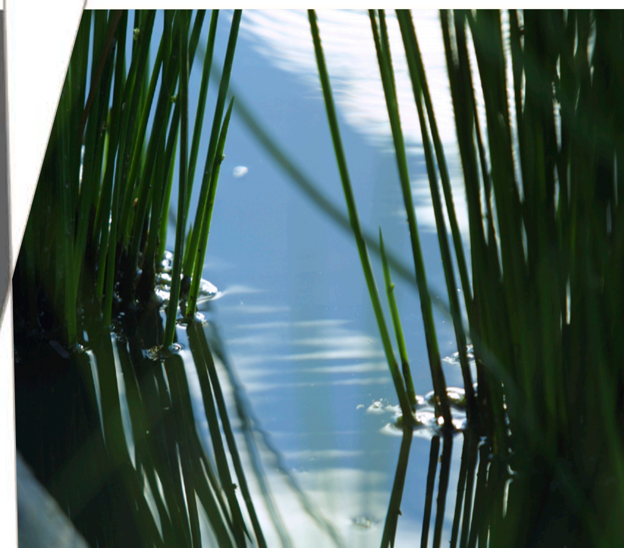
Water Quality Estimation and Monitoring Optimization

UNRBA Monitoring Program Development and Implementation

E213006400



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Executive Summary

The Upper Neuse River Basin Association (UNRBA) has asked Cardno ENTRIX to assist in developing a monitoring program aimed at re-examining the Falls Lake Nutrient Management Strategy under the adaptive management provisions of the Falls Lake Rules. Among other monitoring objectives, this program will include routine monitoring at tributary sites identified as important for quantifying loading of nutrients to Falls Lake (henceforth, "lake loading sites") as well as at jurisdictional boundaries in order to aid UNRBA members in calculations of annual jurisdictional loads.

This technical memorandum (TM) describes the statistical approach used to develop recommendations for sampling frequency for the first year of monitoring at lake loading and jurisdictional boundary locations; additional components of the monitoring plan will be discussed in the forthcoming UNRBA Monitoring Plan TM. In addition to the statistical approaches described in this memo, the monitoring recommendations were guided by budget considerations and feedback from UNRBA member organizations. Cost estimates provided in this memo are preliminary figures for discussion and comparison purposes and could likely be altered by many factors. These costs will be provided within the context of the other proposed monitoring studies in the UNRBA Monitoring Plan TM.

The basic premise behind the statistical approach presented in this TM is that, all else being equal, a site which is less-well estimated by statistical models should be sampled more frequently than a site which is well estimated. To assess the relative ability of models to estimate water quality at individual sites, two statistical models were developed. Model One uses an approach based on available site-specific historical nutrient data along with data on covariates (additional related parameters). Model Two uses a spatial modeling approach which uses the historic dataset, but does not depend on the availability of site-specific nutrient data for simulating data for a given site; this model is useful for assessing how well models may estimate water quality at previously un-monitored locations. This TM uses these models in conjunction with flow estimation methods presented in a previous TM to explore an approach for determining monitoring frequency based the magnitude of estimated loads and a desired level of confidence in these estimates.

The results of the two water quality models were used to inform sampling plans which focus effort at locations that benefit most from increased sampling frequency. The models show that roughly weekly sampling for 5 years for TP (n=260) and twice monthly for TN (n=120) would yield about 90% confidence in the ability to predict mean nutrient concentrations within ± 10%. Sampling TSS weekly would achieve with 90% confidence that the mean could be estimated within 10 to 20%. This level of sampling, if applied at all sites, is likely to be cost-prohibitive given the UNRBA's projected budget. This document shows that the Flat River, Eno River, Little River, Ellerbe Creek, and Knap of Reeds Creek are estimated to provide the largest contribution of nutrients (approximately 75-80% of the total load) to Falls Lake. Sampling these locations at a weekly frequency would allow much of the load to be estimated with a relatively high degree of confidence. Sampling frequencies may be reduced further (e.g. to every-other week) if historical data (data collected before the start of the present UNRBA monitoring program) are used to support future model development. Sampling the remaining lake loading sites less frequently (monthly in the first year) would yield less-confidence in estimates, but the reduced confidence over smaller portions of the total load is a recommended cost-saving tradeoff. Sampling at sites determined to provide the smallest portion of the load may be able to be reduced even further in subsequent years, following a year of data collection to verify model output.

The approach is also applied to jurisdictional boundary sites and sites are ranked according to their expected loads. At least initially, however, UNRBA members have indicated that desired confidence in load estimates is independent from expected magnitude of those loads; that is, loading at all jurisdictional sites should be estimated with the same anticipated degree of confidence regardless of how large the jurisdiction's load is expected to be. Therefore, a uniform monitoring program is recommended with a frequency between monthly and bi-monthly, with the choice of frequency to be revisited by the UNRBA annually.

The statistical models described in this TM were developed with the specific goal of exploring questions related to sampling frequency. In general, all models are developed with specific objectives in mind and caution needs to be exercised in applying models outside of this predefined scope. The models described in this TM were not specifically designed for making water-quality predictions to be used in specification of boundary conditions for future lake response models, although future revisions and refinements may be able to build upon their framework for this purpose. Refined versions of these models, along with other methods such as USGS's LOADEST model, would provide the UNRBA with the flexibility of multiple statistical methods to predict and verify daily water quality concentrations at Falls Lake loading sites.

1 Introduction and Project Background

In 2010, the Environmental Management Commission (EMC) passed the Falls Lake Nutrient Management Strategy, requiring two stages of nutrient reductions (N.C. Rules Review Commission 2010). The method used by the NC Division of Water Quality (DWQ)—now the Division of Water Resources (DWR)—for setting nutrient loading targets in the Falls Lake Nutrient Management Strategy is the Falls Lake Nutrient Response Model, which was developed with the Environmental Fluid Dynamics Code (EFDC) model (NCDENR 2009). In 2011, the Upper Neuse River Basin Association (UNRBA) began a project to re-examine the Falls Lake Nutrient Management Strategy under the adaptive management provisions of the Falls Lake Rules.

Cardno ENTRIX is assisting the UNRBA in developing a monitoring plan that supports the re-examination process. The UNRBA Monitoring Program must cost-effectively support multiple UNRBA objectives. Six objectives were identified in Task 4: Review of Existing Models and Recommendations for Future Studies (Cardno ENTRIX 2013) and the Path Forward Committee of the UNRBA prioritized three of these objectives to be the focus of the monitoring program:

1. Lake response modeling,
2. Support of regulatory options,
3. Source allocation and estimation of jurisdictional loading.

Monitoring in <u>support of regulatory options</u> will be discussed in the forthcoming UNRBA Monitoring Plan TM and is not explicitly discussed in this TM.

Monitoring in relation to <u>lake response modeling</u> includes several sub-objectives. First, loading of water quality constituents (e.g. nutrients, carbon, chlorophyll, and sediments) is an important driver of the Falls Lake Nutrient Response Model. Because loading targets for the watershed were set, at least in part, based upon this model, understanding loading and how loading relates to water quality parameters of concern within Falls Lake is an important UNRBA objective. This objective may be partially met through routine monitoring of tributary loads. Second, any revisions to the Nutrient Response model will need to be calibrated to observed data within Falls Lake; therefore, another objective of monitoring in relation to the lake response modeling is to assure that adequate in-lake data are collected, by UNRBA and/or DWR, to allow for model calibration. This data should provide a long-term record of important modeling targets (e.g. chlorophyll, temperature, dissolved oxygen) along with estimates of expected spatial and temporal variation so that calibration targets can be adequately characterized. Finally, the calibration of the lake response model requires input of many parameters describing in-lake transformations and various physical, chemical, and biological processes. Some additional sampling may help narrow the range of appropriate values of a few influential parameters.

With respect to lake response modeling, the current TM focuses on the periodic monitoring related to loading of water quality constituents to Falls Lake and focuses on how sample size (number of observations) relates to confidence in the ability to characterize water quality on days for which measurements are not made. These analyses guide recommendations to allocate effort to sites which contribute the largest portion of nutrients to Falls Lake. Special studies and short-term projects related to lake response modeling will be presented in the UNRBA Monitoring Plan TM.

Finally, some monitoring of <u>jurisdictional loads</u> has also been identified by the UNRBA due to the requirement in the Falls Lake Rules that jurisdictions calculate baseline jurisdictional loading. Acceptable methods to determine jurisdictional loads, however, have not been provided by the State. The collection of some routine data at 21 locations within the Falls Lake watershed can help guide jurisdictions in the development of methods to calculate these loads. With regard to jurisdictional loading, this TM will discuss the relationship between sample size (number of observations) and the precision with which models presented here can estimate mean loads in order to guide the UNRBA in selecting monitoring frequencies to meet their needs.

Altogether, this technical memorandum (TM) discusses how statistical models developed from existing water quality data can address important questions regarding the design of the monitoring program and guide the frequency of sample collection related to the long-term monitoring requirements of the UNRBA's three monitoring objectives.

Section 2 presents the impetus for statistical analysis in relation to determining sampling frequency.

Section 3 presents models which were developed to inform sampling frequency, including model equations, covariates, and model fitting methods.

Section 4 presents results of the models and model fit statistics.

Section 5 demonstrates how model output was used to categorize sites according to level of monitoring effort recommended

Finally, Section 6 presents recommendations for relative sampling frequencies for all tributary monitoring locations. These recommendations are based on model output, budget constraints, and feedback from UNRBA member organizations. These are intended to be a guide for allocating relative effort among stations and may be adjusted according to changing needs and priorities of the UNRBA.

2 Statistical Model Support of Monitoring Program Design

The most accurate—but most expensive—way to estimate daily water quality is to measure it directly. Indeed, two of the three UNRBA monitoring objectives (lake response modeling and estimation of jurisdictional loading) would ideally be supported by continuous measurement of flow and daily (or even more frequent) sampling of relevant water quality parameters. Unfortunately, this level of monitoring is not financially feasible and the technology for continually measuring all parameters in-situ is still under development. Collecting relevant data at just the lake loading sites on a daily basis would likely cost over $4 million annually. Sampling the same locations on a weekly basis is estimated to cost over $700,000 per year and would limit the UNRBA's ability to obtain the complete dataset needed to meet other monitoring program goals.

Because of the significant expense of routine monitoring, it is important to keep project goals in mind when determining monitoring frequency and to identify the frequencies that balance project goals with the available budget. One set of tools that can help negotiate that balance are statistical models. These tools, when paired with historical data, can be used to quantify the tradeoffs between reduced sampling frequency and the resulting certainty with which water quality can be characterized. This allows a better understanding of the gains that additional dollars spent on monitoring can provide.

As identified in Section 1 of this TM, characterizing loading to Falls Lake is one of the UNRBA's primary monitoring objectives. The UNRBA Modeling Framework for the Re-examination of Stage II proposes an updated version of the EFDC model which was previously used by DWR to develop the Falls Lake Rules. The existing version of the Falls Lake Nutrient Response Model requires estimates of daily flow and nutrient inputs from 17 tributaries around Falls Lake. When developing the initial Falls Lake model, DWR did not have daily observations of relevant parameters to meet the model's input requirements. Instead, they used linear interpolation between monthly observations to simulate daily estimates of necessary water quality parameters at sites with available data. For sites without observations, DWR used linear interpolation with monthly data from nearby sites as input to the model. For parameters without available tributary data (e.g. total organic carbon and chlorophyll *a*), DWR interpolated between observations at nearby lake monitoring stations and used those values as inputs to the lake model. The limited data available for model input has been previously identified as a gap that UNRBA would like to fill with its monitoring program. While daily monitoring remains out of reach, identifying locations and sampling frequencies which provide the largest improvements in model confidence is a priority which can be aided by quantitative statistical models.

In addition to informing sampling frequencies, statistical models have the ability to provide daily estimates of water quality data for time periods without daily measurements. Such simulated data could be used as input to the Falls Lake Nutrient Response Model to characterize boundary conditions. There are multiple possible models that could be used to simulate daily values from a set of observations, including linear interpolation as was performed by DWR. Other models include USGS' LOADEST model and empirical regression models. *The current TM presents one set of watershed regression models based on data collected within the Falls Lake watershed and asks how well these models can simulate water quality given a limited number of observations, whether certain sites are better predicted than others, and how confidence in simulated values is affected by sample size.* The primary purpose of this TM is to use the answers to these questions, along with expected site-specific water quality and flow, to identify sites which are candidates for increased sampling frequency (relative to a baseline frequency) due to either their expected load or the uncertain nature of that expected load.

The statistical models used in this analysis relate measured water quality concentrations (total phosphorus, for instance) to measurements of properties that may contribute to the observed concentration, such as precipitation, temperature, season, and stream flow (collectively termed “covariates”). When data on these covariates are available at a finer resolution than the water quality data itself, they can be used with a model to provide estimates of water quality on the days when it was not measured. If these covariates do contribute to the observed variation in water quality, then a model using these covariates will do a better job of estimating water quality than a model in which they are not included. No model perfectly represents reality, but metrics are available to judge how well a model is working compared to its stated goals (see section 4). Importantly, these metrics can be used to help identify which covariates are useful for estimating water quality (and which are not) and they can be used to evaluate, by location, a model’s ability to provide estimates of water quality on days without measurements.

Differences in the model’s predictive ability among locations can help prioritize which sites should be sampled more frequently than others to better support the UNRBA program and refine the estimation methodology. All else being equal, a site that is less-well predicted by models should be sampled more frequently than a site that is well predicted. This is necessarily a relative comparison and, as this TM has noted, ideally data would be collected continuously at all locations. However, given that measurements will be made less frequently than daily, collecting data more frequently at less-well predicted sites allows monitoring dollars to be applied in a way that increases their utility compared to a one-size-fits-all uniform-frequency sampling plan. Adjusting sampling frequency in this way provides more observations at sites that aren’t predicted as well which will improve the accuracy of the daily simulated values used in the EFDC model. Furthermore, additional data can improve future model predictions by providing more precise estimates of the model terms that describe the relationships between observed water quality and the covariates (see section 5).

In addition to informing monitoring design, the models presented here are a good option, but not the only option, to be used for simulating daily water quality values for the purpose of providing input to future revisions of the EFDC Lake Response model. A full evaluation and comparison of methods for this purpose is outside the scope of this TM. This TM focuses on the models’ use for sampling design and points out some areas in which the models could be refined to improve their predictive power. However, even if these models are ultimately not used in simulating data for EFDC model input, they *are* currently useful in describing how well sites may be predicted relative to each other and in identifying sites which may benefit from more frequent sampling than others.

Another of the UNRBA’s monitoring objectives is to collect data which enable the characterization of jurisdictional loading. While daily simulated values are not explicitly necessary for this purpose, the models presented here also apply to jurisdictional boundary locations and can be used to describe the relationship between sampling frequency and confidence in estimates of water quality. This information can be used by the UNRBA to guide decisions regarding monitoring frequencies at jurisdictional boundary locations.

Just as models aren’t perfect representations of reality, it’s also important to keep in mind that data are not perfect either. Even if there were no error in sampling or analytical techniques, a single data point collected on a given day would only be representative of the tributary at the location and instant at which it was collected. The extent to which that data point represents the average value for the 24-hour period (the value used for the lake modeling effort) is unknown. Additionally, models cannot predict events or changes in water quality that are determined by factors which are not included in the model. For instance, the types of models discussed here cannot predict future violations of discharge permits or unlawful additions of sediment or nutrients to Falls Lake tributaries. However monitoring may not capture these events either; if discharge events happen at the scale of hours or days and monitoring happens at the scale of weeks or months. Capturing these inputs to Falls Lake would be a matter of chance. Prioritization of sites where these events are likely to occur will not be informed by model output; this would need to happen via discussions with and input from UNRBA members.

2.1 Statistical Model Use to Prioritize Monitoring Resources

Because of the need to use models to estimate water quality between sampling events and because of the need to understand the uncertainty associated with model predictions and specifically how that should influence the sampling design, this TM and its associated modeling efforts were developed with the following goals:

1. Use models and the associated evaluations of their fits to identify which locations of interest are predicted well (or poorly) by reasonable and cost-effective models, and therefore which sites are candidates for reduced (or increased) sampling frequencies relative to a baseline frequency (monthly sampling).
2. Identify models which can be continually used and revised to adaptively assess model predictions at all monitoring locations with the goal of identifying sites which are candidates for reduced sampling frequency in future years.

Provide the framework for an alternative to linear interpolation for estimating daily water quality concentrations and, in the process, identify which readily-available covariates best predict water quality parameters of concern.In addition to categorizing sites according to how well they can be predicted, there may be other reasons to choose to sample a site more frequently than others. For example, the magnitude of the expected load may influence monitoring priorities. Sites for which variability in nutrient concentrations cannot be predicted well, but which are expected to have very low flows (e.g. small drainage areas) paired with a low average nutrient concentration might not need to be sampled as frequently.

To address the goals outlined above, this TM presents two statistical models developed for predicting daily water quality concentrations—one that predicts at sites for which data already exist and another that can predict at any latitude or longitude regardless of the presence of prior samples.

