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Through the National Nonpoint Source Monitoring Program **(NNPSMP)**, states monitor and evaluate a subset of watershed projects funded by the Clean Water Act Section 319 Nonpoint Source Control Program.

The program has two major objectives:

1. To scientifically evaluate the effectiveness of watershed technologies designed to control nonpoint source pollution
2. To improve our understanding of nonpoint source pollution

NNPSMP Tech Notes is a series of publications that shares this unique research and monitoring effort. It offers guidance on data collection, implementation of pollution control technologies, and monitoring design, as well as case studies that illustrate principles in action.

Explanatory Variables: Improving the Ability to Detect Changes in Water Quality in Nonpoint Source Watershed Studies

Introduction

An important objective of many nonpoint source (NPS) watershed projects is to document water quality changes and associate them with changes in land management. Accounting for major sources of variability in water quality and land treatment/land use data increases the likelihood of isolating water quality trends resulting from best management practices (BMPs). Correlation of water quality and land treatment changes alone is not sufficient to infer causal relationships. Factors not related to BMPs may be causing the water quality changes, such as changes in land use, climatic, or hydrologic conditions. These factors are often referred to as explanatory variables or covariates.

Including explanatory variables in water quality trend analyses yields estimates of changes that are closer to those that would have been measured if the ”non-BMP” factors did not vary over time. For example, precipitation totals and patterns that differ substantially between the periods before and after BMPs are implemented can essentially shroud the impacts of the BMPs on water quality. By accounting for, or filtering out, these changes in precipitation it becomes easier to isolate changes in water quality that may be associated with the BMPs. In statistical terms, accounting for variability in water quality due to these other factors decreases “unexplained” variation in the now-adjusted[1] water quality data, facilitating documentation of statistically significant trends.

This Tech Note describes explanatory variables that are often important in NPS watershed studies and offers suggestions on how to determine which explanatory variables should be tracked for a specific project. Techniques to incorporate explanatory variables into statistical trend models are highlighted, and example data sets are provided. The

[1] Data are considered to be “adjusted” after values are altered using appropriate statistical methods to account for explanatory variables.

statistical trend approaches discussed here are parametric. Although explanatory variables are also part of biological monitoring efforts, this Tech Note focuses on water chemistry.

Information provided here is directed primarily to water quality personnel, but all involved in a NPS watershed project should find the following three sections useful in deciding which explanatory variables to monitor. The subsequent section on statistical trend analysis approaches and the examples (with sample data sets) are written with additional statistical details intended for data analysts.

What are Explanatory Variables and Why are They Important in NPS Watershed Studies

Definition of Explanatory Variable

Explanatory variables can be defined in several, related ways. In statistical trend analysis, explanatory variables are broadly defined as variables that can be used to explain some of the variability in the response of a primary variable of interest. The response variable is usually referred to as the "Y" or "Dependent" variable. The explanatory variables are the "X" or "Independent" variables.

In NPS watershed studies, explanatory variables refer to the variables that affect the relationship between the dependent variable (e.g., water quality variable) and the independent variable of primary interest (e.g., trend). Inclusion of measured values of explanatory variables in trend analysis enables adjustment for their influence on measured water quality variables. Under this definition, variables such as streamflow and season would be examples of explanatory variables, as well as paired water quality values from a control (non-treated) watershed.

Another definition commonly found in statistics books is applicable to studies in which a response is measured in two or more categorical treatments. In this case, a covariate is a continuous variable that is correlated to the response (Y) variable and therefore "explains" some of the variation in Y in addition to that explained by the categorical treatment variable. For example, a NPS watershed study might use Pre- and Post- BMP time

Basic Terms[1]

Categorical Variable: A variable that can take on one of a limited, and usually fixed, number of possible values (e.g., seasons).

Continuous Variable: A variable that can take on any value between its minimum and maximum value (e.g., flow rate).

Control: The absence of treatment with BMPs or other land treatment. Pertains to the control watershed in NPS monitoring studies.

Control Variable: A water quality variable (e.g., nitrate) measured in a control watershed at the same time it is also measured in the treatment watershed, resulting in a paired observation.

Covariate: Essentially equivalent to explanatory variable.

Dependent or Response Variable: The "Y" variable in an equation, typically the primary water quality variable of interest in NPS watershed studies.

Explanatory Variable: Variable that affects the relationship between the primary water quality variable of interest and the primary land treatment variable of interest (e.g., flow).

Factor: A variable that influences the value of the primary variable. Independent and explanatory variables are factors influencing the value of the primary water quality variable of interest in NPS watershed studies.

Independent Variable: Each "X" variable in an equation (e.g., trend variable, land treatment variable such as acres with cover crops, control watershed water quality variable, and other explanatory variables such as flow or season.

LS-Means: The mean values of Y for each time period that have been adjusted for explanatory variable values.

Primary Variable: The water quality variable of primary interest (e.g., total phosphorus).

Treatment: The application of BMPs or land treatment during a monitoring study. Occurs in the treatment watershed of a NPS monitoring study.

[1]Definitions are tailored to the purposes of this Tech Note.

periods as categorical treatments, with water quality values from a non-treated watershed or environmental variables such as streamflow used as covariates.

Used in this Tech Note, an explanatory variable is any variable (continuous or categorical) that may influence the response of the primary water quality variables to BMP implementation. Of particular interest are the explanatory variables that can be used to adjust for the variations in the water quality variable(s) due to variations in hydrologic and climatic conditions. Within this context, many statisticians prefer to call these 'explanatory variables' rather than 'covariates,' but the terms are almost interchangeable in practice.

Importance of Explanatory Variables in Watershed Experimental Design

Because of the complexity and variability of pollutant transport pathways, climate, BMP performance, soils, biological communities, and the many other attributes of watersheds, it is generally not possible to document the impacts of BMPs on typical NPS pollutants (nutrients, sediment, bacteria) by simply monitoring BMP implementation and the pollutant of interest (e.g., nitrogen). For example, while reduced tillage practices have been shown to reduce soil erosion and off-site delivery of sediment, actual delivery of sediment to a monitoring point in a stream can also be influenced by other sources such as eroding streambanks. Streambank erosion, in turn, can be influenced by precipitation, flow patterns, and the degree to which bedload sediment is carried by the stream. A measured reduction in suspended solids concentrations at the monitoring site, therefore, may be the result of other factors in addition to the acreage under reduced tillage, including a reduction in precipitation and streamflow. These other non-BMP factors must be accounted for to isolate the effects of the BMPs.

The most important step in documenting water quality improvements due to BMP implementation is the selection of experimental design. The best experimental designs incorporate paired observations from both a treated watershed (where BMPs are applied) and a comparison watershed that serves as a "control" (Dressing and Meals 2005). In a paired-watershed design, these watersheds are referred to as the treatment and control watershed, whereas in above/below-before/after designs (functionally equivalent to nested-pair designs[2]) the watersheds may be referred to as treatment and control or as above and below watersheds. For both of these designs, however, one watershed is treated with BMPs and the other is maintained as a control with no BMPs added.[3] A properly selected control watershed factors out the effects of hydrologic variation and inherent watershed differences to help isolate changes due to the land treatment.

2 In a nested-pair design the treatment watershed can either be within a smaller headwater subwatershed or cover nearly the entire watershed with the exception of a small untreated subwatershed.

3 Note that studies may include multiple treatment watersheds for comparison with the control watershed.

These two designs incorporate two monitoring periods (calibration and treatment periods) to allow for comparisons of statistically valid relationships established between paired observations of the same primary variable in the two watersheds before and after BMPs are implemented. Differences in the paired-observations relationships from the two monitoring periods are used as evidence of the effects of the BMPs. In these studies, the primary variable(s) is considered a response variable when measured in the treatment watershed and an explanatory variable when measured in the control watershed.

Explanatory variables play an important role in the analysis of data from other monitoring designs as well, including above/below and single-station trend designs (Dressing and Meals 2005). These weaker monitoring designs, in fact, generally rely more on the use of explanatory variables to tease out the effects of BMPs on measured water quality because they do not have the built-in control of the two stronger designs described above. This creates a need, for example, to use flow, precipitation, land use, and other factors in statistical analyses to account for their influence on the measured parameter(s) of interest.

Tracking of relevant meteorologic, hydrologic, and land use factors is essential to document the impacts of land management and BMPs on water quality. With this information, analysts can account for the influence of non-BMP factors to more accurately interpret the impacts of NPS management. Observed changes (or lack thereof) could be artifacts of hydrologic and/or meteorologic variability or some other hidden variable that also changes over time (Hirsch et al., 1982; Joiner, 1981; Baker 1988). Therefore, the addition of explanatory variables helps ensure an unbiased estimate of the true differences over time due to BMP implementation.

The ability to detect trends can be increased by the incorporation of explanatory variables into trend models, thereby decreasing the unexplained variance in the models. For the same reason, the amount of change in water quality needed to be able to detect statistically significant changes is decreased (Spooner et al. 2011). In addition, use of explanatory variables may also minimize the influence of outlier observations (Joiner, 1981). Adjustment for explanatory variables such as stream discharge can also reduce autocorrelation (e.g., correlation between the current observation and the past or adjacent observations) which will increase the effective sample size and increase the power to detect trends.

Explanatory Variables Commonly Used in NPS Watershed Studies

This section lists and describes various types of explanatory variables that can be of importance in NPS monitoring efforts. How to incorporate these variables into monitoring designs is addressed in the subsequent section.

Watershed Design Variables from the "Control Watershed"

The control variables that are measured as a direct part of the experimental design (for paired-watershed, above/below-before/after, or nested-pair designs) are explanatory variables (Table 1). These paired observations from the control watershed could be from the same date, the same time period for composite samples, or from the same storm event as those from the treatment watershed. For example, weekly, flow-weighted composite samples taken at the outlet of both control and study (or above/below) watersheds would satisfy this requirement.

Table 1. Explanatory variables from control watersheds.

Watershed Design	Control Explanatory Variables
Paired watershed	Concentration or load values from the control watershed that can be paired with the treatment watershed water quality values
Above/Below-Before/After	Concentration or load values from the upstream watershed that can be paired with the treatment watershed
Nested watershed	Concentration or load values from the non-treated watershed that can be paired with the treatment watershed

BMPs and Land Use

The basic hypothesis associated with NPS watershed implementation projects is that implementation of BMPs or other land management measures will cause an improvement in water quality, so it follows that measurement of this activity is essential. Quantitative documentation of land treatment trends is a necessary step in linking water quality to land treatment in statistical analysis.

Examples of quantitative measures of land treatment include:

- Number or percent of watershed animal units under animal waste management
- Acres or percent of cropland in cover crops or residue management
- Annual manure-based nutrient or fertilizer application rate and extent
- Extent and capacity of stormwater infiltration practices

Land use changes can influence water quality in a number of ways, including changing hydrology (e.g., increased impervious surface), altering temperature regimes (e.g., decreased shading of stream), and modifying pollutant source areas (e.g., cropland converted to pasture). These changes must also be recorded to help isolate the impact of BMPs and land treatment on measured water quality. Land use modifications that could affect water quality include:

- Conversion from pasture to row crops or changes in cropping patterns
- Agricultural set-asides

- Changes in the number of animals or animal units per acre
- Closure of animal operations
- Changes in impervious land areas
- Stream channel modification
- Roadway maintenance

Water quality and land use/treatment data must be matched (spatially and temporally) if water quality changes are to be attributed to BMP implementation. For example, land-based data must be collected on a watershed basis for linkage to water quality monitoring data. The frequency at which BMPs and land use are tracked varies as described in Meals et al. (2014). Generally, attributes and activities that change little over time (e.g., broad land use categories) may need to be assessed only at the beginning and end of a project, whereas more dynamic features (e.g., field-level crop and yield information) may need to be tracked annually or semi-annually. Some activities such as manure applications or street sweeping should be tracked on a more frequent, often seasonally-variable basis.

