ABSTRACT

EL-KHOURY, LAYLA CONSOLO. Validating Positive Openness Raster Data for Indicating Locations of Streambed Incision and Streambank Erosion. (Under the direction of Dr. Barbara Doll).

Prioritizing streams for restoration and enhancement often requires surveying and assessing hundreds of miles of streams to identify the best suited locations. Fifty-two sites and three reaches in the Mine Creek watershed, Raleigh, NC were visited to test the US Geological Survey (USGS)'s positive openness geospatial data layer as a potential tool for identifying problem areas to target for restoration projects. This geospatial data identifies the locations of concave surfaces using high-resolution topographic data to calculate relief angles. The 52 sites were selected to represent a range of positive openness relief angles. Sites where the City of Raleigh recorded citizen reports of erosion were also considered in site selection. The presence or lack of erosion was verified at each location, and all erosion observed was classed as either mass wasting, unstable undercutting, surface scour, or no erosion. Bank Erosion Hazard Index (BEHI) assessments and Near Bank Stress (NBS) ratings were also conducted at all sites to assess erosion potential. Permanent cross-sections were established at seven of the individual sites exhibiting the most severe erosion. The cross sections were surveyed at the start of the study and again one year later to quantify lateral erosion rates.

Statistical analyses were conducted to evaluate relationships between the positive openness value, the presence and type of erosion, and individual BEHI and NBS streambank erosion potential variables. Statistical analysis revealed that PO value was useful in identifying locations of mass wasting and undercutting of streambanks, which represent more extreme erosion conditions. PO value did not relate well to the total BEHI scores of streambank erosion potential. However, PO value did show some relationship with the field measured streambank

height. Statistical models were developed by combining measured bank heights and erosion rates with positive openness as the predictor variable to estimate a total load of sediment and nutrients carried downstream to Shelley Lake from the eroding banks. Results of this study indicate that the positive openness data layer may be useful for finding locations of erosion, which would assist with identifying potential sites in need of stabilization prior to field assessments, saving time and resources. The PO layer also appears to offers an approach for predicting sediment and nutrient loads at various spatial scales. The procedures developed by this study for estimating sediment loads and associated nutrient loads did not consider streambed and floodplain deposition, which are essential for estimating total loads transported to downstream waterways. However, the procedures should serve as a starting point for others. To further validate PO, more sites and reaches across a larger study area should be assessed, and more cross-sections should be established and monitored to strengthen the relationship between PO and erosion rates.

Validating Positive Openness Raster Data for Indicating Locations of Streambed Incision and Streambank Erosion

by
Layla El-Khoury

A thesis submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Master of Science

Biological and Agricultural Engineering

Raleigh, North Carolina
2022

APPROVED BY:

Dr. Barbara Doll
Committee Chair

Dr. Celso Castro-Bolinaga

Dr. Karl Wegmann

DEDICATION

This thesis is dedicated to my friends and family. To my mom (Nancy Consolo), dad (Habib El-Khoury) and sister (Yasmine El-Khoury), thank you for all of your support, encouragement and making me smile and laugh when I got overwhelmed. To my friends – Grace Mook, Emily Vickery, Emily Horowitz, LilyGrace Wolfe, Delaney Galvin and Alexa Simeonsson – thank you always being there for me and reminding me to take care of myself.

This thesis is also dedicated to all the dancers who were in my piece, *Force of Flows* – LilyGrace Wolfe, Rachel Morris, Maddy Kotyra, Kellsie Jennings, Athena He-DeMontaron, Delaney Galvin, Caroline Foy, Ariana Fajerman, and Rachel Crouse. Without you I would not have been able to merge my two passions of dance and stream restoration/ecological engineering together and share my research with such a large audience. Thank you to Tara Mullins for giving me the opportunity to choreograph a piece about my research.

A huge thank you to my advisor Dr. Barbara Doll. You gave me all of the tools, resources and opportunities to make this a successful thesis and experience. I am thankful for your support and encouragement to create a dance piece about my research. I could not have asked for a better advisor and mentor.

BIOGRAPHY

Layla El-Khoury was born in Raleigh, NC on June 11th, 1997. She grew up in Wake Forest, NC, graduating from Franklin Academy High School in 2015 as valedictorian. After attending one year at the University of Michigan, Layla transferred to North Carolina State University where she found her love for environmental and ecological engineering. She graduated magna cum laude with a B.S. in Biological Engineering with an environmental concentration in 2020.

When transferring to NC State, Layla was drawn to the Biological and Agricultural Engineering Department due to their extension work and research done in the department that directly benefits local communities and those abroad. Some of her undergraduate courses influenced her long-term career direction. She developed a keen interest for statistics and modeling in her Applied Statistics for Environmental Data Analysis class taught by Dr. Natalie Nelson. During lectures on fluvial geomorphology and stream restoration given by Dr. Barbara Doll, Layla knew that she found the area that she wanted to focus on. After graduating in May 2022, she accepted an offer to work with Dr. Barbara Doll in the Biological and Agricultural Engineering Department. After finishing her Master's degree, Layla will start working towards her PhD under Dr. Barbara Doll.

Since she was three years old, Layla has been dancing and started choreographing and teaching in 2016. When she started graduate school, she knew that she wanted to choreograph a piece about her research. In fall 2021, she choreographed a piece, *Force of Flows*, to educate the public on streambank erosion. It was performed by members of the State Dance Company.

ACKNOWLEDGMENTS

I would first like to acknowledge my advisor (Dr. Barbara Doll) and committee members (Dr. Karl Wegmann and Dr. Celso Castro-Bolinaga). Without them this research and thesis would not have been possible. I would also like to thank NC Urban Stormwater Consortium and City of Raleigh for funding this project.

A special thank you to my advisor Dr. Barbara Doll. I am thankful for all her advisement and providing me the opportunities to incorporate everything I am passionate about into this work. I have learned so much from her expertise and years of experience with the field work, writing and how to critically look at the data. I am grateful to her always being there to listen and provide direction when I needed it. I appreciate her constant optimism.

Jack Kurki-Fox has been a tremendous help both in the field and with the technical support. Without all of his help, we would have never been able to collect and process the data required. His expertise has been invaluable and I appreciate his realistic outlook.

A big thank you to Dr. Natalie Nelson. From all of her classes and working in her lab, I learned invaluable skills with how to clean, process, and visualize data in R. Without that skillset, processing this data would have been much harder.

Thank you to everyone at USGS – Krissy Hopkins, Charlie Stillwell and Laura Gurley. I truly appreciate all of their insight and guidance for how to extract the necessary data and allowing me to help with the start of their project. Without them, I would not have the higher resolution positive openness layer.

I would also like to thank Heather Dutra from the City of Raleigh Stormwater Program. Thank you to her for her insight about what would be most helpful to the City for prioritizing projects. Also thank you for providing feedback on the resources we put together.

Thank you to Megan Carr, Dana Mugisa, Alexis Swanson and Molly Landon, among others, for their constant support, encouragement and understanding.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: Introduction and Literature Reviews

Introduction

Excess sediment negatively impacts downstream waters by degrading instream habitats, reducing reservoir capacity, and increasing drinking water treatment facilities costs, among others impacts (DWER, 2000; U.S. EPA, 2017). Streambank erosion can be the most significant process contributing to in-stream sediment loads (Stott, 1997; Voli et al., 2013). Eleven studies reviewed by Purvis and Fox (2016) reported that eroding streambanks contributed 17 to 92% of total sediment loads. Similarly, Palmer (2014) reported that eroded streambanks could contribute as much as 51% of the annual sediment load. Streambed incision and associated bank failures can result in structural damage or failures that can become a public safety hazard (Simon and Rinaldi, 2006). In addition, excess sediment in streams has ecological impacts like covering spawning fish habitats, disturbing filter feeders, and decreasing the biodiversity of species, thus reducing ecosystem functions and services (Florsheim et al., 2008; Gage et al., 2004). Many cities and counties want to allocate water and stormwater fees towards stream restoration efforts to reduce erosion impacts to downstream reservoirs, public utilities and private property. As a result, they often seek to direct restoration efforts to streams with the greatest potential for reducing downstream sediment loads. Prioritizing streams for restoration often requires survey and assessment of hundreds of miles of streams to identify the best suited locations for restoration. Therefore, developing a systematic, efficient approach that maximizes desktop geospatial tools for identifying problem areas that can reduce effort and maximize their limited resources is essential. Further, better predicting erosion rates and identifying and verifying tools for quantifying streambank erosion volumes are needed.

With more than 29.7 miles of stream channel included on the U.S. Environmental Protection Agency's 303d list of impaired waterways in their jurisdiction, the City of Raleigh has initiated an Integrated Watershed Management Plan (IWMP) focused on identifying and prioritizing streams and riparian corridors for improvement. In addition, the City received 1711 erosion complaints from residents between 1986 to 2018 (City of Raleigh, 2020). With approximately 766 miles of streams included within their jurisdiction, it is imperative that the City develop a systematic, efficient approach for identifying problem areas that maximizes their limited resources.

In 2003, the City of Raleigh established a stormwater fee program that supports management, maintenance and repair of the stormwater system, including pipes, streams, lakes and dams. The goal is to improve the stability and health of the streams in order to reduce impacts on structures and infrastructure, improve downstream water quality, and reduce flooding risks and impacts. Desktop geospatial analysis tools combined with targeted field assessment protocols could aid the City in identifying target streams that are suffering the most erosion and subsequently degrading downstream water resources. However, manually assessing the condition of all of the City's streams would be prohibitive.

The US Geological Survey (USGS)'s recently developed 'positive openness' raster dataset for North Carolina is a potential desktop geospatial layer for identifying eroding streambanks. This geospatial data identifies the locations of concave surfaces using high-resolution topographic data to calculate relief angles (Rowley et al., 2018). Validation of the tool's ability to identify eroding and unstable streams in urban and suburban watersheds is needed as tree cover and structures may affect surface angle measurements. As the watershed with the greatest number of complaints in Raleigh, NC, Mine Creek watershed will be used to validate the positive openness layer. This project aimed to test the ability of the USGS positive openness data for identifying eroding streams in the Mine Creek watershed. If successful in this watershed, then this data could be added to the City's IWMP Program's Desktop Data Collection. In addition, if successful, this approach could be adopted and integrated across the state to provide a reproducible and more efficient method for identifying sources of streambank instability and sediment that may be contributing to the degradation of downstream waterways and resources.

Literature Review

Sediment Budgets

Urbanization increases impervious surfaces, which in turn alters the hydrology of watersheds. Higher peak flows and shorter lag times generate more energy from stormwater runoff-driven flows causing channel incision and widening (Hupp et al., 2013; Wohl et al., 2015). While sediment transport naturally occurs, the system can be knocked out of equilibrium if too much sediment moved or deposited, altering the ecosystem services provided (Florsheim et al., 2008; Hupp et al., 2013). Changes to the system can be detrimental such as the degradation of habitats (Florsheim et al., 2008; Gage et al., 2004) and increases in contaminants (i.e., sediment and nutrients) (Hopkins et al., 2018; U.S. EPA, 2017). Locating areas of severe erosion and deposition, and gauging the relative impact of channel instability as a source of sediment and nutrients is vital to developing a watershed management plan to address the impacts of sedimentation and eutrophication.

One way to examine the various sources and sinks of sediment dynamics within a watershed is through a sediment budget; however, there is no standardized methodology to construct a sediment budget. In addition, sediment transport varies greatly both spatially and temporarily making it challenging to measure sediment transport for a watershed and predict sediment loads. (Walling and Collins, 2008). In recent years, there has been an increased need for quantifying erosion at a watershed scale (Hopkins et al., 2018; Palmer et al., 2014; Purvis and Fox, 2016).

One method of constructing a sediment budget is tracing sediment by tracking radionuclides. Many studies using this methodology trace measurements of Cesium-137 (^{137}Cs), produced by testing nuclear weapons in the 1950s and 60s. This isotope can be detected up to 40 years later. Soil samples are collected at various locations throughout a study area to determine sediment distribution across the watershed (Walling and Collins, 2008).

Fingerprinting sediment is another approach used to build a sediment budget (Walling and Collins, 2008). Soil samples are collected across the watershed from possible sediment sources, along with suspended sediment samples. All samples are tested for concentrations of various elements on radionuclides to identify the sediment sources (Voli et al., 2013; Walling and Collins, 2008). Voli et al. (2013) used a Monte Carlo simulation to estimate the percentage contribution from each source. Radiocarbon dating of woody materials and sediment was used for estimating the age of alluvial deposits along streambanks (Voli et al., 2013).

Allmendinger et al. (2007) and Gellis et al. (2017) constructed sediment budgets by measuring erosion and deposition rates through the watershed and extrapolating the results based on stream order. Both studies used cross-sectional surveys to measure erosion but utilized the surveys differently. Allmendinger et al. (2007) used cross-sectional surveys to measure streambank erosion while Gellis et al. (2017) used them to document changes in the channel bed and floodplain. In contrast, Gellis et al. (2017) used erosion pins to measure erosion and deposition along streambanks.

Allmendinger et al. (2007) created a sediment budget for first-order streams to determine the sediment input into the Good Hope Tributary in Montgomery County, Maryland. The sediment budget was simplified to exclude sediment storage due to a lack of floodplains along the first-order streams. Upland erosion was estimated from regression and sediment stored on floodplains was estimated using dendrochronology (Allmendinger et al., 2007). The study found that floodplain storage, upland erosion and channel erosion were similar in magnitude in their contribution to the sediment budget.

In Difficult Run, Virginia, Gellis et al (2017) used powdered white feldspar clay as a field marker to measure deposition on floodplains. Multiple measurements were taken over the monitoring period including after Tropical Storm Lee and Super Storm Sandy (Gellis et al., 2017). The Gellis et al. study captures the influence of extreme events on sediment transport within the watershed, allowing the comparison of erosion rates under different hydrologic conditions. The difference between the measured input of sediments from the bed, streambanks and bars and sediment storage subtracted from measured sediment export was assumed to equal the amount of upland erosion (Gellis et al., 2017).

Noe et al. (2022) developed a watershed budget for the Chesapeake Bay watershed using various model predictions for streambank, floodplain, suspended sediment, TN and TP loads. Watershed attributes for the model were collected from geospatial data, while reach-scale geomorphometry of channels and floodplains was gathered from LiDAR. RUSLE2 was used to estimate upland erosion delivered to streams. Dendrogeomorphology was used to measure streambank erosion rates. Extensive data collection and monitoring were needed to develop the

Random Forest and SPARROW models to estimate the various pollutant loads to the Bay. (Noe et al., 2022).

Sediment budgets are constructed using various methods; however, they all have the same principle components: channel erosion, upland erosion and floodplain storage. Many variabilities within these principle components of sediment transport have yet to be fully understood or completely captured by models. There is a lot of uncertainty with identifying trends and patterns for erosion and deposition on varying temporal and spatial scales making it difficult to model (Walling and Collins, 2008). The temporal scale of the monitoring period is another important factor in capturing the dynamics of erosion (Florsheim et al., 2008; Palmer et al., 2014; Purvis and Fox, 2016). Longer monitoring periods allow a larger range of conditions to be experienced, i.e., wet and dry years, extreme storm evets like tropical storms and hurricanes, and land use changes. Palmer et al. (2014) noted wet versus dry years significantly impacted the annual sediment load. Longer monitoring periods will lead to a truer annual average erosion rate (Gamble, 2021; Palmer et al., 2014). Often, a few sites with measured erosion have been used to estimate erosion rates across an entire watershed, leading to an underestimation of sediment loads as found by Purvis and Fox (2016). New methods should be based on larger samples that spatially cover the entire watershed. A wider sample range will allow stronger relationships to be developed between measured streambank erosion and explanatory factors of erosion. If the explanatory factors are pulled from GIS data layers, then sediment loads can be estimated on a larger scale with minimal effort. Recent studies like the one by Noe et. al (2022) have taken advantage of geospatial layers to extract data for reaches on a larger scale. Utilizing geospatial layers reduces time, effort and resources to collect data that can be used to predict sediment loads compared to more traditional methods of quantifying and measuring erosion in the field.

Quantifying Streambank Erosion Rates

As many studies have discovered, streambank erosion can be a significant source of sediment (Gellis et al., 2017; Palmer et al., 2014; Purvis and Fox, 2016; Voli et al., 2013) but the specific contribution from streambanks may not be considered within models for sediment loads (Gellis et al., 2017). Many methods can be used to quantify streambank erosion, like physical measurements from the field or remote desktop methods.

Physical Measurements

Erosion rates are commonly measured using cross-sectional surveys and toe pins (Purvis and Fox, 2016). Electronic surveys of cross-sections can be performed with a total station that accurately measures specific points. The point density affects the resolution of the survey, where too few points cannot accurately capture streambank retreat. Undercut banks are difficult to survey with total stations and are not captured from digital elevation models (DEM); therefore, they are often ignored or excluded. Erosion pins can be installed at the toe of the bank or horizontally into the bank at specified intervals.

Myers et al. (2019) compared horizontal erosion pins and total station surveys to determine streambank erosion rates along Indian Mill Creek, Michigan. 2’ x 0.5” rebar pins were installed in each bank section with one pin for every 1 m of bank height. The total station was set on a control point with 3 mm accuracy. Undercut banks were surveyed by measuring the distance to the back of the undercut. At each 3 m interval along the 18 m sites, top and toe of the bank shots were taken along with two to three evenly spaced shots along the bank (Myers et al., 2019). The erosion pins had a lower spatial resolution than the total station survey. There was a 650% difference between the erosion pins and total station results. The total station data had an error of

5.5 cm due to the tripod sitting on an unstable muddy surface or recording errors. Both methods worked well on either vegetated or bare banks (Myers et al., 2019).

Horizontal erosion pins can be disturbed during bank erosion, resulting in overestimations of erosion rates (Myers et al., 2019). Toe pin studies are commonly used to measure bank erosion in small channels but are not well suited for watersheds greater than 10,000 km^2 due to time and cost (Williams et al., 2020a). As erosion pins are unable to capture spatial variations along banks, they are best for capturing erosion at specific points and unable to capture episodic streambank erosion but can be accurate to ± 3 mm (Purvis and Fox, 2016).

Remote Desktop Methods

Aerial imagery analysis is another method to quantify streambank retreat that is more conducive for larger watersheds and longer time periods. Seasonality affects the usefulness of aerial imagery. It can be nearly impossible to see the streambanks in images taken during leaf-on conditions, especially for smaller streams. The National Agriculture Imagery Program (NAIP) produces frequent surveys with sub-meter resolution useful to estimate streambank retreat, allowing streambank migration greater than 1 m to be detected. Aerial images should be selected so the migration change is greater than the spatial resolution of the images, which is often accomplished by using larger time intervals. This analysis is usually performed by hand through GIS software like ArcMap. Manually delineating stream banks typically produces highly accurate results but is time-consuming and leaves room for subjectivity, limiting the ability to replicate studies (Williams et al., 2020a). As technology continues to improve the resolution of aerial imagery will increase allowing studies to use shorter temporal scales and analyze smaller channels.

In a study by Purvis and Fox (2016), aerial imagery from the NAIP with 1 m resolution were analyzed in ArcMap 10. The top of banks were traced leaving out gravel bars. There was an estimated error of 1 m from georeferencing and bank identification. The sediment loading (kg/yr) was calculated by multiplying the eroded polygon area (m^2) by the depth of top soil (m) and soil bulk density (kg/m^3) (Purvis and Fox, 2016). A limitation of this method is the exclusion of gravel and point bars. The height of bars is lower than the bank height so if the bank height was used to account for that volume of deposited sediment it would overestimate it. If the bar heights were measured and a soil sample taken to determine bulk density then bars could be included in the analysis.

Williams et al. (2020) developed an automated Python and ArcPy model called Aerial Imagery Migration Model (AIMM) that produced migration maps and sediment volumes from streambank erosion for large watersheds. AIMM is the only package measuring morphodynamics and river characteristics to produce both migration maps and volume calculations. It requires four inputs: two aerial images, a digital elevation model (DEM) and a river centerline file. The depositional and erosional volumes of each area were calculated from multiplying each area by an estimated bank height from a DEM analysis. Bank height estimates for various polygon sizes were divided into quartiles where 20 were randomly selected for analysis. With nearly vertical eroding banks, bank height of erosion polygons was calculated by multiplying the standard deviation of elevation values by four in the eroding polygon. Depositional zone bank heights were estimated as the difference in median elevation in the depositional area since the geometry was uneven (Williams et al., 2020a). A limitation of the AIMM model is the estimation of the bank height. It assumes the bank angle is about 90 degrees. If there is significant undercutting or very mild bank angles that are less than 90 degrees, the methods used for both erosional and depositional banks may not be valid. In particular, undercutting banks seem to be the most difficult to measure, survey and estimate erosion rates and eroded sediment volumes.

Comparing the calculated volume loss from AIMM to hand delineations, there was a significant time difference. AIMM took one and a half hours to complete analysis while it took an average of ten hours for manual bank delineations (Williams et al., 2020a). Reducing time for calculating bank retreat and erosion volumes not only reduces costs and resources but would also allow examinations for large scale areas. The frequency of high-resolution aerial images combined with AIMM would increase the possibility of studies examining streambank erosion on watershed scales over longer periods of time. Trends of streambank erosion could be identified from longer study periods, relating to the evolution of streams.

LiDAR surveys are another method that can be applied to quantify streambank erosion rates. Differences in digital elevation models (DEM) produced through LiDAR (light detection and ranging) data can be used to detect geomorphic changes (Schaffrath et al., 2015). LiDAR uses point clouds to capture three-dimensional surfaces from laser-based measurements (Myers et al., 2019). The data typically are collected along strips of flightlines with 10-30% overlap between strips. The overlap can create errors when calibrating the data that can be corrected with the original GPS and laser data to filter out the overlapping points. Schaffrath et al. (2015) used a total station to gather checkpoint data in heavily vegetated areas to better define the DEM uncertainty for these locations. Cloud point density is a more accurate representation of uncertainty in DEMs that result from vegetation. It correlates with the vegetation density rather than basing the DEM uncertainty on vegetation height. Cloud point density values near one indicate that the above-ground point density is higher than then the bare-ground point density, which is indicative of dense vegetation (Schaffrath et al., 2015).

Comparing Methods

Different methods of measuring erosion rates provide varying resolutions and spatial scales that make a direct comparison of results difficult. Aerial imagery and geomorphic change analysis capture reachwide streambank retreat, while cross-sectional surveys and pins represent erosion only for a specific point. Foliage from heavily vegetated banks can inhibit aerial imagery analysis, LiDAR and total station surveys. Aerial photos should be used from periods with no leaves and the least amount of vegetation to easily discern the top of the bank (Myers et al., 2019; Purvis and Fox, 2016; Williams et al., 2020a). Similar to aerial imagery, DEM data accuracy can be affected by dense vegetation. The chance that the laser pulse will reach the ground is inversely proportional to the vegetation density.

Undercut banks are the most difficult to measure, survey, and estimate erosion rates requiring a standardized method for dealing with this bank type. Bank angles are commonly assumed to be near vertical for simplification of analysis, which ignores the bank angle effect on the amount of erosion and timing of bank failure. AIMM and aerial imagery analysis assume that the eroding banks are nearly vertical excluding bank angles. The assumption of vertical banks and the exclusion of undercut banks creates a bias in bank erosion studies. However, bank angles are an important factor in stream bank evolution, and often indicate the dominant process causing bank failure. Mass wasting often occurs with undercut banks which is a different process than fluvial erosion. However, fluvial erosion and bank failure are not exclusionary. Bank undercutting can be caused by fluvial erosion eventually leading to mass wasting. Both types of erosion result in different amounts of eroded sediment and timing of when streambank eroded sediment enters the channel (Simon and Rinaldi, 2006). Bank angles need to be included in the estimations for eroded sediment volumes to capture the spatial variability along streambanks. Therefore, future efforts should focus on identifying reliable approaches to account for varying bank angles smaller or larger than 90 degrees when estimating streambank erosion volumes through aerial imagery analysis. In addition, a standardized method to measure undercut banks with a total station needs to be developed so studies can begin to incorporate undercut banks in their analysis. Creating guidelines recommending the best methods for measuring and predicting erosion rates based on stream type, physiographic regions and resulting resolution will help to ensure the most appropriate methods are applied.

Table 1. Comparing methods to measure erosion rates.

Method	**Resolution**	**Spatial Scale**	**Temporal Scale**	**Time**	**Limitations**
Toe Pins	± 3 mm[2]	< 10,000 km^2 [1,2,3]	Short, months or years[1,3]	Dependent on size of site	Captures erosion at specific locations
Horizontal Erosion Pins	± 3 mm[2]	< 10,000 km^2 [1,2,3]	Short, months or years[1,3]	Dependent on size of site	Captures erosion at specific locations
Total Stations	5.5 cm[1]	Reaches[1]	Months or years[2,3]	Dependent on size of site	Accuracy affected by point density; better at capturing specific locations
Aerial Imagery	Dependent on imagery resolution[2,3]	Reaches, Watersheds[2,3]	Years[2,3]	10 hours[3]	Migration rates must be greater than photo resolution; exclude bars[3]
AIMM: Aerial Imagery	1 m[3]	Reaches, Watersheds[3]	Years[3]	1.5 hours[3]	Requires little vegetation; cannot be used in forested areas[3]
AIMM: DEM	2 m	Reaches, Watersheds[3]	Years[3]	1.5 hours[3]	Assumes vertical banks[3]

[1] (Myers et al., 2019) [2] (Purvis and Fox, 2016) [3] (Williams et al., 2020a)

Boothroyd et al. (2020) indicated that past fluvial geomorphology studies had been limited spatiotemporally by the traditional field methods and desktop computing. Applying geospatial techniques that use cloud-based computing further opens the possibility of examining channel processes on larger spatial scales and over longer periods (Boothroyd et al., 2021; Schaffrath et al., 2015) which will help document the episodic nature of streams. Additionally, it would allow for capturing both short and long-term rates of erosion through the same method (Boothroyd et al., 2021).

Predicting Streambank Erosion Rates

The Bank Assessment for Non-point Source Consequences of Sediment (BANCS) model is a commonly used "empirically derived, process-integrated-streambank erosion prediction model" (Rosgen, 2001a). It is used to predict annual erosion rates for specific physiographic regions. It is composed of two parameters: the Bank Erosion Hazard Index (BEHI) and the near bank stress (NBS) rating. To fit a regression model, the model must be calibrated for a certain region by combining measured streambank erosion rates with BEHI assessments and NBS ratings. The regression model usually uses NBS as the predictor variable and BEHI as the categorical variable, as seen in the figure below.

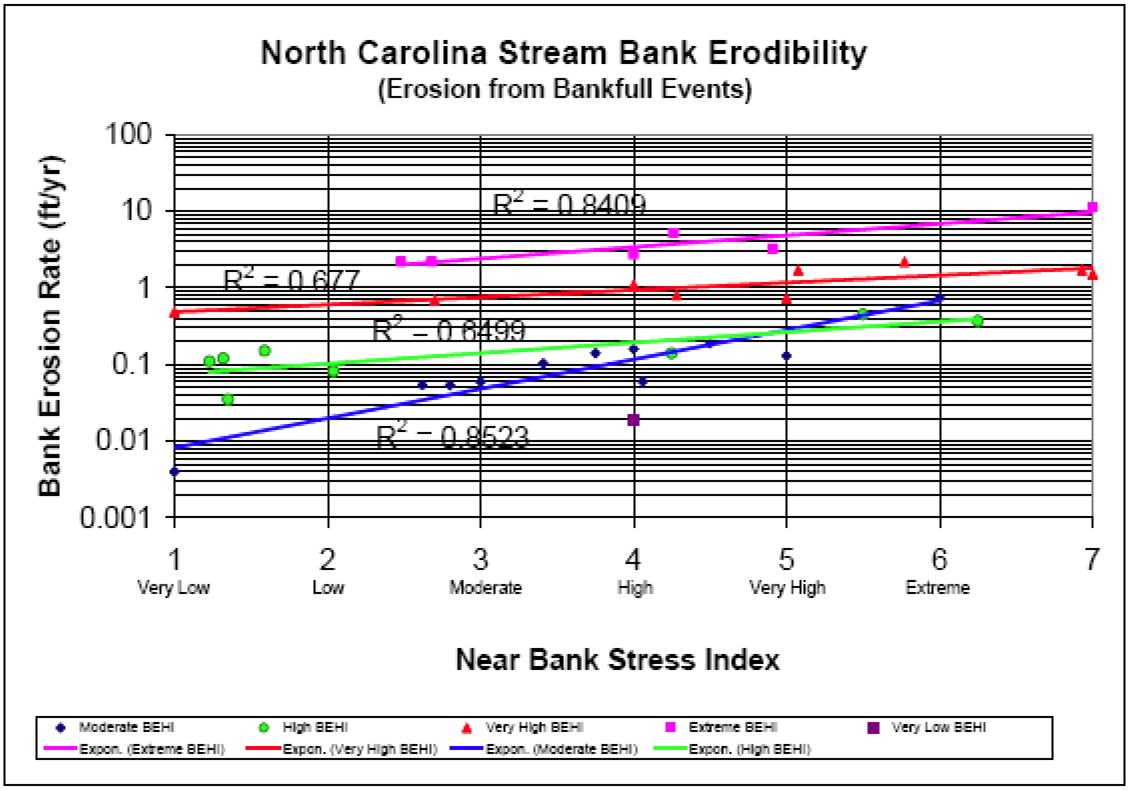


Figure 1. NC stream bank erodibility curves (Doll et al., 2003).

Van Eps et al. (2004) conducted BEHI and NBS assessments on the West Fork White River, in Arkansas. The accuracy of the model developed by Van Eps et al. (2004) depended on discharge. The model was most accurate for predicting erosion rates when the discharge was close to the discharge during the study period. During the study, the discharge was close to bankfull; if the model is applied when the discharge is lower or higher than bankfull discharge, accuracy will decline (Van Eps et al., 2004). Unfortunately, many studies do not report the discharge. Therefore, the flow rate during the period of surveys should be recorded and noted for future use of the model.

Ghosh et al. (2016) conducted BEHI and NBS assessments along the Bakreshwar River, India, testing if these two assessment protocols were good predictors of streambank erosion. The curve was unsatisfactory due to substantial erosion from high seasonal water levels along segments dominated by non-cohesive laterite soils. The BEHI-NBS calibration model only predicted similar erosion rates to observed values for four out of the 24 segments, and 13 segments had very different predicted erosion rates (Ghosh et al., 2016). There is no current method to measure the critical shear stress and erodibility coefficient for non-cohesive materials (Midgley et al., 2012). Future studies should focus on streambank erosion for non-cohesive banks to understand why BANCS does not seem to predict erosion rates well for these banks. Gaining a better understanding of non-cohesive material shear stress and erodibility will help predict erosion rates across various methods.

A recent study by Gamble (2021) applied the BANCS model in Virginia's Valley and Ridge region. BEHI and NBS could not capture the variability of bank retreat in the region with an R^2 value of less than 0.1. Only two BEHI categories were found in this study, high and very high. The two categories were combined into one curve since there was no difference found between the erosion rates (Gamble, 2021).

Different physiographic characteristics as well as watershed and channel modifications by humans produce different erosion rates, restricting the spatial range a BANCS model can be applied to. Similar erosion rates were found between the Colorado data and data from a study in North Carolina. Rosgen suspected the comparability was due to similar alluvial composite banks (Rosgen, 2001a). The West Fork White River, Arkansas model developed by Van Eps et al. (2004) had erosion rates up to 2.8 times greater than erosion rates for models calibrated for Colorado and North Carolina. Differences in magnitudes of erosion rates will be dependent on watershed characteristics, hydrology, soil conditions, geology and degree of anthropogenic disturbances. Variations also exist within physiographic regions, dependent on their spatial extent. Any BANCS model used within the same region should be validated for the study site to ensure it is a good fit to predict erosion rates. The BANCS model does not seem to perform well in physiographic regions with non-cohesive dominated streambanks or high hydrodynamic variability as seen with the Ghosh et al. (2016) and McMillan et al. (2017) study. Process-based models may be better able to capture the high variability in regions like the Northern Gulf of Mexico coastal plain and other areas with non-cohesive soils.

Future studies should explore how to modify the existing BEHI and NBS factors and to identify missing parameters that may help to improve predictions of streambank erosion rates. McMillan et al. (2017) began to delve into this by modifying NBS Methods 2 and 5 to consider channel dynamics. Gamble (2021) explored modifying NBS to have a stronger theoretical basis using four alternative NBS methods: two hydrograph-based methods and two DuBoys methods. The hydrograph methods quantified the number of peak flows above baseflow and percentage of time above baseflow. The first method used the DuBoys equation to estimate shear stress and the second standardized the estimated DuBoys shear stress with the radius of curvature. The modified BANCS curves produced with the hydrograph NBS had lower R^2 than the traditional NBS curves but had lower p-values. Using the modified DuBoys equation for shear stress had the best $R^2 = 0.045$, explaining about 4% of the variance (Gamble, 2021). Even with the modification of NBS, the BANCS model was able to explain less than 5% of the variance in bank retreat. The low performing model indicates that there are several fundamental drivers of erosion rates that are not included in the model like hydrology and watershed characteristics as well as anthropogenic alterations.

Across the board there is a lack of standardized procedures for measuring and predicting streambank erosion rates. The lack of standardization makes replication of study results difficult as many BEHI parameters and the NBS Method 1 are based on visual assessments. Results are thereby subjective to the assessor, where the level of training impacts the accuracy of the ratings (Bigham et al., 2018). The subjectivity in assessing some BEHI parameters and required calibration for different physiographic regions suggested BEHI was not always the best method to predict erosion rates. The factors that influence the rate of streambank erosion are interrelated making it more complex to replicate in an empirical based model.

Identifying Streambank Erosion

Opportunities to identify, monitor and predict streambank erosion remotely are becoming possible through the technological advances that have increased the accessibility, quality and amount of high-resolution topographic data. Not only has the data collection improved but also the tools that can be used to process and store all of the data allowing for more computation power (Schaffrath et al., 2015). Boothroyd et al. (2021) indicate that past fluvial geomorphology studies have been limited spatiotemporally by traditional field methods. Adding geospatial data into the fold not only allows for expansion of the spatiotemporal scale of but also enables potential site identification of problematic areas prior to any field assessments. Palmer et al. (2014) started exploring the relationship between 1-m LiDAR data and locations of severe erosions to identify severe erosion in other watersheds.

Collecting LiDAR data is expensive and most cost effective for areas larger than 20 mi^2 (Hohenthal et al., 2011). The equipment is costly and it requires advanced expertise, especially for projects that require high resolution data (Yen et al., 2011). Extensive processing is required to transform the LiDAR data into a usable state as apparent by the methodology outlined by Schaffrath et al. (2015) and Hohenthal et al. (2011). There are multiple methods to select from when transforming the data such as analytical hill-shading, sky-view factor (SFV) and openness. The intended purpose of the data will dictate the best method to use. Hill-shading is limited by the use of a single light that makes is hard to depict structures parallel to the light source and is best suited for visualizing objects with sharp and well-defined edges. Openness is best at representing concave surfaces, "superficially resemble[ing] digital images of shaded relief" (Yokoyama, 2002). Positive openness represents depressions where the angles are less than 90°. Another additional benefit of positive openness is a lesser degree of sensitivity to noise in the DEMs (Yokoyama, 2002).

Because of the technical difficulty and time necessary to process DEM data, the use of USGS's positive openness pre-processed data layer will save time and reduce costs. Applying the positive openness layer in analysis and interpreting the results requires less technical capabilities than creating the initial DEM from the topography data, allowing less experienced GIS users to extract information. Moving towards a world of sharing and compiling datasets and procedures could help to create a more complete and comprehensive understanding of environmental processes. Daxer (2020) outlines steps to compute openness using QGIS from a DEM. The ability to use free software to generate positive openness makes it more accessible. Applying geospatial techniques opens the possibility to examine channel processes on larger spatial scales and longer time periods to gain a better understanding of the episodic nature of streams. It could capture both short and long term rates of change (erosion). If the positive openness layer proves an effective tool for evaluating channel incision and instability, it could potentially be applied by state and federal natural resource agencies for prioritizing areas for restoration intervention. Refining this data, better understanding its potential and increasing its availability and understanding about its use, could also assist city and county municipalities with their stormwater, water quality and stream restoration prioritization efforts.

CHAPTER 2: Validating Positive Openness to Identify Incised and Eroding Streams

Methods – Mine Creek Watershed, Raleigh, NC

Site Selection

The test of the USGS positive openness dataset was focused on the Mine Creek watershed (Figure 2). Located in North Raleigh, Mine Creek drains into Shelley Lake, which is the centerpiece of a popular community park. The 28-acre lake has been impacted by sediment. The Mine Creek watershed is about 10 square miles in size and contains approximately 43 miles of streams. The watershed is fully developed with 17.7% impervious cover, but also includes 600 acres of open space that is primarily concentrated along riparian corridors. The City has received 311 erosion complaints in the Mine Creek watershed, which exceeds all other sub-basins in the City's jurisdiction. 90% of the soils in the watershed fall under Hydrological soil group B (USGS, 2022). Cecil-Urban and Pacolet-Urban land complex are the most common soils found in the watershed each covering about 31% of the watershed. These soils come from granite and schist rock (NRCS, 2022). The average slope of the main channel is 0.0062 ft/ft (USGS, 2022) and the mean slope of all the channels in the Mine Creek watershed ATLAS Hydrography GIS layer is 0.022.

By visiting both locations where channel incision is indicated and where it is not, combined with field assessment of the erosion potential at each location, the study documented the accuracy of the USGS positive openness raster data. Second, by physically measuring and documenting erosion rates for the eroding streambanks, the approximate load of sediment that is reaching Shelley Lake as a result of upstream streambank instability was estimated.

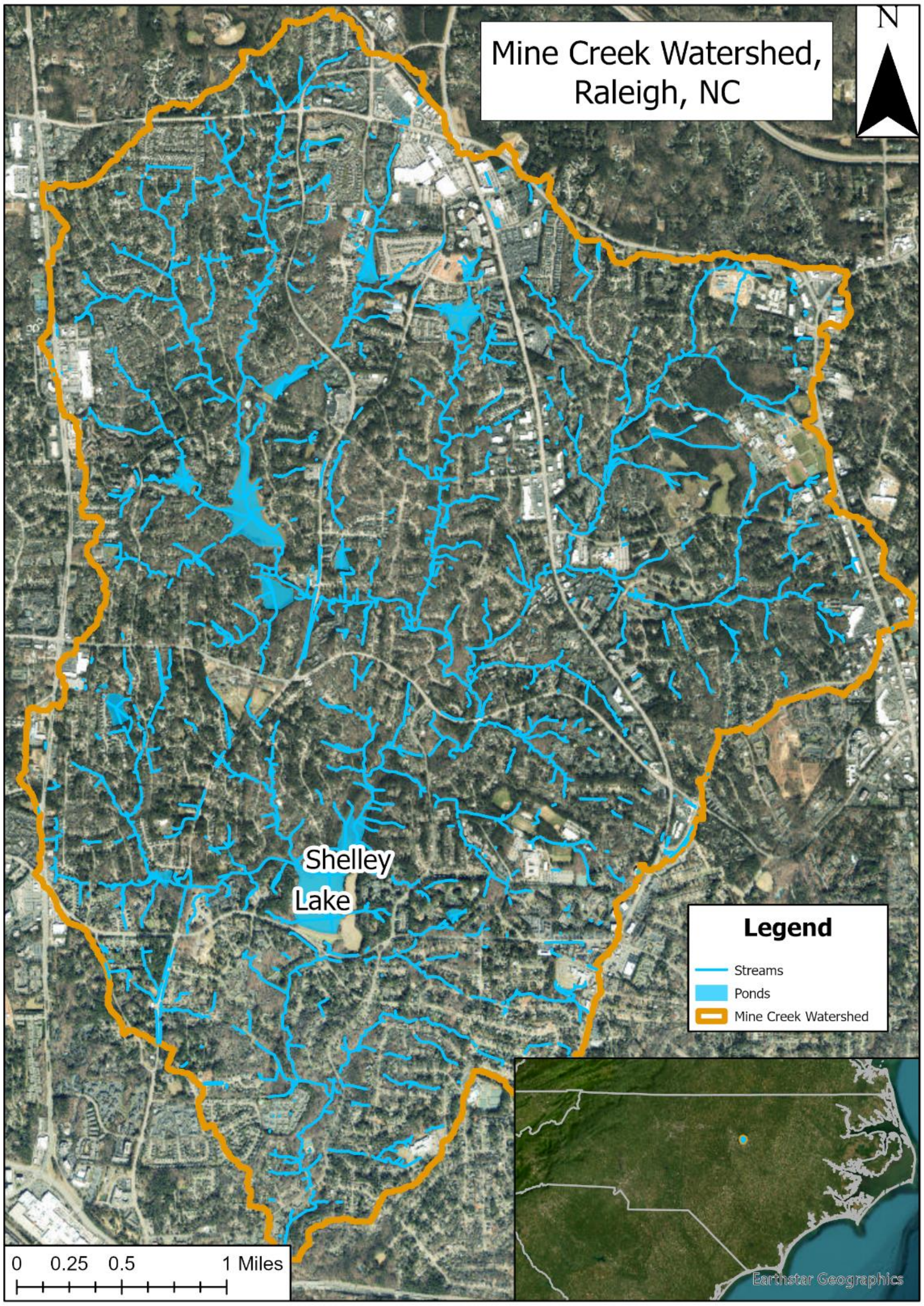


Figure 2. Map of Mine Creek watershed, Raleigh, NC.

USGS provided mapped locations using positive openness principles indicating areas of high and very high likelihood of incised channels. This original positive openness layer from USGS has a 3 m resolution built from the 2013 and 2015 North Carolina state LiDAR data at 10 ft and 30 ft resolution (Rowley et al., 2018). Fifty-four (54) sites distributed across the Mine Creek watershed that are easily accessible from greenways and public open spaces were selected for assessment. The validity of the positive openness layer was tested by including sites with a range of conditions including channel size, presence of erosion complaints and positive openness value and the density of the signal (Figure 4). Watershed area, rather than channel width, was used to categorize the size of the channel in order to avoid subjective measurement variability (Johnson and Heil, 1996). For example, channel width can vary depending on the location at which it is measured, the top of bank or bankfull. Also, unstable and eroding channels often exhibit large variability in channel width across short longitudinal distances. Selecting bankfull features is open to interpretation and identifying features on incised and eroded streams is difficult and sometimes impossible. Erosion complaints from residents have been collected by the City of Raleigh since 1986. Each site was categorized by the size of the watershed, presence of erosion complaint and positive openness (PO) signal and the density of the 3m resolution positive openness value. Table 2 breaks down the distribution of sites based on PO and erosion complaint categories. The majority of sites have watershed areas less than 1 mi^2 as seen below in Figure 3.

