Correlation between Riparian Buffers and Water Quality in North Carolina Watersheds

by

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ABSTRACT

Stream water quality is often impacted by changes in land use such as deforestation or conversion of wetlands to agricultural or developed land use. Since streams, or other surface water such as lakes and reservoirs serve as drinking water sources for millions of people across the U.S., Water Treatment Plants are the most common water resource management option for treating degraded stream water for drinking water purposes. However because treatment plants are capital intensive, land use conservation as both a water resource management option and ecological management option is now widely being adopted. In particular, forest cover in watersheds are recognized as providing unique ecosystem services; the ability of forests to acts as natural water filters could drive down water treatment costs and offer a cost-effective way to provide clean drinking water.

The purpose of this study is therefore to test the hypothesis that an increase of forest cover in watersheds and riparian buffers leads to water quality improvement. Land use metrics were generated from geospatial analysis using ArcGIS. Intake points were located for 31 WTPs across North Carolina, and their corresponding watershed boundaries were delineated. The 2006 National Land Cover and Land Use dataset was used to determine percent of forest cover, impervious cover and agricultural cover at three different spatial scales; watershed, 300ft riparian buffer and 100ft riparian buffer. In addition, monthly water quality data of two water quality parameters, Turbidity and Total Organic Content (TOC) were obtained from the NC Division of Environment and Natural Resources. The water quality data were reported as monthly averages between 2009 and 2012 for Turbidity and between 2009 and 2012 for TOC. Simple and multiple regressions were conducted for available explanatory variables, including percent of forest cover, impervious cover, agricultural cover and watershed size.

The results of the regression analyses overall indicated that percent of forest cover in all three spatial scales strongly affected mean TOC while agricultural land cover within the 100ft riparian buffer strongly affected mean Turbidity. Impervious cover did not seem to have strong effects on water quality. Therefore it is recommended that the efforts should be directed at minimizing agricultural land cover within riparian buffers or diverting agricultural runoff from streams to reduce Turbidity. Protection of forest cover to reduce TOC concentration in streams should also be prioritized. Across the three different spatial scales, 100ft riparian buffers should continue to be protected as well. These measures will help towards maintaining the quality of drinking water sources.

CHAPTER 1: INTRODUCTION

According to the U.S Census Bureau (2013), in the past two years the population of North Carolina has risen by 2.3%, almost twice as much as the national average of 1.3%. Combined with economic growth in the state, development in North Carolina has been increasing steadily over the past years. The North Carolina Department of Commerce's report on 2011 NC Economic Index attributes this population growth to the influx of immigrants both from abroad and from other regions of the United States (Bunn and Ramirez 2011). The report further states that NC is going through an economic transition from a more labor driven economy to one that is more based on knowledge or service industries. Despite the recent recession, labor productivity in the state is growing at a faster rate than that of the U.S. on average, and translating into higher Real GDP for the economy (Bunn and Ramirez 2011).

Population and economic growth inevitably lead to rapid and increasing developments in infrastructure such as roads, housing, water facilities, parks and playgrounds, as urban areas expand to accommodate the influx of people. Such expansion in urbanization leads to changes in natural land use. Wetlands, forested areas, and other natural environments are altered, or eliminated to make way for urban sprawl. The natural land use over time changes, leading to increases in impervious cover as a result of deforestation and increases in agricultural land as well as land fragmentation. These impacts are commonly known to have adverse impacts on water quality and aquatic habitat in rivers and streams. For instance, as much as 10% of impervious cover is known to significantly degrade stream quality by increasing discharge into the stream which then results in channelization, sedimentation and loss of riparian vegetation (Doll et al 2002).

Agricultural lands in particular affect water quality of runoff as water-soluble nutrients such as nitrates, phosphorous, and sulfates that are present in fertilizers and pesticides, are transported through runoff into streams and rivers. On the other hand, deforestation exposes more soil to water erosion as a consequence of which runoff is filled with sediment particles as it enters natural waterways (Lai 1997). The adverse effects are not only on the streams themselves by lowering water quality, but also on aquatic habitats as well. Apart from sediment loading in rivers, deforestation reduces important inputs into rivers and streams that are required to maintain these habitats, such as leaf litter and woody debris that provide essential organic inputs (Sweeny et al 2004). Other anthropogenic impacts that affect water quality and aquatic habitat include effluent and industrial discharge into rivers and streams. These discharges alter water chemistry, making raw water contaminated for human consumption.

Water Treatment Plants (WTPs) are largely considered as a critical water resource management practice to treat degraded stream water for drinking purposes. These treatment plants are part of an elaborate and extensive water supply system that consists of 4 important elements; (i) water source referred to as ‘raw water’, (ii) water storage, (iii) treatment facilities, and (iv)distribution facilities. When raw water is drawn or pumped in from the surface water source and transmitted to WTPs, it is treated both chemically and physically for pathogens, bacteria, suspended solids and sediments, color, taste, odor, dissolved organic and inorganic compounds, hardness and total dissolved solids. Some of the major operations and processes that take place in water treatment plants consist of screening, aeration, mixing flocculation, sedimentation, filtration, coagulation, precipitation, disinfection and chemical oxidation (Linsley et al 1992).

A major concern of the WTP process is the quality of drinking water provided to consumers. In order to provide water that is within the U.S. EPA’s drinking water standards, raw water is subjected to the intense chemical and physical processes mentioned above. Degraded raw water quality going into a WTP requires more rigorous treatment in order to meet U.S. EPA’s drinking water standards. This increases both treatment and capital costs for WTPs. WTPs and their treatment processes are costly and expensive to maintain. It is estimated that North Carolina’s drinking water infrastructure requires almost $11 billion dollars investment over the next 20 years in order to meet drinking water demands (ASCE 2009). In the face of these rising costs, it is becoming increasingly clear that treatment alone cannot and should not be the only option.

Protecting forests is now being considered as another alternative to protecting drinking water resources. As mentioned earlier, deforestation and land use changes to urbanization and agriculture have detrimental impacts on water quality. Preventing or minimizing such drastic land use changes can help maintain the quality of water in streams and lakes. Ernst et al (2004) argue that protecting forests helps reduce sedimentation and erosion, and purifies water by filtering pollutants, which then leads to a cost effective way to improve water quality. This was quantified in a research by the Trust for Public Land (Washington D.C). In this study they estimated that higher forest cover (as a percent of the total area in a watershed) corresponded with lower water treatment costs; a 10 percent increase in the forest cover of a watershed led to a 20 percent decrease in treatment costs (Ernst et al. 2004).

The ability of forests to provide clean water for human consumption is considered an 'ecosystem service'. The Ecological Society of America (2000) defines ecosystem services as the many benefits that humans receive or obtain from natural environments which include resources such as forests and streams, flood reduction, better water quality, recreation and much more. Valuing forests as an ecosystem service translates into economic benefits. The state of Virginia (as of 2011) saves an estimated $5 billion annually from forested land cover that provides water quality services (Paul, 2011). New York City's watershed protection program that diverted funds from water treatment facilities to preserving riparian forests and protecting habitats around the reservoirs resulted in savings of about $4 billion to $6 billion that would have been otherwise been used for the construction of a water treatment facility (Whelan 2010). While the US has historically leaned towards water treatment facilities for providing drinking water, the value of ecosystem services and the many benefits that can be reaped is slowly gaining momentum. This MP report is therefore an attempt to quantify the natural capability of forests to protect drinking water resources by looking at land use and land cover patterns in various riparian buffers in watersheds across North Carolina and their effect on water quality.

1.1 Objectives

The main objective of the Masters Project (MP) is to determine the correlation between the percent of forest cover of riparian buffers in watersheds across North Carolina, and the concentration of Turbidity and total organic carbon (TOC) in raw water coming into water treatment plants. In order to best assess how forest cover affects these water quality parameters, forest cover is being quantified at the watershed level and within 300ft and 100ft riparian buffers of streams in the watershed. The hypothesis -- based on similar studies -- is that the higher the forest cover within a watershed or riparian buffers, the lower the concentration of Turbidity and TOC because of the forests' capacity to treat storm water and agricultural runoff and improve the quality of the surface water resource before it reaches the stream, river, or reservoir. A correlation may help develop a stronger case to acquire forested land in the riparian buffer zone of a watershed to improve water quality.

The water quality parameter, Turbidity is representative of the suspended solids in the raw water that correlate largely with deforestation and subsequent erosion. The U.S. EPA drinking water quality standard for Turbidity is 0.3 Nephelolometric Turbidity Units - NTU (U.S. EPA 2012). Treatment of Turbidity in raw water by WTPs requires a series of processes which include screening, sedimentation, flocculation, coagulation, and filtration. Without such rigorous treatment, turbid drinking water can have indirect significant effects on human health by preventing the removal of many bacteria and pathogens which can cause water borne diseases (USGS 2013).

The second water quality parameter, Total Organic Carbon (TOC) is an indicator of the total carbon in organic compounds (or contaminants) dissolved in the water. The U.S. EPA's requirement for WTPs to monitor and reduce TOC levels in drinking water arises due to the DBPs - Disinfectant By-Products. These by-products are a result of the disinfection chemical chlorine, which is used for water treatment. Chlorine reacts with organic compounds in raw water to form these by-products which can potentially be carcinogenic (Cooper 2001). Therefore reducing organic compounds (total carbon) in raw water can limit the DBPs in drinking water. The U.S. EPA does not have a set standard for TOC levels in drinking water but rather stipulates percent of TOC reductions based on the initial TOC and alkalinity ($CaCo_3$ mg/L) concentration in raw water (**Appendix I: Table 1**). The D/DBP Rule-Stage 1(U.S. EPA 2010) requires TOC reduction varying from about 15% to 50%.

1.2 Clean Water Management Trust Fund

The client for this MP - North Carolina Clean Water Management Trust Fund (CWMTF) aims to address issues pertaining to water resources in North Carolina by funding projects that pertain to improving water quality, protecting clean and unpolluted water, and conserving riparian buffers. Established in 1996, CWMTF receives funds from the North Carolina General Assembly to finance projects by conservation non-profits, local and state agencies that concern water quality issues (CWMTF, 2012).

Through this research report, CWMTF is specifically looking at the benefits of acquiring land in riparian buffers in watersheds in North Carolina, to protect the quality of water resources in the long term, as opposed to the treatment of polluted drinking water through water treatment facilities. Therefore, this project will explore land use and land cover within riparian buffers and watersheds, with a specific focus on forest cover.

CHAPTER 2: LITERATURE REVIEW

Land use within the riparian buffer will be analyzed in this MP and in particular, forest cover. Protecting forests for water quality is an accepted watershed management practice. Forests have been known to act as buffers, intercepting agricultural runoff, and preventing erosion and sedimentation from flowing into rivers that are a drinking water resource for communities. Research early on has proven that forested riparian areas and indeed undeveloped (or undisturbed) watersheds as well are linked to high water quality in rivers and streams, especially for reducing sediment loads (Karr and Schlosser 1978). Therefore creating and protecting forests in a catchment, or at the minimum, in the riparian buffer is a scientifically established practice. According to Todd & Weidner (2011), forests are responsible for 2/3rds of clean water in rivers and streams in the 48 states of the US. They have termed forests as 'watershed services' because of forests' capacity to contribute towards clean water in rivers/streams. Furthermore, according to Ernst, Gullick & Nixon (2004) there is greater awareness amongst water utilities of the value of protecting forests to improve water quality. In a study of two sub watersheds of Grimes Greek and Eelpot Creek in New York State having similar land use but different proportion of agricultural land and forested land use, the Turbidity concentrations were higher in Eelpot Creek sub-watershed which lacked thick forest buffers and had a significant proportion of cultivated land (George 2009).

The literature review section of this paper has been conducted to determine four main ideas or themes of the peer reviewed literature on land use and water quality analysis. Some of the papers compare catchment wide impacts on water quality with riparian buffer impacts while others assess the variable effect of differing riparian buffer widths on water quality. Due to wide array of water quality parameters, different parameters have been analyzed in the papers as well, in most cases depending on the land use type in the region, the nature and sources of point and non-point pollutants sources and the geography of the region. The literature review is also not restricted to the U.S. As a globally recognized watershed management issue, watershed and riparian buffer land use analysis have been conducted across the globe, in countries such as India, China, Japan, Indonesia and Canada. In order to synthesize the literature review, this section has been divided into the four main themes.

2.1 Watershed and Riparian Buffer Comparisons

Many studies have documented and studied the effect of forest cover in a watershed and its impact on stream water quality and its ecology, with the use of geospatial and statistical regression analysis in correlating land use change patterns with water quality. Some papers have contrasted and compared this relationship across multiple scales such as in an entire watershed and within 100ft buffers in attempts to answer an 'ongoing dispute' (Silva 2001) of whether land use within an entire watershed is more important for water quality in streams or that within the designated riparian buffers. From a management perspective, the scales at which such watershed management practices need to be implemented are critically important and peer reviewed articles have much to say on the topic.

Published literature on this watershed management topic has heavily relied on GIS and multivariate analysis tools (Silva 2001). In a study of three watersheds in Ontario, geospatial analysis was used in order to assess influences of land use in the entire catchment and within a 100m riparian buffer, the quality of water flowing in the streams across three seasons. Land use as determined by GIS was the predicator variable while water quality parameters were the response variable, and transformed to a logarithmic function. The output of the multiple regression model showed that when forest cover increased, the concentrations of the water quality parameters Cu, TS and CL, decreased. On the other hand, agricultural cover did not seem to have any major significant effect on water quality. This study shows how different types of land use and land cover categories can correlate with different types of parameters of water quality. This study concluded overall that between the two scales of spatial analysis (watershed scale and 100m riparian buffer scale), the land use within the watershed seemed to largely influence water quality parameters (Silva 2001).

In a more complicated riparian buffer analysis, Newbold et al (2010) examined long-term water quality function of a riparian buffered watershed, a non-buffer control watershed, and a reforested watershed. Stream water was sampled from 1992 to 2007 for nitrate and phosphorus concentration tests. Analysis of variance (ANOVA) with Turkey's multiple comparison test was used for both year-to-year variance analysis and within-year spatial variance analysis. Since the regression slope remained 1.00 ± 0.06 over the entire period, temporal difference introduced no additional variance, so that one-way ANOVA can be used which accounts only for the spatial variance. Another component of the study was to estimate the removal of nutrients and sediments by the riparian buffer (i.e. retention within the riparian buffer). Groundwater and storm-generated overland flow were sampled in the watershed. Specifically, sediments and nutrients in overland flow were analyzed by a single two-way ANOVA with Turkey's test, for the effects of different positions within the watershed. The results show that a total of 43% sediments were removed, with the 32% removal in Zone 3 (an upstream grass filter strip) significant and another 11% removal in Zone 2 (a reforested strip downslope from Zone 3) insignificant. This does not necessarily mean that Zone 2 is not effective in sediment remove but that by the time water reaches this Zone it is most likely filtered because of already passing through Zone 3 which removed sediments (Newbold et al 2010).

2.2 Riparian Buffer Widths Analysis

In North Carolina, a case study was conducted in the southern Appalachian region to examine different water quality responses to timber harvest between non-buffer, 10m buffer and 30m buffer watersheds (Clinton 2011). Another watershed without harvest activities was also included for reference. Percent of harvested areas ranged from 1.2% to 4.4% within whole watersheds. Grab samples were collected during both pre-harvest and post-harvest periods for the test of nitrate, total suspended solids (TSS), and other physic-chemical water properties. Statistical analysis, namely Turkey's pairwise comparisons, were performed to determine if the temporal differences between pre-harvest and post-harvest monthly means are significant, in order to compare the treatment effects among sites. The analysis included all tested water properties, separated by base flow and storm flow conditions. Specifically, the results for TSS show that during base flow periods, TSS significantly decreased for the reference, 10m buffer and 30m buffer watersheds after the harvests, while insignificantly increased for the non-buffer watershed; during storm flow periods, TSS insignificantly decreased for all of the four watersheds. Given the results of all other water quality parameters, the general conclusion is that 10m wide buffers may provide effective protection to water quality after harvest activities (Clinton 2011) which is about 30ft, one third of U.S. EPA's requirement for a riparian buffer.

Despite the U.S. EPA's riparian buffer width recommendation of 100ft, various studies have attempted to address a threshold for the width within which streams are prevented from degrading. Hook (2003) conducted a simulation study in Montana foothills meadow, tailored specifically to sediment retention potential of rangeland riparian buffers of varying widths ranging from 1m to 6m. Plots with different vegetation types and slopes were selected as study areas. Other factors were incorporated by treatments, such as clipping for different stubble heights and adding sediment at multiple heights on slope for different width of riparian buffers. Runoff was sampled until sediment concentrations approached background levels. Data analysis consisted of analyses of variance and regression models using multiple statistical approaches. The purpose of variance analyses was to determine correlations between various factors and sediment retention, as well as the interactions between factors; while the regression was to find the best-fit models that explained most variation in sediment retention. As a result, mean sediment retention ranged from 63% to 99%. The most determinant factor was buffer width (mean sediment retentions were 83, 94, and 99% for 1m, 2m, and 6m buffer widths), followed by vegetation type. Also, as the buffer width increased, the influence of vegetation types lowered. Moreover, the best-fit regression model (R^2 = 0.85) included buffer width, slope, and biomass (one outcome from different vegetation types) as significant explanatory variables. Overall, the simulation provides quantitative information about sediment retention capacity determination for riparian buffers, and identifies the significance of buffer width for future riparian buffer management (Hook 2003).