The models presented in this TM could also be refined for future use in specific hypothesis testing about the effects of changes in the watershed on water quality. Examples might include testing hypotheses about changes in water quality after discrete management actions (e.g. WWTP upgrades) or estimating gradual trends in water quality through time (e.g. effects of multiple BMP implementations over a period of years).

2.2 Monitoring Implications

Statistical models for water quality prediction were developed by Cardno ENTRIX to help design the Upper Neuse River Basin Association's monitoring program. Statistical models based on existing monitoring data are used to determine where and when water quality can be predicted with a reasonable degree of confidence as well as to identify locations where models should not be used to predict current and future water quality conditions.

The program will be optimized for cost and data needs with respect to uncertainty characterization. The monitoring program is being designed to be flexible and adaptive. The initial monitoring data will be reviewed for use in refining the monitoring program in future years. An annual review of monitoring data and statistical model updates will be used to support future monitoring program adjustments based on data analysis results and UNRBA's evolving needs for supporting the re-examination objectives.

The statistical models provide the expected daily mean nutrient concentrations as well as the width of the confidence intervals around the mean. This information can be used to adjust sampling frequency as needed. Sites with high nutrient loading have a larger influence on Falls Lake Nutrient Response model chlorophyll *a* predictions than sites with low nutrient loading and should be monitored more frequently.

Sites which are well-predicted by models (e.g. sites with narrow confidence intervals (CIs)) may not need to be sampled as frequently as sites with wide CIs. The UNRBA may want to consider sampling sites with narrow prediction intervals on a quarterly basis and then each year use the statistical model to test whether samples are significantly different from predictions. If so, the frequency of sampling can be adjusted accordingly. Sampling frequency in year-one need not dictate frequency in all subsequent years; as the amount of data increases and the models' predictive capacities are reassessed, UNRBA may be able to reduce sample frequency at many locations while increases in uncertainty at other locations may indicate increased sampling is justified.

3 Model Development

Two separate models were developed for use in simulating water quality and are described below.

Model 1 – Site Specific Model, is used for simulating water quality at sites for which historical data exist. The model simulations are informed by the historical data specific to the location of interest.

Model 2 – Spatial Model, is used for simulating water quality at sites for which historical data are not available. Simulations are informed by spatial relationships among locations and water quality.

Each model was developed for use in simulating the water quality parameters Total Nitrogen (TN), Total Phosphorus (TP), and Total Suspended Solids (TSS). Total Organic Carbon (TOC) was included in Model 1 only. The small number of samples available throughout the watershed limited the development of Model 2 for TOC. The first statistical model is a linear regression model of water quality parameters as a function of time, site and other predictor variables (e.g. precipitation and stream flow). The second statistical model replaces the explicit model term for site (which is in the first model) with a generic spatial latitude/longitude component. The result is that the first model is useful for predicting at sites where historical monitoring has occurred, and will generally do so more accurately than the second model, but the second model is more flexible in that it can predict water quality at locations with no historical monitoring data.

Both models were developed using historical data available in the Falls Lake watershed between 1999 and 2011. This data was compiled in a previous effort by Cardno ENTRIX to examine existing data in the watershed and further details can be found in Cardno ENTRIX Data Review TM November 2012. In all, 47 unique tributary locations had data available for TN, 55 locations for TP, 40 for TSS, and 13 locations had data available for TOC.

Both models were developed as tools for informing monitoring design and for understanding whether certain sites are better predicted relative to others. These are predictive models in the sense that they can provide predictions of water quality for a given set of covariate values; however, they were not developed specifically for this purpose. Refinements in model development including incorporating spatial variation in precipitation and temperature and more thoroughly exploring the set of potential covariates may increase the predictive power of these models and would be necessary steps before these models were used to provide daily estimates of water quality for lake response modeling. The models were developed with readily available covariates that are logically and scientifically related to water quality concentrations. The model selection process was rigorous but not exhaustive and the results presented here should be interpreted not as the best these models can do, but rather as their minimum performance. Refinements may make them better, but they will always be able to perform as well as presented here.

3.1 Model 1: For Prediction at Locations with Historical Data

Model 1 predicts water quality parameters using available information such as precipitation and time of year. Specifically, Model 1 is a general linear regression model relating the natural logarithm (ln) of each water quality parameter to a set of predictor variables as follows:

$$\ln\left(\mathrm{WQ}_{\mathrm{lymn}}\right) = \mu + \gamma_{\mathrm{l}} + \tau_{\mathrm{y}} + \delta_{\mathrm{m}} + \mathrm{x}_{\mathrm{lymn}}\beta + \varepsilon_{\mathrm{lymn}}$$

where $\mathrm{WQ}_{\mathrm{lymn}}$ is the n^{th} water quality measurement at site l, in year y and month m. In the model, μ is the intercept, γ_{l} is the effect for location l, τ_{y} is the effect of year y, δ_{m} is the effect of month m, and $\mathrm{x}_{\mathrm{lymn}}$ is the vector of covariates for observation $\mathrm{WQ}_{\mathrm{lymn}}$. Additionally, β is the vector of regression parameters relating the predictor variables to the water quality measurements and ε_{lymn} is the error term which includes sources of variation not captured by the model's predictor variables. Error terms were verified to be independent and identically-distributed normal random variables. This model was fit separately for each of four water quality parameters TN-N, TP-P, TOC and TSS and can also be applied to any other water quality parameters for which data exist. For purposes of monitoring design, a single global model was created for each of the four parameters and was fit to data from all locations jointly. Each location with historical data has its own value of the location parameter, γ_l, allowing predictions to vary by location. Because the model includes an explicit term for location, the model is only able to predict water quality at historically monitored locations. However, future monitoring at previously unmonitored locations would enable this model to be applied to those new sites for analysis or prediction. The year and month terms, τ_y and δ_m, respectively, account for differences from one year to the next as well as seasonal patterns within years. The covariates x_{lymn} and their associated regression parameters β allow the model to account for environmental or other physical variables that may explain variation in water quality. The predictor variables included in each water quality model are presented in Table 3-1.

Table 3-1 List of Model 1 Covariates included in each Water Quality Model

The symbol * denotes an interaction term between two predictor variables.

TN	TP	TSS	TOC
Precipitation	Precipitation	Precipitation	Precipitation
Precipitation*Catchment Area	Precipitation*Catchment Area	Precipitation*Catchment Area	Precipitation*Catchment Area
ln(Flow)	ln(Flow)	ln(Flow)	ln(Flow)
$[\ln(\text{Flow})]^2$	$[\ln(\text{Flow})]^2$	$[\ln(\text{Flow})]^2$	$[\ln(\text{Flow})]^2$
Maximum Daily Temperature	Maximum Daily Temperature	Maximum Daily Temperature	
Precipitation on Day Prior	Precipitation on Day Prior	Precipitation on Day Prior	
Precipitation Two Days Prior	Precipitation Two Days Prior	Precipitation Two Days Prior	

Due to the availability of many fewer existing TOC measurements compared to the other water quality parameters, the TOC model is simpler than the other models and does not contain a year effect τ_y. which contributed minimally to the fit of the TOC model.

Regarding the predictor variables, both daily precipitation and maximum daily temperature were obtained from a single location in the basin to cover the period of 1999-2011 and were applied to all sites in the entire basin. More spatially-explicit versions of these predictor variables could be considered for future model versions.

Similarly, five unregulated flow gages in the basin provide the flow information used for all sites. For each site, the most representative flow gage was selected based on professional judgment considering both proximity to the gaged location and similarities in land use within the watersheds. The flows measured at the gage itself were then prorated based on drainage area to convert flow at the flow gage to predicted flow at the site of interest.

Standard model-checks were conducted to ensure there were no problematic violations of model assumptions. It was noted that some locations had more variable water quality measurements than others. In particular, locations downstream of wastewater treatment plants often had highly variable water quality measurements. Future model versions could account for this behavior explicitly and uncertainty measures adjusted accordingly. However for planning the monitoring design, model fits assumed constant variability at all locations.

Model 1 was developed to meet multiple objectives related to monitoring design and planning, and thus Model 1 may later be enhanced or improved for very specific purposes. Future versions, for example based on additional or refined environmental predictors, may predict water quality parameters better than the current version. Then these predictions could be used in lieu of physical monitoring. As another example, Model 1 may be extended to test for trends through time in a water quality parameter at a particular site of interest.

3.2 Model 2: For Prediction at Locations without Historical Data

Because not all sites under consideration for future monitoring have been monitored previously, a second model was fit to aid in prioritizing these sites. These potential monitoring sites include approximately 21 jurisdictional boundaries and 12 ungaged Falls Lake tributaries where we want to understand water quality and nutrient loading. Model 2 differs from Model 1 in that there are no explicit location terms in Model 2. Instead, Model 2 is spatial in that the latitude and longitude of each water quality observation is entered into the model and general spatial patterns and trends are considered by the model. Model 2 is a geospatial statistical model. The form of Model 2 for a given water quality parameter is as follows:

$$\ln\left(\mathrm{WQ_{ymn}}\right) = \mathrm{f}(\mathrm{lat_{ymn}}, \mathrm{long_{ymn}}) + \tau_{\mathrm{y}} + \delta_{\mathrm{m}} + \mathrm{x_{ymn}}\beta + \varepsilon_{\mathrm{ymn}}$$

where $WQ_{ymn}$is the n^{th} water quality measurement in year y and month m. The spatially-referenced water quality measurement is taken at latitude/longitude $lat_{ymn}, long_{ymn}$ and the year and month effects are the same as in Model 1. The set of explanatory variables $\boldsymbol{x}_{ymn}$ includes additional information relative to Model 1, namely land-use and other physical characteristics of a monitoring location. Note Model 2 was not fit for TOC due to the limited spatial coverage of historical monitoring for this parameter.

In Model 2, the function $f(lat_{ymn}, long_{ymn})$ is a smoothly varying spline function of locations. Such a model is useful for modeling spatial trends and patterns and ultimately borrowing information from nearby locations when predicting at a new location. Model 2 is a type of geospatial model called a generalized additive model (Wood 2006). Generalized additive models (GAMs) have become common modeling tools in environmental applications, including water quality assessments (e.g. Richards et al. 2010; Trossman et al. 2011). A GAM has the flexibility to incorporate predictor variables in a similar way to standard linear regression models while also incorporating the spatial patterns which often exist in observational environmental data. In addition to water quality predictions, Model 2 provides associated uncertainty measures in the form of prediction intervals for WQ parameters of interest.

Various potential predictor variables were considered for each model with a combination of subject-knowledge and the model selection tool Akaike's Information Criterion (AIC – Akaike 1974, Burnham and Anderson 2002). For example, including predictor variables in Model 2 that are not available in new locations would limit the model's ability to predict in those new locations. The predictor variables included in the TN, TP and TSS models are presented in Table 3-2. A number of additional covariates were evaluated for inclusion in Model 2, but if they did not improve model fit, they were not included in the final model. Table 3-2 includes some of the additional covariates that were evaluated and found not to improve model fit.

Table 3-2 List of Model 2 Covariates included in each Water Quality Model

The symbol * denotes an interaction term between two predictor variables.

Model 2 Covariates used for each Water Quality Parameter: TN, TP, and TSS	Model 2 Covariates considered, but which did not improve model predictions
Precipitation	Elevation of location where sample was taken
Precipitation*Catchment Area	Percent of land that is agricultural in a location's catchment
ln(Flow)	Percent of land that is developed in a location's catchment
[ln(Flow)]2	Geology: percent of a location's catchment that is Carolina Slate Belt
Terrain slope index 1	Geology: percent of a location's catchment that is Raleigh Belt
Terrain slope index 2	Geology: percent of a location's catchment that is Triassic Basin
Elevation index 1	Geology: percent of a location's catchment that is Coastal Plain
Elevation index 2	Maximum temp for the day of the observation
Percent impervious surface in 2006	Minimum temp for the day of the observation
Percent wetlands in 2006	Natural logarithm of flow
5-year peak flow level	Precipitation one day prior
Percent forest in 2006	Precipitation two days prior

Finally, continuous predictor variables were centered and scaled (by their means and standard deviations, respectively) in order to improve computation during model fitting. All models were fit in the R programming language for statistical computing (R Core Team 2013). Generalized Additive Models were fit using the R Package mgcv (Wood 2006).

4 Model Application and Results

Both models described in section 3 were applied to yield information relevant to designing the UNRBA monitoring program. This section describes the application of these models which includes summaries of model performance (e.g. fit statistics) and appropriate model output useful for decision-making. The two general models are used to compare locations that will be monitored in order to prioritize the locations based on:

1. Magnitude of WQ parameters (e.g. identifying sites with high nutrient concentrations)
2. Ability to predict WQ parameters using the statistical models described above
3. Amount of existing information useful for prediction in future years (previous monitoring effort)

4.1 Model Fits and Diagnostics

Final model specification resulted from exploratory data analysis as well as discussion with water quality experts. For measurements to be included in the model fits, all covariates used by the model must have been available on the same day as the measurements.

4.1.1 Model 1

Model 1 was applied to four WQ parameters: TN, TP, TSS and TOC. Table 4-1 summarizes key fit statistics for each WQ parameter model, including the R^2 (coefficient of determination) and sample size involved in the fit. Models for all parameters were highly significant ($p << 0.0001$). Visual model checks were performed to identify lack of model fit issues. Figures 4-1 through 4-4 demonstrate plots of the Model 1-based WQ predictions against the actual measurements. Points near the red line represent measurements that are well-predicted by Model 1.

Table 4-1 R-squared Values, Sample Sizes, and Root Mean Square Error (RMSE) for the Linear Models (Model 1) fit for each WQ Parameter

The RMSE is provided in log-units, which are the units of the model.

Parameter	R-squared value	Sample Size	RMSE
TN	0.67	1886	0.17
TP	0.51	2229	0.39
TSS	0.55	1081	0.55
TOC	0.73	162	0.072

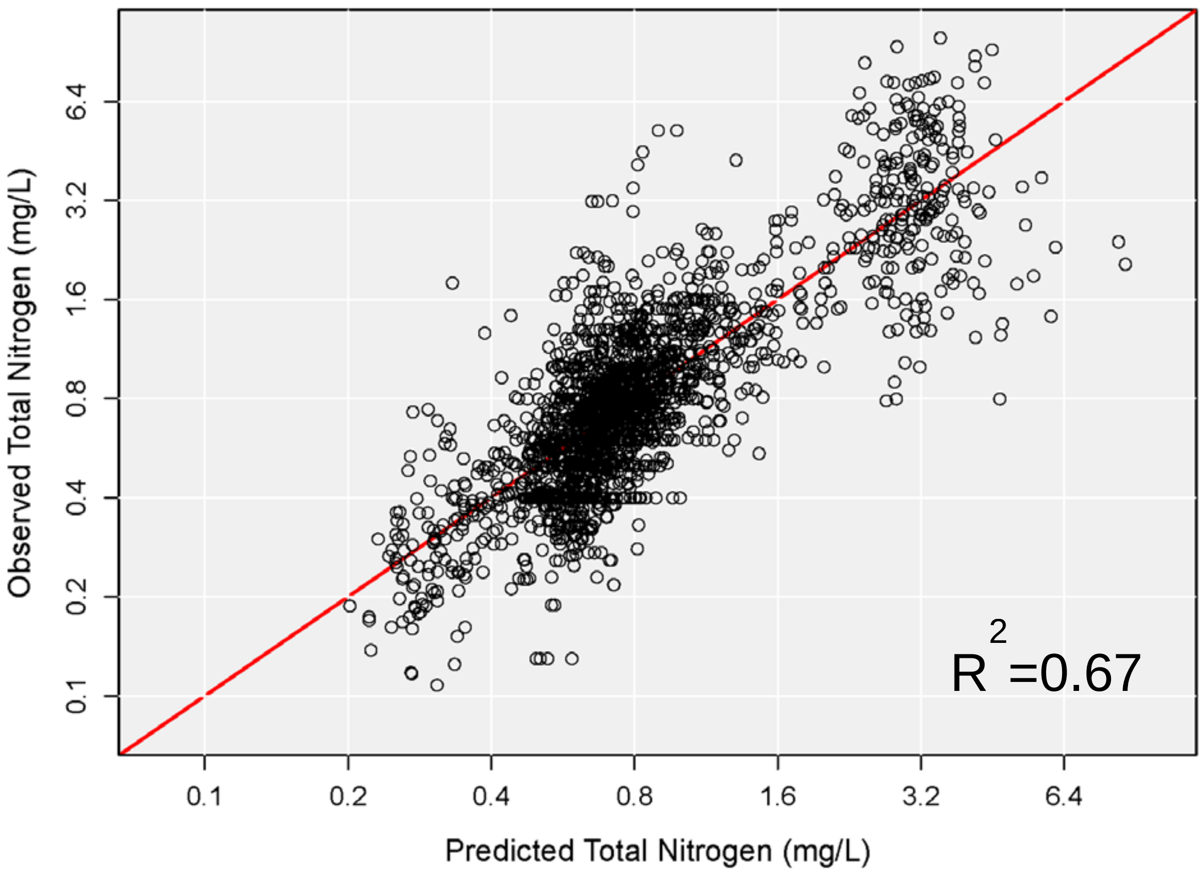

Figure 4-1 Observed Compared to Predicted Total Nitrogen Concentrations from Model 1

Axes are on the log scale and the red line is the 1:1 line.