Table 2. Distribution of sites for the 3m PO value and erosion complaints categories.

PO value 3m	**None (18)**	**Low (14)**	**Moderate (7)**	**High (63)**
No Complaints (80)	18	11	7	44
Complaints (22)	0	3	0	19

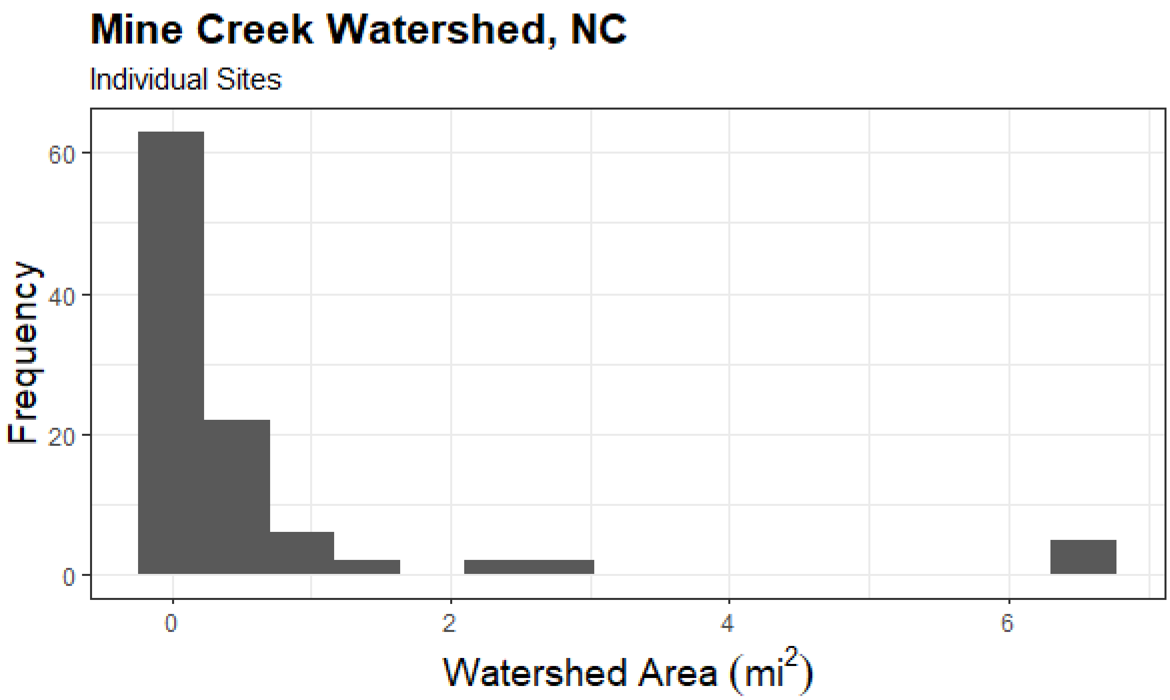


Figure 3. Histogram of the watershed areas for each individual site.

Positive openness density was visually classified based on the amount of high (orange) and very high (red) signal. Examples of classifications are provided in Figure 4. Using Zonal Statistics as a Table, the minimum, mean, and maximum PO value were retrieved for each site using the 1m resolution PO layer received from USGS. The 1m PO values range from 56.73 to 87.27 where a lower value indicates a higher degree of incision. It is hypothesized that a lower PO value is associated with more severe erosion and higher values are indicative of minimal to no erosion (stable banks). PO values from 81 to 84 are shown in orange indicating moderate incision and erosion. PO values less than 81 are depicted in red, indicating higher incision and more severe erosion. Any PO value greater than 84 is not shown. These PO categories were defined by USGS prior to analysis.

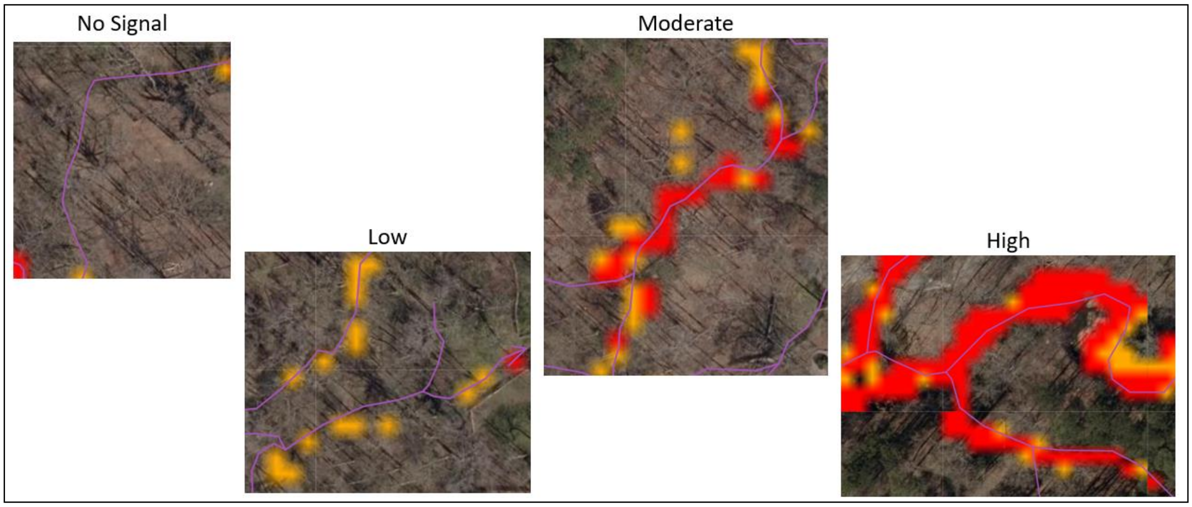


Figure 4. Examples of no, low, moderate, and high degrees of 3m resolution PO classification as provided by USGS.

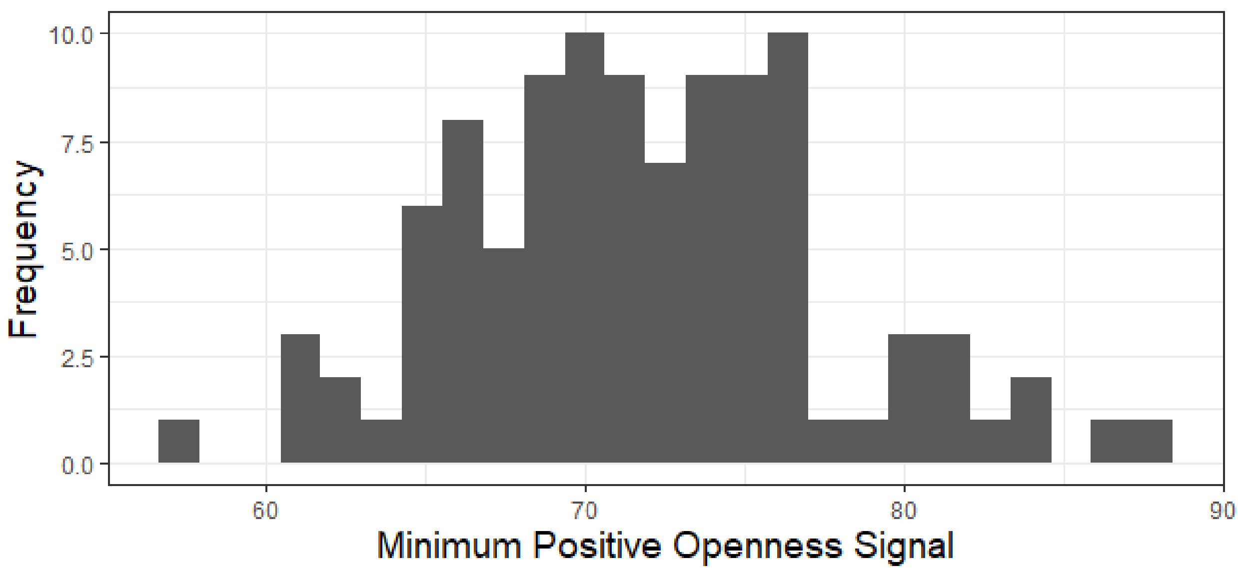


Figure 5. Histogram of minimum 1m PO value for all individual sites.

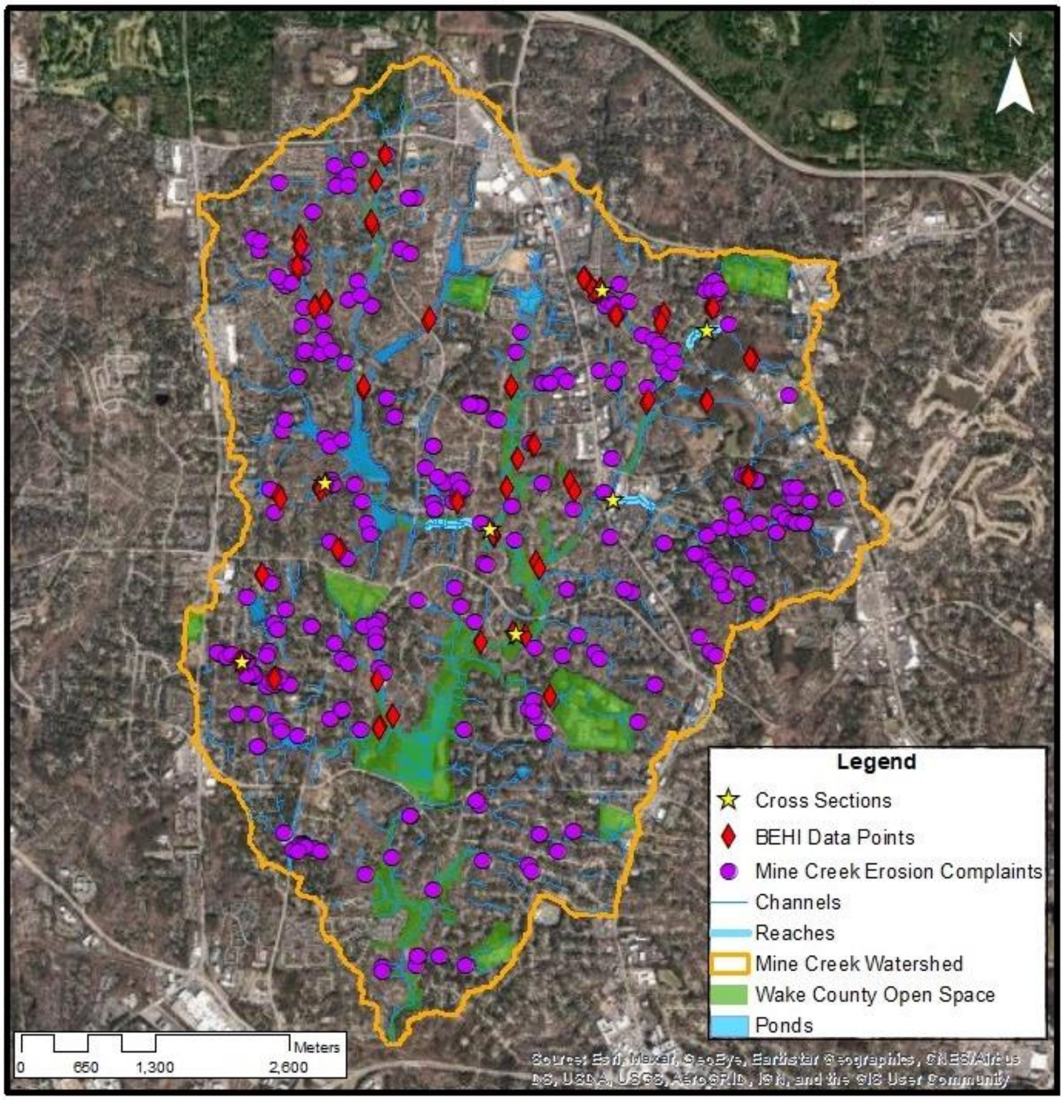


Figure 6. Map of Mine Creek individual sites, reaches, and cross-sections.

Permanent cross-sections (Figure 6) were established at seven of the individual sites exhibiting the most severe erosion. The cross sections were surveyed at the start of the study and again one year later. The cross section measurements were used to determine lateral erosion rates and to estimate the total sediment and nutrient loads carried downstream from the eroding banks. The seven study cross sections were also used to validate the streambank erosion rates predicted by the NC Stream Bank Erodibility curves (Doll et al., 2003) using the BEHI/NBS assessment data for each location. A reachwide BEHI assessment was performed on three stream reaches approximately 1000 feet in length in order to gauge the accuracy rate for the positive openness value. The positive openness value was present along the entire stretch.

Field Methods – Site Assessment/BEHI Data Collection

Field assessment for BEHI was completed in December 2020 and January 2021. A total of 52 individual sites were assessed. A few additional sites were added in the field to capture a better range of PO values. A few sites were eliminated due to access issues or because repair measures had already been installed. At each site, a BEHI assessment was conducted on both sides of the bank as close to the randomly selected site as possible (Bigham et al., 2018; Doll et al., 2003; Rosgen, 2001a). The bank segment with the worst erosion near the potential BEHI site was selected if erosion was present. If the stream reach was straight, the BEHI assessment was taken from the opposing left and right banks. If the stream was sinuous, the BEHI was collected along two opposite and adjacent outside meander bends. The streambank GPS coordinates and BEHI measurements were recorded using a Geode GPS unit linked to ArcGIS Collector, a GIS based data collection application. The length of the eroding bank was measured using the Geode to mark the start and end points where the section of the bank would receive the same BEHI score. Photos and documentation of any past stabilization efforts were also collected. The bank height, root depth and bank angle were measured in the field. Bankfull was also measured in the field if good indicators of bankfull were present. If not, bankfull was later estimated from NC Piedmont rural regional curve (Harman et al., 1999). The rural regional curve was selected over the urban curve since it gave a smaller bankfull height, which assumes a greater potential for erosion by increasing the bank height to bankfull height ratio. In the field, Near Bank Stress (NBS) was visually estimated using Rosgen's Method 1, which assigns NBS level based on the location of the streambank relative to channel meander bends and the presence or absence of mid-channel bars (Bigham et al., 2018; Rosgen, 2001a). Additional details are presented in Appendix A – Mine Creek BEHI/NBS Field Procedures. See Rosgen (2001) and Bigham et al. (2018) for more detail on the BEHI/NBS methodology.

Field Methods – Reachwide BEHI Assessments

In order to determine the accuracy percentage of the PO value, reachwide BEHI assessment were performed on three study reaches of approximately 1000 feet in length with a high 3m PO value present along the entire length of the channel. The reach surveys were completed in March of 2021. Study reach locations are is shown in blue on Figure 6.

Field Methods – Permanent Cross-Section Surveys

In January 2021, seven permanent cross-sections were established, surveyed and resurveyed a year later in January 2022. The surveys of both years were overlaid to determine the annual bank retreat that has occurred at each location. In addition, because erosion generally occurs in a non-uniform manner, survey points were also collected along the top of the streambanks to supplement the cross-section surveys.

Cross-sections were marked with rebar pins with plastic caps, wooden stakes and flagging tape. Survey points were taken at each point of inflection along the cross-section. More points were taken in the stream channel compared to the floodplain since the focus was on capturing the bank profile to estimate the annual bank retreat. A Topcon GT 505 Series total station was used to survey all cross-sections and top of banks. The total station has an accuracy of 2 mm + 2 ppm under ideal conditions (Topcon, 2016).

The precision of the survey’s data was estimated at 0.1 feet based on the survey error determined from repeat surveys of cross-sections by two field teams at 21 cross-sections located at eight streams at Virginia study sites. The NCSU team used the Topcon GT, and the NCSU

Virginia team used Trimble R10-2 GNSS System RTK, Trimble S5 Robotic Total Station and Trimble TSC-3 Survey Controller. The difference between the two surveys was measured by calculating the distance from the NCSU team survey point to the VA team survey point and taking an average of all the distances. Several factors that can contribute to survey error reducing the data precision. These are comprised of human error (e.g. incorrectly setting the rod height, taking points when the rod is not completely vertical, collecting the survey shot before the rod is in contact with the ground, etc.) and environmental conditions (e.g. animal or human disturbance of the survey pin, freeze/thaw cycles moving the pin, etc.). Based on the survey error, any measured bank retreat of less than 0.1 ft was excluded from the analysis.

Undercut banks are difficult to survey and are often eliminated from studies (Myers et al., 2019; Williams et al., 2020b). Two methods were used to capture undercut banks depending on the location setup of the total station. If the total station was set up on the bank opposite the undercut, the prism was placed directly against the bank and the rod height was set at 0 ft (Figure 7). Removing the prism from the rod makes it easier to adjust the position of the prism to the desired location. If the total station was not positioned well to capture an undercut bank, a second person measured the horizontal offset between the survey rod and the point of inflection at a 90° angle. The offset value was added to the point name so the station could be manually adjusted afterward.

Figure 7. Methods used to survey undercut banks including prism against streambank with 0 feet for rod height (left) and horizontal offset measurements (right).

Field Methods – Soil Sampling

A maximum of four soil samples were taken from the banks at each of the cross-sections during the first year visit to all sites. Disturbed soil samples were collected by hammering a soil core sampler into the bank. The volume of the cylinder was 288.44 cm^3. The soil was removed from each cylinder and placed in labeled bags. The soil samples were analyzed for Total Nitrogen (TN), Total Phosphorus (TP) and bulk density at the BAE Environmental Analysis Laboratory. TN was measured following the APHA 4500 N_{org} B methodology, and TP measurements followed the APHA 4500-P F methodology. The ASTM D 2937 method was followed to measure bulk density (EAL, 2020). Measured results could be used to estimate nutrient loading Shelley Lake from the streambank erosion, if an accurate estimate of sediment load to the Lake were available.

Quantifying Streambank Retreat

The bank retreat that occurred for the left and right bank between the year 1 and year 2 surveys was calculated for both banks at all of the cross-sections. Survey data were exported into Excel, then corrected based on survey notes. A graphical overlay of the cross section data for both years of survey data was created. The graphical overlays for each cross section were used to set the top and bottom elevation for each bank by visually identifying the "vertical" portion of the bank. The selected top of bank elevation was the lower of the two surveys and the selected bottom of bank elevation was the higher of the two surveys (Figure 8). Slumped material was excluded so as not to skew the results. The horizontal station of the streambank at year 1 and at year 2 was interpolated for every 0.5 ft elevation interval between the top to bottom of the bank excluding the channel bed and floodplain. The absolute value of the horizontal distance between the stations was used to estimate the bank retreat. If a bank showed deposition rather than erosion, the aggradation was quantified using the same procedure. Any bank retreat values that fell within the survey error (<0.1 ft) were classified as 0 ft/yr bank retreat. Any point bars or stream banks that only represent deposition (no erosion present) were excluded from further analysis because BEHI was developed for eroding banks and is not conducive for deposition (Rosgen, 2001a).

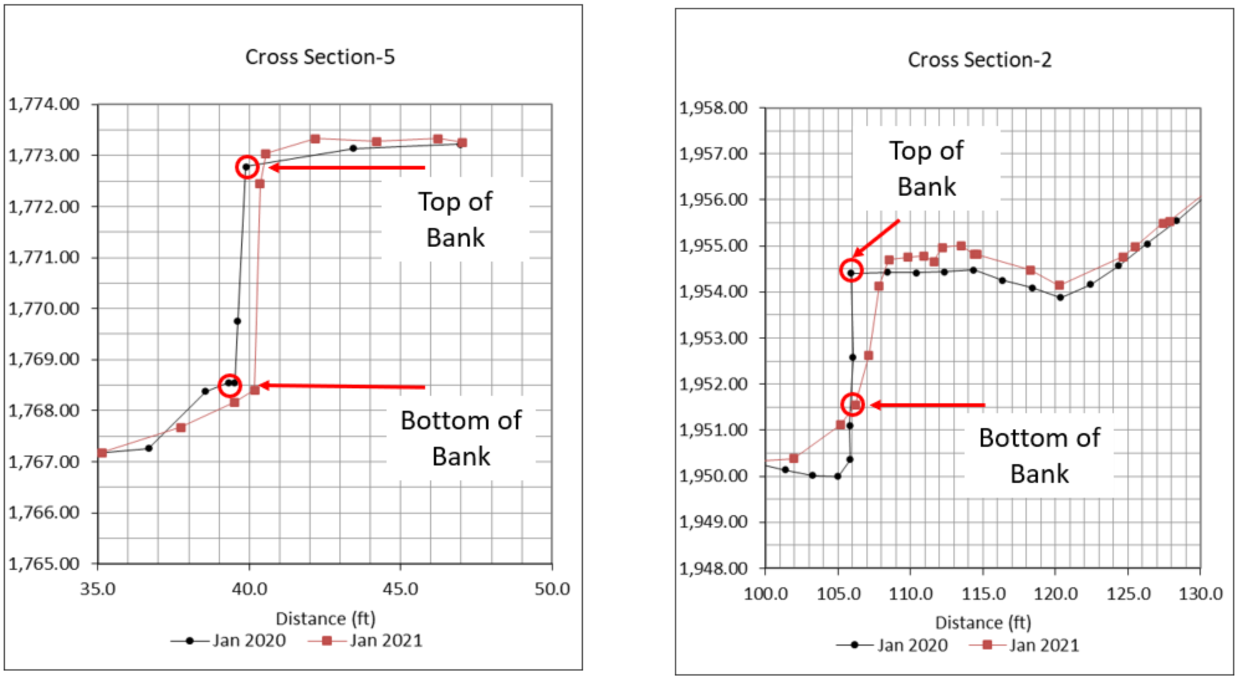


Figure 8. Example of streambank cross sections used to demonstrate the selection of the top and bottom of the bank values needed to estimate the 1-year bank retreat values from survey sites.

Post-Processing Methods - BEHI

The BEHI data for the three reaches were processed following the same method outlined in Appendix B. The individual BEHI data and locations were combined with the BEHI data and location for the three study reaches into one layer in ArcGIS. For the individual BEHI locations, if the bankfull height was not measured in the field from lack of indicators, the hydraulic geometry curves for the rural Piedmont of North Carolina were used to calculate the bankfull height using the watershed area (Harman et al., 1999). The watershed area was calculated using two different methods. First, a GIS shapefile with one point for each individual BEHI assessment location was uploaded to StreamStats. Each point was automatically associated with a defined hydrography line and the watershed boundary was delineated for each specific point using the Streamstats Batch Method. Eight locations were not close enough to a defined hydrography polyline in StreamStats. The watersheds for those sites were delineated using ArcGIS Pro. For the reaches, not all of the BEHI points had a measured bankfull height. Since there were often good bankfull indicators along the reaches, the most commonly measured value for bankfull height along the reach was selected as the bankfull height for any missing measurements. For any BEHI points where the bank height was less than the bankfull height, the bankfull height was set equal to the bank height.

Analyzing Positive Openness and BEHI Data

Positive openness is calculated by taking the average of zenith angles for all eight compass directions at a point within the radial distance limit. The average of the zenith angles is "viewed above the surface" (Yokoyama, 2002). A flat horizontal surface has a positive openness of 90°. A positive openness of less than 90° means that the location is on average lower than its surrounding elevations (Stillwell, 2022). Figure 4 symbolizes larger positive openness values in orange and smaller positive openness values in red. Positive openness is a stand-in for the bank angle. However, it is not equivalent to the bank angle since positive openness is an average of the zenith angles from directly downstream, directly upstream, perpendicular to the left and right banks and four diagonals. The positive openness will always be higher than 45° even with extremely incised streams, skewing the values closes to 90° (Stillwell, 2022).

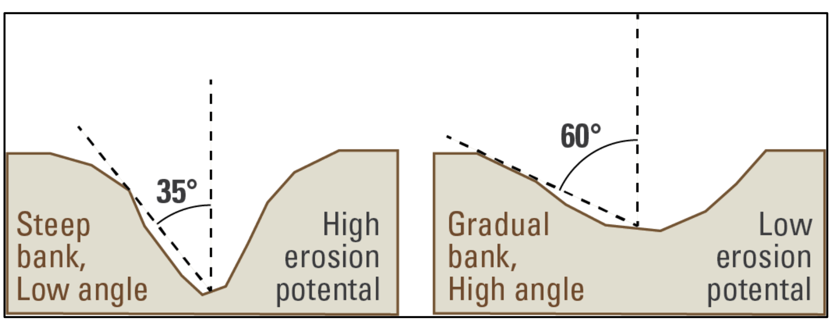


Figure 9. Positive openness diagram depicting the relationship between positive openness value and erosion potential (Gurley, 2022).

Using 1 m resolution positive openness data, statistics for the positive openness data associated with each BEHI data point were extracted in ArcGIS. A 10 ft buffer was created for each BEHI data point for the individual sites since the accuracy of the Geode GPS ranged from 2-10 ft depending on tree canopy, satellite position and cloud coverage. The Zonal Statistics as Table tool was used to extract the minimum, maximum, range, mean, standard deviation and sum of the PO value for the 10 ft buffer area around each BEHI station point. This data was joined to the MC BEHI data layer and data from the ATLAS hydrography layer was spatially joined to each site (Appendix E). It was then imported to a comma-delimited file to analyze in RStudio. The ATLAS hydrography is a polyline layer for the state of North Carolina illustrating the location of water resources with various regulatory considerations, developed by NCDOT and updated in April 2020 (NCDOT, 2020).

Several different sized buffers were created for the reach analysis to examine the effect the buffer type and size had on the correlation between the positive openness value and presence or lack of erosion. Five types of buffers were created. The first three were centered on the BEHI top of bank line with buffer distances of 5, 10 and 15 ft. 10 ft buffers were created on just the outside and inside of the streamline, separated by right and left banks.

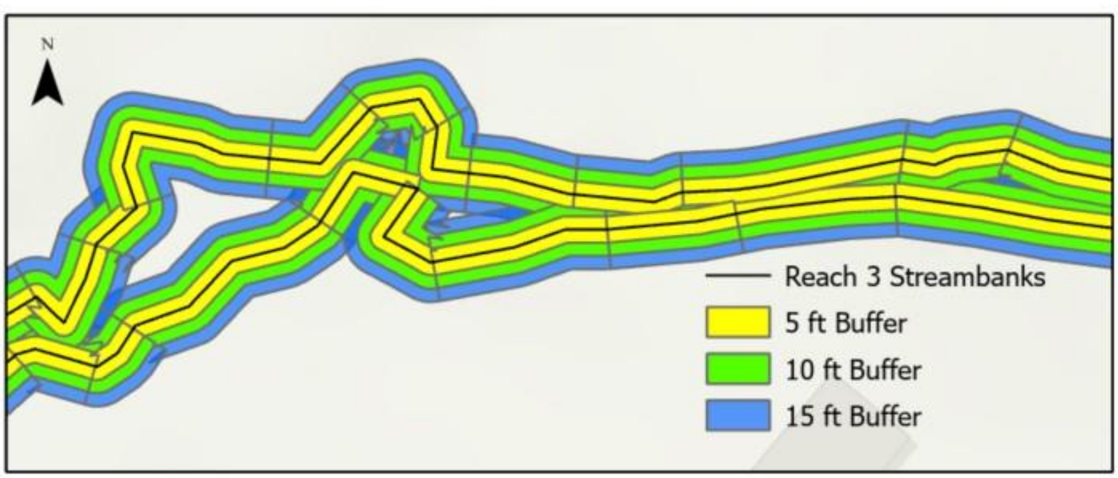


Figure 10. Example of the 5, 10 and 15 ft buffers created for the reaches.

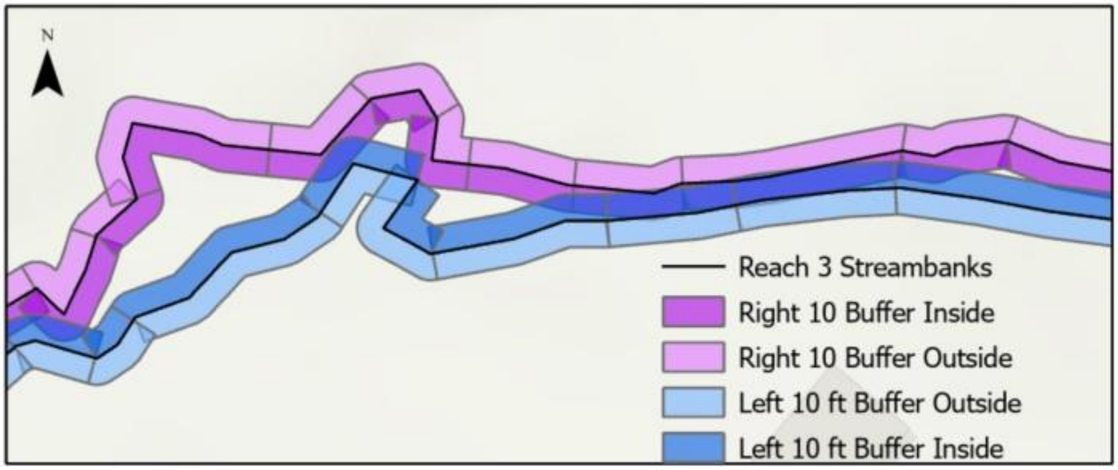


Figure 11. Example of the 10 ft inside and outside buffers created for the left and right banks.

In RStudio, R-markdown files were created for the individual sites and reaches. A correlation plot was created for all BEHI factors and PO statistics. The individual sites also included stream order and slope from the ATLAS stream layer. Different boxplots and scatterplots were created based on the correlation plots to further examine any significant relationships. ANOVA and Tukey's HSD were applied to the individual dataset, reach dataset, and a combined dataset for all of Mine Creek to statistically determine if the minimum PO value could detect a difference in the erosion condition and BEHI category. The minimum PO value is the minimum pixel value from the PO layer within the buffer area and represents the highest degree of incision. For all of the analyses, the minimum PO value was used. It represents the most conservative choice since it assumes the worst case. A higher degree of incision is associated with steeper and taller streambanks that have experienced greater erosion than banks with higher PO values. The minimum PO value had the strongest relationships with the various BEHI factors.

The PO value was also obtained for the left and right banks at each cross-section. The BEHI points associated with each cross-section were used to create buffers to get the PO statistics. Cross-section 5 and 6 only have one associated BEHI point since the opposing bank was a point bar where deposition occurs. Therefore, a point was created for the opposing bank. Refer to Appendix D – Obtaining Positive openness value in ArcGIS Pro for the procedure log used to obtain the PO value statistics.

Calculating Annual Sediment and Nutrient Loads

A methodology was developed to estimate the total annual sediment and nutrient load from streambank erosion that could be carried downstream to Shelley Lake based on site measurements, geospatial analysis and modeling. Figure 12 outlines the procedure developed to estimate the eroded volume from streambanks.

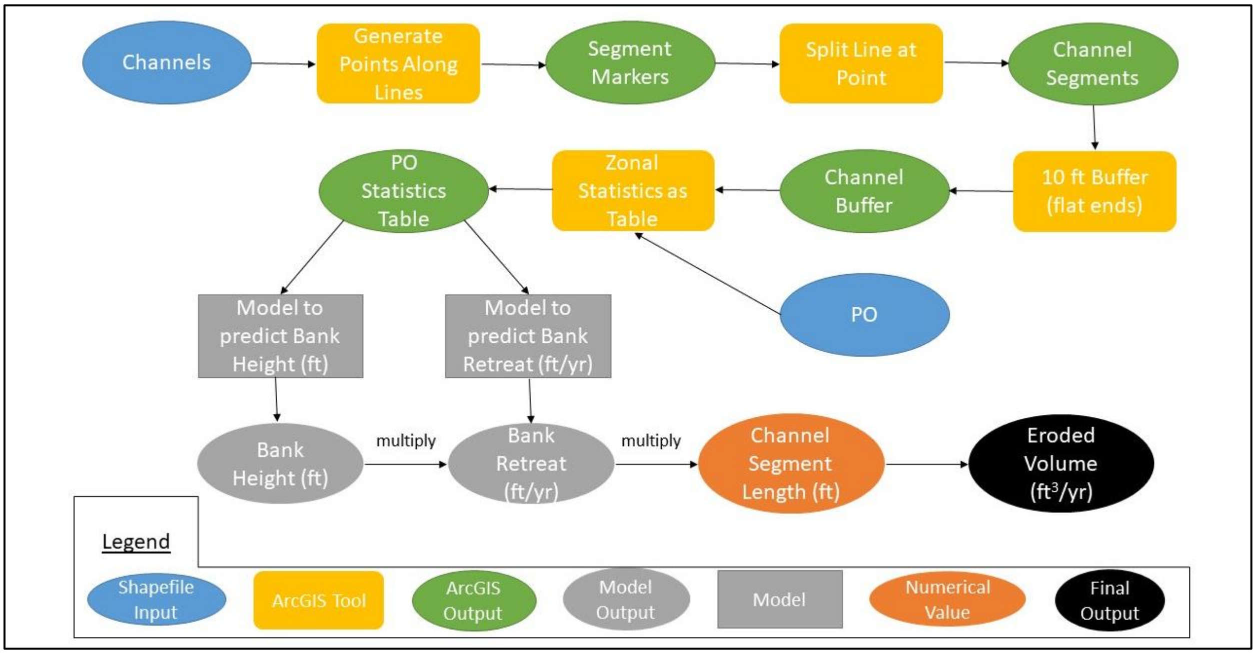


Figure 12. Procedure to estimate streambank sediment volume.

The initial steps performed in ArcGIS are intended to quantify a minimum PO value along the stream channel polyline layer. First, stream channels were divided into 50 ft sections using the Generate Pointe Along Lines tool to create a point every 50 ft along the channels and split the channel into segments with Split Line at Point tool. The length of channel segment should be adjusted based on the area of analysis. Once the channel was split into the segmented lengths, a 10 ft buffer was created. If this was done on a stream where the width is significantly greater than Mine Creek, the buffer size might need to be larger to encompass the entire channel better. Next, the Zonal Statistics as Table tool was used to find the minimum PO value associated with each channel segment. The table produced from the Zonal Statistics as Table tool were joined to the channel segment layer. This attribute table was exported and saved as a .csv file, later imported into RStudio for the remaining steps.

A model was developed to predict bank height with the measured bank heights using minimum PO value as the predictor variable. Only the data from the individual sites were used to create the bank height model since doing so yielded a better fitting model than the model using all of the data. Statistical analysis was used to determine the best fitting linear regression model using 5 folds to validate the model. A second model was created to predict annual bank retreat from the measured bank retreat on the outside bends of the seven cross-sections, again using the minimum PO value as the predictor variable.

The predicted bank height and predicted bank retreat for each channel segment was multiplied by each channel segment's length to produce an estimated volume of erosion from streambanks in feet cubed. To present this value in tons of sediment per year, the volume was converted to grams and then multiplied by the average measured bulk density (g/cm^3). Next, the sediment load was normalized by dividing by the total length of streams (Walter et al., 2007; Wegmann et al., 2013). Finally, the predicted sediment load was converted to an erosion rate by dividing the average and maximum sediment loads (ft^3/yr) by the average predicted bank height (ft) and the total stream length (ft).

The TN and TP loads were estimated by multiplying the volume of sediment (grams) by the average measured TN and TP concentrations (mg/g of dry weight). The average bulk density, TN and TP values were obtained from laboratory analyses of the soil samples taken at each cross-section. The total load in pounds of TN and TP estimated from streambanks was divided by the watershed area (10 mi^2) to compare the potential load of nutrients coming from streambanks to watershed loading rates reported by others.

Results and Discussion

Individual Sites

The correlation plot below (Figure 13) quantifies the strength of the relationship between the PO value and BEHI factors. The minimum, maximum, mean and median PO value all have the strongest correlation with the measured bank height. The next strongest correlation is with the bank height to bankfull height ratio. The correlation between the visually categorized 3m PO value and the 1m PO value is just as strong as the correlation between the 1m PO value and bank height. However, the BEHI score did not exhibit strong correlation with PO value. The correlation was poor for both the 1m and 3m resolution PO value though the correlation is stronger with the 1m resolution indicating the more refined the PO layer may be more accurate for identifying the presence of erosion.

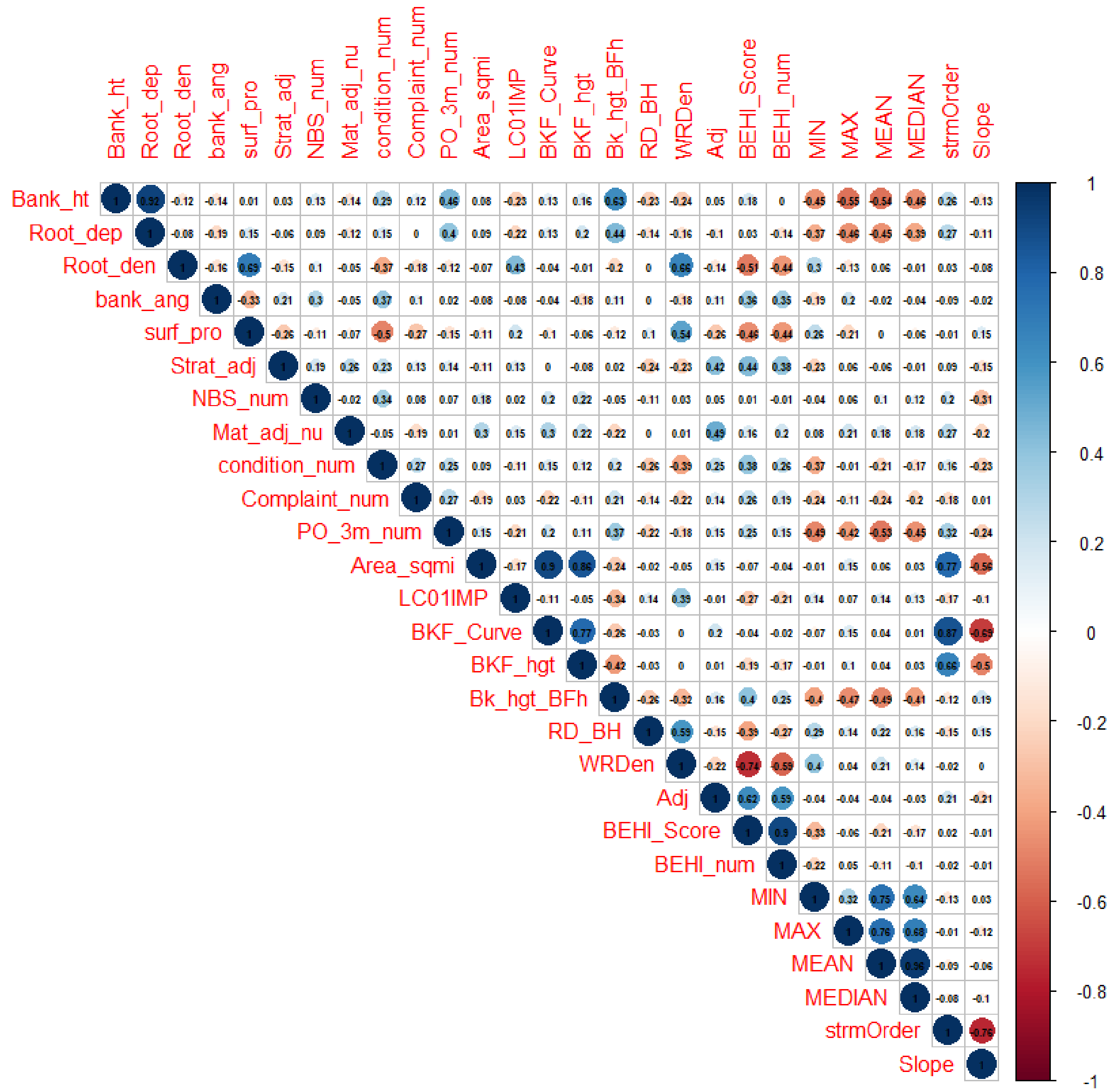


Figure 13. Correlation plot for individual sites.

A study by Bigham et al. (2018) on the sensitivity of BEHI revealed that bank height is the most sensitive parameter. The bank height has the greatest impact on BEHI score and can cause a shift in the BEHI category from measurement errors. While the bank height did not have a strong correlation with the BEHI score in this study, it did have a strong correlation with the PO value. There is a stronger correlation with the BEHI score and bank height to bankfull height ratio. The correlation suggests that the bank height is a strong indicator of the presence of erosion, similar to the findings by Bigham et al. (2018).

Boxplots of the positive openness value versus erosion condition type as categorized in the field are provided below in Figure 14 through Figure 17. The minimum PO value shows the best relationship between PO value and erosion type. The minimum, mean, median and maximum PO value were pulled from the statistics of each buffer. A lower PO value indicates a higher degree of incision and likely steeper slopes. As expected the lowest PO value (minimum PO value) has the strongest correlation with the observed erosion conditions. Except for the maximum PO value, the sites with no erosion had the smallest signal standard deviation. Stable banks will have little change over time. Eroding banks have much greater variability in their severity with differing bank heights and bank angles. This variability translates to greater variability of PO value associated with eroding banks. Less incision is seen with surface scour banks than unstable undercut and mass wasting banks. Unstable undercut and mass wasting are more severe types of erosion often associated with steeper bank angles and larger bank height to bankfull height ratios.