2.3 Various Water Quality Parameters Assessed

In a study by Jones et al (2001) the concentrations of both nutrients and sediment loadings were compared against land use metrics for about 148 water quality points in the mid-Atlantic region and their delineated watersheds. After eliminating watersheds for which water quality data was incomplete and missing, 78 watersheds remained for the analysis. The geospatial analysis in this study aggregated the fifteen NLCD land use classifications into five broad classifications; water, barren, forest, agriculture and wetlands. Nutrients (nitrogen, ammonia, nitrate total and dissolved phosphorous) and suspended sediments concentrations obtained from the water monitoring points from the U.S Geological Survey, were averaged from 1989 to 1994. Using land use as the independent variable and the water quality data as the dependent variable in the regression analysis (using SAS 1990), the final results suggested that land use metrics were largely responsible for nitrogen concentrations yields, dissolved phosphorous and suspended sediment concentrations in the streams (Jones et al, 2001).

Miller and Schoonover (2011) examined the correlation between land cover and parameters of water quality in the Lower Kaskaskia River Watershed located in the state of Illinois. They collected grab samples from the forty-three sub catchments. These catchments ranged in size from 12 to 50 km^2. The samples were then separated into base flow and storm flow largely based on precipitation data. The water physicochemical properties for test include several ions, Turbidity, TSS, bacteria, and others. Two statistical approaches were taken. The first approach involved stepwise regression models. These were used to determine how the water quality indicators related to land cover within the whole catchment (agriculture, forest, urban, and water). The second approach used ANOVA with Turkey's test were conducted to determine the significant differences between classified watersheds (percent of agriculture, urban, and village). For sediment, the results showed that whole catchment forest cover had significantly negative effects on total suspended sediments only during base flow conditions, while urban cover was a significant variable during both flow conditions (base and storm flow). From the perspective of catchment classification, agricultural catchments had significantly higher concentrations of Turbidity and TSS especially in the base flow samples while the urban catchments had significantly lower Turbidity during storm flow conditions (Miller and Schoonover 2011).

Lee at al (2003) did a field study in a riparian buffer in the state of Iowa, for the purpose of comparing the effectiveness of sediment, nitrogen, and phosphorus trapping capacities between the 7.1m switchgrass buffer and the 16.3m switchgrass/woody buffer. These two buffers shared a common cropland source area, and the switchgrass/woody buffer was the extension of the switchgrass buffer with additional parts of woody buffer more close to the stream. Samples of runoff were collected to assess runoff amount and the transport of sediments and nutrients, from three selected sites representing the non-buffer, 7.1m buffer and 16.3m buffer. The study specifically targeted rainfall events. In this study, the statistical analysis component of this study included general linear model tests and Least Significant Difference (LSD) tests. The results show that the switchgrass buffer trapped 95.3% of the sediments, while the switchgrass/woody buffer trapped 97.2% of all sediments. The runoff and transport of the sediments (TSS) and other nutrients were all significantly different for the three conditions of non-buffer, switchgrass buffer, and switchgrass/woody buffer. The overall conclusion is that the switchgrass buffer managed to trap the sediments and nutrients more effectively. On the other hand, the switchgrass/woody buffer soluble nutrients trapping capacity was also significant. Another focus of the study was the correlations between effectiveness of riparian buffers and total rainfall amount as well as rainfall intensity. The results show that for nearly half of the runoff metrics, both total rainfall amount and rainfall intensity had significantly negative correlations with the effectiveness of the riparian buffers.

2.4 Varying Land use classification comparisons

While Miller and Schoonover (2011) focused on land use in an entire watershed, Anbumozhi et al (2005) did a study pertaining to assessing how riparian buffers effected water quality. Due to agricultural and livestock activities, pollutants increase from upland to the confluence point. The purpose of the study was to examine the capacity of riparian buffer zones to control nonpoint source pollutions and protect stream water quality. For this purpose, the study was conducted at a global scale. The countries involved included Japan, Indonesia and India. In these countries, a comparison of the water quality parameters of stream water that passed through riparian and non-riparian zones was done. The results from the Tokachigawa

Watershed in Japan show that nutrient concentrations such as NO_3^- were significantly lower in riparian forest. Also, the area of riparian forest strips had a linear relationship with NO_3^- concentration. The effects are more evident in buffer zones located along streams of higher order. The comparisons of Chlorine, Ammonium and Nitrate concentrations across three sub-watersheds in Indonesia and one sub-watershed in India show that pollution levels in riparian forest and forest were much lower, compared to agricultural land use sites, and watersheds with high agricultural land use percent exported more pollutants. It is also noticeable that the conversion from riparian forest to agricultural land can remove the self-cleansing ability of watershed, which should be considered in the watershed management (Anbumozhi et al 2005).

In China, 42 sites located in 100m wide riparian buffers throughout the upper Han River basin were sampled to determine the concentrations of different water quality parameters (Li et al 2009). Besides spatial analysis, the study also took seasonal influence into consideration, thus the analysis for rainy season and dry season were separated. Land cover was categorized into forest land, shrub, agriculture, urban and bare lands, and 9 sub-watersheds were delineated. The statistical analysis consisted of two parts. First, Pearson correlation analysis and principal components analysis were used. These were used to assess water quality variables and their contributions to the total variance. Second, the effect of land cover on water quality was analyzed in two steps. Results from Pearson correlation analysis show that forest cover and bare land cover types were the two land coves that usually had significant correlations with certain elements or ions in water samples. Stepwise multiple linear regression indicates that variability in water quality parameters can generally be explained by forest and shrub land cover; however, although the significance of forest cover for major ions was identified, the relationship between forest cover and Turbidity was still uncertain in this study (Li et al 2009).

CHAPTER 3: METHODOLOGY

The MP consists of a geospatial analysis and statistical component in order to meet the objectives discussed earlier. They are described below.

3.1 Geospatial Analysis

The geospatial analysis is one of the major components of the MP and was used to generate land use metrics required for the statistical analysis. ArcGIS (ESRI 2009) was used in determining the percent of forest cover in the riparian buffers of watersheds in North Carolina.

3.1.1 Obtaining and Downloading Data

The North Carolina stream network and county boundaries were provided by the client - CWMTF. The Digital Elevation Models (DEMs) for the state of NC were downloaded from the United States Geological Survey (USGS) National Map Viewer. These National Elevation Datasets (NEDs) were 1 arc second rasters (i.e. pixel size 30m x 30m) and the time period for the development of these datasets was stated as 2009. The NED consists of pixel images of the surface of the U.S. with elevation levels in meters. The coordinate system of these NEDs is usually in decimal degrees and complies with the North American Datum 1983 (NAD 1983). The USGS typically has three different resolutions of NEDs available for public use; 30m, 10m and 3m, though 3m resolution is very limited (NED 2012). Higher resolution DEMs require more time to process in ArcGIS. For this MP, 3m and 10m resolution accuracies were not required, nor would have been possible given the many watersheds delineated in the time frame stipulated for the project. Therefore the 30m NED (or DEM) was used.

Similarly, national Land Use and Land Cover (LULC) raster datasets (30m by 30m pixel size) for the state of NC were obtained by downloading from the USGS National Map Viewer. This LULC was developed by the USGS in 2006 and is referred to as the National Land Cover Database (NLCD). The NLCD 2006 is the latest land cover database available by the USGS and is collected by satellites. Previous NLCDs were collected in 2001 and 1992 (NLCD 2012).

The NLCD consists of the following 20 land cover classifications (NLCD 2012):

- ***Open Water***: consists of water bodies (rivers, lakes, streams, reservoirs) with less than 25% vegetation
- ***Perennial Ice/Snow***: ice and snow covering more than 25% of the total cover
- ***Developed Open Space****:* consists of lawns grass, housing, parks, golf courses and less than 20% impervious cover
- ***Low Intensity Development****:* consists of impervious cover less than 20% and a mix of vegetation and construction
- ***Medium Intensity Development:*** consists of impervious cover between 50 to 79% and a mix of vegetation and construction
- ***High Intensity Development:*** consists of highly developed areas with impervious cover between 80 to 100%
- ***Barren Land:*** areas consisting of deserts, bedrock, glacial debris, dunes etc.
- ***Deciduous Forest:*** consists of trees greater than 5m tall with >20% of vegetation cover; leaves fall seasonally.
- ***Evergreen Forest:*** consists of trees greater than 5m tall with >20% of vegetation cover; leaves are on trees all year around.
- ***Mixed Forest:*** consists of trees greater than 5m tall with >20% of vegetation cover and evergreen and deciduous not exceeding more than 75% of the total cover.
- ***Dwarf Scrub:*** found only in Alaska- shrubs less than 20cm tall
- ***Shrubs:*** shrubs less than 5m tall and more than 20% vegetation.
- ***Grasslands:*** consists of more than 80% total vegetation
- ***Sedge:*** found only in Alaska- more than 80% vegetation
- ***Lichens:*** found only in Alaska- more than 80% vegetation
- ***Moss:*** found only in Alaska- more than 80%vegetation
- ***Pasture/Hay:*** consists of grasses, legumes; used for grazing or hay crop production- more than 20% vegetation
- ***Cultivated Crops:*** areas of crop planting, includes vineyards and orchards- more than 20% vegetation
- ***Woody Wetlands:*** shrubs and forest areas covered with water- more than 20% vegetation
- ***Emergent Herbaceous Wetlands:*** herbaceous vegetation covered with water **-**more than 20% vegetation

In order to correlate forest cover with raw water from WTPs, a list of 150 water treatment facilities in NC was provided by the NC Division of Environment and Natural Resources- Public Supply Section. This list included the plants IDs, names, population served, and 2011 monthly water pumped by the plants in millions of gallons. Based on the NC rules governing public water supply systems' definition of medium sized plants (NCDENR 2010), which is about 3,500 to

50,000 people served by the plants, the list was refined to 96 medium sized water treatment plants.

3.1.2 Water Intake Locations

Since the purpose of the MP is to correlate raw water quality with forest cover in the riparian buffers of watersheds, watershed boundaries were delineated from the raw water intakes of the treatment plants. For security reasons, water intake points are not available for the public to use and therefore the intake points had to be determined. This was done by using a combination of resources such as GIS (stream network and image layers), Google maps (www.maps.google.com), websites (if available) of the water treatment plants with their intake source (river, stream, reservoir or lake) and address (intake points are generally, in most cases, located close to the treatment facility hence locating the physical location of the facility itself helps determine the approximate location of the intake). For a majority of the WTPs, the intake points could not be located with certainty. The final list of WTPs for which intake points were determined contained 31 plants. These intake points were created in ArcGIS10 and projected in NAD_1983_StatePlane_North_Carolina_FIPS_3200.

3.1.3 Watershed Delineation

The elevation dataset consisted of multiple raster tiles for the state of NC. The watersheds for the intakes were expected to be located across multiple tiles, hence they were combined together to create 3 large DEMs by using the Mosaic tool in ArcGIS and projected in the same projection used for the intake points.

For delineating the watersheds, a hydrologic geo-processing model was built in ArcGIS (**Appendix II: Figure 1**). This figure shows the processes used to delineate one watershed. The mosaicked and projected DEM raster was processed by the 'Fill' tool. This tool helped fill in any sinks in the raster. If not filled, these sinks can result in imperfections in the output. The filled DEM output was then used as an input for the 'Flow Direction' tool. This tool creates a raster output with integer values ranging from 1 to 255 to indicate the direction of flow. The 'Flow Accumulation' tool was then run for the flow direction output. Flow accumulation output consists of a raster that shows accumulated flow to each pixel (30m x 30m cell). The NC stream network shapefile provided by the client was overlaid on the flow accumulation output to validate the output. The intake point was then ‘snapped’ to the flow accumulation network by using the ‘Snap to pour point’ tool. Snapping the intake point (or pour point) to the flow accumulation output ensures that the intake point is lined with the cell of the highest flow. The ‘snapping distances’ were adjusted (from 50m to about 150m) to ensure proper snapping. If the intake point is not aligned with flow accumulation, the watershed boundary does not delineate. The last step of this geo-processing model consisted of the ‘Watershed’ tool. This tool used the ‘snapped’ intake point and the flow direction raster to delineate the watershed boundary. This hydrologic geo-processing model was repeated thirty more times to delineate the watersheds of all the intake points (**Appendix III: Hydrologic Geo-processing Model Scripts**).

3.1.4 LULC Analysis

After the watershed boundaries were delineated, the LULC raster dataset was used to determine forest cover, impervious cover, and agricultural land cover as a percent of the total watershed area as well as the percent of the total area within 300ft and 100ft buffers from streams in the watersheds. This analysis was conducted using ArcGIS. The ‘Buffer’ tool was used to create 300ft and 100ft buffers from streams in each watershed. The ‘Extract by Mask’ tool was then used to extract LULC within the buffers. The resulting output was then exported as .dbf file and processed in Microsoft Excel.

As mentioned earlier, the LULC dataset consisted of 20 classifications. For the sake of simplicity in the analysis, forest cover represented deciduous, evergreen, mixed forests, and shrubs. While shrubs are not classified as ‘forests’, they are used in riparian buffers for water quality management and hence were included in this category. Impervious cover included low, medium and high intensity development, while agricultural land included the pasture/hay, and cultivated crops classifications in the LUCL dataset.

3.2 Statistical Analysis

Variables for statistical analysis included water quality parameters of Turbidity and TOC, which were provided by the North Carolina Division of Environment and Natural Resources, as well as variables from the geospatial analysis, namely percent of forest cover, impervious cover and agricultural cover in entire watersheds, 300ft stream buffer and 100ft stream buffer, watershed size, and water intake sources categorized as reservoir, lake, river and creek. Turbidity and TOC data was reported on a monthly basis, specifically from November 2009 to September 2012 for Turbidity, and from January 2006 to November 2012 for TOC. However, not all the water treatment plants had complete data (i.e. a reported value for every month), but the quantity of missing points was not large enough to cause problems in the statistical analysis.

3.2.1 Exploratory data analysis

Given the available data, finding an approach to address the time series water quality data was in need since the data spans about four and seven years for Turbidity and TOC respectively. Panel data, also known as cross-section time-series data, is often used when variables of each observation are measured across time. However, because all variables except for Turbidity and TOC were invariant over all time periods, panel data is not applicable for this study. Since the objective of the study is to determine the correlation between water quality and percent of forest cover, the priority is to examine the effect of forest cover on average water quality concentrations. Furthermore, no obvious trend was found in the two water quality parameters throughout different months and seasons. Thus, means of Turbidity and TOC across time were selected for each water treatment plant as a metric of the WTPs’ raw water quality.

Before any statistical analysis for the effect of forest cover, a descriptive data analysis was performed in order to get an overview of the data. First, summary statistics was conducted for all variables. The output provided information about mean, standard deviation and range of these variables. Second, boxplots were plotted as the representation of the distributions. Boxplots locate the three quartiles, which divide data into four equal groups from smallest to largest. This allows the data to be observed in a way that observations are converged in some ranges, while dispersed in others. Also, boxplot is an effective tool to check the normality of data distribution, which is the underlying assumption of most statistical analysis.

3.2.2 Correlation between explanatory variables

Examining correlations between different explanatory variables served as an extension for data exploration and may offer informative explanations for the results of later statistical models. Two types of correlations were of major concern. First, land cover percentages (forest, impervious and agricultural cover) were correlated with each other and against watershed size at three spatial scales of watershed, 300ft buffer and 100ft buffer respectively. Second, percent of each land cover class in the entire watersheds was also correlated against the same land cover percentage in the 300ft and 100ft riparian buffers. The STATA command "corr" was used for this analysis, and the outputs showed both sign and magnitude of these correlations, represented as R. In addition, graph matrices were plotted in STATA and histograms of the percent of three land cover types at the three spatial levels (watershed, 300ft buffer and 100ft buffer) were plotted in Microsoft Excel.

3.2.3 Regression models

After the exploratory data analysis, a proper model for the examination of the effect of forest cover on water quality was determined. Linear regression model was chosen because it quantifies the effect of the explanatory variables on the response variable, and the significances of these associations are testable. However, the problem is that if the means of Turbidity and TOC are taken directly for analysis, they were treated as equally accurate, regardless of their variance across months. In this case, a weighted regression model is a good fit. In a weighted least square regression model, input data points are given unequal attentions. In other words, each observation is given its proper amount of influence over the parameter estimates based on its precision. The inversed variance was selected as the weight, since mean water quality parameters with less variance among months were more precise. In STATA, there are four different commands for weighted regression, as frequency weights (fweight), sampling weights (pweight), analytic weights (aweight) and importance weights (iweight). The command of analytic weights was chosen because it is often used when the cases are averages and some cases are measured with more precision than others; also, the inversed variance is a common weight for analytic weights.