It is important to note that associations between land use observations and water quality patterns can be confounded by the timing of the source activities (USDA 2003). For example, road salt is applied under icing conditions, while washoff tends to occur during periods of thawing or rainfall. Matching weekly water quality and land use/treatment data in this case could result in associating high salinity levels with periods of no road salt application. As another example, nutrient concentrations peak during wet periods, but manure is not usually applied when fields are muddy. Using weekly data, high nutrient concentrations could be associated with periods of no manure application. An understanding of pollutant pathways and lag time and some creative data exploration are often needed to effectively pair land use/treatment observations with water quality data.

Methods of reporting and quantifying land treatment and land use are described in detail in Tech Notes 11 (Meals et al. 2014).

Seasonality and Cyclic Patterns

A portion of observed temporal variability in water quality data may be cyclical or vary by seasons. Within-year seasonal variations, for example, can be due to natural and man-made changes such as rainfall patterns, fertilizer/cropping patterns, and leaching through the soil profile when active plant growth is slower (e.g., winter or when crops are removed). Seasonality also occurs when the value of an observation collected in one season is related to the observations taken in the same season in a previous year (Brocklebank and Dickey, 1986).

Other cycles, such as diurnal or weekly, are also commonly observed in water quality datasets. For example, King et al. (1983) measured large diurnal and seasonal variations in sediment concentrations from field runoff. Diurnal variations were caused by irrigation schedules, and seasonal variations were characterized by maximum sediment concentrations in June and July with a dramatic drop during July due to declining erosion rates after cultivation.

Explanatory variables that can be used to account for seasonal changes include:

- Monthly or seasonal indicator variables
- Sine and cosine trigonometric functions
- Other explanatory variables that also exhibit seasonal patterns (e.g., streamflow)

Time series models can also incorporate seasonality using a "differencing" technique.

Details on how to calculate explanatory variables for each of these seasonal adjustment approaches are given in Attachment 1.

Meteorologic and Hydrologic Variables

Meteorologic and hydrologic processes also contribute to the variability in water quality data, often accounting for a portion of the seasonal variation noted above due to seasonal patterns in rainfall amount and intensity.

Hydrologic and meteorologic variables include:

- Stream discharge/flow (stage height is sometimes a surrogate)
- Antecedent flow conditions prior to a storm
- Storm volume
- Duration of time to peak of storm hydrograph
- Rising or falling limb of storm hydrograph
- Direction of the change in flow
- Magnitude/peak of event maximum discharge
- Precipitation
- Storm event intensity and frequency
- Ground water table depth
- Humidity
- Salinity
- Water or air temperature

How to Determine Which Explanatory Variables are Most Important to Measure and Incorporate into Trend Analyses

Some watershed projects begin with a dataset that can be explored for relationships between primary and explanatory variables. Many projects, however, begin with no data or such a small dataset that possibilities for analysis are limited. In these cases, project personnel should examine data from nearby, similar watersheds and examine the literature for information to guide selection of explanatory variables. Past studies have shown that a number of explanatory variables are generally useful in most projects. Where projects base selection of explanatory variables on information from similar watersheds or from the literature, it is important to confirm these relationships in the current study as data are collected.

It is important to keep in mind that monitoring designs should begin with clear goals and an outline of data analysis plans designed to determine if these goals have been met (Dressing and Meals 2005). The types and uses of explanatory variable data needed for statistical analyses should be considered and specified before monitoring begins. Reassessment of the value of selected explanatory variables is a necessary component of data analysis, and exploratory analysis of new data may reveal relationships between variables that were not expected. For these and other reasons, projects should examine data frequently (e.g., monthly) to ensure that the monitoring program is on track to meet objectives. The information below is designed to help both projects with existing data and those that are essentially starting from scratch.

General Rules of Thumb

Both projects beginning with and without a rich dataset should apply some basic rules of thumb when selecting explanatory variables.

- The date should be associated with every variable value, thus allowing assignment of month or season to address seasonal considerations.
- The literature has many examples of relationships between flow measurements and pollutant concentrations and loads (Baker 1988, Foster 1980, Johnson et al. 1969, Lowrance and Leonard 1988, and Schilling and Spooner 2006), so flow or a flow surrogate (e.g., stage) should be measured whenever possible.
- Runoff begins with precipitation and a multitude of studies has shown the effects of rainfall intensity and amount on runoff quality and amount, so precipitation should be measured or weather data obtained from a nearby existing weather station.
- Information on land use and ground cover is essential to most projects, particularly given that BMPs are generally targeted on the basis of land use and management.

- Any sources that will be treated (e.g., cropland, streambanks, lawns) should be monitored using explanatory variables that relate to water quality and the BMPs being implemented (e.g., animal units with access to and excluded from streams, nutrient application rates and yield by crop type).
- Some variables of potential use are very inexpensive to track and can be dropped later if found to be useless. Examples include water and air temperature and salinity or conductivity.

In addition to the list above, projects should consider variables that have been found to be useful as explanatory variables in other monitoring efforts in the watershed, nearby, or in studies reported by state or university water quality experts.

Projects should also consider explanatory variables based on their knowledge of the watershed, the pollutant sources to be treated, and pollutant pathways. A watershed implementation plan can be the source of much of this information and should be examined as part of the monitoring design process.

Analysis of Existing Data

For projects that have existing data, the rules of thumb outlined above can be challenged and tested, and a more refined examination of potentially useful explanatory variables can be performed. Some available exploratory techniques are described below, and readers are referred to Meals and Dressing (2005) for additional information and procedures.

Basic graphical techniques available in both spreadsheet software and more advanced statistical packages provide a quick, visual means of exploring relationships between two variables. The two-dimensional scatterplot, for example, is one of the most familiar graphical methods for examining the relationships between variables. This is a simple plot of paired values of one variable against another. Scatterplots can help reveal associations between two variables, whether the relationship is linear, whether different groups of data lie in separate regions of the scatterplot, whether variability is constant over the full range of data, and if seasonal patterns are evident. Figure 1 illustrates a scatterplot that indicates a relationship between suspended sediment concentration (SSC) concentration and flow.

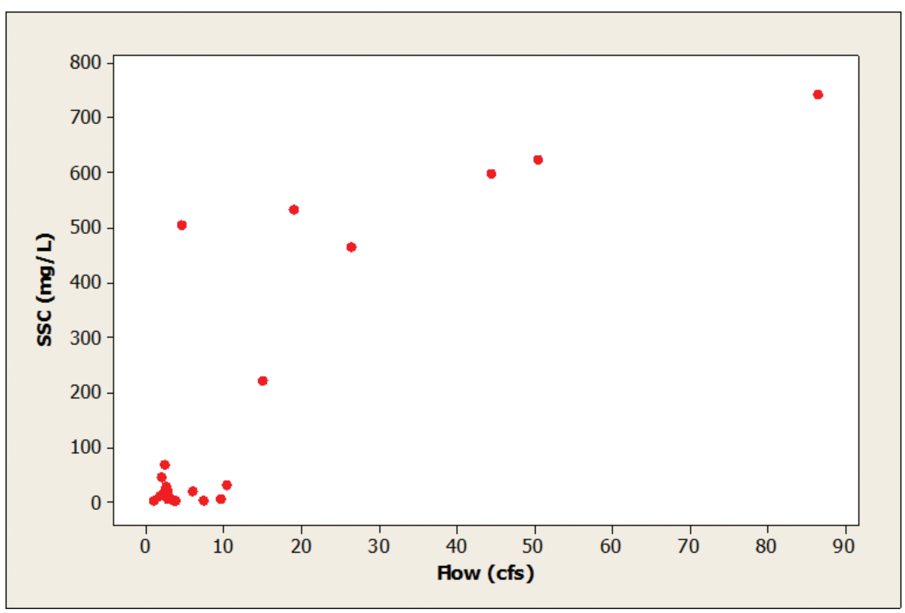

Figure 1. Scatterplot of SSC versus flow.

Box and Whisker plots can reveal important explanatory variables. For example, if data are stratified into groupings of the explanatory variable, inspection of the Box and Whisker plots may reveal their importance. In this application, concentration/load values would be on the Y-axis, and groupings of the potential explanatory variable on the X-axis. Examples may include data stratified by season, baseflow and stormflow, or land management types. Visual inspection of medians and extreme values may indicate the need to use these variables as an explanatory variable.

Time series plots of water quality variable values versus time can reveal seasonal patterns in data. For example, weekly flow data from the Corsica River, MD, Clean Water Act Section 319 National Nonpoint Source Monitoring Program (NNPSMP) Project shows a pattern that indicates a seasonal pattern that should be accounted for in the monitoring program (Figure 2).

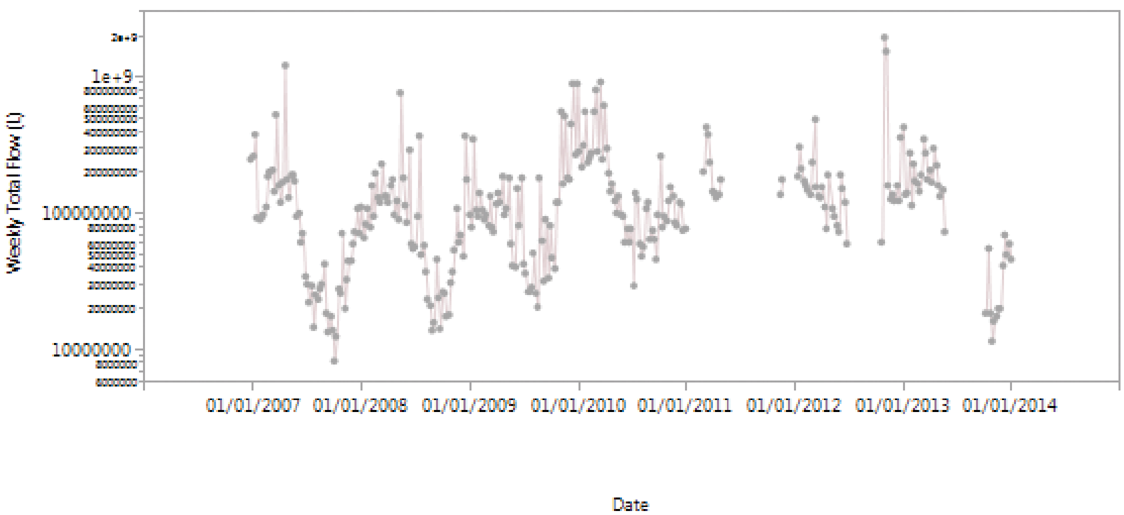

Figure 2. Time series of weekly flow from the Three Bridges Branch subwatershed of Corsica River National Nonpoint Source Monitoring Program Project.

Although graphical approaches can help to reveal strong candidates for explanatory variables, they are not rigorous statistical approaches and do not reveal potential correlations between the explanatory variables being considered (e.g., multicollinearity). Examples of more advanced statistical approaches are provided below.

