M.S. Project Report

Investigating Surrogate Parameters for Total Suspended Solids in the Webb Branch Watershed, Blacksburg, Virginia

by

Todd Aronhalt

Project Report submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Master of Science

In

Civil and Environmental Engineering

Randel L. Dymond, Co-Chair
Vinod K. Lohani, Co-Chair
Erich T. Hester

May 2, 2016
Blacksburg, VA
Acknowledgements

First and foremost, I would like to thank Dr. Dymond and Dr. Lohani for providing me the opportunity to work in the Learning Enhanced Watershed Assessment (LEWAS) Lab. Dr. Lohani’s enthusiasm for real-time water monitoring motivated me to produce high caliber work. Dr. Dymond’s experience and knowledge in the fields of urban hydrology and stormwater management was instrumental throughout the course of my project and report. Moreover, I thank Dr. Dymond for helping me transition from Biology to Civil Engineering and providing advice and guidance along the way.

I would like to thank Dr. Hester for his interest in the subject of my project and for sharing his experiences in the field of stream restoration with me.

I thank all the members of the LEWAS Lab for their work in keeping the field site operational. Their efforts contributed towards the success of this project, specifically by ensuring that our field site was recording high quality data. I particularly would like to thank James Taylor for putting in long hours coding and keeping the entire system online. Josh Gozum, Serena Emanuel, and Thomas Westfall were helpful in maintaining the field instruments and also in performing calibrations.

Although I did not interact with Walter McDonald and Daniel Brogan as much as others, I thank them for their prior work in the lab and their dedication to the LEWAS. Specifically, I would like to thank Walter for always lending an ear when I had general hydrology or engineering questions. The OWLS was incredibly helpful in tracking storms in real time and deciding when to sample. I have Daniel to thank for that.

Last but not least, I would like to extend thanks to Julie Petruska for getting me set up in Durham to do TSS analysis. Without her help and the lab space in Durham, I would not have been able to do this project.
Table of Contents

List of Figures ........................................................................................................ iv
List of Tables ........................................................................................................... iv
List of Appendix Figures ........................................................................................ iv
List of Appendix Tables.......................................................................................... iv
1. Introduction ......................................................................................................... 1
2. Review of Literature ......................................................................................... 3
   2.1 Overview ....................................................................................................... 3
   2.2 Influence of particle properties on the TSS-Turbidity relationship ................ 4
   2.3 Site specificity of the TSS-Turbidity relationship ......................................... 5
   2.4 TSS-Turbidity relationship in relation to land use and seasonality ............... 5
3. Methods ............................................................................................................. 7
   3.1 Study Site: Webb Branch Watershed............................................................ 7
   3.2 Field Instruments ....................................................................................... 8
   3.3 TSS Sampling and Analysis ....................................................................... 11
   3.4 Statistical Methods ................................................................................... 12
4. Results and Discussion ..................................................................................... 16
   4.1 Final regression models ............................................................................. 16
   4.2 Comparison of regression models .............................................................. 17
   4.3 Comparison of regression results to previous studies .................................. 19
   4.4 Case study: Application of regression equation to estimate sediment load over a 24hr time period ............................................................. 20
   4.5 Comparison of model 2 to a multivariate model developed by the USGS for the Roanoke River in Roanoke, Virginia ............................................ 23
   4.6 Challenges encountered during model development ................................. 25
5. Conclusions ....................................................................................................... 28
   5.1 Conclusions ............................................................................................... 28
   5.2 Future Work ............................................................................................. 29
References ............................................................................................................ 31
Appendix .............................................................................................................. 35
List of Figures

Figure 3.1. (a) Stroubles Creek watershed and associated land cover ........................................8
  (b) Drainage network contributing flow to Webb Branch ......................................................8
Figure 3.2. Above ground reach of Webb Branch between the culvert running underneath West
Campus Drive and the Upper Duck Pond ..................................................................................9
Figure 3.3. Self-cleaning turbidity sensor installed in the Hydrolab MS5 .................................11
Figure 3.4. Scatterplot matrix of selected continuously monitored parameters and TSS ........13
Figure 4.1. (a) Comparison of actual vs predicted TSS values for model 1 .............................17
  (b) for model 2 ......................................................................................................................17
  (c) for model 3 ......................................................................................................................17
Figure 4.2. Discharge measurements from both the ADCP and Ultrasonic Level Sensor for a
single rainfall event during May 2, 2016 .................................................................................19
Figure 4.3. Hydrograph and pollutograph for Dec. 1, 2015 .................................................21
Figure 4.4. Estimated sediment load for Dec 1, 2015 using model (2) and (3) .......................22
Figure 4.5. Hydrograph and pollutograph for April 22 through April 23, 2016 .......................28

List of Tables

Table 3.1. Hydrolab self-cleaning turbidity sensor technical data ........................................11
Table 4.1. Summary of final regression equations .................................................................16
Table 4.2. Range of values for the explanatory variables ....................................................16
Table 4.3. Bias correction factors for SSL computations .....................................................22
Table 4.4. Retransformed TSS equations back into original units ........................................23
Table 4.5. Comparison of suspended sediment regression equations developed by the USGS for
Roanoke, VA and the equations developed herein for Blacksburg, VA. ..............................25

List of Appendix Figures

Figure A1. Model 1 diagnostic plots of the residual errors ...................................................37
Figure A2. Plot of the residuals vs lagged residuals for model 1 ...........................................37
Figure A3. Model 2 diagnostic plots of the residual errors ....................................................38
Figure A4. Plot of the residuals vs lagged residuals for model 2 ...........................................38
Figure A5. Model 3 diagnostic plots of the residual errors ....................................................39
Figure A6. Plot of the residuals vs lagged residuals for model 2 ...........................................39

List of Appendix Tables

Table A1. Summary of TSS data and corresponding continuously monitored parameters ......35
Table A2. Summary of regression output for simple and multiple linear regression ..........36
# 1. Introduction

Runoff from urban areas constitutes a major source of non-point source pollution entering surface waters. Pollutants carried in stormwater runoff include sediment, bacteria, heavy metals, hydrocarbons, nutrients (e.g., phosphorous and nitrogen), and household and/or industrial chemicals (EPA, 1992). Pollutants can enter natural water bodies during precipitation events through either the municipal stormwater network or directly via overland runoff from impervious surfaces. To mitigate the environmental impact of non-point source pollution on surface waters receiving stormwater runoff, state regulatory agencies have developed Total Maximum Daily Loadings (TMDLs) of specific pollutants for streams designated as impaired on the 303(d) listing, in accordance with the Clean Water Act of 1972 (33 U.S.C §1251 et seq.). Further, a TMDL implementation plan is designed to meet the requirements set forth by the TMDL; however, understanding the effectiveness of Best Management Practices (BMPs) to reduce pollutant loads is often limited by water quality monitoring programs.

Water quality monitoring programs have traditionally relied on grab sampling, or “snap shot” sampling, to characterize water quality (i.e., nutrient and solids concentrations) and compute pollutant loads in rivers and streams. Grab samples are discrete water samples taken at an instant in time, representative of stream conditions at the time of sampling (Levine et al., 2014). Historically, monitoring programs have relied on a number of discrete water samples taken over a finite time period (e.g., several months), coupled with discharge data, to construct pollutant loadings. Computed pollutant loadings aid resource managers in assessing the effectiveness of management programs designed to reduce the influx of pollutants to natural waterways and meet regulatory TMDL criteria. However, the accuracy of calculated loadings directly relies on the ability of monitoring regimes to accurately capture a wide range of stream conditions, as suspended sediment concentrations and nutrients are often correlated with discharge (Jones et al., 2012; Henjum et al., 2010). For example, Rasmussen (2008) noted that at least 90 percent of the total annual sediment load for several streams in Northeast Kansas was transported during less than 2 percent of the time period. Personnel, monetary, and logistic constraints make capturing data at the frequency needed for accurate loading calculations impractical or very expensive. Traditional monitoring practices are lagging behind in their effectiveness to adequately characterize pollutant fluxes, while stormwater regulations are continuing to evolve alongside stormwater BMPs.
Continuous *in-situ* water quality monitoring has allowed for remote, high-frequency data collection of a number of parameters (e.g., temperature, dissolved oxygen, turbidity, specific conductivity, etc.) used to characterize water quality, alleviating the need for labor intensive monitoring programs and increasing the temporal resolution of data records (Kirchner et al., 2004). While remote monitoring equipment is not without its limitations (e.g., sensor fouling, power requirements, data quality, etc.), the technology represents an advantage to agencies and individuals concerned with monitoring stream conditions, particularly in impaired waterways.