(a) Simple linear regression model

To address our study question, a simple regression model was built that included percent of forest cover as the explanatory variable and water quality parameter as the response variable. Since t-test is used to identify the significance of the coefficients, the assumption of normality is still applicable in regressions. The boxplots from the descriptive data analysis showed whether the variables were normally distributed. Then the STATA command "ladder" was performed to check possible transformations for all variables. The transformation with the smallest chi2 (2) value and the largest p-value is the best option. However, only log transformation is commonly used, because other transformation forms induce interpretation difficulties. From the results, log transformation was suitable for Turbidity, TOC and watershed size, and the chi2 (2) values for all other variables in the identity form (i.e. no transformation) were not large enough to be unacceptable (**Appendix I: Table 2**). Thus, Turbidity, TOC and watershed size were log transformed in regression models, and other variables were kept in their original forms. For Turbidity and TOC, because taking the mean of the logged values does not equal taking the log of the mean values, all the monthly values were log transformed before calculating the mean. However, since zero values existed in the TOC dataset (i.e. these TOC levels were below the minimum detection limit) and log zero is undefined, the minimum TOC value in the whole dataset was added as the detection limit to all values due to the unavailability of the minimum detection limit information. The simple regression function is given as:

$$\ln(WATER_i) = \beta_0 + \beta_1 \, FOREST_i + \varepsilon_i \qquad \textbf{Equation 1}$$

where $WATER_i$ is either Turbidity or TOC (TOC plus detection limit), $FOREST_i$ is the percent of forest cover in the entire watershed, 300ft or 100ft riparian buffer areas, and ε_i is the error term. This regression was run six times in order to examine different scenarios with regard to the relationship between water quality and forest cover. The coefficient β_0 represents the Turbidity or TOC level when the percent of forest cover is zero, yet the sign and magnitude of the coefficient β_1 is more of the concern, which represents the quantitative effect of forest cover on water quality. Besides the coefficient β_1, other values that worth noticing include p-value (or t) of β_1, as well as the R-squared of the model. The 95% confidence interval is usually viewed as the threshold of significance, in other words, the coefficient with a p-value less than 0.05 (or $|t|>1.96$) is considered to be significant, meaning there is convincing evidence to reject the null hypothesis that the effect of the forest cover equals to zero. In other words, there is significant linear relationship between water quality and percent of forest cover. R-squared is important because it represents the percentage of variation in water quality parameters that can be explained by forest cover. The higher the R-squared, the better the regression line fits the set of data.

Our hypothesis for the regression is that percent of forest cover increase in watersheds and riparian buffers significantly lead to the reduction of Turbidity and TOC, which means we expect a negative coefficient β_1 with a p-value less than 0.05. Also, we expect β_1 to be large enough, so that the conservation of forested areas could lead to much improvement in water quality.

However, a regression model is valid only if the assumptions underlying it are satisfied. The most common problem for a simple linear regression is heteroskedasticity, which means the residuals (difference between response variable's observed value and its predicted value) vary with the explanatory variable, or the variance of the error term is not constant. We expected the residuals to be independent from the explanatory variable, and to have a mean of 0. Heteroskedasticity is often a by-product of other violation of assumptions, and does not result in biased parameter estimates. Rather, it affects the significance test for the coefficients, since the assumption of minimizing sum of squared residuals in a least squares regression model is violated. Thus, it is necessary to check the residuals distribution after the "regress" command in STATA. There are several ways for residual checking, such as the Breusch-Pagan test using the STATA command of "hettest", the residuals versus fitted plots (residuals in y-axis, and explanatory variable in x-axis), and checking the distribution of the residuals using histogram and kernel density plot . If the residuals are not normally distributed (from the results of histogram and kernel density plot) and are not randomly scattered in the residuals versus fitted plots, heteroskedasticity can be problematic, just as what was found in this study (**Appendix II: Figure 2**). Thus, a robust regression was employed to address this problem, which corrected the standard error for the coefficients by ignoring the assumptions for independence and identical distribution. Although residuals check was not performed for all simple regressions, robust regressions were always better in any cases. To conclude, the regression models in this study were both weighted and with robust standard errors.

The primary focus of this study is on correlating forest cover with water quality, but other geospatial characteristics also influence water quality. These correlations were determined by separate simple linear regression models, using the same type of model as described above. These simple linear regression models were used as a supplement of the multiple regression models, due to the fact that the coefficients and their significance change with the inclusion of other variables, so that it is possible that the significance of certain variables are reduced because of the existence of other more strongly affecting variables. Turbidity and TOC were regressed individually with land cover types in the whole watershed, 300ft buffer and 100ft buffer, and with watershed size. This led to 20 simple weighted linear regressions in total. In addition, scatterplots were made for each simple regression model with the line fitted in a weighted way (inversed variance across time series of Turbidity or TOC), and values of R-squared of the models were labeled on the plots.

(b) Multiple linear regression model

Multiple linear regression models incorporate more than one explanatory variable, thus including more potential influencing factors and raising the overall percentage of variation in the response variable explained by the model. Since water quality is determined complicatedly by many confounding factors, only if these factors are all observed and incorporated could the regression model being truly valid. However, the chance of attributing the effects caused by other factors to percent of forest cover can only be reduced by identifying the effect of forest cover, when all other variables with available data are held constant.

In multiple regression models of this study, explanatory variables included percent of forest cover, impervious cover and agricultural cover, watershed size, and water source. The 31 water treatment plants under analysis extract water from four different types of sources: reservoir, lake, river and creek. Three of the sources were included as dummy variables, namely reservoir, lake and river. Dummy variable takes a value of either 1 or 0. For example, for the reservoir dummy variable, the value equals 1 if the water source is reservoir; otherwise, it equals 0. Three dummy variables were incorporated instead of four in order to avoid the dummy variable trap. Dummy variable trap is referred to the multicollinearity resulting from including all the dummy variables as well as the constant term. If this happens, the sum of all dummy variables for each observation equals 1, which is identical and thus perfectly correlated with the constant term. The multiple linear regression is given as:

$$\ln(\mathrm{WATER}_i) = \beta_0 + \beta_1\,\mathrm{FOREST}_i + \beta_2\,\mathrm{IMPERVIOUS}_i + \beta_2\,\mathrm{AGRICULTURE}_i + \beta_4 \ln(\mathrm{WATERSHED\ SIZE}_i) + \beta_5\,\mathrm{RESERVOIR}_i + \beta_6\,\mathrm{LAKE}_i + \beta_7\,\mathrm{RIVER}_i + \varepsilon_i$$ **Equation 2**

where WATER_i is either Turbidity or TOC (TOC plus detection limit), FOREST_i, $\mathrm{IMPERVIOUS}_i$ and $\mathrm{AGRICULTURE}_i$ are the percent of forest cover, impervious cover and agricultural cover in the entire watershed, 300ft or 100ft riparian buffer areas, and ε_i is the error term. Thus, multiple regression models were run six times, in which three for them were for Turbidity and another three were for TOC, and each time with one spatial scale (watershed, 300ft buffer and 100ft buffer) of land cover types.

The interpretations of the coefficients in multiple regression models are similar to that of simple regression models. With regard to assumptions, the heteroskedasticity problem was fixed by using robust standard error. However, since there are more than one explanatory variable in the model, the problem of multicollinearity may emerge if any of these explanatory variables are strongly correlated. The dummy variable trap mentioned above is one example. If this happens, these correlated variables provide redundant information about the response. As a consequence, at least one of the coefficients of the correlated variables will be affected, in the form of the increase in standard error and the corresponding increase in p-value, thus driving down the credibility of the significance of the coefficient (a large p-value lead to less significance) and making the results to be misleading. The "corr" command is used in STATA to determine the degree of correlation as described above. A more convenient way to decide if multicollinearity is problematic in the model is to use the "vif" command after running a regression. Generally speaking, multiple linear regression with vif greater than 10 are problematic. In this case, we are especially concerned whether forest cover, impervious cover and agricultural cover are strongly correlated, since the increase in agricultural activities and other forms of development directly lead to the decrease in forest cover. Thus, the check of multicollinearity becomes necessary.

In order to double check the results and examine if the effect of percent of forest cover on Turbidity and TOC are constant at different time periods, seasonal multiple regression models were also conducted following the same method described above, when winter was defined from November to January, spring from February to April, summer from May to July, and autumn from August to October. Instead of using means of log transformed Turbidity or TOC across the whole time, seasonal means were selected as the response variables in these seasonal models. Correspondingly, inversed variances of log transformed monthly values for each season were select as analytical weights. Therefore, there were six multiple regression models for each season, and twenty-four seasonal regression models in total.

CHAPTER 4: RESULTS

4.1 Geospatial Analysis

As mentioned in the methodology section, the intake points of the WTPs were determined. A total of 31 intakes points for the treatment plants were identified (**Appendix I: Table 3**). The sources of these intakes points consisted of a mix of rivers/streams, lakes and reservoirs. About 14 sources were rivers/streams, 11 were lakes and 6 were reservoirs (**Appendix I: Table 4**). The intake points were geographically distributed across mid and western North Carolina, largely in the piedmont and highlands (**Appendix II: Figure 3**). Intake points that were located next to the North Carolina border and which indicated that these watersheds crossed state borders were dropped from the final list of intake points.

A total of 31 watersheds were delineated based on the intake points (**Appendix II: Figure 4**). The watersheds were of varying sizes, from about $98m^2$ to about $890{,}000m^2$. Some of the smaller watersheds overlapped within the larger watersheds. Most of the smaller watersheds were located in western North Carolina (**Appendix I: Table 4**).

The forest cover, impervious cover and agricultural land cover of the watersheds were determined as the percent of the total area of the watershed. Forest cover varied between 40% to about 98% across the watersheds (**Appendix II: Figure 5**), while impervious cover and agricultural land cover varied between 0.009% to 12% and 0.02% to 43%, respectively (**Appendix II: Figure 6 and Figure 7**). Forest cover was generally the dominant cover type in the watersheds as opposed to the other two cover types. (**Appendix I: Table 4**). In the 300ft buffer area, forest cover varied from 40% to about 98%, while impervious cover and agricultural land cover varied between 0% to 6.5% and 0.03% to 23%, respectively. In the 100ft buffer area, forest cover varied from 30% to about 99%, while impervious cover and agricultural land cover varied between 0% to 5% and 0% to 16%, respectively (**Appendix I: Table 4**). Overall, forest cover represented a larger percentage of the total area of the watersheds, and the 300ft and 100ft stream buffers.

4.2 Statistical Analysis

4.2.1 Exploratory data analysis

In summary statistics, normalized standard deviation was calculated by dividing standard deviation by mean of each variable, in order to allow comparisons of dispersion between variables, especially between percent of forest cover, impervious cover and agricultural cover. The results showed that the distributions of percent of forest cover were the most centralized, with the normalized standard deviations of 0.30, 0.23 and 0.24 in watershed, 300ft buffer and 100ft buffer. In other words, percent of forest cover varies in a relatively narrow range among the 31 analyzed watersheds. In contrast, the statistics were 1.03, 0.95, 0.93 for percent of impervious cover, and 0.81, 0.69 and 0.68 for percent of agricultural cover. In addition, watershed size was the most dispersed variable with a normalized standard deviation of 1.67, this could also be observed from its broad range of 98 to 894974 square meters. (**Appendix I: Table 5**)

Boxplots provided more information with regard to distributions of the variables (**Appendix II: Figure 8**). For water quality parameters of Turbidity and TOC, the distributions were both skewed to the right, meaning parameters with small values were more converged. The median of Turbidity was about 6 NTU, which was less than the mean of 9.94 NTU, and the Interquartile range (IQR, i.e. middle 50%) of Turbidity was about 3 to 14 NTU. The median of TOC was about 3 mg/L, approximating the mean, and the IQR of TOC was about 2 to 7 mg/L. In addition, two outliers with large values were found in the Turbidity distribution.

Watershed size distribution was extremely right skewed, with two large outliers far away from other values. As of the percent of land cover types, only the distributions of percent of impervious cover were all right skewed, in watershed, 300ft buffer and 100ft buffer, while the skewnesses were not consistent for percent of forest cover and agricultural cover. In general, the distributions that were roughly subject to normality included percent of forest cover in 300ft buffer and 100ft buffer, and percent of agricultural cover in 300ft buffer.

4.2.2 Correlations between explanatory variables

From the results executed in STATA, the correlations between the three land cover classes and watershed size were relatively low, with R less than or approximating 0.30. Moreover, watershed size was negatively correlated with percent of forest cover, and was positively correlated with percent of impervious cover and agricultural cover. As were expected, the correlations between the three land cover types were much stronger. Percent of forest cover was closely related with percent of agricultural cover in watershed with the highest absolute value of R (0.76); however, the correlations were significantly reduced when scales of analysis were narrowed down to 300ft and 100ft buffer, with R of -0.41 and -0.13 respectively. The correlations between percent of forest cover and percent of impervious cover were constant in watershed, 300ft buffer and 100ft buffer, with R of -0.63, -0.67 and -0.60. In addition, percent of impervious cover and percent of agricultural cover were positively correlated in watershed and 300ft buffer and were negatively correlated in 100ft buffer, but these correlations were very weak. (**Appendix I: Table 6**)

Between the different scales of watershed, 300ft buffer and 100ft buffer, the three land cover types all showed very strong correlations, with R ranging from 0.75 to 0.95. The correlations between 300ft buffer and 100ft buffer scales were the strongest for all of the three land cover types, specifically 0.94 for percent of forest cover, 0.95 for percent of impervious cover and 0.95 for percent of agricultural cover. Furthermore, the correlations between watershed and 300ft buffer scale were stronger than those between watershed and 100ft buffer scale, for all of the three land cover types. (**Appendix I: Table 7**)

In addition, similar results were found in graph matrices consisting of scatterplots between explanatory variables (**Appendix II: Figure 9**) and histograms (**Appendix II: Figure 10**). Variables with strong correlations (i.e. high absolute value of R) showed observable linear relationships in graphs, such as the three land cover types in different scales.

4.2.2 Simple linear regression model

Among all the explanatory variables, four of them did not significantly affect Turbidity (p-value>0.05, when using 95% confidence interval), including forest cover in 100ft buffer (p=0.217), impervious cover in watershed (p=0.053), impervious cover in 300ft buffer (p=0.082), and impervious cover in 100ft buffer (p=0.615); while only four coefficients were significant when regressed with TOC, namely percent of forest cover in watershed, 300ft buffer and 100ft buffer, and percent of impervious cover in watershed(**Appendix I: Table 8**). Since there was one explanatory variable in each model, small p-values had corresponding large R-squared, meaning relatively high percent of variation in water quality parameters was explained by this single one explanatory variable.

For Turbidity, the effects of percent of agricultural cover were the most significant ones, and the explained percent of variation in Turbidity could be as high as 65.86% (i.e. R-squared=0.6586) when agricultural cover in 100ft buffer was the explanatory variable. This R-squared is high for a simple regression model. Also, watershed size explained 49.49% in the variation of Turbidity, as the second most significant variable following agricultural cover. Percent of forest cover in watershed and in 300ft buffer had significant correlations with Turbidity, with p-values of 0.001 and 0.021, and R-squared of 0.35 and 0.20.

For TOC, the effects of percent of forest cover were more significant than their effects for Turbidity, when they were in 300ft or 100ft buffer. Also, percent of forest cover explained more variation in TOC than other variables, with R-squared values of 0.32, 0.34 and 0.20.

The sign and magnitude of the coefficients are also important. For log-linear models, when the response variable was log transformed and the explanatory variable was in its original form, the coefficient could be interpreted in the way as one unit increase in the explanatory variable was associated with a $100\beta_1$% (β_1 was denoted in Equation 1) increase in the response variable. For example, one unit increase in percent of forest cover in watershed was associated with a 1.51% decrease in Turbidity. For log-log models, when both the response variable and the explanatory variable were log transformed, the coefficient could be interpreted as a 1% increase in the explanatory variable was associated with a β_1% increase in the response variable. The only log-log model in our study was the model with watershed size as the explanatory variable, and all other models were log-linear models. The interpretation for the coefficient of watershed size was that a 1% increase in watershed size was associated with 0.15% increase in Turbidity. The interpretations for TOC were slightly different, since the detection limit of 0.154 mg/L was added to TOC before log transformation. For example, the interpretation could be one unit increase in percent of forest cover in watershed was associated with a 1.20% decrease in the sum of TOC and 0.15 mg/L; and a 1% increase in watershed size was associated with 0.0065% increase in the sum of TOC and 0.15 mg/L. Percent of forest cover had negative correlation with water quality parameters, meaning more forest cover led to water quality improvement, while all other variables had positive correlations. One important thing about interpretation was that the effects were all average effects across time, since we took the mean Turbidity and TOC instead of the monthly data.

From the two-way scatterplots, the correlations were comparable through visual display of point distribution and values of labeled R-squared (**Appendix II: Figure 11**). This was a non-parametric way to examine correlations between two variables.

4.2.3 Multiple linear regression model

The multiple regression models showed similar results in the sense of significantly correlated variables in each model, regardless of whether percent of forest cover, impervious cover and agricultural cover were incorporated as the level of watershed, 300ft buffer or 100ft buffer (**Appendix I: Table 9**).