Statistical Measures to Determine Important Explanatory Variables

Univariate analyses

Correlation and regression analysis between primary and explanatory variables can help identify important relationships that can guide selection and use of explanatory variables in subsequent data analysis. Correlation analysis is supported by both spreadsheet and advanced statistical software. The output of a correlation analysis between two variables includes the correlation coefficient (r), which ranges from -1 to 1, and a probability value indicating the statistical significance of the correlation. The regression of a "Y" variable on an "X" variable reveals if there is a significant relationship as well, but also yields information on the significance, magnitude, and direction of the slope of the relationship. Similarly, correlation or regression analysis of primary variables with seasonal explanatory variables (e.g., sine/cosine seasonal components, monthly indicator variables) can be performed to test for significant seasonal patterns.

Analysis of variance (ANOVA) and the non-parametric Kruskal-Wallis test are methods that can be used to test for differences between seasons. ANOVA analyzes the differences between group means whereas Kruskal-Wallis uses ranks to test whether samples originate from the same distribution.

Another approach to determining if a seasonal element exists in a dataset is to examine the autocorrelation structure, or the similarity between observations as a function of the time lag between them. This type of test is generally not available in spreadsheet software, but is commonly found in statistical software packages. A seasonal component in a data time series can be indicated by a strong positive autocorrelation at the seasonal lag value corresponding to the length of the seasonal cycle. For example, an annual cycle will appear as a strong positive autocorrelation at lag 12 when the data consists of monthly values. Negative autocorrelations may also appear at lag intervals corresponding to one-half of the seasonal cycle length. So, while seasonality introduces variability to a dataset, it can also introduce autocorrelation which is discussed in greater detail under *Data Examination and Required Adjustments*. Thus, attention must be given to seasonality in the analysis of trends in NPS watershed studies, both to explain some of the variability in the primary variable and to adjust for seasonally-based autocorrelation to ensure valid results.

Multivariate analyses

Multivariate statistical procedures such as factor analysis, principal component analysis (PCA), and canonical correlation analysis (CCA) are advanced procedures that can be used to define (and perhaps subsequently adjust for) complex relationships among variables such as precipitation, flow, season, land use, or agricultural activities that influence NPS problems. These procedures require a rich dataset that many projects will not have before monitoring begins. Projects can also use these methods later, however, to analyze newly collected data to strengthen regression analyses.

Projects with robust historic datasets can apply PCA and factor analysis to help determine the most important water quality indicators and stressors, aiding in the selection of water quality and land use/treatment variables to be used in the monitoring program. PCA is a multivariate technique for examining linear relationships among several quantitative variables, particularly when the variables are correlated to each other. This technique can be used to determine the relative importance of each independent variable and determine the relationship among several variables. The results of PCA can often be enhanced through factor analysis, which is a procedure that can be used to identify a small number of factors that explain the relationships among the original variables. One important aspect of factor analysis is the ability to transform the factors (i.e., reconfigure the linear combinations of original variables) from PCA so that they make more sense scientifically. The SAS procedures PROC PRINCOMP and PROC FACTOR can be used for these analyses (SAS Institute 2013).

CCA is a technique for analyzing the relationship between two sets of multiple variables (e.g., a set of nutrient variables and a set of hydraulic/climatic variables). This multivariate approach examines said relationship "by finding a small number of linear combinations from each set of variables that have the highest possible between-set correlations" (SAS Institute 1985). These linear combinations of variables can be used to guide selection of explanatory variables at the beginning of a monitoring program.

The reader is referred to statistics textbooks, statistical software package guidance, and other sources for additional information on these multivariate techniques.

Incorporating Explanatory Variables in Statistical Trend Analyses

Explanatory variables can be incorporated into statistical trend analyses in a number of ways depending on the monitoring design used and the pattern of the trend. Monitoring designs addressed in this section include paired-watershed, above/below-before/after, nested-pair, and single-station trend designs.

Trend Patterns

Possible trend patterns illustrated in Figure 3 include step, linear, monotonic, and ramp trends. A step trend is applicable when the BMPs are implemented in a short timeframe and a rapid water quality response is expected. A linear trend may be applicable when BMPs are implemented over time or water quality improvements are expected to be achieved over an extended period of time due to lag time associated with the gradual implementation and establishment of BMPs. Monotonic trends exhibit a gradual change

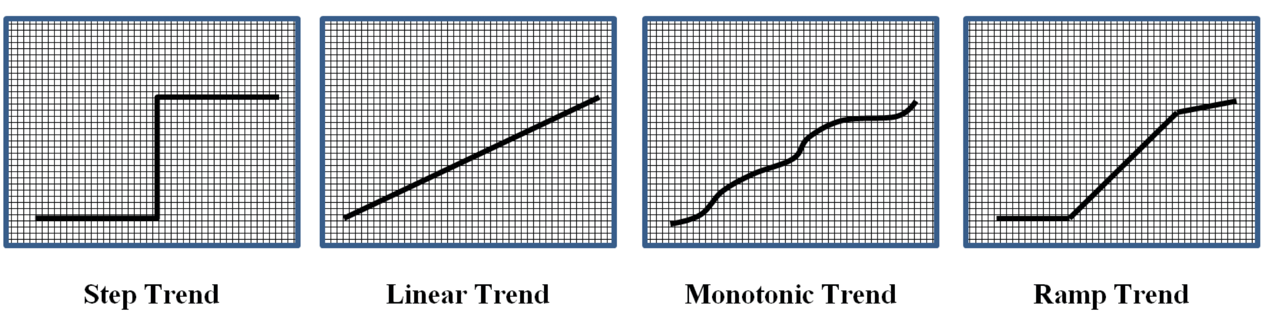

Figure 3. Possible trend patterns for water quality data.

over time that is consistent in direction, but not necessarily linear. Ramp trends may include time periods of little change (e.g., pre-BMP) followed by improving trends as BMP implementation occurs, and perhaps a leveling out when maximum water quality improvement has been achieved. The methods presented in this section focus on step, linear, and monotonic trends.

Statistical Test Assumptions

The degree to which the data meet test assumptions must be assessed to ensure appropriate application of either parametric or nonparametric tests. Assumptions for the residuals[4] from parametric trend tests are generally:

- Data are normally distributed and independent
- Variance is homogenous (i.e., variance doesn't change over time)
- Residuals from the regression models are independent and normally distributed

Clearly, some of these tests can be performed prior to trend analysis, whereas others such as testing of residuals are completed as part of the trend analysis.

Data Examination and Required Adjustments

Exploratory data analysis (EDA) procedures should be applied to determine if a dataset satisfies the requirements of planned statistical tests. Readers are referred to Meals and Dressing (2005) for detailed information on EDA and data transformation in addition to what is presented below.

Data Distribution and Transformation

Most statistics software packages contain a range of options for testing whether a dataset meets the distributional requirements of a statistical test, while spreadsheet software may be limited to tests for kurtosis and skewness. Nonpoint source datasets are often characterized by skewness caused by a long right tail in the distribution (i.e., higher values typically occurring during high flows). While many data transformations are possible, the log-transformation is most commonly used in NPS watershed studies to reduce skewness and enable valid results from parametric statistical trend tests. Data should be re-tested after transformation to confirm that test requirements are met.

Autocorrelation

Time series data collected through monitoring of water resources often exhibit autocorrelation (also called serial correlation or dependent observations) where the value of an observation is closely related to a previous observation (usually the one immediately before it). Autocorrelation in water quality observations is usually positive in that high

[4] Residuals are the differences between the observed and predicted values of the dependent variable (Y) in statistical trend analysis.

values are followed by high values and low values are followed by low values. For example, streamflow data often show autocorrelation, as numerous high wet-weather flows tend to occur in sequence, while low values follow low values during dry periods. Autocorrelation can also be introduced by seasonality in a dataset.

Autocorrelation can affect statistical trend analyses and their interpretations because it reduces the effective sample size (degrees of freedom). Adjustment for autocorrelation is needed to ensure that trend tests yield valid results. For example, in a typical weekly or biweekly water quality dataset with positive autocorrelation, the significance of simple step and linear trends given by the test statistic is artificially increased if autocorrelation is not considered in the trend analysis, in some cases indicating a trend when it does not exist. In these cases, autocorrelation can be addressed by using a software regression program that incorporates the autocorrelation in the error term, for example PROC AUTOREG by SAS (SAS Institute 2010). Alternatively, a correction of the standard deviation of the slope estimate and revised confidence intervals can be used (see p. 11 of Spooner et al. 2011). Aggregating data by computing monthly means or medians from weekly data throughout the period of record will reduce autocorrelation, but this approach also reduces the sample size and information content of the dataset.

Trend Analysis: Statistical Models and Examples

The following sections provide details on appropriate statistical models to use for analysis of step and linear trends and examples using sample datasets accessible by the reader. Brief summaries of step and linear trend approaches are provided for readers with limited expertise or interest in statistics, followed by more detailed discussions for those with greater interest or expertise. Discussions highlight ways to incorporate explanatory variables into the analyses. Additional considerations are highlighted in Attachment 1.

Step Trends

Summary of Statistical Approach

Analysis of covariance (ANCOVA) is the most appropriate parametric test for assessing a step trend between mean water quality values from before and after BMPs are implemented. This method incorporates explanatory variables to isolate the effects of the BMPs. The appropriate statistical model will either accommodate a change in both slope and mean or just a change in mean. Explanatory variables can be added to either model. A t-test is performed to determine if there is a significant difference between the mean Y values (adjusted for explanatory variables) from the two periods.

Detailed Discussion of Statistical Method

The graphical depictions of conceptualized step trends in Figure 4 can be used to help select the appropriate statistical trend analysis model for NPS studies using the paired-watershed, above/below-before/after, and single-station trend monitoring designs. In the paired-watershed design (Figures 4A and 4B), for example, the regression relationships of the paired water quality observations from the treatment (Y-axis) and control (X-axis) watersheds are compared between the calibration (pre-BMP) and treatment (Post-BMP) periods. The trend test is the "step change" improvement in the treatment watershed calculated by comparing the LS-mean values of the water quality variable for each period. LS-means are means of the Y variable that have been adjusted for the explanatory variable values. The calculation of LS-means is described in detail on page 20. The red lines in Figures 4A and 4B indicate the comparison ("difference") of the treatment watershed LS-means from the calibration and treatment periods evaluated at the control watershed value of "X-mean" which is the mean of all sampled values in the control watershed over the entire sampling duration (both treatment and calibration period). In the above/below-before/after watershed study design (Figures 4C and 4D), the regression relationships of the paired water quality observations from the downstream (Y-axis) and upstream (X-axis) watersheds are similarly compared between the pre-BMP and post-BMP time periods. For a nested-pair watershed design, the paired values from the treatment watershed would be the "Y" variable and those from the control watershed would be the "X" variable as shown in Figures 4A and 4B. For a single-station trend design the water quality values in the pre- and post-periods are tested for a step change after adjusting for variability in at least one measured explanatory variables (e.g., stream flow as in Figures 4E and 4F).