One pitfall currently associated with *in-situ* water quality sensors is their inability to directly measure nutrient and suspended solid concentrations. However, in the last decade, researchers and government agencies, such as the United States Geological Survey (USGS), have developed regression methods for relating continuously monitored parameters (e.g., turbidity, stream discharge, water temperature, etc.) to a host of water quality constituents (Horsburgh et al., 2010).

Of the many continuously monitored parameters investigated, turbidity has been identified as a reliable surrogate parameter for estimating suspended solid concentrations (Gray and Gartner, 2009). Turbidity is an optical measure of the scattering of light due to suspended particles, and thus has a direct relationship with the amount of suspended particles in a sample volume (Rice et al., 2012). However, the relationship between turbidity and suspended sediment may be variable depending on physical particle properties such as composition (i.e., organic or inorganic), size, and color (Gippel, 1995; Merten, Capel, and Minella 2014). Moreover, it has been suggested that the relationship between turbidity and suspended solids is watershed specific due to spatial variability in geology and soil type across basins (Grayson et al., 1996; Gippel, 1995). Additionally, streams are dynamic systems, undergoing cycles of erosion and deposition, and subject to seasonal changes in relation to discharge and temperature, among other factors. Sources of sediment and the relative influence of variables driving sediment transport may differ among watersheds with differing land use and hydrology, ultimately affecting which variables are most strongly correlated with suspended solid concentrations (Gellis, 2013).

This project report investigates the potential of using real-time continuously monitored water quality parameters at the Learning Enhanced Watershed Assessment System (LEWAS) lab field site located in Webb Branch of Stroubles Creek on the Virginia Tech (VT) campus to estimate total suspended solids (TSS) concentration via regression methods.
The LEWAS Lab, hosted by the Engineering Education Department, is comprised of an interdisciplinary research group including graduate and undergraduate students focused on real-time environmental monitoring and the educational benefits of implementing a web-based application into the classroom, allowing the exploration of environmental data. The Online Watershed Learning System (OWLS) is a web based application which allows users – students or the general public – to access, graph, and download real-time hydrologic and weather data from the Webb Branch watershed. The OWLS is a branch of the LEWAS which arose from the need to create a platform that presents time series data and engineering concepts in a coherent manner (McDonald et al., 2015a). Both OWLS and historical LEWAS data have been integrated into engineering courses at VT and elsewhere to facilitate learning and connect hydrology concepts to real world data (McDonald et al., 2015b). More information regarding the LEWAS Lab and its activities can be found by visiting http://www.lewas.centers.vt.edu. The OWLS web page is accessible via http://www.lewas.centers.vt.edu/dataviewer/index.html

The remainder of this project report is structured as follows. Chapter 2 provides a review of the literature including previous work on the development of surrogate relationships in relation to suspended sediment. Chapter 3 describes the study site and LEWAS lab at VT, and the approach taken to develop a surrogate relationship for total suspended solids, including regression and model validation techniques. Chapter 4 presents the results of the analysis and discusses the significance of the findings. Chapter 5 presents a case study utilizing the developed surrogate relationship. Chapter 6 summarizes the research and discusses its relevance to water quality monitoring in Webb Branch.

2. Review of Literature

2.1 Overview

There is a real need to monitor suspended sediment, particularly in urban areas, as its deleterious ecological impacts are well documented (Walsh et al., 2005; Bilotta and Brazier, 2008). Currently, in situ sensors with the ability to measure suspended solid concentrations do not exist – meaning TSS cannot be continuously monitored. Developing a high frequency data set which characterizes suspended sediment transport for a particular basin is difficult and often impractical. As such, alternative methods to characterize fluvial sediment fluxes have been sought (Gray and Gartner, 2009). Because suspended solids have a direct physical relationship
with turbidity (i.e., the optical scattering of light), numerous investigations utilizing statistical regression techniques have been conducted exploring the use of turbidity as a surrogate parameter for suspended solids with favorable results (Gray and Gartner, 2009; Horsburgh et al., 2010; Gippel, 1995).

2.2 Influence of particle properties on the TSS-Turbidity relationship

Although a number of particle characteristics such as size, composition, and color can affect turbidity, the relationship between turbidity and suspended solids is generally linear (Merten, Capel, and Minella 2014; Grayson et al., 1996; Jastram et al., 2010). Deviations from this linear relationship may indicate a changing particle size in reference to increasing suspended sediment concentrations (Gippel, 1995). Higher stream discharges may have the ability to suspend a greater fraction of larger particles than smaller flows, potentially influencing the nature of this relationship.

Jastram et al. (2010) evaluated the particle composition of 21 samples collected from the Roanoke River (Roanoke, VA) in an effort to link turbidity to both suspended solids as well as particle size. The authors found that including explanatory variables representing both particle diameter and turbidity in the regression model further reduced unexplained variance in estimating suspended solid concentrations. Moreover, it was determined that stage and water temperature were adequate in describing the variation in the percentage of particles less than 0.063 mm. Subsequently, stage and water temperature were evaluated in the regression model; however, water temperature was found not to be a significant explanatory variable and was removed from the final predictive model.

Whiting (2013) provides a similar investigation into the effects of particle size on estimating suspend solids at various sites in the Little Bear River watershed (Cache Valley, UT). An analysis of particle diameters revealed varying particle size distributions at different turbidity values. This difference was most notable when comparing high turbidity values to low values. To account for this difference a categorical variable was included in the regression model, indicating whether turbidity was below or above a specified value or break point. The categorical variable representing turbidity level (i.e., below/above threshold) was significant in the regression models of 4 of the 6 study sites. For the remaining two study sites, turbidity was the only significant variable included in the regression model. Discharge was considered, and found to be significant, in each regression model, but was ultimately left out of the final models, in the interest of
simplicity, because the reduction in unexplained variance when including discharge was negligible.

2.3 Site specificity of the TSS-Turbidity relationship

Variations in particle size distributions and hydrological characteristics across watersheds, and even among similar sites within a watershed, provide evidence that the TSS-Turbidity relationship is site specific. Many other studies have arrived at this same conclusion (Jones et al., 2011; Christensen, 2001; Ryberg, 2006; Rasmussen, Lee, and Ziegler, 2008). In a departure from this rationale, Hyer et al. (2015) investigated the potential of developing a regional regression model for the Commonwealth of Virginia. Suspended sediment and turbidity data from 29 USGS monitoring stations within Virginia were used to develop site specific regression models. Slopes and intercepts of the site specific models were then compared to the overall mean slope and intercept values by comparing the 99 percent confidence interval of the site specific models to the 99 percent confidence interval of the overall mean slope and intercept. The authors found no significant difference between 19 of the site specific values and the overall mean slope and intercept. While the authors acknowledge the fact that 10 of the study sites were significantly different from the proposed regional model, no detailed explanation as to why is given. The sites selected for this study varied spatially both in relation to physiographic province and watershed size, which may explain the dissimilarity between some of the specific sites and the regional model.

2.4 TSS-Turbidity relationship in relation to land use and seasonality

Regression equations for suspended solids have been developed with success for both urban and rural watersheds of varying sizes. Data from several USGS monitoring sites in the city of Atlanta, GA were used to construct site specific regression equations for suspended solids with turbidity as the sole explanatory variable (Horowitz, 2009). While the derived relationships were similar between sites in the city, the author notes that they are not interchangeable. Settle et al. (2007) examined surrogate parameters for suspended solids in an urban and urbanizing basin using a multivariate approach and found that in addition to turbidity, specific conductance and pH were correlated with suspended solids concentration, and may warrant inclusion in regression models describing urban watersheds. During storm events in urban watersheds characterized by a large percentage of impervious areas, both specific conductance and pH decrease in response to the large volume of impervious surface runoff entering urban streams (personal observation).
Using a rainfall simulation apparatus situated over a section of actual road, Miguntanna et al. (2010) emulated stormwater runoff conditions and found turbidity to be strongly correlated with TSS.

Of the several thousand hydrological monitoring stations the USGS maintains across the nation, several are part of ongoing studies relating continuous monitoring parameters to select water quality constituents. Rasmussen (2008) examined surrogate parameters for several watersheds representing urban, urbanizing, and rural land uses, and found turbidity alone to be a significant predictor of total suspended solids. Similarly, Christensen (2001) developed regression equations for a large watershed characterized by forest and agriculture with turbidity solely as the explanatory variable. Jones et al. (2011) collected data at a USGS gaging station in a large watershed dominated by agricultural land use and investigated surrogate parameters for total suspended solids, including categorical variables representing seasonality. Their results indicated that total suspended solid concentrations were not correlated with spring snowmelt conditions – unlike total phosphorus. For several sites ranging from 20 to 96 percent urban land use in Wisconsin, Baldwin et al. (2012) constructed regression models using turbidity alone as the best predictor of TSS. Interestingly, water temperature and sine Julian Day were significant explanatory variables in their initial model development – suggesting a seasonal component to TSS concentration – however both variables only slightly decreased variability in the model, and thus were excluded from the final regression model for simplicity.