For Turbidity, three variables were significant, including percent of agricultural cover (positive effect), watershed size (positive effect) and reservoir (negative effect). Take the watershed scale model for example, p-value was 0.017 for agricultural cover, 0.001 for watershed size, and 0.020 for reservoir, and the overall R-squared for the model was 0.76. The coefficient for percent of forest cover could be interpreted as one unit of increase in percent of forest cover was associated with 0.68% decrease in Turbidity, holding all other variables constant. However, the coefficient was not statistically significant with a p-value of 0.37, and the magnitude of the effect was reduced from 1.51% in simple regression to 0.677% in multiple regressions. The interpretation of the dummy variable reservoir was interpreted as, if the water source was reservoir, the Turbidity was decreased by 0.42 NTU, compared to water coming from creek (the dropped dummy variable), holding all other variables constant. The signs and magnitudes of the three dummy variables reflected which water source contributed to higher level of Turbidity. The results were slightly different for these dummy variables with regard to the sign of the coefficient of river. In the watershed scale model, river contributed to higher level of Turbidity compared to creek (the coefficient of river was 0.06); however, in the 300ft buffer and 100ft buffer scale models, the sign of river were negative, meaning river lowered Turbidity compared to creek. Overall, the signs and magnitudes of the dummy variable coefficient suggested that Turbidity was higher in water from rivers or creeks, and was the lowest in water from reservoirs (Turbidity from different sources: river/creek > lake > reservoir).

For TOC, percent of forest cover was the only significant variable, p-values for all other variables were larger than 0.05. In the watershed scale model, one unit increase in percent of forest cover was associated with 1.69% decrease in the sum of TOC and 0.154 mg/L, holding all other variables constant. The effect did not vary too much compared to 1.20% in simple regression model. The effects of percent of forest cover in 300ft buffer and 100ft buffer were similar, namely 1.77% and 1.51%.

The mean VIFs for all models were less than 10, and none of the VIF values for individual variables were larger than 10, which meant multicollinearity was not problematic for these models.

In seasonal regression models, results vary from the regression models across the whole time and with each other, especially when Turbidity was the response variable. For example, in the Turbidity models, percent of agricultural cover remained the most strongly affecting variable in winter and spring; however, only the coefficients of percent of agricultural cover in 100ft buffer were significant in summer and autumn (not significant on watershed and 300ft buffer scales). Percent of forest cover was positively associated with Turbidity in a significant way in winter and spring, while the correlations were insignificant and negative in summer and autumn. For TOC, percent of forest cover was the only significant explanatory variable in almost all models, and the correlations were negative, as what was found in the models across the whole time (**Appendix I: Table 10**).

CHAPTER 5: DISCUSSION

The analysis of Turbidity (averaged across the months) showed that concentrations were significantly higher than the current standard of 0.3 NTU in drinking water. The mean of the average Turbidity concentrations was about 9.94 NTU even though the median was 6 NTU. The notable variance between mean and median was primarily because of the two large outliers. For TOC the mean and median were very similar, about 3mg/L. No standard for TOC concentrations in drinking water has been set by the EPA except that higher concentrations of TOC require a higher percentage of removal. The mean of the concentrations are already within the lowest bracket of percentage removal as stated by the EPA guidelines (i.e. requiring between 15% to 35% removal).

While the primary focus of this MP is on forest cover in riparian buffers, of the two other land cover classes, impervious and agricultural land, only agricultural land cover seem to strongly affect water quality.

5.1 Land Use Cover across the Three Spatial Scales

The results indicated that percent of forest cover at the watershed scale was distributed in a narrow range across the watersheds while impervious and agricultural land covers varied relatively widely across the watersheds, with impervious varying the most. Within the 300ft and 100ft buffer, the same pattern was seen - impervious and agricultural land covers were more varied than forest cover. Even though impervious cover had the widest variation when compared to the other two land use types at all three levels, at below 2% impervious cover (in all three scales), the percent impervious cover values converged. As impervious cover increased above 2%, it differed by a larger factor between the watersheds. Studies have shown that impervious cover above 10% can rapidly lead to stream ecology and water quality degradation (Schueler, 1994). The land use analysis of this MP showed impervious cover in all watersheds (and the riparian buffers) to be below 10% with the exception of one. Despite these low percentages, impervious cover showed strong negative correlations with forest cover across the three scales of analysis (watershed: -0.63; 300ft buffer: -0.67; 100ft buffer: -0.60). On the other hand, agricultural land cover was only closely correlated to forest cover at the watershed scale (watershed: -0.76; 300ft buffer: -0.41; 100ft buffer: -0.13).

Analyzing the land cover at three different scales can have implications for watershed management practices. The U.S. EPA has recommended the use of 100ft stream buffers to protect stream quality and habitat, but it is important to see if land use patterns within these stream buffers are correlated with patterns at the watershed scale. Some studies that have analyzed land use patterns in stream buffers across watersheds have deliberately chosen buffers in such a way that there is no correlation between land use in riparian buffers and the watershed scale so that watershed management practices aimed at conserving forests can be focused on riparian buffers. If land use patterns in riparian buffers are significantly linked to patterns in the entire watershed, then that makes the case for protecting forests in entire watersheds, not just the buffers. Across the 31 watersheds in this study, very strong correlations were seen between land use patterns in the watersheds, and patterns in the 300ft and 100ft buffers. However, the correlations were much stronger between the watersheds and 300ft buffers than between the watershed and 100ft buffers when R values were around 0.9 and 0.8 respectively.

5.2 Land Use Cover Effects on Water Quality- Simple Regression Models

The analysis of the simple regressions also seemed to agree with the above observations (i.e. land use pattern correlations between watersheds and riparian buffers). Wherever a statistically significant correlation was seen for a particular land use type at the watershed scale, a statistically significant correlation was also observed for 300ft buffer, except for impervious cover and TOC in which the only significant correlation was at the watershed scale. For Turbidity, increase in percent of forest cover is more effective in the watershed scale (R-squared: 0.35) towards water quality improvement than within 300ft buffer (R-squared: 0.21) and 100ft buffer (R-squared: 0.084); 1% increase of forest cover in the watershed will theoretically ‘lower’ Turbidity concentrations by 1.5%, whereas 1% of forest cover in the 300 and 100ft buffer will lower Turbidity by 1.4% and 0.82% respectively. However, the differences between the three spatial scales are not very significant, especially between the watershed and

300ft buffer. Of the three land cover types, agricultural cover correlated in the most statistically significant way (R-squared in watershed: 0.48; in 300ft buffer: 0.64; in 100ft buffer: 0.66), even more than forest cover with Turbidity at all three spatial scales (p= 0.000).

On the other hand, TOC correlated very strongly with forest cover at all the spatial scales (R-squared in watershed: 0.32; in 300ft buffer: 0.34; in 100ft buffer: 0.20), and with impervious cover only at the watershed scale (R-squared: 0.19). Based on these simple two variable regressions alone, it appears that agricultural land use is the most significant affecting factor for Turbidity, and forest cover for TOC. For obvious reasons, the simple regressions are limited because they do not consider other variables.

5.3 Land Use Cover Effects on Water Quality- Multiple Regression Models

However, the weighted multiple regression models showed no significant correlations between forest cover and Turbidity at any spatial level unlike the simple regression model which at least showed a correlation at the three different spatial scales. Agricultural land cover though correlated strongly (with Turbidity), just as it had in the simple regression model. Likewise, when TOC was the response variable in the multiple regressions analysis, forest cover was the only land cover type showing statistically significant correlations at all spatial scales.

Literature is rich in attributing Turbidity levels in water to deforestation. The multiple regression models however do not indicate that relationship; the model indicated an insignificant positive correlation between forest cover and Turbidity, even though the simple regressions showed significant negative correlations. There are several explanations for the unexpected results. First, the sample size is relatively small, and values of percent forest cover of these watersheds are all above 40%, some are even as high as above 90%. It is possible that there might be a threshold of forest cover above which concentration of Turbidity in streams does not change with the increase in forest cover significantly. Second, the locations of the watersheds across North Carolina (i.e. the piedmont and the highlands) may also be a contributing factor to the regression model outputs as streams in highlands are usually of better quality.

Third, the highly variable watershed sizes could also be the likely cause of the different and varied correlations observed between forest cover and Turbidity. Watershed size is an important factor because the spatial distribution of the urban (developed) areas and forest cover can impact water quality at the intake point. For example the overall percent forest cover in a particular watershed may be on the higher side (above 70%), but the intake point might perhaps be located within the vicinity of an industrialized area, and may not show the low Turbidity concentrations expected. It is also relevant whether the intake points were located upstream or downstream of the urban, industrial or agricultural areas.

Fourth, correlating average Turbidity concentrations could also be a likely cause of the unexpected results seen in the multiple regression models. Averaging monthly Turbidity concentrations over approximately 50 months could create discrepancies in the analysis as well as using inversed variance as weights, which ignore the seasonal distribution for Turbidity. In this event, seasonal multiple regression models were run as described in Chapter 3 & 4 and negative correlations were only observed in summer and autumn between forest cover and Turbidity though they were not statistically significant. Dividing the concentrations into seasonal averages improved the results slightly, perhaps an indication of the fact that individually monthly concentrations represent the relationship more clearly between forest cover in a watershed and Turbidity than the mean of the concentrations.

There can be a number of other unobservable confounding factors that could also have contributed to the unexpected results. The coefficient of the percent of forest cover is biased unless all significant affecting variables are included into the model. It was observed that after more significant correlated variables such as percent of agricultural cover, watershed size and water source dummies were controlled, percent of forest cover was no longer negatively and significantly related to Turbidity. This was because we attributed the effect of agricultural cover, watershed size and water source to forest cover. Therefore, if other significant affecting variables were ignored, the magnitude, sign and significance of the coefficient of percent of forest cover would still be subject to change from what were presented in the current multiple regression models.

CHAPTER 6: RECOMMENDATIONS FOR CLIENT

The results of the analysis, linking forest cover to TOC and agricultural land cover to Turbidity could have implications for land use management in the 31 watersheds analyzed in the study and therefore, we propose the following recommendations to our client:

- Since the simple regression models showed agricultural land cover to strongly affect Turbidity, and between the three scales, 100ft riparian buffer had the most affect, we recommend that the client should focus on minimizing agricultural land cover within 100ft riparian buffers to improve water quality (specifically Turbidity). If agricultural land cover cannot be minimized in the 100ft buffer, then measures should be taken to at least intercept runoff from agricultural fields so that it can be treated before entering streams and lakes.
- The simple regressions showed forest cover to strongly affect TOC, and the within the three different spatial scales of analysis, the affect did not vary too much (i.e., R-squared ranged between 0.2 and 0.3), we recommend that the client should continue to focus their efforts and fund projects that aim to protect forests in 100ft riparian buffers.
- Impervious cover across the watersheds and within the scales is already very low (as percent of total area within the watershed and 300ft and 100ft riparian buffers) and did not seem to strongly affect Turbidity or TOC at any spatial scale. Therefore our client should focus on forest and agricultural land covers, though impervious cover should not be completely ignored. Future studies of this kind should perhaps focus on addressing some of the challenges (and confounding factors) we highlighted to determine the effect of impervious cover on water quality.
- At observing land cover affects between the three different spatial scales we found that for the three land cover types, strong affects were seen between land cover in the entire watershed and the 300ft and 100ft riparian buffers. However, the affects were stronger between the watershed and 300ft buffer. Therefore our client should continue to focus on 100ft riparian buffers in order to improve water quality.

CHAPTER 7: CONCLUSION

The analysis of land cover and raw water quality pumped in by water treatment plants from different surface water sources was complex and challenging. The limitations of this study primarily lay in three aspects, (i) small sample size, (ii) monthly time series data and, (iii) difficulty to incorporate all covariates. With additional analysis of seasonal regression models, it was found that seasonal models were not as effective as expected. The reason is likely that Turbidity did not necessarily distribute similarly within the defined seasons. Thus, more sophisticated models such as de-trend or de-cycle models are needed for future studies for the real trend through time to be detected.

However despite the limitations, the fact that this study demonstrated that TOC was strongly affected by forest cover and Turbidity by agricultural land implies that forest cover and agricultural land cover both play an important role in effecting water quality in rivers and lakes. Given the current scenario of aging water infrastructure in the U.S as mentioned earlier in this report, water utilities may increasingly have to adopt riparian buffer protection in order to provide drinkable water to millions of people.

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APPENDIX I: TABLES

Table 1: EPA Requirements for TOC reductions

Source Water TOC (mg/L)	Source Water Alkalinity, mg/L as $CaCO_3$		
	0 – 60	> 60 to 120	> 120
> 2 to 4	35%	25%	15%
> 4 to 8	45%	35%	25%
> 8	50%	40%	30%

Table 2: Examination of possible transformations for all variables

Variable	identity (chi 2)	log (chi 2)
Turbidity	13.73	1.14
TOC	8.58	2.04
watershed size	22.66	1.33
forest cover _ watershed	6.93	8.39
forest cover _ 300ft buffer	2.36	0.05
forest cover _ 100ft buffer	1.41	9.99
impervious cover _ watershed	6.48	-
impervious cover _ 300ft buffer	4.25	-
impervious cover _ 100ft buffer	4.76	-
agricultural cover _ watershed	9.24	13.24
agricultural cover _ 300ft buffer	10.59	11.48
agricultural cover _ 100ft buffer	10.38	-

Table 3: Water Treatment Plants

INTAKE POINT	WTP NUMBER	NAME	COUNTY	CITY	POPULATION SERVED
1	NC0201015	GRAHAM, CITY OF	ALAMANCE	MEBANE	14048
2	NC0201010	BURLINGTON, CITY OF	ALAMANCE	BURLINGTON	52034
3	NC0201010	BURLINGTON, CITY OF	ALAMANCE	BURLINGTON	52034
4	NC0304010	ANSON COUNTY WATER SYSTEM	ANSON	LILESVILLE	13000
6	NC0111010	ASHEVILLE CITY OF	BUNCOMBE	ASHEVILLE	124300
5	NC0111010	ASHEVILLE CITY OF	BUNCOMBE	ASHEVILLE	124300
7	NC0112010	VALDESE, TOWN OF	BURKE	VALDESE	13700
8	NC0114030	GRANITE FALLS, TOWN OF	CALDWELL	GRANITE FALLS	6250
9	NC0114010	LENOIR, CITY OF	CALDWELL	GRANITE FALLS	19500
10	NC0118015	NEWTON, CITY OF	CATAWBA	NEWTON	13984
11	NC0319015	PITTSBORO, TOWN OF	CHATHAM	PITTSBORO	3812
12	NC0319126	CHATHAM CO WATER SYSTEM	CHATHAM	APEX	12901
13	NC0123020	KINGS MOUNTAIN, TOWN OF	CLEVELAND	KINGS MOUNTAIN	12550

14	NC0229010	LEXINGTON, CITY OF	DAVIDSON	LEXINGTON	22415
15	NC0230010	MOCKSVILLE, TOWN OF	DAVIE	MOCKSVILLE	4655
16	NC0235015	LOUISBURG, TOWN OF	FRANKLIN	LOUISBURG	4101
17	NC0136025	BESSEMER CITY, TOWN OF	GASTON	BESSEMER CITY	5340
18	NC0136065	DALLAS, TOWN OF	GASTON	DALLAS	6795
19	NC0136020	MOUNT HOLLY, CITY OF	GASTON	MT HOLLY	13656
21	NC0343010	DUNN, CITY OF	HARNETT	ERWIN	11747
22	NC0144040	MAGGIE VALLEY SANITARY DIST	HAYWOOD	MAGGIE VALLEY	9520
23	NC0144010	WAYNESVILLE, TOWN OF	HAYWOOD	WAYNESVILLE	14520
24	NC0149010	STATESVILLE, CITY OF	IREDELL	STATESVILLE	27322
25	NC0351010	SMITHFIELD, TOWN OF	JOHNSTON	SMITHFIELD	10660
26	NC0157015	HIGHLANDS, TOWN OF	MACON	HIGHLANDS	5675
27	NC0157010	FRANKLIN, TOWN OF	MACON	FRANKLIN	9575
28	NC0363010	SOUTHERN PINES, TOWN OF	MOORE	PINEBLUFF	12000
29	NC0377010	HAMLET WATER SYSTEM	RICHMOND	HAMLET	9630
30	NC0188010	BREVARD, CITY OF	TRANSYLVANIA	BREVARD	8700
31	NC0195101	APPALACHIAN STATE UNIV WTP	WATAUGA	BOONE	11150
32	NC0100010	BURNSVILLE, TOWN OF	YANCEY	BURNSVILLE	3950