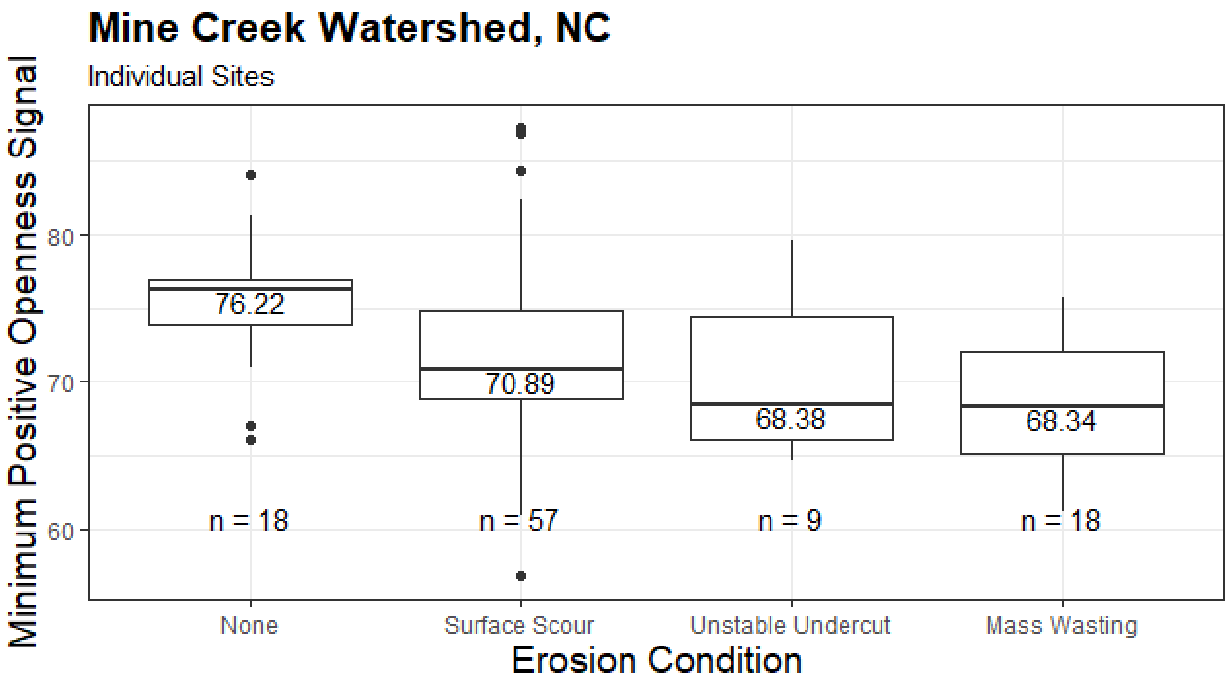


Figure 14. Boxplot of minimum PO value versus erosion condition for individual sites segregated by the type of erosion found at each location.

The mean and median PO values versus erosion conditions are fairly similar. There is a complete overlap between the mean and median PO values for sites with no erosion and those with surface scour (Figure 15 and Figure 16). Unlike in Figure 14, there is not a decrease in PO value with an increase in the severity of erosion in Figure 17. The clearest relationship between the severity of erosion and PO value is with the minimum PO. Based on the findings of this study, it appears that the minimum PO value is best for identifying locations of likely streambank erosion.

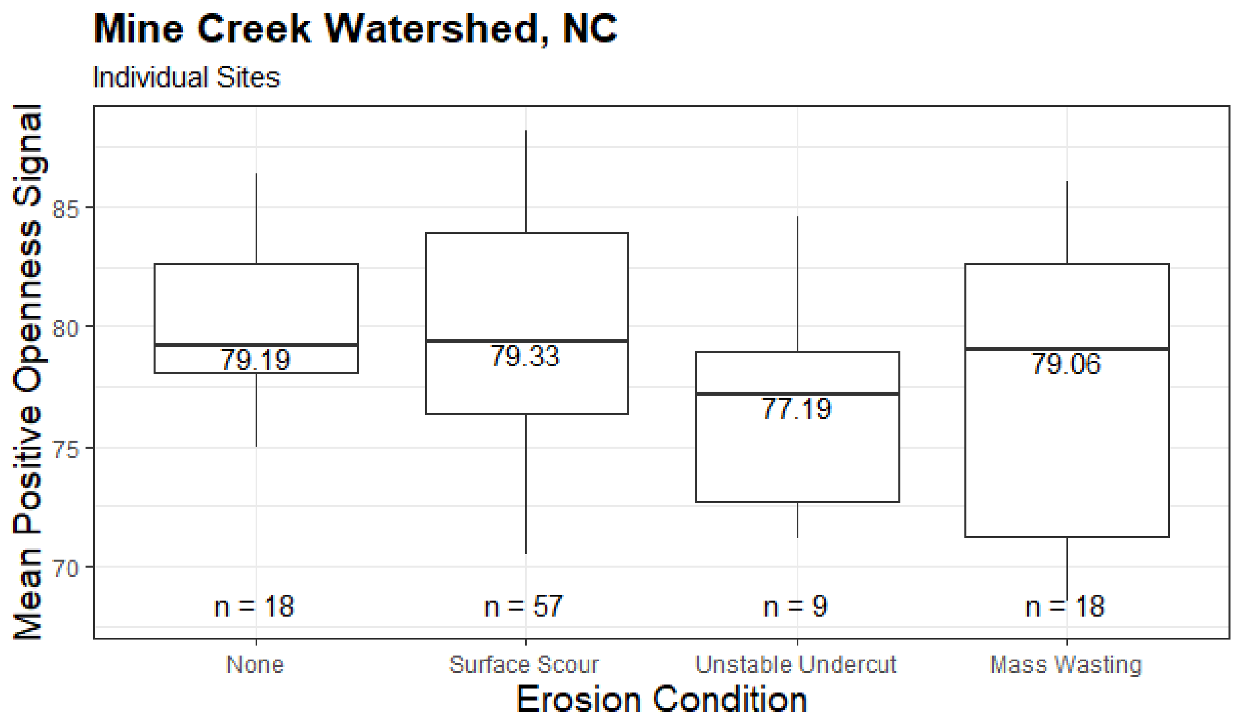


Figure 15. Boxplot of mean PO value versus erosion condition for individual sites segregated by the type of erosion found at each location.

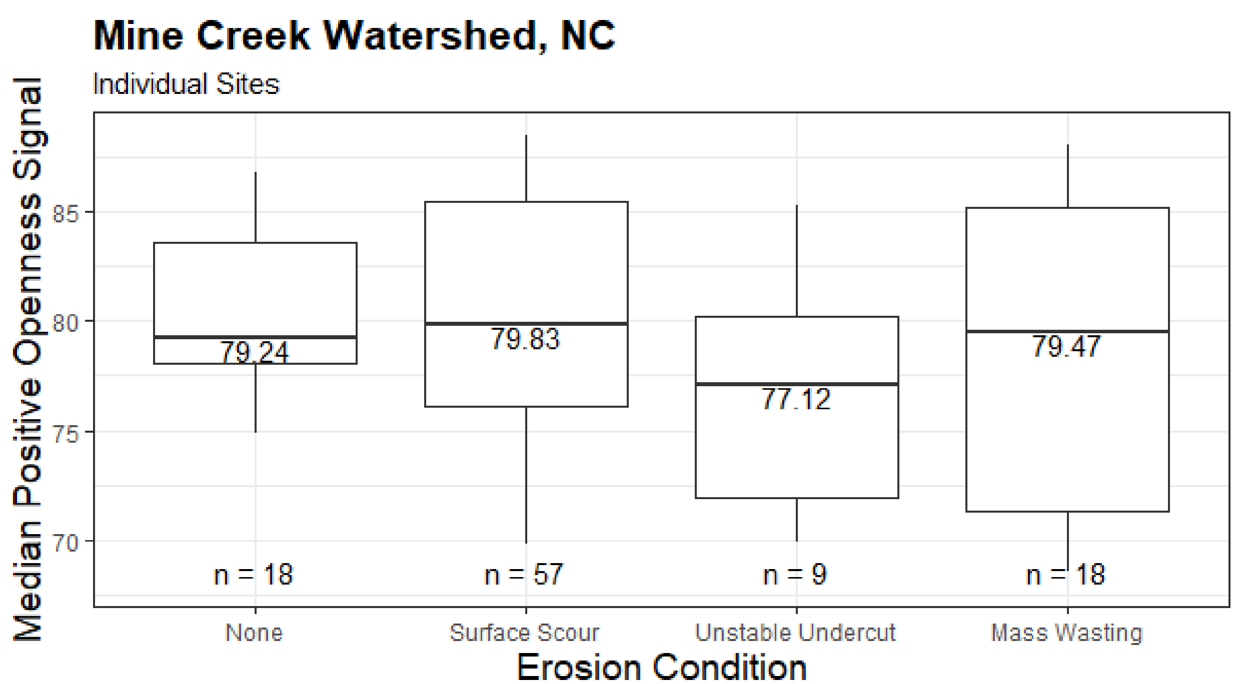


Figure 16. Boxplot of median PO value versus erosion condition for individual sites segregated by the type of erosion found at each location.

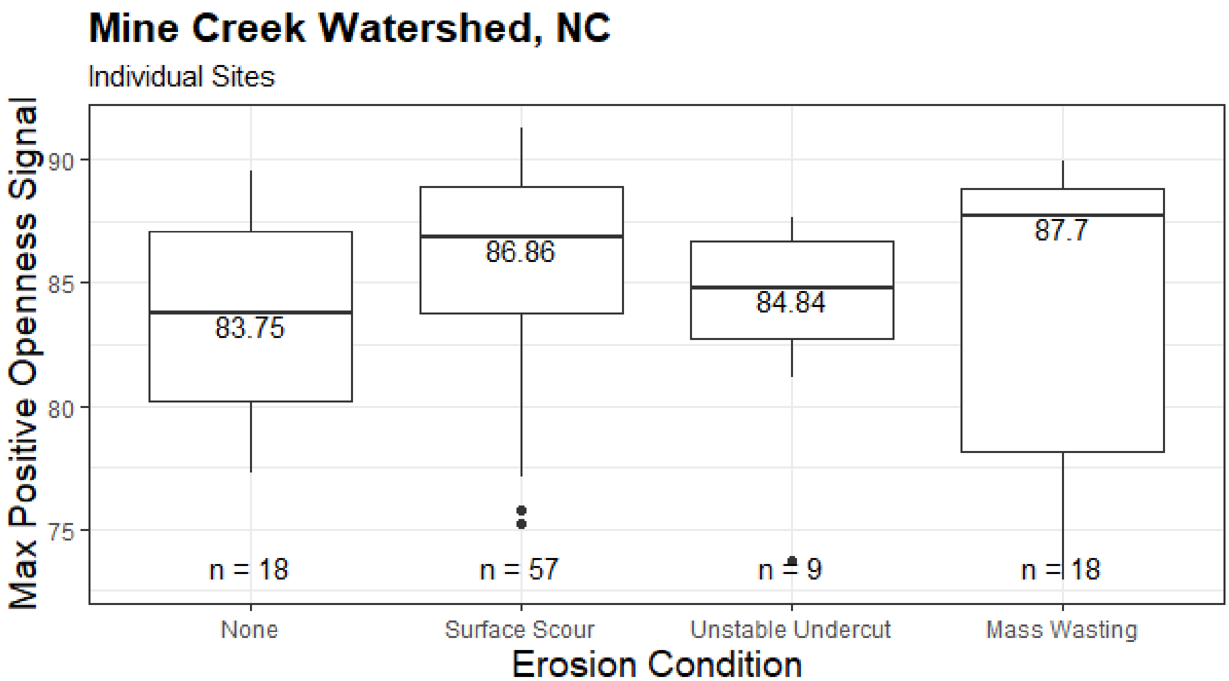


Figure 17. Boxplot of max PO value versus erosion condition for individual sites segregated by the type of erosion found at each location.

Table 3. P-values from Tukey's HSD test comparing the minimum PO values for all individual sites segregated by the type of erosion found at each location.

	P-value
None-Mass Wasting	0.000896
None-Unstable Undercut	0.055441
None-Surface Scour	0.060823
Surface Scour-Mass Wasting	0.10232
Surface Scour-Unstable Undercut	0.739797
Unstable Undercut-Mass Wasting	0.91968

Table 3 shows the p-values from Tukey's HSD test to see if there was statistical difference in the minimum PO value for the different erosion conditions. Using the threshold of 0.05, a significant statistical difference was found only between the locations exhibiting no erosion and the locations that exhibited mass wasting. The p-value for the difference between the no erosion and unstable undercut locations is right on the significance threshold and no erosion compared with surface scour is also slightly above the 0.05 threshold. The full statistical results from Tukey's HSD test and the ANOVA test can be found in Appendix F – Statistical Analysis Results.

Tukey's HSD test corroborates the boxplot findings, validating that the minimum PO value can be used to detect differences between sites with no erosion and unstable undercut/mass wasting. Mass wasting is the most severe erosion type. Therefore, the minimum PO value could be used to pinpoint locations of the most severe erosion along streams from the desktop. Field assessments could then be limited to the pre-selected sites, minimizing time and resources spent in the field to select sites for stabilization/restoration.

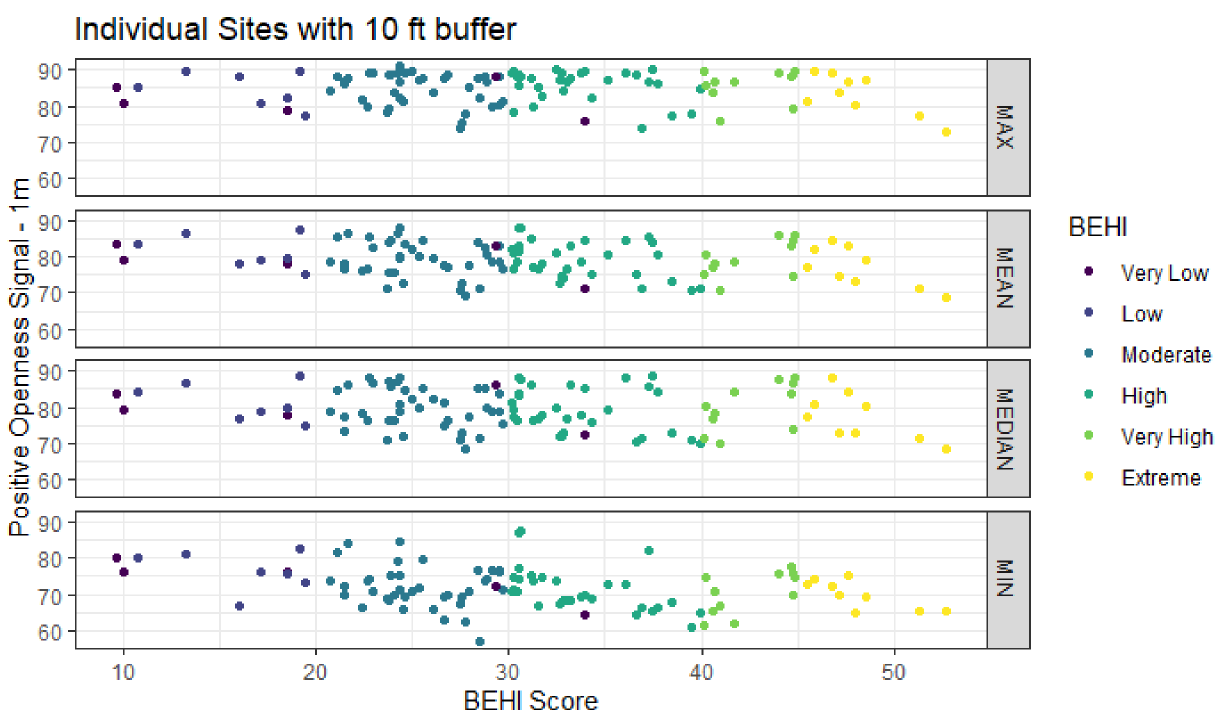


Figure 18. Minimum Positive openness value versus BEHI score for individual sites.

Figure 18 provides a scatterplot of 1m PO value versus the BEHI score. There is no distinguishable pattern between the BEHI score and the PO value. Despite receiving a high BEHI score, a couple of sites were placed in a very low BEHI category, due to the presence of bedrock as per the BEHI assessment guidelines (Rosgen, 2001b). The sites classified under extreme BEHI have lower PO values than the very low BEHI sites. There is a lot of variation and scatter within the moderate, high and very high categories.

Figure 19 shows a boxplot of the minimum PO value versus each BEHI category. The median of the minimum PO value of the very low and low BEHI categories does not fall within any of the interquartile ranges of the other BEHI categories. Moderate, high, very high and extreme BEHI categories have similar boxplots and median values with less than a 1.5 difference in PO value. The minimum PO value seems to differentiate between sites with very low/low BEHI and those with moderate/high/very high/extreme BEHI. This finding validates the previous conclusion that the minimum PO value can distinguish between sites with no erosion and sites with erosion. More refinement or additional geospatial layers are required to categorize sites with a higher level of precision to place them into each BEHI category. The current analysis indicates that very low/low and moderate/high/very high/extreme categories should be lumped together.

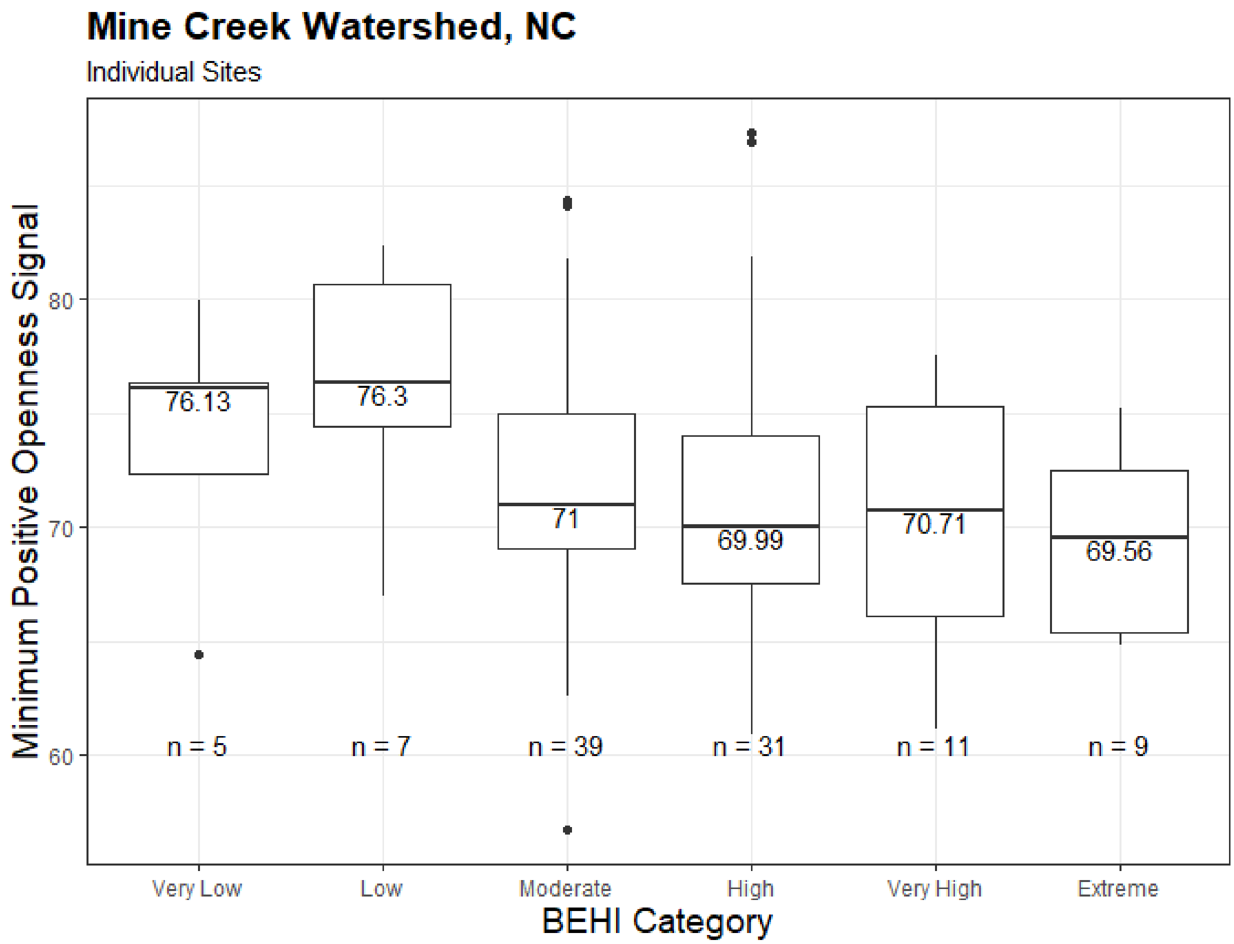


Figure 19. Boxplot of minimum positive openness value versus BEHI category.

Figure 20 illustrates the relationship between the minimum PO 1m signal and BEHI score divided according to stream order. There is no distinguishable pattern between the BEHI score and minimum PO value. ANOVA and Tukey's HSD tests were performed to validate that there was no statistical difference in the mean of the minimum PO value for each BEHI category. Since all p-values exceeded 0.05, no p-values are reported here. The statistical test results are reported in Appendix F – Statistical Analysis Results.

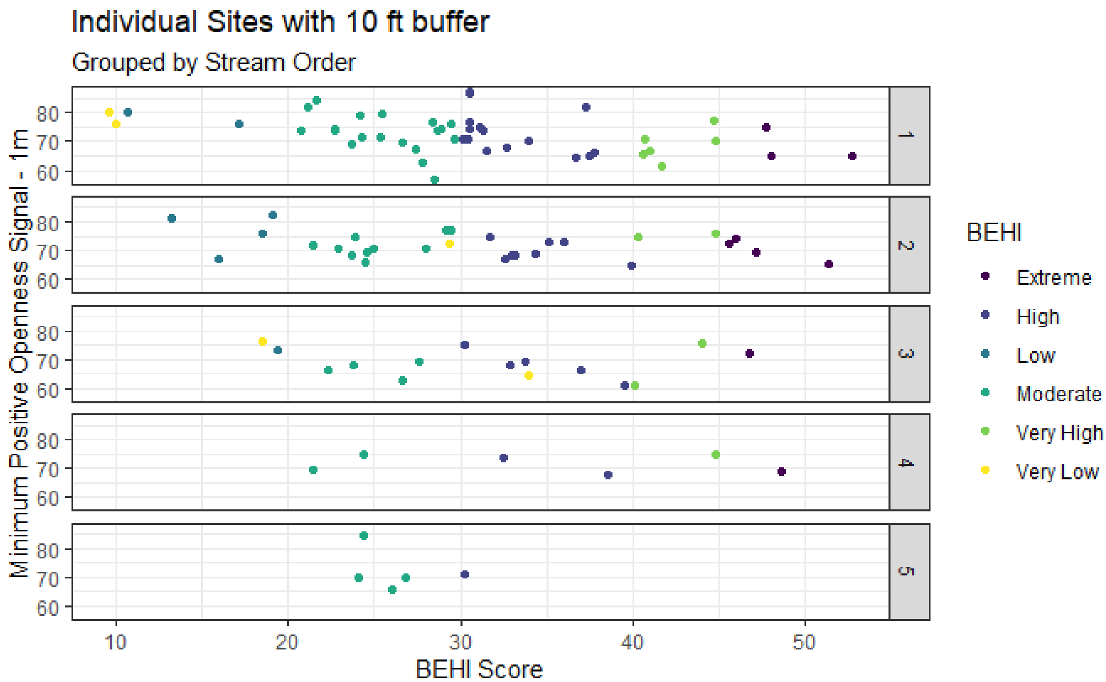


Figure 20. Scatterplot of BEHI Score versus minimum positive openness split by stream order.

Reaches

Correlation plots for each reach and all reaches combined (Figure 21 through Figure 24) illustrate the strength of the relationship between BEHI factors and the PO value using the 10 ft buffers. The minimum PO value has the strongest correlation with the bank angle (-0.57), followed by BEHI Score (-0.56), BEHI category (-0.54) and bank height (-0.49) for Reach 1. The strongest correlations with the minimum PO value for Reach 2 were: bank height to bankfull height ratio (-0.62), BEHI category (-0.54), and bank height (-0.51). The minimum PO value for Reach 3 did not strongly correlate with any factors. The strongest correlation for Reach 3 was the root depth (-0.36). With all reaches combined together, the strongest correlations with minimum PO were with bank height to bankfull height ratio (-0.43) followed by bank height (-0.38).

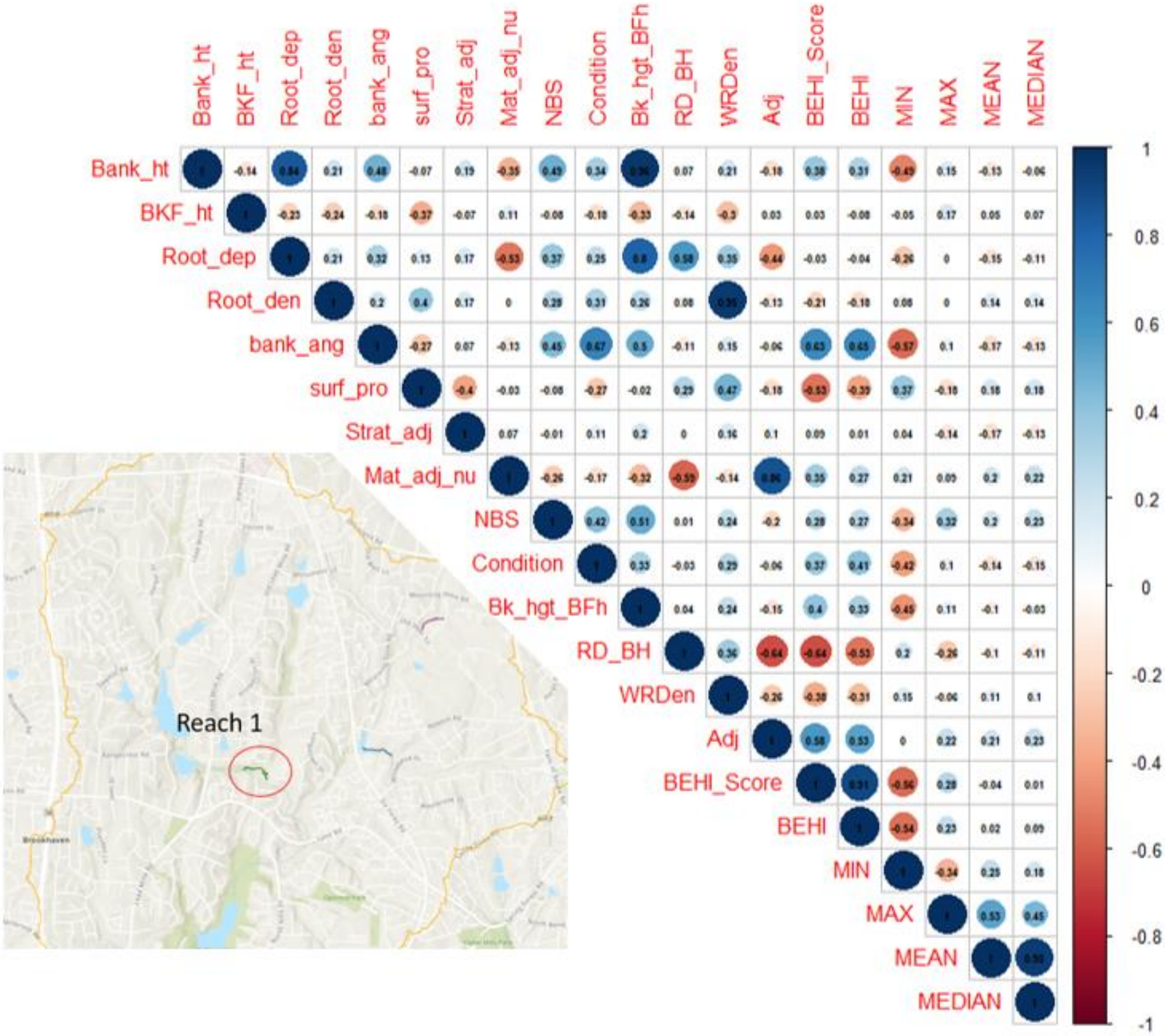


Figure 21. Correlation plot for Reach 1.

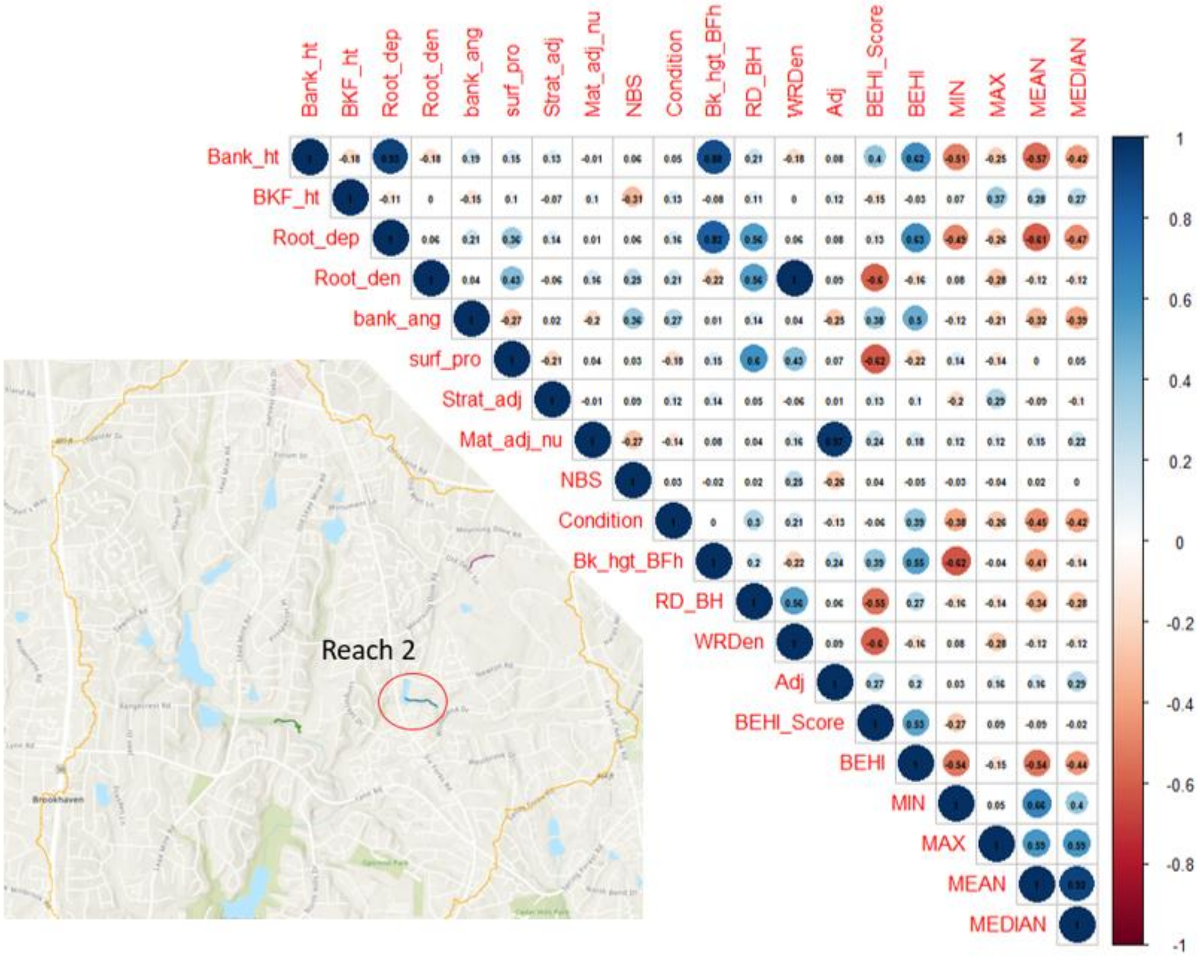


Figure 22. Correlation plot for Reach 2.

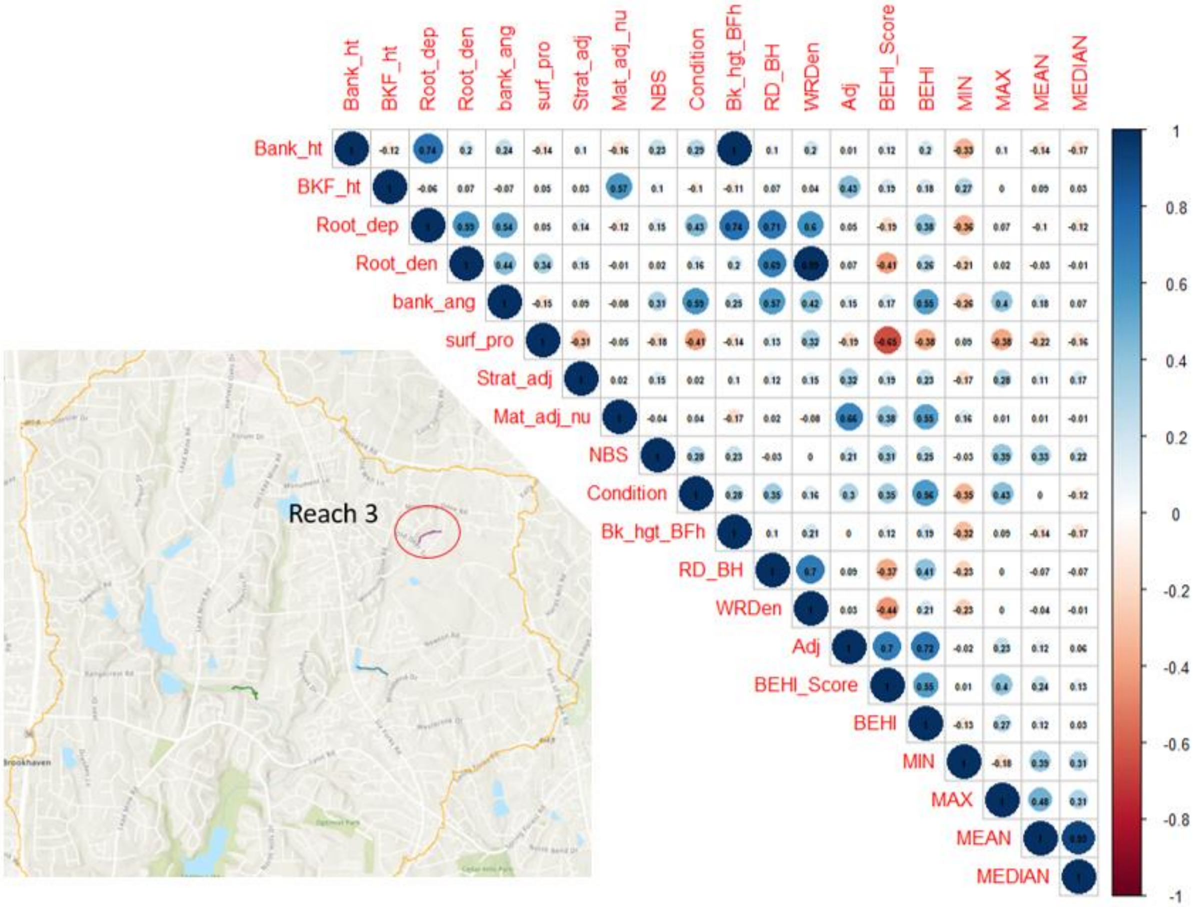


Figure 23. Correlation plot for Reach 3.

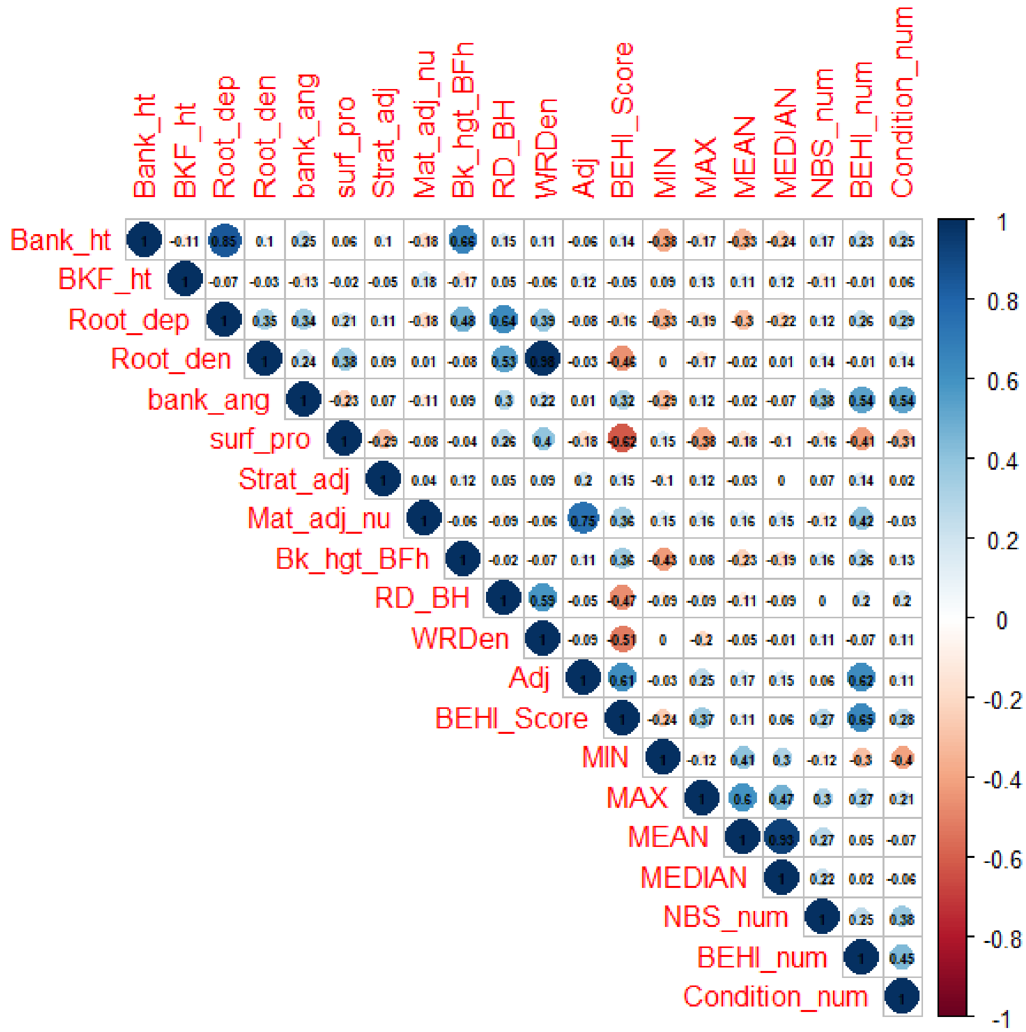


Figure 24. Correlation plot for all reaches combined together.

The correlation plots for the reaches (Figure 21, Figure 22, Figure 23, and Figure 24) have similar results with the variables with the strongest linear relationship with the minimum PO value but all vary. Reach 1 showed the strongest correlations between the PO value and the BEHI Score and BEHI category. Reach 1 is the furthest downstream and closest to Shelley Lake. Reach 3, located the furthest upstream, exhibited the poorest correlations. The results are not adequate to draw statistical conclusions, but suggest that the minimum PO value better identifies erosion at downstream sites compared to headwater locations. Further studies could investigate the difference in PO layer's precision in smaller headwaters compared to larger streams.

However, no relationship was found between the stream order and the minimum PO value in the individual site analysis. The drainage area could be evaluated to see how the PO value differs.

It is worth noting that Mine Creek is located in a colluvial valley, which is typically more confined than alluvial valleys (NEH, 2007). The PO value may better identify erosion in alluvial valleys that allow greater variation in streambank composition and movement.

The correlations between the PO value and BEHI score were as expected for Reach 1. The minimum PO value exhibited the strongest correlations across the board for the three buffers with varying widths. Reach 2 had the worst correlations between PO value and BEHI score. The highest correlation found for Reach 2 was -0.27 which is still fairly low. Reach 3 had the best correlation with the maximum PO value. Figure 23 shows the maximum PO value was slightly correlated with the minimum PO value. Further investigations are needed to determine the cause for this. As pointed out previously, the location of the reaches may be an influencing factor as to the differing trends seen with the correlations.

Various buffer types were tested to see the effect on the correlation between the PO value and BEHI score. The best correlations for each reach are highlighted in green in Table 4 and Table 5. All three reaches had the best correlation with the 10 ft buffers but Reach 1 and Reach 2 with the minimum PO value while Reach 3 had the highest correlation with the maximum PO value.

Since the 10 ft buffers produced the strongest correlations, 10 ft was used to create the buffers on the outside or inside along the streambanks. All three reaches had differing patterns showing no consistent trend. The only similarity was all three had the best correlation with the right bank.

Table 4. Correlation between the BEHI score and positive openness value for different sized buffer types.

	Correlation	10 ft	5 ft	15 ft
Reach 1	PO Mean & BEHI Score	-0.04	0.00	0.03
	PO Min & BEHI Score	-0.56	-0.35	-0.50
	PO Max & BEHI Score	0.28	0.33	0.16
	PO Median & BEHI Score	0.01	0.03	0.07
Reach 2	PO Mean & BEHI Score	-0.09	-0.05	-0.05
	PO Min & BEHI Score	-0.27	-0.05	-0.05
	PO Max & BEHI Score	0.09	0.01	0.01
	PO Median & BEHI Score	-0.02	-0.04	-0.04
Reach 3	PO Mean & BEHI Score	0.24	0.13	0.30
	PO Min & BEHI Score	0.01	-0.05	0.02
	PO Max & BEHI Score	0.40	0.28	0.33
	PO Median & BEHI Score	0.13	0.09	0.28

Table 5. Correlation between the BEHI score and positive openness value for different sized buffer types for left and right banks.

		Left 10 ft		Right 10 ft	
	Correlation	**Outside**	**Inside**	**Outside**	**Inside**
Reach 1	PO Mean & BEHI Score	-0.02	-0.26	-0.02	-0.27
	PO Min & BEHI Score	-0.29	-0.36	-0.36	-0.72
	PO Max & BEHI Score	0.26	0.16	0.38	0.43
	PO Median & BEHI Score	-0.01	-0.35	0.01	-0.25
Reach 2	PO Mean & BEHI Score	0.11	0.11	-0.65	-0.19
	PO Min & BEHI Score	0.15	-0.15	-0.52	-0.26
	PO Max & BEHI Score	0.03	0.25	0.14	-0.42
	PO Median & BEHI Score	0.12	0.13	-0.67	-0.13
Reach 3	PO Mean & BEHI Score	0.05	-0.03	0.47	0.30
	PO Min & BEHI Score	-0.25	0.06	0.21	-0.01
	PO Max & BEHI Score	0.47	-0.38	0.24	0.59
	PO Median & BEHI Score	0.29	0.02	0.46	0.14

Reach 1 had better correlations for the inside buffers on both the right and left banks. The outside right buffer was better than the inside right buffer for Reach 2. The buffers for the left banks were fairly similar. Reach 3 was a mixture of both with the right buffers exhibiting stronger correlations than the left buffers. The best correlation was with the right inside buffer but the left side had a slightly better correlation for the outside than inside. There was no consistent trend found.