It is evident that turbidity by itself is often determined to be the main predictor of suspended sediment, yet various studies highlighted above have included additional parameters in the regression model. The inclusion of other variables such as discharge or stage seems to depend on the particular hydrological characteristics of individual catchments. For three Chesapeake Bay tributaries in Virginia, Jastram et al. (2009) found a regression model involving turbidity and discharge to be the best estimator of suspended solid concentrations. Lee et al. (2012) reported similar results when evaluating explanatory variables for suspended sediment in Houston, Texas. The general suggested procedure for building a surrogate relationship via regression methods is to sequentially evaluate parameters for significance starting with turbidity and subsequently including parameters that may further explain variance in the model (Helsel and Hirsch, 2002). The inclusion of additional parameters other than turbidity in the regression
model appears to be dependent on the individual hydrologic characteristics of a watershed, which may be influenced by land use (Lee et al., 2012).

3. Methods

The overall goal of this report was to develop a predictive tool to estimate total suspended solids using turbidity, and possibly other continuously monitored parameters, using regression methods. The following sections provide background information on characteristics of the Webb Branch watershed, field instruments used at the LEWAS field site for continuous environmental monitoring, TSS sampling and analysis procedures, and statistical regression techniques applicable to the development of surrogate relationships.

3.1 Study Site: Webb Branch Watershed

The Webb Branch watershed (2.78 km$^2$) is a sub-watershed of the Stroubles Creek watershed (24.76 km$^2$) located in Blacksburg, VA (Figure 3.1). The Webb Branch watershed is located in the upper portion of the Stroubles Creek watershed with its headwaters originating in the Town of Blacksburg and flowing into a retention pond, known as the Upper Duck Pond on the VT Campus before emptying into Stroubles Creek. Webb Branch is one of two first order streams contributing flow to the VT Duck Ponds and ultimately to Stroubles Creek. The Webb Branch watershed is 95% urbanized with a significant portion of the stream flowing underground and is heavily influenced by runoff from impervious surfaces during storm events. Consequently, the stream experiences higher peak flows, more frequent overtopping of its banks, and increased erosion.

The section of Stroubles Creek beginning below the Lower Duck Pond and extending to the downstream confluence with Wall’s Branch is currently listed as impaired on the state’s 303(d) list by the Virginia Department of Environmental Quality (VDEQ, 2014). This section is impaired for benthic macroinvertebrates and $E. coli$. Sediment has been identified as the primary stressor for benthic macroinvertebrates (VDEQ, 2003). A TMDL implementation plan was developed in 2006 to reduce sediment loading to the stream (VDEQ, 2006). Macroinvertebrate sampling combined with grab samples of turbidity, total solids, and total suspended solids were included in the monitoring program to assess the effectiveness of BMPs designed to reduce sediment input to Stroubles Creek, outlined in the implementation plan. The ability to estimate sediment loadings to Stroubles Creek based on continuous in situ measurements would be a
valuable tool in understanding how construction or land disturbance activities contribute to the deterioration of Troubles Creek, and also in gauging the effectiveness of stormwater measures designed to reduce sediment loading.

Figure 3.1. (a) Troubles Creek watershed and associated land cover (b) Webb Branch watershed and drainage network contributing flow to Webb Branch (Raamanathan, 2014).

3.2 Field Instruments

The LEWAS lab employs a variety of monitoring equipment at the field site, located adjacent to West Campus Drive upstream of the Upper Duck Pond (Figure 3.2). Field instruments are powered by solar panels and are also tied into the Virginia Tech grid power network as a means of auxiliary power. A Raspberry Pi micro-computer, housed in a control box at the field site, transmits data from equipment sensors over the wireless network to a server database on campus. The OWLS application retrieves data from the database, displaying it to the end user.

The LEWAS site utilizes an Acoustic Doppler Current Profiler (ADCP) as a primary means of stream discharge measurement and an Ultrasonic Level Sensor as a secondary means of
discharge measurement. The ADCP is an Argonaut ADCP-SW unit mounted to a concrete base and staked into the stream bed. Prior research (Rogers, 2013) established that the index velocity

Figure 3.2. Above ground reach of Webb Branch between the culvert running underneath West Campus Drive and the Upper Duck Pond. Photograph (March 2016) is looking downstream.

method was suitable for computing discharge at the site location. The ADCP also provides a stage reading. The stream cross section at the ADCP location is surveyed on a yearly basis and evaluated against past data to discern if any significant changes in cross section geometry have occurred which would warrant a new index velocity rating. A Global Water WL705-003 Ultrasonic Water Level Sensor housed in a section of PVC piping is attached to the inside wall of the upstream culvert, approximately 15 ft behind the culvert outlet. A trapezoidal weir acts as a flow controlling structure located at the outlet of the culvert. Stage measurements from the Ultrasonic Level Sensor are used in conjunction with an empirically derived weir equation to
compute discharge (equation 3.1). Measurements are recorded at a 1 minute sampling frequency for both the ADCP and Ultrasonic Level Sensor.

\[ Q = 10.867h^2 - 8.8104h + 2.3178 \]  

where:

- \( Q \) = Discharge (cfs)
- \( h \) = Stage behind the weir (ft)

Weather measurements at the site are obtained by a Vaisala WXT520 weather transmitter and a Weathertronics 6010 tipping bucket rain gauge. The Vaisala WXT520 measures wind speed, wind direction, rainfall intensity, hail intensity, humidity, and barometric pressure at a 1 minute sampling interval. The tipping bucket rain gauge records rainfall at a 0.01 inch resolution.

A Hydrolab MS5 multiprobe sonde, mounted in the thalweg of the channel, measures water quality parameters. The MS5 sonde is equipped with sensors to measure turbidity, pH, specific conductance, temperature, pH, and oxidation reduction potential (ORP) at a 3 minute sampling interval. The sonde is calibrated approximately every 2-3 weeks, depending on the season and the potential for sensor fouling. The turbidity sensor is a self-cleaning ISO 7027 compliant unit (90° detector with near IR wavelength) which measures turbidity in Nephelometric Turbidity Units (NTU) with an upper limit of 3000 NTU (Figure 3.3). Sensor accuracy and resolution details are listed in Table 3.1. During calibration, the sensor is calibrated with an 800 NTU Formazin standard solution.
Figure 3.3. Self-cleaning turbidity sensor installed in the Hydrolab MS5 sonde.

Table 3.1. Hydrolab self-cleaning turbidity sensor technical data.

<table>
<thead>
<tr>
<th>Range</th>
<th>0 - 3000 NTU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>± 1% 0 - 100 NTU</td>
</tr>
<tr>
<td></td>
<td>± 3% 100 - 400 NTU</td>
</tr>
<tr>
<td></td>
<td>± 5% 400 - 3000 NTU</td>
</tr>
<tr>
<td>Resolution</td>
<td>0.1 NTU 0 - 400 NTU</td>
</tr>
<tr>
<td></td>
<td>1 NTU 400 - 3000 NTU</td>
</tr>
</tbody>
</table>

3.3 TSS Sampling and Analysis

Water samples were manually collected by grab sampling at the LEWAS field site over a variety of hydrological conditions between November 2015 and February 2016. Discrete, single point samples were collected as near to the *in situ* multi probe sonde as possible. The single point sample technique was chose over width-integrated or depth-integrated sampling techniques due to the small size of the stream. Moreover, for the nearby Roanoke River, Jastram et al. (2010) found the difference in suspended sediment concentration between equal-width-interval and
single point techniques to not be significant. Samples were collected no shorter than 15 minutes apart at intervals corresponding with turbidity measurements. The 15 minute sampling interval is consistent with studies carried out by the USGS and others; serial correlation issues are typically not encountered. Attempts were made to capture as many storm events as possible over the sampling time period. In total, 9 discrete runoff events were captured with multiple samples collected during each event. Of the 9 events sampled, two correspond to snowmelt runoff entering the stream in large quantities. The number of discrete samples collected totaled 27. For quality control, 3 duplicate samples were collected over the course of the entire sampling period. The rule of thumb for sediment sampling is to incorporate one duplicate or replicate sample for every 10 samples in the sampling regime (Edwards and Glysson, 1999). Relative percent difference for each duplicate sample was calculated with an overall mean of 7.2%.