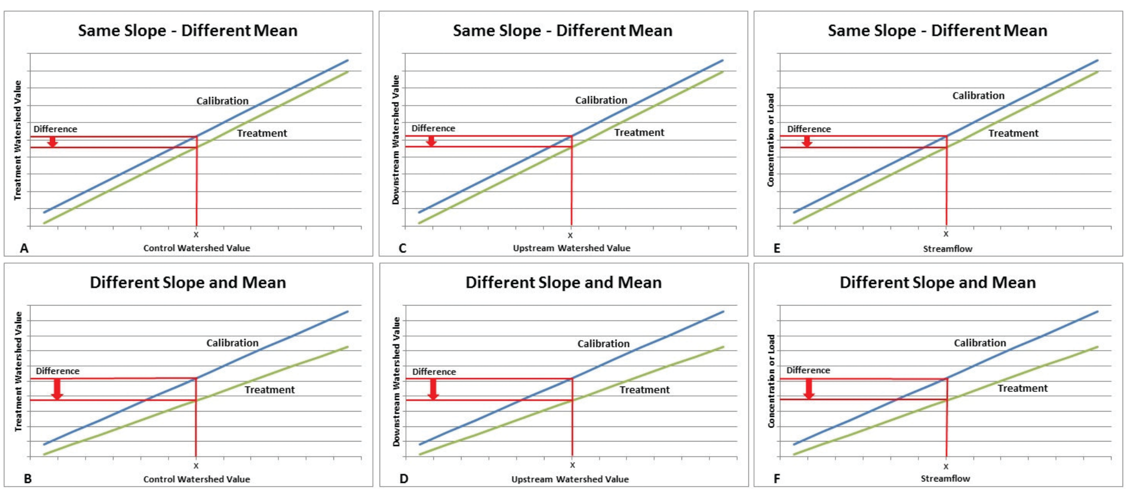

Figure 4. Conceptualized regression plots for step changes between pre- (calibration) and post-BMP (treatment) time periods for data from a paired-watershed design (A and B), an above/below-before/after design (C and D), and a single-station step trend design (E and F).

In a statistical step trend model, the trend variable is "categorical," meaning that all values can be 'grouped' into each of the distinct time periods: pre- or post-BMP. A t-test or analysis of variance (ANOVA) would be used to test for the step trend when evaluating only the mean water quality values before and after BMPs are implemented. Such a trend test, however, would not incorporate explanatory variables and would generally not be suitable for isolating the effect of BMPs. The ANOVA or t-test model becomes ANCOVA when explanatory variables are added to the model. ANCOVA combines the features of ANOVA with regression (Snedecor and Cochran 1989) and can be used to compare LS-mean values from each period instead of simply comparing the unadjusted means.

When applied to the analysis of paired-watershed data (Figures 4A and 4B), ANCOVA is used both (a) to compare pre- and post-BMP regression equations between water quality measurement values (e.g., sediment concentration/load) for the treatment and control watersheds and (b) to test for differences in the average value (e.g., of sediment concentration/load) for the treatment watershed between the two time periods after adjusting for measured values of the control watershed and other explanatory variables.

In the analysis of an above/below-before/after watershed design (Figures 4C and 4D), the control variable is the upstream values (e.g., concentration/loads) which are paired with the values obtained from the monitoring site downstream of BMP treatment. The ANCOVA is used to determine if significant changes occurred in the downstream values in the post-BMP period compared to the pre-BMP period, after adjustment for variations in the upstream values.

In the analysis of a single-station step trend design (Figures 4E and 4F), the control variable is values of the hydrologic variable (or other appropriate explanatory variable) which are paired with the values obtained from the monitoring site downstream of BMP treatment. The ANCOVA is used to determine if significant changes occurred in the downstream values in the post-BMP period as compared to the pre-BMP period, after adjustment for variations in the explanatory variable(s) values.

There are two basic steps to performing ANCOVA:

1. Determine the proper form of statistical trend model, considering both if the slopes are the same in the pre- and post-BMP periods, as well as inclusion of explanatory variables.
2. Calculate the adjusted means (LS-means) and their confidence intervals to determine if there is a significant difference in the water quality pollutant values between the two periods. This is the estimate for the magnitude of change between the pre- (calibration) and post- (treatment) BMP periods.

The trend model that allows for different slopes for the pre- and post-BMP periods in the regression of the treatment watershed variable (Y-axis) on the control watershed variable (X-axis) is called the "Full Model" (Figures 4B, 4D, and 4F). If there is no statistically significant evidence of different slopes, a "Reduced Model" that assumes the same slope for each time period is appropriate (Figures 4A, 4C, and 4E). For example, in the paired-watershed study:

- **Full Model:** The slope of these relationships changes from calibration to treatment period (Figure 4B). A change in slope indicates that pollutant concentrations for the treatment watershed exhibited different response to conditions that also resulted in changes in the control watershed values, or magnitude, after BMPs were applied as compared to the calibration period.

- **Reduced Model:** The slope of the relationship between the treatment watershed concentrations/loads and control watershed concentrations/loads remains constant throughout both time periods (Figure 4A).

The homogeneity of slopes (i.e., same or different slopes) is tested using the full model to determine which of these statistical trend models is appropriate by evaluating the significance of the interaction term (b_3 in Equation 1). The full model for the paired-watershed or above/below-before/after watershed designs is:

$$Y_t = b_0 + b_1 X_{1t} + b_2 X_{2i} + b_3 (X_{1t} * X_{2i}) + \sum_{c=4}^{d+3} b_c (X_{ct}) + e_t$$

Equation 1. Full regression model.

Where:

t = time of sample (e.g., date of sample taken; could also be sequential such as day or week or month since sampling began)

i = time period (e.g., pre-BMP or "Calibration" period or post-BMP or "Treatment" period)

Y_t = observation for Y at time t (e.g., weekly pollutant concentration or load from treatment watershed or downstream monitoring station)

X_{1t} = observation for X_1 at time t (X_1 is the pollutant concentration or load from the control watershed or upstream monitoring station that is paired with Y_t)

X_{2i} = Step Trend Variable value in period i (e.g., "0" for the "Calibration" period and "1" for the "Treatment" period). Because the values are not continuous, X_2 is a categorical variable.

$(X_{1t} * X_{2i}) = X_3$ = interaction term that enables different regression slopes for the pre-and post- BMP periods

X_{ct} = observation for X_c (covariate or explanatory variable) at time t

b_0 = y-intercept of the pre-BMP (calibration) period regression line (i.e., during the period for which X_{2i}=0)

b_1 = slope of the pre-BMP (calibration) period regression line (i.e., during the period for which X_{2i}=0)

b_2 = regression coefficient on the trend variable X_{2i}. Mathematically, this is also the difference in the Y-intercept between the calibration and treatment periods.

b_3 = regression coefficient indicating the statistical significance of the interaction term (e.g., statistical evidence of a different regression slope in the calibration vs. BMP treatment periods). Mathematically, this is also the difference in the slopes between the calibration and treatment periods.

b_c = regression coefficient for explanatory variable X_c

k = number of time periods (with only a calibration and treatment period, k=2)

d = number of explanatory variables in addition to the control watershed variable and trend terms. For example, if only flow was used as a covariate, d=1 and the explanatory variable for flow would be X_4.

e_t = residuals or experimental error for the t^{th} observation for Y (This would be V_t for an autocorrelated error structure, not discussed here.)

Notes:

- Equation 1 can be expanded to more than two time periods, with the number of X terms added for the Step Trend Variable equal to k-1. For example, if there were three separate time periods for calibration, implementation of BMPs, and post-implementation of BMPs, then the two X terms would be X_{2a} (with a 0, 1, and 0 value for the calibration, implementation, and post-implementation periods, respectively) and X_{2b} (with a 0, 0, and 1 value for the calibration, implementation, and post-implementation periods, respectively).
- As a practical matter, most software programs handle this categorical variable as a Class, Group, Categorical, or similar variable type so the actual X values do not have to be calculated by the user. Because the “0” and “1” values may be assigned by the software program in alphabetical order of the names of the time periods, it is best to assign the X_2 variables values such that they are ordered alphabetically or numerically in the sequential time order. For example, calibration comes before treatment and “c” comes before “t” so calibration and treatment would be conveniently assigned “0” and “1”, respectively. One could name the same two periods “calibration” and “BMPs,” but they would be assigned “1” and “0”, respectively, requiring extra care in the interpretation of the statistical output.
- Because of the form of the trend model, additional explanatory variables (X_c) are assumed to have similar relationships to the water quality (Y) variable for each time period (e.g., no interaction terms with these variables and the trend variable. If this assumption is not expected to be valid, those interactions terms can be tested and the model adjusted if required.

- X_{2i} is also used to depict the step trend for the single-station trend design. X_{1t} becomes the key explanatory variable (e.g., stream flow), and other explanatory variables (X_c) can be included as appropriate.

This full statistical model allows the slopes to be different for each time period. Substituting the values of X_{2i} into Equation 1 for the calibration (X_{21}=0) and treatment (X_{22}=1) periods, respectively, yields Equations 2 and 3:

$$Y_t = b_0 + b_1 X_{1t} + \sum_{c=4}^{d+3} b_c (X_{ct}) + e_t$$

Equation 2. Full regression model for the calibration period.

$$Y_t = (b_0 + b_2) + (b_1 + b_3)_* (X_{1t}) + \sum_{c=4}^{d+3} b_c (X_{ct}) + e_t$$

Equation 3. Full regression model for treatment period.

The homogeneity of slopes is determined by looking at the statistical significance of the interaction term, b_3 in the statistical software program output. The full model is the correct model if the interaction term is significant. If there is no evidence for separate slopes, then a reduced model with the same slopes assumed for each group (based on pooled data) should be used.

When the reduced model with common slopes is used, the interaction term is dropped and the trend model is rerun. Equation 4 would then be used to describe the linear regression for each time period (i) which would have the same slope, but be allowed to have different intercepts:

$$Y_t = b_0 + b_1 X_{1t} + b_2 X_{2i} + \sum_{c=3}^{d+2} b_c (X_c) + e_t$$

Equation 4. Reduced regression model.

Where:

b_1 = slope of both the pre-BMP (calibration) and post-BMP (treatment, X_{2i}=1) period regression lines

$(b_0 + b_2)$ = y-intercept of the post-BMP (X_{2i}=1) period regression line

Y_t, X_{1t}, X_{2i}, c, d, b_0, b_2, b_c, X_c, and e_t are defined as above.

Finally, to test for a statistically significant trend, the LS-means and their confidence intervals are examined. LS-means correct for the bias in the X_1 and X_c values between the pre- and post-BMP periods. The LS-mean of each period (pre- and post- BMP periods) is the period mean for Y (Y_i) adjusted to the overall mean value of each of the X_1 and X_c values. In other words, the LS-means are the calibration and treatment period regression values for the treated watershed evaluated at the mean of all the control watershed and explanatory values over both time periods (e.g., mean of all the X values). Operationally, inserting the mean of all X values into the regression equations for the calibration and treatment periods and evaluating the equations for the estimated adjusted value of Y_i will yield the LS-mean values for each period, respectively. A t-test on the adjusted LS-means then determines if there is sufficient evidence to conclude that the adjusted LS-mean for the treatment period is different from the adjusted LS-mean for the calibration period. Most statistics software provides this information. The red lines in Figure 4 indicate the comparison of LS-means from the pre-BMP and post-BMP periods. For example, in Figure 4A, for the same concentration in the control watershed, there is a lower LS-mean value for the treatment watershed in the post-BMP period, indicating an improvement in water quality after BMP implementation.

Caution must be used when interpreting the results of comparing adjusted means in the full model with individual slopes. When the slopes are not parallel, the comparisons of adjusted means may not be the most meaningful question. One may be more interested in the behavior over the entire range of X. For example, the regression lines may cross, potentially indicating a breakpoint where BMP effectiveness kicks in as described by Meals (2001). In this case a graphical presentation may be most appropriate.

Step Trend Example

Analysis of step trends is illustrated in Attachment 2 using data from Sinbad Creek (a simulated dataset based upon a watershed study). Step trend analysis was chosen for this example because implementation of livestock exclusion and pasture management occurred rapidly between the two monitoring sites and a step improvement in water quality was anticipated. Weekly TP and TSS loads were simulated from weekly grab samples and continuous flow monitoring conducted before and after BMP implementation.