The separate buffer delineations for the right and left streambanks had stronger correlations with BEHI score compared to the buffers that combined both sides of the stream. However, it is difficult to recommend the best buffer approach for determining the PO statistics since no consistency was found among the three reaches. More reach data needs to be collected and analyzed to create a standard for extracting the PO value along the streams.

Using the minimum PO value to identify erosion locations versus no erosion seems more promising with both the individual sites and reaches producing the same trends as seen in Figure 14 and Figure 25. There is a stronger relationship between the BEHI categories and minimum PO value for all three reaches compared to the individual sites. Many variations were discovered for all of the BEHI categories, which created overlap of the interquartile ranges for each category, except for very high and extreme. With the increase in erosion potential, there is a decrease in the median minimum PO value except for the extreme category. Further analysis is needed to determine why the extreme BEHI sites do not have the lowest PO value. Even though only four BEHI assessment locations scored very low, they had almost as much variation in PO value as moderate which had 73 locations. In addition, there are a couple of outliers, two for the moderate and one for the extreme. All the outliers are on the lower end of the PO value. Further investigation of the outlier locations may be worthwhile to see if there may be a reason that the minimum PO value is much lower compared to the other PO values for BEHI locations that fall within the same category.

The boxplot of the minimum PO value versus erosion condition for all the reaches (Figure 25) looks similar to the boxplot for the individual sites. For the reaches, mass wasting has the smallest variation. Unstable undercut streambanks exhibit lower PO values than any other erosion condition.

The boxplot of the minimum PO value versus BEHI category shows substantial overlap between all categories except very high. Very low and low have higher medians than moderate, high and very high. The medians for moderate, high and very high decrease.

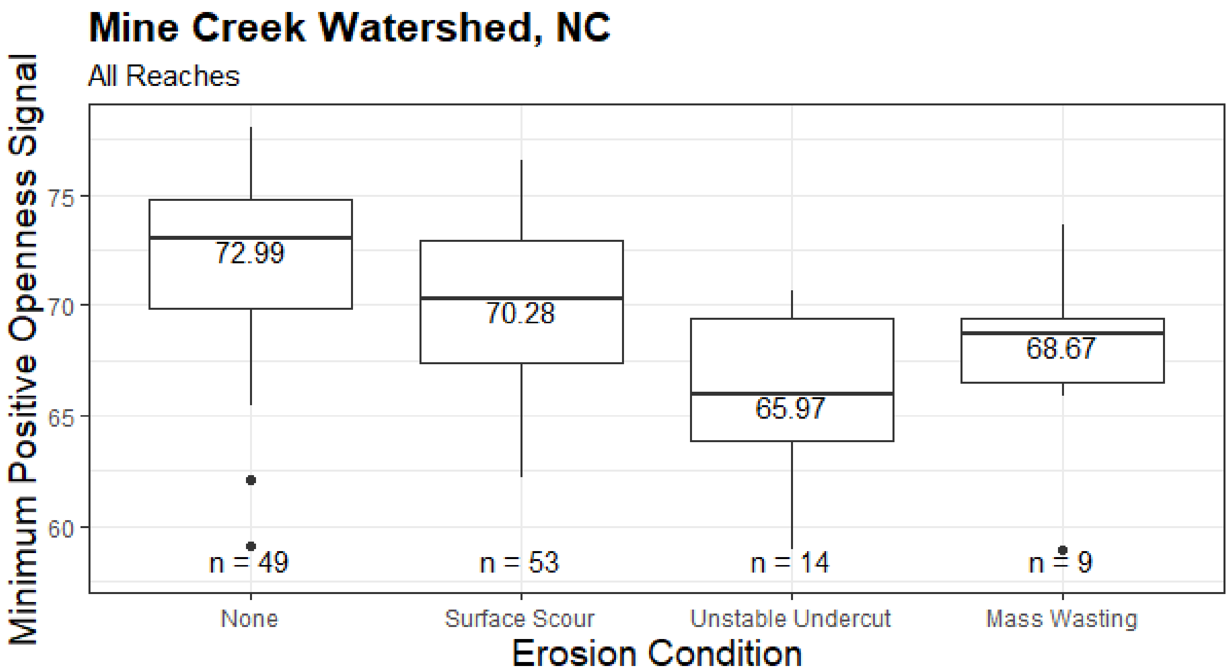


Figure 25. Boxplot of minimum positive openness value versus erosion condition for all reaches sites segregated by the type of erosion found at each location.

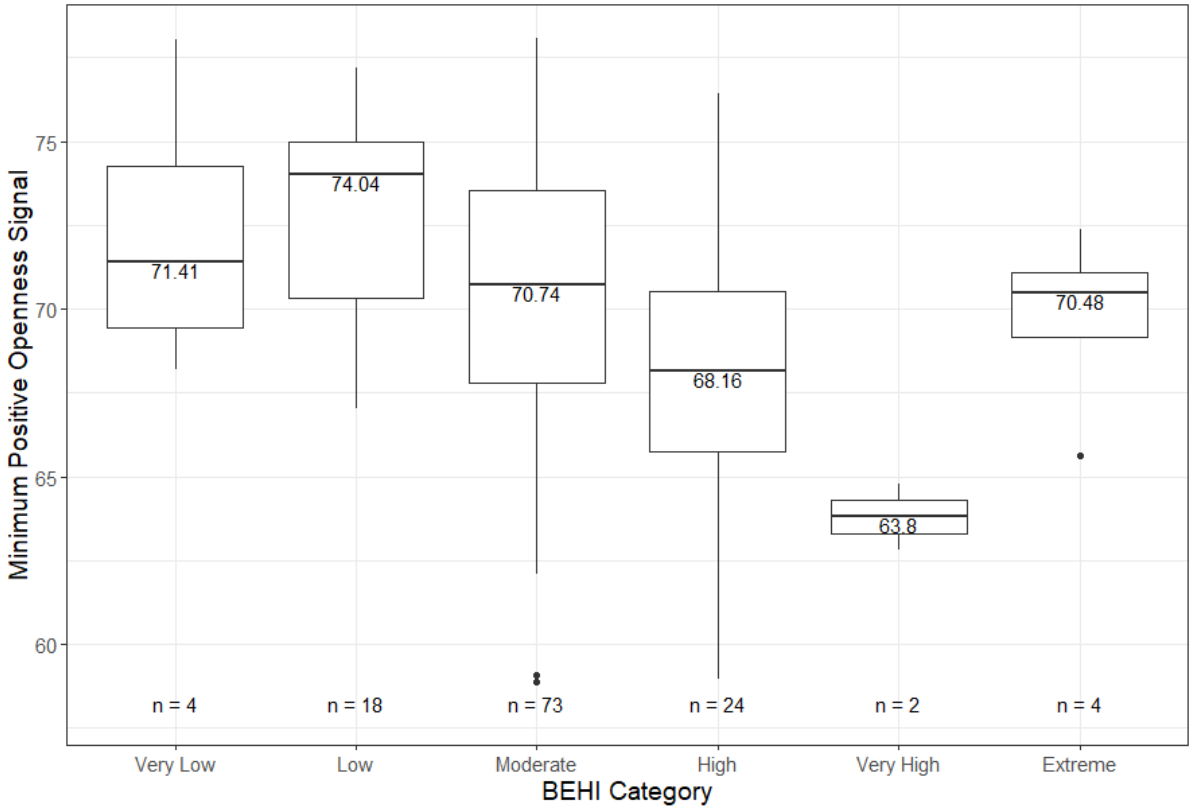


Figure 26. Boxplot of minimum positive openness value versus BEHI category for all reaches sites segregated by the BEHI category found at each location.

Tukey's HSD test results show a statistical difference between no erosion and unstable undercut, no erosion and mass wasting, and surface scour and unstable undercut. No erosion and surface scour are slightly above the 0.05 threshold. The minimum PO value is not as strongly related to the BEHI category. A statistical difference can be distinguished between low and high and low and very high categories but not between the remaining BEHI categories. Tukey’s test results are provided below in Table 4.

Table 6. P-values from Tukey's HSD test for all reaches examining differences in PO value segregated by streambank erosion category.

	P-value
None-Unstable Undercut	0.000013
Surface Scour-Unstable Undercut	0.0058877
None-Mass Wasting	0.0148499
None-Surface Scour	0.0625257
Surface Scour-Mass Wasting	0.3373083
Mass Wasting-Unstable Undercut	0.7858273

Table 7 provides the results of Tukey's HSD test for the PO value for each BEHI category. Very low and low BEHI categories have p-values of 1, signifying that these categories can be combined. Very low and low are sometimes combined when creating erosion curves for a region. Interestingly, very low and extreme also have a very high p-value. They are expected have a small p-value and are statistically different. A possible explanation for the closeness of the high p-value between the very low and extreme sites is that some of the very low sites had steeper banks composed of bedrock automatically placing them in the very low category (Rosgen, 2001a). Colluvial settings may inhibit establishing a relationship between PO value and BEHI erosion categories.

Table 7. P-values from Tukey's HSD test for all reaches examining differences in PO value for each BEHI category.

	P-value
Low-High	0.0066
Low-Very High	0.0421
Very Low-Very High	0.1546
Moderate-High	0.1794
Moderate-Very High	0.2030
Low-Moderate	0.2811
Very Low-High	0.4235
Extreme-Very High	0.5306
High-Very High	0.6752
Low-Extreme	0.7739
Very Low-Moderate	0.9484
Very Low-Extreme	0.9492
Extreme-High	0.9800
Moderate-Extreme	0.9995
Low-Very Low	1.0000

Table 8 summarizes the total bank length, percentage of eroding banks, volume of erosion and average reachwide minimum PO value for the right and left banks of all reaches. The percentage of eroding banks is further divided into the percentage of surface scour, unstable undercutting and mass wasting.

Table 8. Reach summary of eroding banks' percentage, erosion volume, and minimum PO value.

Reach	Bank	Total bank length (ft)	% Total Banks Eroding	% Surface Scour	% Unstable Undercut	% Mass Wasting	Mean Reachwide minimum PO value
1	Right	1554	32.84	21.99	7.59	3.26	71.19
	Left	1612	33.31	11.20	9.76	12.36	70.63
2	Right	1374	36.29	26.23	8.21	1.85	71.75
	Left	1329	36.07	30.60	1.96	3.51	69.46
3	Right	1238	25.96	17.30	6.97	1.70	68.84
	Left	1236	29.86	26.59	3.28	0	70.01

Cross-sections

Both banks, on all cross-sections exhibited measureable bank retreat within the one year monitoring period of January 2021 to January 2022. All of the ratios of measured area and width of top of bank (TOB) and width to values from the NC Piedmont rural regional curve increased from year 1 to year 2, except for W_{bkf}/W_{wbk*} for cross-section 6. The ratios indicate that the channels are widening as the banks erode. The cross-sections with the largest measured bank retreat values have some of the smaller ratios of measured top of bank area to the regional curve bankfull area, measured bankfull area to regional curve bankfull area, measured TOB width to regional curve bankfull area, and measured bankfull width to regional curve bankfull width (cross-sections 1, 3 and 6). Cross-sections 1, 3 and 6 are still actively eroding where the channel is continuing to widen. The other four cross-sections are beginning to reach the end of their degradation stage with decreasing amounts of erosion. This may be a sign that these cross-sections may start to aggrade in the upcoming years, following Simon's channel evolution stages, if there are no additional anthropogenic disturbances that trigger more erosion (Simon, 1989).

Table 9. Summary of watershed area and cross-section measurements for all cross-setions.

		A_{TOB}/A_{bkf*}		A_{bkf}/A_{bkf*}		W_{TOB}/W_{bkf*}		W_{bkf}/W_{bkf*}	
XS	**Watershed Area (mi^2)**	**2021**	**2022**	**2021**	**2022**	**2021**	**2022**	**2021**	**2022**
1	2.88	2.52	2.90	1.10	1.28	2.18	2.36	1.70	1.70
2	0.95	14.44	14.37	2.77	2.90	6.01	4.15	3.56	3.68
3	0.36	11.21	11.91	0.97	0.93	4.81	4.84	1.50	1.87
4	0.15	22.0	20.87	7.35	5.39	8.97	10.29	4.54	4.99
5	0.13	26.88	26.18	6.72	5.62	7.31	7.91	3.91	3.98
6	6.41	3.31	3.36	2.52	1.96	2.12	2.25	1.80	1.64
7	0.09	56.97	59.49	6.24	6.97	7.70	8.61	4.71	5.31

A_{TOB} = measured top of bank area from surveys | A_{bkf*} = bankfull area from NC Piedmont rural regional curve
A_{bkf} = measured bankfull area from surveys | W_{TOB} = measured top of bank width from surveys
W_{bkf*} = bankfull width from NC Piedmont rural regional curve | W_{bkf} = measured bankfull width from surveys
* Point bar so no BEHI data was taken

Table 10. Summary of BEHI, NBS and Bank Retreat for cross-sections.

								Bank Retreat (ft/yr)				
ID	**XS**	**Bank**	**Condition**	**Complaint**	**BEHI Score**	**BEHI**	**NBS**	**Max**	**Mean**	**Min**	**NC Curve**	**Minimum PO value**
MC240	1	Left	MW	No	44.83	Very High	very high	6.17	0.80	0.00	1	74.73
MC455	1	Right	None	No	23.18	Moderate	very low	9.74	2.81	0.00	0.009	73.96
MC163	2	Left	MW	No	40.13	Very High	low	0.80	0.30	0.00	0.6	61.14
MC444	2	Right	SC	No	25.50	Moderate	very low	0.55	0.18	0.00	0.009	69.11
MC173	3	Left	SC	No	24.95	Moderate	very high	1.53	0.58	0.00	0.3	70.59
MC372	3	Right	None	No	27.79	Moderate	very low	6.54	1.87	0.12	0.009	71.35
MC203	4	Left	MW	No	33.16	High	high	2.26	1.33	0.00	0.2	68.21
MC203_XS	4	Right	*	No	NA	NA	NA	0.25	0.00	0.00	NA	72.55
MC288_XS	5	Left	*	Yes	NA	NA	NA	0.77	0.17	0.00	NA	84.98
MC288	5	Right	MW	Yes	52.68	Extreme	moderate	1.10	0.26	0.00	1.5	65.12
MC92_XS	6	Left	*	No	NA	NA	NA	0.66	0.00	0.00	NA	76.32
MC92	6	Right	SC	No	24.34	Moderate	very high	3.81	1.80	0.00	0.3	84.31
MC222	7	Left	SC	Yes	23.65	Moderate	moderate	0.15	0.00	0.00	0.15	64.18
MC220	7	Right	MW	Yes	36.65	High	moderate	2.36	1.52	0.22	0.05	68.81

There is a wide distribution in the difference between the measured bank retreat and the bank retreat estimated from the NC erosion curve using the BEHI/NBS data (see Figure 27). Only the outside curves of banks are shown in the figure, excluding banks that exhibited deposition. In general, the average bank retreat was closest to the value from the erosion curve. A 0 ft/yr difference represents where the measured bank retreat equals the erosion curve. Positive values indicate the measured bank retreat exceeds the predicted value. Negative difference values indicate measured bank retreat was less than the curve-predicted bank retreat. All of the minimum measured bank retreat values are less than the predicted value except for cross-section 7. Cross-section 7 was the only cross-section have a minimum bank retreat value greater than 0 ft/yr. Cross-section 5 is the only cross-section where the bank retreat estimated with the curve was greater than all measured bank retreat values.

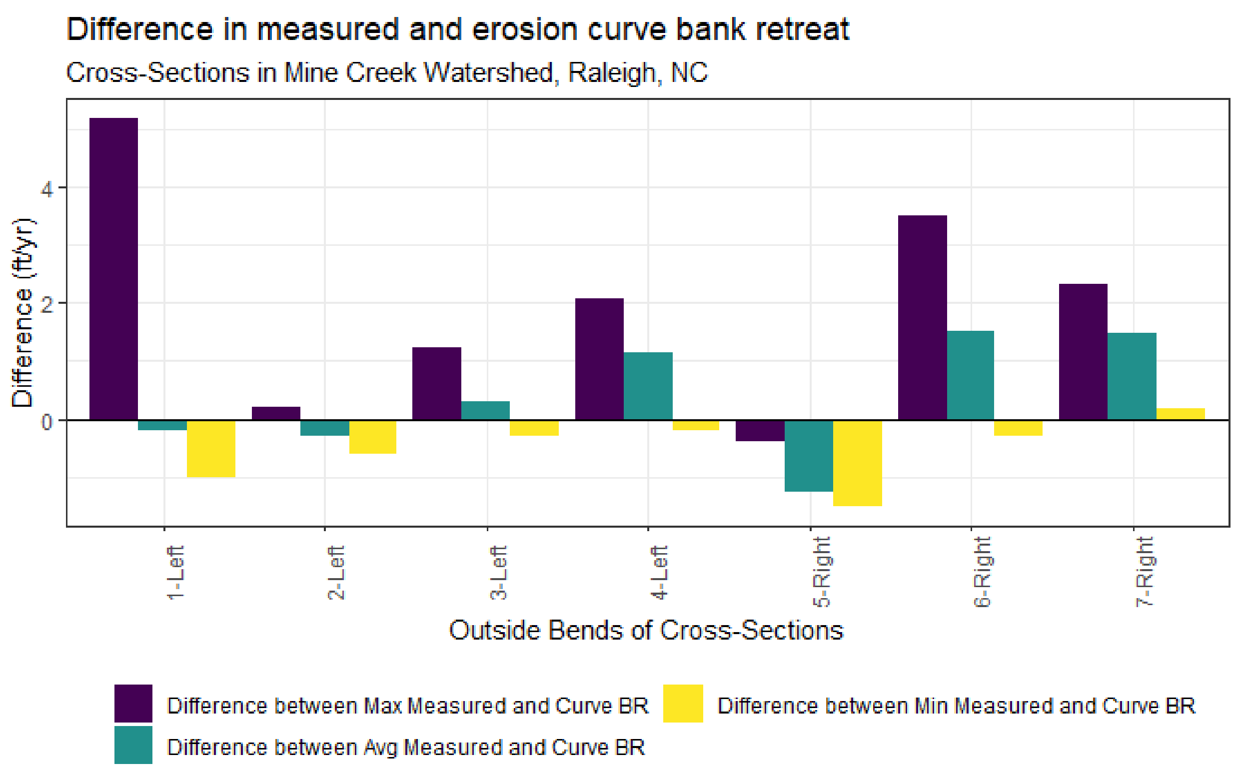


Figure 27. The difference between the average, minimum, and maximum measured streambank retreat and the predicted streambank retreat (Doll et al., 2003) for all cross-sections.

The plot below indicates that there is a fairly strong relationship between the measured bank retreat from the outside of bends and the minimum PO value. Establishing and monitoring additional cross-sections to provide additional data and more broad spatial coverage of the entire watershed is therefore recommended to further evaluate this relationship. Additional data may result in a statistically acceptable model for predicting bank retreat using the minimum PO signal.

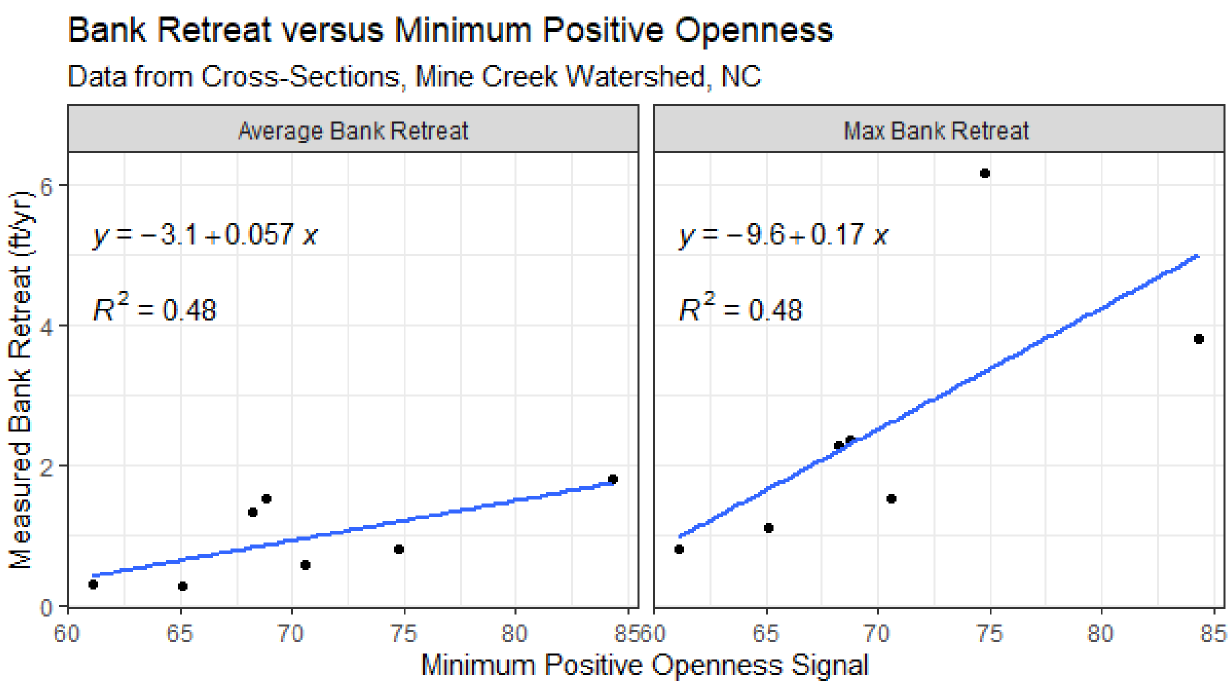


Figure 28. Measured bank retreat versus minimum positive openness.

Top of Bank

The volume of eroded sediment for the outer bend of each cross-section was estimated from TOB surveys following the same methodology used to estimate bank retreat using aerial imagery. Table 11 shows the summary of the results from the TOB surveys. Table 12 compares the eroded volumes estimated from TOB surveys and those estimated using the measured bank retreat from cross-section surveys. Except for cross-section 1, the maximum bank erosion volume was closest to the TOB erosion volume. The findings in Table 12 suggest that when using cross-sections to estimate reachwide retreat, it may be best to use the maximum measured bank retreat rather than the average bank retreat. Additional data is needed to adequately test this hypothesis.

Table 11. The volume of erosion and deposition from top of bank cross-section surveys.

XS	Bank	Erosion (ft^3)	Deposition (ft^3)
1	Left	477.6	359.1
2	Left	1252.7	308.6
3	Left	195.3	213.4
4	Left	5622.0	258.0
5	Right	1085.5	304.4
6	Right	2008.9	1302.0
7	Right	1817.0	789.6

Table 12. Comparison of Erosion Volume from TOB versus bank retreat.

XS	Bank	TOB Erosion (ft^3)	Max BR Erosion (ft^3)	Avg BR Erosion (ft^3)	Min BR Erosion (ft^3)
1	Left	477.6	1762.2	288.5	0
2	Left	1252.7	485.4	182.0	0
3	Left	195.3	238.7	90.5	0
4	Left	5622.0	1328.9	782.0	0
5	Right	1085.5	1092.2	258.1	0
6	Right	2008.9	1524.0	720.0	0
7	Right	1817.0	1298.0	836.0	121.0

Both estimations of volume assume a 90º bank angle. The cross-section estimation assumes a uniform bank retreat across the entire length of the BEHI section. In addition, there is some approximation when estimating the length of the eroding bank. The aerial imagery base map in ArcGIS Pro was unusable for Mine Creek due to the high density of forested coverage, making it nearly impossible to decipher the TOB. TOB is clearly defined in the PO layer, but it is still an approximation with a 1 m pixel size. The approximation of each bank's length could be a contributing factor to the wide ranges of erosion volumes between the two methods. The same bank height was used for both methods.

All BEHI Data

Mine Creek BEHI data from the individual sites and reaches were combined. This combined dataset was used to determine what minimum PO value correlates with the erosion type and BEHI category that should be seen in the field through performing ANOVA and Tukey's HSD test. Complete results can be found in Appendix F – Statistical Analysis Results. The minimum PO value can be used to distinguish differences between all types of erosion except mass wasting and unstable undercut, based on Tukey's HSD test results provided in Table 13. Unstable undercut precipitates mass wasting as the top of the bank eventually breaks off as the toe of the bank is eroded away. Therefore, where unstable undercut is identified, mass wasting will most likely follow unless intervention is made.

Table 13. P-values from Tukey's HSD test for all Mine Creek data examining differences in PO value segregated by streambank erosion category.

	P-value
None-Unstable Undercut	0.0000335
None-Mass Wasting	0.0001021
Surface Scour-Unstable Undercut	0.0119160
Surface Scour-Mass Wasting	0.0343666
None-Surface Scour	0.0396096
Mass Wasting-Unstable Undercut	0.9727184

Based on these findings, it is recommended to adjust the USGS PO categories initially used to visualize the severity of incision and erosion. For example, the PO layer could be visualized based on erosion category: no erosion, surface scour and mass wasting. Mass wasting would be a combined category including unstable undercut. The median minimum PO values associated with the erosion categories are lower than the values initially selected by USGS who selected 81-84 for moderate erosion and less than 81 for more severe erosion.

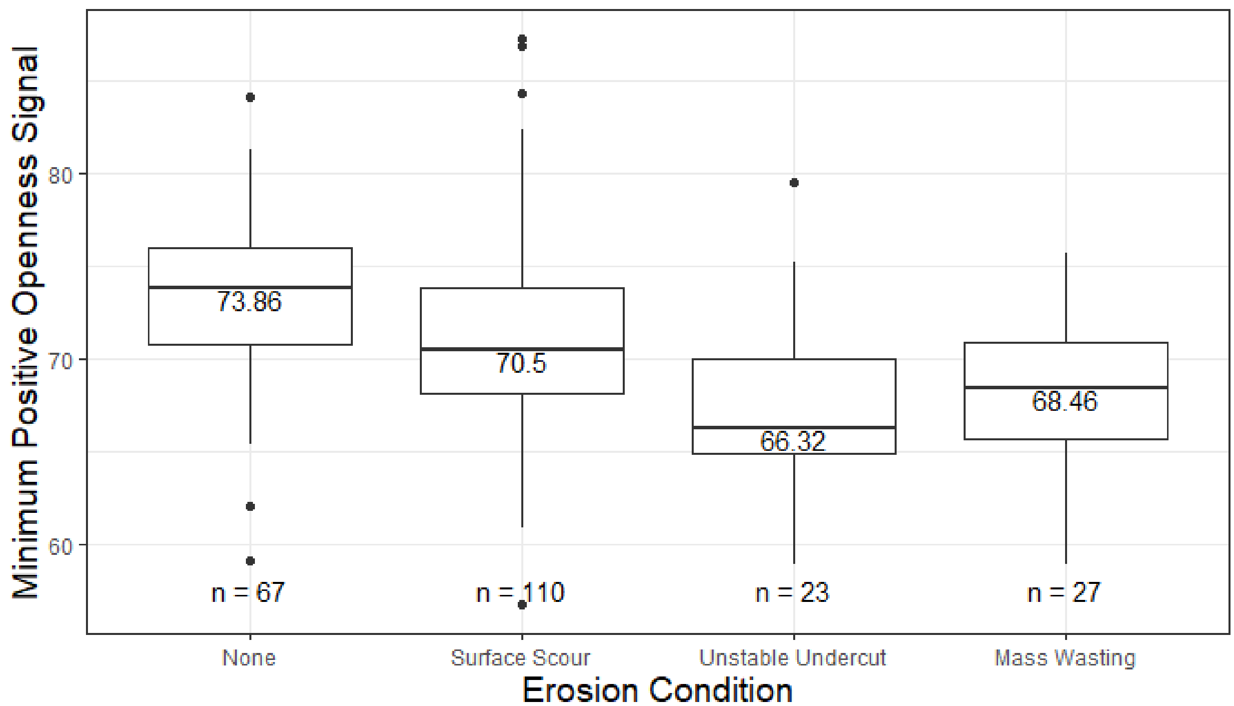


Figure 29. Boxplot of minimum positive openness value versus erosion condition for all data segregated by the type of erosion found at each location.

The only statistical difference that can be distinguished using the minimum PO value for BEHI categories is between low and high. Low and very low, high and very high, extreme and very high, and high and extreme do not show any difference in the PO value among these categories. Very low and low are often combined into one erosion curve, so are high and very high. Tukey's HSD test of PO values verifies that merging these datasets is a reasonable approach. Using the PO value as a basis, there is essentially no difference in the sites that received a very low and low BEHI score and the same holds true for the other pairs with very high p-values. Based on these statistical tests, the PO layer is best used to identify the erosion condition found at each locations. However, there is not a strong enough relationship between PO and BEHI to use just the PO layer to identify the BEHI category in order to estimate bank retreat.

Table 14. P-values from Tukey's HSD test for all Mine Creek data examining differences in PO value segregated by BEHI category.

	P-value
Low-High	0.016
Low-Moderate	0.103
Low-Very High	0.105
Low-Extreme	0.177
Very Low-High	0.450
Very Low-Very High	0.502
Very Low-Extreme	0.623
Very Low-Moderate	0.791
Moderate-High	0.795
Moderate-Very High	0.896
Moderate-Extreme	0.969
Low-Very Low	0.999
High-Very High	1.000
Extreme-Very High	1.000
High-Extreme	1.000

Soil Sampling Results

Table 15 provides the results for the soil samples taken on the outside bend of each cross-section. Stratification was present at cross-section 2 requiring two soil samples to be collected (one from each layer).

Table 15. Soil sample results for all outside bends at all Mine Creek cross-sections.

Sample ID	**TN (mg/kgDW)**	**TP (mg/kgDW)**	**Dry Weight (g)**	**Bulk Density (g/cm^3)**
MC-1-Left	359.27	190.40	423.02	1.47
MC-2-Left-Top	263.03	208.92	324.04	1.12
MC-2-Left-Bottom	677.29	319.22	322.49	1.12
MC-3-Left	296.46	139.39	474.67	1.65
MC-4-Left	192.23	90.14	482.48	1.67
MC-5-Right	207.51	232.21	347.94	1.21
MC-6-Right	338.65	173.80	376.61	1.31
MC-7-Right	1160.00	169.50	352.45	1.22

Sediment and Nutrient Loads

Several approaches for computing total sediment loads from eroding streambanks throughout the Mine Creek watershed were considered and tested in RStudio. However, none of the models produced relating BEHI to positive openness or bank retreat produced a reliable enough statistical relationship for this computation. Despite showing a strong trend between measured erosion rates and PO value at the seven cross sections, this does not provide enough data to reliably estimate bank retreat based on minimum PO value for the entire watershed. However, we prepared a sample procedure for this effort to estimate the total watershed sediment and nutrient loads from streambank erosion that are reaching Shelley Lake. This effort aims to show how the minimum PO value can be used for estimating if future data produces better models.

Individual site assessment data was used to develop the model to predict bank height. The individual site model produced a better statistical model than one that combined all the data (individual sites and reaches). The model was tested using five k-folds cross-validation. The table below contains the R^2 and RMSE values from each of the k-folds. Additional future data may produce a stronger relationship between the measured bank height and minimum PO value.

Table 16. R^2 and RMSE reported values from k-fold cross-validation model to predict bank height.

R^2	RMSE
0.37	0.10
0.34	0.12
0.40	0.11
0.39	0.11
0.45	0.11

The diagnostic plots illustrate the assumptions that the errors are normally distributed, homoscedasticity of errors and observations are independent. The residuals vs. fitted plot show the values to be centered about zero and points fall along the one-to-one line in the Q-Q plot.

There are no true outliers in the residuals vs. leverage plot since none of the points are outside the 0.5 lines, but there a couple of points that could be potential leverage points. Since this is a natural system where extreme events do occur, it is important to include all observations within the model.

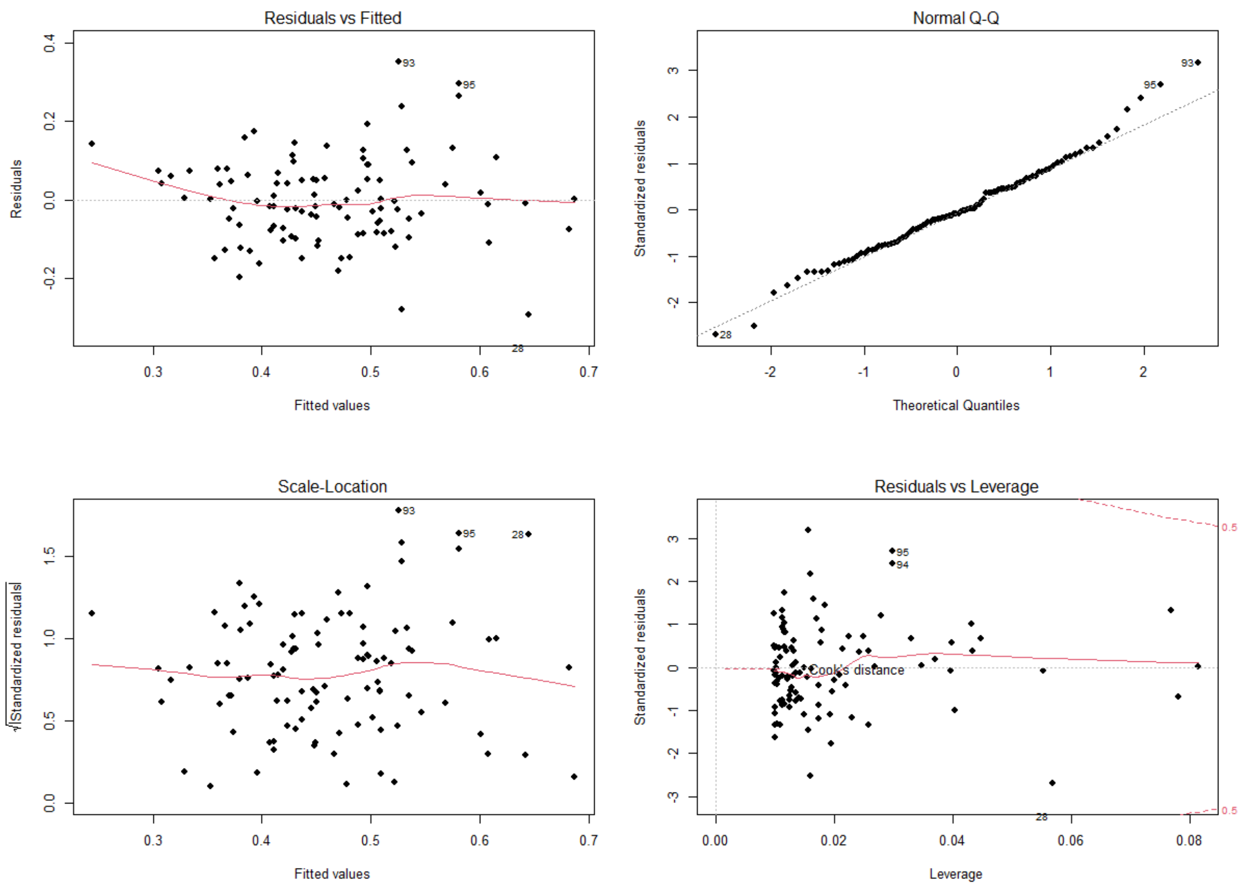


Figure 30. Diagnostic plots for the bank height model.

The final model produced using all of the individual site data has an R^2 of 0.36 and RMSE of 0.11. The model explains 36% of the variation in bank height. The linear regression is below. In order to uphold the assumptions of a linear regression model and produce the best fit, the response variable had to be transformed.

Equation 1. Linear Regression equation to predict bank height using minimum PO value.

$$1/\sqrt{Bank\ Height} = 0.01451 * Minimum\ PO - 0.5788$$

In RStudio, the bank height model was used to predict $1/\sqrt{bank\ height}$ for each channel segment using the PO value associated with each segment. This value was raised to the negative second power to report the bank height in feet. Refer to Appendix I – Estimating Sediment and Nutrient Loads for the full R script.

A correlation of 0.09 between the minimum PO value and estimated bank retreat values from the NC Erosion Curve made it impossible to develop a model to predict bank retreat using the Erosion Curve.

Figure 28 shows a much stronger relationship between minimum PO value and measured bank retreat. As a result, the measured bank retreat from the outside bend obtained from the seven cross-sections was used to develop the model.

A linear regression was constructed for the average and maximum measured bank retreat. The diagnostic plots shown in Figure 31and Figure 32 are not the best, but it is not easy to have good diagnostic plots with only seven data points. The Q-Q plot is reasonable with the points falling along the one-to-one line for Figure 31. The residuals vs fitted values are not fully centered about zero for both average and maximum bank retreat. In Figure 32, the residuals vs leverage plot indicate that data point 12 (MC92) is an outlier because it is outside the 1 line. Outliers should be discarded if they occur by chance (Dhakal, 2017). MC92 will be kept in the model since it is not a measurement error but a representation of the potential extreme bank retreat. A linear regression model was created excluding MC92 which did change the regression equation and increased the R^2 value of the model. The model used for the final calculations of the sediment and nutrient loads included the outlier to better capture the full range of possible bank retreat values.

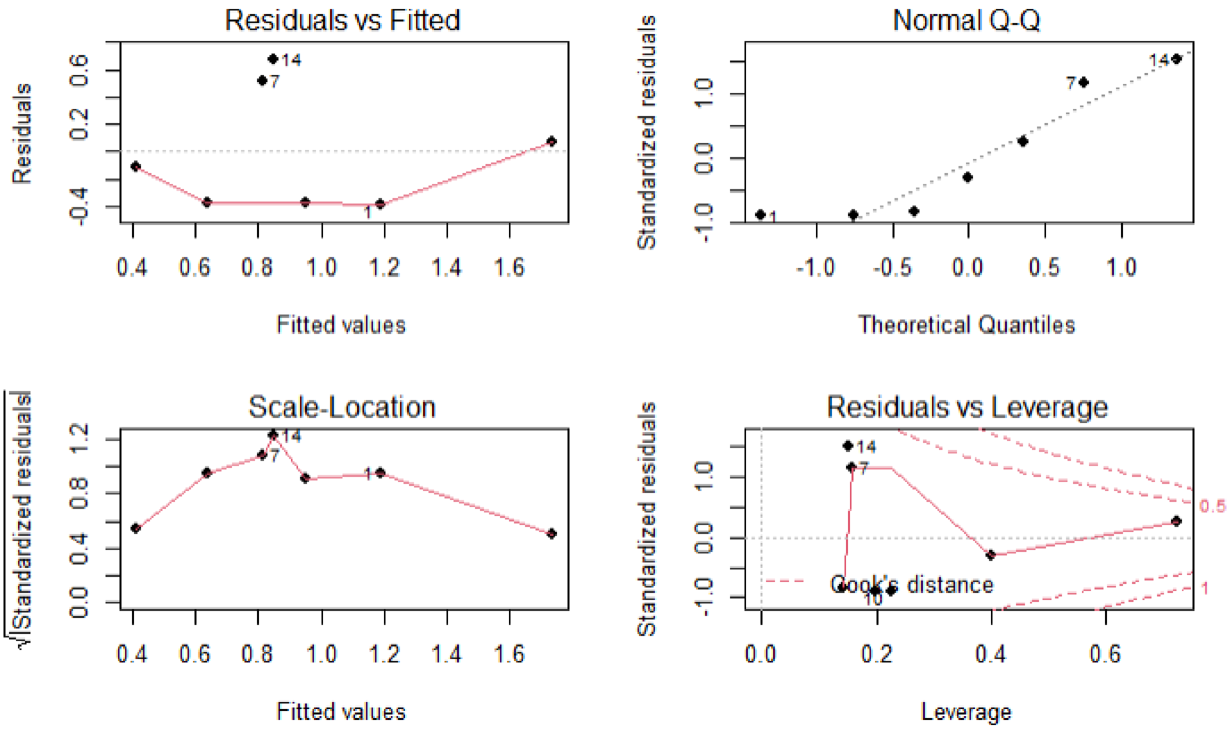


Figure 31. Diagnostic plots for the linear regression predicting average bank retreat using minimum PO value.

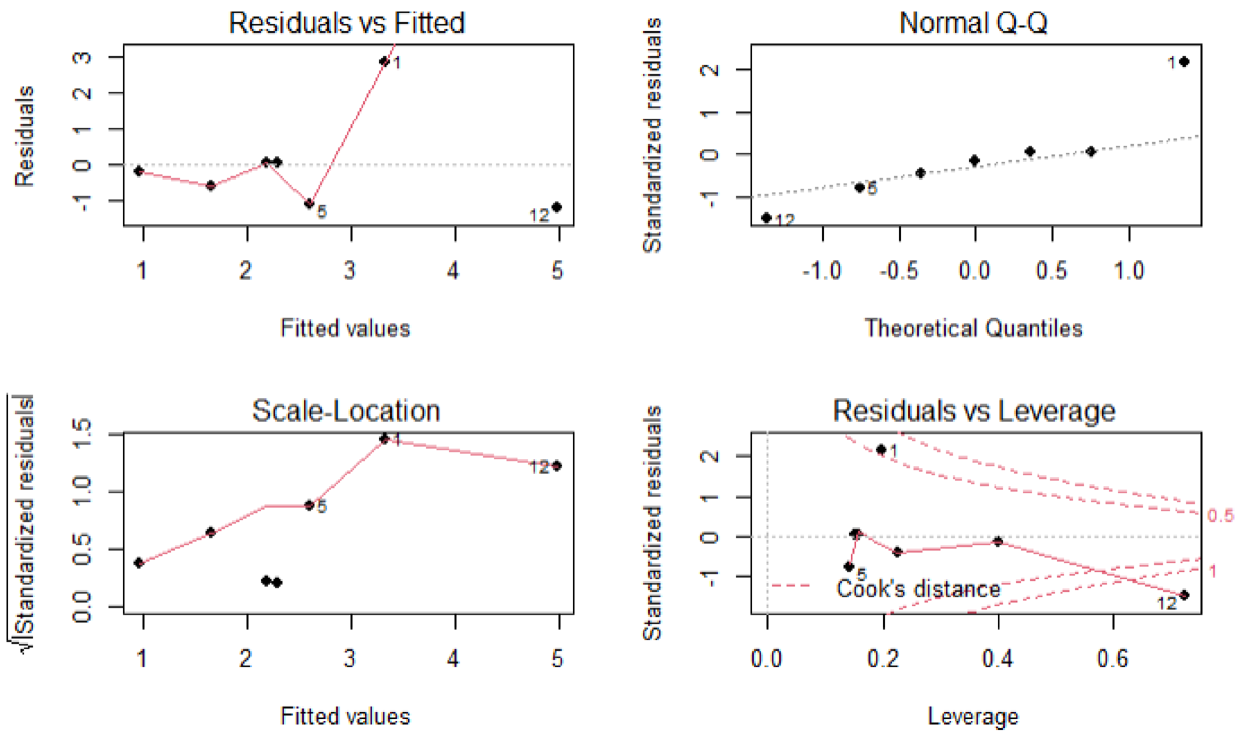


Figure 32. Diagnostic plots for the linear regression predicting maximum bank retreat using minimum PO value.