Determination of TSS (mg/L) was conducted according to Standard Methods 2540D using Whatman 934-AH glass fiber filters (Rice et al., 2012). Samples were stored at 4°C for no longer than 7 days in accordance with procedures outlined in Standard Methods 2540D. The longest time period a sample was stored prior to TSS analysis was 6 days. Field parameters corresponding to TSS sample times were downloaded from the LEWAS database and stored in an excel spreadsheet along with the relevant TSS values. Data for TSS and corresponding continuously monitored parameters can be found in Table A1.

3.4 Statistical Methods

Surrogate relationships relate one or more easily measured variables to a variable or constituent of interest and are generally based on statistical regression techniques. The most common type of regression demonstrated in the literature is linear regression. To ensure a linear regression model was the appropriate form, a scatterplot correlation matrix of the data (Figure 3.4) was investigated to discern the relationship between all continuously monitored parameters and TSS. Previous studies have characterized TSS as being strongly correlated with turbidity. Visual analysis of the correlation matrix revealed a clear linear correlation between turbidity and TSS. All statistical procedures were performed with the R statistical programming environment (https://www.r-project.org).
Simple linear regression and multiple linear regression were both used to construct models to estimate TSS. Both procedures rely on the method of least squares to minimize the total variance of the resulting model. Simple linear regression attempts to explain or predict the response variable using only one explanatory variable. The general form of the linear regression model is described by equation 3.2.

\[ y_i = \beta_0 + \beta_1 \times x_i + e_i \quad i = 1, 2, 3 \ldots n \]  \[3.2\]

where:
- \( y_i \) represents the \( i^{th} \) observation of the response variable
- \( \beta_0 \) represents the intercept
- \( \beta_1 \) represents the coefficient of the explanatory variable
- \( x_i \) represents the \( i^{th} \) observation of the explanatory variable
- \( e_i \) represents the residual error associated with the \( i^{th} \) observation
- \( n \) represents the number of observations included in the sample
Multiple linear regression is an expansion of simple linear regression, allowing for more than one explanatory variable. Multiple linear regression is useful for predicting observations that are correlated with two or more independent variables or for the inclusion of categorical variables. The general form of the multiple linear model is similar to that of the simple linear model, and is given in equation 3.3.

\[ y_i = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 ... \beta_k * x_k + e \quad i = 1,2,3 ... n \]  

[3.3]

where the terms used are identical to those described for simple linear regression with the addition that \( k \) represents the number of explanatory variables in the model.

For both simple and multiple linear regression, several statistical assumptions regarding the residual errors must be met in order for the regression model to be deemed valid (Hirsch and Helsel, 2002). The residual errors must be normally distributed, have constant variance (homoscedasticity), be independent (i.e., not exhibit serial correlation), and have a mean of zero. Violating any of these assumptions can lead to errors in estimates of coefficients, confidence intervals, or could indicate model misspecification.

Although there are two general approaches to linear regression model building, the approach most applicable to developing surrogate relationships is to start with the simplest model, utilizing only one explanatory variable, and then proceed through a sequence comprised of evaluating other variables for potential inclusion in the model. It is important to let the data guide the regression analysis, and to not attempt to erroneously fit the data to a preconceived form or expectation. However, there is a difference between statistical significance and practical significance, and this should influence the analysis; variables evaluated for inclusion in the regression model should exhibit some physical relationship to the response variable (i.e., one might choose to include discharge or water temperature over air temperature or barometric pressure).

Initially, simple linear regression was performed to determine if turbidity alone could adequately estimate TSS. A diagnostic check of the residual errors revealed non-constant variance among the residuals, visually evident in a plot of the fitted values vs residuals. A log10 transformation of both TSS and turbidity resulted in constant variance among the residuals. Data transformations of the response variable, explanatory variable, or both are a common method used to eliminate non-constant variance. Moreover, of the available transformations (e.g., square root, natural log, reciprocal, etc.), the log10 transformation is common in water resources and
has been employed in many surrogate relationship equations (Helsel and Hirsch, 2002). Cook’s distance and leverage values were assessed to identify potential outliers; no extreme outliers were evident. Normality of the residuals was confirmed via a Q-Q plot, and a correlation test of the lagged residuals, using Kendall’s tau, revealed no serial correlation. Diagnostic plots of the residual errors are located in the Appendix.

Multiple regression was then explored to determine if the addition of other variables reduced total variation in the model compared to using turbidity as the only explanatory variable. Stream flow, stage, specific conductance, and water temperature were all significant in the regression equation when included individually with turbidity. Specific conductance was highly correlated with discharge and stage, resulting in multicollinearity within the model. Multicollinearity in the explanatory variables can affect the variance of the coefficients and reduce the statistical power of the model. Thus, any model form containing both specific conductance and discharge or stage was ruled out. The inclusion of stream temperature, in addition to turbidity and discharge or stage, only slightly increased the explanatory power of the model and thus was eliminated. Turbidity and discharge or stage were investigated for multicollinearity, because discharge and turbidity are typically correlated, but the variance inflation factors were low. In summary, the inclusion of either stage or discharge as an explanatory variable, in addition to turbidity, improved the explanatory power of the model when compared to simple linear regression using turbidity alone as the predictor variable. Finally, assumptions associated with the residual errors of both multiple regression models were checked, via residual diagnostic plots, and found to be consistent with those of a valid linear regression model. Again, diagnostic plots of the residual errors are located in the Appendix.

The root mean square error (RMSE) and predicted residual error of the sum of squares (PRESS) statistic were computed for each regression model and used to identify the model with the best prediction capabilities. The PRESS statistic is a form of leave-one-out cross validation, typically used on small data sets where a “test” data set is not available, and is commonly used by the USGS to evaluate predictive capabilities. An often overlooked component of statistical regression is assessing how well the regression model performs in predicting the response variable from future observations – observations not included in the sample data used to estimate the model. While the coefficient of determination ($R^2$) is a good measure of how well the regression model fits the sample data, it cannot provide any insight into how well the model fits
other data sampled from the same population. The danger in assuming that a model with a high \( R^2 \) possesses good prediction capabilities is that the model may merely be over fit to the sample data, and in reality, is a poor predictor of future observations.

4. Results and Discussion

4.1 Final regression models

The final regression equations resulting from both the simple linear regression and multiple regression, along with respective coefficient of determination values are listed in Table 4.1. Intercepts and slope coefficients were all significant at the 95% confidence level. Table 4.2 summarizes the range of values for the parameters employed in the regression analysis. Comprehensive regression outputs for each equation are listed in the Appendix.

![Table 4.1 – Summary of final regression equations.](image)

<table>
<thead>
<tr>
<th>Regression Equation</th>
<th>Adj. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) ( \log_{10}(TSS) = -0.92574 + 1.33816 \times \log_{10}(\text{Turb}) )</td>
<td>0.909</td>
</tr>
<tr>
<td>(2) ( \log_{10}(TSS) = -0.8522 + 1.0573 \times \log_{10}(\text{Turb}) + 0.4695 \times \log_{10}(Q) )</td>
<td>0.941</td>
</tr>
<tr>
<td>(3) ( \log_{10}(TSS) = -0.71229 + 1.07039 \times \log_{10}(\text{Turb}) + 1.23408 \times \log_{10}(S) )</td>
<td>0.949</td>
</tr>
</tbody>
</table>

where:

- \( \text{TSS} = \) Total Suspended Solids (mg/L)
- \( \text{Turb} = \) Turbidity (NTU)
- \( \text{Q} = \) Discharge (cfs) computed from the Ultrasonic Level Sensor via eq. 3.1
- \( \text{S} = \) Stage (ft) computed by the ADCP

![Table 4.2 – Range of values for the explanatory variables.](image)

<table>
<thead>
<tr>
<th>Variable/Parameter</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turbidity</td>
<td>22.6 – 449 NTU</td>
</tr>
<tr>
<td>Discharge</td>
<td>4.4 – 38.4 cfs</td>
</tr>
<tr>
<td>Stage</td>
<td>1.26 – 3.14 ft</td>
</tr>
</tbody>
</table>

All three models were assessed for goodness-of-fit parameters and prediction capabilities. The PRESS statistic for each model, in the order listed in table 4.1, was 0.67, 0.45, and 0.38.
smaller PRESS statistic indicates stronger predictive performance, as it encapsulates the error between the regression equation and a future response variable observation (i.e., a future TSS observation). The RMSE for each model was 0.148, 0.117, and 0.109, respectively. The RMSE is the best unbiased estimator of the standard deviation of the residual errors. Although discharge and turbidity are often correlated with each other, the calculated variance inflation factor (VIF) between the two was 2.24. A VIF equal to 1 indicates no correlation between variables while a VIF greater than 5 suggests a moderate to strong degree of correlation, indicating multicollinearity (Hirsch and Helsel, 2002). The VIF for turbidity and stage was 1.92.