Linear Trend Over Time Analysis

Summary of Statistical Approach

The most appropriate parametric test for gradual trends is regression analysis. This approach requires paired observations of the primary variable and any explanatory variables used in the statistical model. Statistical models can be selected that address linear or ramp trends, and all appropriate explanatory variables (e.g., control watershed values, discharge, BMPs) can be added to the model. Simple linear regression involves a single explanatory variable, while multiple linear regression incorporates two or more explanatory variables. Values of the primary variable are regressed against time and the explanatory variables, with a trend indicated by a slope on the trend (e.g., date) variable that is statistically different from zero.

Detailed Discussion of Statistical Method

Data from long-term, fixed-station monitoring programs where gradual responses such as those due to incremental BMP implementation are likely to occur are more aptly evaluated with trend analyses that correlate the response variable (i.e., pollutant concentration or load) with time and other independent explanatory variables such as measures of BMP implementation, control watershed or upstream station values, and discharge.

The basic steps to performing trend analysis with explanatory variables include:

1. Obtain paired observations of the primary and explanatory variables for each sampling date.
2. Select the proper form of the statistical model. The type of trend should be specified based upon the timing of BMP implementation and the pattern of the water quality response (i.e., linear, or ramp trend). Include the appropriate explanatory variables.
3. From the regression analysis, obtain the estimate of the slope on trend (e.g., date). If the slope is statistically different from zero, calculate the amount of pollutant change over the monitoring period.

The form of the regression model for a ***linear trend*** over time would be:

$$Y_t = b_0 + b_1 X_{1t} + b_2 X_{2t} + \sum_{c=3}^{d+2} b_c (X_{ct}) + e_t$$

Equation 5. Regression model for linear trend.

Where:

t = time of sample (e.g., date of sample taken; could also be sequential such as day or week or month since sampling began)

Y_t = observation for Y at time t (e.g., weekly pollutant concentration or load from treatment watershed or downstream monitoring station)

X_{1t} = observation for X_1 at time t. For the paired, nested, or above/below-before/after design, X_1 is the pollutant concentration or load from the control watershed or upstream monitoring station that is paired with Y_t. This variable is dropped for the single-station monitoring design.

X_{2i} = the t^{th} time observation, X_t could be input as:

- a date value such as 6/5/13
- the number of days, weeks, or months since the start of monitoring
- a ramp trend variable (e.g., 0 for pre-BMP; 1, 2, 3, ………99 for post-BMP)

X_{ct} = observation for X_c (covariate or explanatory variable) at time t

b_0 = the overall intercept term. Note that this model does allow the intercept for each season or month to differ when indicator variables are used for seasons or months.

b_1 = regression coefficient on the control variable X_1

b_2 = regression coefficient on the trend variable X_{2t}

b_c = regression coefficient for explanatory variable X_c

k = number of time periods (with only a calibration and treatment period, k=2)

d = number of explanatory variables in addition to the control watershed variable and trend terms. For example, if only flow was used as a covariate, d=1 and the explanatory variable for flow would be X_3.

e_t = residuals or experimental error for the t^{th} observation for Y (This would be V_t for an autocorrelated error structure, not discussed here.)

For this statistical model, if the test on the t-statistic for b_1 indicates that the slope versus time is significantly different from zero, the null hypothesis is rejected and it can be concluded that there is a linear trend in Y over time. The trend rate is equal to b_1.

Note that this form of the regression model assumes that the overall trend is similar after adjusting for the explanatory variables. The validity of this assumption can be tested by including interaction terms. For example, the slopes of trends may vary by season, indicating the need to add an interaction term to account for seasonal influence. For additional insights into the broader topic of monotonic trend analyses, see Meals et al. (2011).

Linear Trend Example

Data from the Corsica River, MD, NNPSMP project (MDNR 2012) are used to illustrate linear trend analysis in Attachment 3. Linear trend analysis was chosen for this example because the impact of winter cover crops on TN concentration and load was expected to be gradual. Monitoring included continuous discharge and weekly flow-weighted composite samples for analysis of TN. The example dataset is from one of three treatment watersheds: Three Bridges Branch Subbasin. The data and conclusions are preliminary and project monitoring is expected to continue for at least 2 more years.

Summary and Recommendations

The often extreme variability in NPS-related water quality data creates challenges in data interpretation that can only be met through sound design and execution of the monitoring plan coupled with defensible statistical analysis of the data. All NPS watershed projects designed to document water quality improvements and relate them to improved land management and treatment with BMPs should include explanatory variables in their monitoring programs. By collecting data on explanatory variables, projects strengthen their capabilities to detect true changes in water quality and isolate the likely causes of those changes.

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Attachment 1.

Additional Information on Incorporating Explanatory Variables into Parametric Approaches

Incorporating Seasonal Patterns into Trend Analysis

A range of options exist for factoring cyclic seasonal patterns into trend analysis, including the following four approaches:

- Using monthly or seasonal indicator variables
- Using sine and cosine trigonometric functions
- Using other explanatory variables that also exhibit seasonal patterns (e.g., streamflow)
- Using time series models with seasonal "differencing"

Monthly or Seasonal Indicator Variables

A common approach is to simply add monthly (or other seasonal) indicators to each observation in the dataset and incorporate these indicator variables into a regression model. The number of indicator variables needed is S-1, where S represents the number of time periods (e.g., months, seasons). For example (S-1) would be 11 when the cycle is annual, but where the same months behave similarly over the years. Each indicator variable (X_1 through X_{11}) is assigned a value of 0 or 1, as illustrated below:

X_1 = "1" for "January" but "0" otherwise

X_2 = "1" for "February" but "0" otherwise

…

X_{11} = "1" for "November" but "0" otherwise

Note: December values would all be represented by "0" values for X_1-X_{11}

These indicator variables enable the adjustment (or evaluation) of each monthly/seasonal trend. This approach forms the basis for seasonal adjustments used in nonparametric trend tests as illustrated in Example 3 in Meals et al. (2011).

Trigonometric Functions

The trigonometric approach assumes that the sine or cosine term realistically simulates annual, semiannual, seasonal, or more frequent cycles. For annual cycles, 2 trigonometric terms would be used:

- $\sin(2\pi t/n)$
- $\cos(2\pi t/n)$

Where:

t=1,2,3...N (N=total number of samples)

n = number of samples per year (e.g., 12 for monthly data, 52 for weekly data)

$2\pi/n$ is known as the "fundamental frequency", sometimes denoted as ω_0

Note: a date variable (e.g., DATE) can be used instead of t with n=365.25 because 'DATE' is a daily value.

Adding only an annual cycle assumes that the seasonal component can be described by a perfectly shaped sine wave, which is generally not the case. Additional terms corresponding to multiples of the fundamental frequency (also known as harmonics) should be added as explanatory variables. For example, if the sinusoidal model allowed a cycle every 12 months and every 6 months (twice the fundamental frequency), then the explanatory variables you would calculate to add to the statistical trend analyses would be:

- $\sin(2\pi t/n)$
- $\cos(2\pi t/n)$
- $\sin(2\pi t/2n)$
- $\cos(2\pi t/2n)$

Additional sine and cosine terms should be used until all the significant harmonics are represented. For example, if the maximum number of harmonics were used, there would be 11 explanatory variables for monthly data with a fundamental period of 12 months.

These trigonometric functions are added to the regression model such that Equation 1 becomes, for example:

Equation 6. Regression model with trigonometric functions.

$$Y_t = b_0 + b_1 X_{1t} + b_3(X_{1t} * X_{2i}) + b_{d+4}\sin\left(\frac{2\pi t}{n}\right) + b_{d+5}\cos\left(\frac{2\pi t}{n}\right) + \sum_{c=4}^{d+3} b_c (X_{ct}) + e_t$$

Where:

b_{d+4} and b_{d+5} are coefficients for the sine and cosine terms, respectively, and other terms are defined above and as for Equation 1.

Explanatory Variables with Seasonal Patterns

The third approach would be to use other explanatory variables that exhibit seasonal patterns similar to those of the primary variable(s) (e.g., streamflow or precipitation). The addition of such explanatory variables may account for a significant portion of the seasonal behavior, but the residuals of the trend statistical model should be tested to evaluate if significant seasonal patterns remain after addition of such explanatory variables. These variables would simply be added as X_c variables in Equations 1-5.

Differencing

A fourth approach is to incorporate seasonality into a time series model using a technique called differencing. With this approach, the differences in monthly observations between each month and the same month in the previous year are calculated to create a new time series that is then used in a time series analysis. A downside of this approach is that the power to detect trends may be decreased. Readers are referred to Brocklebank and Dickey (1986) and other sources for additional information on this approach.

Incorporating Variables Measured Very Frequently or Continuously into Trend Analysis

Trend analyses require that the explanatory series of data (X_t) has a one-to-one pair with the dependent variable series (Y_t). Hydrologic and meteorologic data, however, are often collected more frequently than water quality samples. When matching water quality observations with variables measured more frequently it may be necessary to calculate summary values of these explanatory variables. For example, water quality sampling may be performed biweekly, but streamflow or ground water depth may be measured continuously, hourly, or daily. Depending on the specific explanatory variable, the primary variable observation can be paired with the mean, median, total, or extremes of the values measured for the explanatory variable over the timeframe represented by the primary variable observation.

Incorporating Discrete or Infrequently Measured Explanatory Variables into Trend Analysis

Most of the explanatory variables in NPS watershed studies are continuous variables, as illustrated by the X-axis in Figures 4A-4F. Some land management variables, however, are discrete (e.g., number of cattle in a watershed) and most are usually recorded less frequently than water quality data. When performing trend analyses, the land management information for a given X variable may need to be repeated for the time range applicable to the analysis. For example, the conservation tillage acreage in a watershed may not change throughout the summer, so that same acreage would be paired with each water quality value recorded for the summer.

Attachment 2.

Sinbad Creek. Above/Below-Before/After Watershed Design

A. Procedure using JMP software (SAS 2013)

a. SAS Institute. 2013b. JMP® Version 11.0.1, 2013. SAS Institute Inc., Cary, NC. *http://www.jmp.com/software/* (Accessed 7-18-14).
Using their own statistics software, readers are encouraged to perform this analysis using the data set Sinbad.xlsx.

b. Analyze => Fit Model => Select "Y" Variable. Add variables to the Model Effects ("X" and "PERIOD"), highlight PERIOD and X variables in Select Column, select "Cross" in Model Effects to include interaction term, =>Run. Note that the Y variable is the downstream TP load (Log10_TP_Load_Downstream), while the upstream TP load (Log10_TP_Load_Upstream) and PERIOD are the explanatory X variables. PERIOD timeframes were selected to reflect conditions before and after installation of livestock exclusion and pasture management between the two monitoring sites.

c. Note regarding data setup:

   i. The input data set has columns for each of the variables: Y (Log10_TP_Load_Downstream), X (Log10_TP_Load_Upstream), PERIOD, and DATE. Although DATE is not used in this example, it is useful to match the values in each row for Y, X, and PERIOD to the correct sample collection date so that the Y and X values are correctly paired. PERIOD can be "0" and "1" or "Calibration" and "Treatment" or any other numeric or character value desired. But, be aware that internal to SAS, "0" and "1" values will be generated based upon the alphabetical order – something to consider when interpreting the solutions for the regression line equations for each time period.

d. Note: if data exhibit autocorrelation (e.g., autoregression, order 1 or AR(1) error series), a corrected standard error on the differences between LS-means (which can be found in Table 7) can be estimated using Equation 7 (Spooner at al. 2011). The corrected standard error can then be used in the t-test to determine if this difference is statistically different from zero.

$$se_{corrected} = se_{uncorrected} \times \sqrt{\frac{(1+\rho)}{(1-\rho)}}$$

Equation 7. Correction of standard error for autocorrelation.