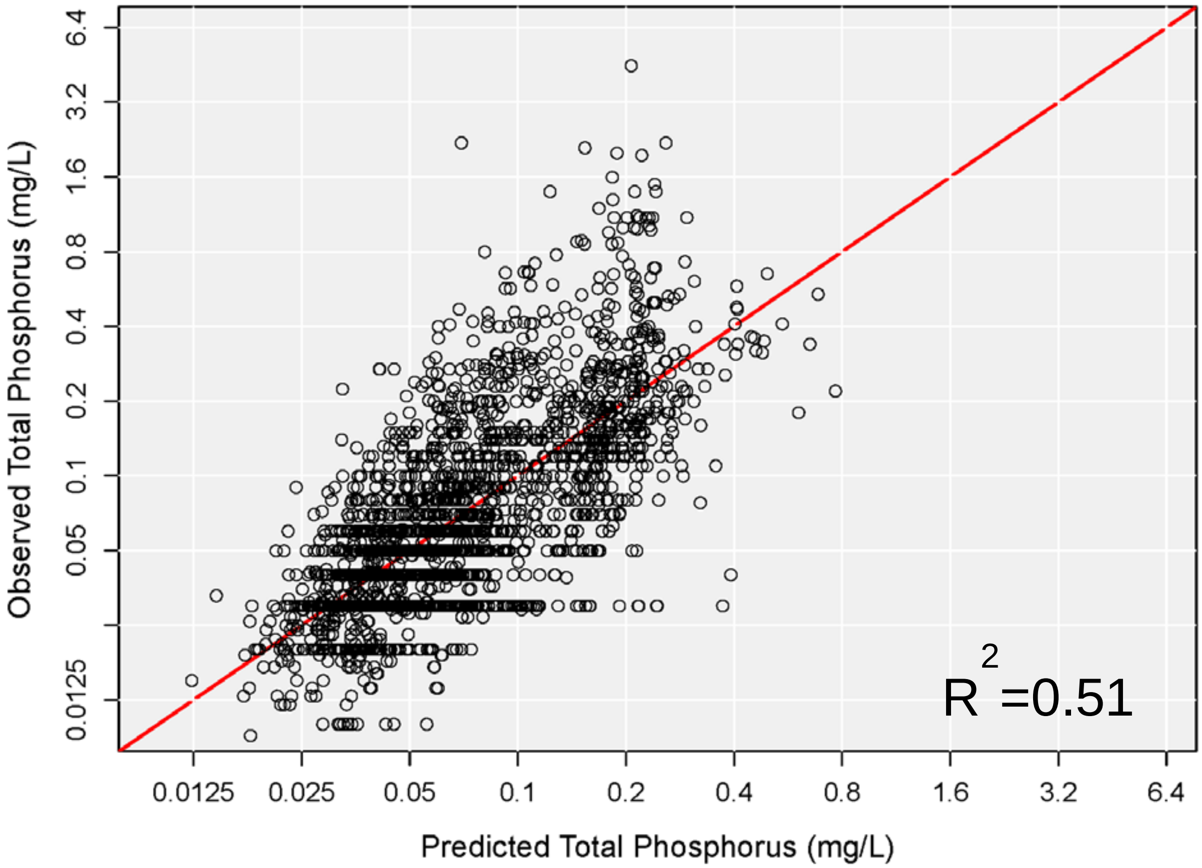

Figure 4-2 Observed Compared to Predicted Total Phosphorus Concentrations from Model 1

Axes are on the log scale; the red line is the 1:1 line where predictions are the same as observed values. (The banding in observed values are artifacts of laboratory reporting methods, significant figures, and different laboratory reporting limits.)

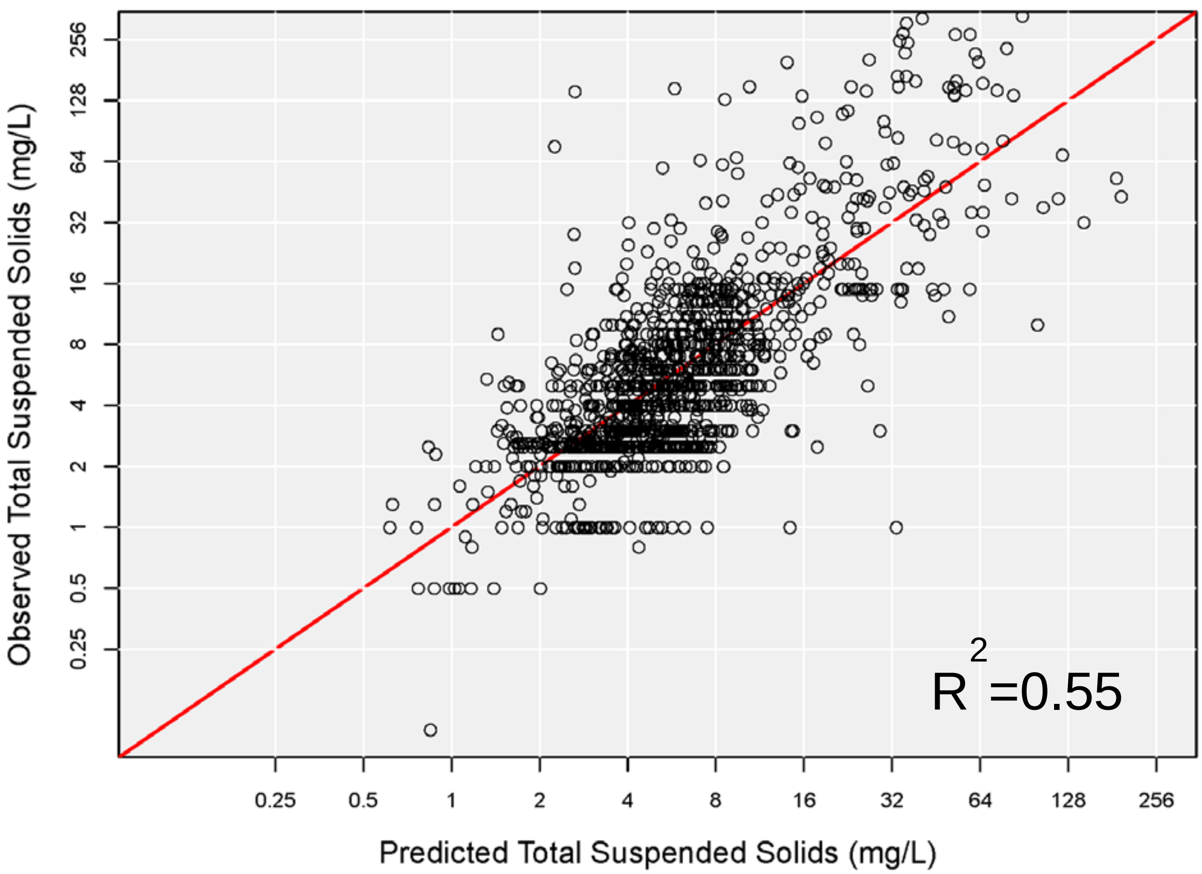

Figure 4-3 Observed Compared to Predicted Total Suspended Solids Concentrations from Model 1

The axes are on the log scale and the red line represents the 1:1 line.

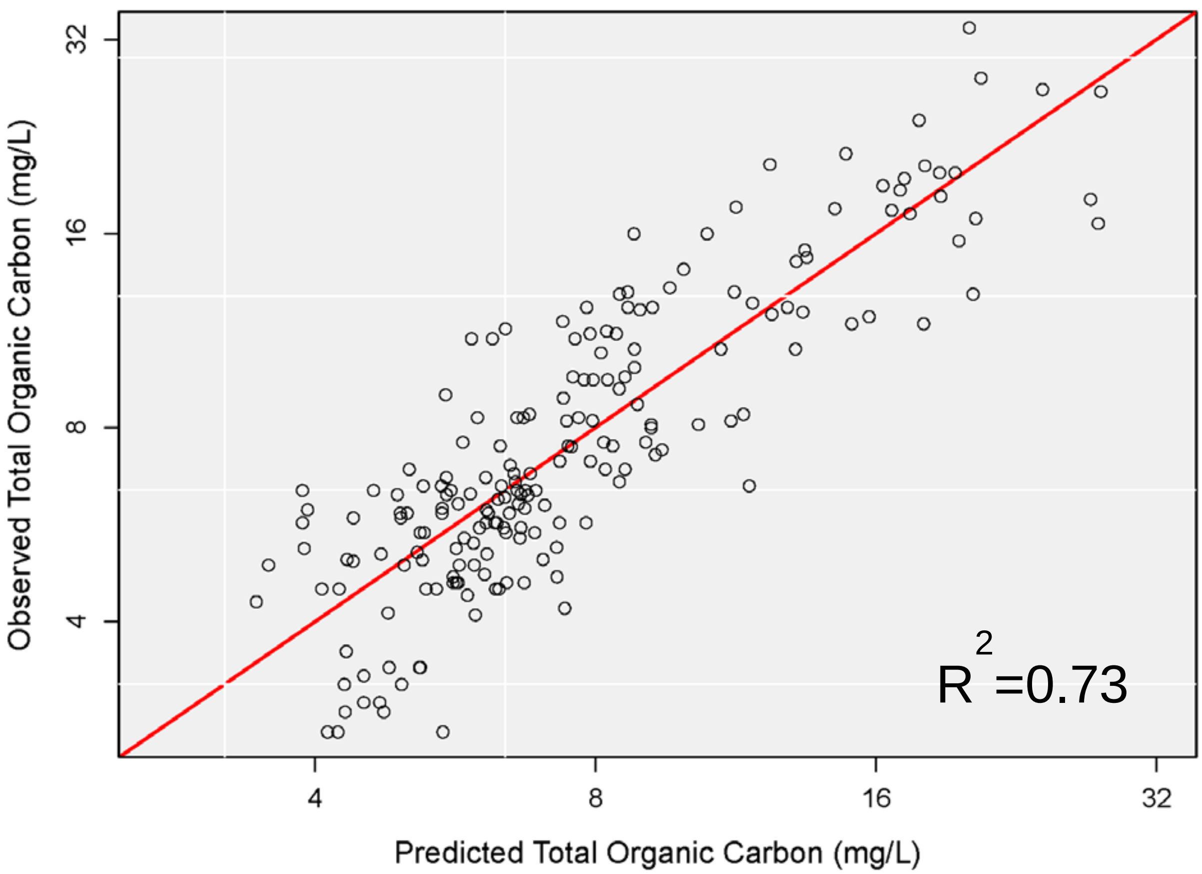

Figure 4-4 Observed Compared to Predicted Total Organic Carbon Concentrations from Model 1

Axes are on the log scale and the red line is the 1:1 line.

4.1.2 Model 2

Specification (development) of Model 2 relied on knowledge gained during exploratory analysis as well as from specification of Model 1. Model 2 is an alternative to Model 1 that allows for prediction of WQ values at locations that have no historical monitoring. As described above, Model 2 accomplishes this through the identification of spatial relationships over the watershed instead of identifying and estimating location-specific behavior as is the case with Model 1.

Because Model 2 does not explicitly include terms for location, Model 2 is not expected to fit the historical data set as well as Model 1, but Model 2 has the flexibility to predict at new locations with no historical monitoring. Indeed Model 2 exhibited slight decreases in R^2 relative to Model 1, as shown in Table 4-2. These reductions are not large, however, suggesting that the covariates added to the model in place of specific location parameters (e.g. forest, wetland, and impervious surface cover along with measures of watershed slope and elevation) are useful surrogates. Model 2 was not fit to the parameter TOC due to the small number of unique locations where TOC measurements were available.

Table 4-2 R-squared Values, Sample Sizes, and Root Mean Square Error (RMSE) for the Spatial Model (Model 2) fit for the WQ Parameters TN, TP, and TSS

RMSE is provided in the model units of ln(TN), ln(TP), and ln(TSS).

Parameter	R-squared value	Sample Size	RMSE
TN	0.64	1982	0.19
TP	0.47	2338	0.43
TSS	0.54	1145	0.54

Similar to Model 1, Model 2 suggests no systematic model problems based on evaluation of plots of the fitted versus observed WQ measurements (Figures 4-5-4-7).

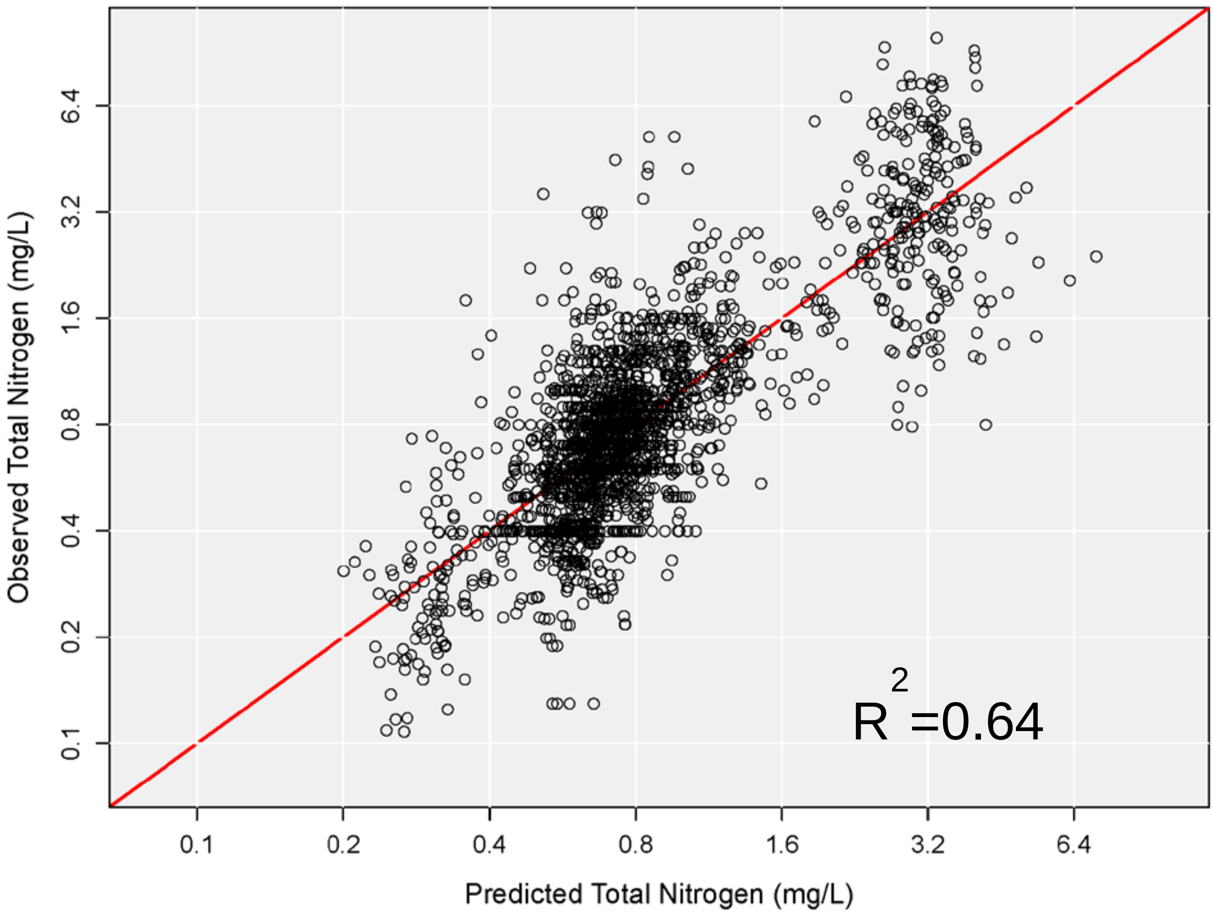

Figure 4-5 **Observed Compared to Predicted Total Nitrogen Concentrations from Model 2**

Axes are on the log scale and the red line represents the 1:1 line.