4.2 Comparison of regression models

Figure 4.1 shows plots of predicted vs actual TSS (mg/L) values for the three respective regression models, along with a 1:1 line. Points above the 1:1 line represent data points where the respective regression equation overestimates TSS and points below the line represent data points where the regression underestimates TSS.

Figure 4.1. Comparison of (a) actual vs predicted TSS values for model (1) with turbidity as the explanatory variable, (b) actual vs predicted values for model (2) with discharge and turbidity as explanatory variables, and (c) actual vs predicted values for model (3) with stage and turbidity as explanatory variables.

Both of the multivariate models (2 and 3) represent a reduction in total variance and improved predictive capabilities when compared to the univariate model. This is evident by the respective $R^2$ and PRESS statistic values, which are expressed graphically in the plots of actual vs predicted TSS (Figure 4.1). While turbidity by itself could be considered an adequate estimator of TSS, its predictive power is improved by the addition of either stage or discharge
variables. The strength of the correlation between TSS and turbidity depends on whether or not particle size is constant across varying turbidity values. If particle size differs across turbidity values then that represents additional unexplained variance within the regression model. If the change in particle size is assumed to be a function of discharge, since higher velocities associated with greater discharges exert a greater shear stress on the stream bed and banks, then a multivariate model containing either stage or discharge may account for this additional unexplained variance, reducing total variation within the regression model. While the multivariate models do not seem to differ greatly, their similarity is readily explained by the correlation between stage and discharge. Discharge is a function of stage, naturally, and either variable should be expected to exhibit relatively the same reduction in total variance.

A multivariate form containing either variable was presented in the results analysis for versatility of use. At present, discharge calculated from stage measurements taken by the Ultrasonic Level Sensor is the most reliable method of calculating discharge at the LEWAS field site, due to the fact that a weir equation was derived using a scale model of the trapezoidal weir located at the outlet of the culvert. Intense flooding during the summer of 2015 caused large changes in the stream cross section at the location of the ADCP. Consequently, a new index-velocity rating is needed to accurately relate velocity measured by the ADCP to stream discharge. Moreover, the current index-velocity rating produces noisy discharge data compared to flow computations from Ultrasonic Level readings. This may be a result of low flows at baseflow and eddying motions. Discharge calculated from the ADCP would have undoubtedly introduced error into the regression equation. The inaccuracy of ADCP discharge measurements, when compared to the Ultrasonic Level Sensor, is shown in Figure 4.2
Stage readings from the ADCP exhibit less noise over time and were deemed more reliable than discharge from the ADCP. The advantage of constructing two models, one relying on measurements from the ADCP and the other the Ultrasonic Level Sensor, is that they are auxiliary to each other. In the event that either instrument is intentionally removed, is fouled, or suffers downtime, an accurate estimation of TSS can still be made. Currently, it is suggested to use model (3) as the primary equation to estimate TSS since stage measurements from the ADCP can be readily accessed in real time. Moreover, the lower relative PRESS statistic associated with model (3) suggests it may perform better in predicting future TSS values.

4.3 Comparison of regression results to previous studies

The development of a univariate model that adequately relates turbidity to TSS and a multivariate model relating TSS to either stage or stream discharge is consistent with the results of other studies that have aimed to explore surrogate relationships for suspended sediment. Similar $R^2$ values (0.84 – 0.96) are reported in many of the studies discussed previously. While some studies have discovered that turbidity is the only significant predictor variable for TSS (Jones et al., 2011; Whiting, 2013; Grayson et al., 1996), or found that the addition of discharge
or stage to the regression model yields no further reduction in unexplained variance, others have
discovered a significant improvement in explanatory power when including discharge or stage
(Jastram et al., 2009; Jastram et al., 2010; Baldwin et al., 2012). The general explanation given
for this discrepancy is that the relationship between turbidity and discharge varies across
watersheds. For an individual storm event, peak turbidity may arrive before the peak of the
hydrograph, may coincide with peak discharge, or may lag behind the hydrograph – a
phenomenon known as hysteresis (Lawler et al., 2006). Moreover, the nature of hysteresis may
vary from storm event to storm event, even for an individual watershed (Gellis, 2013). This is
why in some cases discharge or stage is highly correlated with turbidity and in other cases, the
correlation is minimal. Jastram et al. (2009) and Jastram et al. (2010) showed that, for rivers in
the piedmont province of Virginia, the combination of the variables stage and turbidity was the
best estimator of suspended sediment.

While some studies (Jones et al., 2011; Jastram et al., 2010) have suggested a seasonal
relation to TSS, whether or not seasonality was a factor for estimating TSS in this study was
inconclusive. Specifically, it is correlations between TSS and water temperature or Julian day
which suggest that TSS concentration is influenced by season. Intuitively, this makes sense, as
higher discharges, which may suspend coarser particles, typically correspond with intense spring
and summer storms. Additionally, the nature of sediment supply may vary across seasons. In the
studies that have suggested a seasonal component to TSS flux, the sampling period spanned a
year or more. This study spanned November 2015 to February 2016, encapsulating late fall and
winter. A longer sampling period would be needed to reliably evaluate whether there is a
seasonality component to TSS flux.

4.4 Case study: Application of regression equation to estimate sediment load over a 24hr
time period

To demonstrate the practicality of the developed regression equations, model (2) and
model (3) were applied to continuous data for December 1, 2015, to estimate the sediment
loading over a 24 hour time period. A time series plot of discharge and turbidity is shown in
Figure 4.2.
Procedures followed for the computation of suspended sediment loading (SSL) are outlined in Rasmussen et al. 2009. Instantaneous TSS (mg/L) values were calculated by applying model (2) to the data set representing turbidity and flow observations sampled at a 3 minute interval, and transforming the values back into the original units of mg/L. A similar procedure was followed utilizing model (3), but with stage data instead of discharge data. Transformed values were then multiplied by Duan’s bias correction factor (eq. 4.2). Retransformation from log units to original units introduces a slight bias, usually causing the transformed values to be underestimated, due to the fact that the transformation is not linear (Helsel and Hirsch, 2002). The bias arises from the fact that while the response estimate for a given set of input parameter values is a mean estimate of the response variable, retransformation into the original units of the response variable does not maintain this property, and the transformed response is now an approximate median estimate of the response variable (Duan, 1982). Bias correction factors corresponding to each model are given in table 4.3. Sediment loading for the entire day can be calculated from equation 4.1.
\[
SSL_{day} = \sum_{i=1}^{n} 28.3168 \frac{L}{ft^{3}} \frac{(TSS_{i} + TSS_{i-1})}{2} \frac{(Q_{i} + Q_{i-1})}{2} \frac{(t_{i} - t_{i-1})}{10^{6} mg} \tag{4.1}
\]

where:

- \(SSL_{day}\) = Sediment loading for the day in kg
- \(TSS_{i}\) = TSS (NTU) at \(t_{i}\)
- \(TSS_{i-1}\) = TSS (NTU) at \(t_{i-1}\)
- \(Q_{i}\) = Discharge (cfs) at \(t_{i}\)
- \(Q_{i-1}\) = Discharge (cfs) at \(t_{i-1}\)
- \(t_{i}\) = Time (sec) at \(t_{i}\)
- \(t_{i-1}\) = Time (sec) at \(t_{i-1}\)

Estimated sediment transported over the entire day was 1236 kg and 1135 kg for model (2) and (3), respectively (Figure 4.3). Percent difference between calculated loads was 8.5%.

![Figure 4.3. Estimated sediment load for Dec 1, 2015 using model (2) and (3).](image)

Table 4.3 – Bias Correction Factors for SSL Computations.

<table>
<thead>
<tr>
<th>Model</th>
<th>BCF</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>1.06</td>
</tr>
<tr>
<td>(2)</td>
<td>1.04</td>
</tr>
<tr>
<td>(3)</td>
<td>1.03</td>
</tr>
</tbody>
</table>
$$BCF = \frac{\sum_{i=1}^{n} 10^{e_i}}{n}$$ \quad [4.2]

Table 4.4 – Retransformed TSS Equations Back into Original Units.