Where:

ρ = autocorrelation coefficient at lag 1

se = standard error on the differences of the LS-means

e. The percent decrease in the original, untransformed scale can be calculated by (Spooner et al., 2011):

$$\left[1-\left(\frac{10^{LS-means\,(treatment\ period)}}{10^{LS-means\,(calibration\ period)}}\right)\right]*100$$

Equation 8. Equation to calculate percent decrease on the original, untransformed data scale when log10 transformed data are used in the step trend analysis.

f. Note: the statistical analysis steps are the same for the paired-watershed study design. The treatment watershed variable values are on the "Y" axis and the paired control watershed variables values are on the "X" variable.

B. Example: Weekly TP loads, Log10 Transformed, Analysis using JMP

Step 1. Exploratory Data Analysis

Data were first examined to determine if they were independent and normally distributed. Log transformation of TP loads (lbs/week) was needed to meet the normality requirement.

Step 2. Full Model, Log10 TP Weekly Load

The full model was used to test for homogeneity of slopes between the calibration and treatment periods (Figure 5). JMP output for regression analysis is organized in a number of reports (SAS 2013). Information in the Parameter Estimates report (Table 2) indicates that the interaction term is not statistically significant (Prob>0.2517). Thus, there is no evidence that the slope of the relationship between the downstream and upstream weekly load pairs is different in the treatment period as compared to the calibration period. It is therefore appropriate to rerun the trend model without the interaction term to enable the same (pooled over all the data) slope for both time periods.

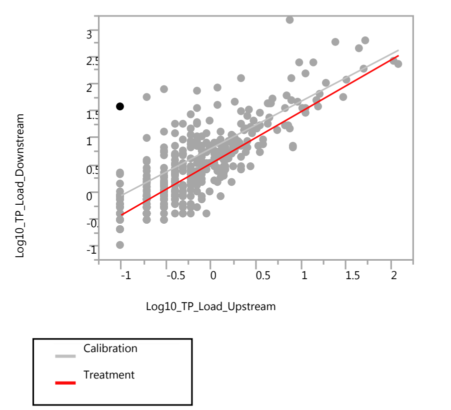

Figure 5. Full model regression plot for log TP.

Table 2. Parameter Estimates report for full model regression for log TP.

Term	Estimate	Std Error	t Ratio	Prob> |t|
Intercept	0.8052209	0.033064	24.35	<.0001*
Log10_TP_Load_Upstream	0.8683563	0.061154	14.20	<.0001*
Period[Treatment-Calibration]	-0.293827	0.042749	-6.87	<.0001*
Period[Treatment-Calibration]*(Log10_TP_Load_Upstream+0.20483)	0.0847582	0.073843	1.15	0.2517

Interaction Term is not significant, Reduced model more appropriate

Step 3. Reduced Model, Log10 TP Weekly Load

As noted in Step 2, the interaction term is not included in the reduced model to allow for a common, or pooled slope (Figure 6). The adjusted R^2 (RSquare Adj) in the Summary of Fit report (Table 3) indicates that 69 percent of the variability in downstream log TP loads is explained by the model. The Analysis of Variance report provides the F Ratio which is the test statistic for assessing whether the model differs significantly from a model where all predicted values are equal to the response mean (Table 4). The Prob>F gives the *p*-value for the test, with small values (<.0001* in this case) considered evidence that there is at least one significant effect in the model. The Parameter Estimates report (Table 5) shows that the slope (Log10_TP_Load_Upstream=0.9264871) is significant (Prob<.0001), confirming a strong relationship between the downstream and upstream paired data.

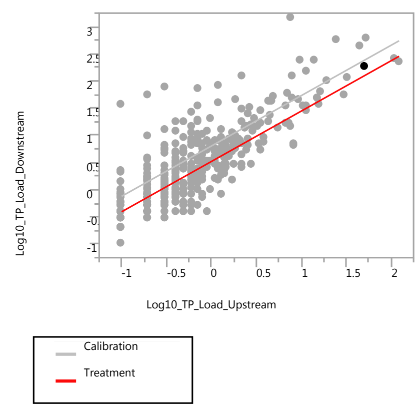

Figure 6. Reduced model regression plot for log TP.

Table 3. Summary of Fit report for log TP reduced regression model.

RSquare	0.695487
RSquare Adj	0.693979
Root Mean Square Error	0.389958
Mean of Response	0.428103
Observations (or Sum Wgts)	407

Table 4. Analysis of Variance report for log TP reduced regression model.

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	140.31375	70.1569	461.3542
Error	404	61.43518	0.1521	**Prob > F**
C. Total	406	201.74893		<.0001*

Table 5. Parameter Estimates report for log TP reduced regression model.

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.805526	0.033076	24.35	<.0001*
Log10_TP_Load_Upstream	0.9264871	0.03429	27.02	<.0001*
Period[Treatment-Calibration]	-0.284982	0.042065	-6.77	<.0001*

The Effect Tests report (Table 6) provides the F statistic for testing whether the effect of the variable (source) is zero, with the *p*-value for the test given as Prob>F. In this case, both Log10_TP_Load_Upstream and PERIOD have a significant effect. Figure 7 shows the Prediction Expression, or the equation used to predict the response. For example, the following equation (with rounding) would be applicable for the treatment (post-BMP) period.

$$\text{Log10\_TP\_Load\_Downstream} = 0.806 + 0.926 \times \text{Log10\_TP\_Load\_Upstream} - 0.285$$

The t-test of the LS-means from the calibration (0.61575720) and treatment (0.33077542) periods indicates a statistically different (and reduced) level of TP loading in the treatment period (Table 7). The Durbin-Watson test result in Table 8 indicates that there is some positive autocorrelation of the residuals (ρ = 0.3076). Durbin-Watson scores range between 0 and 4, with a value of 2 indicating no correlation. Ideally, the standard deviation would be corrected (as described above under A.d.) and the test for significance of the difference between the LS-means re-run (not shown here—see Attachment 3 for example). Because the data were log-transformed, the decrease on the original (non-log) scale is calculated using Equation 8 (Spooner et al. 2011) with results shown in Equation 9. The result of this analysis indicates a change of 48 percent.

Table 6. Effect Tests report for log TP reduced regression model.

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Log10_TP_Load_Upstream	1	1	111.01378	730.0308	<.0001*
Period	1	1	6.97966	45.8985	<.0001*

$$0.8055260260474 + 0.92648709415127 \ast \text{Log10\_TP\_Load\_Upstream} + \text{Match}\left(\text{Period}\right)\begin{bmatrix} \text{"Calibration"} \Rightarrow 0 \\ \text{"Treatment"} \Rightarrow -0.2849817816042 \\ \text{else} \Rightarrow . \end{bmatrix}$$

Figure 7. Prediction Expression for log TP reduced regression model.

Table 7. Student's t testing of difference in LS-means of log TP.

α=0.050 t=1.96585
LSMean[i] By LSMean[j]

Mean[i]-Mean[j] Std Err Dif Lower CL Dif Upper CL Dif	Calibration	Treatment
Calibration	0 0 0 0	0.28498 0.04206 0.20229 0.36767
Treatment	-0.285 0.04206 -0.3677 -0.2023	0 0 0 0

Level			Least Sq Mean
Calibration	A		0.61575720
Treatment		B	0.33077542

Levels not connected by same letter are significantly different.

Level	- Level	Difference	Std Err Dif	Lower CL	Upper CL	p-Value
Calibration	Treatment	0.2849818	0.0420647	0.2022888	0.3676748	<.0001*

Table 8. Durbin-Watson test for independence of residuals from the regression model for Log10_TP_Load_Downstream.

Durbin-Watson	Number of Obs.	AutoCorrelation	Prob<DW
1.3730166	407	0.3076	<.0001*

$$\left[1-\left(\frac{10^{LS-means(treatment\ period)}}{10^{LS-means(calibration\ period)}}\right)\right]*100$$

or

$$\left[1-\left(\frac{10^{0.61576}}{10^{0.33078}}\right)\right]*100$$

= 48% average reduction in weekly TP loads

Equation 9. Calculation of decrease on the original (non-log) scale.

C. Example: Weekly TSS loads, Log10 Transformed, Analysis using JMP

Data were first examined to determine if they were independent and normally distributed. Log transformation of TSS loads (lbs/week) was needed to meet the normality requirement. Testing of the full model revealed that the interaction term is significant (Prob=0.0005) (Table 9) and the full model is appropriate (Figure 8).

Tables 9–12 provide information similar to that described in the previous example. For example, Table 9 shows that the slope (Log10_TSS_Load_Upstream=0.5551274) is significant (Prob<.0001), confirming a strong relationship between the downstream and upstream paired data. The adjusted R^2 in Table 10 indicates that 60 percent of the variability in downstream log TSS loads is explained by the model. The F Ratio test results in Table 11 indicate that there is at least one significant effect in the model.

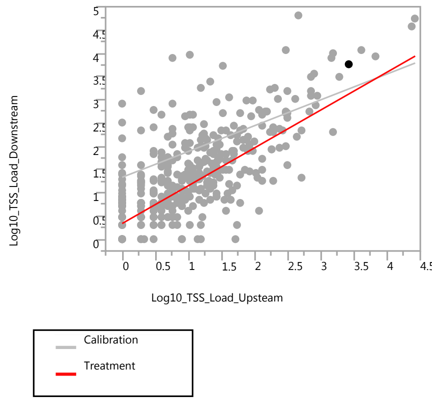

Figure 8. Full model regression plot for log TSS.

The LS-means in Table 12 show a statistically significant reduction in TSS loads in the treatment period (1.2466732) as compared to the calibration period (1.9527570). Examination of the slopes in Figure 8, however, indicates that the reductions in TSS are greater at conditions with lower TSS (e.g., lower flows). Figure 9 shows the prediction expression for Log10_TSS_Load_Downstream.

No significant autocorrelation of residuals of the regression was observed (See Table 13 for the Durbin Watson test). Because the data were log-transformed, Equation 8 (results in Equation 10) was used to estimate a change of 80 percent in mean weekly TSS loads from the pre- to the post-BMP periods.

Table 9. Parameter Estimates report for log TSS full regression model.

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	1.3345455	0.088332	15.11	<.0001*
Log10_TSS_Load_Upstream	0.5551274	0.056535	9.82	<.0001*
Period[Treatment-Calibration]	-0.706084	0.063528	-11.11	<.0001*
Period[Treatment-Calibration]*(Log10_TSS_Load_Upstream-1.11364)	0.2586197	0.074072	3.49	0.0005*

Table 10. Summary of Fit report for log TSS full regression model.

RSquare	0.60489
RSquare Adj	0.601779
Root Mean Square Error	0.589063
Mean of Response	1.483762
Observations (or Sum Wgts)	385

Table 11. Analysis of Variance report for log TP reduced regression model.