Figure 28 above shows the two linear regression models used to predict average and maximum bank retreat with minimum PO value. The figure below shows how the linear regression model changes when the outlier (MC92) is removed.

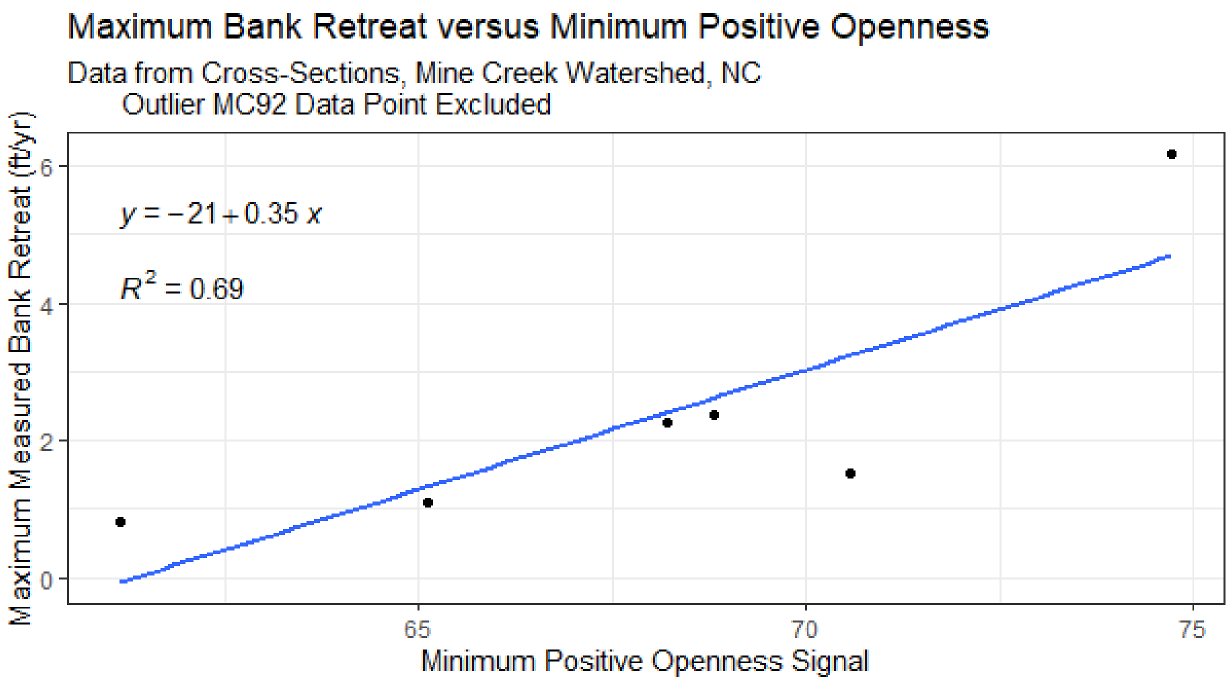


Figure 33. A linear regression model to predict maximum bank retreat excluding the outlier.

Table 17 reports the estimated average and maximum sediment, TN and TP loads in Mine Creek Watershed that drains to Shelley Lake. These values should not be used as a basis for any management decisions. The estimates were provided to demonstrate how to estimate sediment and nutrients loads using the minimum PO value.

Table 17. Estimated sediment and nutrient loads going to Shelley Lake.

Average Sediment Load (tons)	39,150
Maximum Sediment Load (tons)	87,489
Average TN Load (lbs)	34,401
Maximum TN Load (lbs)	76,985
Average TP Load (lbs)	14,874
Maximum TP Load (lbs)	33,274

Assuming an average depth of six feet across the 28 acre surface area, we estimated the volume of Shelley Lake to be approximately 7,318,080 ft^3. Based on the predicted average and maximum sediment load from streambank erosion, Shelley Lake would fill with sediment in 3.5 to 8 years. This estimate is inaccurate given the lake has yet to fill with sediment since the dam that created the lake was constructed in 1975 (US National Dams, 2022). This prediction is unrealistic because it applies an overly simplistic model that assumes all sediment eroded from streambanks reaches Shelley Lake and that all eroded material deposits in the lake. The rate of erosion and deposition changes from upstream to downstream. Usually there is a greater floodplain storage downstream as a floodplains widens (Wohl et al., 2015). The downstream floodplain storage can balance out upstream erosion leaving the watershed in equilibrium (Noe et al., 2022; Wohl et al., 2015). Since this study was focused on identifying and measuring erosion, no data on deposition and sediment storage on the floodplain and within the channels was collected. Floodplain depositions can be a significant component of the sediment budget. Floodplain storage was estimated to make up 50% of the sediment yield for Good Hope Tributary, Maryland (Allmendinger et al., 2007). Incorporating deposition into the model would provide a more accurate estimate of the total sediment exported to Shelley Lake.

In addition, the model assumes that all streambanks are eroding. In actuality, only eroding banks will contribute to the sediment load and some of the eroded material will deposit in stream segments before reaching Shelley Lake. Further, some portion of the fine clay and silt material will remain in suspension and flow through the lake into downstream waters. The model also does not account for watershed-based sediment sources from construction, tillage and other land uses that contribute to instream sediment loads (Hatfield and Maher, 2009). Regression equations, like RUSLE2, could be used to estimate upland erosion (Allmendinger et al., 2007; Noe et al., 2022). Further refinement of the relationship between minimum PO value and eroded sediment volume deposited downstream is needed to factor in the aggradation and differentiate between suspended and bed loads. For example, if suspended sediment incoming to Shelley Lake had been monitored, the difference between the estimated eroded sediment and suspended sediment could be assumed to represent the stored and deposited sediment. This approach is similar to how Gellis et al. (2017) estimated upland erosion as the difference between the measured sediment export and sediment inputs.

The model produced an average sediment loading rate of 0.11 tons/ft/yr (tons per linear foot of stream length per year) and a maximum rate of 0.24 tons/ft/yr (equal to 2.53 ft^3/ft/yr average and 5.66 ft^3/ft/yr maximum). This estimate is less than the 0.2 to 4 tons/ft/yr reported by Walter et al. (2007) based on compiled data for southeastern and central Pennsylvania streams. Our estimates however fall within the lower end of the 1.8 to 158.9 ft^3/ft/yr range reported by Wegmann et al. (2013) for the NC Piedmont. Hopkins et al. (2018) estimated 45,959 tons/yr of eroded streambank sediment for Difficult Run watershed, Virginia. Dividing that by the watershed area, the amount of streambank erosion per square mile is 490 tons/mi^2/yr for Difficult Run (Hopkins et al., 2018). The eroded streambank erosion for Mine Creek per square mile (3915 tons/mi^2/yr) is about eight times that estimated amount for Difficult Run. Both are suburban watersheds with similar impervious cover percentages within the Piedmont region. By comparison to the Hopkins et al. (2018) study, the Mine Creek models are over likely estimating streambank erosion.

The average erosion rate is 0.43 ft/yr and the maximum erosion rate is 0.96 ft/yr. The mean of the measured average bank retreat from the outside bend of all the cross-sections is 0.94 ft/yr. The mean measured average bank retreat is close to the maximum erosion rate estimated from the predicted sediment load going to Shelley Lake. The bank erosion estimates from the models are not unreasonable but the assumption that all the sediment is deposited in Shelley Lake is inaccurate.

Sediment-bound N and P loads from streambank erosion in Difficult Run were estimated to be 28,513 kg/yr and 13,918 kg/yr respectively (Hopkins et al., 2018). The estimated average N and P loads for Mine Creek are slightly higher. When standardizing the loads based on the watershed area, the N and P loads for Mine Creek are about 10 to 11 times greater than those estimated for Difficult Run. Therefore, there could be more incoming N and P to Mine Creek from streambank erosion compared to Difficult Run since the nutrient load estimates are even higher than the eroded sediment load estimate.

The average and maximum TN load from streambanks divided by the watershed area for Mine Creek that reaches Shelley Lake were estimated at 3,440 lbs/mi^2 and 7,699 lbs/mi^2, respectively. The average and maximum TP loading rates (compared to the watershed area) are 1,487 lbs/mi^2 and 3,327 lbs/mi^2 respectively. The TP estimates are significantly larger than the 700 to 2,340 lbs/mi^2 reported for Winston-Salem, NC (Line et al., 2002). Studies have reported TN loading rates of 913 lbs/mi^2 to 21,980 lbs/mi^2 and TP rates of 17 lbs/mi^2 to 3,557 lbs/mi^2 for urban areas (Line et al., 2002). Our estimate of TP loading from streambanks for Mine Creek is comparable to the upper end of the reported range for watershed loading of TP from land-based sources, while the TN load estimated is in the low to moderate range. It should be noted that the estimates of TN and TP loads for Mine Creek are dependent on the estimated sediment load; therefore, refinement of the sediment loading estimate will also improve the estimate of TN and TP loads.

The procedures developed for estimating sediment loads and associated nutrient loads to Shelley Lake should serve as a starting place for others to build off. A limitation of the models produced by this effort was the use of a single predictor variable, the minimum PO value. While the minimum PO value represents the degree of incision of the stream, multiple additional factors that likely contribute to the rate of erosion were not evaluated. Geospatial data layers such as soil type, channel slope or adjacent land use cover could potentially improve the model fit. These factors were not incorporated since the objective of this study was to determine if the minimum PO could identify streambank erosion. The models developed in this study only address the streambank erosion component of the overall sediment regime. Sediment deposition, floodplain storage and upland erosion must all be added in order to understand the full picture of the sediment regime within the Mine Creek watershed.

Conclusions and Recommendations

For this study, 52 individual sites and three study reaches of approximately 1000 feet in length located in the Mine Creek watershed of North Raleigh were assessed for streambank condition and future erosion potential. Erosion potential was estimated by applying the BANCS method, which includes qualitative and quantitative assessments of variables believed to contribute to the erosion potential for streambanks. The assessment of results were compared to the geospatial mapping of positive openness. Various buffer configurations were used to quantify the degree of positive openness value for each assessment location and along the channel length for each study reach. Statistical analyses were conducted to evaluate relationships between the positive openness value and the presence and type of erosion as well as individual streambank erosion potential variables. Statistical analysis revealed that PO value was useful in identifying locations of mass wasting and undercutting of streambanks, representing more extreme erosion conditions. PO value did not relate well to the total scores of streambank erosion potential. However, the PO value did show some relationship with the streambank height. Results of this study indicate that the positive openness data layer may be useful for identifying locations of erosion, enabling the identification of potential sites in need of stabilization prior to field assessments, and saving time and resources.

Seven permanent cross sections in areas with more severe erosion were surveyed two times, one year apart. Data from the survey was used to calculate the rate of annual bank retreat. Measured retreat rates showed a wide distribution in the difference between the predicted retreat obtained from the NC Erosion Curves based on the assessment of BEHI and NBS for the eroding bank at each cross section. The average bank retreat was closest to the value from the erosion curve. Comparing the measured bank retreat and the minimum PO value suggested a strong positive linear relationship. Based on this finding, it appears promising that a statistically usable model to predict bank retreat could be developed by collecting additional bank retreat measurements throughout the entire watershed. The next steps should focus on improving the relationships in this study and considering the fluctuation in erosion rates dependent on the erosion condition. Multiple years of data from repeated surveyed cross-sections would be needed to provide a truer estimate of the average erosion rate. The model could be improved by assigning a bank retreat value based on the identified erosion condition. Recording the conditions data was collected under, such as the frequency and intensity of storm events and flow data from gages would provide additional inputs to the model, enabling the study trends between measured erosion and hydrologic and climatic conditions.

While the data collected in this study did not render statistically viable models for estimating the total sediment and nutrient loads produced by streambank erosion in the Mine Creek watershed, a procedure was developed for future consideration. The procedure was then used to estimate the sediment and nutrient loading supplied to Shelley Lake as a result of streambank erosion. This estimate aimed to demonstrate how the PO layer could potentially be used for watershed and water quality analyses. Sediment and nutrient load estimates from this procedure were comparable to results of streambank erosion loads from other studies. The estimate also indicated that TP loads from streambank erosion could be high relative to other watershed sources, while TN loads could be in the low to moderate range.

A distributed model approach is required to capture the spatial variability of streambank erosion within a watershed. Distributed models require more data to cover the range of conditions which is more intensive and time-consuming than using a lumped model approach (Merritt et al., 2003). Different erosion rates would need to be estimated for different stream orders and different erosion types with consideration given to the stage of channel evolution. More recent approaches for estimated sediment loads have begun to consider longitudinal variation of erosion rates by differentiating rates based on stream order (Gellis et al., 2017; Hopkins et al., 2018; Noe et al., 2022). These approaches still neglect to address the stage of evolution. While a stream could visually appear to still be actively eroding, it could be shifting from an incising and widening channel to one that is aggrading. The annual erosion rate will adjust to reflect the evolution stage. As the access and ability to process geospatial data on larger scales continues to improve, more of the spatial and temporal variability of streambank erosion will be able to be captured and modeled.

Many efforts to measure or predict streambank erosion have focused on reach scales rather than larger watershed scales, limiting our understanding of how of streambank erosion associated with channel disturbance and evolution contributes to long-term sediment loading rates. Insufficient data or the inability to collect data for the entire watershed prevents measurements of long-term erosion rates (Boothroyd et al., 2021; Florsheim et al., 2008). Instream sediment and nutrient loads for the watershed are needed to develop a comprehensive watershed management plan though it is often difficult or impossible to collect data on a watershed scale (Myers et al., 2021). Fortunately, more recent efforts have developed methods to identify severity of erosion potential (Halefom and Teshome, 2019) and predict erosion on watershed scales (Djoukbala et al., 2019). Based on the results of this study, the USGS positive openness layer appears to offer an approach to identifying the severity of erosion on streambanks and predicting sediment and nutrient loads at various spatial scales.

References

Allmendinger, N. E., Pizzuto, J. E., Moglen, G. E., Lewicki, M. (2007). A Sediment Budget for an Urbanizing Watershed, 1951-1996, Montgomery County, Maryland, U.S.A.1: A Sediment Budget for an Urbanizing Watershed, 1951-1996, Montgomery Co., Maryland, U.S.A. *JAWRA Journal of the American Water Resources Association*, *43*(6), 1483–1498. https://doi.org/10.1111/j.1752-1688.2007.00122.x

Bigham, K. A., Moore, T. L., Vogel, J. R., Keane, T. D. (2018). Repeatability, Sensitivity, and Uncertainty Analyses of the BANCS Model Developed to Predict Annual Streambank Erosion Rates. *JAWRA Journal of the American Water Resources Association*, *54*(2), 423–439. https://doi.org/10.1111/1752-1688.12615

Boothroyd, R. J., Williams, R. D., Hoey, T. B., Barrett, B., Prasojo, O. A. (2021). Applications of Google Earth Engine in fluvial geomorphology for detecting river channel change. *WIREs Water*, *8*(1). https://doi.org/10.1002/wat2.1496

City of Raleigh. (2020, February 10). [Personal Communication].

Daxer, C. (2020). Topographic Openness Maps and Red Relief Image Maps in QGIS. https://doi.org/10.13140/RG.2.2.18958.31047

Dhakal, C. P. (2017). DEALING WITH OUTLIERS AND INFLUENTIAL POINTS WHILE FITTING REGRESSION. *Journal of Institute of Science and Technology*, *22*(1), 61–65. https://doi.org/10.3126/jist.v22i1.17741

Djoukbala, O., Hasbaia, M., Benselama, O., Mazour, M. (2019). Comparison of the erosion prediction models from USLE, MUSLE and RUSLE in a Mediterranean watershed, case of Wadi Gazouana (N-W of Algeria). *Modeling Earth Systems and Environment*, *5*(2), 725–743. https://doi.org/10.1007/s40808-018-0562-6

Doll, B. A., Grabow, G. L., Hall, K. R., Halley, J., Harman, W. A., Jennings, G. D., Wise, D. E. (2003). *Stream Restoration: A Natural Channel Design Handbook*.

DWER. (2000). Sediment in streams. Retrieved July 7, 2020, from https://www.water.wa.gov.au/water-topics/waterways/managing-our-waterways2/water-notes

EAL. (2020, April). EAL Analytical Methodology and Instrumentation.

Florsheim, J. L., Mount, J. F., Chin, A. (2008). Bank Erosion as a Desirable Attribute of Rivers. *BioScience*, *58*(6), 519–529. https://doi.org/10.1641/B580608

Gage, M. S., Spivak, A., Paradise, C. J. (2004). Effects of Land Use and Disturbance on Benthic Insects in Headwater Streams Draining Small Watersheds North of Charlotte, NC.

Southeastern Naturalist, *3*(2), 345–358. https://doi.org/10.1656/1528-7092(2004)003[0345:EOLUAD]2.0.CO;2

Gamble, R. S. (2021, June 12). *Evaluating Streambank Retreat Prediction Using the BANCS Model in the Valley and Ridge Physiographic Province* (Thesis). Virginia Tech. Retrieved from https://vtechworks.lib.vt.edu/bitstream/handle/10919/103819/Gamble_RS_T_2021.pdf?sequence=1&isAllowed=y

Gellis, A. C., Myers, M. K., Noe, G. B., Hupp, C. R., Schenk, E. R., Myers, L. (2017). Storms, channel changes, and a sediment budget for an urban-suburban stream, Difficult Run, Virginia, USA. *Geomorphology*, *278*, 128–148. https://doi.org/10.1016/j.geomorph.2016.10.031

Ghosh, K. G., Pal, S., Mukhopadhyay, S. (2016). Validation of BANCS model for assessing stream bank erosion hazard potential (SBEHP) in Bakreshwar River of Rarh region, Eastern India. *Modeling Earth Systems and Environment*, *2*(2), 95. https://doi.org/10.1007/s40808-016-0172-0

Gurley, L. (2022, March 23). USGS Positive Openness.

Halefom, A., Teshome, A. (2019). Modelling and mapping of erosion potentiality watersheds using AHP and GIS technique: a case study of Alamata Watershed, South Tigray, Ethiopia. *Modeling Earth Systems and Environment*, *5*(3), 819–831. https://doi.org/10.1007/s40808-018-00568-6

Harman, W. A., Jennings, Gregory D., Patterson, Jan M., Clinton, Daniel R., Slate, Louise O., Jessup, Angela G., … Smith, Rachel E. (1999). Bankfull Hydraulic Geometry Relationships for North Carolina Streams. AWRA Wildland Hydrology Proceedings.

Hatfield, R. G., Maher, B. A. (2009). Fingerprinting upland sediment sources: particle size-specific magnetic linkages between soils, lake sediments and suspended sediments. *Earth Surface Processes and Landforms*, *34*(10), 1359–1373. https://doi.org/10.1002/esp.1824

Hohenthal, J., Alho, P., Hyyppä, J., Hyyppä, H. (2011). Laser scanning applications in fluvial studies. *Progress in Physical Geography: Earth and Environment*, *35*(6), 782–809. https://doi.org/10.1177/0309133311414605

Hopkins, K. G., Noe, G. B., Franco, F., Pindilli, E. J., Gordon, S., Metes, M. J., … Hogan, D. M. (2018). A method to quantify and value floodplain sediment and nutrient retention ecosystem services. *Journal of Environmental Management*, *220*, 65–76. https://doi.org/10.1016/j.jenvman.2018.05.013

Hupp, C. R., Noe, G. B., Schenk, E. R., Benthem, A. J. (2013). Recent and historic sediment dynamics along Difficult Run, a suburban Virginia Piedmont stream. *Geomorphology*, *180–181*, 156–169. https://doi.org/10.1016/j.geomorph.2012.10.007

Johnson, P. A., Heil, T. M. (1996). UNCERTAINTY IN ESTIMATING BANKFULL CONDITIONS. *Journal of the American Water Resources Association*, *32*(6), 1283–1291. https://doi.org/10.1111/j.1752-1688.1996.tb03497.x

Line, D. E., White, N. M., Osmond, D. L., Jennings, G. D., Mojonnier, C. B. (2002). Pollutant Export from Various Land Uses in the Upper Neuse River Basin. *Water Environment Research*, *74*(1), 100–108. https://doi.org/10.2175/106143002X139794

Merritt, W. S., Letcher, R. A., Jakeman, A. J. (2003). A review of erosion and sediment transport models. *Environmental Modelling & Software*, *18*(8–9), 761–799. https://doi.org/10.1016/S1364-8152(03)00078-1

Midgley, T. L., Fox, G. A., Heeren, D. M. (2012). Evaluation of the bank stability and toe erosion model (BSTEM) for predicting lateral retreat on composite streambanks. *Geomorphology*, *145–146*, 107–114. https://doi.org/10.1016/j.geomorph.2011.12.044

Myers, D. T., Rediske, R. R., McNair, J. N. (2019). Measuring Streambank Erosion: A Comparison of Erosion Pins, Total Station, and Terrestrial Laser Scanner. *Water*, *11*(9), 1846. https://doi.org/10.3390/w11091846

Myers, D. T., Rediske, R. R., McNair, J. N., Allen, M. E. (2021). Watershed and streambank erosion modeling in a coldwater stream using the GWLF-E model: application and evaluation. *Modeling Earth Systems and Environment*, *7*(3), 1551–1564. https://doi.org/10.1007/s40808-020-00882-y

NCDOT. (2020). NC ATLAS Hydrography, 45.

NEH. (2007). Technical Supplement 3E--Rosgen Stream Classification Technique--Supplemental Materials. In *National Engineering Handbook* (210th–VI ed., p. 24). National Engineering Handbook.

Noe, G. B., Hopkins, K. G., Claggett, P. R., Schenk, E. R., Metes, M. J., Ahmed, L., … Hupp, C. R. (2022). Streambank and floodplain geomorphic change and contribution to watershed material budgets. *Environmental Research Letters*, *17*(6), 064015. https://doi.org/10.1088/1748-9326/ac6e47

NRCS. (2022, May 10). Mine Ceek Soil Resource Report Wake County, North Carolina.

Palmer, J. A., Schilling, K. E., Isenhart, T. M., Schultz, R. C., Tomer, M. D. (2014). Streambank erosion rates and loads within a single watershed: Bridging the gap between temporal and spatial scales. *Geomorphology*, *209*, 66–78. https://doi.org/10.1016/j.geomorph.2013.11.027

Purvis, R. A., Fox, G. A. (2016). Streambank sediment loading rates at the watershed scale and the benefit of riparian protection: Streambank Sediment Loading Rates at the Watershed

Scale. *Earth Surface Processes and Landforms*, *41*(10), 1327–1336. https://doi.org/10.1002/esp.3901

Rosgen, D. L. (2001a). A practical method of computing streambank erosion rate. In *Proceedings of the Seventh Federal Interagency Sedimentation Conference* (Vol. 2, p. 10). Reno, NV.

Rosgen, D. L. (2001b). A Stream Channel Stability Assessment Methodology. In *Proceedings of the Seventh Federal Interagency Sedimentation Conference* (Vol. 2, pp. 9–15). Reno, NV.

Rowley, T. H., Hopkins, K. G., Terziotti, S. (2018). *Geomorphological Features of North Carolina* [Data set]. U.S. Geological Survey. https://doi.org/10.5066/P9PRAVAQ

Schaffrath, K. R., Belmont, P., Wheaton, J. M. (2015). Landscape-scale geomorphic change detection: Quantifying spatially variable uncertainty and circumventing legacy data issues. *Geomorphology*, *250*, 334–348. https://doi.org/10.1016/j.geomorph.2015.09.020

Simon, A. (1989). A model of channel response in disturbed alluvial channels. *Earth Surface Processes and Landforms*, *14*(1), 11–26. https://doi.org/10.1002/esp.3290140103

Simon, A., Rinaldi, M. (2006). Disturbance, stream incision, and channel evolution: The roles of excess transport capacity and boundary materials in controlling channel response. *Geomorphology*, *79*(3–4), 361–383. https://doi.org/10.1016/j.geomorph.2006.06.037

Starr, R. (2013). *Maryland Trust Fund Geomorphic Monitoring*. Retrieved from https://dnr.maryland.gov/streams/Documents/2013TFTraining_BANCS_Davis.pdf

Stillwell, C. (2022, May 26). Positive openness clarification.

Topcon. (2016). GT Series Robotic Total Station. Topcon Corporation. Retrieved from https://www.topconpositioning.com/sites/default/files/product_files/gt_series_broch_7010_2214_revb_sm.pdf

U.S. EPA. (2017). *National Water Quality Inventory: Report to Congress* (No. 841- R-16– 011).

US National Dams. (2022). Shelley Lake Dam. Retrieved May 31, 2022, from https://nationaldams.com/dams/shelley-lake-dam-35y5rx7

USGS. (2022, May 10). Mine Creek Watershed StreamStats Report.

Van Eps, M. A., Formica, S. J., Morris, T. L., Beck, J. M., Cotter, A. S. (2004). Using a Bank Erosion Hazard Index (BEHI) to estimate annual sediment loads from streambank erosion in the West Fork White River Watershed. In *Self-Sustaining Solutions for Streams, Wetlands, and Watersheds, 12-15, September 2004*. American Society of Agricultural and Biological Engineers. https://doi.org/10.13031/2013.17386

Voli, M. T., Wegmann, K. W., Bohnenstiehl, D. R., Leithold, E., Osburn, C. L., Polyakov, V. (2013). Fingerprinting the sources of suspended sediment delivery to a large municipal drinking water reservoir: Falls Lake, Neuse River, North Carolina, USA. *Journal of Soils and Sediments*, *13*(10), 1692–1707. https://doi.org/10.1007/s11368-013-0758-3

Walling, D. E., Collins, A. L. (2008). The catchment sediment budget as a management tool. *Environmental Science & Policy*, *11*(2), 136–143. https://doi.org/10.1016/j.envsci.2007.10.004

Walter, R., Merritts, D., Rahnis, M. (2007). *ESTIMATING VOLUME, NUTRIENT CONTENT, AND RATES OF STREAM BANK EROSION OF LEGACY SEDIMENT IN THE PIEDMONT AND VALLEY AND RIDGE PHYSIOGRAPHIC PROVINCES, SOUTHEASTERN AND CENTRAL PA*. Report to the Pennsylvania Department of Environmental Protection, Lancaster, Pennsylvania.

Wegmann, K. W., Osburn, C. L., Lewis, R. Q., Peszlen, Mitasova, H. (2013). *Legacy Sediments and Stream Water Quality: Estimating Volume, Nutrient Content, and Stream Bank Erosion in 303(d)-Impaired Waterways of the North Carolina Piedmont* (No. 435). Water Resources Research Institute of the University of North Carolina.

Wildlands Hydrology Consultants. (2003).

Williams, F., Moore, P., Isenhart, T., Tomer, M. (2020a). Automated measurement of eroding streambank volume from high-resolution aerial imagery and terrain analysis. *Geomorphology*, *367*, 107313. https://doi.org/10.1016/j.geomorph.2020.107313

Williams, F., Moore, P., Isenhart, T., Tomer, M. (2020b). Automated measurement of eroding streambank volume from high-resolution aerial imagery and terrain analysis. *Geomorphology*, *367*, 107313. https://doi.org/10.1016/j.geomorph.2020.107313

Wohl, E., Bledsoe, B. P., Jacobson, R. B., Poff, N. L., Rathburn, S. L., Walters, D. M., Wilcox, A. C. (2015). The Natural Sediment Regime in Rivers: Broadening the Foundation for Ecosystem Management. *BioScience*, *65*(4), 358–371. https://doi.org/10.1093/biosci/biv002

Yen, K. S., Ravani, B., Lasky, T. A. (2011). *LiDAR for Data Efficiency* (No. WA-RD 778.1). University of Carlifornia at Davis.

Yokoyama, R. (2002). Visualizing Topography by Openness:A New Application of Image Processing to Digital Elevation Models. *PHOTOGRAMMETRIC ENGINEERING*, *68*(3), 9.

APPENDICES

Appendix A – Mine Creek BEHI/NBS Field Procedures

To perform the assessment a survey rod, angle finder and pocket tape are the required materials. Using a GPS device and app to collect to the data and GPS location of the assessment makes it easier to process data afterwards. A two-person assessment team is recommended to more easily facilitate bank height measurements and photo collection. One person can carry the GPS device while collecting measurements from the streambank while another person can enter the data and collect photos to upload into the app.

1. **Measure the bank height (ft)** using a survey rod from the toe of the bank to the top of the bank. Be sure to hold the rod vertical when measuring the bank height. Collect a photograph while the survey rod is on the bank to document the streambank height.

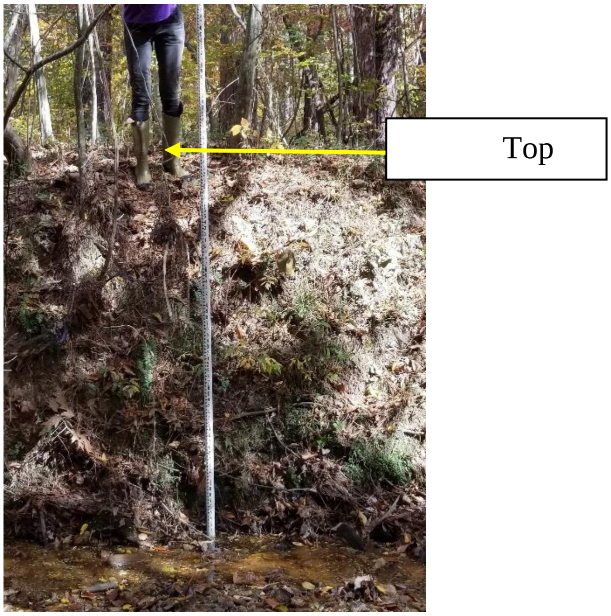


Figure 34. Measuring bank height.

2. **Locate and measure the bankfull height (ft).** A reliable bankfull indicator may be located upstream or downstream of the site. If needed skip this until it can be measured; then go back and edit the appropriate point. For more help to identify bankfull indicators watch the Bankfull Identification & Field Measurement Procedure video.
    a. For stable streams with little streambank erosion and indicators of frequent overbank flow evidenced by sandy deposits and wrack lines of leaves and debris on the floodplain, the bankfull height is most likely at or very near the top of the bank.

b. For streams with pervasive erosion and unstable streambanks, look for bankfull indicators within the channel such as “flat sandy depositional surfaces” or the top of point bars (Elon, 2005; Leopold et al, 1995).
c. If no bankfull indicators can be found use hydraulic regional curves for the region to estimate the bankfull depth. The NCSU BAE Technical Resources page has regional curves for North Carolina.

3. **Determine the total root depth (ft).** If the rooting depth is noncontiguous vertically along the bank, sum the rooting depth of each section with roots for the total root depth (see Figure below).

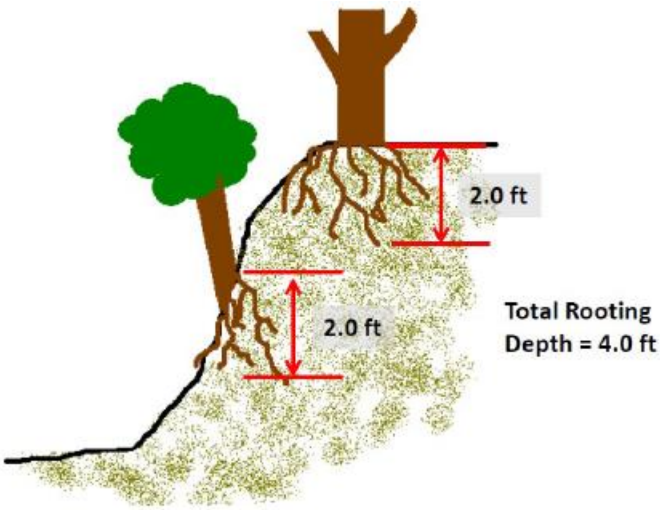


Figure 35. Measuring root depth (Starr, 2013).

4. **Estimate the root density (%).** This is a visual assessment based on how much of the bank the roots cover. The person collecting the data is usually better placed to view the entire stretch of the eroding bank.

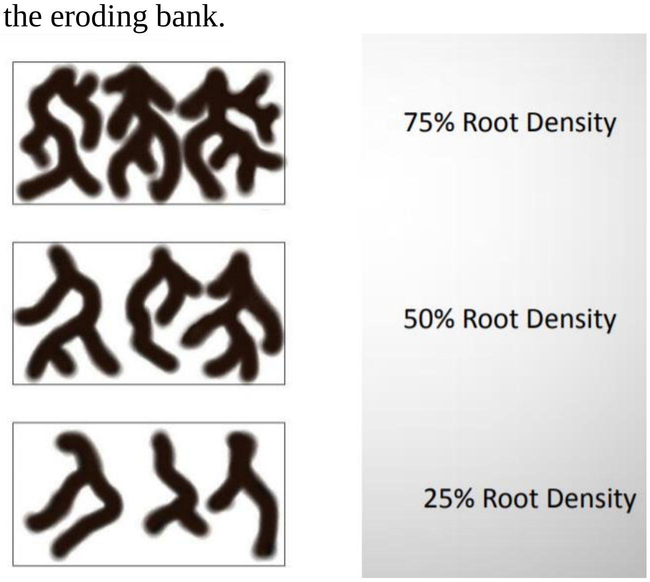


Figure 36. Root density percentage (Starr, 2013).

Figure 37. 10% root density.

Figure 38. 30% root density.

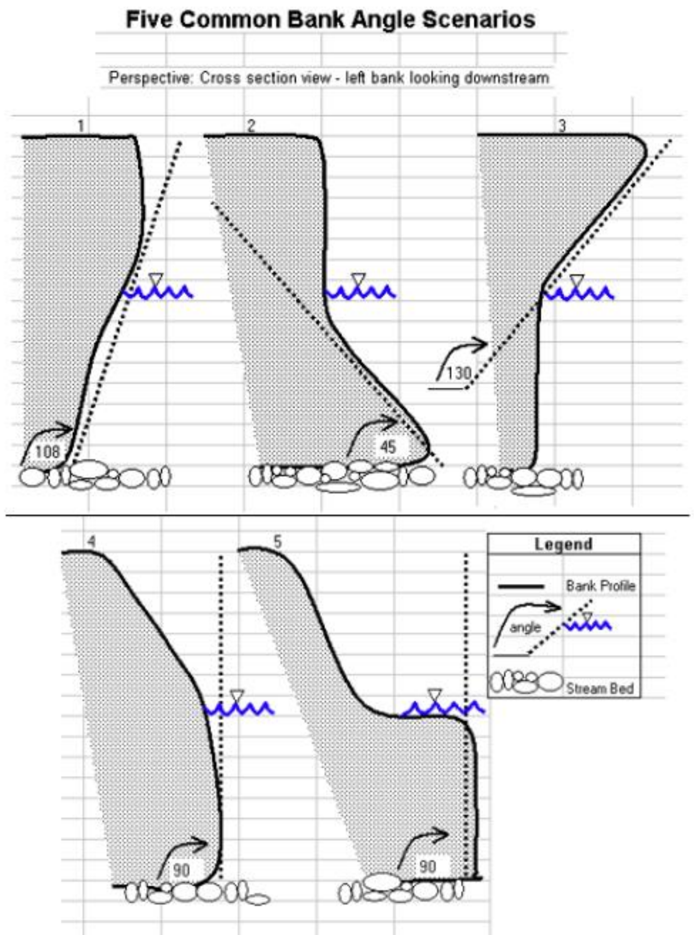
Figure 39. 40% root density. Since there additional root besides the roots from the grasses the density percentage increases to 40%. If was just the grass roots then I would select 30% root density.

Figure 40. 50% root density. Root depth goes all the way down and about 50% of the root depth (whole bank) is covered in roots.

Figure 41. 60% root density.

Figure 42. 75% root density.

5. **Measure the bank angle (degrees) from the horizontal.** Lay the survey rod against the bank and use a clinometer to measure the bank angle. Refer to the figure below to determine which bank slope to measure. A vertical bank would have an angle of 90 degrees.



Source: Rosgen 2003

Figure 43. Common bank angle scenarios (Starr, 2013; Wildlands Hydrology Consultants, 2003). (Permission to use this image obtained from Wildland Hydrology Consultants)

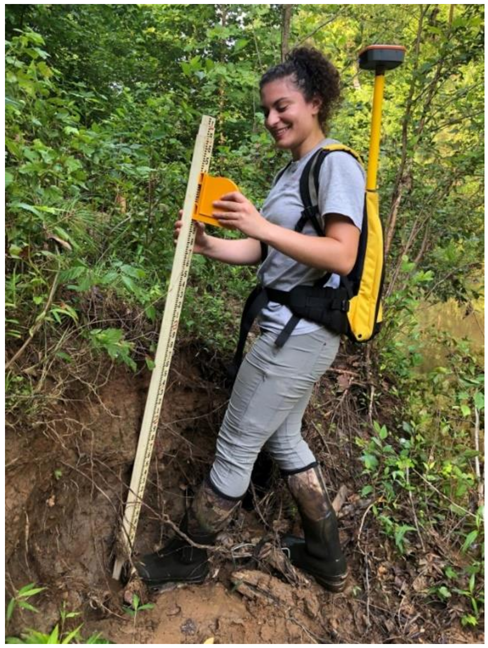


Figure 44. Measuring bank angle.

6. **Visually estimate the surface protection percentage.** This includes large boulders, armoring, roots and vegetation.
7. **Examine the soil type of the bank to determine if adjustments are required.** Feel the soil to determine if it is silt/clay or if there is sand present. When rolled in your fingers, clay will form a ribbon. The longer the ribbon, the higher the clay content in the soil. Rubbing the soil between finger tips to feel the texture, can help you to estimate the amount of sand grains in the soil.
    a. Bedrock = Very Low BEHI
    b. Boulders = Low BEHI
    c. Cobble = Decrease BEHI category by one level if gravel/sand is less than 50% of the bank composition.
    d. Gravel = Add 5-10 points depending on the percentage of sand
    e. Sand = Add up to 10 points depending on the percentage of sand (higher percentage of sand warrants more points)
        i. I usually select 2, 3, 5, 7 or 10 for the amount of sand present. 2 would be mostly silt/clay with a small amount of sand while 10 is pure sand.
    f. Silt/Clay = No adjustment needed
8. **Examine the bank for stratification.** If stratification is present add 5-10 points depending on the number and location of unstable layers in relation to the bankfull stage.
9. **Determine NBS for the study bank.** There are 7 different methods varying in complexity. For more information refer to Rosgen (2001) and Bigham et al. (2018)

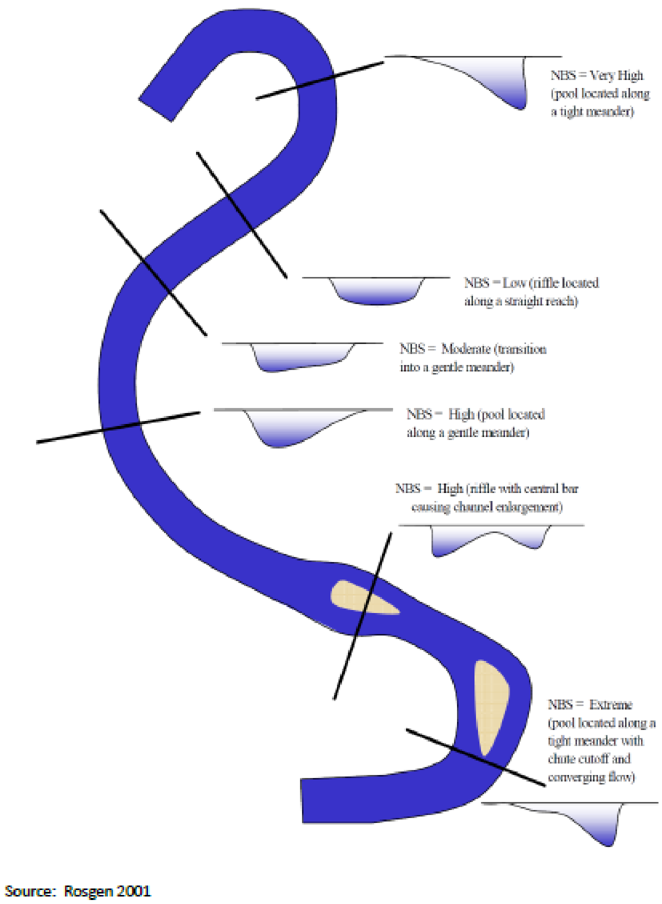


Figure 45. NBS guide (Rosgen, 2001a).
(Permission to use this image obtained from Wildland Hydrology Consultants)

10. **Collect gps points** to indicate the start (upstream point) and end (downstream point) of the eroding bank. **Indicate the Station (Start or End) and Right or Left Bank**; leave all other categories blank. This study bank should have similar conditions i.e. the entire bank section would receive the same BEHI/NBS rating.

Appendix B – Processing BEHI Reach Data Procedure Log

Following steps were performed in ArcGIS Desktop 10.8. The coordinate system should be WGS_1984_Web_Mercator_Auxiliary_Sphere.