<table>
<thead>
<tr>
<th>Model</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>( TSS = 0.126 \times Turb^{1.338} )</td>
</tr>
<tr>
<td>(2)</td>
<td>( TSS = 0.147 \times Turb^{1.057} \times Q^{0.470} )</td>
</tr>
<tr>
<td>(3)</td>
<td>( TSS = 0.200 \times Turb^{1.070} \times S^{1.234} )</td>
</tr>
</tbody>
</table>

where:
- \( TSS \) = Total Suspended Solids (mg/L)
- \( Turb \) = Turbidity (NTU)
- \( Q \) = Discharge (cfs) computed from the Ultrasonic Level Sensor via eq. 3.1
- \( S \) = Stage (ft) computed by the ADCP

4.5 Comparison of model 2 to a multivariate model developed by the USGS for the Roanoke River in Roanoke, Virginia

As part of the Roanoke River Flood Reduction Project in Roanoke, Virginia, the USGS monitored geomorphic response and suspended sediment transport in the Roanoke River to assess the effect of construction activity on the resident Roanoke Log Perch population, which is an endangered species (Jastram et al., 2015). Jastram et al. (2010) developed a surrogate relationship for suspended solids concentration (SSC) using 21 pairs of turbidity and stage data, collected over 9 stormflow events during a single year, at the Route 117 Bridge. While surrogate relationships are thought to be site specific Hyer et al. (2015) demonstrated that for some sites in Virginia, surrogate relationships are similar. The purpose of this section is to compare the surrogate relationship developed by the USGS for the Roanoke River with the corresponding multivariate regression model for Webb Branch.

While Roanoke and Blacksburg are located in the Valley and Ridge physiographic province and share much of the same underlying geology, the two locations differ in their watershed characteristics. The Webb Branch watershed in Blacksburg covers a very small area compared to the Roanoke River watershed which encompasses 912 km². The Webb Branch watershed is highly urbanized while land cover for the Roanoke River watershed is dominated by forest (70%), developed land (19.5%), and agriculture (9.5%). The Roanoke River experiences
much higher peak flows than Webb Branch and has the capacity to transport much higher sediment loads than Webb Branch. Additionally, the composition of sediment entering the Roanoke River may differ from that of Webb Branch. For instance, organic matter may make up a large portion of suspended solids in the Roanoke River because a large amount of its surrounding land cover is forest.

Despite the aforementioned differences, the models developed in this report are consistent with those found in Jastram et al. (2010). Suspended sediment was able to be accurately estimated \(R^2 > 0.9\) with turbidity alone as an explanatory variable, for both Roanoke and Blacksburg. Moreover, a multiple regression using both turbidity and stage decreased total variance within the regression model, evident by a lower relative PRESS statistic. Reasons explaining this were discussed in section 4.2. Table 4.5 compares the respective univariate and multivariate models for Blacksburg and Roanoke. Of particular note is the suspended solids analytical technique employed in the Roanoke study which analyzes suspended solids concentration (SSC). SSC and TSS are often used interchangeably, but they refer to slightly different analytical techniques for characterizing the concentration of fluvial suspended sediment. SSC refers to ASTM Method D 3977-97 while TSS refers to Standard Methods 2540D. The main difference between these two analytical methods is that SSC is a measure of the total amount of suspended solids in a sample volume while TSS is a measure of the suspended solids in an aliquot (typically 100 mL) taken from a sample volume. An in-depth investigation into the differences between TSS and SSC can be found in Gray et al. (2000). Additionally, the authors of the Roanoke study used a natural log data transformation instead of the typical log10 transformation commonly seen in USGS studies. The reason for this was that the natural log transformation is required by the USGS software LOADEST. LOADEST is a USGS Fortran program for estimating constituent loads using regression techniques (Runkel et al., 2004).
Table 4.5. Comparison of suspended sediment regression equations developed by the USGS for Roanoke, VA and the equations developed herein for Blacksburg, VA.

<table>
<thead>
<tr>
<th>Type¹</th>
<th>Regression Equation</th>
<th>Adj. R²</th>
<th>PRESS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Blacksburg, VA</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SLR</td>
<td>$\log_{10}(TSS) = -0.92574 + 1.33816 \times \log_{10}(Turb)$</td>
<td>0.909</td>
<td>0.67</td>
</tr>
<tr>
<td>MLR</td>
<td>$\log_{10}(TSS) = -0.71229 + 1.07039 \times \log_{10}(Turb) + 1.23408 \times \log_{10}(S)$</td>
<td>0.949</td>
<td>0.38</td>
</tr>
<tr>
<td><strong>Roanoke, VA</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SLR</td>
<td>$\ln(SSC) = 0.2012 + 0.9863 \times \ln(Turb)$</td>
<td>0.921</td>
<td>1.38</td>
</tr>
<tr>
<td>MLR</td>
<td>$\ln(SSC) = 0.337 + 0.888 \times \ln(Turb) + 0.254 \times \ln(S)$</td>
<td>0.938</td>
<td>1.12</td>
</tr>
</tbody>
</table>

¹ Refers to the model type being simple linear regression or multiple linear regression

4.6 Challenges encountered during model development

Several challenges were encountered through the course of this project. As with any remote monitoring station, field sensors are subject to potential fouling. Due to the urban nature of the watershed, during storm events a large amount of debris comes through the culvert in the form of tree branches, miscellaneous trash, and debris from construction sites (personal observation). Efforts were made during data collection to keep the sonde frame, particularly the end extending below the water surface, free of trash and debris. This was to ensure high quality turbidity data. Moreover, typically after an intense storm, the sonde is removed from its housing, its sensors cleaned with a soft bristle brush, and the inside of the housing is also cleaned. During extreme flooding events (e.g., early June 2015) there is potential for sediment to become completely compacted in the void spaces inside the sonde housing. In these instances the pipe housing the sonde must be completely removed from the frame and the sonde must be gently dislodged from the sediment trapping it inside the pipe.

Due to the flashy nature of the stream, turbidity and discharge change extremely rapidly, especially during the rising limb of the hydrograph and pollutograph. To ensure that the time stamp of the TSS samples corresponded to that of the field instruments, a wristwatch was synced to Virginia Tech’s time server – the server which the Raspberry Pi uses to time stamp field measurements (https://vtluug.org/wiki/Network_Time_Protocol). This enabled TSS sampling to closely correspond with reported instrument measurements down to the second (approximately). A common explanation for observed outliers (i.e., abnormally high TSS value corresponding to a
low turbidity reading) across studies investigating surrogate parameters is that the sample
volume collected by the sampler is not representative of the volume of water passing across the
sensor at the time of sampling (Jones, 2008).

Perhaps the biggest obstacle during the course of this project report was monitoring a
known issue regarding the functioning of the turbidity sensor, specifically the self-cleaning
wiper. The specific ramifications for measured turbidity values are discussed in the subsequent
paragraph. The RS-232 communications protocol that the LEWAS is currently using to interface
with the field instruments does not allow for complete autonomous control of the sonde (Paul
Johnson, personal communication, Nov. 17, 2015). Under normal operating conditions as
defined in the Hydrolab user manual, the sonde is deployed in the field via ANSI mode with data
logging to the internal memory. In between measurements the sonde enters a sleep mode, to
minimize power consumption. The turbidity optical lens wiper is triggered by the sonde coming
out of sleep. In other words, the action to initiate a wiping cycle is not set by the specified
sampling interval but by the sonde exiting sleep mode, which is tied to the sampling interval.
This nuisance has ramifications when controlling the sonde remotely via the terminal using the
RS-232 protocol because the RS-232 protocol does not allow for control of sonde sleep/power
settings. The sonde cannot be deployed remotely using the RS-232 protocol. It can be powered
on, powered off, or rebooted, but it cannot be programmed to enter sleep mode, and the self-
cleaning wiping action cannot be initiated. This is the crux of the issue. The short term fix for
this issue is to simply manually deploy the sonde with a laptop via the Hydras3 software (ANSI
mode with data logging to the internal memory) at the field site each time the sonde is taken
offline for calibration. In a phone call to Paul Johnson at Hydrolab discussing the issue, three
long term solutions were suggested:

1. Switch to the SDI-12 communication protocol which allows for control of power settings
2. Write code that would run on the Raspberry Pi to kick the sonde into and out of TTY
   mode before each measurement
3. Install a power relay at the field site, effectively powering he sonde off and on before
each measurement
Option one is the most appropriate solution. Moreover, all the instruments at the field site are capable of using the SDI-12 protocol. Ideally, all the instruments should be switched over. The RS-232 protocol is better suited for situations where the field instrument is programmed using the manufactures software installed on a laptop. The SDI-12 protocol was specifically designed for environmental data acquisition (http://www.sdi-12.org), and is best suited for situations where programming access to the individual sensors is controlled by a data recorder (e.g., a Raspberry Pi).