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	202.39860	67.4662	194.4295
Error	381	132.20539	0.3470	**Prob > F**
C. Total	384	334.60399		<.0001*

$$
\begin{aligned}
&1.33454551015318 \\
&+\ 0.5551273661457 * \text{Log10\_TSS\_Load\_Upsteam} \\
&+\ \text{Match}\big(\text{Period}\big)\begin{bmatrix} \text{"Calibration"} \Rightarrow 0 \\ \text{"Treatment"} \Rightarrow -0.7060837718243 \\ \text{else} \Rightarrow . \end{bmatrix} \\
&+\ \text{Match}\big(\text{Period}\big)\begin{bmatrix} \text{"Calibration"} \Rightarrow \big(\text{Log10\_TSS\_Load\_Upsteam} - 1.11363896479171\big) * 0 \\ \text{"Treatment"} \Rightarrow \big(\text{Log10\_TSS\_Load\_Upsteam} - 1.11363896479171\big) * 0.25861970995305 \\ \text{else} \Rightarrow . \end{bmatrix}
\end{aligned}
$$

Figure 9. Prediction Expression for log TSS full regression model.

Table 12. **Student's t testing of difference in LS-means of log TSS.**

α=0.050 t=1.96621 LSMean[i] By LSMean[j]		
Mean[i]-Mean[j] Std Err Dif Lower CL Dif Upper CL Dif	Calibration	Treatment
Calibration	0 0 0 0	0.70608 0.06353 0.58117 0.83099
Treatment	-0.7061 0.06353 -0.831 -0.5812	0 0 0 0

Level			Least Sq Mean
Calibration	A		1.9527570
Treatment		B	1.2466732
Levels not connected by same letter are significantly different.			

Level	- Level	Difference	Std Err Dif	Lower CL	Upper CL	p-Value
Calibration	Treatment	0.7060838	0.0635282	0.5811739	0.8309936	<.0001*

Table 13. **Durbin-Watson test for independence of residuals from the regression model for Log10_TSS_Load_Downstream.**

Durbin-Watson	Number of Obs.	AutoCorrelation	Prob<DW
1.905797	385	0.0426	0.1545

$$\left[1-\left(\frac{10^{LS-means(treatment\ period)}}{10^{LS-means(calibration\ period)}}\right)\right]*100$$

or

$$\left[1-\left(\frac{10^{1.95275}}{10^{1.24667}}\right)\right]*100$$

= 80% average reduction in weekly TSS loads

Equation 10. Calculation of decrease on the original (non-log) scale.

Attachment 3.

Corsica River Single-Station Trend Monitoring Design

A. Procedure using JMP software (SAS 2013).

a. SAS Institute. 2013b. JMP® Version 11.0.1, 2013. SAS Institute Inc., Cary, NC. *http://www.jmp.com/software/* (Accessed 7-18-14).
Using their own statistics software, readers are encouraged to perform this analysis using the data set Corsica.xlsx.

b. Analyze => Fit Model => Under "Model Specifications"

i. Select "Y" Variable (for this example, LTN_Conc or LTN_Load, which are the log-transformed weekly flow-weighted composite concentration or weekly load, respectively).

ii. Select Trend variable (in this example, DATE) and add to "Construct Model Effects". The Date variable is stored internally as a number that increases by one each subsequent day.

iii. Select other Explanatory Variables:

1) In this example, MONTH is included as a seasonal indicator variable, and has been set up in the data table as a "Modeling Type = Ordinal". This will enable 11 df for the 12 months. Equivalently, X1, X2, …, X11 indicator variables could be created with values of 0 or 1 (see Attachment 1 for procedure details).

2) In this example, annual cover crop acres (COVER CROP (acres)) is also included because the BMP installed was winter cover crops.

3) In this example, log10 weekly flow (L_FLOW) is added as an explanatory variable for the weekly concentration data.

iv. =>Run

c. Note: if data exhibit autocorrelation (e.g., autoregression, order 1 or AR(1) error series), a corrected standard error on the trend slope (which can be found as "Std Error" for DATE in the "Parameter Estimates" report, Table 16) can be estimated using Equation 11 (Spooner at al. 2011). The corrected standard error can then be used to re-test for the statistical significance of the trend.

$$se_{corrected} = se_{uncorrected} \times \sqrt{\frac{(1+\rho)}{(1-\rho)}}$$

Equation 11. Correction of standard error for autocorrelation.

Where:

ρ = autocorrelation coefficient at lag 1

se = standard error on the trend slope

d. Calculate percent change over time. The percent decrease in the original, untransformed scale can be calculated by (Spooner et al. 2011):

$$Ave\ change\ on\ log\ scale = Slope(date) * (\#monitored\ years) * 365.25$$

$$\%Decrease = (1 - 10^{(change\ on\ log\ scale)}) * 100$$

The 365.25 factor is used because the slope is calculated on the DATE variable which is internally stored as a value that increments by 1 each day.

Equation 12. Equation to calculate percent decrease on the original, untransformed data scale when log10 transformed data are used in the linear trend analysis. This assumes the trend variable is DATE, coded as a 'date' format.

e. To plot the predicted values from the regression trend model:
   i. On the top left of "Regression Output", select Save Columns → Predicted Values. This will save a new column containing the predicted values at the end of the JMP data table.
   ii. From the main data table menu: Graph→ Overlay Plot → Select Predicted Value as the "Y" and DATE as the "X" → OK
   iii. On top of the Overlay Plot, select "Connect Through Missing" to add a line connecting the points.

B. Example: Weekly TN Composite Samples Concentrations, Log10 Transformed vs Date, Analysis using JMP

Step 1. Exploratory Data Analysis

Data were first examined to determine if they were independent and normally distributed. Log transformation of TN concentration (mg/l) was needed to meet the normality requirement.

Step 2. Trend Model, Log10 TN Weekly Concentration

The best trend model included explanatory variables for seasonality (MONTH), log transformation of weekly total flow (liters) (L_FLOW), and annual cover crop acres (COVER CROP (acres)). The R-Square value (adjusted) indicates that 35 percent of the variability in weekly LTN_Conc is explained by the model (Table 14). The F Ratio test results in Table 15 indicate that there is at least one significant effect in the model. Table 16 shows that the slope (DATE) of -1.261e^{-9} is statistically significant (Prob>[t] <.0001*). Using equation 12, the average percent change was:

$$Ave\ change\ on\ log\ scale = 1.26145e^{-9} * (6.8\ years) * 365.25$$

$$= -0.31331$$

$$\%Decrease = (1 - 10^{(change\ on\ log\ scale)}) * 100$$

$$= 52\%$$

Table 14. Summary of Fit report for LTN concentration regression model.

RSquare	0.385474
RSquare Adj	0.351198
Root Mean Square Error	0.095831
Mean of Response	0.513519
Observations (or Sum Wgts)	266

Table 15. Analysis of Variance report for LTN concentration regression model.

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	14	1.4459194	0.103280	11.2461
Error	251	2.3050953	0.009184	**Prob > F**
C. Total	265	3.7510147		<.0001*

Table 16. Parameter Estimates report for LTN concentration regression model.

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	4.2651538	0.793788	5.37	<.0001*
Date	-1.261e-9	2.37e-10	-5.32	<.0001*
Month[2-1]	0.046479	0.028005	1.66	0.0982
Month[3-2]	-0.024229	0.02693	-0.90	0.3692
Month[4-3]	0.0277314	0.025257	1.10	0.2733
Month[5-4]	0.0271395	0.02698	1.01	0.3154
Month[6-5]	0.0060973	0.028441	0.21	0.8304
Month[7-6]	-0.021351	0.030881	-0.69	0.4900
Month[8-7]	-0.019748	0.032455	-0.61	0.5434
Month[9-8]	-0.009332	0.032457	-0.29	0.7740
Month[10-9]	-0.06902	0.031078	-2.22	0.0273*
Month[11-10]	-0.074561	0.030027	-2.48	0.0137*
Month[12-11]	0.081474	0.030368	2.68	0.0078*
L_Flow	0.0512238	0.020067	2.55	0.0113*
Cover Crop (acres)	5.5619e-5	3.076e-5	1.81	0.0717

```
4.26515376658483
+ -1.2614484339e-9 * Date
                   ( 1    ⇒ 0                )
                   ( 2    ⇒ 0.04647902655987 )
                   ( 3    ⇒ 0.02225010622135 )
                   ( 4    ⇒ 0.04998146276337 )
                   ( 5    ⇒ 0.07712098472535 )
                   ( 6    ⇒ 0.08321826742822 )
+ Match( Month )   ( 7    ⇒ 0.06186734188715 )
                   ( 8    ⇒ 0.04211981592741 )
                   ( 9    ⇒ 0.03278782521484 )
                   ( 10   ⇒ -0.036232018719  )
                   ( 11   ⇒ -0.1107931562189 )
                   ( 12   ⇒ -0.0293191830414 )
                   ( else ⇒ .                )
+ 0.05122380507772 * L_Flow
+ 0.0000556187006 * Cover Crop (acres)
```

Figure 10. Prediction Expression for LTN concentration regression model.

The terms "Month[2-1]", etc., are the coefficient estimates for the seasonal indicator variables. They indicate how much the average of each month's values differs from the overall mean values. They are used in the regression predictor equation (Figure 10).

Three of the four explanatory variables (DATE, MONTH, L_FLOW) used in the regression model have a significant effect at the 95% confidence level, with COVER CROP (acres) having an effect at the 90% confidence level (Table 17). Figure 10 shows the Prediction Expression, or the equation used to predict the response. For example, the following equation (with rounding) would be applicable for April (MONTH=4):

$$LTN\_Conc = 4.26515 + (-1.26145)e^{-9} \times DATE + 0.04998 + 0.05122 \times L\_FLOW + 0.0000556 \times COVER\ CROP\ (acres)$$

Table 17. Effect Tests report for LTN concentration regression model.

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Date	1	1	0.26017293	28.3300	<.0001*
Month	11	11	0.74580806	7.3828	<.0001*
L_Flow	1	1	0.05983779	6.5157	0.0113*
Cover Crop (acres)	1	1	0.03003297	3.2703	0.0717

Figure 11 shows the plot of predicted values of LTN_Conc versus DATE. The seasonal pattern and an overall decreasing trend are clear from this figure. JMP also provides the user "leverage plots." These leverage plots show the impact of adding an explanatory variable or "effect" to the model, given the other explanatory variables already in the model. For example, Figures 12 and 13 show the strong influence of DATE and MONTH on LTN concentration, supporting the pattern found in Figure 11. The influence of COVER CROP (acres) is less pronounced (p=0.07, see Table 16), yet COVER CROP (acres) is still significant at the 90% confidence level (Figure 14).

The Durbin-Watson test result in Table 18 indicates that there is some positive autocorrelation of the residuals (ρ=0.3945). In this case, the adjusted standard error becomes 3.6e-10 (versus 2.37e-10 in Table 16) using the approach described above under A.c. This results in a revised t Ratio and Prob>[t] of -3.5 and <0.001, respectively, for DATE in Table 16. The trend remains significant.

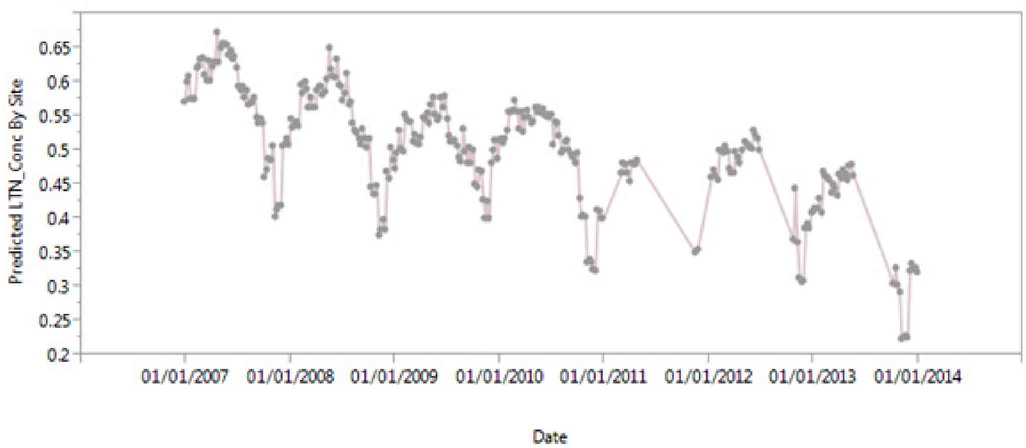

Figure 11. Plot of predicted values versus date for LTN concentration regression model.