Table 4: Watershed Characteristics

WTP ID	Name	Water Source	Watershed Size (sq.meter)	Whole Watershed			300ft Buffer from Streams in Watershed			100ft Buffer from Streams in Watershed		
				% F	% I	% A	% F	% I	% A	% F	% I	% A
NC0201015	TREATMENT_PLT_GRAHAM-MEBANE	Reservoir	17123	48.8	2.8	31.9	59.3	1.4	23.6	65.4	1.0	15.2
NC0201010	TREATMENT_PLT_MACKINTOSH PLANT	Lake	33527	49.1	5.0	31.4	60.7	3.1	20.8	65.9	2.2	13.0
NC0201010	TREATMENT_PLT_ED THOMAS FP	Reservoir	27048	51.2	1.5	36.1	63.9	0.5	23.6	71.7	0.2	13.4
NC0304010	TREATMENT_PLT_ANSON CO WTP	Lake	894974	54.4	4.3	23.3	59.2	2.6	19.5	62.9	1.9	14.3
NC0111010	TREATMENT_PLT_NORTH FORK WTP	Reservoir	5459	96.7	0.1	0.0	97.8	0.0	0.1	97.7	0.0	0.1
NC0111010	TREATMENT_PLT_ASHEVILLE WILLIAM DEBRUHL	Reservoir	1962	96.7	0.0	0.0	98.1	0.0	0.1	99.7	0.0	0.1
NC0112010	TREATMENT_PLT_VALDESE WTP	Lake	268411	77.7	1.7	8.8	73.7	1.3	11.1	73.2	1.2	10.1
NC0114030	TREATMENT_PLT_GRAN FALLS WTP	Lake	281296	76.3	2.0	9.1	73.7	1.3	11.1	73.2	1.2	10.1
NC0114010	TREATMENT_PLT_LENOIR WTP	Lake	276757	76.9	1.9	8.8	73.7	1.3	11.1	73.2	1.2	10.1
NC0118015	TREATMENT_PLT_NEWTON WTP	River	54569	68.1	4.1	16.8	74.1	2.6	12.1	78.7	1.8	7.9
NC0319015	TREATMENT_PLT_PITTSBORO WTP	River	328751	46.6	7.9	28.6	57.1	4.7	20.6	62.6	3.6	12.9
NC0319126	TREATMENT_PLT_CHATHAM CO WTP	Lake	61423	50.0	12.4	6.6	55.7	6.5	5.8	56.3	4.1	4.0
NC0123020	TREATMENT_PLT_KINGS MTN WTP	Lake	17535	40.1	2.3	42.7	58.1	1.6	23.3	65.5	1.6	15.0
NC0229010	TREATMENT_PLT_OLD LEXINGTON	Lake	18108	44.5	3.9	29.4	55.1	2.0	19.8	57.8	1.5	14.9
NC0230010	TREATMENT_PLT_HUGH LAGLE WTP	Creek	46121	57.3	0.7	33.4	69.9	0.5	21.7	77.9	0.4	13.6
NC0235015	TREATMENT_PLT_LOUISBURG WTP	River	112444	59.0	1.6	20.5	64.0	0.8	15.4	67.6	0.6	9.4
NC0136025	TREATMENT_PLT_BESSEMER CTY WTP	Creek	3492	48.7	1.9	37.2	67.1	0.5	21.0	71.0	0.4	13.5
NC0136065	TREATMENT_PLT_DALLAS WTP	River	144947	50.4	7.4	29.7	63.5	4.5	19.5	69.6	3.8	13.1
NC0136020	TREATMENT_PLT_MT HOLLY WTP	Reservoir	160991	43.1	7.6	23.7	50.6	5.6	14.8	54.4	5.3	10.9
NC0343010	TREATMENT_PLT_A B UZZELL WTP	River	706604	51.1	6.0	22.6	57.8	3.5	16.7	60.8	2.6	10.9
NC0144040	TREATMENT_PLT_MAGGIE VLLY WTP	Creek	3506	88.9	0.5	2.3	82.4	1.4	3.4	83.3	1.7	2.8
NC0144010	TREATMENT_PLT_WAYNESVILLE WTP	Reservoir	3366	97.7	0.1	0.0	98.0	0.1	0.0	97.6	0.1	0.0

NC0149010	TREATMENT_PLT_STATESVILLE WTP	Lake	30332	55.3	1.2	33.7	68.6	0.4	20.8	74.9	0.2	13.8
NC0351010	TREATMENT_PLT_SMITHFIELD WTP	River	304345	50.2	8.9	15.5	56.5	5.6	11.5	59.1	3.9	7.1
NC0157015	TREATMENT_PLT_HIGHLANDS WTP	Lake	2282	53.9	4.1	1.5	39.7	5.4	0.8	37.0	4.1	0.5
NC0157010	TREATMENT_PLT_FRANKLIN WTP	River	11934	88.0	0.3	6.0	76.7	0.5	13.9	73.5	0.5	16.1
NC0363010	TREATMENT_PLT_DROWNING CREEK	Creek	47426	52.3	1.0	11.4	51.3	0.3	3.8	40.5	0.1	1.9
NC0377010	TREATMENT_PLT_HAMLET WTP	Lake	948	50.0	6.8	3.8	48.0	3.4	0.2	29.5	4.3	0.0
NC0188010	TREATMENT_PLT_BREVARD WTP	Creek	2946	98.3		0.3	95.8		0.8	94.7		1.2
NC0195101	TREATMENT_PLT_ASU FLTR PLT	Creek	98	82.8	0.6	6.1	71.6	2.7	4.6	76.8	4.2	0.0
NC0100010	TREATMENT_PLT_BURNSVILLE WTP	River	12086	94.4	0.1	2.5	86.0	0.1	6.4	83.4	0.2	6.6

***F = Forest, I= Impervious, A= Agriculture**

Table 5: Summary Statistics

Variable	Number of observations	Mean	Standard deviation	Normalize standard deviation	Minimum	Maximum
Mean Turbidity (NTU)	31	9.94	10.12	1.02	0.47	41.43
Mean TOC (mg/L)	31	3.47	2.49	0.72	0.39	7.88
Watershed size (square meters)	31	125187.5	209577.6	1.67	98	894974
Percent of forest cover in watershed	31	64.47	19.49	0.30	40.10	98.30
Percent of impervious area in watershed	31	3.51	3.61	1.03	0.00	13.22
Percent of agricultural cover in watershed	31	16.90	13.61	0.81	0.02	42.70
Percent of forest cover in 300ft buffer	31	67.99	15.32	0.23	39.67	98.11
Percent of impervious area in 300ft buffer	31	2.17	2.07	0.95	0.00	6.88
Percent of agricultural cover in 300ft buffer	31	12.20	8.37	0.69	0.03	23.63
Percent of forest cover in 100ft buffer	31	69.53	16.51	0.24	29.46	99.67
Percent of impervious area in 100ft buffer	31	1.79	1.67	0.93	0.00	5.42
Percent of agricultural cover in 100ft buffer	31	8.47	5.72	0.68	0.00	16.14

Table 6: Correlations between Explanatory Variables

	Watershed size	Percent of forest cover	Percent of impervious cover	Percent of agricultural cover
WATERSHED SCALE				
Watershed size	1.0000			
Percent of forest cover	-0.2217	1.0000		
Percent of impervious cover	0.3074	-0.6284*	1.0000	
Percent of agricultural cover	0.1363	-0.7595**	0.1585	1.0000
300 ft Stream Buffer				
Watershed size	1.0000			
Percent of forest cover	-0.2351	1.0000		
Percent of impervious cover	0.3068	-0.6672*	1.0000	
Percent of agricultural cover	0.2650	-0.4092	0.0620	1.0000
100 ft Stream Buffer				
Watershed size	1.0000			
Percent of forest cover	-0.1747	1.0000		
Percent of impervious cover	0.2331	-0.6008*	1.0000	
Percent of agricultural cover	0.3001	-0.1245	-0.0727	1.0000

Correlations with absolute value larger than 0.5 are marked with *, with absolute value larger than 0.75 are marked with **, with absolute value larger than 0.9 are marked with ***.

Table 7: Correlations between the Three Land Cover Classes

	Entire Watershed	300 ft Buffer	100 ft Buffer
Forest Cover			
Watershed	1.0000		
300 ft Buffer	0.9013***	1.0000	
100 ft Buffer	0.7628**	0.9440***	1.0000
Impervious Cover			
Watershed	1.0000		
300 ft Buffer	0.9077***	1.0000	
100 ft Buffer	0.8219**	0.9452***	1.0000
Agricultural Land Cover			
Watershed	1.0000		

300 ft Buffer	0.9426***	1.0000	
100 ft Buffer	0.8194**	0.9500***	1.0000

Correlations with absolute value larger than 0.5 are marked with *, with absolute value larger than 0.75 are marked with **, with absolute value larger than 0.9 are marked with ***.

Table 8: Simple Regression Models

regression	**coefficient**	**p-value**	**R-squared**
Response variable: Turbidity			
forest cover _ watershed	-0.0151	0.001***	0.3534
forest cover _ 300ft buffer	-0.0141	0.021**	0.2016
forest cover _ 100ft buffer	-0.0082	0.217	0.0837
impervious cover _ watershed	0.0478	0.053*	0.1459
impervious cover _ 300ft buffer	0.0685	0.082*	0.0903
impervious cover _ 100ft buffer	0.0337	0.615	0.0139
agricultural cover _ watershed	0.0286	0.000***	0.4817
agricultural cover _ 300ft buffer	0.0506	0.000***	0.6371
agricultural cover _ 100ft buffer	0.0719	0.000***	0.6586
X: watershed size	0.1466	0.000***	0.4949
Response variable: TOC			
forest cover _ watershed	-0.0120	0.002***	0.3196
forest cover _ 300ft buffer	-0.0177	0.001***	0.3374
forest cover _ 100ft buffer	-0.0103	0.015**	0.2043
impervious cover _ watershed	0.0276	0.004***	0.1894
impervious cover _ 300ft buffer	0.0352	0.125	0.0938
impervious cover _ 100ft buffer	0.0221	0.562	0.0196
agricultural cover _ watershed	0.0021	0.676	0.0104
agricultural cover _ 300ft buffer	0.0029	0.704	0.0071
agricultural cover _ 100ft buffer	0.0026	0.798	0.0024
watershed size	0.0065	0.769	0.0022

*** = 99% confidence, ** = 95% confidence, * = 90% confidence.

Table 9: Multiple Regression Models

	Percent of forest cover	Percent of impervious cover	Percent of agricultural cover	Watershed size (log)	Reservoir (dummy)	Lake (dummy)	River (dummy)
Response variable: Turbidity							
Watershed Scale							
Coefficient	0.0068	0.0163	0.0238	0.0903	-0.4214	-0.0192	0.0619
p-value	0.367	0.488	0.017**	0.001***	0.020**	0.914	0.766
300ft buffer							
Coefficient	0.0024	0.0226	0.0357	0.0755	-0.3907	-0.0964	-0.0192
p-value	0.583	0.380	0.000***	0.005***	0.018**	0.491	0.911
100ft buffer							
Coefficient	0.0004	0.0245	0.0517	0.0688	-0.3786	-0.1501	-0.0367
p-value	0.897	0.466	0.001***	0.013**	0.024**	0.309	0.838
Response variable: TOC							
Watershed Scale							
Coefficient	-0.0169	-0.0021	-0.0076	0.0103	0.0208	-0.0006	0.0819
p-value	0.007***	0.916	0.203	0.689	0.922	0.996	0.665
300ft buffer							
Coefficient	-0.0177	0.0005	0.0045	0.0029	-0.0090	-0.0001	0.1021
p-value	0.001***	0.990	0.449	0.909	0.962	1.000	0.640
100ft buffer							
Coefficient	-0.0151	-0.0333	0.0092	0.0012	0.1456	0.0998	0.2825
p-value	0.001***	0.558	0.515	0.964	0.355	0.523	0.214

*** = 99% confidence, ** = 95% confidence, * = 90% confidence.

Table 10: Multiple Regression Models for Seasons

		Percent of forest cover	Percent of impervious cover	Percent of agricultural cover	Watershed size (log)	Reservoir (dummy)	Lake (dummy)	River (dummy)
Winter (Nov-Jan)	**Response variable: Turbidity**							
	Watershed size							
	Coefficient	0.0132	0.0374	0.0254	0.1022	-0.3189	-0.0515	0.0141
	p-value	0.009***	0.043**	0.001***	0.000***	0.012**	0.676	0.932
	300ft buffer							
	Coefficient	0.0066	0.0510	0.0330	0.0693	-0.2925	-0.0783	-0.0218
	p-value	0.003***	0.001***	0.000***	0.003***	0.009***	0.367	0.861
	100ft buffer							
	Coefficient	0.0042	0.0440	0.0411	0.0780	-0.2720	-0.0522	-0.0073
	p-value	0.026**	0.081*	0.001***	0.001***	0.025**	0.570	0.961
	Response variable: TOC							
	Watershed size							
	Coefficient	-0.0161	-0.0109	-0.0089	0.0127	0.1428	-0.0100	0.0911
	p-value	0.033**	0.765	0.253	0.603	0.439	0.960	0.773
	300ft buffer							
	Coefficient	-0.0198	-0.0506	0.0018	0.0149	0.1325	0.0016	0.2128
	p-value	0.000***	0.372	0.787	0.528	0.339	0.991	0.389
	100ft buffer							
	Coefficient	-0.0150	-0.0665	0.0096	-0.0055	0.1284	-0.0364	0.2116
	p-value	0.000***	0.168	0.420	0.834	0.331	0.791	0.287
Spring (Feb-Apr)	**Response variable: Turbidity**							
	Watershed size							
	Coefficient	0.0134	0.0350	0.0381	0.0775	-0.5594	0.7083	0.0591
	p-value	0.027**	0.116	0.000***	0.007***	0.000***	0.694	0.790
	300ft buffer							
	Coefficient	0.0052	0.0434	0.0497	0.0652	-0.5006	-0.0975	-0.1023
	p-value	0.221	0.085*	0.000***	0.017**	0.003***	0.450	0.560
	100ft buffer							
	Coefficient	0.0022	0.0594	0.0677	0.0732	-0.4394	-0.1851	-0.1399
	p-value	0.513	0.071*	0.000***	0.007***	0.015**	0.180	0.471

	Response variable: TOC							
	Watershed size							
	Coefficient	-0.0137	0.0137	-0.0038	0.0292	0.1308	-0.1053	-0.0229
	p-value	0.019**	0.490	0.556	0.111	0.247	0.470	0.909
	300ft buffer							
	Coefficient	-0.0170	0.0197	0.0072	0.0339	0.1157	-0.0701	-0.0020
	p-value	0.005***	0.620	0.252	0.167	0.262	0.614	0.993
	100ft buffer							
	Coefficient	-0.0117	0.0050	0.0097	0.0319	0.2218	-0.0185	0.1228
	p-value	0.003***	0.933	0.493	0.362	0.055	0.914	0.631
Summer (May-Jul)	**Response variable: Turbidity**							
	Watershed size							
	Coefficient	-0.0000	-0.0047	0.0120	0.1073	-0.6737	-0.1590	-0.0505
	p-value	0.996	0.887	0.370	0.008***	0.001***	0.450	0.807
	300ft buffer							
	Coefficient	-0.0009	-0.0067	0.0224	0.0943	-0.6204	-0.1865	-0.0725
	p-value	0.903	0.893	0.118	0.022**	0.001***	0.351	0.709
	100ft buffer							
	Coefficient	-0.0026	-0.0237	0.0397	0.0682	-0.6383	-0.2060	-0.0337
	p-value	0.658	0.589	0.031**	0.065*	0.000***	0.317	0.853
	Response variable: TOC							
	Watershed size							
	Coefficient	-0.0132	0.0082	-0.0041	0.0161	0.0688	-0.0939	-0.0554
	p-value	0.013**	0.675	0.499	0.435	0.638	0.560	0.801
	300ft buffer							
	Coefficient	-0.0150	-0.0049	0.0026	0.0194	0.1573	0.0187	0.0797
	p-value	0.006***	0.922	0.679	0.458	0.308	0.911	0.750
	100ft buffer							
	Coefficient	-0.0123	-0.0352	0.0053	0.0113	0.1978	0.0430	0.1655
	p-value	0.000***	0.543	0.687	0.737	0.159	0.795	0.447
Autumn	**Response variable: Turbidity**							
	Watershed size							
	Coefficient	-0.0068	-0.0263	0.0028	0.1032	-0.3290	-0.2057	0.1334
	p-value	0.540	0.446	0.828	0.007***	0.167	0.454	0.625
	300ft buffer							
	Coefficient	-0.0064	-0.0437	0.0142	0.0924	-0.3043	-0.2341	0.1155

(Aug-Sep)	p-value	0.451	0.379	0.314	0.024**	0.171	0.367	0.647
	100ft buffer							
	Coefficient	-0.0049	-0.0414	0.0323	0.0662	-0.3466	-0.3065	0.0781
	p-value	0.410	0.396	0.099*	0.125	0.104	0.249	0.753
	Response variable: TOC							
	Watershed size							
	Coefficient	-0.0185	-0.0092	-0.0099	0.0023	0.0192	0.1048	0.1015
	p-value	0.002***	0.547	0.055*	0.922	0.933	0.308	0.505
	300ft buffer							
	Coefficient	-0.0165	0.0026	0.0019	-0.0100	-0.0091	0.0681	0.0943
	p-value	0.003***	0.932	0.678	0.662	0.967	0.508	0.601
	100ft buffer							
	Coefficient	-0.0151	-0.0171	0.0104	-0.0021	0.0550	0.0672	0.1742
	p-value	0.001***	0.754	0.297	0.929	0.784	0.567	0.420

