USGS National Water Information System, Gage #14222500 East Fork Lewis River Near Heisson). This site has web published summary statistics based on approved daily-mean flow data for this gage. Although it is recognized that the main stem East Fork Lewis River is not monitored for water quality by the LISP or

SCMP project, it does have the longest period of flow record for a free flowing river in the vicinity of the project monitoring. It is also assumed, even with its larger size and substantial headwaters areas within the Cascade foothills, that the East Fork's overall general flow pattern integrates and is indicative of drought and wet periods for the region.

Table C1 and Figure C2 show that the East Fork Lewis River flow period generally coinciding with the August 2002 – December 2006 LISP and SCMP monitoring period was substantially drier than average.

Annual Water Year Rank	**Water Year**	**Annual WY Mean Flow (cfs)**	**Difference From Annual Mean**
1	2001	410.7	-44%
49	2002	779.2	6%
16	2003	604.6	-18%
24	2004	655.8	-11%
11	2005	551	-25
33	2006	706.3	-4
Median WY Rank Out of 77 Years	**Median Annual Flow (cfs)**	**77 Year Mean Annual Flow (cfs)**	**WY 2001 -2006 Average Annual Difference**
39	742.6	735	-16%

Table C1. Summary of Water Year 2001-2006 Flows on East Fork Lewis River at Heisson.* Statistics are based on 77 years of daily mean flow data.