1. Add World Imagery as the basemap

2. Change symbology of BEHI point layer to distinguish between different stations.

    TOC → BEHI points → Properties → Symbology
    Categories → Unique values → Value field: Station → Add All Values
    BEHI: Green triangle; START and END: red circle

3. Trace the top of bank from the start and end of the study reach.

    Scale: 1:850 (as close as you can zoom in with clarity)
    Drawing Toolbar → Line → trace along each side of the bank

4. Convert both lines drawn into a shapefile

    Tool: Drawing Toolbar → Convert Graphics to Features
    Use the same coordinate system as: the data frame
    Output shapefile: SiteName_streambanks.shp
    Select automatically delete after conversion
    Add layer to map: Yes

5. Adjust vertices as needed when zooming into as far as possible and zooming out to 1:1,500 to ensure accuracy.

    Tool: Editor Toolbar -> Edit Vertices
    Delete, add and/or move vertices as needed

6. Add a field to SiteName_streambanks.shp for the bank side.

    TOC → SiteName_streambanks → Attribute Table
    Add Field
    Name: Bank_Side
    Type: Text
    Field Properties: Length, 10

7. Fill in right and left banks for either line (use BEHI points to determine right and left side).

    TOC → SiteName_streambanks → Edit Features → Start Editing
    Select field in attribute table and fill in Left and Right
    Save Edits

8. Break each bank line into segments encapsulating each BEHI point. The end of each segment are the START/END points.

    Tool: Editor Toolbar → Split Tool
    Frequently save edits
    Stop Editing

9. Add a new field for the length in ft of each segment.

    TOC → SiteName_streambanks → Attribute Table
    Add Field
    Name: Length_ft
    Type: Double
    Field Properties: default

10. Calculate the length of each bank segment.

    TOC → SiteName_streambanks → Attribute Table → Length_ft
    Calculate Geometry:
    Property: Length
    Coordinate System: Use coordinate system of the data source
    Units: Feet US (ft)

11. Add a field to BEHI_points.

    TOC → BEHI_points → Attribute Table
    Add Field
    Name: Stream_1
    Type: Text

12. Add a field to BEHI_points for unique identifier for each point.

    TOC → BEHI_points → Attribute Table
    Add Field
    Name: ID
    Type: Text

13. Select BEHI points for selected site.

    Tool: Select by Attributes
    Layer: BEHI_points
    Method: Create a new selection
    SELECT *FROM BEHI_Points WHERE: Stream = Stream Name (from get unique values)
    TOC → BEHI_points → Attribute Table → View only those selected
    Edit Features → Start Editing

14. Create a unique identifier for each point to identify points easily between GIS and Excel.

Right click on ID → Field Calculator
ID = [Stream_1] & [OBJECTID]

15. Add field for SiteName_streambanks.shp.

TOC → SiteName_streambanks.shp → Attribute Table
Add Field
Name: Number
Type: Short Integer

16. Fill in Number field in SiteName_streambanks.shp

Right click Number → Field Calculator
Number = [FID]

17. To decipher different stream segments change SiteName_streambanks symbology.

TOC → SiteName_streambanks → Properties → Symbology
Categories → Unique values → Value field: Number → Add All Values
Change width to 2

18. Select just BEHI points.

Tool: Select by Attributes
Layer: BEHI_Points
Method: Create a new selection
SELECT * FROM BEHI_POINTS WHERE: Station = 'behi'

19. Select just BEHI points from site you are working on

Tool: Select by Attributes
Layer: BEHI_Points
Method: From current selection
SELECT * FROM BEHI_POINTS WHERE: Stream = StreamName

20. Create a new layer with selected BEHI points.

TOC → BEHI_Points → Data → Export Data
Export: Selected features
Use the same coordinate system as: this layer's source data
AbbreviatedStreamName_behi_pts.shp
Select yes to add exported layer to map

NOTE Turn off original BEHI_points layer

21. Create a buffer for AbbreviatedStreamName_behi_pts.shp

Tool: Buffer
Input Features: AbbreviatedStreamName_behi_pts.shp
Output Feature Class: AbbreviatedStreamName_#m_buffer.shp
Distance: Linear Unit 2-5 m (select size appropriate for site depending on size of stream and length of streambank segments)

22. Edit buffer layer so each buffer only intersects one streambank segment

TOC → AbbreviatedStreamName_#m_buffer.shp → Edit Features → Start Editing
Adjust individual buffers as needed
Save Edits
Stop Editing

23. Join StreamName_streambanks.shp together.

Tool: Dissolve
Input Features: StreamName_streambanks
Output Feature Class: StreamName_streambanksDiss
Dissolve_Field(s): Number

24. Add field to StreamName_streambanksDiss for length of each segment.

TOC → SiteName_streambanksDiss.shp → Attribute Table
Add Field
Name: Length_ft
Type: Short Integer

25. Calculate length of each bank segment.

TOC → SiteName_streambanksDiss → Attribute Table → Length_ft
Calculate Geometry:
Property: Length
Coordinate System: Use coordinate system of the data source
Units: Feet US (ft)

26. Spatially join BEHI points to streambank segments

Tool: Spatial Join
Target features: Name_StreambanksDiss
Join features: BEHI_2m_buffer
Output feature class: Name_streambanks_behi
Match option: INTERSECT

27. Export the Name_streambanks_behi data into the BEHI Excel sheet to calculate the BEHI score.

TOC → Name_streambanks_behi → Attribute table
Select all → right click on row → Copy selected
Paste data into empty Excel sheet
Paste only data columns need from Excel sheet into BEHI Excel sheet

28. Create Excel (.xlsx) sheet with just BEHI to import into ArcGIS. Refer to table below for required columns and how to rename them.

Table 18. Abbreviations for Importing BEHI Data to ArcGIS

Abbreviation	Name
ID	ID name (Stations in Excel sheet)
Bkf_hgt	Bankfull height
Bk_hgt_BFht	Bank height/bankfull height ratio
BHI	Bank height/bankfull height ratio index
RD_BH	Root depth/bank height (%)
RDI	Root depth/bank height index
WRDen	Weighted root density (%)
WRDenI	Weighted root density index
BAI	Bank angle index
SPI	Surface protection index
Adj	Total adjustment
BEHI_Score	BEHI total score
BEHI	BEHI category
Per_bank	Percent of Total Bank Eroded (%)
NSB_num	Numeric number assigned to each NBS category (very low = 1, low = 2, moderate = 3, high = 4, very high = 5, extreme = 6)
BEHI_num	Numeric number assigned to each BEHI category (very low = 1, low = 2, moderate = 3, high = 4, very high = 5, extreme = 6)
Condition_num	Numeric number assigned to each erosion condition (none = 1, surface scour = 2, unstable undercut = 3, mass wasting = 4)

29. Import behi_import.xlsx sheet into ArcGIS.

TOC → Name_streambanks_behi → Join
Choose the filed in this layer that the join will be based on: ID
Choose the table to join to this layer: behi_import.xlsx
Choose the field in the table to base the join on: ID
Join options: Keep all records
Validate Join

30. Export data to a new shapefile to save it with the joined data.

TOC → Name_streambanks_behi → Data → Export Data
Export: All features
Use the same coordinate system as: this layer's source data
Output feature class: Name_streambanks_behi_final

Appendix C – Delineating Watersheds

1. Clip the str900nc raster data to the watershed size

    Tool: Clip Raster
    Input Raster: str900nc
    Output Extent: watershed
    Output Raster Dataset: str900nc_MC
    NoData Value: 0

    NOTE Do not calculate statistics when importing str900nc into ArcGIS Pro.

2. Convert the raster data to polylines.

    Tool: Raster to Polyline
    Input Raster: str900nc_MC
    Field: Value
    Output polyline features: RasterT_str900n1
    Background value: NoData
    Uncheck Simplify polylines

3. Create a new layer of the points being used to delineate watersheds since the locations of these points will be moved.

    Contents → MC_watershed_pts → Right click
    Data → Export Features
    Input Features: MC_watershed_pts
    Output Location: MC_watershed.gdb
    Output Name: MC_points

4. Snap the MC_points to the polylines (RasterT_str900n1)

    Tool: Snap (Editing Tools)
    Input Features: MC_points
    Snap Environment:
        Features: RasterT_str900n1
        Type: Edge
        Distance: 30 meters (want this distance to be as small as possible)

5. Examine points, move any points onto a polyline that should be on a polyline. For those points that have very small watersheds and are on smaller channels, their watersheds will need to be delineated in ArcGIS Pro.

6. Rerun the snap tool to make sure any points moved to be on the polylines are actually on the line.

    Tool: Snap (Editing Tools)
    Input Features: MC_points
    Snap Environment:
        Features: RasterT_str900n1
        Type: Edge
        Distance: 30 meters (want this distance to be as small as possible)

7. Add Latitude and Longitude fields to MC_points

    Open attribute table → Add Field
    Name: LAT
    Type: Double
    Name: LONG
    Type: Double

8. Add value to the LAT field

    Calculate Geometry
    Property: Point y-coordinate
    Coordinate System: Current Map [Map]
    Coordinate Format: Decimal Degrees

9. Add value to the LONG field

    Calculate Geometry
    Property: Point x-coordinate
    Coordinate System: Current Map [Map]
    Coordinate Format: Decimal Degrees

10. Select all points the have been snapped to the polylines

    Tool: Select Layer By Location
    Input Features: MC_points
    Relationship: Intersect
    Selecting Features: RasterT_str900n1
    Selection type: New Selection

11. Create new layer with just the selected points

    Right click on MC_points
    Data → Export Features
    Input Features: MC_points
    Output Location: streamstats
    Output Name: streamstats.shp

12. Upload the appropriate files associated with streamstats.shp to StreamStats V5.04 Batch

    Processing Tool (https://streamstatsags.cr.usgs.gov/ss_bp/)
    Study Area: NC
    Local ID Field: ID (ID field in shapefile used to ID each site)
    Select Delineate, Compute Basin Chars, Compute Flow Stats

<u>Delineate Watersheds in ArcGIS Pro</u>

13. Create new layer with MC_points that were not snapped to the polylines

    Switch selection in MC_points
    Data → Export Features
    Input Features: MC_points
    Output Location: MC_watesheds.gdb
    Output Name: gis_watershed.shp

14. Examine gis_watershed data points and see if there would be overlapping watersheds. If there points that would create overlapping watersheds; select the most upstream points and create a new layer.

    Data → Export Features
    Input Features: gis_watershed
    Output Location: MC_watesheds.gdb
    Output Name: watershedpts_1.shp

Figure 46. Example of nested watersheds.

15. Switch selection in gis_watershed and create another new layer with other points. Create as many layers are needed to avoid overlapping watersheds.

    Data → Export Features
    Input Features: gis_watershed
    Output Location: MC_wateshеds.gdb
    Output Name: watershedpts_2.shp

    NOTE The following are the groups of points:

    - MC90 (calculated this watershed with all the points but it only did this watershed since this was the largest)
    - Watershed_pts1: MC234, MC246, MC111
    - Watershed_pts2: MC190, MC123
    - Watershed_pts3: MC186, MC126

16. Fill in the dem_burn layer.

    Note This layer is a DEM of the MC watershed where it's been burned where roads and bridge are

    Tool: Fill
    Input Surface Raster: dem_burn
    Output raster: Fill_dem_bur1

17. Determine the flow direction.

Tool: Flow Direction (Spatial Analyst Tools)
Input surface raster: Fill_dem_bur1
Output flow direction raster: FlowDir_Fill1
Flow Direction Type: D8 (fastest type and good method for this area)

18. Calculate the flow accumulation

Tool: Flow Accumulation (Spatial Analyst Tools)
Input flow direction raster: FlowDir_Fill1
Output accumulation raster: FlowAcc_Flow1
Output data type: Float
Input flow direction type: D8

19. Adjust symbology of FlowAcc_Flow1 to see the channels better.

FlowAcc_Flow1 → Symbology → Statistics → DRA

20. Move points so they are on the channel lines.

21. Recalculate the LAT and LONG coordinates using Calculate Geometry.

22. Create new field in gis_watershed called number.

Name: Number Type: Long
Number Format: Numeric
Enter values the equal the same number as number in site name
Save Edits

23. Snap gis_watershed1 points using Snap Pour Point (want the smallest distance possible)

Tool: Snap Pour Point
Input raster: gis_watershed
Pour point field: Number
Input accumulation raster: FlowAcc_Flow1
Output raster: SnapPour_MCpts
Snap distance: 1 (distance units matches coordinate system)

24. Create watersheds

Tool: Watershed (Spatial Analyst Tools)
Input D8 flow direction: FlowDir_Fill1
Input raster: SnapPour_MCpts
Output raster: Watershed_gis

25. Convert raster watershed to polygons

Tool: Raster to Polygon
Input raster: Watershed_1
Field: Value
Output polygon features: Watershed1_poly
Check simplify polygons

26. Add new field for the area in square miles

Watershed1_poly → Attribute Table → Add field
Name: Area_sqmi
Type: Double
Number Format: Numeric

27. Calculate the area of each watershed

Area_sqmi column
Calculate Geometry
Property: Area
Area Unit: Square miles (United States)
Coordinate System: Current map

Appendix D – Obtaining Positive openness value in ArcGIS Pro

PO value – Individual Sites

1. Created a new layer with just individual BEHI data points (102 total)

2. Create a 10 ft buffer around each BEHI point.

    Tool: Buffer
    Input Features: MC_individ_behi_pts
    Output Feature Class: MC_individ_buff_10
    Distance: Linear value; 10 feet
    Method: Planar
    Dissolve Type: No Dissolve

3. Get statistics from Positive Openness layer for each BEHI point

    Tool: Zonal Statistics as Table
    Input raster or feature zone data: MC_individ_buff_10
    Zone field: ID
    Input value raster: mine_clip_2015_OPEN-POS_R20_D16.tif
    Output table: individ_PO_1m_stats
    Percentile values: 90
    Percentile interpolation type: Auto-detect

PO value – Reaches

1. Create 3 copies of the streambank BEHI data, one for each buffer (5 ft, 10 ft, and 15 ft).

    Repeat for each buffer size and name appropriately
    Tool: Export Features
    Input Features: MC_Reach1_streambanks_behi
    Output Location: MC_PO.gdb
    Output Name: MC_Reach1_streambanks_behi_5ft_PO.shp

2. Create a 10 ft buffer for each line

    Tool: Buffer
    Input Features: MC_Reach1_streambanks_behi
    Output Feature Class: MC_Reach1_buff_10
    Distance: Linear value; 10 feet
    Side Type: Full
    End Type: Flat
    Method: Planar
    Dissolve Type: No Dissolve

3. Get statistics from Positive Openness layer for each BEHI point

    Tool: Zonal Statistics as Table
    Input raster or feature zone data: MC_Reach1_buff_10
    Zone field: ID
    Input value raster: mine_clip_2015_OPEN-POS_R20_D16.tif
    Output table: Reach1_10buff_ PO_1m_stats
    Percentile values: 90
    Percentile interpolation type: Auto-detect

    NOTE there was one streambank in Reach1 that was not labeled as left

4. Join the Reach1_10buff_PO_1m_stats table to the MC_Reach1_streambanks_10ft_PO layer

    Tool: Add Join
    Input Join Table: MC_Reach1_streambanks_10ft_PO
    Input Join Field: ID
    Join Table: Reach1_10buff_PO_1m_stats
    Join Table Field: ID
    Check Keep All Target Features
    Validate Join

5. Repeat steps and 1-4 for a 5 ft and 15 ft buffer

6. Select just left streambanks.

    Tool: Select by Attributes
    Input Rows: MC_Reach1_streambanks_behi
    Selection Type: New selection
    Where: bank is equal Left

7. Create a new feature layer with just the left streambank

    Tool: Export Features
    Input Features: MC_Reach1_streambanks_behi
    Output Location: MC_PO.gdb
    Output Name: MC_Reach1_leftbanks_behi_PO.shp

8. Switch the selection so only right banks are selected and create a new feature layer.

    Tool: Export Features
    Input Features: MC_Reach1_streambanks_behi
    Output Location: MC_PO.gdb
    Output Name: MC_Reach1_rightbanks_behi_PO.shp

9. Create 10 ft buffer for the left side of the bank for the inside.

    Tool: Buffer
    Input Features: MC_Reach1_leftbanks_behi
    Output Feature Class: MC_Reach1_left _buff_10
    Distance: Linear value; 10 feet
    Side Type: Left
    End Type: Flat
    Method: Planar
    Dissolve Type: No Dissolve

10. Get statistics from Positive Openness layer for each BEHI point

    Tool: Zonal Statistics as Table
    Input raster or feature zone data: MC_Reach1_left_buff_10
    Zone field: ID
    Input value raster: mine_clip_2015_OPEN-POS_R20_D16.tif
    Output table: Reach1_left_PO_1m_stats
    Percentile values: 90
    Percentile interpolation type: Auto-detect

11. Join the Reach1_left_PO_1m_stats table to the MC_Reach1_leftbanks_PO layer

    Tool: Add Join
    Input Join Table: MC_Reach1_leftbanks_PO
    Input Join Field: ID
    Join Table: Reach1_left_PO_1m_stats
    Join Table Field: ID
    Check Keep All Target Features
    Validate Join

12. Create 10 ft buffer for the left side of the bank for the outside.

    Tool: Buffer
    Input Features: MC_Reach1_leftbanks_behi
    Output Feature Class: MC_Reach1_left _buff_10_out
    Distance: Linear value; 10 feet
    Side Type: Right
    End Type: Flat
    Method: Planar
    Dissolve Type: No Dissolve

13. Get statistics from Positive Openness layer for each BEHI point

    Tool: Zonal Statistics as Table
    Input raster or feature zone data: MC_Reach1_left_buff_10_out
    Zone field: ID
    Input value raster: mine_clip_2015_OPEN-POS_R20_D16.tif
    Output table: Reach1_leftout_PO_1m_stats
    Percentile values: 90
    Percentile interpolation type: Auto-detect

14. Join the Reach1_leftout_PO_1m_stats table to the MC_Reach1_leftbanks_out_PO layer

    Tool: Add Join
    Input Join Table: MC_Reach1_leftbanks_out_PO
    Input Join Field: ID
    Join Table: Reach1_leftout_PO_1m_stats
    Join Table Field: ID
    Check Keep All Target Features
    Validate Join

15. Repeat steps 9-14 for the right side of the bank.

16. Repeat right and left banks but buffer the inside of the streambanks

PO value – Cross-Sections

1. Create a new layer with all BEHI points associated with cross-sections. Use photos to help identify BEHI points.

2. Add points to MC_XS_PO_pts layer for cross-sections with only one BEHI point. We want a right and left bank point at each cross-section.

3. Create a 10 ft buffer at each point. Create 10 ft buffer for the left side of the bank for the outside.

    Tool: Buffer
    Input Features: MC_XS_PO_pts
    Output Feature Class: XS_Buffer
    Distance: Linear value; 10 feet
    Method: Planar
    Dissolve Type: No Dissolve

4. Get statistics from Positive Openness layer for each BEHI point.

    Tool: Zonal Statistics as Table
    Input raster or feature zone data: XS_Buffer

Zone field: ID
Input value raster: mine_clip_2015_OPEN-POS_R20_D16.tif
Output table: XS_PO_stats
Percentile values: 90
Percentile interpolation type: Auto-detect

5. Join the XS_PO_stats table to the MC_XS_PO_pts layer

Tool: Add Join
Input Join Table: MC_XS_PO_pts
Input Join Field: ID
Join Table: XS_PO_stats
Join Table Field: ID
Check Keep All Target Features
Validate Join

6. Save it as a new layer.

Contents → MC_XS_PO_pts → Right click
Data → Export Features
Input Features: MC_XS_PO_pts
Output Location: MC_shp
Output Name: MC_XS_PO

Appendix E – Joining ATLAS layer with BEHI layer in ArcGIS Pro

Adding ATLAS Stream data layer to the selected points used to create watersheds.

1. Create a new layer from the selected watershed points

    Contents → MC_watershed_pts → Right click
    Data → Export Features
    Input Features: MC_watershed_pts
    Output Location: MC_Inidividual_Sitesgdb
    Output Name: MC_atlas

2. Examine points, move any points onto a polyline that should be on a polyline.

3. Snap the MC_atlas to the polylines (ATLAS_Hydrology_v1_2_Raleigh)

    Tool: Snap (Editing Tools)
    Input Features: MC_atlas
    Snap Environment:
        Features: ATLAS_Hydrology_v1_2_Raleigh
        Type: Edge
        Distance: 20 meters (want this distance to be as small as possible)

4. Double check all points are on a polyline; if not move them closer and rerun Step 3.

5. Spatial join the stream order from Atlas layer to MC_atlas layer.

    Tool: Spatial Join
    Target features: MC_atlas
    Join features: ATLAS_Hydrology_v1_2_Raleigh
    Output feature class: MC_atlas_SpatialJoin
    Match option: INTERSECT
    Fields: From ATLAS_Hydrology_v1_2_Raleigh layer only keep:
        AU_ID, strmOrder, Magnitude, strmDrop, Slope, Impact

6. Add the strmOrder and slope data for each site to all the individual BEHI points.

    Tool: Join Field
    Input Table: MC_individ_BEHI_PO
    Input Join Field: Individual
    Join Table: MC_atlas_SpatialJoin
    Join Table Field: Inidividual
    Fields: strmOrder, Slope

7. Save it as a new layer.

Contents → MC_individ_BEHI_PO → Right click
Data → Export Features
Input Features: MC_individ_BEHI_PO
Output Location: MC_Inidividual_Sitesgdb
Output Name: MC_individ_BEHI_PO_ATLAS

Appendix F – Statistical Analysis Results

All statistical analysis was performed in R-Studio.

Individual Sites

The residual plots (Figure 47) show the data can be assumed to be normally distributed with the points nearly all falling along the one-to-one line in the Q-Q plot. Only the ends differ from the one-to-one line but not enough to be a cause for concern. The Residuals versus Fitted plots show the residuals to be fairly distributed and centered around zero requiring no transformations to be applied to the data.

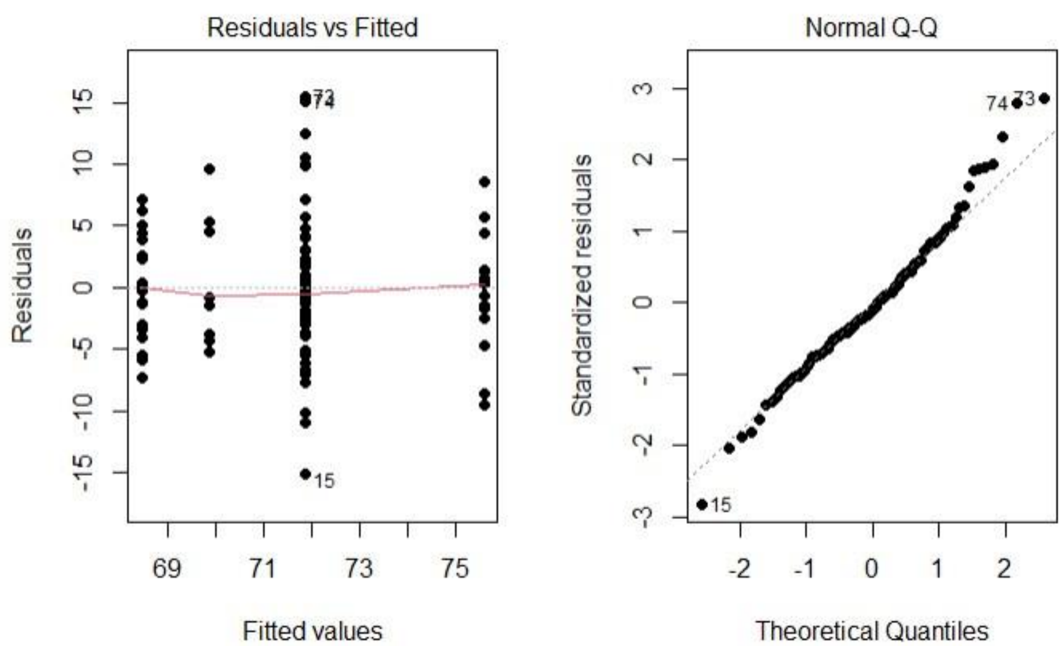


Figure 47. Residual plots from the ANOVA test for the erosion condition type.

The ANOVA test results show a significant p-value of 0.0015 which is less than 0.05. This means there is sufficient evidence that one of the means of Condition type is significantly different from the others. Tukey's HSD test results reveal no erosion is statistically different from mass wasting. No erosion & unstable undercut and no erosion & surface scour are on the border of the 0.05 threshold. Gathering more data can help elucidate if there is a true different between sites with no erosion, unstable undercut and surface scour. The mean minimum PO value for no erosion is 75.6, 71.9 for surface scour, 69.9 for unstable undercut and 68.5 for mass wasting.

```
> anova(fit)  # ANOVA tables
Analysis of Variance Table

Response: MIN
                     Df  Sum Sq Mean Sq F value   Pr(>F)
as.factor(Condition)  3  488.03 162.678  5.5452 0.001475 **
Residuals            98 2874.99  29.337
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(fit)
                     Df Sum Sq Mean Sq F value  Pr(>F)
as.factor(Condition)  3    488  162.68   5.545 0.00147 **
Residuals            98   2875   29.34
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> fit$coefficients
                      (Intercept)     as.factor(Condition)Surface Scour as.factor(Condition)Unstable Undercut
                        75.573683                             -3.711667                             -5.687808
     as.factor(Condition)Mass Wasting
                        -7.097111
>
> # see which erosion condition types are different from eachother
> TukeyHSD(fit,ordered=T)
  Tukey multiple comparisons of means
    95% family-wise confidence level
    factor levels have been ordered

Fit: aov(formula = MIN ~ as.factor(Condition), data = mc_PO3)

$`as.factor(Condition)`
                                 diff         lwr       upr     p adj
Unstable Undercut-Mass Wasting 1.409302 -4.37005089  7.188656 0.9196804
Surface Scour-Mass Wasting     3.385444 -0.44202591  7.212915 0.1023200
None-Mass Wasting              7.097111  2.37828866 11.815933 0.0008960
Surface Scour-Unstable Undercut 1.976142 -3.10157126  7.053855 0.7397968
None-Unstable Undercut         5.687808 -0.09154494 11.467162 0.0554414
None-Surface Scour             3.711667 -0.11580371  7.539137 0.0608227
```

Figure 48. ANOVA and Tukey's HSD test results for the indivudal sites testing differences in erosion condition type.

The residual plots (Figure 49) show the assumption that the data is normally distributed is upheld. Nearly all the points fall along the one-to-one line in the Q-Q plot. Only the ends differ from the one-to-one line but not enough to be a cause for concern. The Residuals versus Fitted plots show the residuals to be fairly distributed and centered around zero requiring no transformations to be applied to the data.

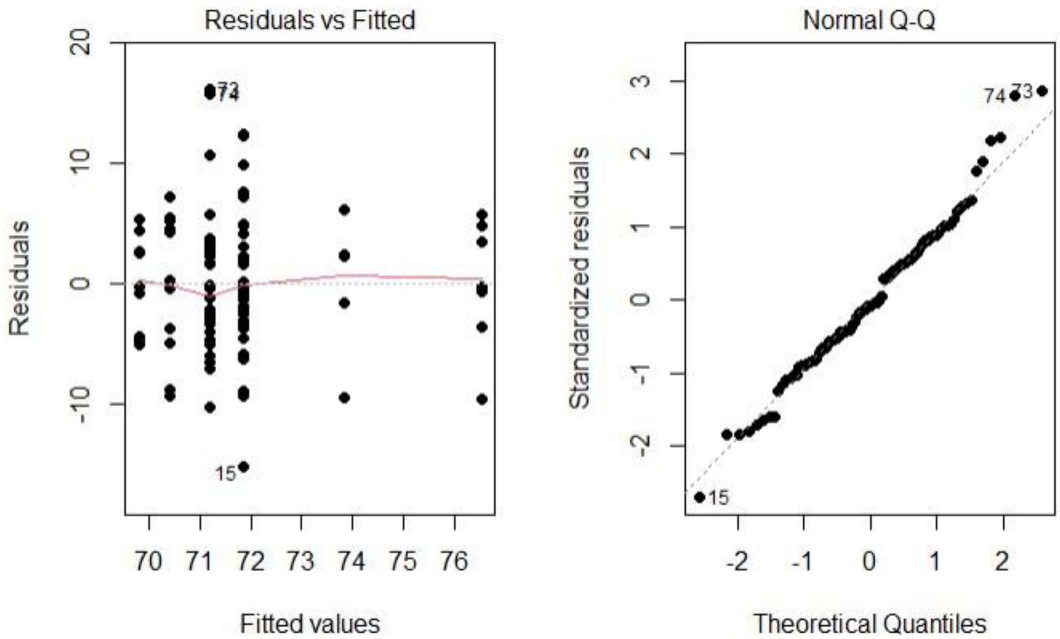


Figure 49. Residual plots from the ANOVA test examining differences in the BEHI category.

```
> anova(fit_behi)  # ANOVA tables
Analysis of Variance Table

Response: MIN
                Df  Sum Sq Mean Sq F value Pr(>F)
as.factor(BEHI)  5  245.27  49.055  1.5105 0.1937
Residuals       96 3117.75  32.477
> summary(fit_behi)
                Df Sum Sq Mean Sq F value Pr(>F)
as.factor(BEHI)  5  245.3   49.05    1.51  0.194
Residuals       96 3117.7   32.48
> fit_behi$coefficients
            (Intercept)      as.factor(BEHI)High       as.factor(BEHI)Low  as.factor(BEHI)Moderate as.factor(BEHI)Very High
             69.8052622                1.3982024                6.7287408                2.0676816                0.6082321
 as.factor(BEHI)Very Low
              4.0200092
>
> # see which erosion condition types are different from each other
> TukeyHSD(fit_behi,ordered=T)
  Tukey multiple comparisons of means
    95% family-wise confidence level
    factor levels have been ordered

Fit: aov(formula = MIN ~ as.factor(BEHI), data = data)

$`as.factor(BEHI)`
                        diff       lwr       upr     p adj
Very High-Extreme  0.6082321 -6.840629  8.057093 0.9998937
High-Extreme       1.3982024 -4.876894  7.673299 0.9869368
Moderate-Extreme   2.0676816 -4.060894  8.196257 0.9228831
Very Low-Extreme   4.0200092 -5.223785 13.263803 0.8032811
Low-Extreme        6.7287408 -1.623100 15.080582 0.1874210
High-Very High     0.7899704 -5.026238  6.606179 0.9987221
Moderate-Very High 1.4594495 -4.198367  7.117266 0.9749246
Very Low-Very High 3.4117771 -5.526857 12.350411 0.8761442
Low-Very High      6.1205087 -1.892274 14.133292 0.2377438
Moderate-High      0.6694791 -3.318275  4.657233 0.9964834
Very Low-High      2.6218068 -5.365087 10.608700 0.9308717
Low-High           5.3305384 -1.604589 12.265665 0.2315661
Very Low-Moderate  1.9523276 -5.919970  9.824626 0.9789080
Low-Moderate       4.6610592 -2.141778 11.463896 0.3542417
Low-Very Low       2.7087316 -6.995231 12.412694 0.9647251
```

Figure 50. ANOVA and Tukey's HSD test results for the indivudal sites testing differences in BEHI category.

The p-value from the ANOVA test is not significant. There is not sufficient evidence to say that the mean minimum PO value is different between any of the BEHI categories. Tukey's HSD makes this up further with no significant p-values.

Reaches

The assumption that the data is normally distributed is upheld is true for both ANOVA tests run to look at difference in erosion conditions and BEHI categories. Nearly all the points fall along the one-to-one line in the Q-Q plot (Figure 51 and Figure 53). Only the ends differ from the one-to-one line but not enough to be a cause for concern. The Residuals versus Fitted plots show the residuals to be fairly distributed and centered around zero requiring no transformations to be applied to the data (Figure 51 and Figure 53).

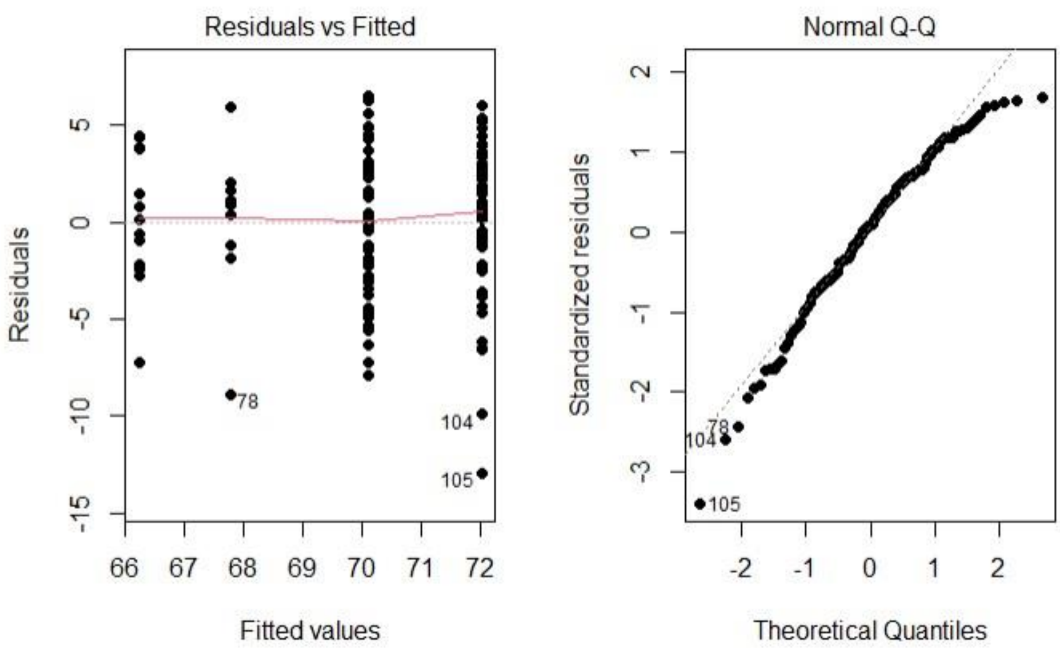


Figure 51. Residual plots from the ANOVA test examining differences in erosion conditions for all reaches.

The null hypothesis that all means are the same can be rejected as the p-value is less than 0.05. This means there is sufficient evidence that one of the means of Condition type is significantly different from the others. Tukey's HSD test results reveal no erosion & mass wasting, surface scour & unstable undercut, and no erosion & unstable undercut have statistically different means. No erosion & surface scour is on the border of the 0.05 threshold like was seen with the individual sites. The mean minimum PO value for no erosion is 72.0, 70.1 for surface scour, 66.2 for unstable undercut and 67.7 for mass wasting.

```
> anova(fit)  # ANOVA tables
Analysis of Variance Table

Response: MIN
                     Df  Sum Sq Mean Sq F value    Pr(>F)    
as.factor(Condition)   3  438.06 146.019  9.8259 7.539e-06 ***
Residuals            121 1798.13  14.861                      
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(fit)
                     Df Sum Sq Mean Sq F value   Pr(>F)    
as.factor(Condition)   3  438.1  146.02   9.826 7.54e-06 ***
Residuals            121 1798.1   14.86                     
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> fit$coefficients
                       (Intercept)      as.factor(Condition)Surface Scour as.factor(Condition)Unstable Undercut
                         72.026878                              -1.921847                             -5.801169
     as.factor(Condition)Mass Wasting
                         -4.260369
>
> # see which erosion condition types are different from eachother
> TukeyHSD(fit,ordered=T)
  Tukey multiple comparisons of means
    95% family-wise confidence level
    factor levels have been ordered

Fit: aov(formula = MIN ~ as.factor(Condition), data = reach3)

$`as.factor(Condition)`
                                     diff         lwr      upr     p adj
Mass Wasting-Unstable Undercut   1.540800 -2.74981644 5.831416 0.7858273
Surface Scour-Unstable Undercut 3.879322  0.86161934 6.897025 0.0058877
None-Unstable Undercut          5.801169  2.75783782 8.844500 0.0000134
Surface Scour-Mass Wasting      2.338522 -1.28205345 5.959098 0.3373083
None-Mass Wasting               4.260369  0.61840499 7.902334 0.0148499
None-Surface Scour              1.921847 -0.06839146 3.912085 0.0625257
```

Figure 52. ANOVA and Tukey's HSD test results for all reaches testing differences in the erosion condition.

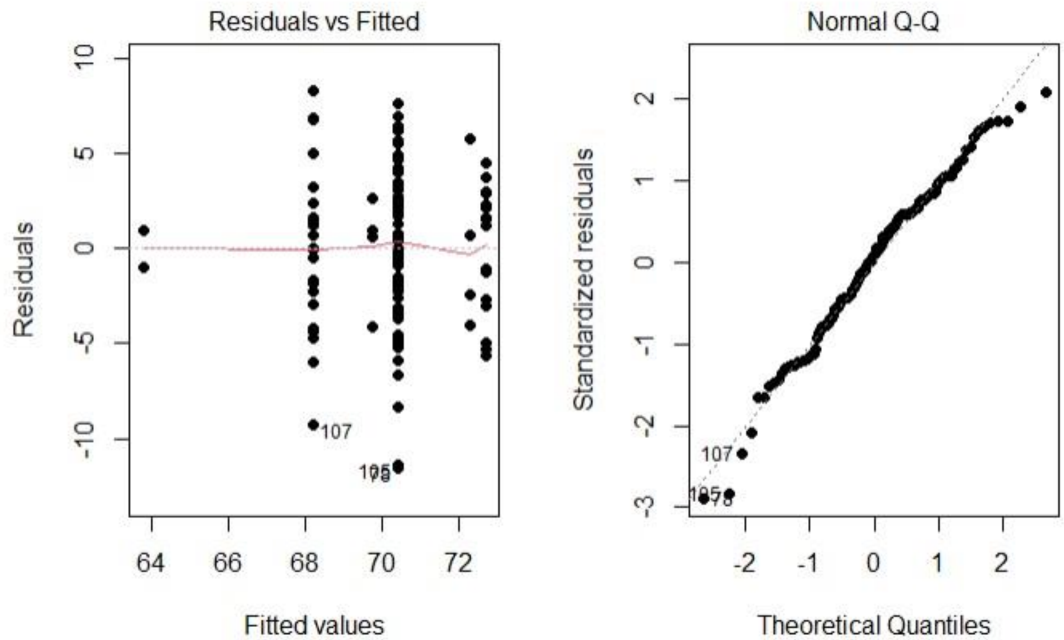


Figure 53. Residual plots from the ANOVA test examining differences in BEHI categories for all reaches.

The null hypothesis that all means are the same can be rejected as the p-value is less than 0.05. This means there is sufficient evidence that one of the means of the BEHI categories is statistically different from the others. Only low & high have statistically different means.

```
> anova(fit_behi)  # ANOVA tables
Analysis of Variance Table

Response: MIN
                 Df  Sum Sq Mean Sq F value   Pr(>F)
as.factor(BEHI)   5  310.29  62.058  3.8345 0.002951 **
Residuals       119 1925.90  16.184
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(fit_behi)
                 Df Sum Sq Mean Sq F value  Pr(>F)
as.factor(BEHI)   5  310.3   62.06   3.834 0.00295 **
Residuals       119 1925.9   16.18
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> fit_behi$coefficients
            (Intercept)      as.factor(BEHI)High       as.factor(BEHI)Low  as.factor(BEHI)Moderate as.factor(BEHI)Very High
             69.7465800               -1.5504203                2.9335521                0.6826506               -5.9436570
 as.factor(BEHI)Very Low
              2.5199245
>
> # see which erosion condition types are different from each other
> TukeyHSD(fit_behi,ordered=T)
  Tukey multiple comparisons of means
    95% family-wise confidence level
    factor levels have been ordered

Fit: aov(formula = MIN ~ as.factor(BEHI), data = reach3)

$`as.factor(BEHI)`
                        diff        lwr       upr     p adj
High-Very High     4.3932367 -4.1832963 12.969770 0.6752218
Extreme-Very High  5.9436570 -4.1483220 16.035636 0.5305998
Moderate-Very High 6.6263076 -1.7258737 14.978489 0.2030391
Very Low-Very High 8.4635815 -1.6283975 18.555561 0.1546354
Low-Very High      8.8772091  0.1914164 17.563002 0.0420894
Extreme-High       1.5504203 -4.7430344  7.843875 0.9799692
Moderate-High      2.2330709 -0.5089107  4.975052 0.1793656
Very Low-High      4.0703448 -2.2231099 10.363799 0.4235411
Low-High           4.4839723  0.8504446  8.117500 0.0065914
Moderate-Extreme   0.6826506 -5.3014605  6.666762 0.9994655
Very Low-Extreme   2.5199245 -5.7201419 10.759991 0.9492347
Low-Extreme        2.9335521 -3.5080042  9.375108 0.7738978
Very Low-Moderate  1.8372739 -4.1468371  7.821385 0.9483955
Low-Moderate       2.2509015 -0.8157804  5.317583 0.2811199
Low-Very Low       0.4136276 -6.0279287  6.855184 0.9999685
```

Figure 54. ANOVA and Tukey's HSD test results for all reaches testing differences in BEHI categories.

Individual Sites and Reaches Combined

The assumption that the data is normally distributed is upheld is true for both ANOVA tests run to look at difference in erosion conditions and BEHI categories. Most points fall along the one-to-one line in the Q-Q plot (Figure 55 and Figure 57). Only the ends differ from the one-to-one line but not enough to be a cause for concern. The Residuals versus Fitted plots show the residuals to be fairly distributed and centered around zero requiring no transformations to be applied to the data (Figure 55 and Figure 57).

The null hypothesis that all means are the same can be rejected as the p-value is less than 0.05. This means there is sufficient evidence that one of the means of Condition type is significantly different from the others. The results from Tukey's HSD test in Figure 56 show all means are statistically different except for mass wasting and unstable undercut. Based on these results, it would be best to create a model using the minimum PO value that predicts the erosion type combing unstable undercut and mass wasting together as one category.