*** = 99% confidence, ** = 95% confidence, * = 90% confidence.

APPENDIX II: FIGURES

Figure 1: Hydrologic Geoprocessing Model for Watershed # 1

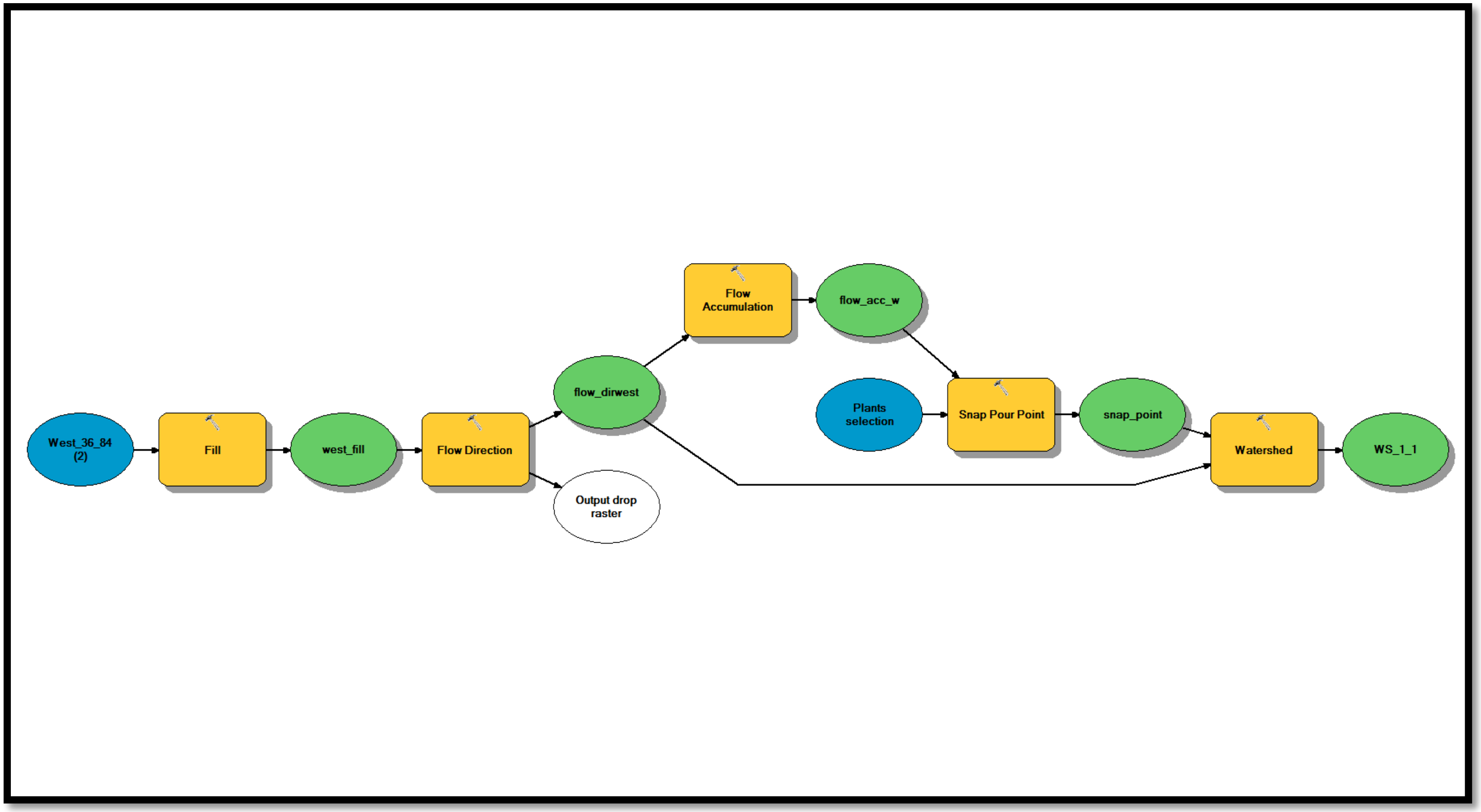


Figure 2: Residual Check for the Regression of Turbidity (log) versus Forest Cover