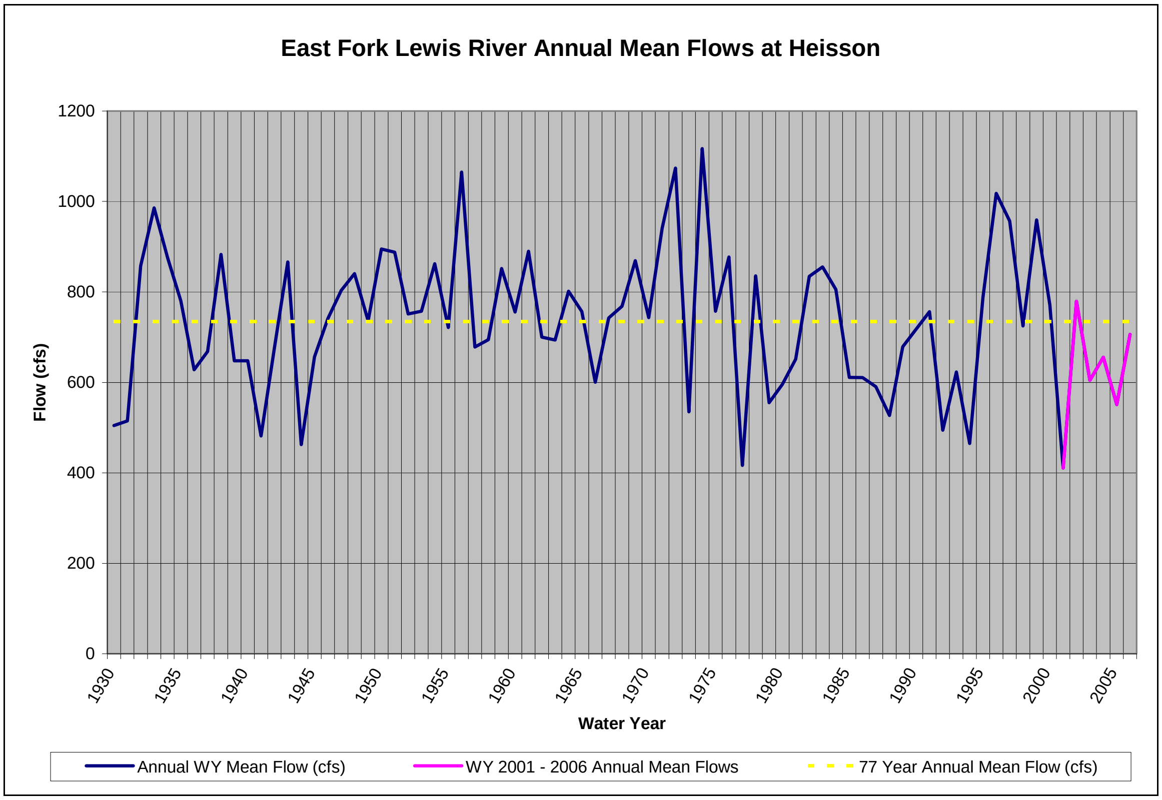
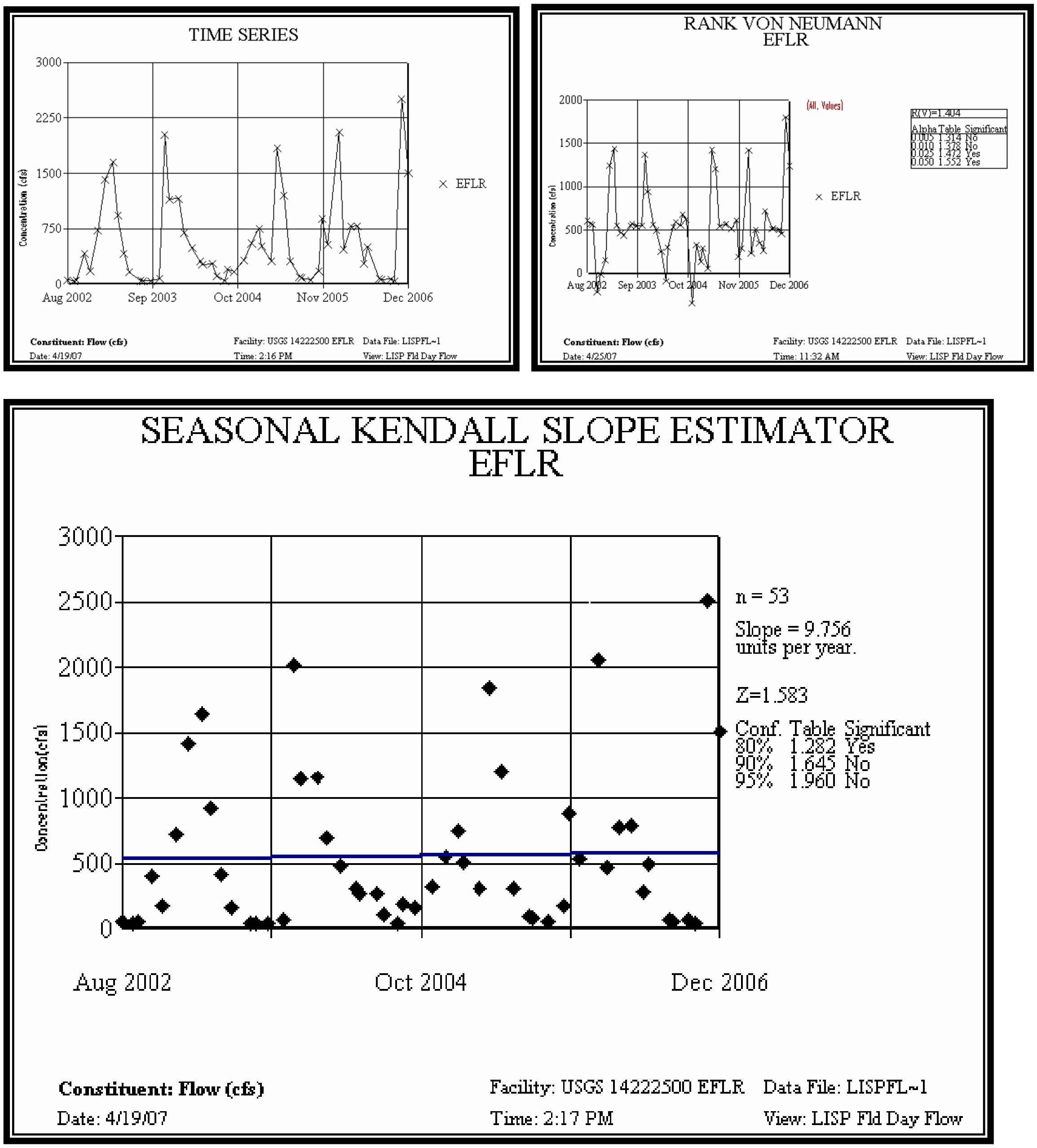


Figure C2. Annual mean flow of the East Fork Lewis River at Heisson Washington WY 1929- WY 2006.