When the turbidity sensor is not initiating a wiping cycle, reported turbidity measurements appear “stuck” at a fixed NTU value. Without a cleaning cycle, organic matter and sediment build up on the surface of the sensor (Figure 3.3). If this phenomenon goes unnoticed, turbidity readings at baseflow appear abnormally elevated and measurements for future storms appear inflated. Figure 4.3 illustrates the influence on the data of this phenomenon. At the beginning of the time period displayed, during baseflow conditions, turbidity values are already elevated, indicating the self-cleaning process is not being initiated before each measurement. There is a sizeable rainfall event during April 22\textsuperscript{nd} where the turbidity peak was greater than 600 NTU. This value is most likely inflated, compared to true conditions, due to elevated baseflow turbidity readings before the storm. During the descending limb of the hydrograph for this storm turbidity values decrease and then level off, appearing stuck at roughly 100 NTU. The sharp decrease in turbidity appearing during the 23\textsuperscript{rd} relates to the sonde being cleaned and redeployed via the Hydros3 software at roughly 15:30 hours. Turbidity readings subsequently return to zero and oscillate above zero for short time periods, indicating the self-cleaning process is being initiated.
While the phenomenon causing unreliable turbidity readings may appear to be a severe issue, it is one of the many unavoidable obstacles encountered when attempting to build a real-time continuous environmental monitoring system without off the shelf software. The lesson here is that the RS-232 protocol is not adequately suited for the LEWAS going forward if the system is going to progress and serve as a prototype model for other locations. Identifying these types of issues and correcting them will only add to the robustness of the LEWAS system as a prototype model for other interested parties currently interested in the system’s capabilities.

5. Conclusions

5.1 Conclusions

The goal of this project report was to examine the potential use of continuously monitored parameters measured at the LEWAS field site as surrogate parameters for estimating total suspended solids. Results of the regression analysis yielded three candidate linear models for estimating TSS: a univariate model utilizing turbidity as an explanatory variable and two multivariate models, one employing discharge in addition to turbidity – the other employing
stage in addition to turbidity. High R² values were observed for each model (> 0.9), however, both multivariate models possessed a lower PRESS statistic compared to the univariate model, indicating that they were better suited for predictive purposes. Other continuously monitored parameters, such as water temperature and specific conductance, were evaluated for significance in the model, but either there were problems of multicollinearity in the model or the addition of a third variable in the multiple regression did not greatly improve the explanatory power of the model.

The accuracy of estimated sediment loadings over time may be increased by the use of regression equations relating surrogate parameters to TSS. To illustrate the practicality of the regression models, sediment load for a 24 hour time period (Dec. 1, 2015) was calculated, using continuous (3 min interval frequency) data from the LEWAS database. A traditional TSS monitoring program utilizing a bi-weekly or monthly sampling frequency would greatly underestimate the annual load if this hydrologic event was missed. If regression equations can be coupled with continuous monitoring stations, watershed managers will have a much better picture of sediment transport through a basin. While it is unknown if surrogate parameters and the resulting regression equations will have any impact on TMDL regulatory criteria or TMDL evaluations, they represent a valuable tool to stormwater managers in gaining insight into a watershed process which was once difficult to characterize.

It is recommended that the regression equation described by model (3) be implemented into OWLS so that TSS may be continuously estimated; however, it is important to note the statistical limitations inherent in the regression equations. The regression equations were developed using a range of parameter values and using values outside those ranges is an extrapolation of the relationship between TSS and the surrogate parameters. Caution should be exercised in interpreting results from input values outside the parameter range of values used in the various regressions.

5.2 Future Work

For future work, it is recommended to extend the data set to encompass data from other seasons. There very well may be a seasonal component to TSS flux in Webb Branch, especially considering that the watershed is highly urbanized, half the town’s population leaves Blacksburg during the summer, and many grounds maintenance operations and landscaping activities occur during the summer. Moreover, data from extreme flood events would improve the overall quality
of the regression equations. Summer thunderstorms have the potential to create these high flood events. Future TSS data points could also be used to test or validate the three regression equations developed in this report.

There are also other surrogate relationships that could be developed for the LEWAS field site. Total Phosphorus (TP) has been shown to be moderately correlated with turbidity as a large portion of transported phosphorus in a watershed is carried by suspended sediment via P sorption onto sediment particles (Grayson et al., 1996; Jones et al., 2011). Although the procedure for analyzing TP is more involved than that for TSS, surrogate relationships have been developed with moderate to strong degrees of explanatory power (Jones et al., 2011). An investigation into surrogate parameters for TP at the LEWAS field site may be valuable because sensors for the continuous monitoring of TP or orthophosphate (soluble reactive phosphate) do not exist at present.

There are other technologies that have the potential to estimate TSS. Acoustic backscatter data from ADCP units have been used to estimate TSS with success (Gray and Gartner, 2009). ADCP backscatter is a function of the amount of suspended particles in the water column, and it is this property which allows it to be related to TSS. The use of ADCP units to estimate TSS is seen much less frequently in the literature compared to turbidity sensors. One of the primary reasons that optical turbidity sensors are used to develop surrogate relationships for TSS over ADCP backscatter data is cost. ADCP units are much more expensive than multiprobe water quality sondes or standalone turbidity sensors. Since the LEWAS field site utilizes both an ADCP and a water quality multiprobe, it may be worthwhile to develop a relationship for TSS based on ADCP backscatter data and compare that to the surrogate relationships developed in this report.
References


### Appendix

Table A1. Summary of TSS sample data and corresponding continuously monitored parameters.