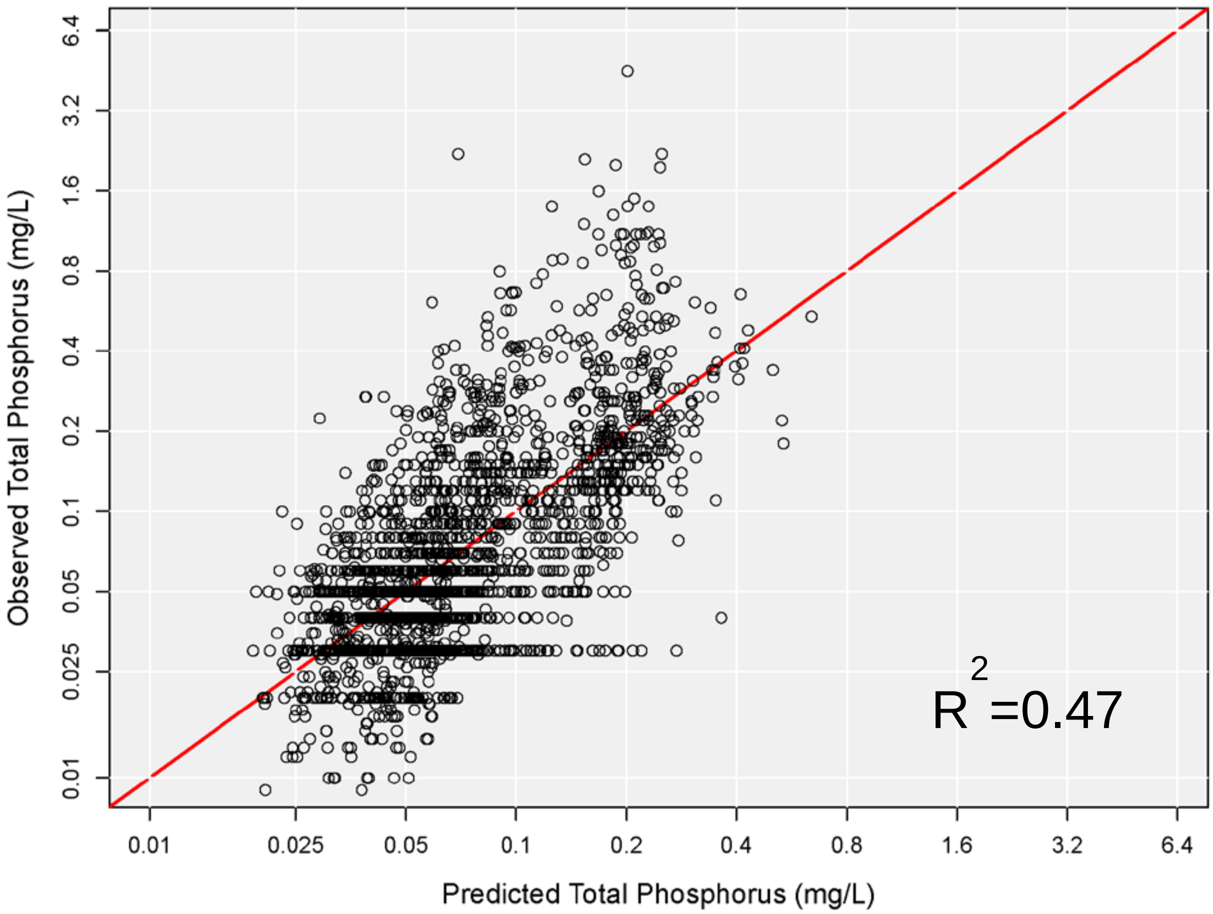

Figure 4-6 Observed Compared to Predicted Total Phosphorus Concentrations from Model 2

Axes are on the log scale and the red line represents the 1:1 line.

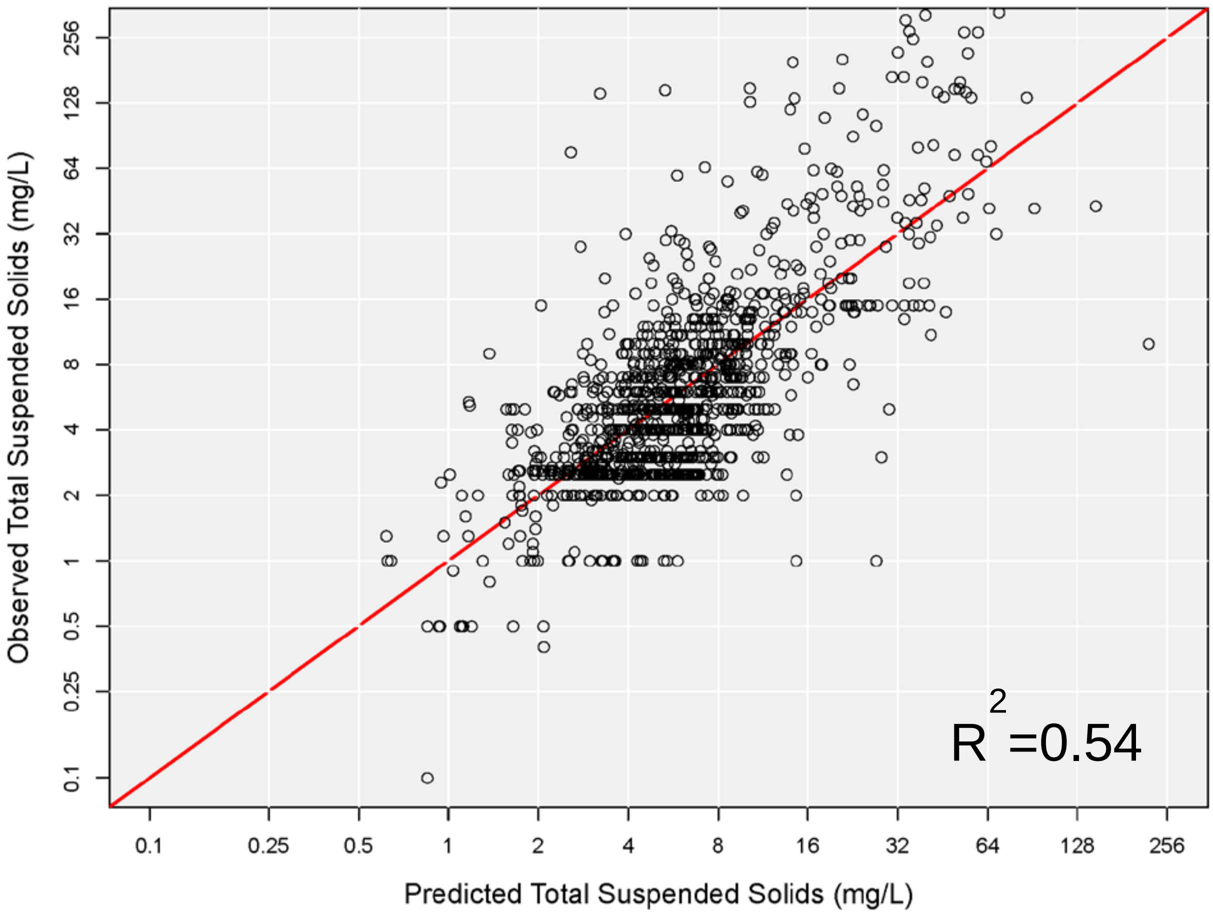

Figure 4-7 Observed Compared to Predicted Total Suspended Solids Concentrations from Model 2

Axes are on the log scale and the red line represents the 1:1 line.

4.2 Model 1 and Model 2 Limitations

Both Model 1 and Model 2 are subject to certain limitations which are described in this section. First, model predictions are not as accurate downstream of large wastewater treatment plants compared to most other locations. This behavior is not unexpected: the impact of waste water treatment plants or large reservoirs on downstream WQ is not accounted for by any of the predictor variables in either model. Such locations were identified visually during model diagnostics. Generally these locations had WQ measurements that were highly variable around the model's corresponding predictions.

Model 1 and Model 2 each account for changes in overall watershed behavior by year, after accounting for other environmental drivers such as precipitation. If particular locations behave differently than general trends, WQ at these locations may be poorly predicted by the models. However, the models can be used to identify such locations as well as investigate them further (e.g. by testing for changes in WQ at a location).

In addition to the unpredictability caused by wastewater treatment plants, locations may be difficult to predict due to other discharges or rapid changes in land-use, causing a location to behave differently than its history would suggest. These changes may be ultimately accounted for by further refinement of the models.

5 Determination of Monitoring Frequency for Existing and Proposed Monitoring Locations

Both Model 1 and Model 2 are useful for predicting WQ as well as indicating the amount of uncertainty associated with those predictions. This section presents examples of relevant output from the two models for consideration when making decisions regarding the UNRBA monitoring design. This section provides the background for the creation of these model-based outputs. Because of the small number of tributary locations with available TOC data, only model output for TN, TP, and TSS will be examined for categorizing monitoring locations with respect to monitoring frequency. After one or two years of collecting TOC data in the watershed, the models could be revisited to assess predictability of TOC and the relationship between sample size and relative error of the mean.

1. Relevant information used to identify potential monitoring locations and determine the appropriate monitoring frequency includes the magnitude of estimated WQ concentrations and loads (e.g. identifying locations with high expected nutrient contributions to Falls Lake).
2. Amount of uncertainty in WQ estimates due to lack of historical information (identifying locations with large confidence intervals for model-estimated nutrient concentrations and therefore potentially large, but uncertain, contributions of nutrients or TSS to downstream waters).

Uncertainty associated with linear model output can be provided as confidence intervals. Confidence intervals describe the ability of the researcher to identify the *expected* nutrient concentration, that is, the ability of the researcher to identify the center of a distribution. An important point is that as more and more data are obtained, the ability of the model to identify the expected concentration improves until it is nearly known perfectly. However, because that expected concentration is simply the center of a distribution, any individual observation of WQ will still vary around this expected value.

Therefore, when designing the monitoring program, it may be informative to consider confidence interval size to describe the amount of historical data available at a location. Sites generally have smaller confidence intervals on their mean estimates when there is lots of data, whereas larger confidence intervals are generally reflective of smaller sample sizes. Confidence intervals on the mean do not account for variation in the actual water quality measurements that occur on a day–to-day or even hour-to-hour basis.

5.1 Sample Size and Relative Error

As discussed, increased sample sizes at a given location lead to improved predictions as measured by smaller confidence intervals. To examine this concept further, one may consider the relative error rates that are expected given different sample sizes. Relative error is calculated as a percent of the mean as follows:

Percent relative error = $\frac{Upper\ predicted\ WQ - average\ WQ}{average\ WQ} \times 100\%$

and is obtained from the confidence intervals (upper bound minus midpoint divided by midpoint). For example, if average WQ is 10 and for a given sample size we expect a 90% confidence interval to range from a low of 5 to a high of 15, then the expected relative error rate (for 90% confidence) is:

$$\left(\frac{15-10}{10}\right) \times 100\% = 50\%\ error$$

Model 1 was used to explore the relationship between sample size and the resulting relative error around the estimate of the mean predictions for TN, TP, and TSS for a 90% confidence interval. The sample size requirements which are expected to yield specified error rates are presented in Table 5-1 (based on 90% Confidence Intervals). These sample sizes represent total sample sizes used in the model and could cover multiple years; for example, a sample size of 60 could be obtained through monthly sampling for five years or weekly sampling for a little more than one year.

Table 5-1 Relative Error Rates for 90% Confidence Interval for Total Nitrogen, Total Phosphorus and Total Suspended Solids

Entries denote the number of samples expected to yield the given error rates.

Relative Error Around the Estimate of the Mean					
	10%	20%	30%	40%	50%
TN	99	27	13	8	6
TP	218	60	29	18	13
TSS	>260	105	51	31	22

5.2 Using Model Output in Determination of Sampling Frequency at Lake Loading Sites and Jurisdictional Boundaries

Establishing the sampling frequency for a monitoring plan requires balancing costs with desired confidence in the characterization of the daily load at each monitoring location. The most confidence comes with collection of instantaneous measurements which unfortunately is not technologically possible for most parameters of interest. Daily sampling is possible and would provide a great deal of confidence in daily water quality concentrations, but the associated cost is in the millions of dollars per year. Given the realities of budget constraints, judgments must be made regarding the acceptable error for model estimates for each location and water quality parameter. Logistically, the easiest monitoring plan is to pick a single sampling frequency which meets the minimum acceptable error threshold and apply that across all locations. However, improvements can be made by applying those same monitoring dollars to monitoring locations differentially. For instance, it is important to have a higher confidence (lower relative error) in predictions for the tributaries contributing the largest proportion of nutrients to Falls Lake while a higher relative error rate (and thus fewer samples) may be acceptable for tributaries which contribute less than a percent or two of the total load.

Historical data provides a foundation for model building and also influences the number of future samples necessary to achieve a desired level of confidence in model predictions. If a location of interest already has the required number of samples to meet the desired relative error of model predictions (Table 5-1), then future sampling could occur at a reduced rate with samples collected only 4-6 times per year in order to verify model performance.

Monitoring frequency is also affected by project goals and needs. For example, information on loading to Falls Lake is required at a daily time step for the EFDC lake model, while jurisdictional loads are calculated as annual averages. Because of these differing goals, these two categories of sites are treated as separate groups to simplify the design of the monitoring plan. Below we discuss how model predictions and confidence intervals can be used to select appropriate monitoring frequencies specific to a given location. Further details on the selection of monitoring locations and proposed monitoring frequency for each are provided in Section 6. The locations presented below to illustrate the methods include more sites than will likely be monitored; some jurisdictional loading locations may not be publicly accessible (Camp Creek at Camp Butner, for example) and in some cases multiple lake loading locations on a single tributary have been included for comparison.

The first step in designing a differential-frequency monitoring plan is to examine the predicted loads and associated uncertainty for each potential monitoring location with the assumption that it might be useful to sample sites with the largest loads frequently in order to reduce the relative error at sites with the largest influence on lake loading. The models presented in this TM provide predictions of water quality concentrations (TN, TP, and TSS) and associated uncertainty. To obtain loads, these concentrations need to be multiplied by expected flow at each tributary. Cardno ENTRIX has previously prepared a Technical Memo on estimating flow at ungaged locations (Cardno ENTRIX Flow Estimation TM March 2014). Here, we use the basin proration technique described in that memo to obtain the 10-year average daily flow at each location (for jurisdictional boundary sites) or 10-year average daily flow to Falls Lake from each tributary (for lake-loading sites). These long-term averages provide a robust comparison of flow among sites which is not unduly influenced by particularly wet or dry years. Specifically, the flow was estimated for each location based on the 10-year USGS flow record from 2004 through 2013.

For monitoring locations with USGS gages installed, the mean flow from the daily record over this period was obtained and applied to the monitoring location. For locations which are partially gaged (e.g. there is a gage upstream of the sampling location), the average flow from the gage was applied to the drainage area represented by the gage. If the gage was unregulated, the same flow (relative to drainage area) was applied to the ungaged drainage area to obtain the total estimated flow for the location. If the gage was regulated, but the flow downstream was not (e.g. the gage is at a dam release or WWTP outfall but the monitoring site is further downstream), the gaged data was applied to the drainage area represented by the gage, but the remaining drainage area contributing to the monitoring location was assigned the mean annual flow (normalized to drainage area) for all unregulated gages in the Falls Lake basin over the 10-year period. This value is 0.60 cfs/mi^2 (± 0.043 SD). The 10-year daily average flow at all potential monitoring locations without upstream gages was estimated using 0.60 cfs per square mile of drainage area. The flow estimates are presented in Tables 5-4 through 5-6 (for lake loading Sites) and 5-8 through 5-10 (for jurisdictional boundary sites). For the lake loading tributaries with more than one potential monitoring location under consideration, the flow was estimated at the most downstream location on the tributary.

Model predictions of WQ were made using models 1 and 2 (as appropriate, based on available data at a proposed monitoring location) for an average day in July 2008. In order to compare model predictions across the two models, predictions need to be made for the same time period, however the choice of date is arbitrary and unimportant. The ranking of sites is unaffected by date selection. July 2008 was selected based on a cursory examination of the historical data as a typical (non-extreme) time period. Predicted water quality concentrations and associated confidence intervals are shown in figures 5-1 through 5-6 and tables 5-4 through 5-6 (for lake loading Sites) and 5-8 through 5-10 (for jurisdictional boundary sites). The confidence intervals are expressed as relative error in the tables (see section 5.1 for details).

A load index was calculated as the product of the estimated flow (cfs) and expected concentration (mg/L) for each site with all applicable unit conversions to obtain load in lbs/day. Because the flow estimates and water quality estimates cover different periods of time, the calculation of load presented in tables 5-4 through 5-10 is an *index* of load rather than a specific prediction or average for any period of time. While the order of magnitude on the relative load index is typical, the load index should be interpreted neither as the actual or predicted load for any particular date, nor as the average load for any particular year or period of years; rather, it simply provides a relative ranking of load predictions.

The upper confidence limit for the load index was calculated as above, but using the expected load plus the relative error of the mean. For example the upper CI on the load index for a site with an expected load of 100 lbs/day and a relative error of 40% would be 140 lbs/day.

To account for this site-specific uncertainty in model predictions, the proposed monitoring locations were then ranked according to the high estimate of their expected load as a proportion of the total expected load to Falls Lake. This proportional load index was calculated for each site as follows: For each of the lake loading monitoring sites, a total load was calculated as the sum of the upper confidence limit on the load at the site of interest plus the mean expected loads from the most downstream stations on each of the remaining 17 tributaries. The upper confidence limit on the loading at each tributary was then divided by this estimated total load to provide an upper estimate of the potential contribution of each tributary to the total lake load. Thus,

$$\text{Proportion of total load from tributary i } = \frac{Load_{UCI,i}}{Load_{UCI,i} + \sum_{S/i} Load}$$

where, $Load_{UCI,i}$ is the upper confidence limit of the load for site *i*, and $\sum_{S/i} Load$ is the sum of the expected (mean) load over all 18 loading sites (S) excluding site i.