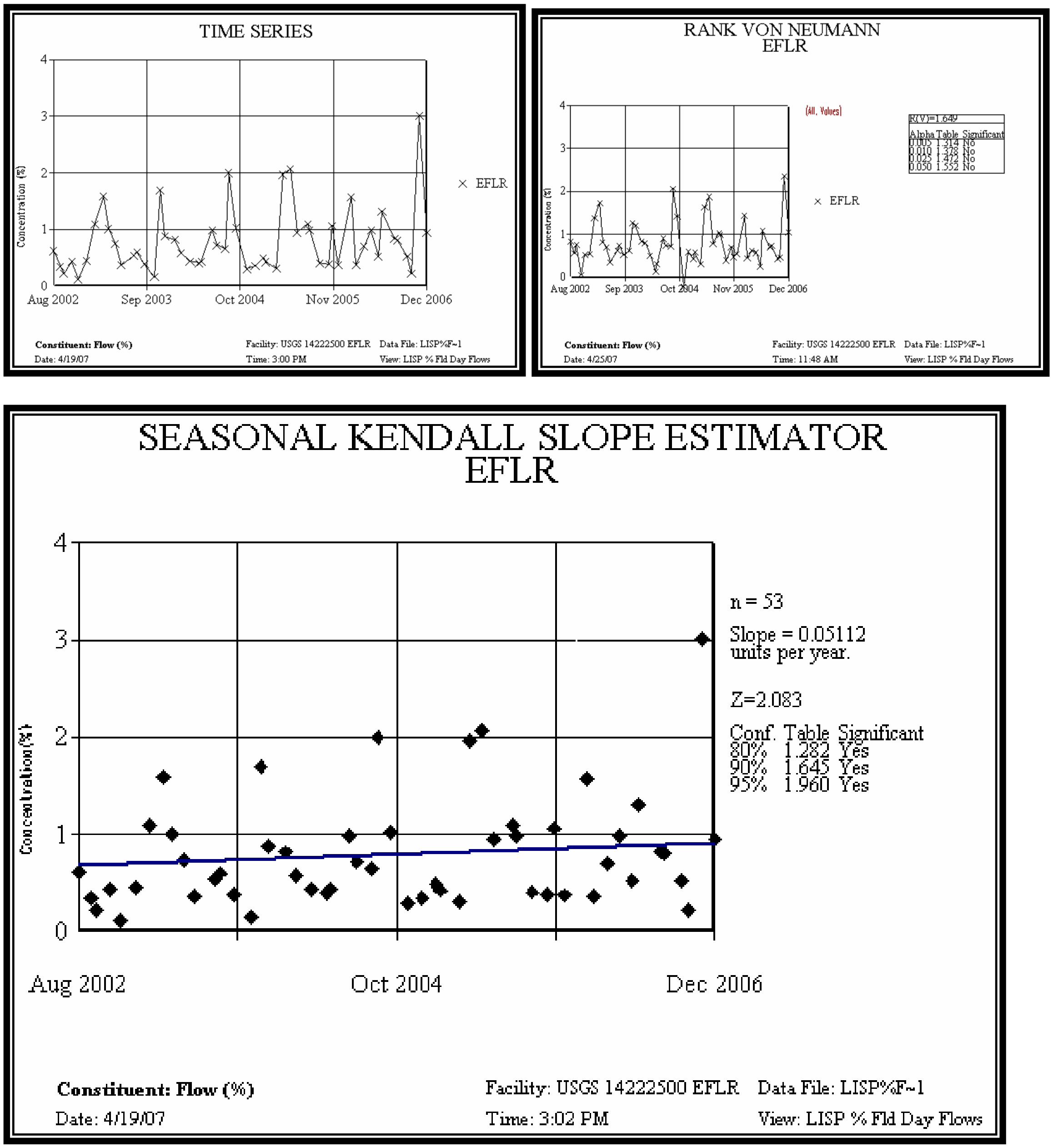
Additionally, trend analysis of flow observations may be used to determine whether the time series of flow has undergone change with time (e.g., changes in flow resulting from changes in basin activities such as reservoirs or diversions). If there are changes in flow resulting from basin activities, then an analysis of trends in flow-adjusted concentrations should not be attempted (U.S.G.S. Water Resources Investigations Report 91-4040, Schertz et al., 1991, p. 25 and Helsel and Hirsch, 1993, p. 332).