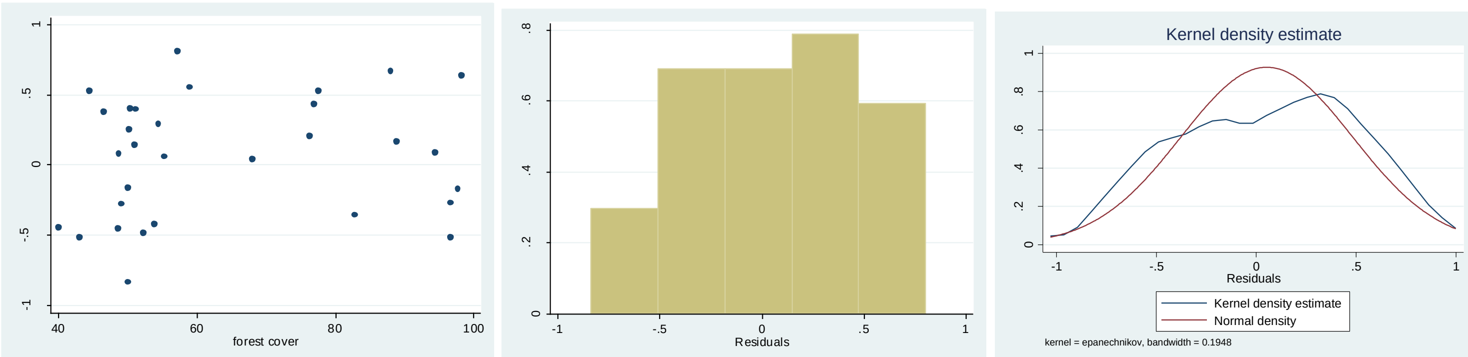


Figure 3: Water Treatment Plants Intake Points

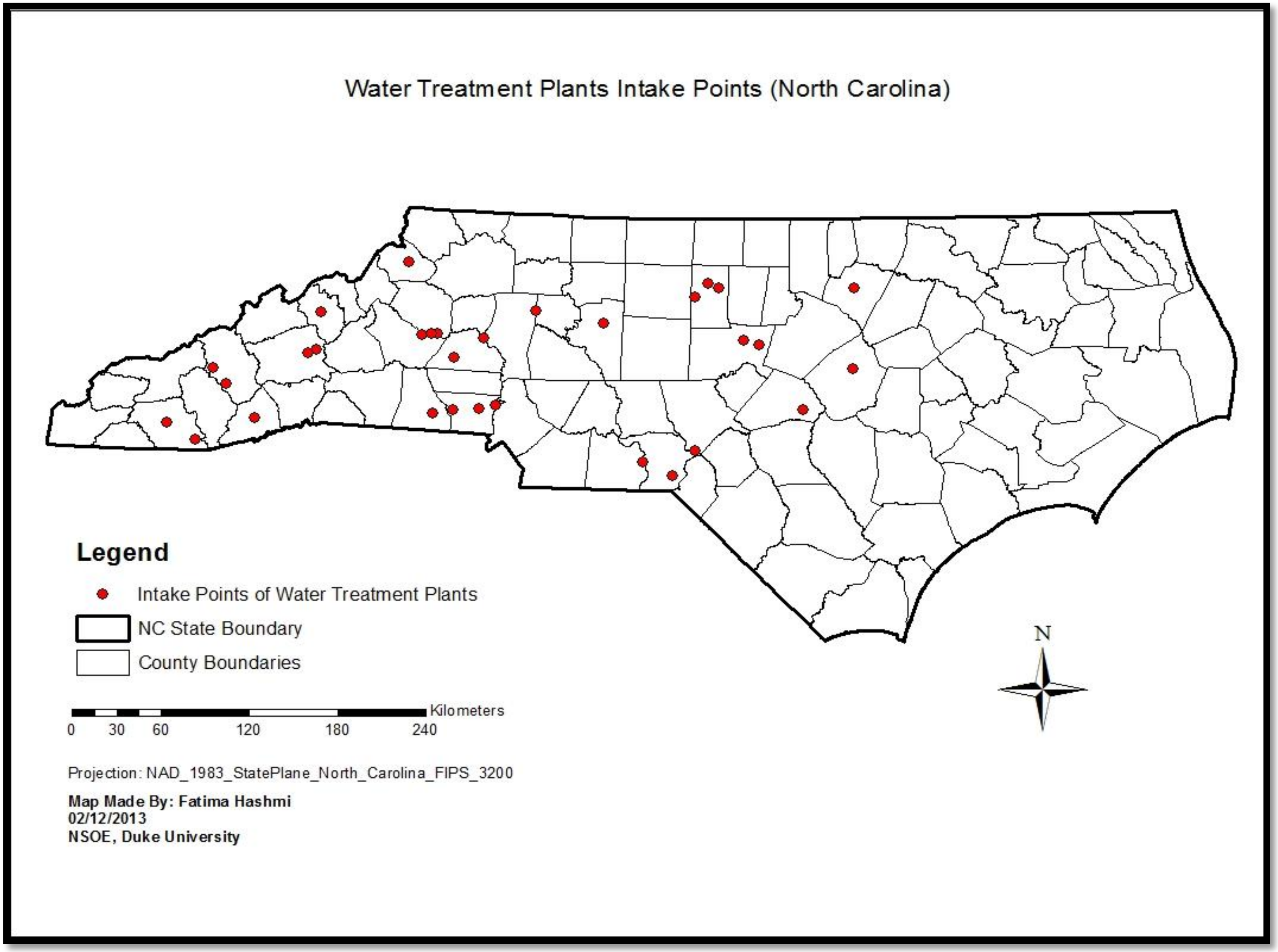


Figure 4: Delineated Watershed from the Intake Points

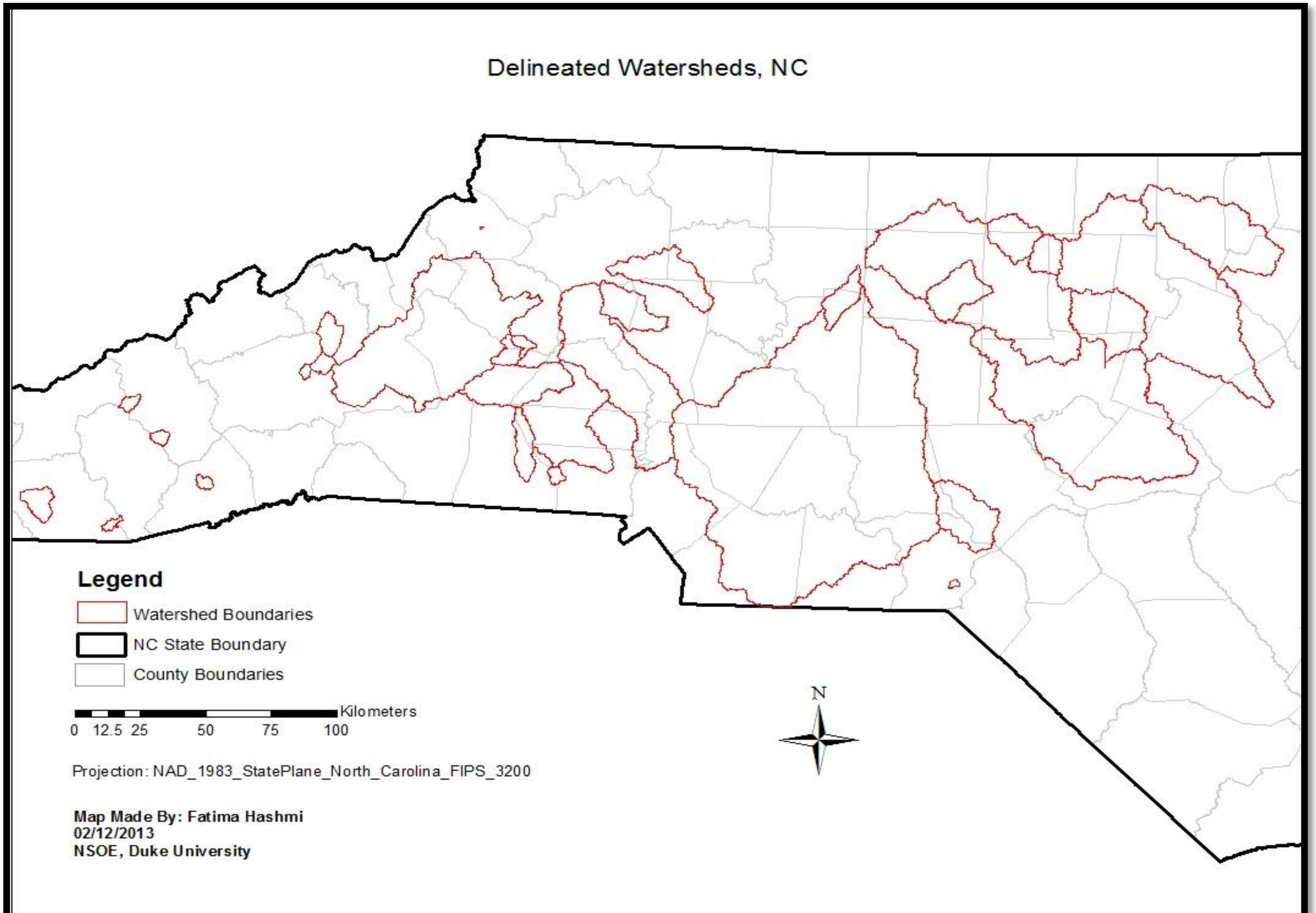


Figure 5: Forest Cover in the Watershed

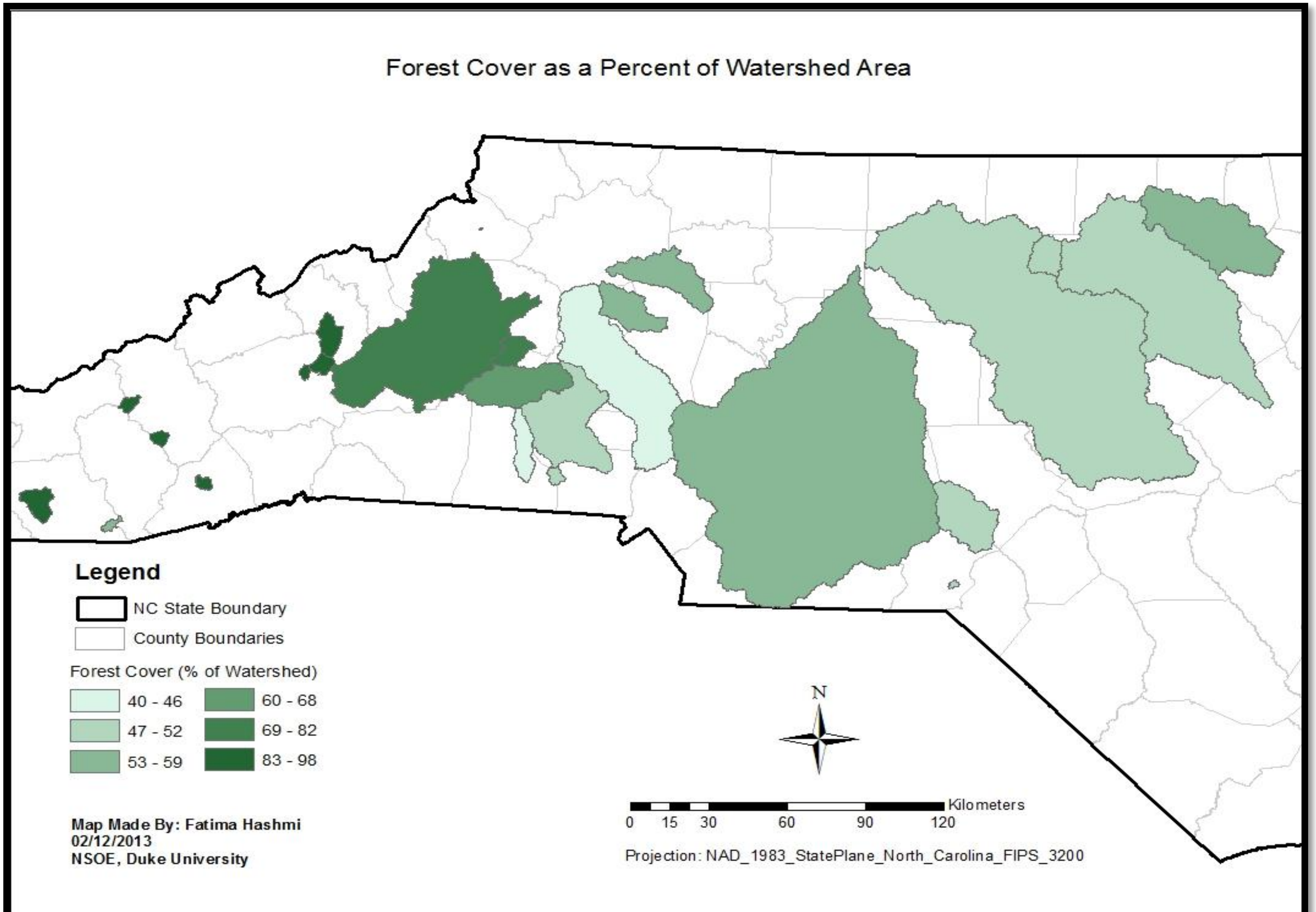


Figure 6: Impervious Cover in the Watershed

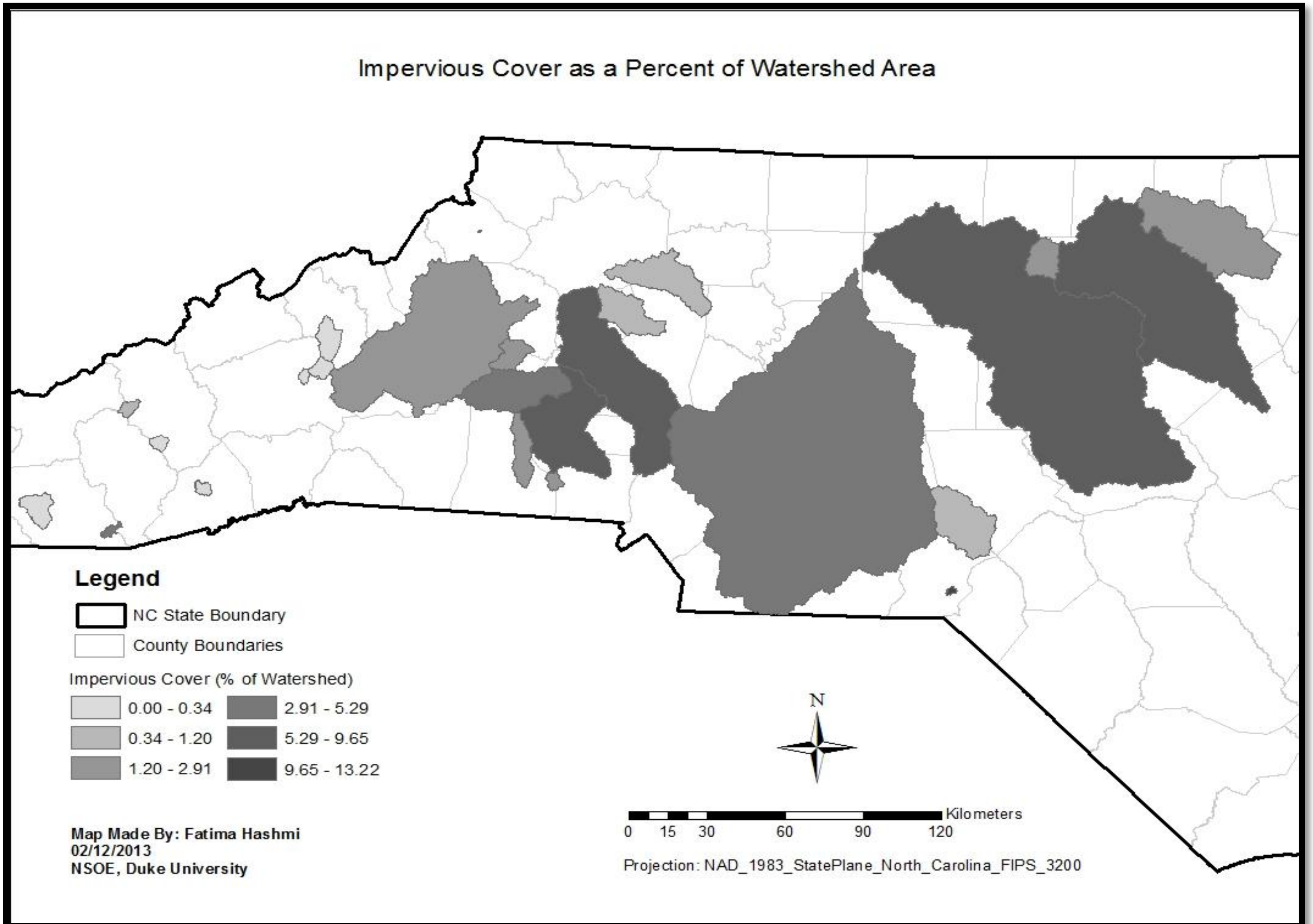


Figure 7: Agricultural Land Cover in the Watershed

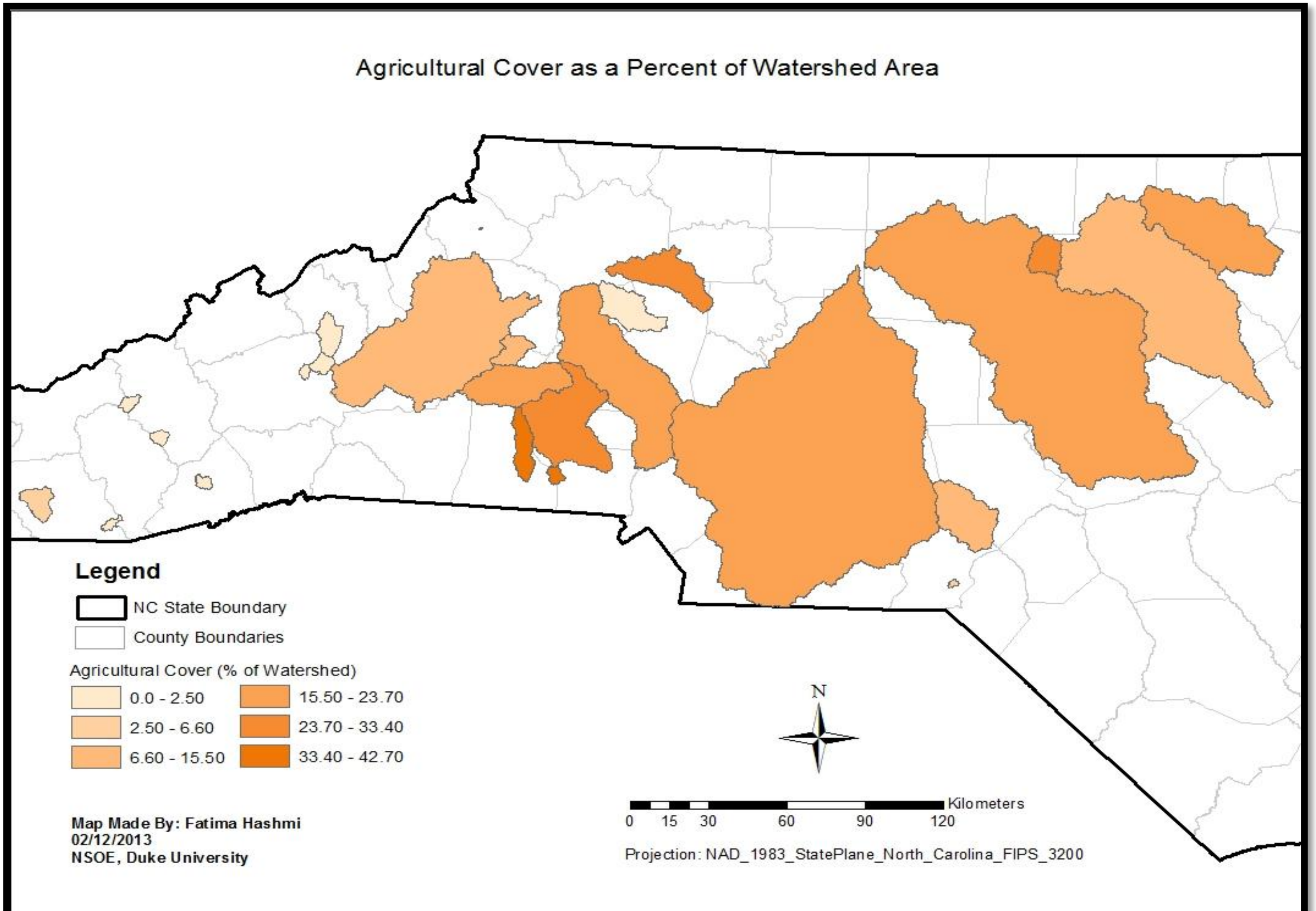


Figure 8: Boxplots of all Variables

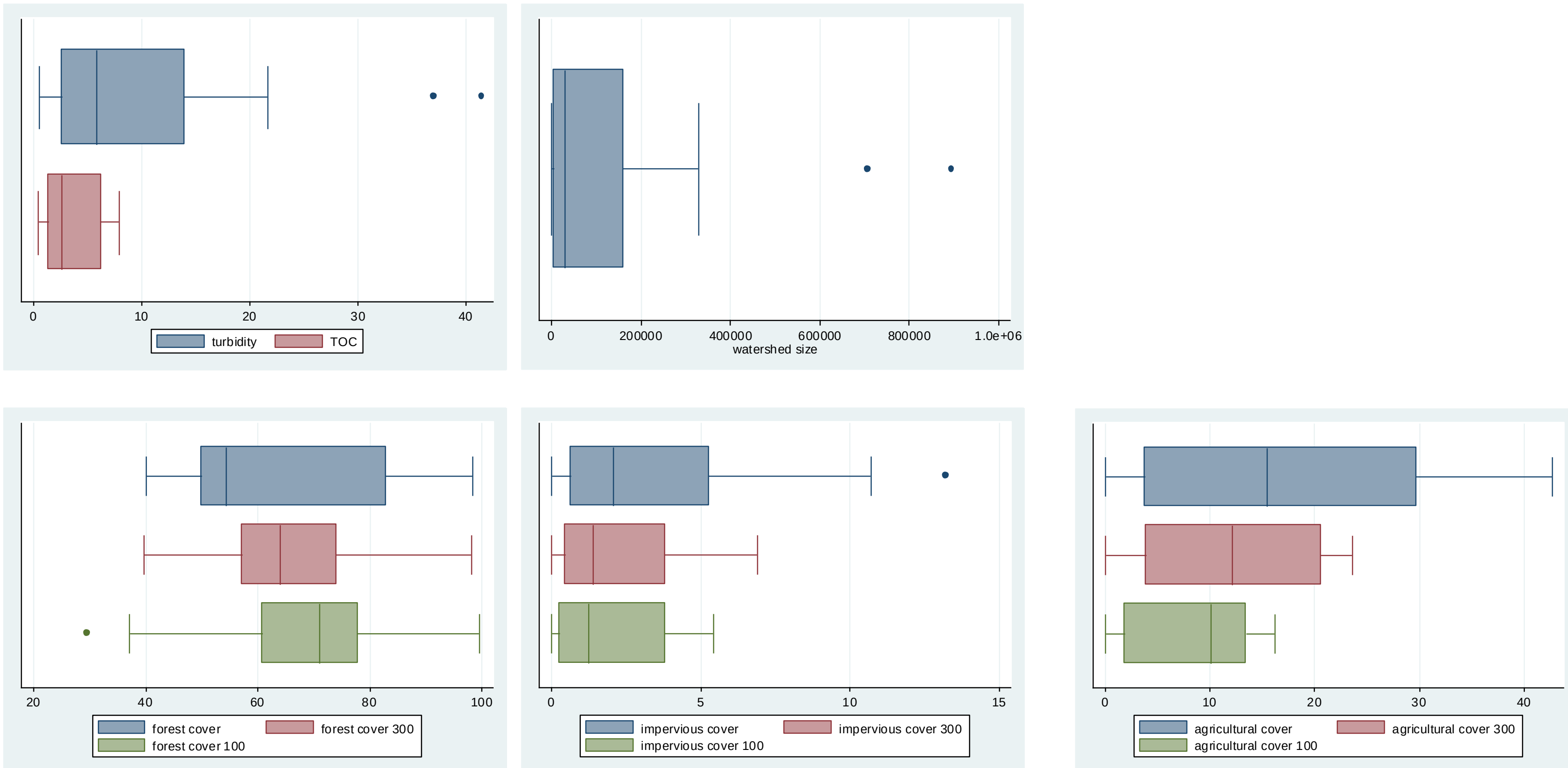
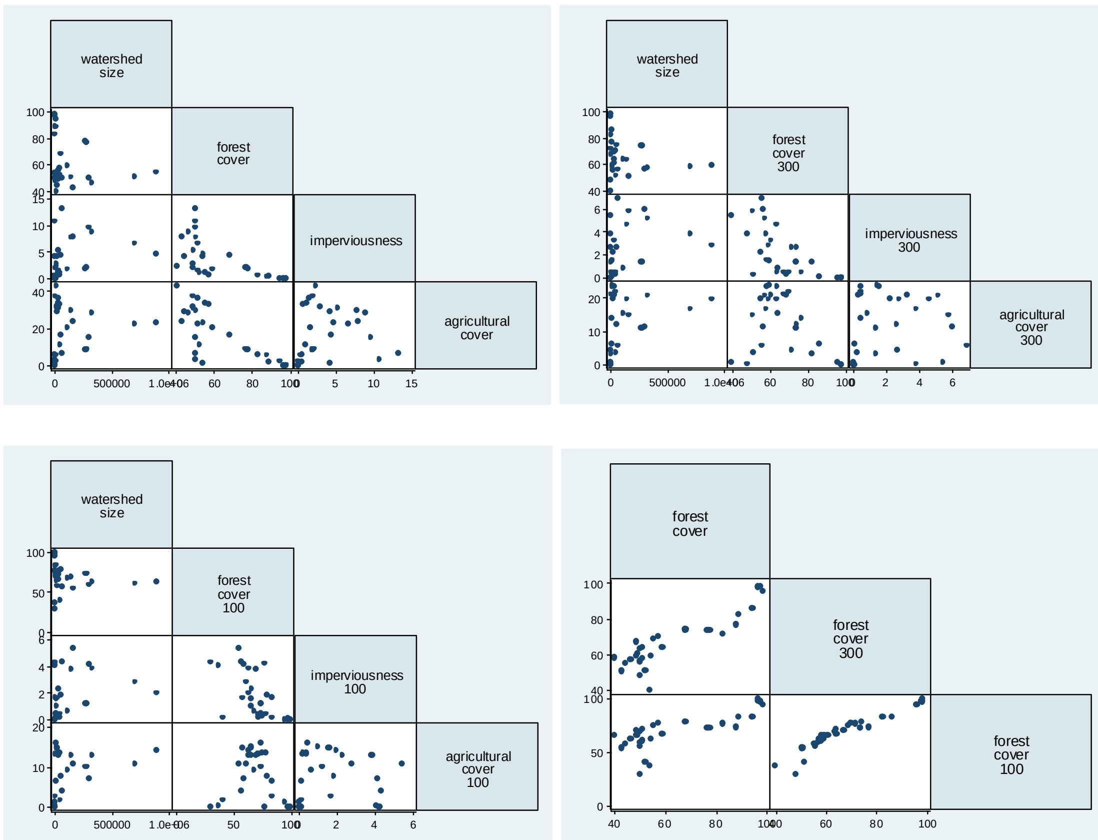
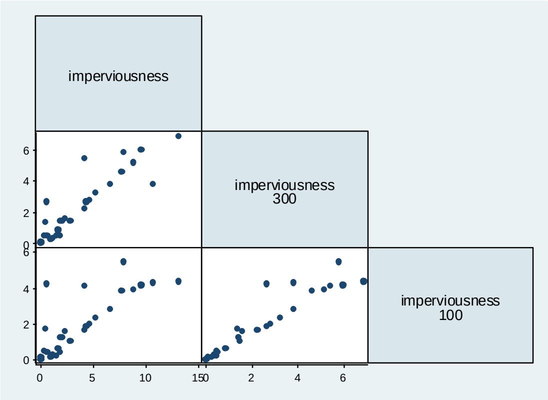