Sites with high expected loads, or moderate expected loads coupled with high uncertainty, are thus ranked higher than sites with low expected loads. As with the load index, this proportional load calculation is also an index—it should not be interpreted as a specific prediction of the contribution from each tributary but rather as a relative index of the uppermost likely value based on preliminary model output. Because error in water quality predictions is compounded by flow, two sites with similar nutrient concentrations and confidence intervals could have very different effects on Falls Lake water quality if their flows are substantially different. Reducing the uncertainty in estimates at a site with high flow will reduce uncertainty in the overall load much more than reducing uncertainty at a site with low flow. By combining WQ predictions, uncertainty, and flow estimates, this ranking is used to focus monitoring effort on the sites with largest impact on Falls Lake loads.

Sites were ranked individually for TN, TP, and TSS and were separated into groups of sites important for estimating tributary loading to Falls Lake and sites important for estimating jurisdictional loads. Tables 5-7 and 5-11 summarize the rankings across all three WQ parameters and are sorted according to the minimum ranking across all parameters. These tables provide a ranking of locations that identifies which locations may benefit from an increased sampling frequency relative to a baseline sampling frequency.

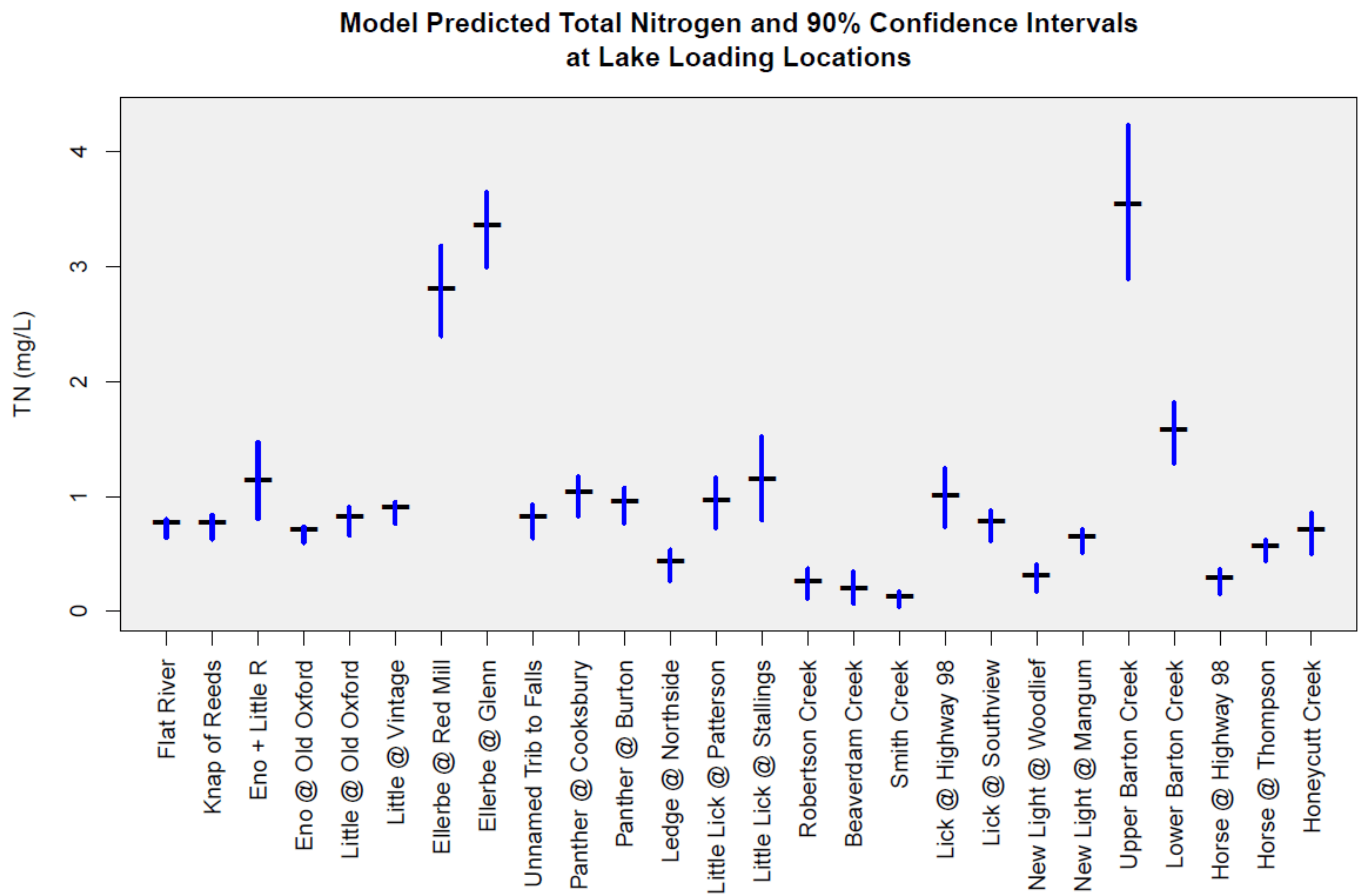

Figure 5-1 Estimated Daily Mean TN for July 2008 and 90% Confidence Intervals for Lake Loading locations

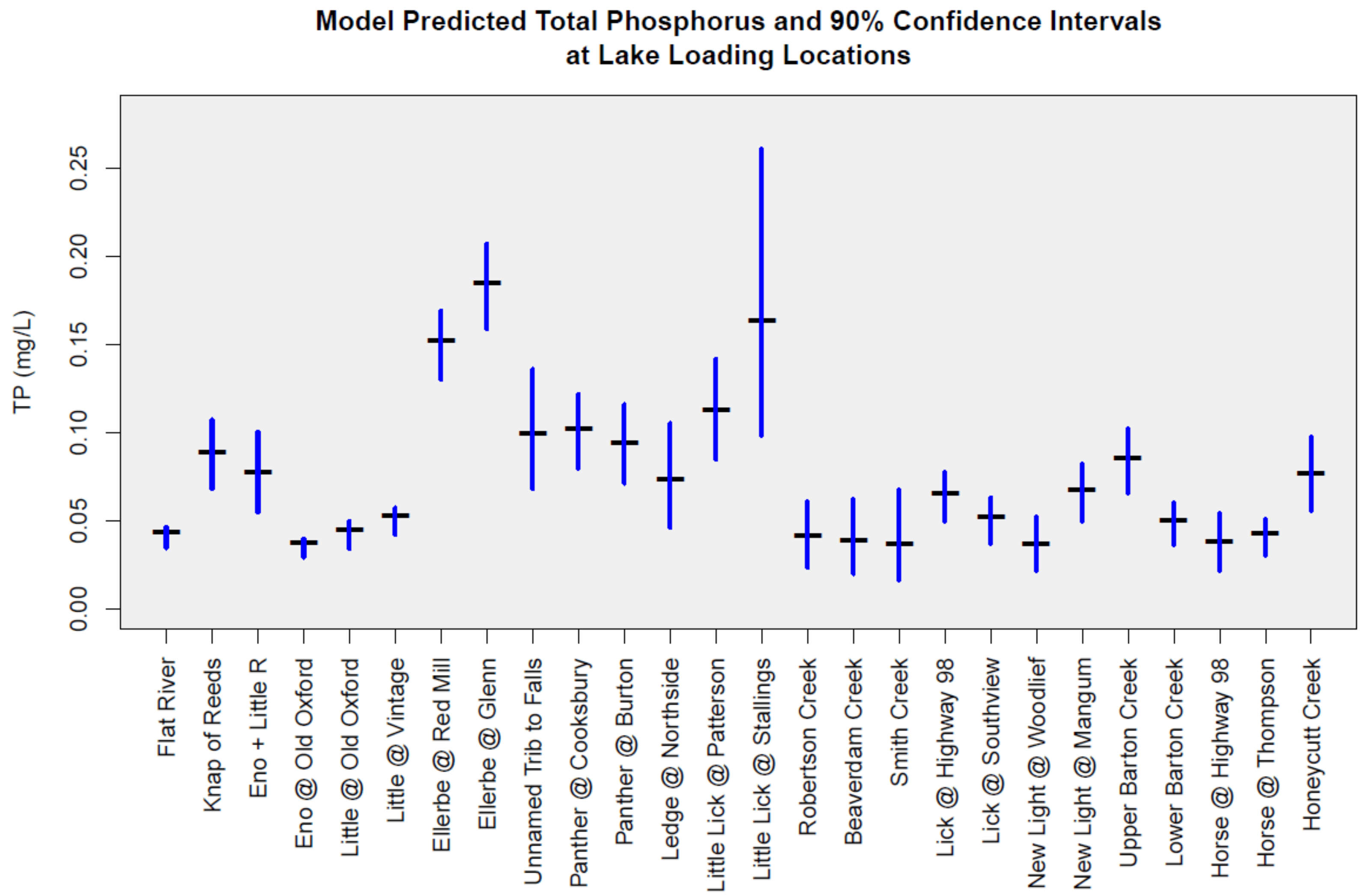

Figure 5-2 **Estimated Daily Mean TP for July 2008 and 90% Confidence Intervals for Lake Loading locations**

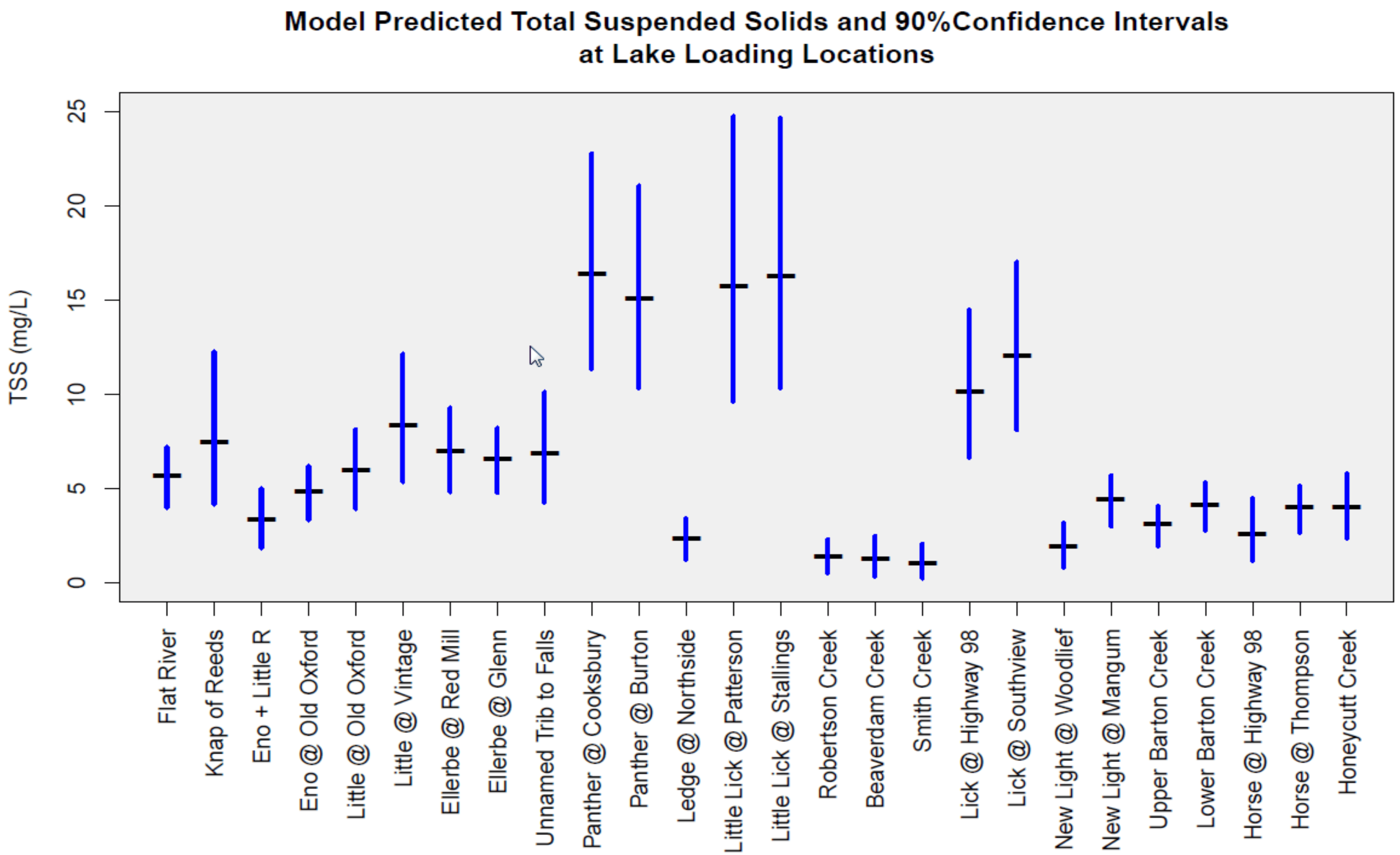

Figure 5-3 Estimated Daily Mean TSS for July 2008 and 90% Confidence Intervals for Lake Loading locations

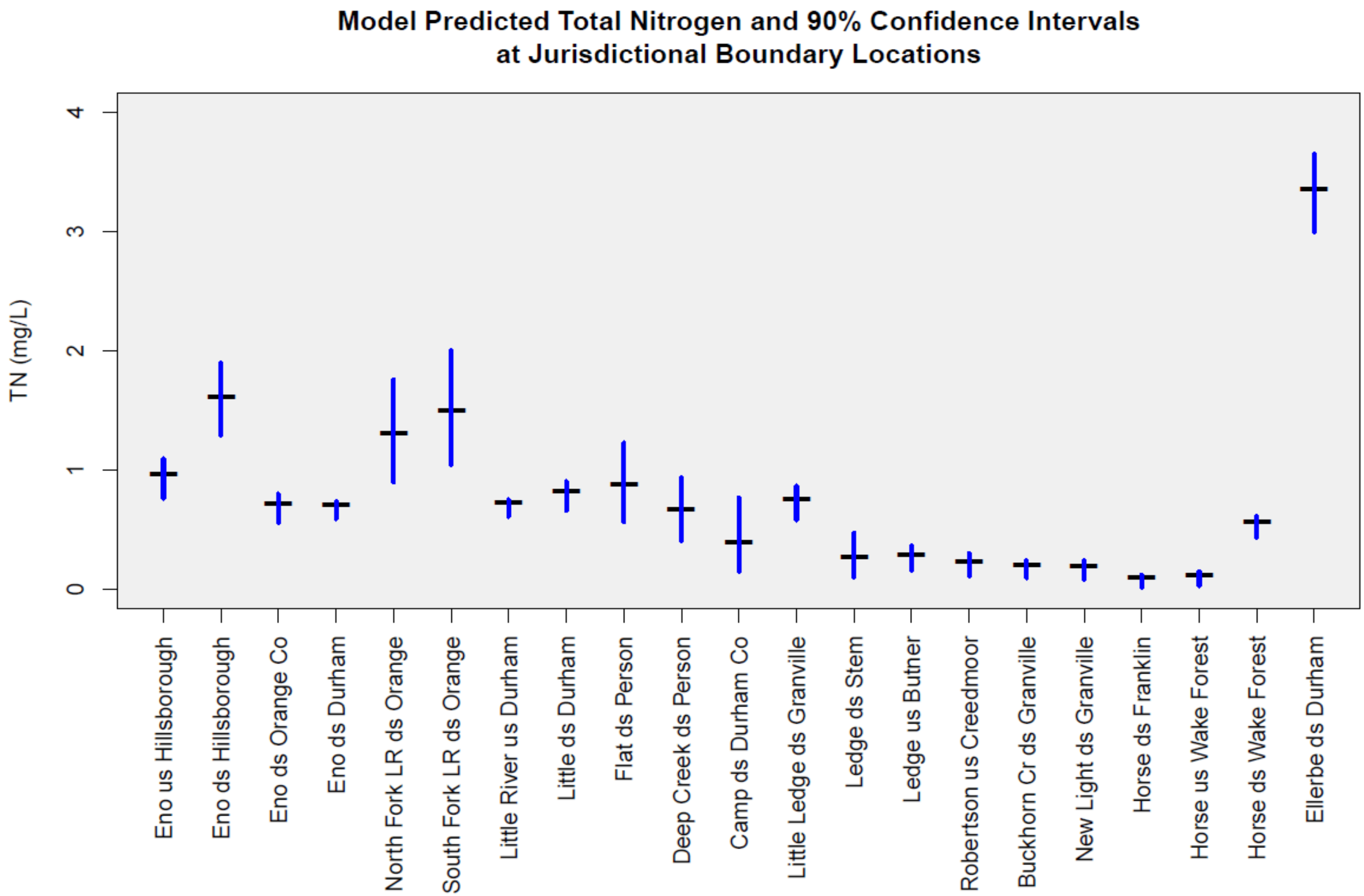

Figure 5-4 **Estimated Daily Mean TN for July 2008 and 90% Confidence Intervals for Jurisdictional Boundary locations**