<table>
<thead>
<tr>
<th>Date &amp; Time</th>
<th>Air Temp. (°F)</th>
<th>Barometric Pressure (inHg)</th>
<th>Stream Discharge (cfs)</th>
<th>Stage (ft)</th>
<th>Water Temp. (°F)</th>
<th>pH</th>
<th>Specific Conductance (μS/cm)</th>
<th>Dissolved Oxygen (mg/L)</th>
<th>Turbidity (NTU)</th>
<th>TSS (mg/L)</th>
</tr>
</thead>
<tbody>
<tr>
<td>11/07/15 11:09</td>
<td>59.7</td>
<td>30.05</td>
<td>4.82</td>
<td>1.38</td>
<td>63.2</td>
<td>7.93</td>
<td>416</td>
<td>8.25</td>
<td>39.4</td>
<td>26</td>
</tr>
<tr>
<td>11/07/15 11:27</td>
<td>57.2</td>
<td>30.07</td>
<td>4.77</td>
<td>1.37</td>
<td>63.1</td>
<td>7.89</td>
<td>409</td>
<td>8.18</td>
<td>38.3</td>
<td>18</td>
</tr>
<tr>
<td>11/07/15 11:51</td>
<td>56.3</td>
<td>30.07</td>
<td>4.44</td>
<td>1.33</td>
<td>62.4</td>
<td>7.9</td>
<td>476</td>
<td>8.19</td>
<td>22.6</td>
<td>9.6</td>
</tr>
<tr>
<td>11/07/15 13:48</td>
<td>52.3</td>
<td>30.06</td>
<td>4.92</td>
<td>1.38</td>
<td>62.3</td>
<td>7.83</td>
<td>340</td>
<td>8.23</td>
<td>41.7</td>
<td>12</td>
</tr>
<tr>
<td>11/07/15 14:06</td>
<td>52.7</td>
<td>30.06</td>
<td>4.48</td>
<td>1.34</td>
<td>61.7</td>
<td>7.84</td>
<td>403</td>
<td>8.27</td>
<td>26.2</td>
<td>10</td>
</tr>
<tr>
<td>11/09/15 10:11</td>
<td>40.1</td>
<td>30.28</td>
<td>6.08</td>
<td>1.48</td>
<td>52.4</td>
<td>8.01</td>
<td>318</td>
<td>9.95</td>
<td>144.9</td>
<td>73</td>
</tr>
<tr>
<td>11/09/15 10:29</td>
<td>40.1</td>
<td>30.29</td>
<td>7.63</td>
<td>1.63</td>
<td>51.8</td>
<td>8.01</td>
<td>296</td>
<td>10.07</td>
<td>108.6</td>
<td>52</td>
</tr>
<tr>
<td>11/09/15 10:47</td>
<td>40.1</td>
<td>30.28</td>
<td>7.44</td>
<td>1.63</td>
<td>52.1</td>
<td>8.01</td>
<td>354</td>
<td>9.88</td>
<td>56.5</td>
<td>39.5</td>
</tr>
<tr>
<td>11/09/15 11:05</td>
<td>40.2</td>
<td>30.28</td>
<td>7.44</td>
<td>1.62</td>
<td>52.2</td>
<td>8.01</td>
<td>367</td>
<td>9.78</td>
<td>49.7</td>
<td>32.5</td>
</tr>
<tr>
<td>11/09/15 14:53</td>
<td>44.6</td>
<td>30.15</td>
<td>11.21</td>
<td>1.90</td>
<td>52.1</td>
<td>7.85</td>
<td>174</td>
<td>9.90</td>
<td>74.4</td>
<td>42</td>
</tr>
<tr>
<td>11/09/15 15:08</td>
<td>44.9</td>
<td>30.15</td>
<td>12.50</td>
<td>1.97</td>
<td>52.2</td>
<td>7.87</td>
<td>191</td>
<td>9.87</td>
<td>72.7</td>
<td>36</td>
</tr>
<tr>
<td>11/18/15 22:50</td>
<td>58.6</td>
<td>30.06</td>
<td>33.45</td>
<td>2.90</td>
<td>57.2</td>
<td>8.08</td>
<td>141</td>
<td>9.30</td>
<td>171.9</td>
<td>220</td>
</tr>
<tr>
<td>11/18/15 23:05</td>
<td>58.5</td>
<td>30.06</td>
<td>37.21</td>
<td>3.01</td>
<td>57.0</td>
<td>7.87</td>
<td>91</td>
<td>9.30</td>
<td>242.3</td>
<td>294</td>
</tr>
<tr>
<td>11/18/15 23:29</td>
<td>58.4</td>
<td>30.06</td>
<td>38.38</td>
<td>3.14</td>
<td>57.0</td>
<td>7.68</td>
<td>67</td>
<td>9.37</td>
<td>128.4</td>
<td>150</td>
</tr>
<tr>
<td>12/01/15 13:38</td>
<td>47.3</td>
<td>29.97</td>
<td>8.21</td>
<td>1.64</td>
<td>51.8</td>
<td>7.7</td>
<td>322</td>
<td>9.62</td>
<td>40.5</td>
<td>9.6</td>
</tr>
<tr>
<td>12/17/15 14:39</td>
<td>52.5</td>
<td>29.68</td>
<td>7.19</td>
<td>1.52</td>
<td>53.0</td>
<td>7.67</td>
<td>248</td>
<td>9.52</td>
<td>36.2</td>
<td>12.4</td>
</tr>
<tr>
<td>12/17/15 15:39</td>
<td>53.2</td>
<td>29.68</td>
<td>5.49</td>
<td>1.35</td>
<td>53.5</td>
<td>7.74</td>
<td>311</td>
<td>9.47</td>
<td>24.4</td>
<td>10</td>
</tr>
<tr>
<td>01/27/16 14:45</td>
<td>39.0</td>
<td>30.03</td>
<td>4.97</td>
<td>1.26</td>
<td>46.6</td>
<td>8.13</td>
<td>1186</td>
<td>10.88</td>
<td>75.3</td>
<td>26.5</td>
</tr>
<tr>
<td>01/27/16 15:09</td>
<td>38.8</td>
<td>30.02</td>
<td>4.97</td>
<td>1.26</td>
<td>46.6</td>
<td>8.12</td>
<td>1211</td>
<td>10.82</td>
<td>97.8</td>
<td>27</td>
</tr>
<tr>
<td>02/01/16 18:09</td>
<td>NA</td>
<td>NA</td>
<td>8.55</td>
<td>1.62</td>
<td>48.0</td>
<td>7.82</td>
<td>991</td>
<td>11.09</td>
<td>193.1</td>
<td>96</td>
</tr>
<tr>
<td>02/03/16 16:26</td>
<td>51.9</td>
<td>29.79</td>
<td>8.96</td>
<td>1.67</td>
<td>48.1</td>
<td>7.67</td>
<td>478</td>
<td>11.23</td>
<td>40.1</td>
<td>12.5</td>
</tr>
<tr>
<td>02/03/16 16:50</td>
<td>52.3</td>
<td>29.80</td>
<td>8.41</td>
<td>1.63</td>
<td>48.3</td>
<td>7.69</td>
<td>503</td>
<td>11.19</td>
<td>35.2</td>
<td>12.5</td>
</tr>
<tr>
<td>02/24/16 14:19</td>
<td>60.6</td>
<td>29.29</td>
<td>26.01</td>
<td>2.40</td>
<td>48.7</td>
<td>7.6</td>
<td>221</td>
<td>11.13</td>
<td>449</td>
<td>396</td>
</tr>
<tr>
<td>02/24/16 14:34</td>
<td>61.7</td>
<td>29.28</td>
<td>21.77</td>
<td>2.27</td>
<td>49.2</td>
<td>7.58</td>
<td>248</td>
<td>11.00</td>
<td>338.4</td>
<td>260</td>
</tr>
<tr>
<td>02/24/16 14:49</td>
<td>62.0</td>
<td>29.27</td>
<td>18.33</td>
<td>2.16</td>
<td>49.5</td>
<td>7.59</td>
<td>280</td>
<td>10.95</td>
<td>258.1</td>
<td>178</td>
</tr>
<tr>
<td>02/24/16 15:37</td>
<td>63.6</td>
<td>29.22</td>
<td>12.75</td>
<td>1.90</td>
<td>50.5</td>
<td>7.63</td>
<td>372</td>
<td>10.72</td>
<td>131.4</td>
<td>80</td>
</tr>
<tr>
<td>02/24/16 16:07</td>
<td>64.0</td>
<td>29.21</td>
<td>9.87</td>
<td>1.75</td>
<td>50.8</td>
<td>7.66</td>
<td>434</td>
<td>10.63</td>
<td>97.5</td>
<td>51</td>
</tr>
</tbody>
</table>
Table A2. Summary of regression output parameters for simple and multiple linear regression models.

<table>
<thead>
<tr>
<th></th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Response variable</td>
<td>logTSS</td>
<td>logTSS</td>
<td>logTSS</td>
</tr>
<tr>
<td>logturb</td>
<td>1.33816 ***</td>
<td>1.0573 ***</td>
<td>1.07039 ***</td>
</tr>
<tr>
<td>Std. Error</td>
<td>(0.08282)</td>
<td>(0.1001)</td>
<td>(0.08631)</td>
</tr>
<tr>
<td>logQ</td>
<td>---</td>
<td>0.4695 ***</td>
<td>---</td>
</tr>
<tr>
<td>Std. Error</td>
<td></td>
<td>(0.1245)</td>
<td></td>
</tr>
<tr>
<td>logS</td>
<td>---</td>
<td>---</td>
<td>1.23408 ***</td>
</tr>
<tr>
<td>Std. Error</td>
<td></td>
<td></td>
<td>(0.27510)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.92574 ***</td>
<td>-0.8522 ***</td>
<td>-0.71229 ***</td>
</tr>
<tr>
<td>Std. Error</td>
<td>(0.15992)</td>
<td>(0.1308)</td>
<td>(0.12944)</td>
</tr>
<tr>
<td>Observations</td>
<td>27</td>
<td>27</td>
<td>27</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.9126</td>
<td>0.9451</td>
<td>0.9525</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.9091</td>
<td>0.9406</td>
<td>0.9485</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>0.154 (df = 25)</td>
<td>0.1246 (df = 24)</td>
<td>0.1159 (df = 24)</td>
</tr>
<tr>
<td>F Statistic</td>
<td>261.1 ***</td>
<td>206.8 ***</td>
<td>240.5 ***</td>
</tr>
<tr>
<td></td>
<td>(df = 1; 25)</td>
<td>(df = 2; 24)</td>
<td>(df = 2; 24)</td>
</tr>
</tbody>
</table>

Note: " * " p-value < 0.05 ; " ** " p-value < 0.01 ; " *** " p-value < 0.001
Figure A1. Model 1 diagnostic plots of the residual errors.

Figure A2. Plot of the residuals vs lagged residuals for model 1. Kendall’s rank correlation $\tau$ p-value = 0.1131 ($H_0 : \text{correlation coefficient} \neq 0$).
Figure A3. Model 2 diagnostic plots of the residual errors.

Figure A4. Plot of the residuals vs lagged residuals for model 2. Kendall’s rank correlation $\tau$ $p$-value $= 0.06365$ ($H_0 : \text{correlation coefficient} \neq 0$).
Figure A5. Model 3 diagnostic plots of the residual errors.

Figure A6. Plot of the residuals vs lagged residuals for model 2. Kendall’s rank correlation \( \tau \) p-value = 0.2545 (\( H_0 \) : correlation coefficient \( \neq 0 \)).