Therefore, a brief analysis of trends in the daily mean flow for the free-flowing East Fork Lewis River was made using both the raw and "normalized" daily mean flow records for the LISP field monitoring dates. For the purposes of this brief analysis, only LISP dates were evaluated because SCMP dates fall within one day of the LISP dates. The LISP monitoring dates' flow values were normalized by dividing their actual daily mean flows by the historical daily mean flow for that particular date. The raw flow data show, as one would expect, typical hydrologic cycles in the times series plot and some serial correlation in the Rank von Neumann plot at an alpha of at least 0.025 (data first deseasonalized then detrended using nonparametric Sen's Slope). The raw data's only significant trend was upward at the 80% confidence level (Figures C3 – C5 East Fork Lewis River LISP Field Day Daily Mean Flows).



Figures C3 – C5. East Fork Lewis River LISP Field Day Daily Mean Flows: Time Series, Rank von Neumann test for serial correlation, and nonparametric Seasonal Kendall Trend test.

The "normalized" flow data also show typical seasonal patterns in the time series plot but no significant serial correlation in the Ran von Neumann plot (data again first deseasonalized then detrended using nonparametric Sen's Slope). However, the "normalized" flow data did have a significant upward trend at the 80%, 90% and 95% confidence levels over the monitoring period's field dates (Figures C6 – C9. East Fork Lewis River "Normalized" Daily Mean Flows as Percent of LISP Field Day's Historical Daily Mean Flows). Plotted trend values less than one indicate LISP field dates with East Fork Lewis River flows below their historical daily means for that date. These results suggest that compared to historical daily mean flows, the actual daily mean flows on the field days of the LISP monitoring runs were usually lower than average and increasing over the monitoring period of this report. This flow trend increases the potential for confounding effects on any non-flow adjusted water quality trend results because they could be driven by increasing flows over the monitoring period.



Figures C6 – C9. East Fork Lewis River "Normalized" Daily Mean Flows as Percent of LISP Field Day's Historical Daily Mean Flows: Time Series, Rank von Neumann test for serial correlation, and nonparametric Seasonal Kendall Trend test.

Appendix D.

Descriptive Statistics and Assumptions Checked for LISP and SCMP Monthly Results, August 2002 – December 2006*:

LISP Station	BRZ 010	CGR 020	CHL 010	CUR 020	GEE 050	JNS 060	MAT 010	MIL 010	RCN 050	WPL 050
Observations	53	53	53	53	53	53	53	53	51	53
Maximums	94	87	93	78	82	98	94	89	96	85
Minimums	25	15	69	23	18	83	65	56	23	18
Means	76.79	47.3	87.32	34.89	65.3	95.53	86.83	76.85	81	65.49
Std. Dev.	16.33	18.99	3.936	17.31	15.79	2.771	5.083	6.874	16.83	17.4
Skewness	-1.749	-0.059	-2.084	1.227	-1.805	-2.657	-1.452	-0.687	-2.401	-1.453