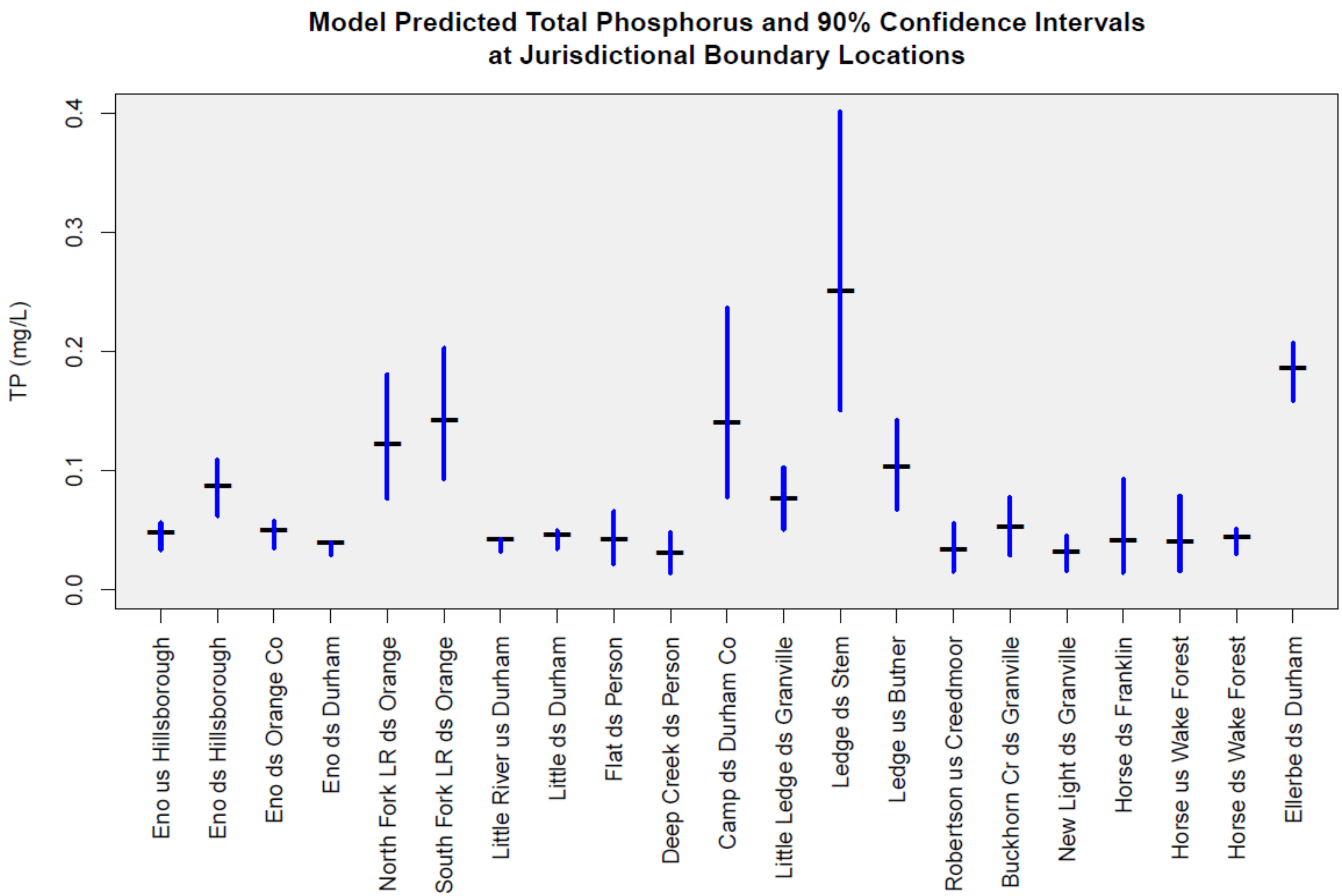

Figure 5-5 **Estimated Daily Mean TP for July 2008 and 90% Confidence Intervals for Jurisdictional Boundary locations**

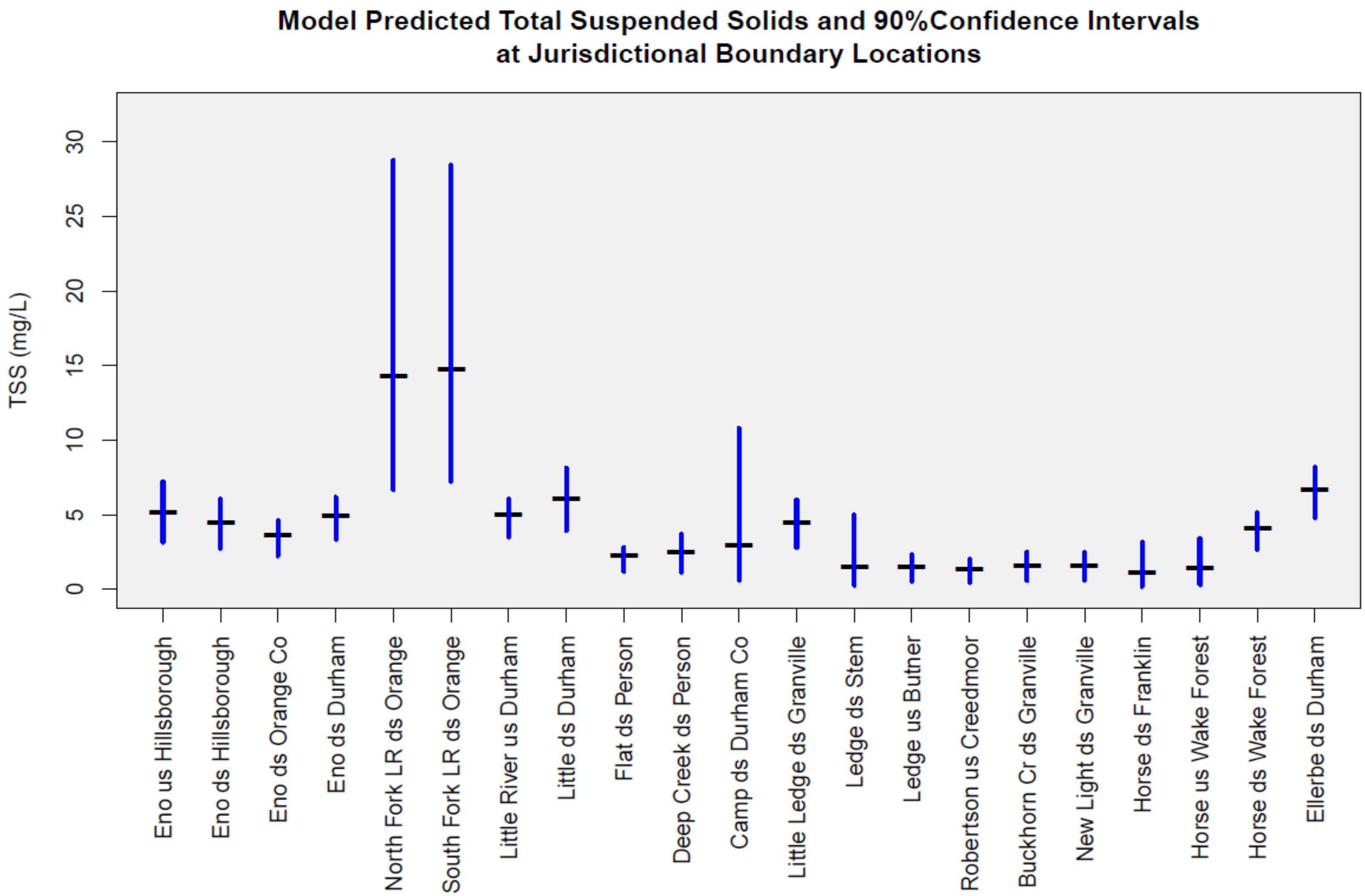

Figure 5-6 Estimated Daily Mean TSS for July 2008 and 90% Confidence Intervals for Jurisdictional Boundary locations

Table 5-4 Modeled TN Concentrations at Potential Lake Loading Monitoring Sites along with an Index of the Total Load to Falls Lake Coming from each Tributary

Cells highlighted in red indicate the highest 33% of sites and those in green the lowest 33%.

Tributary	Road Crossing	Tributary Flow[1] (mean daily, cfs)	Modeled TN Concentration[2] (mg/L)	Relative Error of Mean	Load Index[3] (lb/day)	Upper Confidence Limit of Load Index (lb/day)	Index of Proportional Load from Tributary	Rank, Proportional Load	Model	n
Flat River	at Old Oxford Hwy	96.8	0.72	13%	375	423	21%	4	1	99
Knap of Reeds Creek	off Brickhouse Road	25.5	0.72	16%	99.1	115	6%	8	2	
Eno River + Little River	at Red Mill Road	140	1.08	35%	816	1105	38%	2	2	
Eno River	at Old Oxford Hwy	92.8	0.67	12%	334	374	19%	5	1	113
Little River	at Old Oxford Hwy	43.7	0.77	17%	181	213	11%	7	2	
Little River	at Vintage Hill Pkwy	43.7	0.85	12%	201	225	11%	6	1	105
Ellerbe Creek	at Red Mill Road	41.0	2.74	15%	606	698	35%	3	2	
Ellerbe Creek	at Glenn Road	41.0	3.29	11%	727	806	38%	1	1	214
Unnamed Tributary to Falls	at Northside Road	2.06	0.76	21%	8.49	10.2	0.5%	25	2	
Panther Creek	at Cooksbury Drive	1.94	0.98	19%	10.2	12.2	0.6%	23	2	
Panther Creek	at Burton Road	1.94	0.90	19%	9.44	11.2	0.6%	24	1	28
Ledge Creek	at Northside Road	14.5	0.38	42%	29.4	41.6	2.1%	14	2	
Little Lick Creek	at Patterson Road	8.31	0.91	26%	40.8	51.7	2.7%	13	2	
Little Lick Creek	at Stallings Road	8.31	1.08	39%	48.3	67.3	3.4%	10	1	5
Robertson Creek	at Brassfield Road	8.87	0.20	81%	9.74	17.7	0.9%	19	2	
Beaverdam Creek	at Horseshoe Road	8.22	0.15	130%	6.66	15.3	0.8%	21	2	
Smith Creek	at Lawrence Road	6.36	0.08	116%	2.72	5.89	0.3%	26	2	
Lick Creek	at Hwy 98	8.17	0.95	30%	41.7	54.4	2.8%	12	2	
Lick Creek	at Southview Road	8.17	0.73	20%	32.3	38.9	2.0%	15	1	21
New Light Creek	at Woodlief Road	10.3	0.26	55%	14.4	22.3	1.2%	18	2	
New Light Creek	at Mangum Dairy Rd	10.3	0.60	18%	33.3	39.3	2.0%	16	1	23
Upper Barton Creek	at Mt Vernon Church	4.95	3.47	21%	92.7	112.1	5.8%	9	2	
Lower Barton Creek	at State Rd 1834	6.26	1.53	19%	51.5	61.4	3.2%	11	1	20
Horse Creek	at Hwy 98	8.87	0.24	54%	11.4	17.6	0.9%	20	2	
Horse Creek	at Thompson Mill Rd	8.87	0.52	19%	24.7	29.5	1.5%	17	1	20
Honeycutt Creek	at Honeycutt Road	2.94	0.65	30%	10.4	13.5	0.7%	22	2	

[1]Mean daily flow is the average daily flow for a tributary based on the 10-year average daily flow between 2004 and 2013. For tributaries that are gaged, the average flow for the most downstream gage was applied to the relevant watershed area. If flow at the most downstream gage is regulated, the remainder of the ungaged watershed area was assigned the average ungaged areal flow rate for the basin. For ungaged tributaries, flow was calculated based on basin proration, using the average flow for all unregulated gages.
[2]The modeled concentration is the mean concentration expected for an arbitrarily selected date in July 2008. The selection of the date is unimportant for the task of ranking sites because although values change from day to day, the rankings among sites will not.
[3]The load index is the product of flow and the expected concentration. This is an index because it is not representative of the conditions on any specific date nor is it the annual mean. It is the product of 10-year average flow conditions for a tributary and the modeled concentration at a given site and time. This provides a ranking of sites from highest to lowest contribution to loading to Falls Lake to be used as one factor in allocating monitoring resources.

Table 5-5 Modeled TP Concentrations at Potential Lake Loading Monitoring Sites along with an Index of the Total Load to Falls Lake Coming from each Tributary

Cells highlighted in red indicate the highest 33% of sites and those in green the lowest 33%.

Tributary	Road Crossing	Tributary Flow[1] (mean daily, cfs)	Modeled TP Concentration[2] (mg/L)	Relative Error of Mean	Load Index[3] (lb/day)	Upper Confidence Limit of Load Index (lb/day)	Index of Proportional Load from Tributary	Rank, Proportional Load	Model	n
Flat River	at Old Oxford Hwy	96.8	0.04	16%	20.39	23.75	19%	4	1	134
Knap of Reeds Creek	off of Brickhouse Rd	25.5	0.08	26%	11.64	14.63	12%	6	2	
Eno River + Little River	at Red Mill Road	140	0.07	35%	55.50	75.15	41%	1	2	
Eno River	at Old Oxford Hwy	92.8	0.03	17%	16.90	19.76	16%	5	1	118
Little River	at Old Oxford Hwy	43.7	0.04	21%	9.66	11.64	10%	8	2	
Little River	at Vintage Hill Pkwy	43.7	0.05	17%	11.31	13.27	11%	7	1	105
Ellerbe Creek	at Red Mill Road	41.0	0.15	14%	32.87	37.63	30%	3	1	199
Ellerbe Creek	at Glenn Road	41.0	0.18	15%	38.88	44.60	34%	2	1	217
Unnamed Tributary to Falls	at Northside Road	2.06	0.10	41%	1.06	1.49	1.2%	24	2	
Panther Creek	at Cooksbury Drive	1.94	0.10	24%	1.02	1.26	1.1%	25	2	
Panther Creek	at Burton Road	1.94	0.09	28%	0.92	1.18	1.0%	26	1	28
Ledge Creek	at Northside Road	14.5	0.07	51%	5.40	8.15	6.7%	10	2	
Little Lick Creek	at Patterson Road	8.31	0.11	29%	4.86	6.28	5.2%	11	2	
Little Lick Creek	at Stallings Road	8.31	0.15	64%	6.91	11.31	9.0%	9	1	5
Robertson Creek	at Brassfield Road	8.87	0.04	61%	1.79	2.88	2.4%	15	2	
Beaverdam Creek	at Horseshoe Road	8.22	0.04	76%	1.55	2.73	2.3%	17	2	
Smith Creek	at Lawrence Road	6.36	0.03	102%	1.14	2.30	1.9%	21	2	
Lick Creek	at Hwy 98	8.17	0.06	25%	2.71	3.39	2.8%	13	2	
Lick Creek	at Southview Road	8.17	0.05	31%	2.09	2.74	2.3%	16	1	21
New Light Creek	at Woodlief Road	10.3	0.03	55%	1.86	2.89	2.4%	14	2	
New Light Creek	at Mangum Dairy Rd	10.3	0.06	29%	3.43	4.42	3.6%	12	1	21
Upper Barton Creek	at Mt Vernon Church	4.95	0.08	24%	2.17	2.70	2.2%	18	2	
Lower Barton Creek	at State Rd 1834	6.26	0.05	30%	1.54	1.99	1.7%	22	1	20
Horse Creek	at Hwy 98	8.87	0.03	57%	1.64	2.58	2.1%	19	2	
Horse Creek	at Thompson Mill Rd	8.87	0.04	30%	1.82	2.37	2.0%	20	1	20
Honeycutt Creek	at Honeycutt Road	2.94	0.07	33%	1.16	1.53	1.3%	23	2	

[1]Mean daily flow is the average daily flow for a tributary based on the 10-year average daily flow between 2004 and 2013. For tributaries that are gaged, the average flow for the most downstream gage was applied to the relevant watershed area. If flow at the most downstream gage is regulated, the remainder of the ungaged watershed area was assigned the average ungaged areal flow rate for the basin. For ungaged tributaries, flow was calculated based on basin proration, using the average flow for all unregulated gages.
[2]The modeled concentration is the mean concentration expected for an arbitrarily selected date in July 2008. The selection of the date is unimportant for the task of ranking sites because although values change from day to day, the rankings among sites will not.
[3]The load index is the product of flow and the expected concentration. This is an index because it is not representative of the conditions on any specific date nor is it the annual mean. It is the product of 10-year average flow conditions for a tributary and the modeled concentration at a given site and time. This provides a ranking of sites from highest to lowest contribution to loading to Falls Lake to be used as one factor in allocating monitoring resources.

Table 5-6 Modeled TSS Concentrations at Potential Lake Loading Monitoring Sites along with an Index of the Total Load to Falls Lake Coming from each Tributary

Cells highlighted in red indicate the highest 33% of sites and those in green the lowest 33%.