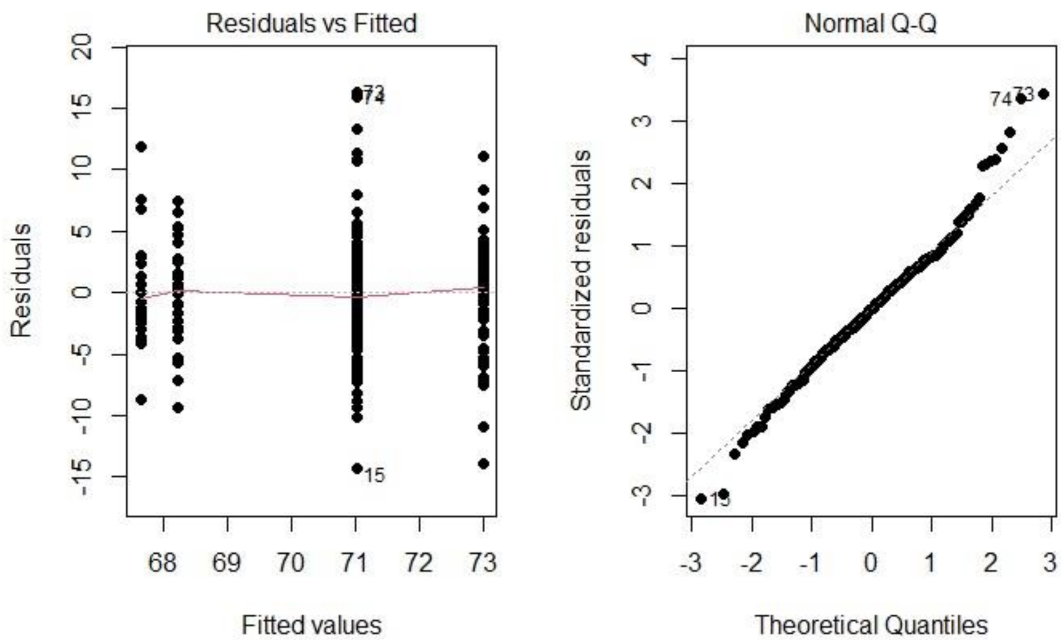


Figure 55. Residual plots from the ANOVA test examining differences in erosion conditions for all Mine Creek data.

```
> anova(fit_condition)  # ANOVA tables
Analysis of Variance Table

Response: MIN
                     Df Sum Sq Mean Sq F value    Pr(>F)    
as.factor(Condition)   3  723.9 241.311  10.763 1.24e-06 ***
Residuals            223 4999.9  22.421                      
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(fit_condition)
                     Df Sum Sq Mean Sq F value   Pr(>F)    
as.factor(Condition)   3    724  241.31   10.76 1.24e-06 ***
Residuals            223   5000   22.42                     
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> fit_condition$coefficients
                         (Intercept)              as.factor(Condition)None     as.factor(Condition)Surface Scour 
                          68.2398843                             4.7398670                             2.7755848 
as.factor(Condition)Unstable Undercut 
                          -0.5819364 
> 
> # see which erosion condition types are different from each other
> TukeyHSD(fit_condition,ordered=T)
  Tukey multiple comparisons of means
    95% family-wise confidence level
    factor levels have been ordered

Fit: aov(formula = MIN ~ as.factor(Condition), data = mc)

$`as.factor(Condition)`
                                   diff         lwr      upr     p adj
Mass Wasting-Unstable Undercut  0.5819364 -2.89596730 4.059840 0.9727184
Surface Scour-Unstable Undercut 3.3575212  0.54727794 6.167764 0.0119160
None-Unstable Undercut          5.3218034  2.35971316 8.283894 0.0000335
Surface Scour-Mass Wasting      2.7755848  0.14313310 5.408036 0.0343666
None-Mass Wasting               4.7398670  1.94588894 7.533845 0.0001021
None-Surface Scour              1.9642822  0.06481748 3.863747 0.0396096
```

Figure 56. ANOVA and Tukey's HSD test results for all Mine Creek data testing differences in the erosion condition.

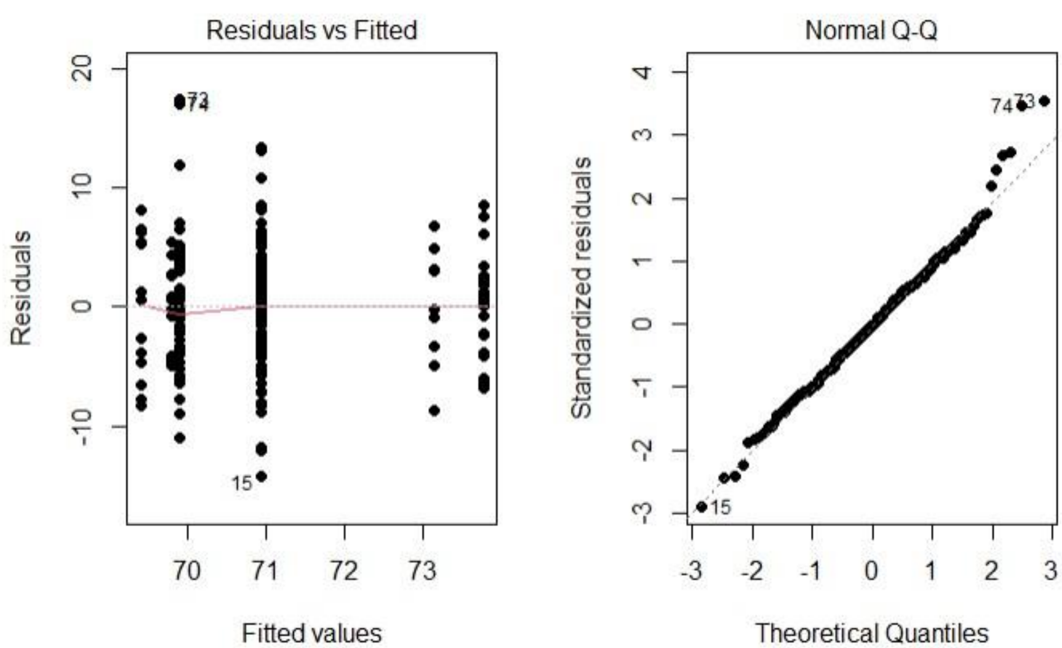


Figure 57. Residual plots from the ANOVA test examining differences in BEHI categories for all Mine Creek data.

The null hypothesis that all means are the same can be rejected as the p-value is less than 0.05. This means there is sufficient evidence that one of the means is significantly different from the others. The results from Tukey's HSD test in Figure 56 show only low and high BEHI categories have statistically different means. Adding additional geospatial parameters along the PO layer could help improve predictions of BEHI categories. As it stands, the PO cannot be solely used to predict the BEHI category.

```
> anova(fit_behi)  # ANOVA tables
Analysis of Variance Table

Response: MIN
                 Df Sum Sq Mean Sq F value Pr(>F)  
as.factor(BEHI)   5  350.7  70.133  2.8846 0.0152 *
Residuals       221 5373.2  24.313                 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> summary(fit_behi)
                 Df Sum Sq Mean Sq F value Pr(>F)  
as.factor(BEHI)   5    351   70.13   2.885 0.0152 *
Residuals       221   5373   24.31                 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> fit_behi$coefficients
             (Intercept)      as.factor(BEHI)High       as.factor(BEHI)Low  as.factor(BEHI)Moderate as.factor(BEHI)Very High 
              69.7872062                0.1039800                3.9720098                1.1447460               -0.3907228 
 as.factor(BEHI)Very Low 
               3.3452800 
> 
> # see which erosion condition types are different from each other
> TukeyHSD(fit_behi,ordered=T)
  Tukey multiple comparisons of means
    95% family-wise confidence level
    factor levels have been ordered

Fit: aov(formula = MIN ~ as.factor(BEHI), data = mc)

$`as.factor(BEHI)`
                       diff        lwr      upr     p adj
Extreme-Very High  0.3907228 -5.1694059 5.950852 0.9999532
High-Very High     0.4947028 -3.8769228 4.866328 0.9995112
Moderate-Very High 1.5354688 -2.6180467 5.688984 0.8955304
Very Low-Very High 3.7360028 -2.4109508 9.882956 0.5021146
Low-Very High      4.3627326 -0.4844752 9.209940 0.1046488
High-Extreme       0.1039800 -4.2676456 4.475606 0.9999998
Moderate-Extreme   1.1447460 -3.0087696 5.298262 0.9686020
Very Low-Extreme   3.3452800 -2.8016736 9.492234 0.6227466
Low-Extreme        3.9720098 -0.8751981 8.819218 0.1766924
Moderate-High      1.0407660 -1.2932799 3.374812 0.7946643
Very Low-High      3.2413000 -1.8558676 8.338468 0.4498327
Low-High           3.8680298  0.4487458 7.287314 0.0164891
Very Low-Moderate  2.2005340 -2.7108506 7.111919 0.7913378
Low-Moderate       2.8272638 -0.3083517 5.962879 0.1034899
Low-Very Low       0.6267298 -4.8837539 6.137214 0.9994990
```

Figure 58. ANOVA and Tukey's HSD test results for all Mine Creek data testing differences in BEHI categories.

Appendix G – Cross-Section Summaries

Figure 59. Pictures of Mine Creek cross-section 1.

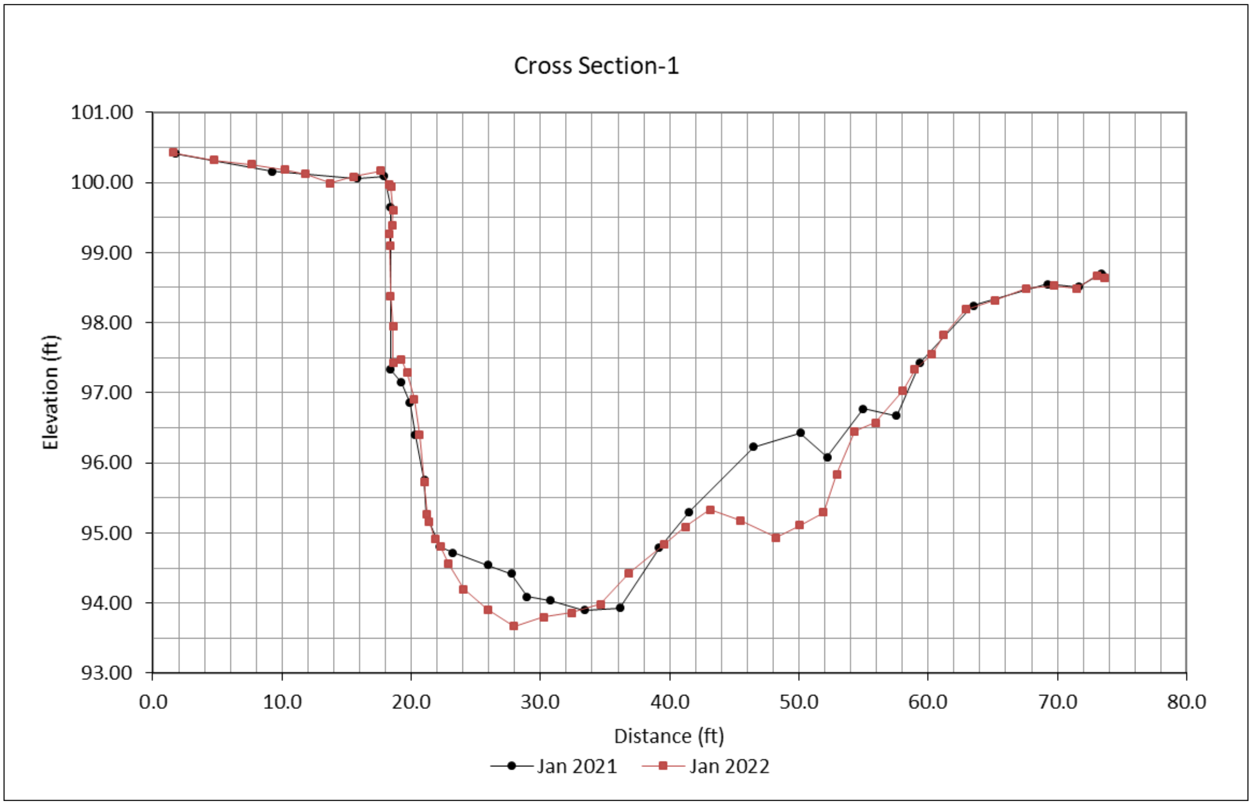


Figure 60. January 2021 and January 2022 survey results for cross-section 1.

	Elevation (ft)		Bank Height (ft)		Bank Retreat (ft/yr)		
	Top of Bank	**Toe of Bank**	**Analysis**	**Measured**	**Max**	**Average**	**Min**
Left Bank	100	93.7	6.3	5.6	-6.17	-0.80	0
Right Bank	98.2	94.8	3.4	3.8	-9.74	-2.81	0

Watershed Area from Streamstats:

DA = 2.88 mi^2

Calculated with NC Rural Piedmont Regional Curves

W_{bkf*} =	18.75	ft	$y = 11.89x^{0.43}$
D_{bkf*} =	2.11	ft	$y = 1.5x^{0.32}$
W/D* =	8.91		
A_{bkf*} =	44.04	ft^2	$y = 21.43x^{0.68}$

Comparison with NC Rural Piedmont Regional Curves

	2021	2022	
W_{TOB}/W_{bkf*} =	2.18	2.36	
W_{bkf}/W_{bkf*} =	1.70	1.70	
A_{TOB}/A_{bkf*} =	2.52	2.90	
A_{bkf}/A_{bkf*} =	1.10	1.28	
	Left	Right	
D_{TOB}/D_{bkf*} =	2.99	1.62	D_{TOB} selected from survey

Comparison of Cross-Sections Dimensions

	2021	2022	
W_{TOB} =	40.95	44.32	ft
A_{TOB} =	111.14	127.53	ft^2
W_{bkf} =	31.89	31.93	ft
A_{bkf} =	48.39	56.57	ft^2
D_{bkf} =	1.56	1.61	ft

BEHI, NBS, Minimum PO Signal

	Left	Right
BEHI Score =	44.83	23.18
BEHI Category =	Very High	Moderate
NBS =	Very High	Very Low
Minimum PO =	74.73	73.96
Erosion =	MW	None

Erosion Condition Key:

NA =	No BEHI point taken
None =	Stable Bank
SC =	Surface Scour
UC =	Unstable Undercut
MW =	Mass Wasting

Figure 61. Pictures of Mine Creek cross-section 2.

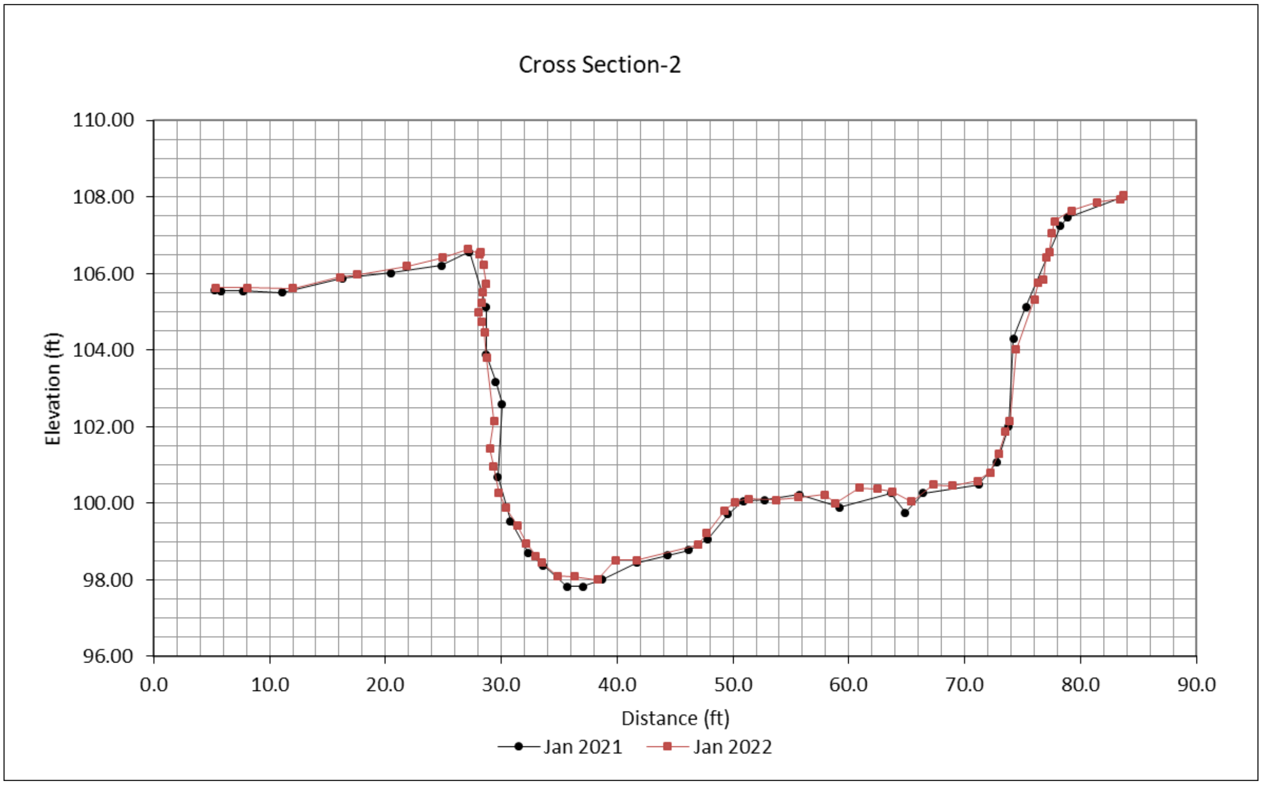


Figure 62. January 2021 and January 2022 survey results for cross-section 2.

	Elevation (ft)		Bank Height (ft)		Bank Retreat (ft/yr)		
	Top of Bank	**Toe of Bank**	**Analysis**	**Measured**	**Max**	**Average**	**Min**
Left Bank	106.2	98.1	8.1	8.2	-0.80	-0.30	0
Right Bank	107.25	100.8	6.45	7	-0.55	-0.18	0

Watershed Area from Streamstats:

DA = 0.95 mi^2

Calculated with NC Rural Piedmont Regional Curves

W_{bkf*} =	11.65	ft	$y = 11.89x^{0.43}$
D_{bkf*} =	1.48	ft	$y = 1.5x^{0.32}$
W/D* =	7.89		
A_{bkf*} =	20.75	ft^2	$y = 21.43x^{0.68}$

Comparison with NC Rural Piedmont Regional Curves

	2021	2022	
W_{TOB}/W_{bkf*} =	6.01	4.15	
W_{bkf}/W_{bkf*} =	3.56	3.68	
A_{TOB}/A_{bkf*} =	14.44	14.37	
A_{bkf}/A_{bkf*} =	2.77	2.90	
	Left	Right	
D_{TOB}/D_{bkf*} =	5.48	4.37	D_{TOB} selected from survey

Comparison of Cross-Sections Dimensions

	2021	2022	
W_{TOB} =	69.98	48.32	ft
A_{TOB} =	299.64	298.14	ft^2
W_{bkf} =	41.50	42.86	ft
A_{bkf} =	57.40	60.21	ft^2
D_{bkf} =	1.49	1.35	ft

BEHI, NBS, Minimum PO Signal

	Left	Right
BEHI Score =	40.13	25.5
BEHI Category =	Very High	Moderate
NBS =	Low	Very Low
Minimum PO =	61.14	69.11
Erosion =	MW	SC

Erosion Condition Key:

NA = No BEHI point taken
None = Stable Bank
SC = Surface Scour
UC = Unstable Undercut
MW = Mass Wasting

Figure 63. Pictures of Mine Creek cross-section 3.

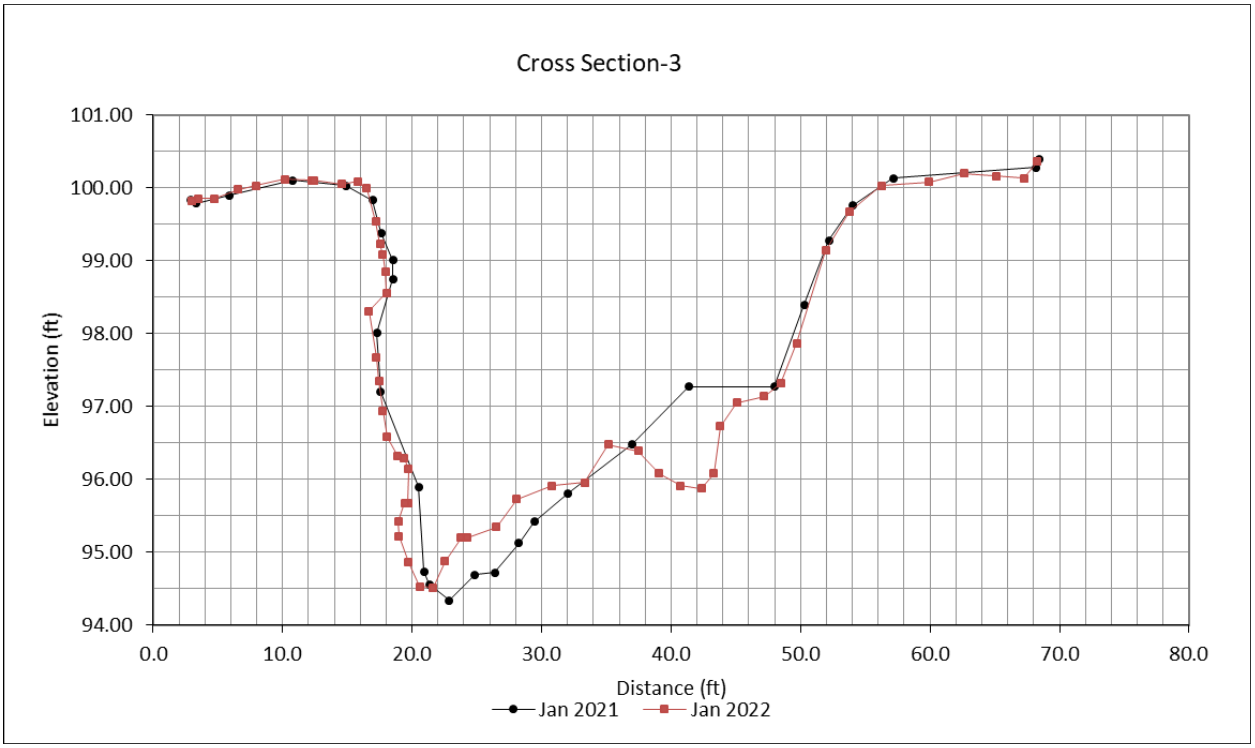


Figure 64. January 2021 and January 2022 survey results for cross-section 3.

	Elevation (ft)		Bank Height (ft)		Bank Retreat (ft/yr)		
	Top of Bank	**Toe of Bank**	**Analysis**	**Measured**	**Max**	**Average**	**Min**
Left Bank	100.3	94.5	5.8	6	-1.53	-0.58	0
Right Bank	100	96.49	3.51	3.7	-6.54	-1.87	-0.12

Watershed Area from Streamstats:

DA = 0.36 mi^2

Calculated with NC Rural Piedmont Regional Curves

W_{bkf*} =	7.70	ft	$y = 11.89x^{0.43}$
D_{bkf*} =	1.09	ft	$y = 1.5x^{0.32}$
W/D* =	7.09		
A_{bkf*} =	10.78	ft^2	$y = 21.43x^{0.68}$

Comparison with NC Rural Piedmont Regional Curves

	2021	2022	
W_{TOB}/W_{bkf*} =	4.81	4.84	
W_{bkf}/W_{bkf*} =	1.50	1.87	
A_{TOB}/A_{bkf*} =	11.21	11.91	
A_{bkf}/A_{bkf*} =	0.97	0.86	
	Left	Right	
D_{TOB}/D_{bkf*} =	5.34	3.23	D_{TOB} selected from survey

Comparison of Cross-Sections Dimensions

	2021	2022	
W_{TOB} =	37.06	37.26	ft
A_{TOB} =	120.95	128.45	ft^2
W_{bkf} =	11.55	14.39	ft
A_{bkf} =	10.45	9.24	ft^2
D_{bkf} =	0.91	0.82	ft

BEHI, NBS, Minimum PO Signal

	Left	Right
BEHI Score =	24.95	27.79
BEHI Category =	Moderate	Moderate
NBS =	Very High	Very Low
Minimum PO =	70.59	71.35
Erosion =	SC	None

Erosion Condition Key:

NA =	No BEHI point taken
None =	Stable Bank
SC =	Surface Scour
UC =	Unstable Undercut
MW =	Mass Wasting

Figure 65. Pictures of Mine Creek cross-section 4.

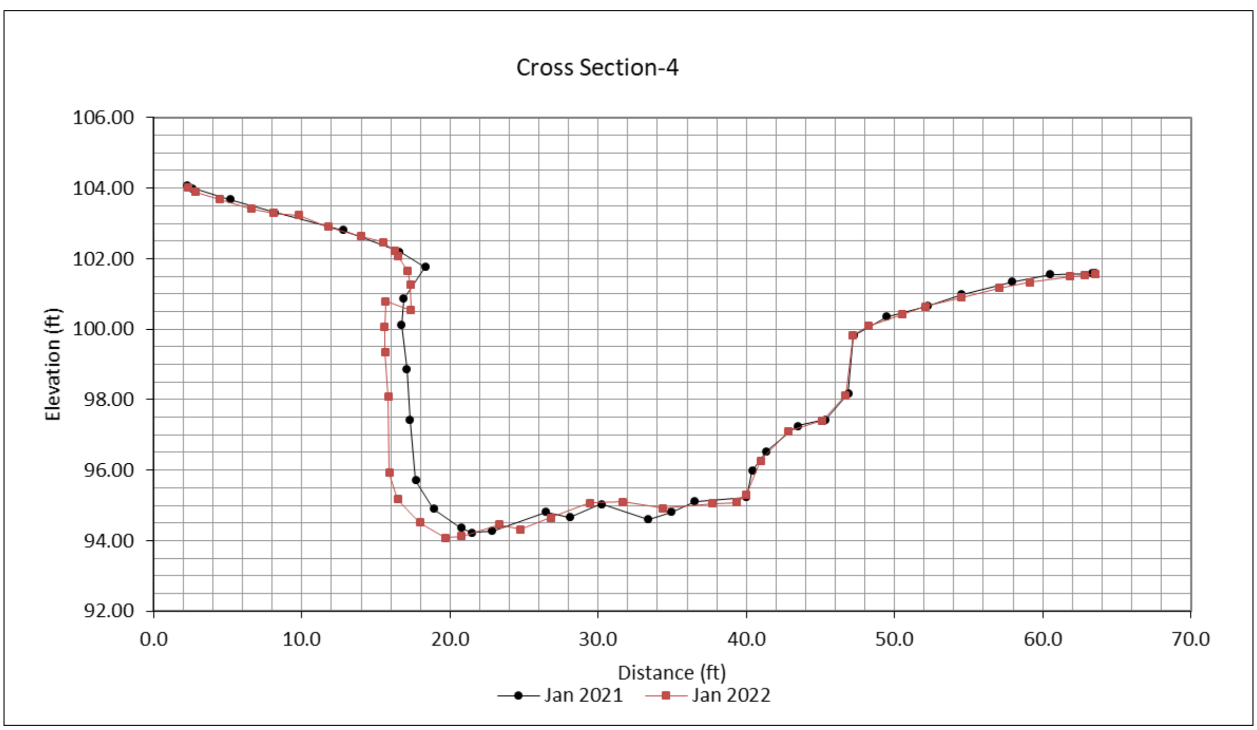


Figure 66. January 2021 and January 2022 survey results for cross-section 4.

	Elevation (ft)		Bank Height (ft)		Bank Retreat (ft/yr)		
	Top of Bank	Toe of Bank	Analysis	Measured	Max	Average	Min
Left Bank	102.5	94.36	8.14	8.4	-2.26	-1.33	0
Right Bank	99.82	95.3	4.52	NA	-0.25	0.00	0

Watershed Area from Streamstats:

DA =	0.15	mi^2

Calculated with NC Rural Piedmont Regional Curves

W_{bkf*} =	5.22	ft	$y = 11.89x^{0.43}$
D_{bkf*} =	0.81	ft	$y = 1.5x^{0.32}$
W/D* =	6.42		
A_{bkf*} =	5.83	ft^2	$y = 21.43x^{0.68}$

Comparison with NC Rural Piedmont Regional Curves

	2021	2022	
W_{TOB}/W_{bkf*} =	8.97	10.29	
W_{bkf}/W_{bkf*} =	4.54	4.99	
A_{TOB}/A_{bkf*} =	22.00	20.87	
A_{bkf}/A_{bkf*} =	7.35	5.39	
	Left	Right	
D_{TOB}/D_{bkf*} =	10.01	5.56	D_{TOB} selected from survey

Comparison of Cross-Sections Dimensions

	2021	2022	
W_{TOB} =	29.80	37.10	ft
A_{TOB} =	128.38	121.74	ft^2
W_{bkf} =	23.69	26.06	ft
A_{bkf} =	42.87	31.42	ft^2
D_{bkf} =	1.71	1.25	ft

BEHI, NBS, Minimum PO Signal

	Left	Right
BEHI Score =	33.16	NA
BEHI Category =	High	NA
NBS =	High	NA
Minimum PO =	68.21	72.55
Erosion =	MW	NA

Erosion Condition Key:

NA =	No BEHI point taken
None =	Stable Bank
SC =	Surface Scour
UC =	Unstable Undercut
MW =	Mass Wasting

Figure 67. Pictures of Mine Creek cross-section 5.

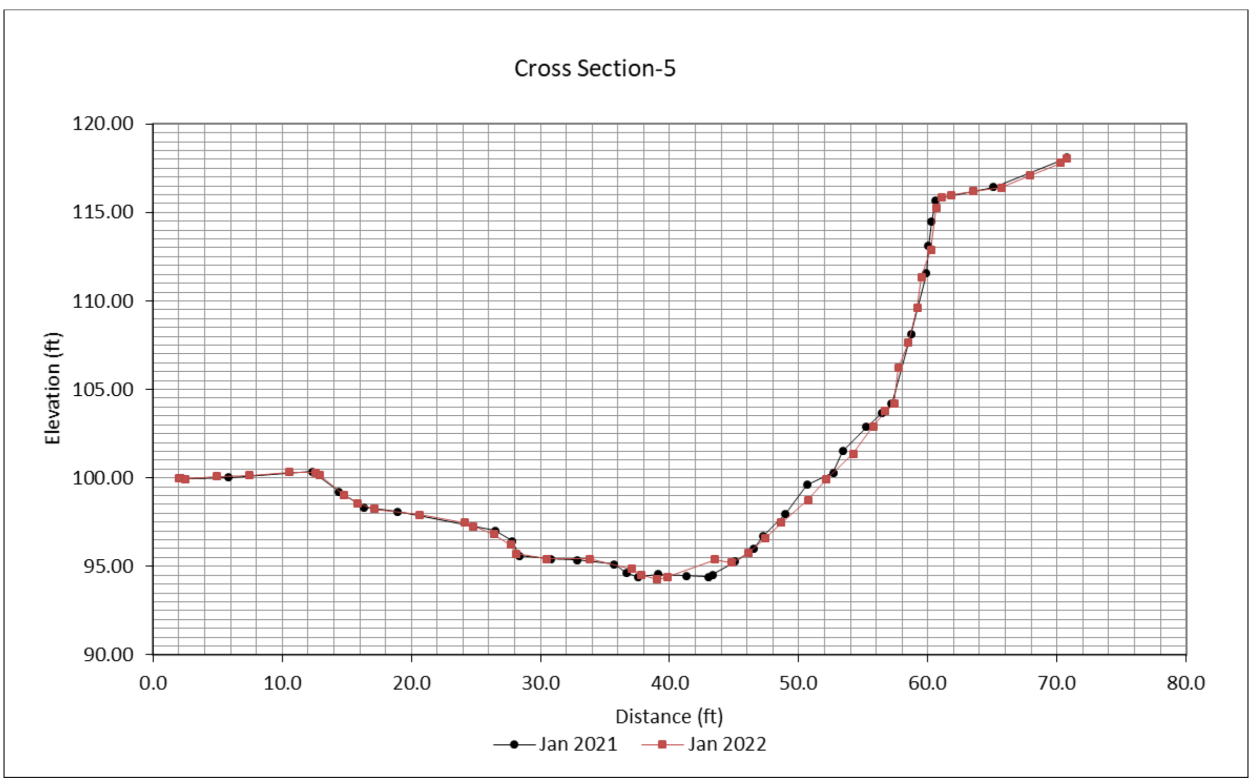


Figure 68. January 2021 and January 2022 survey results for cross-section 5.

	Elevation (ft)		Bank Height (ft)		Bank Retreat (ft/yr)		
	Top of Bank	**Toe of Bank**	**Analysis**	**Measured**	**Max**	**Average**	**Min**
Left Bank	100.2	95.7	4.5	0	-0.77	-0.17	0
Right Bank	115.8	95.2	20.6	17.73	-1.10	-0.26	0

Watershed Area from Streamstats:

DA = 0.13 mi^2

Calculated with NC Rural Piedmont Regional Curves

W_{bkf*} =	4.96	ft	$y = 11.89x^{0.43}$
D_{bkf*} =	0.78	ft	$y = 1.5x^{0.32}$
W/D* =	6.34		s
A_{bkf*} =	5.38	ft^2	$y = 21.43x^{0.68}$

Comparison with NC Rural Piedmont Regional Curves

	2021	2022	
W_{TOB}/W_{bkf*} =	7.31	7.91	
W_{bkf}/W_{bkf*} =	3.91	3.98	
A_{TOB}/A_{bkf*} =	26.88	26.18	
A_{bkf}/A_{bkf*} =	6.72	5.62	
	Left	Right	
D_{TOB}/D_{bkf*} =	5.75	26.33	D_{TOB} selected from survey

Comparison of Cross-Sections Dimensions

	2021	2022	
W_{TOB} =	36.24	39.25	ft
A_{TOB} =	144.51	140.73	ft^2
W_{bkf} =	19.41	19.74	ft
A_{bkf} =	36.11	30.19	ft^2
D_{bkf} =	1.71	1.44	ft

BEHI, NBS, Minimum PO Signal

	Left	Right
BEHI Score =	NA	52.68
BEHI Category =	NA	Extreme
NBS =	NA	Moderate
Minimum PO =	84.98	65.12
Erosion =	NA	MW

Erosion Condition Key:

NA =	No BEHI point taken
None =	Stable Bank
SC =	Surface Scour
UC =	Unstable Undercut
MW =	Mass Wasting

Mine Creek Cross Section-6

Figure 69. Pictures of Mine Creek cross-section 6.

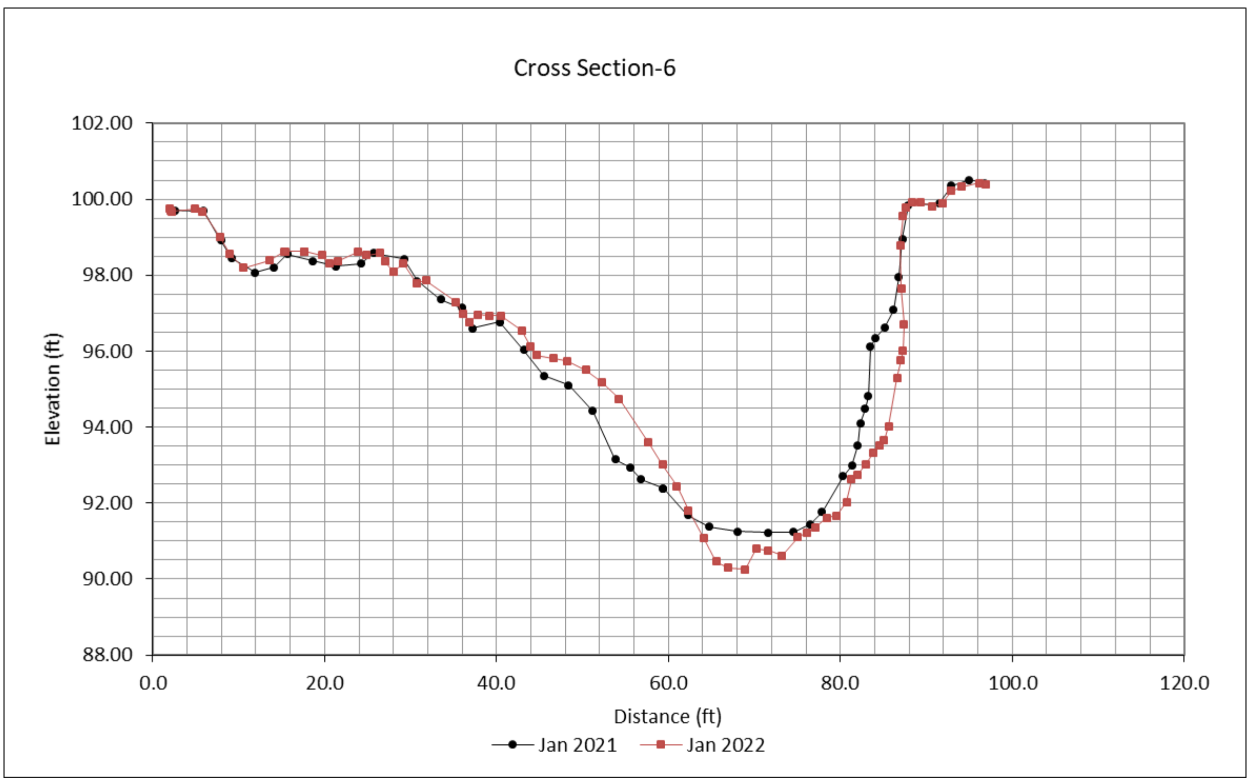


Figure 70. January 2021 and January 2022 survey results for cross-section 6.

	Elevation (ft)		Bank Height (ft)		Bank Retreat (ft/yr)		
	Top of Bank	**Toe of Bank**	**Analysis**	**Measured**	**Max**	**Average**	**Min**
Left Bank	98.3	91.38	6.92	NA	-0.66	0.00	0.00
Right Bank	99.9	91.24	8.66	8	-3.81	-1.80	0.00

Watershed Area from Streamstats:

DA = 6.41 mi^2

Calculated with NC Rural Piedmont Regional Curves

W_{bkf*} =	26.43	ft	$y = 11.89x^{0.43}$
D_{bkf*} =	2.72	ft	$y = 1.5x^{0.32}$
W/D* =	9.72		
A_{bkf*} =	75.80	ft^2	$y = 21.43x^{0.68}$

Comparison with NC Rural Piedmont Regional Curves

	<u>2021</u>	<u>2022</u>	
W_{TOB}/W_{bkf*} =	2.12	2.25	
W_{bkf}/W_{bkf*} =	1.80	1.64	
A_{TOB}/A_{bkf*} =	3.31	3.36	
A_{bkf}/A_{bkf*} =	2.52	1.96	
	<u>Left</u>	<u>Right</u>	
D_{TOB}/D_{bkf*} =	2.55	3.19	D_{TOB} selected from survey

Comparison of Cross-Sections Dimensions

	<u>2021</u>	<u>2022</u>	
W_{TOB} =	56.05	59.45	ft
A_{TOB} =	251.22	254.60	ft^2
W_{bkf} =	47.52	43.32	ft
A_{bkf} =	191.37	148.41	ft^2
D_{bkf} =	3.63	3.31	ft

BEHI, NBS, Minimum PO Signal

	<u>Left</u>	<u>Right</u>
BEHI Score =	NA	24.34
BEHI Category =	NA	Moderate
NBS =	NA	Very High
Minimum PO =	76.32	84.31
Erosion =	NA	SC

<u>Erosion Condition Key:</u>

NA =	No BEHI point taken
None =	Stable Bank
SC =	Surface Scour
UC =	Unstable Undercut
MW =	Mass Wasting

Mine Creek Cross Section-7

Figure 71. Pictures of Mine Creek cross-section 7.

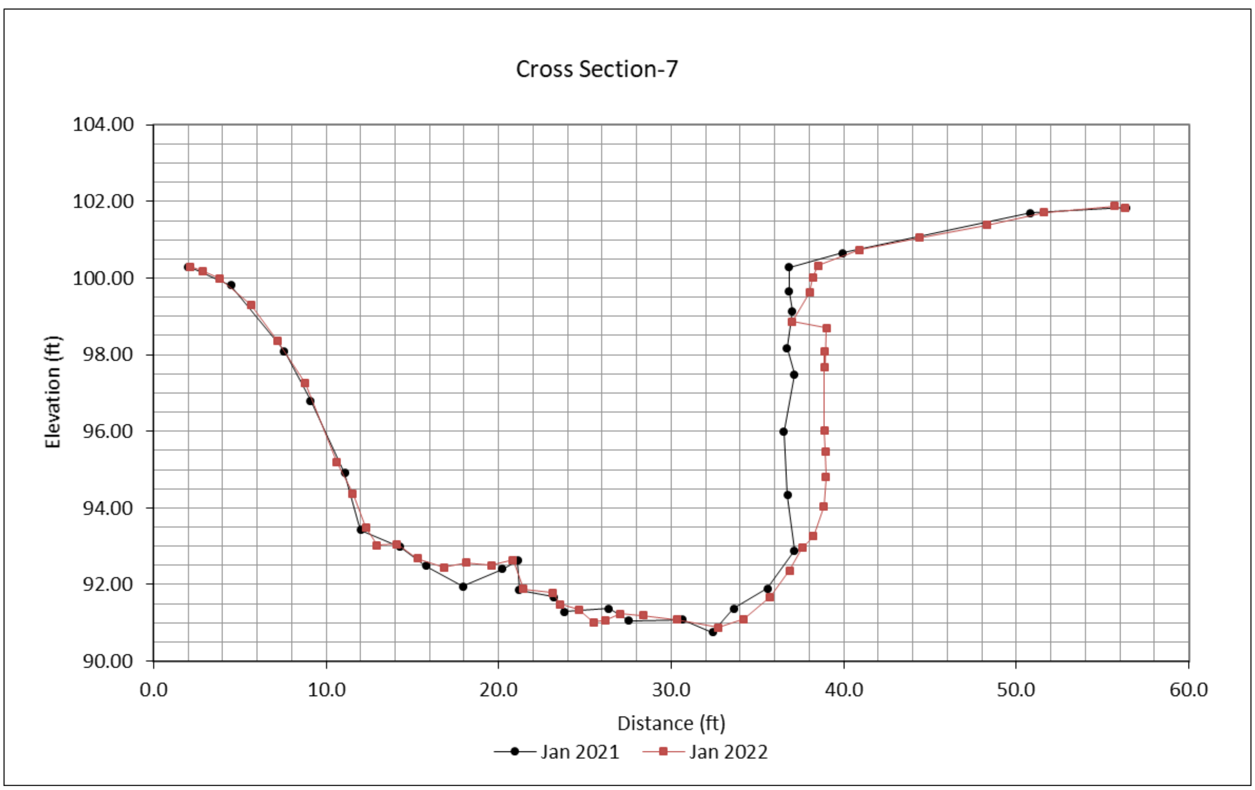


Figure 72. January 2021 and January 2022 survey results for cross-section 7.