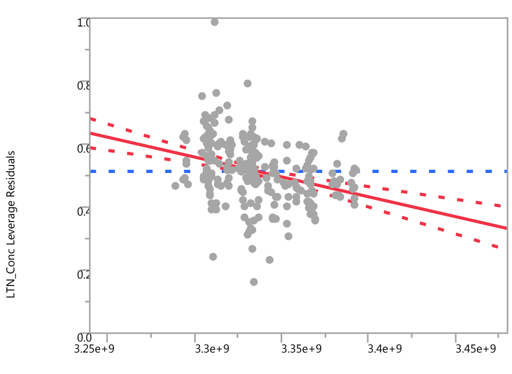

Figure 12. Leverage plot for LTN concentration versus DATE.

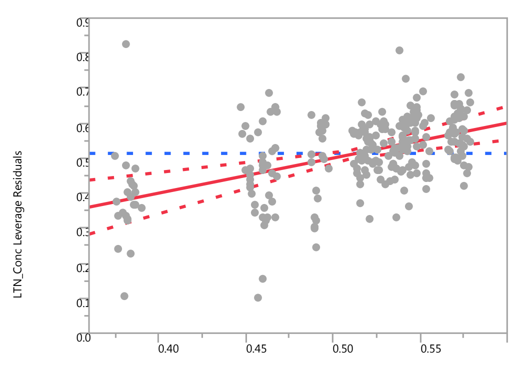

Figure 13. Leverage plot for LTN concentration versus MONTH.

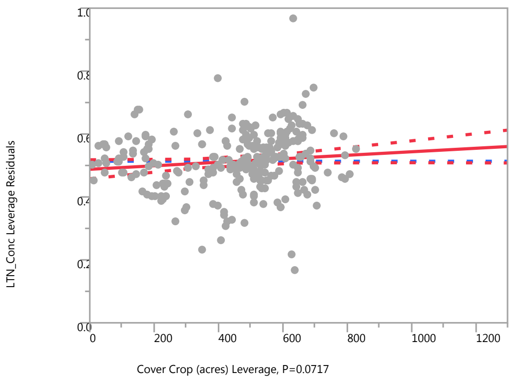

Figure 14. **Leverage plot for LTN concentration versus COVER CROP (acres).**

Table 18. **Durbin-Watson test for independence of residuals from the regression model for log TN concentration.**

Durbin-Watson	Number of Obs.	AutoCorrelation	Prob<DW
1.2062499	266	0.3945	<.0001*

C. Example: Weekly TN Composite Samples Loads, Log10 Transformed vs Date, Analysis using JMP

Step 1. Exploratory Data Analysis

Data were first examined to determine if they were independent and normally distributed. Log transformation of TN load (lbs/week) was needed to meet the normality requirement.

Step 2. Trend Model, Log10 TN Weekly Load

The best trend model included explanatory variables for seasonality (MONTH) and annual cover crop acres (COVER CROP (acres)). The adjusted R^2 is 0.40 (Table 19), and the F Ratio in Table 20 is significant (Prob>F is <0.0001) indicating at least one significant effect in the model. The slope (DATE = $-1.424e^{-9}$) in the regression model appears to be weakly statistically significant (Prob>[t] = 0.0826), as is the coefficient for COVER CROP (acres) (Table 21). The terms "Month[2-1]", etc., are the coefficient estimates for the seasonal indicator variables. They indicate how much the average of each month's values differs from the overall mean values. They are used in the regression predictor equation (Figure 18).

Table 19. Summary of Fit report for LTN load regression model.

RSquare	0.432562
RSquare Adj	0.403289
Root Mean Square Error	0.330382
Mean of Response	2.871705
Observations (or Sum Wgts)	266

Table 20. Analysis of Variance report for LTN load regression model.

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	13	20.968259	1.61294	14.7770
Error	252	27.506355	0.10915	Prob > F
C. Total	265	48.474614		<.0001*

Table 21. Parameter Estimates report for LTN load regression model.

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	7.6392053	2.671289	2.86	0.0046*
Date	-1.424e-9	8.17e-10	-1.74	0.0826
Month[2-1]	0.0309237	0.096542	0.32	0.7490
Month[3-2]	0.1171765	0.092376	1.27	0.2058
Month[4-3]	-0.070419	0.086834	-0.81	0.4182
Month[5-4]	-0.147059	0.092307	-1.59	0.1124
Month[6-5]	-0.132443	0.097628	-1.36	0.1761
Month[7-6]	-0.237887	0.105505	-2.25	0.0250*
Month[8-7]	-0.085802	0.111805	-0.77	0.4435
Month[9-8]	-0.077986	0.111807	-0.70	0.4861
Month[10-9]	0.0491881	0.106858	0.46	0.6457
Month[11-10]	0.2826064	0.100815	2.80	0.0055*
Month[12-11]	0.2625916	0.104015	2.52	0.0122*
Cover Crop (acres)	0.0003233	0.000105	3.09	0.0022*

The significance of the effects of MONTH and COVER CROP (acres) is greater than that for DATE (Table 22), an observation supported by the leverage plots (Figures 15-17).

Table 22. Effect Tests report for LTN load regression model.

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Date	1	1	0.2331510	3.0371	0.0826
Month	11	11	16.763917	13.9621	<.0001*
Cover Crop (acres)	1	1	1.043763	9.5625	0.0022*

Figure 18 shows the Prediction Expression, or the equation used to predict the response. For example, the following equation (with rounding) would be applicable for April (MONTH=4):

$$LTN\_Load = 7.63920 + (-1.42380)e^{-9} \times DATE + 0.07768 + 0.00032 \times COVER\ CROP\ (acres)$$

The plot of predicted values of LTN_load versus DATE shows a clear seasonal pattern (Figure 19). The Durbin-Watson test result in Table 23 indicates that there is some positive autocorrelation of the residuals (ρ=0.4394). Using the approach described above under A.c., the adjusted standard error becomes 1.31e-9 (versus 8.17e-10 in Table 21). This results in a revised t Ratio and Prob>[t] of -1.09 and 0.28, respectively, for DATE in Table 21. The trend (slope on DATE) is now found to not be significant. The regression analysis should then be re-run without DATE as a variable, and focus on changes attributable to COVER CROP.

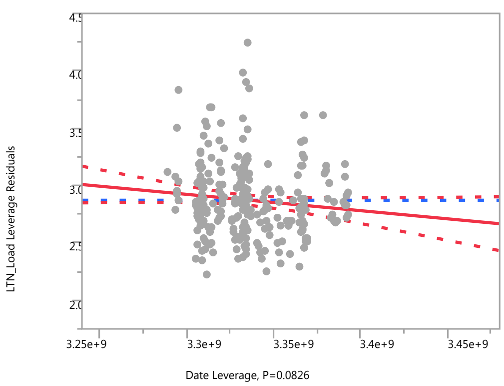

Figure 15. Leverage plot for LTN load versus DATE.

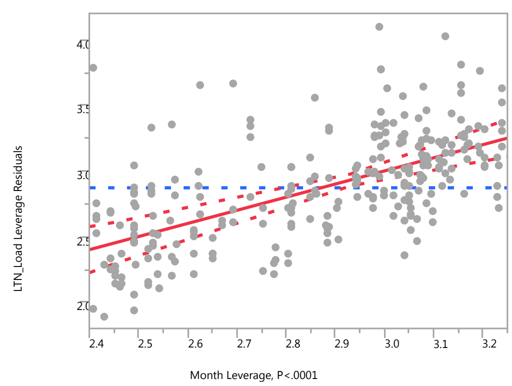

Figure 16. Leverage plot for LTN load versus MONTH.

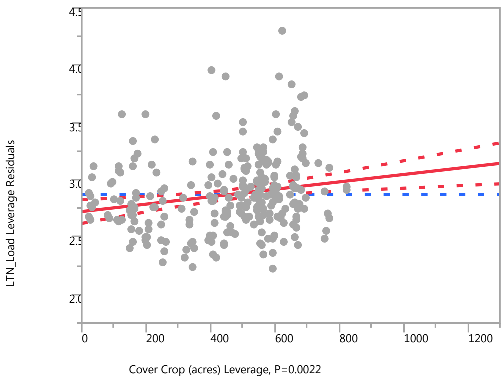

Figure 17. Leverage plot for LTN load versus COVER CROP (acres).

7.639205265396
+ -1.4238026936e-9 * Date
+ Match(Month)
1 ⇒ 0
2 ⇒ 0.03092365404555
3 ⇒ 0.14810015325628
4 ⇒ 0.07768147639311
5 ⇒ -0.0693770708701
6 ⇒ -0.2018203900243
7 ⇒ -0.439707758492
8 ⇒ -0.5255099175318
9 ⇒ -0.6034957007962
10 ⇒ -0.5543075509427
11 ⇒ -0.2717011763667
12 ⇒ -0.0091095692131
else ⇒ .
+ 0.00032332767344 * Cover Crop (acres)

Figure 18. Prediction Expression for LTN load regression model.

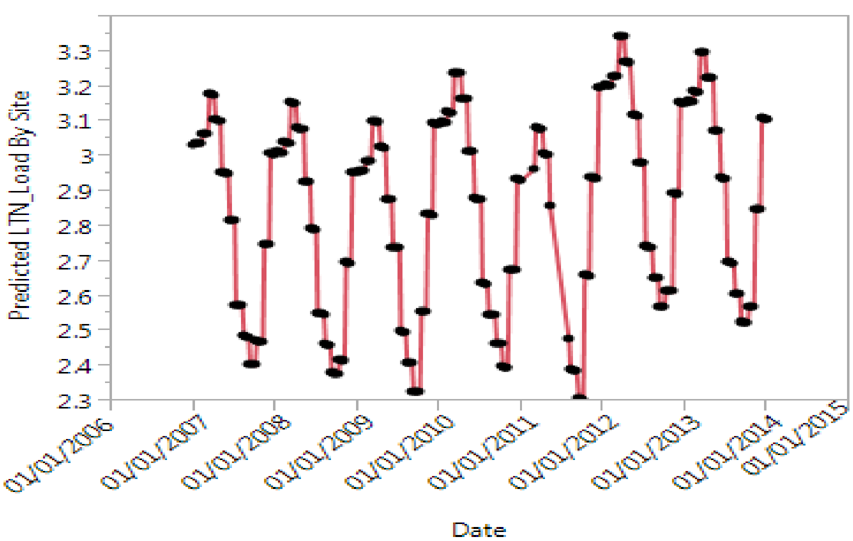

Figure 19. Plot of predicted values versus date for LTN load regression model.

Table 23. Durbin-Watson test for independence of residuals from the regression model for log TN load.

Durbin-Watson	Number of Obs.	AutoCorrelation	Prob<DW
1.119256	266	0.4394	<.0001*