Tributary	Road Crossing	Tributary Flow[1] (mean daily, cfs)	Modeled TSS Concentration[2] (mg/L)	Relative Error of Mean	Load Index[3] (lb/day)	Upper Confidence Limit of Load Index (lb/day)	Index of Proportional Load from Tributary	Rank, Proportional Load	Model	n
Flat River	at Old Oxford Hwy	96.8	4.44	35%	2320	3143	29%	1	1	94
Knap of Reeds Creek	off of Brickhouse Rd	25.5	6.84	72%	941	1615	15%	8	2	
Eno River + Little River	at Red Mill Road	140	2.92	65%	2202	3635	29%	2	2	
Eno River	at Old Oxford Hwy	92.8	4.07	36%	2037	2778	26%	3	1	58
Little River	at Old Oxford Hwy	43.7	5.41	44%	1275	1837	17%	6	2	
Little River	at Vintage Hill Pkwy	43.7	7.72	51%	1821	2742	24%	4	2	
Ellerbe Creek	at Red Mill Road	41.0	6.42	39%	1420	1970	19%	5	2	
Ellerbe Creek	at Glenn Road	41.0	5.33	31%	1178	1546	15%	7	1	125
Unnamed Tributary to Falls	at Northside Road	2.06	6.30	54%	70.0	108	1.1%	21	2	
Panther Creek	at Cooksbury Drive	1.94	15.4	42%	161	228	2.3%	16	2	
Panther Creek	at Burton Road	1.94	14.4	42%	150	213	2.1%	17	1	28
Ledge Creek	at Northside Road	14.5	1.97	66%	154	256	2.5%	14	2	
Little Lick Creek	at Patterson Road	8.31	14.8	60%	662	1061	10.2%	9	2	
Little Lick Creek	at Stallings Road	8.31	15.3	55%	684	1058	10.2%	10	2	
Robertson Creek	at Brassfield Road	8.87	1.05	111%	50.4	106	1.1%	22	2	
Beaverdam Creek	at Horseshoe Road	8.22	0.91	163%	40.3	106	1.1%	23	2	
Smith Creek	at Lawrence Road	6.36	0.71	183%	24.2	68.5	0.7%	26	2	
Lick Creek	at Hwy 98	8.17	9.39	48%	414	611	6.0%	12	2	
Lick Creek	at Southview Road	8.17	11.7	44%	515	742	7.2%	11	1	21
New Light Creek	at Woodlief Road	10.3	1.57	94%	87.4	169	1.7%	20	2	
New Light Creek	at Mangum Dairy Rd	10.3	4.00	37%	222	305	3.0%	13	1	22
Upper Barton Creek	at Mt Vernon Church	4.95	2.70	45%	72.2	104	1.0%	24	2	
Lower Barton Creek	at State Rd 1834	6.26	3.70	38%	125	173	1.7%	19	1	20
Horse Creek	at Hwy 98	8.87	2.22	94%	106	205	2.0%	18	2	
Horse Creek	at Thompson Mill Rd	8.87	3.58	38%	171	237	2.3%	15	1	20
Honeycutt Creek	at Honeycutt Road	2.94	3.56	56%	56.5	88.2	0.9%	25	2	

[1]Mean daily flow is the average daily flow for a tributary based on the 10-year average daily flow between 2004 and 2013. For tributaries that are gaged, the average flow for the most downstream gage was applied to the relevant watershed area. If flow at the most downstream gage is regulated, the remainder of the ungaged watershed area was assigned the average ungaged areal flow rate for the basin. For ungaged tributaries, flow was calculated based on basin proration, using the average flow for all unregulated gages.
[2]The modeled concentration is the mean concentration expected for an arbitrarily selected date in July 2008. The selection of the date is unimportant for the task of ranking sites because although values change from day to day, the rankings among sites will not.
[3]The load index is the product of flow and the expected concentration. This is an index because it is not representative of the conditions on any specific date nor is it the annual mean. It is the product of 10-year average flow conditions for a tributary and the modeled concentration at a given site and time. This provides a ranking of sites from highest to lowest contribution to loading to Falls Lake to be used as one factor in allocating monitoring resources.

Table 5-7 Summary of the Lake Loading Locations and their Ranks with Respect to their Expected Load to Falls Lake

Low values (shaded red) indicate sites with the largest predicted loads and high values (shaded green) indicated locations with the lowest predicted loads based on predicted concentrations of water quality parameters and estimated flows for each tributary.

Tributary	Road Crossing	Rank, TN	Rank, TP	Rank, TSS	Minimum Rank
Eno River + Little River	at Red Mill Road	2	1	2	1
Flat River	at Old Oxford Hwy	4	4	1	1
Ellerbe Creek	at Glenn Road	1	2	7	1
Ellerbe Creek	at Red Mill Road	3	3	5	3
Eno River	at Old Oxford Hwy	5	5	3	3
Little River	at Vintage Hill Pkwy	6	7	4	4
Little River	at Old Oxford Hwy	7	8	6	6
Knap of Reeds Creek	off of Brickhouse Road	8	6	8	6
Little Lick Creek	at Stallings Road	10	9	10	9
Little Lick Creek	at Patterson Road	13	11	9	9
Upper Barton Creek	at Mt Vernon Church Road	9	18	24	9
Ledge Creek	at Northside Road	14	10	14	10
Lick Creek	at Southview Road	15	16	11	11
Lower Barton Creek	at State Rd 1834	11	22	19	11
Lick Creek	at Hwy 98	12	13	12	12
New Light Creek	at Mangum Dairy Road	16	12	13	12
New Light Creek	at Woodlief Road	18	14	20	14
Horse Creek	at Thompson Mill Road	17	20	15	15
Robertson Creek	at Brassfield Road	19	15	22	15
Panther Creek	at end of Cooksbury Drive	23	25	16	16
Beaverdam Creek	at Horseshoe Road	21	17	23	17
Panther Creek	at Burton Road	24	26	17	17
Horse Creek	at Hwy 98	20	19	18	18
Unnamed Tributary to Falls Lake	at Northside Road	25	24	21	21
Smith Creek	at Lawrence Road	26	21	26	21
Honeycutt Creek	at Honeycutt Road	22	23	25	22

Table 5-8 Modeled TN Concentrations at Potential Jurisdictional Boundary Monitoring Sites along with an Index of the Total Load at each Location

The "proportion of total load from tributary" indicates the load at the given location as a percentage of the sum of the loads from all tributary loading sites to Falls Lake to provide a reference. Cells highlighted in red indicate the highest 33% of sites and those in green the lowest 33%.

Tributary	Jurisdictional Boundary	Tributary Flow (mean daily, cfs)	Modeled TN Concentration (mg/L)	Relative Error of Mean	Load Index (lb/day)	Load Index Upper Confidence Limit	Proportion of Total Load from Tributary	Rank, Load Upper CI	Model	n
Eno River	upstream of Hillsborough	36.3	0.91	20%	178	214	11.1%	7	2	
Eno River	downstream of Hillsborough	40.5	1.57	22%	342	416	21.6%	2	1	26
Eno River	downstream of Orange County	69.1	0.69	20%	256	305	15.9%	5	1	24
Eno River	downstream of City of Durham	92.8	0.67	12%	334	374	19.4%	4	1	113
North Fork Little River	downstream of Orange County	13.2	1.25	40%	88.6	124	6.44%	10	2	
South Fork Little River	downstream of Orange County	22.5	1.44	38%	174	241	12.5%	6	2	
Little River	upstream of City of Durham	50.5	0.68	11%	185	205	10.7%	9	1	137
Little River	downstream of City of Durham	43.6	0.77	17%	181	211	11.0%	8	2	
Flat River	downstream of Person County	61.4	0.83	47%	274	404	21.0%	3	2	
Deep Creek	downstream of Person County	19.3	0.62	52%	64.0	97.0	5.04%	11	1	3
Camp Creek	downstream of Durham County	2.99	0.34	125%	5.49	12.4	0.64%	13	2	
Little Ledge Creek	downstream of Granville County	2.24	0.71	22%	8.56	10.5	0.54%	14	2	
Ledge Creek	downstream of Stem	1.08	0.22	116%	1.27	2.75	0.14%	19	2	
Ledge Creek	upstream of Butner	2.10	0.24	50%	2.75	4.13	0.21%	17	2	
Robertson Creek	upstream of Creedmoor	2.66	0.19	64%	2.65	4.35	0.23%	16	2	
Buckhorn Creek	downstream of Granville County	0.73	0.15	58%	0.60	0.96	0.05%	21	2	
New Light Creek	downstream of Granville County	5.94	0.14	68%	4.60	7.74	0.40%	15	2	
Horse Creek	downstream of Franklin County	2.87	0.05	150%	0.77	1.93	0.10%	20	2	
Horse Creek	upstream of Wake Forest	4.27	0.07	128%	1.55	3.53	0.18%	18	2	
Horse Creek	downstream of Wake Forest	7.14	0.52	19%	19.89	23.76	1.23%	12	1	20
Ellerbe Creek	downstream of City of Durham	39.5	3.29	11%	701	776	40.3%	1	1	214

Table 5-9 Modeled TP Concentrations at Potential Jurisdictional Boundary Monitoring Sites along with an Index of the Total Load at each Location

The "proportion of total load from tributary" indicates the load at the given location as a percentage of the sum of the loads from all tributary loading sites to Falls Lake to provide a reference. Cells highlighted in red indicate the highest 33% of sites and those in green the lowest 33%.

Tributary	Jurisdictional Boundary	Tributary Flow (mean daily, cfs)	Modeled TP Concentration (mg/L)	Relative Error of Mean	Load Index (lb/day)	Load Index Upper Confidence Limit	Proportion of Total Load from Tributary	Rank, Load Upper CI	Model	n
Eno River	upstream of Hillsborough	36.3	0.04	30%	8.44	11.0	9.20%	10	2	
Eno River	downstream of Hillsborough	40.5	0.08	33%	17.6	23.5	19.7%	3	1	26
Eno River	downstream of Orange County	69.1	0.05	30%	16.9	22.0	18.4%	4	1	24
Eno River	downstream of City of Durham	92.8	0.03	17%	16.9	19.8	16.6%	6	1	118
North Fork Little River	downstream of Orange County	13.2	0.12	54%	8.26	12.7	10.6%	7	2	
South Fork Little River	downstream of Orange County	22.5	0.14	47%	16.5	24.3	20.3%	2	2	
Little River	upstream of City of Durham	50.5	0.04	15%	10.2	11.7	9.78%	8	1	167
Little River	downstream of City of Durham	43.6	0.04	21%	9.63	11.6	9.72%	9	2	
Flat River	downstream of Person County	61.4	0.04	74%	12.4	21.6	18.1%	5	2	
Deep Creek	downstream of Person County	19.3	0.02	87%	2.58	4.82	4.04%	11	1	3
Camp Creek	downstream of Durham County	2.99	0.13	75%	2.16	3.78	3.16%	12	2	
Little Ledge Creek	downstream of Granville County	2.24	0.07	42%	0.86	1.23	1.03%	19	2	
Ledge Creek	downstream of Stem	1.08	0.24	63%	1.41	2.30	1.93%	13	2	
Ledge Creek	upstream of Butner	2.10	0.10	45%	1.10	1.59	1.33%	16	2	
Robertson Creek	upstream of Creedmoor	2.66	0.03	90%	0.42	0.79	0.66%	20	2	
Buckhorn Creek	downstream of Granville County	0.73	0.05	64%	0.18	0.30	0.25%	21	2	
New Light Creek	downstream of Granville County	5.94	0.03	69%	0.85	1.44	1.20%	17	2	
Horse Creek	downstream of Franklin County	2.87	0.04	152%	0.56	1.42	1.19%	18	2	
Horse Creek	upstream of Wake Forest	4.27	0.03	124%	0.80	1.79	1.50%	15	2	
Horse Creek	downstream of Wake Forest	7.14	0.04	30%	1.47	1.91	1.60%	14	1	20
Ellerbe Creek	downstream of City of Durham	39.5	0.18	15%	37.5	43.0	36.0%	1	1	217

Table 5-10 Modeled TSS Concentrations at Potential Jurisdictional Boundary Monitoring Sites along with an Index of the Total Load at each Location

The "proportion of total load from tributary" indicates the load at the given location as a percentage of the sum of the loads from all tributary loading sites to Falls Lake to provide a reference. Cells highlighted in red indicate the highest 33% of sites and those in green the lowest 33%.

Tributary	Jurisdictional Boundary	Tributary Flow (mean daily, cfs)	Modeled TSS Concentration (mg/L)	Relative Error of Mean	Load Index (lb/day)	Load Index Upper Confidence Limit	Proportion of Total Load from Tributary	Rank, Load Upper CI	Model	n
Eno River	upstream of Hillsborough	36.3	4.54	52%	890.	1352	13.5%	8	2	
Eno River	downstream of Hillsborough	40.5	4.00	48%	874	1291	12.9%	9	1	26
Eno River	downstream of Orange County	69.1	3.37	44%	1255	1804	18.0%	5	1	24
Eno River	downstream of City of Durham	92.8	4.07	36%	2038	2779	27.8%	2	1	58
North Fork Little River	downstream of Orange County	13.2	13.3	108%	942	1956	19.5%	3	2	
South Fork Little River	downstream of Orange County	22.5	13.7	98%	1661	3296	32.9%	1	2	
Little River	upstream of City of Durham	50.5	4.62	32%	1257	1655	16.5%	6	1	115
Little River	downstream of City of Durham	43.6	5.41	44%	1270	1831	18.3%	4	2	
Flat River	downstream of Person County	61.4	1.75	55%	578	897	8.95%	10	2	
Deep Creek	downstream of Person County	19.3	1.99	79%	207	371	3.70%	11	2	
Camp Creek	downstream of Durham County	2.99	2.44	324%	39.4	167	1.67%	13	2	
Little Ledge Creek	downstream of Granville County	2.24	3.91	47%	47.4	69.5	0.69%	16	2	
Ledge Creek	downstream of Stem	1.08	1.08	344%	6.29	27.9	0.28%	19	2	
Ledge Creek	upstream of Butner	2.10	1.05	113%	11.9	25.4	0.25%	20	2	
Robertson Creek	upstream of Creedmoor	2.66	0.91	114%	13.1	28.0	0.28%	18	2	
Buckhorn Creek	downstream of Granville County	0.73	1.16	108%	4.54	9.44	0.09%	21	2	
New Light Creek	downstream of Granville County	5.94	1.14	108%	36.6	76.2	0.76%	14	2	
Horse Creek	downstream of Franklin County	2.87	0.72	322%	11.2	47.1	0.47%	17	2	
Horse Creek	upstream of Wake Forest	4.27	0.96	242%	22.2	75.8	0.76%	15	2	
Horse Creek	downstream of Wake Forest	7.14	3.58	38%	138	191	1.90%	12	1	20
Ellerbe Creek	downstream of City of Durham	39.5	5.33	31%	1135	1489	14.9%	7	1	125

Table 5-11 Summary of the Jurisdictional Boundary Locations and their Ranks with Respect to their Expected Load of TN, TP, and TSS

Low values (shaded red) indicate sites with the largest predicted loads and high values (shaded green) indicated locations with the lowest predicted loads based on predicted concentrations of water quality parameters and flow values for each tributary.

Tributary	Jurisdictional Boundary	Rank, TN	Rank, TP	Rank, TSS	Rank, Minimum
Ellerbe Creek	downstream of City of Durham	1	1	7	1
South Fork Little River	downstream of Orange County	9	2	1	1
Eno River	downstream of City of Durham	3	6	2	2
Eno River	downstream of Hillsborough	2	3	9	2
North Fork Little River	downstream of Orange County	10	7	3	3
Eno River	downstream of Orange County	5	4	5	4
Flat River	downstream of Person County	4	5	10	4
Little River	downstream of City of Durham	7	9	4	4
Little River	upstream of City of Durham	6	8	6	6
Eno River	upstream of Hillsborough	8	10	8	8
Deep Creek	downstream of Person County	11	11	11	11
Horse Creek	downstream of Wake Forest	12	14	12	12
Camp Creek	downstream of Durham County	14	12	13	12
Little Ledge Creek	downstream of Granville County	13	19	16	13
Ledge Creek	downstream of Stem	19	13	19	13
New Light Creek	downstream of Granville County	15	17	14	14
Horse Creek	upstream of Wake Forest	18	15	15	15
Ledge Creek	upstream of Butner	16	16	20	16
Robertson Creek	upstream of Creedmoor	17	20	18	17
Horse Creek	downstream of Franklin County	20	18	17	17
Buckhorn Creek	downstream of Granville County	21	21	21	21

The models cannot tell us what an “acceptable” level of error is. They do tell us that the confidence interval for model predictions decreases with each additional sample, but they also tell us that the decreases in CI from each additional sample relative to previous samples exhibit diminishing returns (Table 5-1). Sampling hourly may increase confidence in model predictions, but the gain may not be large compared to a daily sampling frequency. Ideally, the models would identify the sampling frequency at which the gain in confidence in model output is just offset by a lack of response from the EFDC model output. However, such an analysis is precluded by a lack of confidence in the current calibration of the EFDC model as well as the computational and analytical time required for the hundreds or thousands of EFDC simulations necessary for such an optimization procedure. Determining an “acceptable” degree of error can be informed by the models presented in this memo but ultimately it will need to be decided with budgetary constraints, trade-offs with respect to other monitoring objectives, and political consequences in mind.