SCMP Station	SMN 010	SMN 030	SMN 050	SMN 080	WDN 010
Observations	53	53	53	53	53
Maximums	88	89	93	98	89
Minimums	25	52	26	24	25
Means	75.85	78.85	85.58	92.74	77.77
Std. Dev.	11.04	8.381	10.4	10.05	10.87
Skewness	-2.15	-1.366	-3.846	-6.223	-2.837

Table D1. Descriptive statistics for LISP and SCMP monthly OWQI values for period August 2002 - December 2006. WDN010 monthly OWQI values for period August 2002 – February 2007.*

LISP Station	BRZ 010	CGR 020	CHL 010	CUR 020	GEE 050	JNS 060	MAT 010	MIL 010	RCN 050	WPL 050
Observations	53	53	53	53	52	53	53	53	51	52
Maximums	98	98	98	98	98	98	98	98	98	98
Minimums	10	10	37.45	31.64	10	92.34	42.18	35.99	10	10
Means	72.18	68.54	95.43	91.51	77.86	97.89	87.45	88.58	88.17	66.7
Std. Dev.	28.64	23.51	9.342	13.52	24.11	0.7775	14.03	15.36	20.71	26.47
Skewness	-0.809	-0.548	-5.15	-3.15	-1.56	-7.07	-1.49	-2.34	-2.48	-0.838

SCMP Station	SMN 010	SMN 030	SMN 050	SMN 080	WDN 010
Observations	53	53	53	53	54
Maximums	98	98	98	98	98
Minimums	10	59.1	42.18	76.48	21.07
Means	90.22	90.46	89.87	96.88	84.13
Std. Dev.	16.97	9.383	13.11	3.583	19.37
Skewness	-3.444	-1.642	-2.18	-4.35	-1.85

Table D2. Descriptive statistics for LISP and SCMP monthly Fecal Coliform OWQI subindex values for period August 2002-December 2006. WDN010 has subindex values for August 2002 – February 2007.*

LISP Station	**BRZ 010**	**CGR 020**	**CHL 010**	**CUR 020**	**GEE 050**	**JNS 060**	**MAT 010**	**MIL 010**	**RCN 050**	**WPL 050**
Observations	53	53	53	53	53	53	53	53	51	53
Maximums	65.3	194	7.56	10.8	82.4	2.55	41.5	22.07	36.5	200
Minimums	1.52	0.87	1.19	0.78	2.19	0.24	2.75	1.36	0.94	4.27
Means	10.06	8.756	2.408	3.124	10.4	0.7274	6.68	6.004	6.974	19.36
Std. Dev.	12.55	26.39	1.265	2.462	12.93	0.486	5.686	5.147	6.002	36.64
Skewness	2.625	6.715	2.412	1.303	3.854	2.202	4.637	1.466	2.749	3.847

SCMP Station	**SMN 010**	**SMN 030**	**SMN 050**	**SMN 080**	**WDN 010**
Observations	53	53	53	53	55
Maximums	27.5	22.9	24	15.3	14.4
Minimums	1.79	1.8	2.63	1.09	2.43
Means	6.875	6.01	6.33	3.651	6.109
Std. Dev.	6.265	4.491	4.006	2.311	2.536
Skewness	1.97	1.722	2.152	2.749	1.376

Table D3. Descriptive statistics for LISP and SCMP monthly turbidity values for period August 2002 - December 2006. WDN010 used monthly turbidity values for period August 2002 – February 2007.*

Test for Serial Correlation:

Sequentially deaseasonalized and detrended monthly OWQI scores, fecal coliform OWQI subindex scores, and turbidity data were analyzed using the Rank von Nuemann statistical procedure to test for serial correlation or lack of independence in each station's data. The null hypothesis is that there is no serial correlation present in the data (Intelligent Decision Technologies, Ltd., 1998, pp. 69-70). The following section addresses results of this statistical test of independence for the LISP and SCMP stations.

No significant serial correlation was found in the August 2002 – December 2006 monitoring period data when monthly defined seasons were applied in this study. If any results had significant serial correlation, the p-values for those stations' trend tests should be interpreted conservatively.

Therefore, no figures are given below depicting serial correlation.