	Elevation (ft)		Bank Height (ft)		Bank Retreat (ft/yr)		
	Top of Bank	**Toe of Bank**	**Analysis**	**Measured**	**Max**	**Average**	**Min**
Left Bank	100.3	93.5	6.8	8	-0.15	0.00	0
Right Bank	100.28	90.9	9.38	10	-2.36	-1.52	-0.22

Watershed Area from Streamstats:

DA = 0.09 mi^2

Calculated with NC Rural Piedmont Regional Curves

W_{bkf*} =	4.20	ft	$y = 11.89x^{0.43}$
D_{bkf*} =	0.69	ft	$y = 1.5x^{0.32}$
W/D* =	6.07		
A_{bkf*} =	4.13	ft^2	$y = 21.43x^{0.68}$

Comparison with NC Rural Piedmont Regional Curves

	2021	2022	
W_{TOB}/W_{bkf*} =	7.70	8.61	
W_{bkf}/W_{bkf*} =	4.71	5.31	
A_{TOB}/A_{bkf*} =	56.97	59.49	
A_{bkf}/A_{bkf*} =	6.24	6.97	
	Left	Right	
D_{TOB}/D_{bkf*} =	9.83	13.57	D_{TOB} selected from survey

Comparison of Cross-Sections Dimensions

	2021	2022	
W_{TOB} =	32.32	36.17	ft
A_{TOB} =	235.48	245.88	ft^2
W_{bkf} =	19.80	22.28	ft
A_{bkf} =	25.77	28.83	ft^2
D_{bkf} =	1.17	1.19	ft

BEHI, NBS, Minimum PO Signal

	Left	Right
BEHI Score =	23.65	36.65
BEHI Category =	Moderate	High
NBS =	Moderate	Moderate
Minimum PO =	64.18	68.81
Erosion =	SC	MW

Erosion Condition Key:

NA =	No BEHI point taken
None =	Stable Bank
SC =	Surface Scour
UC =	Unstable Undercut
MW =	Mass Wasting

Appendix H – Cross-Section Top of Bank Sediment Volume Procedure Log

All of the following steps were completed in ArcGIS Pro. This was repeated for each cross-section.

1. Import cross-section TOB Year 1 and Year 2 surveys.

2. Define the coordinate system to run tools in ArcGIS Pro. Repeat for second year.

    Tool: Define Projection
    Input Dataset or Feature Class: TOBYear1
    Coordinate System: WGS_1984_Web_Mercator_Auxiliary_Sphere

3. Create a new feature class.

    Tool: Create Feature Class
    Feature Class Location: geodatabase.gdb
    Feature Class Name: Construction_line
    Geometry Type: Polyline
    Has M: No
    Has Z: No
    Coordinate System: WGS_1984_Web_Mercator_Auxiliary_Sphere

4. Draw construction lines at the beginning and end of the TOB surveys making sure to intersect both TOB lines. Place the construction lines where the end of the shorter survey (see figure below).

    Edit → Create Features → TOBYear1
    Construction Tools: Line
    Save

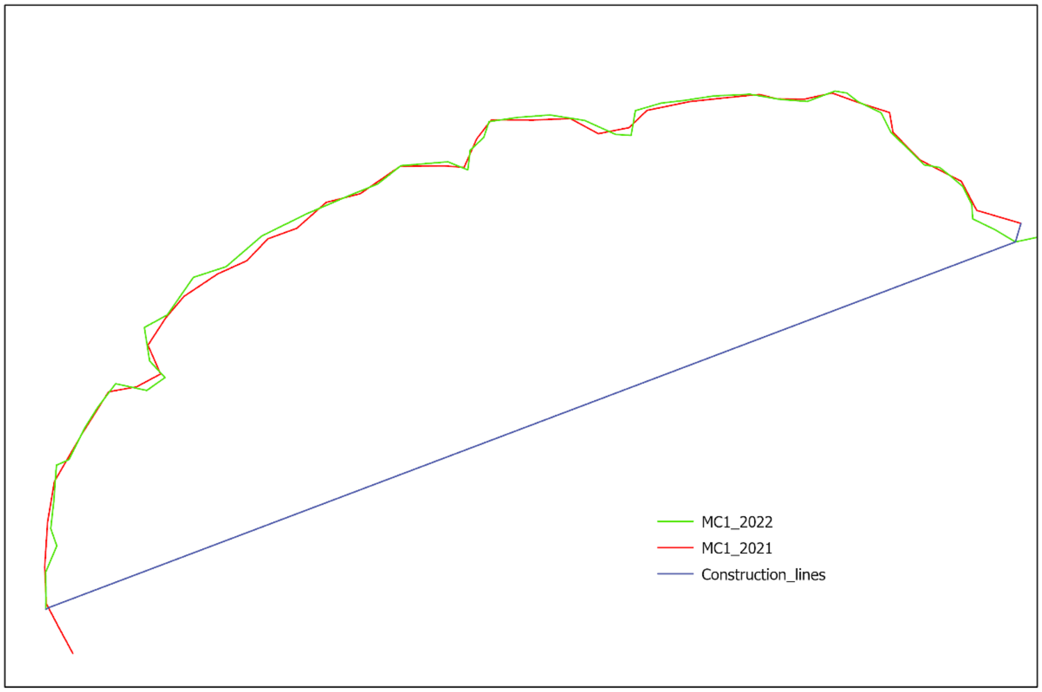


Figure 73. TOB construction line placement.

5. Create a polygon from polylines.

   Tool: Feature to Polygon
   Input Features: TOBYear1; Construction line
   Output Feature Class: XS1_Year1_polygon.shp

   Repeat for Year 2.

6. Join Year 1 and Year 2 polygons

   Tool: Union
   Input Features: XS1_Year1_polygon.shp; XS1_Year2_polygon.shp
   Output Feature Class: XS1_Year1_Year2_change.shp

7. Add field to XS1_Year1_Year2_change.shp

   TOC → XS1_Year1_Year2_change.shp → Attribute Table → Add Field
   Name: Change
   Type: Text

8. Label polygon sections as erosion or deposition.

    TOC → XS1_Year1_Year2_change.shp → Start Editing → Attribute Table
    Change & FID_XS1_Year1_polygon = -1 → Type Erosion
    Change & FID_XS1_Year2_polygon = -1 → Type Deposition
    Delete row where FID_XS1_Year1_polygon and FID_XS1_Year2_polygon =1

9. Separate the multipart polygon for erosion and deposition into single polygons.

    Tool: Dissolve
    Input Features: XS1_Year1_Year2_change
    Output feature class: XS1_Year1_Year2_change_Dissolve
    Dissolve Field(s): Change
    Uncheck "Create multipart features (optional)

10. Add field for area for XS1_TOB_polygon.shp.

    Contents → XS1_Year1_polygon.shp → Attribute Table → Add field
    Name: Area_ft2
    Type: Double
    Number Format: Numeric

11. Calculate the area of each polygon.

    XS1_Year1_polygon.shp → Attribute Table → Area_ft2
    Calculate Geometry
    Property: Area
    Units: Square Feet (US)
    Coordinate System: Current Map
    (WGS_1984_Web_Mercator_Auxiliary_Sphere)

12. Remove any polygon less than 0.1 ft^2.

    Tool: Select Attributes
    Input Rows: XS1_Year1_polygon
    Selection Type: New selection
    Expression Where: Area_ft2 is less than or equal to 0.1

    Delete selected rows.

13. Add field for volume for XS1_Year1_Year2_change_Dissolve.shp.

    Contents → XS1_Year1_Year2_change_Dissolve → Attribute Table → Add field
    Name: Volume_ft3
    Type: Double
    Number Format: Numeric

14. Add field for measured bank height for XS1_Year1_Year2_change_Dissolve.shp.

Contents → XS1_Year1_Year2_change_Dissolve → Attribute Table → Add field
Name: Bank_ht
Type: Double
Number Format: Numeric

NOTE The bank height is gotten from the measured bank height in the field on that side of the bank.

15. Add measured bank height in feet.

Contents → XS1_Year1_Year2_change_Dissolve
Calculate Field
Expression Type: Arcade
Bank_ht = measured bank height value

16. Calculate the volume of sediment.

Contents → XS1_Year1_Year2_change_Dissolve
Calculate Field
Expression Type: Arcade
Volume_ft3 = Area_ft2*Bank_ht

17. Summarize total area and volume of erosion and deposition.

Tool: Summary statistics
Input Table: XS1_Year1_Year2_change_Dissolve.shp
Field: Area_ft2; Statistic Type: Sum
Field: Volume_ft3; Statistic Type: Sum
Case field: Change

Appendix I – Estimating Sediment and Nutrient Loads

Steps 1 -14 were completed in ArcGIS Pro.

1. Merge channels into one polyline.

    Select all channel polylines.
    Edit → Modify → Merge

2. Generate points every 50 ft along the channel polyline.

    Tool: Generate Points Along Lines
    Input Features: MC channels
    Output Feature Class: MCchannels_PointsAlongLines
    Point Placement: By distance
    Distance: 50 ft

3. Split the channel at each point.

    Tool: Split Line at Point
    Input Features: MC channels
    Point Features: MCchannels_PointsAlongLines
    Output Feature Class: MC_channels_split
    Search Radius: 2 meters

    NOTE When the search radius was 0 meters, the line was not split at every single point (even though it appeared each point was on the line) but it was when the search radius was increased.

4. Create a new field for the length of each segment.

    Contents → MC_channels_split → Attribute Table → Add field
    Name: Length_ft
    Type: Double
    Number Format: Numeric

5. Calculate the length of each channel segment.

    MC_channels_split→ Attribute Table → Length_ft
    Calculate Geometry
    Property: Length
    Units: Feet (United States)
    Coordinate System: Current Map (WGS_1984_Web_Mercator_Auxiliary_Sphere)

6. Remove channel segments less than 1 ft. It is recommended to make a copy of the original layer.

    Tool: Select By Attributes
    Input Rows: MC_channels_split
    Selection Type: New Selection
    Where: Length_ft is less than 1

    Delete all selected rows.

7. Create a new field for an ID name of each segment.

    Contents → MC_channels_split → Attribute Table → Add field
    Name: ID
    Type: Text

8. Add ID.

    Contents → MC_channels_split
    Calculate Field
    Expression Type: Python 3
    ID = OBJECTID

9. Create a 10 foot buffer for every segment.

    Tool: Buffer
    Input Features: MC_channels_split
    Output Feature Class: MC_channels_split_Buffer
    Distance: Linear value; 10 feet
    Side Type: Full
    End Type: Flat
    Method: Planar
    Dissolve Type: No Dissolve

    NOTE Buffers do not work on extremely small lengths.

10. Get statistics from Positive Openness layer for each BEHI point

    Tool: Zonal Statistics as Table (Spatial Analyst)
    Input raster or feature zone data: MC_channels_split_Buffer
    Zone field: ID
    Input value raster: mine_clip_2015_OPEN-POS_R20_D16.tif
    Output table: ALL_MC_PO_Stats
    Percentile values: 90
    Percentile interpolation type: Auto-detect

NOTE Received "Warning 010566: Some cells may not have been rasterized". There were some buffers that overlapped too much at intersection points. 70 of the channel segments were not rasterized.

11. Join the ALL_MC_PO_Stats table to the MC_channels_split layer

    Tool: Add Join
    Input Join Table:
    Input Join Field: ID
    Join Table: ALL_MC_PO_Stats
    Join Table Field: ID
    Check Keep All Target Features
    Validate Join

12. Select all rows with raster data.

    Tool: Select By Attributes
    Input Rows: MC_channels_split
    Selection Type: New Selection
    Where: MIN is not null

13. Export all selected rows to a new layer.

    TOC → MC_channels_split → Data → Export Data
    Export: Selected features
    Use the same coordinate system as: this layer's source data
    MC_channels_predict.shp
    Select yes to add exported layer to map

14. Export attribute table of MC_channels_predict to a csv file.

15. Upload the csv file into the R Script set up with the models to estimate the volume of erosion in tons/yr and also in tons/yr and TN and TP loads in lbs/yr. The following shows the code and output for the analysis and models used to predict the sediment and nutrient loads.

Predicting Sediment and Nutrient Loads from Streambank Erosion – R Script

Layla El-Khoury

5/13/2022

```
# set working directory
setwd("C:/Users/lcelkhou/OneDrive/Documents/NCSU/Thesis/Mine Creek")

# Read in data
mc <- read.csv('MC_All.csv')
shelley <- read.csv('shelley_lake_channels.csv')

# replace blank Condition with None, spell out others
mc$Condition[mc$Condition==" "] <- "None"
mc$Condition[mc$Condition=="SC"] <- "Surface Scour"
mc$Condition[mc$Condition=="UC"] <- "Unstable Undercut"
mc$Condition[mc$Condition=="MW"] <- "Mass Wasting"
```

Procedure to use minimum PO to predict volume of erosion from streambanks

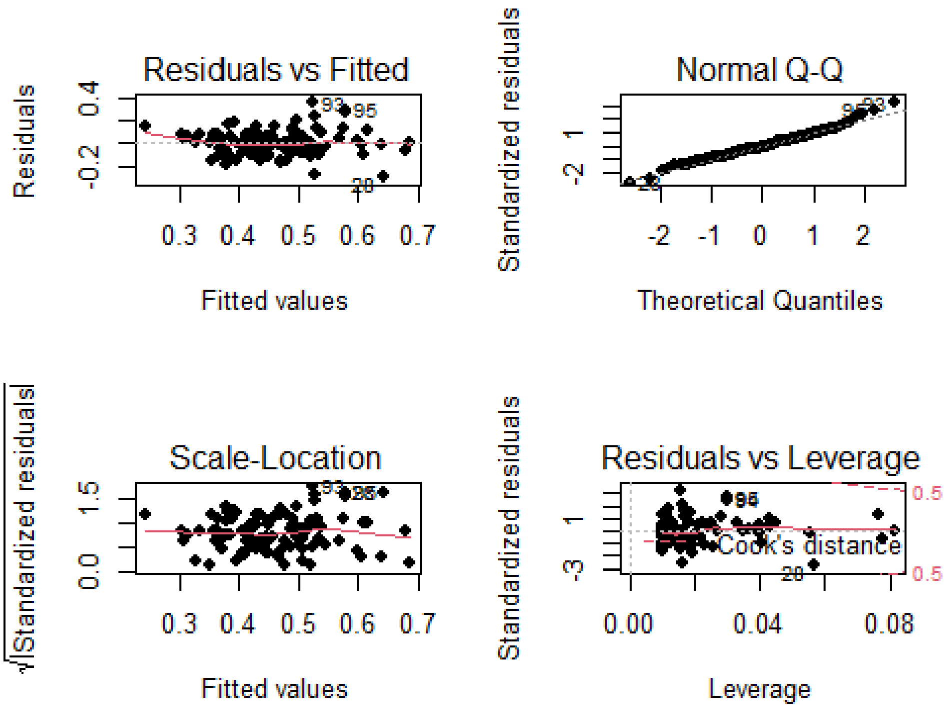
Step 1. Predict Bank Height

Estimate the bank height for each stream segment using the regression from minimum PO value and measured bank heights. Just the individual site data was used for this model since it produced a better model than when all the data was used.

```
# Read in data
individ <- read.csv('MC_individ.csv')
```

Linear regression: Transforming Response Variable

```
fit2 <- lm(1/sqrt(Bank_ht)~MIN,individ)

# residual diagnostics
par(mfrow=c(2,2))
plot(fit2,pch=19)
```




```
# fit summary
summary(fit2)

##
## Call:
## lm(formula = 1/sqrt(Bank_ht) ~ MIN, data = individ)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.29091 -0.07703 -0.00942  0.06373  0.35127
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.578805   0.138482  -4.180 6.26e-05 ***
## MIN          0.014509   0.001924   7.541 2.18e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1116 on 100 degrees of freedom
## Multiple R-squared:  0.3625, Adjusted R-squared:  0.3561
## F-statistic: 56.87 on 1 and 100 DF,  p-value: 2.175e-11
```

The diagnostic plots illustrate the assumptions that the errors are normally distributed, there is homoscedasticity of errors and observations are independent. The residuals vs fitted plot show the values to be centered around zero and points fall along the one-to-one line in the Q-Q plot. In the residuals vs leverage plot, there are no true outliers since none of the points are outside the 0.5 lines but there a couple of points that could be potential leverage points.

Testing Model

```
#  linear regression transforming response variable
kfolds <- createFolds(individ$Bank_ht,
                      k = 5,
                      returnTrain = TRUE)
kfolds
```

```
## $Fold1
##  [1]   1   2   3   4   5   6   8   9  10  11  14  15  17  18  20  21  22  23  24
## [20]  26  27  28  29  30  31  32  34  35  36  37  38  39  40  41  42  43  44  45
## [39]  46  47  48  50  51  52  53  54  55  58  59  60  61  62  64  65  68  69  70
## [58]  72  73  74  75  76  77  78  79  80  82  83  84  85  86  87  90  91  92  93
## [77]  94  97  98 100 101 102
##
## $Fold2
##  [1]   1   2   3   5   7   8   9  10  11  12  13  16  17  18  19  21  23  24  25
## [20]  26  27  28  29  30  31  33  34  35  36  37  39  40  41  42  47  48  49  51
## [39]  53  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70  71
## [58]  72  73  74  77  79  80  81  82  84  85  86  87  88  89  90  91  92  93  94
## [77]  95  96  99 100 101 102
##
## $Fold3
##  [1]   1   3   4   6   7   8   9  10  12  13  14  15  16  17  18  19  20  22  23
## [20]  24  25  26  28  29  30  31  32  33  34  35  37  38  40  41  42  43  44  45
## [39]  46  49  50  51  52  55  56  57  58  59  61  62  63  64  66  67  68  71  72
## [58]  75  76  77  78  80  81  82  83  84  85  86  88  89  90  91  92  93  94  95
## [77]  96  97  98  99 100 101
##
## $Fold4
##  [1]   1   2   4   5   6   7   8  10  11  12  13  14  15  16  18  19  20  21  22
## [20]  25  26  27  28  30  31  32  33  35  36  38  39  42  43  44  45  46  47  48
## [39]  49  50  52  53  54  56  57  58  59  60  61  63  65  66  67  69  70  71  73
## [58]  74  75  76  78  79  80  81  82  83  84  86  87  88  89  93  94  95  96  97
## [77]  98  99 100 102
##
## $Fold5
##  [1]   2   3   4   5   6   7   9  11  12  13  14  15  16  17  19  20  21  22  23
## [20]  24  25  27  29  32  33  34  36  37  38  39  40  41  43  44  45  46  47  48
## [39]  49  50  51  52  53  54  55  56  57  60  62  63  64  65  66  67  68  69  70
## [58]  71  72  73  74  75  76  77  78  79  81  83  85  87  88  89  90  91  92  95
## [77]  96  97  98  99 101 102
```

```
bank_ht_out <- data.frame()

# Loop through k folds
for (i in 1:length(kfolds)) {
  fold <- kfolds[[i]]
  training <- individ[fold,]
  testing <- individ[-fold,]

  # Train the model
  bank_ht_model <- train(1/sqrt(Bank_ht) ~ MIN,
                     data = training,
                     method = "lm")

  # Quantify performance with testing data
```

```r
  bankht_train_pred <- training %>% mutate(pred = predict(bank_ht_model, new=training
))%>%
  mutate(r2 = 1-(sum((Bank_ht-pred)^2))/(sum((Bank_ht-mean(Bank_ht))^2)),
            pearsonr2 = cor(Bank_ht, pred, method = "pearson")^2)
  bankht_test_pred <- testing %>% mutate(pred = predict(bank_ht_model, new=testing))%
>%
  mutate(r2 = 1-(sum((Bank_ht-pred)^2))/(sum((Bank_ht-mean(Bank_ht))^2)),
            pearsonr2 = cor(Bank_ht, pred, method = "pearson")^2)
  fold_results <- data.frame(r2 = bank_ht_model$results[3], RMSE = bank_ht_model$resu
lts[2])

  # Append `out` data frame with the results of the new fold
  bank_ht_out <- bind_rows(bank_ht_out, fold_results)
}
bankht_train_preds <- bankht_train_pred %>% summarize(r2, pearsonr2)
bankht_test_preds <- bankht_test_pred %>% summarize(r2, pearsonr2)
bank_ht_out
```

```
##    Rsquared      RMSE
## 1 0.3395932 0.1162816
## 2 0.3474787 0.1193641
## 3 0.3357625 0.1177090
## 4 0.3277330 0.1132988
## 5 0.3882309 0.1108749
```

```r
summary(bank_ht_model)
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.277352 -0.078415 -0.000293  0.064629  0.295709
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.602667   0.141506  -4.259 5.56e-05 ***
## MIN          0.014809   0.001974   7.503 7.56e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1045 on 80 degrees of freedom
## Multiple R-squared:  0.413,  Adjusted R-squared:  0.4057
## F-statistic: 56.29 on 1 and 80 DF,  p-value: 7.555e-11
```

Final Bank Height Bank Model

```r
# final model
bank_ht_model_final <- train(1/sqrt(Bank_ht) ~ MIN,
                    data = individ,
                    method = "lm")
summary(bank_ht_model_final)
```

```
##
## Call:
```

```
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.29091 -0.07703 -0.00942  0.06373  0.35127
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.578805   0.138482  -4.180 6.26e-05 ***
## MIN          0.014509   0.001924   7.541 2.18e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1116 on 100 degrees of freedom
## Multiple R-squared:  0.3625, Adjusted R-squared:  0.3561
## F-statistic: 56.87 on 1 and 100 DF,  p-value: 2.175e-11
```

```
bank_ht_model_final
```

```
## Linear Regression
##
## 102 samples
##   1 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 102, 102, 102, 102, 102, 102, ...
## Resampling results:
##
##   RMSE       Rsquared   MAE
##   0.1181703  0.3289066  0.09249373
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```
bank_ht_model_final$finalModel
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Coefficients:
## (Intercept)          MIN
##    -0.57880      0.01451
```

Predict Bank Height (ft)

Use the developed model to predict bank height values for all Mine Creek channel segments.

```
# predict bank height

shelley_pred <- shelley %>%
  mutate(bank_ht_sqrt = predict(bank_ht_model_final, new=shelley)) %>%
  mutate(bank_ht_ft = round(bank_ht_sqrt^(-2), digits = 1))
```

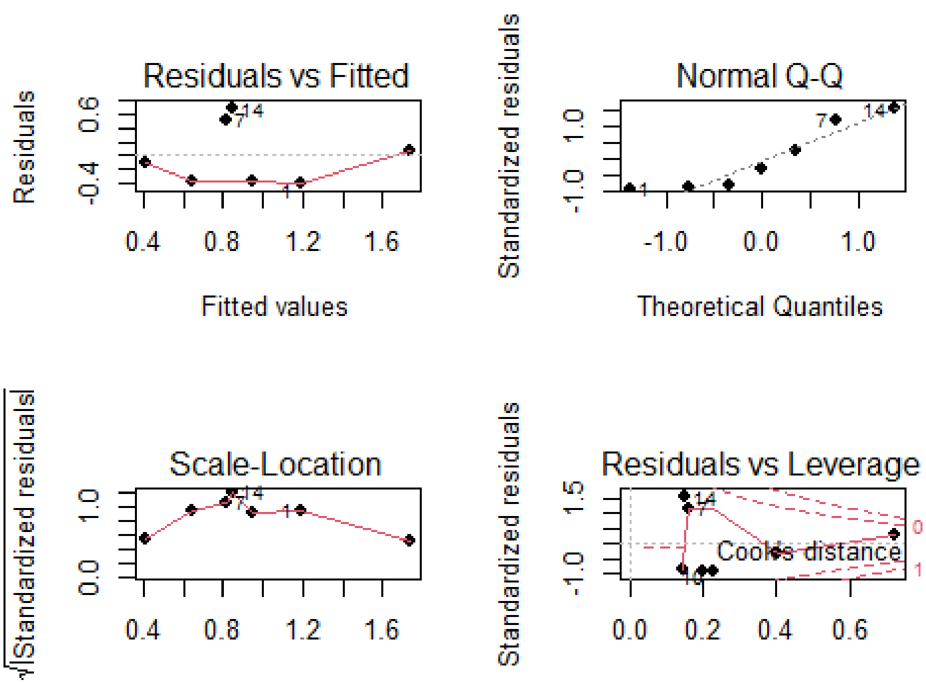
Step 2. Predict Bank Retreat

Predict both the average bank retreat and maximum bank retreat. These linear regressions were developed from measured bank retreat from the seven cross-sections in Mine Creek Watershed and the minimum PO value at each cross-section.

```
# read in data
xs <- read.csv("MC_XS_Analysis.csv")

# create subset of data that is just outside of bends
# 1 left, 2 left, 3 left, 4 left, 5 right, 6 right, 7 right
xs_outside <- subset(xs, ID == "MC240" | ID== "MC163"| ID== "MC173"| ID== "MC203"| ID
== "MC288"| ID== "MC92"| ID== "MC220")

# combine just avg and max bank retreat
xs_outBR <- gather(xs_outside, 'max_br', 'avg_br', key = "Measured_BR", value = "BR")
```

Linear Regression to Predict Average and Maximum Bank Retreat

```
fit_avg <- lm(avg_br~MIN,xs_outside)

# residual diagnostics
par(mfrow=c(2,2))
plot(fit_avg,pch=19)
```

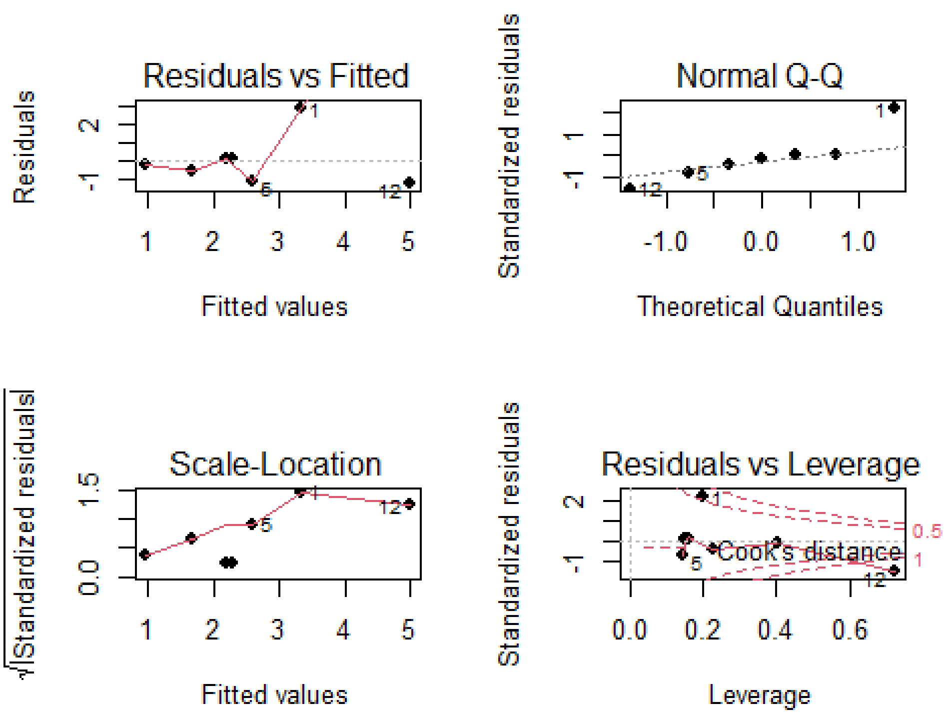



```
# fit summary
summary(fit_avg)

##
## Call:
```

```
## lm(formula = avg_br ~ MIN, data = xs_outside)
##
## Residuals:
##        1        3        5        7       10       12       14
## -0.38785 -0.11176 -0.37116  0.51435 -0.37900  0.06504  0.67038
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3.08033    1.86910  -1.648    0.160
## MIN          0.05711    0.02642   2.162    0.083 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4822 on 5 degrees of freedom
## Multiple R-squared:  0.4832, Adjusted R-squared:  0.3798
## F-statistic: 4.674 on 1 and 5 DF,  p-value: 0.08298
```

The diagnostic plots are not the best but there are only seven data points. The Q-Q plot is pretty decent. The residuals vs fitted values are not fully centered around zero.

```
fit_max <- lm(max_br~MIN,xs_outside)

# residual diagnostics
par(mfrow=c(2,2))
plot(fit_max,pch=19)
```




```
# fit summary
summary(fit_max)
```

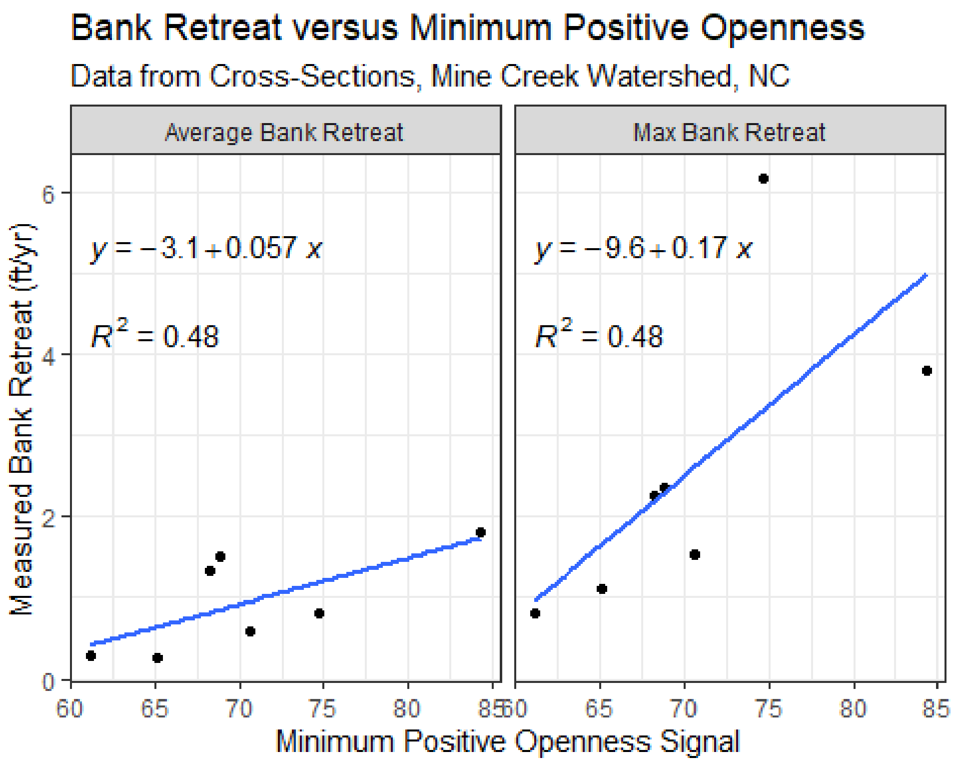
```
##
## Call:
## lm(formula = max_br ~ MIN, data = xs_outside)
##
## Residuals:
##        1        3        5        7       10       12       14
##  2.84572 -0.16672 -1.07527  0.06638 -0.55701 -1.17626  0.06316
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -9.6413     5.7454  -1.678   0.1542
## MIN           0.1735     0.0812   2.137   0.0857 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.482 on 5 degrees of freedom
## Multiple R-squared:  0.4773, Adjusted R-squared:  0.3727
## F-statistic: 4.565 on 1 and 5 DF,  p-value: 0.08569
```

The diagnostic plots for the max bank retreat model are not great but it is difficult to have good diagnostic plots with only seven data points. The residuals vs leverage plot indicate that data point 12 (MC92) is an outlier since it is outside the 1 line. Due the limited number of data points, this point will be kept in the model.

Final Bank Retreat Models

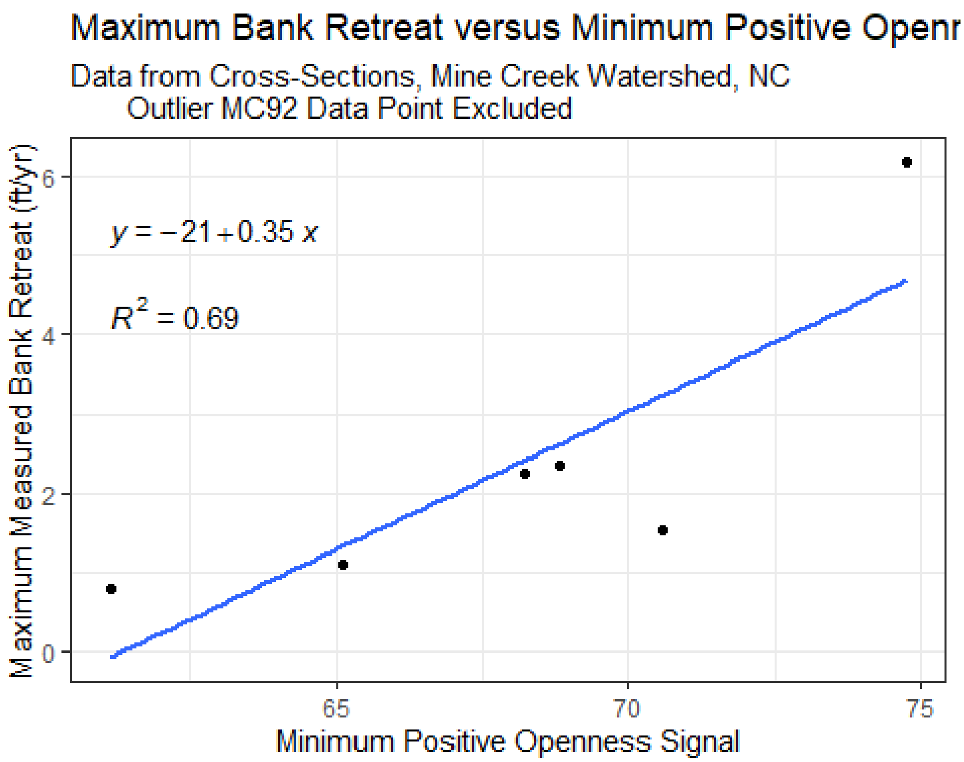
There is a model for average bank retreat and one for maximum bank retreat.

```
# rename facet_wrap labels
supp.labs <- c("Average Bank Retreat", "Max Bank Retreat")
names(supp.labs) <- c("avg_br", "max_br")

# avg and max on same plot
ggplot(xs_outBR,aes(x = MIN, y = BR)) +
  geom_point() +
  geom_smooth(method = "lm", se=FALSE) +
  stat_regline_equation(label.y = 5.3, aes(label = ..eq.label..)) +
  stat_regline_equation(label.y = 4.3, aes(label = ..rr.label..))+
  theme_bw()+
  xlab("Minimum Positive Openness Signal")+
  ylab("Measured Bank Retreat (ft/yr)")+
  labs(title = "Bank Retreat versus Minimum Positive Openness",
       subtitle = "Data from Cross-Sections, Mine Creek Watershed, NC")+
  facet_wrap(~Measured_BR, labeller = labeller(Measured_BR = supp.labs))
```



Examine the effect of the outlier (MC92) on the maximum bank retreat linear regression.

```
      # remove MC92
xs_out_subset <- xs_outside[!(xs_outside$ID=="MC92"),]

# avg and max on same plot
ggplot(xs_out_subset,aes(x = MIN, y = max_br)) +
  geom_point() +
  geom_smooth(method = "lm", se=FALSE) +
  stat_regline_equation(label.y = 5.3, aes(label = ..eq.label..)) +
  stat_regline_equation(label.y = 4.3, aes(label = ..rr.label..))+
  theme_bw()+
  xlab("Minimum Positive Openness Signal")+
  ylab("Maximum Measured Bank Retreat (ft/yr)")+
  labs(title = "Maximum Bank Retreat versus Minimum Positive Openness",
       subtitle = "Data from Cross-Sections, Mine Creek Watershed, NC
       Outlier MC92 Data Point Excluded")
```



Predict Average and Maximum Bank Retreat (ft/yr)

Use the developed model to predict bank height values for all Mine Creek channel segments.

```
# predict bank retreat

shelley_pred <- shelley_pred %>%
  mutate(avg_br = round(predict(fit_avg, new=shelley), digits = 1)) %>%
  mutate(max_br = round(predict(fit_max, new=shelley), digits = 1))
```

Step 3. Estimate Eroded Sediment Loads from Streambanks

Multiple the length of the stream segment with the predicted bank height and predicted bank retreat. An estimated volume will be provided for both average bank retreat and maximum bank retreat capturing the potential range.

```
# estimate volume

shelley_pred <- shelley_pred %>%
  mutate(avg_vol_ft3 = round(Length_ft*bank_ht_ft*avg_br, digits = 1)) %>%
  mutate(max_vol_ft3 = round(Length_ft*bank_ht_ft*max_br, digits = 1))
```

Step 4. Report Volume in tons/yr

Multiple the volume of eroded sediment by the average bulk density. The average bulk density is from soil sample analysis from the seven cross-sections is 1.35 g/cm^3.

```
	# estimate volume

shelley_pred <- shelley_pred %>%
  mutate(avg_vol_cm3 = conv_unit(avg_vol_ft3,"ft3", "cm3")) %>%
  mutate(max_vol_cm3 = conv_unit(max_vol_ft3,"ft3", "cm3")) %>%
  mutate(avg_grams = avg_vol_cm3*1.35) %>%
  mutate(max_grams = max_vol_cm3*1.35) %>%
  mutate(avg_tons = round(avg_grams/907185, digits = 1)) %>%
  mutate(max_tons = round(max_grams/907185, digits = 1))
```

The average annual tons of sediment from streambanks depositing in Shelley Lake are 3.915^{4}. The maximum annuals tons of sediment going downstream to Shelley Lake are 8.7489^{4}.

Step 5. Estimate TN and TP Loads

Multiply the average measured TN and TP concentration (mg/gDW) by the mass of predicted sediment (g).The average TN is 0.44 mg/gDW, and the average TP is 0.19 mg/gDW.

```
	# estimate volume

shelley_pred <- shelley_pred %>%
  mutate(TN_mg_avg = round(avg_grams*0.44, digits = 1)) %>%
  mutate(TP_mg_avg = round(avg_grams*0.19, digits = 1)) %>%
  mutate(TN_mg_max = round(max_grams*0.44, digits = 1)) %>%
  mutate(TP_mg_max = round(max_grams*0.19, digits = 1)) %>%
  mutate(TN_lbs_avg = round(conv_unit(TN_mg_avg,"mg", "lbs"), digits = 1)) %>%
  mutate(TP_lbs_avg = round(conv_unit(TP_mg_avg,"mg", "lbs"), digits = 1)) %>%
  mutate(TN_lbs_max = round(conv_unit(TN_mg_max,"mg", "lbs"), digits = 1)) %>%
  mutate(TP_lbs_max = round(conv_unit(TP_mg_max,"mg", "lbs"), digits = 1))
```

The average annual TN load from streambanks depositing in Shelley Lake is 3.4401^{4} lbs. The maximum annual TN load is 7.6985^{4} lbs. The average annual TP load from streambanks depositing in Shelley Lake is 1.4874^{4} g. The maximum annual TP load is 3.3274^{4} lbs.

Is this a reasonable estimation of the sediment load?

Based on the average and maximum sediment loads, how many years would it take to fill in Shelley Lake? This model assumes that all streambanks undergo erosion, all the eroded material reaches Shelley Lake and is deposited in the lake.

```
	# volume of Shelley Lake (ft3)
shelley_area_acres <- 28
shelley_area_ft2 <- conv_unit(shelley_area_acres,"acre", "ft2")
depth_ft <- 6 # assumed average depth of Shelley Lake
shelley_vol_ft3 <- shelley_area_ft2*depth_ft
shelley_vol_ft3

	## [1] 7318080

	# volume of sediment (ft3)
avg_ft3 <- round(sum(shelley_pred$avg_vol_ft3), digits =0) # avg vol of sediment ft3,
928515 ft3
```

```
max_ft3 <- round(sum(shelley_pred$max_vol_ft3), digits =0) # max vol of sediment ft3, 2076274 ft3

max_yrs <- shelley_vol_ft3/avg_ft3 #7.881488
min_yrs <- shelley_vol_ft3/max_ft3 #3.524622
```

Shelley Lake would fill in between 3.5 to 8 years.

Normalize sediment load by stream length

```
stream_length_ft <- round(sum(shelley_pred$Length_ft), digits =0)

avg_sed_tons <- round(sum(shelley_pred$avg_tons), digits =0)
max_sed_tons <- round(sum(shelley_pred$max_tons), digits =0)

# normalized sediment load by stream length
avg_sed_tons_ft <- avg_sed_tons/stream_length_ft # 0.11
max_sed_tons_ft <- max_sed_tons/stream_length_ft # 0.24

avg_sed_ft3_ft <- avg_ft3/stream_length_ft
max_sed_ft3_ft <- max_ft3/stream_length_ft
```

The average rate of sediment produced is 0.11 tons/ft/yr and the maximum rate of sediment is 0.24 tons/ft/yr (tons per linear foot of stream length per year). The average rate of sediment produced is 2.53 ft^3/ft/yr and the maximum rate of sediment is 5.66 ft^3/ft/yr (tons per linear foot of stream length per year).

How does the predicted sediment load compare to the measured erosion rates?
Divide the average and maximum sediment loads (ft^3/yr) by the average predicted bank height (ft) and total stream length (ft).

```
# average predicted bank height (ft)
avg_bh_pred <- mean(shelley_pred$bank_ht_ft)
avg_br_pred <- avg_ft3/(stream_length_ft*avg_bh_pred)
max_br_pred <- max_ft3/(stream_length_ft*avg_bh_pred)
```

The average erosion rate is 0.43 ft/yr and the maximum erosion rate is 0.96 ft/yr.