The results of the water quality models (in combination with previous EFDC sensitivity analyses) can be used to identify plausible sampling plans which focus effort on the tributary locations that benefit most from increased sampling frequency. Modeled loads from the upper lake tributaries (Flat River, Eno River, Little River, Ellerbe Creek, and Knap of Reeds Creek) provide the largest contribution of nutrients to the lake and also drive much of the EFDC sensitivity. Increasing confidence in estimates of nutrient, carbon, sediment, and chlorophyll loading from these tributaries would contribute substantially to confidence in the estimates of total load to the lake. The models show that roughly weekly sampling for 5 years would yield enough samples to allow models to predict daily mean values with a relative error of 10% and 90% confidence for TP (n=260) and sampling twice monthly would provide a similar level of confidence for TN estimates (n=120). Sampling TSS weekly would not achieve the 10% relative error, but would achieve a relative error between 10 and 20%. Obtaining this level of confidence for the five largest contributors of nutrients to Falls Lake while sampling other sites less frequently may be a useful way to balance budgetary concerns with desired confidence in lake loading estimates.

Based on the analyses above, a discussion of recommended sampling frequencies for both lake loading and jurisdictional boundary locations is presented in the final section of this TM (Section 6).

6 Recommendations for Monitoring Program Design for Watershed Sampling Sites

6.1 Recommended Lake Loading Monitoring Locations and Sampling Frequency

Potential monitoring locations for lake loading sites have been identified based on ease of access (usually at road crossings where samples could be obtained either by sampling from a bridge or, if necessary, from the streambank) and proximity to the lake; these locations are shown in Figure 6.1. For some tributaries, two sites have been identified as potential locations for lake loading monitoring: an upstream site based on an existing (or past) monitoring station and a site at a road crossing further downstream. The advantages of the downstream locations are that they cover a larger drainage area and thus may be more representative of the true tributary loading. We have chosen these downstream sites to be at locations outside of the flood zone of Falls Lake based on site elevation, however there may be other site-specific reasons that existing monitoring entities have chosen the upstream sites. We will discuss these sites with local experts to obtain feedback on their feasibility before making a final recommendation to the UNRBA.

Parameters recommended for inclusion in the monitoring program are listed in table 6-1 and include routine field parameters to characterize the chemistry and biology of the streams as well as lab analyses for nutrients, sediment, and carbon. Parameter selection will be explored further in the upcoming Five-Year Monitoring Plan TM; this table is presented here to provide context for the monitoring plan and cost estimates.

Table 6-1 Parameters Recommended for Routine Sampling at Lake Loading Locations

Parameters	Description
Temperature, dissolved oxygen, pH, conductivity	Field parameters for stream characterization
Ammonia, nitrate plus nitrite, total Kjeldahl nitrogen	Nitrogen species for estimating tributary loading
Ortho-phosphorus and total phosphorous	Phosphorus species for estimating tributary loading
Total suspended solids	Sediment delivery to Falls Lake
Total organic carbon and dissolved organic carbon	Characterize carbon loading to Falls Lake
Color and UV absorbance	Indicators of carbon content and source
Chlorophyll *a*	Measure loading of chlorophyll from tributaries to Falls Lake
Carbonaceous Biochemical Oxygen Demand (CBOD5)	Used to partition labile versus refractory forms of carbon and nutrients, necessary for EFDC model input

In total, there are 17 tributary loading sites which are included in the Falls Lake Nutrient Response Model for which estimates of nutrient, chlorophyll, and sediment load are required. If the Eno and Little Rivers are monitored separately, there would be a total of 18 monitoring locations for the purposes of measuring loading to Falls Lake. There is a possibility that monitoring could occur on the Eno River at Red Mill Road which is downstream from the confluence with the Little River which could reduce the number of locations to 17; however, monitoring these rivers separately would facilitate multiple uses of the data including source allocation, watershed modeling, and BMP prioritization among others. Because of these reasons, member jurisdictions have requested (and Cardno ENTRIX recommends) that these rivers be monitored separately.

Given a desire to include monitoring at all input tributaries to Falls Lake, a sampling plan uninformed by the model results presented in this TM might include a constant monitoring frequency across all 18 locations. Monthly sampling for all 18 tributaries is estimated to cost roughly $160,000 per year (excluding costs of data and project management), but may not sample the largest tributaries frequently enough to narrow the confidence intervals to desired levels. Monthly sampling over 4 years would result in 48 samples per site which corresponds to relative errors of between 30 and 40% for TSS, between 20 and 30% for TP, and between 10 and 20% for TN (Table 5.2). Sampling weekly, however, (208 samples over four years) might reduce the relative error of model simulated data to roughly 10% for TN and TP and to less than 20% for TSS, but the cost at nearly $700,000 per year would be prohibitive. Using model output, we can distinguish among the 18 tributary locations to identify locations where increased sampling would provide the most value. The largest five tributaries account for over 80% of the total predicted load of TN and over 75% of the predicted load of TP. Sampling these five tributaries weekly for four years would reduce the relative error of model predictions to roughly 10% for TN and TP and less than 20% for TSS. Thus, increasing sampling frequency at just five locations can yield more precise estimates for 75 to 80% of the total nutrient load. Of these five locations, Flat River and Eno River have on the order of 100 data points for TN and TP already, and Ellerbe Creek has roughly 200 data points for each, although less than half of these are for the period after the waste water treatment plant upgrades. Taking advantage of the data already available at these sites would reduce the sampling frequency required to achieve a 10% relative error on the predictions to twice monthly. The SGWASA waste water treatment plant is undergoing upgrades which mean the historical data will not be informative of future loads; sampling Knap of Reeds creek twice monthly over four years would provide nearly 100 samples which would produce estimates with 10% relative error for TN and between 10 and 20% relative error for TP.

The smallest 6 tributaries contribute just 2% of the modeled TN and about 6% of the modeled TP load to Falls Lake. Reducing sampling frequency at these locations can allow monitoring dollars to be allocated elsewhere while reducing precision on model estimates of load for only a small fraction of the total lake loading. These sites are candidates for monthly monitoring for approximately a year to verify model predictions (especially at sites which have not previously been sampled) followed by reduced sampling in subsequent years to free up sampling funds for short-term studies as directed by the UNRBA. Recommended sampling frequencies are summarized in Table 6-2. The estimated cost of this monitoring scenario is approximately $220,000 per year (excluding the costs of data and project management). This is a rough estimate only to determine that the selected frequencies are within the limits of the projected monitoring budget.

Table 6-2 Tributary Locations for Lake Loading Monitoring and Recommended Sampling Frequency for the First Year of Monitoring

Three tributaries have two sites listed. Only one of each of these pairs will be monitored and the final site determination will be made based upon field visits of the sites.

	Waterbody	Road Crossing	Latitude	Longitude	Drainage Area (mi2)	Recommended Frequency
1	Knap of Reeds Creek	access off of Brickhouse Rd	36.118226	-78.798476	44.7	Every other week
2	Flat River	at Old Oxford Hwy	36.131900	-78.827981	169	Every other week
3	Little River	at Old Oxford Road	36.081667	-78.854722	104	Every other week
4	Eno River	at Old Oxford Hwy	36.072642	-78.862700	149	Every other week
5	Ellerbe Creek	at Glenn Rd	36.059583	-78.832200	21.9	Every other week
6	Panther Creek	at Burton Rd	36.033593	-78.812568	2.60	Monthly
7a	Little Lick Creek	at Patterson Road	36.004633	-78.787502	13.8	Monthly
7b	Little Lick Creek	at Stallings Rd	35.986681	-78.799173	10.1	Monthly
8	Lick Creek	at Southview Rd south of Hwy 98	35.977936	-78.749565	10.8	Monthly
9	Unnamed Tributary	at Northside Road	36.084307	-78.748911	3.43	Monthly
10	Ledge Creek	at Northside Road	36.103426	-78.708157	20.9	Monthly
11	Robertson Creek	at Brassfield Road	36.102984	-78.659167	12.0	Monthly
12	Beaverdam Creek	at Horseshoe Road	36.091260	-78.639854	12.7	Monthly
13	Smith Creek	at Lawrence Road	36.088429	-78.602448	6.30	Monthly
14a	New Light Creek	at Woodlief Road	36.024974	-78.616262	17.1	Monthly
14b	New Light Creek	at Mangum Dairy Rd	36.027012	-78.601325	12.3	Monthly
15a	Horse Creek	at Hwy 98 (Durham Road)	35.977288	-78.574052	14.8	Monthly
15b	Horse Creek	at Thompson Mill Rd	35.979137	-78.561741	11.9	Monthly
16	Upper Barton Creek	at Mt Vernon Church Road	35.959915	-78.678645	8.26	Monthly
17	Lower Barton Creek	at State Rd 1834 aka Norwood Rd	35.943928	-78.659621	10.4	Monthly
18	Honeycutt Creek	at Honeycutt Road	35.912558	-78.622060	2.76	Monthly

6.2 Recommended Jurisdictional Boundary Monitoring Locations and Sampling Frequency

Sampling locations for 21 jurisdictional boundary monitoring were visually identified using GIS stream, street, and county and municipal boundary layers and were chosen to be located at road crossings as near to the appropriate jurisdictional boundary as possible (Figure 6.1). The jurisdictional boundary locations are listed in Table 6-3 and are displayed on Figure 6.1 Jurisdictions are required to calculate annual loads at these locations in order to determine the baseline jurisdictional loads. However, acceptable methods to determine jurisdictional loads have not been provided by the state. Monitoring along with models which can predict daily nutrient concentrations can be used together to calculate annual loads at these locations. Most of the jurisdictional boundary sites do not have historical data available and therefore Cardno ENTRIX recommends sampling all boundary locations monthly in the first year to obtain data which can be used to assess model predictions. If sampling continued monthly for four years (48 samples), model predictions of TN would be expected to have a relative error between 10 and 20% and predictions of TP would be expected to have a relative error between 20 and 30%. Some sites are expected to have much lower loads than other sites and, for future years, the UNRBA may wish to discuss whether all sites, regardless of the magnitude of load need to be predicted with the same level of confidence.

Parameters recommended for monitoring at the jurisdictional boundary locations include those listed in table 6-1 with the exception of chlorophyll *a,* dissolved organic carbon, color, and $CBOD_5$. These parameters are not necessary at jurisdictional boundary sites, however, depending upon values observed at lake loading sites in the first year of monitoring, it is possible (but perhaps not likely) that inclusion of these parameters at some jurisdictional boundary sites may indicated in future years.

The cost of monitoring 21 jurisdictional boundary locations monthly is estimated to be nearly $150,000 per year in field and lab analysis costs only. Depending upon the final selection of lake loading monitoring locations, one or two of the 21 jurisdictional boundary locations may be included as lake loading locations, thus slightly reducing this estimated cost. Based upon preliminary feedback from the Path Forward Committee of the UNRBA, this monitoring frequency may be reduced in the final monitoring plan to between quarterly and monthly for the first year.

Table 6-3 Tributary Sampling Locations for Jurisdictional Boundary Monitoring

	Waterbody	Road Crossing	Boundary	Latitude	Longitude	Drainage Area (mi^2)
1	Eno River	at Dimmocks Mill Road	upstream of Hillsborough	36.070127	-79.129530	60.5
2	Eno River	at Hwy 70 and Riverside Drive	downstream of Hillsborough	36.075417	-79.071636	73.2
3	Eno River	at Cole Mill Road	downstream of Orange County	36.059290	-78.978042	121
4	North Fork Little River	at New Sharon Church Road	between Orange and Durham Counties	36.180164	-78.975432	21.9
5	South Fork Little River	at Guess Road (Hwy 157)	between Orange and Durham Counties	36.145465	-78.962187	37.4
6	Little River	at Johnson Mill Rd	upstream of City of Durham	36.141643	-78.919265	78.3
7	North Flat River	at Highway 57	downstream of Roxboro	36.310638	-78.969420	15.8
8	North Flat River	at Helena-Moriah Road	before confluence with South Flat	36.288983	-78.942891	32.8
9	South Flat River	at Highway 57	before confluence with North Flat River	36.256842	-78.944337	54.4
10	Flat River	at Moores Mill Rd	downstream of Person county	36.241864	-78.905769	102
11	Deep Creek	at Smith Rd	downstream of Person County	36.240278	-78.888885	32.1
12	Camp Creek	at Camp Butner	between Durham and Granville Counties	36.209510	-78.805304	4.99
13	Little Ledge Creek	at Old Weaver Trail	downstream of Granville	36.075904	-78.720953	3.74
14	Ledge Creek	at Old Route 75	downstream of Stem	36.194856	-78.729220	1.79
15	Ledge Creek	at W Lyon Station Rd	upstream of Butner	36.176079	-78.714097	3.49
16	Robertson Creek	at Sam Moss Hayes Road	upstream of Creedmoor	36.139193	-78.660785	4.43
17	Buckhorn Creek	at Buckhorn Lane	between Granville and Wake Counties	36.048080	-78.609717	1.21
18	New Light Creek	at Bold Run Hill Road	between Granville and Wake Counties	36.037485	-78.592078	9.90
19	Horse Creek	at Holden Road	between Franklin and Wake Counties	36.024301	-78.518988	4.78
20	Horse Creek	at Purnell Road	upstream of Wake Forest	36.007058	-78.529087	7.11
21	Horse Creek	at Thompson Mill Rd	downstream of Wake Forest	35.979137	-78.561741	11.9

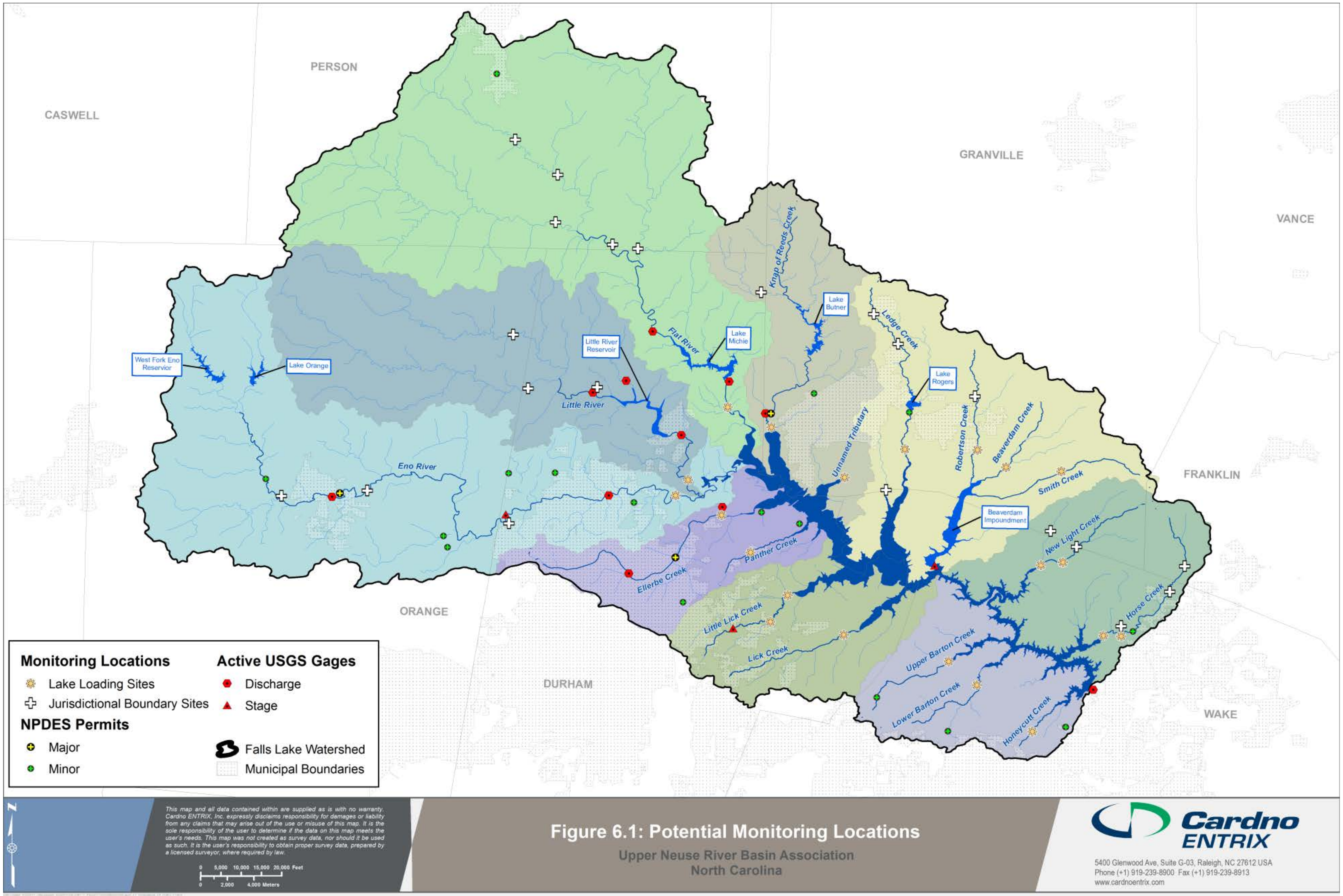

Figure 6-1 Potential Monitoring Locations

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