Figure 9: Graph Matrices of Explanatory Variables




imperviousness
imperviousness 300
imperviousness 100

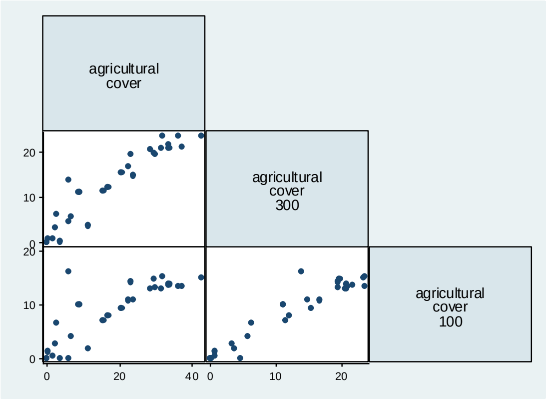

agricultural cover
agricultural cover 300
agricultural cover 100

Figure 10: Histograms of Land Cover

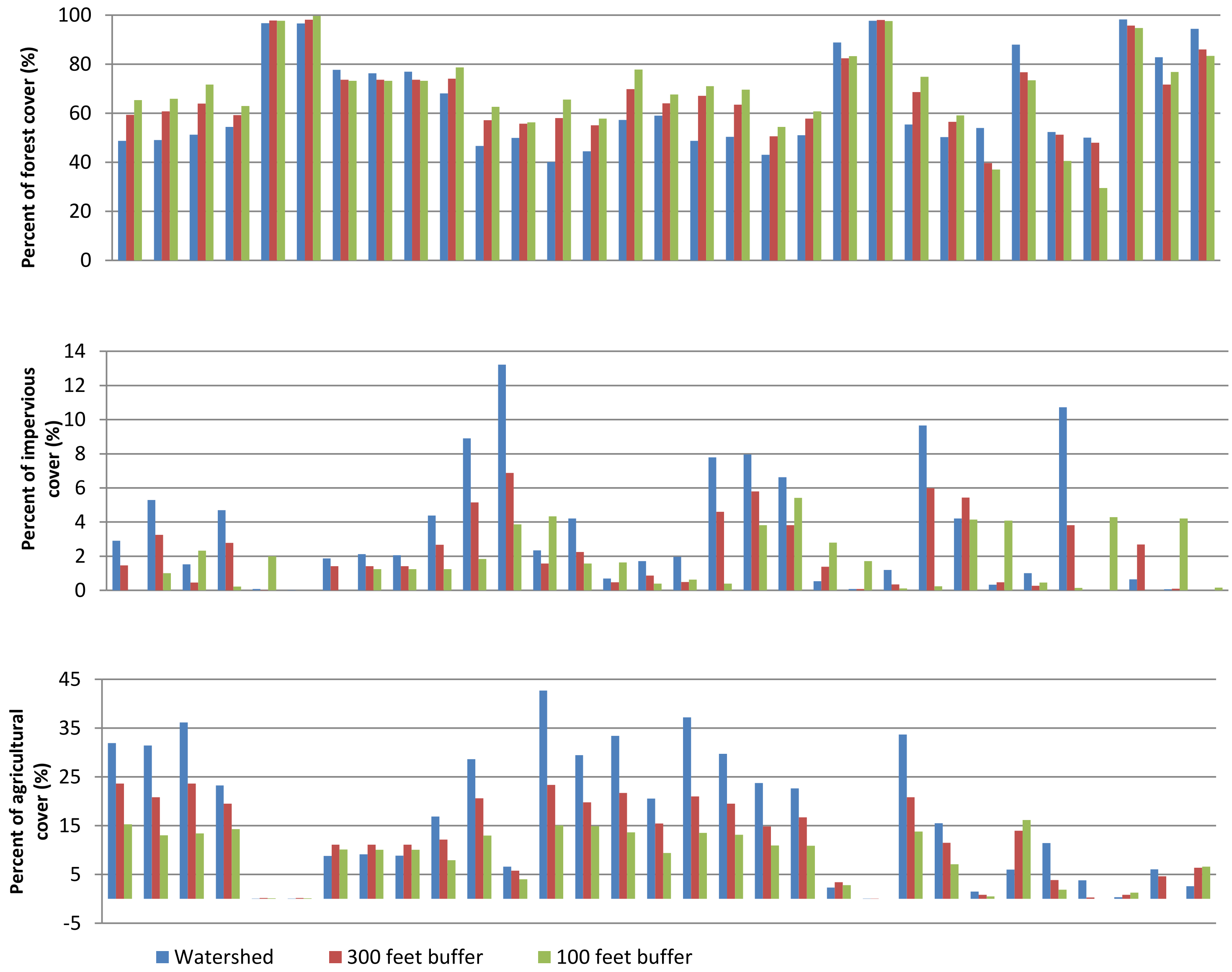
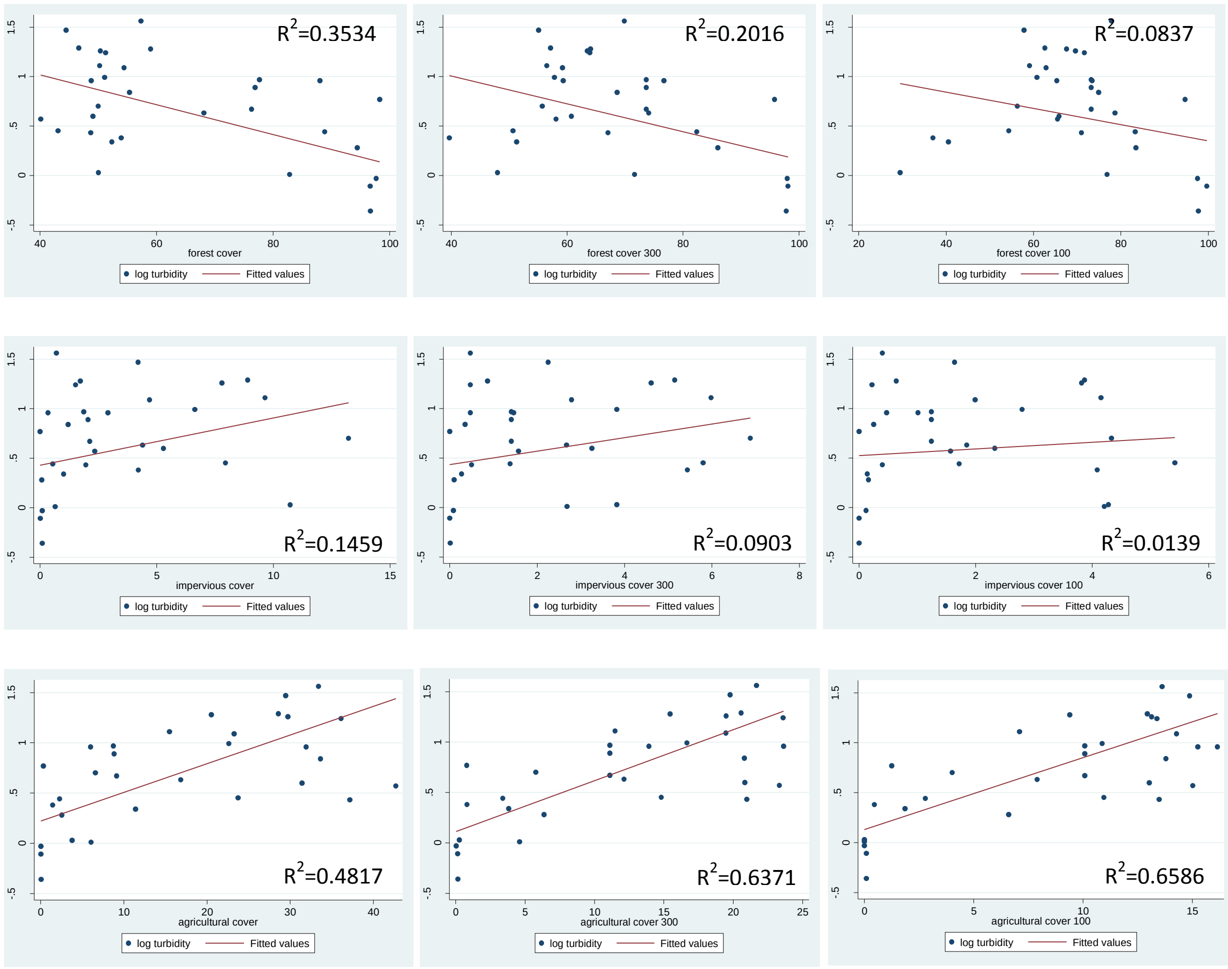
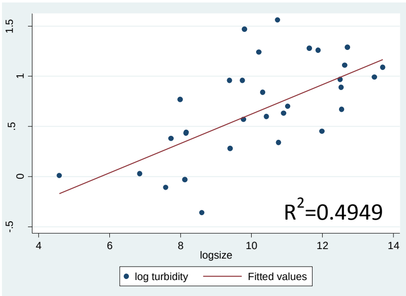
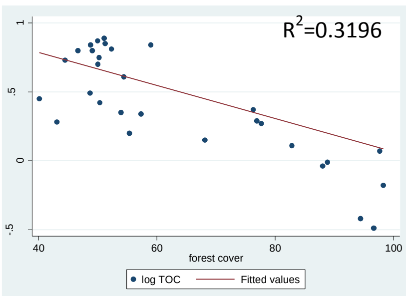
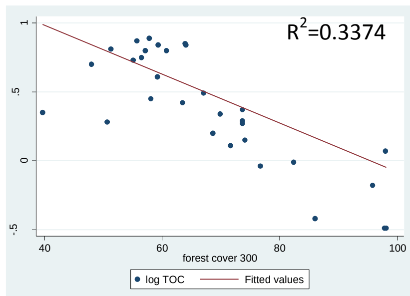


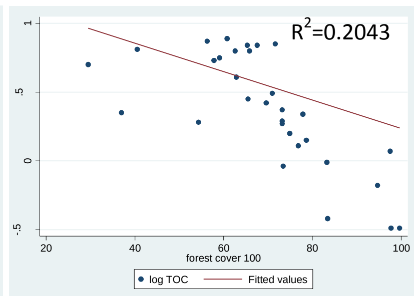
Figure 11: Scatterplots for Simple Regression Models

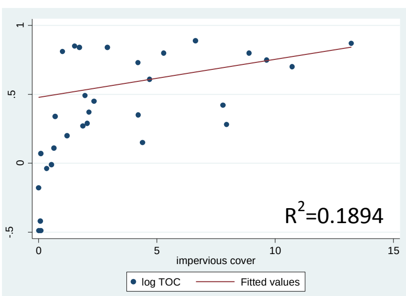


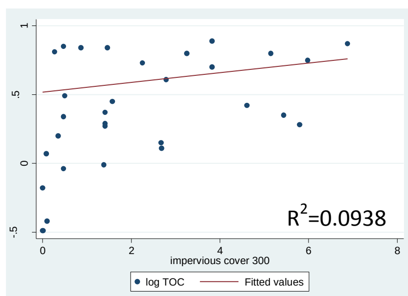

R^2=0.4949
logsize
log turbidity
Fitted values

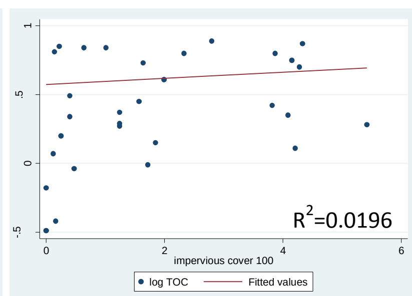

R^2=0.3196
forest cover
log TOC
Fitted values

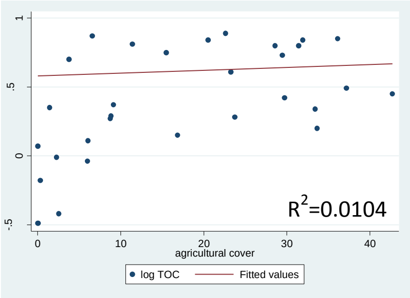

R^2=0.3374
forest cover 300
log TOC
Fitted values

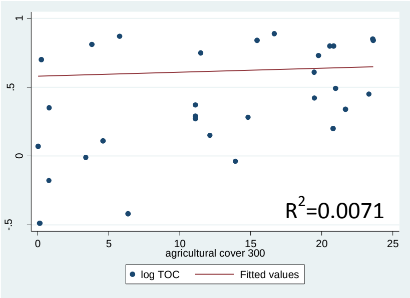

R^2=0.2043
forest cover 100
log TOC
Fitted values

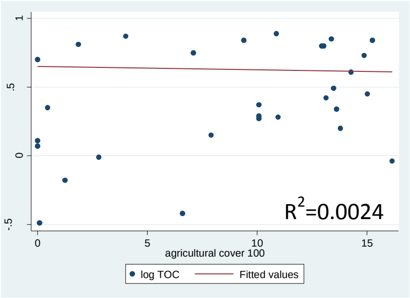

R^2=0.1894
impervious cover
log TOC
Fitted values


R^2=0.0938
impervious cover 300
log TOC
Fitted values


R^2=0.0196
impervious cover 100
log TOC
Fitted values


R^2=0.0104
agricultural cover
log TOC
Fitted values


R^2=0.0071
agricultural cover 300
log TOC
Fitted values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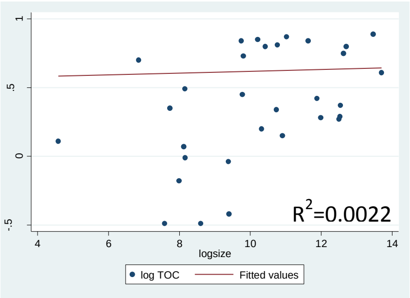
agricultural cover 100
log TOC
Fitted values


R^2=0.0022
logsize
log TOC
Fitted values

APPENDIX III: HYDROLOGIC GEO-PROCESSING MODEL SCRIPTS

Watershed ID # 1

```
# -*- coding: utf-8 -*-
# ---------------------------------------------------------------------------
# Hydrologic.py
# Created on: 2013-02-12 13:44:28.00000
#   (generated by ArcGIS/ModelBuilder)
# Description:
# ---------------------------------------------------------------------------

# Import arcpy module
import arcpy

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")


# Local variables:
Plants_selection = "Plants selection"
West_36_84__2_ = "West_36_84"
west_fill = "C:\\WorkSpace\\DEMS\\Projected_Rasters\\west_fill"
flow_dirwest = "C:\\WorkSpace\\DEMS\\Projected_Rasters\\flow_dirwest"
Output_drop_raster = ""
flow_acc_w = "C:\\WorkSpace\\DEMS\\Projected_Rasters\\flow_acc_w"
snap_point = "C:\\WorkSpace\\DEMS\\Projected_Rasters\\snap_point"
WS_1_1 = "C:\\WorkSpace\\DEMS\\Projected_Rasters\\ws_1_1"

# Process: Fill
arcpy.gp.Fill_sa(West_36_84__2_, west_fill, "")

# Process: Flow Direction
arcpy.gp.FlowDirection_sa(west_fill, flow_dirwest, "NORMAL", Output_drop_raster)

# Process: Flow Accumulation
arcpy.gp.FlowAccumulation_sa(flow_dirwest, flow_acc_w, "", "INTEGER")

# Process: Snap Pour Point
arcpy.gp.SnapPourPoint_sa(Plants_selection, flow_acc_w, snap_point, "0", "Id")

# Process: Watershed
arcpy.gp.Watershed_sa(flow_dirwest, snap_point, WS_1_1, "VALUE")
```

Watershed ID # 18, 9, 6, 32, 7, 8

```
# -*- coding: utf-8 -*-
# ---------------------------------------------------------------------------
# 1.py
# Created on: 2013-02-12 13:46:29.00000
```

```
#   (generated by ArcGIS/ModelBuilder)
# Description:
# ---------------------------------------------------------------------------

# Import arcpy module
import arcpy

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")

# Set Geoprocessing environments
arcpy.env.outputCoordinateSystem = "PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_American_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAMETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]"
arcpy.env.snapRaster = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\December_02\\Dec_02_WS\\extract_10"
arcpy.env.extent = "cb100_07 selection 4"
arcpy.env.cellSize = "30"
arcpy.env.geographicTransformations = ""
arcpy.env.mask = "cb100_07 selection 4"


# Local variables:
all_rasters2 = "all_rasters2"
cb100_07_selection = "cb100_07 selection"
Plants_selection = "Plants selection"
all_rasters2__2_ = "all_rasters2"
cb100_07_selection_2 = "cb100_07 selection 2"
Plants_selection_2 = "Plants selection 2"
Plants_selection_3 = "Plants selection 3"
Plants_selection_3__2_ = "Plants selection 3"
Plants_selection_4 = "Plants selection 4"
all_rasters2__3_ = "all_rasters2"
cb100_07_selection_4 = "cb100_07 selection 4"
all_rasters2__4_ = "all_rasters2"
Plants_selection_5 = "Plants selection 5"
Plants_selection_5__2_ = "Plants selection 5"
Plants_selection_6 = "Plants selection 6"
Plants_selection_7 = "Plants selection 7"
Plants_selection_5__3_ = "Plants selection 5"
Plants_selection_6__2_ = "Plants selection 6"
Plants_selection_7__2_ = "Plants selection 7"
Plants_selection_8 = "Plants selection 8"
extract_6 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\December_02\\Dec_02_WS\\extract_6"
ext_6proj = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_6proj"
ext_6fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_6fill"
ext_6fdir = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_6fdir"
Output_drop_raster = ""
ext_6facc = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_6facc"
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snp_6_32 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_6_32"
ws_6_32 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_6_32"
extract_7_8 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\extract_7_8"
ext_7_8proj = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_7_8proj"
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ext_7_8fdir = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_7_8fdir"
Output_drop_raster__2_ = ""
ext_7_8facc = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_7_8facc"
snp_7_8 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_7_8"
ws_7_8 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_7_8"
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snp_8 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_8"
ws_8 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_8"
extract_10 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\extract_10"
ext_10proj = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_10proj"
ext_10fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_10fill"
ext_10fdir = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_10fdir"
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ext_10facc = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_10facc"
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snp_11 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_11"
ws_11 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_11"
snp_18 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_18"
ws_18 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_18"

# Process: Extract by Mask
arcpy.gp.ExtractByMask_sa(all_rasters2, cb100_07_selection, extract_6)

# Process: Project Raster
arcpy.ProjectRaster_management(extract_6, ext_6proj, "PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_American_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAMETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]", "NEAREST", "30", "", "",
```

```
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]")

# Process: Fill
arcpy.gp.Fill_sa(ext_6proj, ext_6fill, "")

# Process: Flow Direction
arcpy.gp.FlowDirection_sa(ext_6fill, ext_6fdir, "NORMAL", Output_drop_raster)

# Process: Flow Accumulation
arcpy.gp.FlowAccumulation_sa(ext_6fdir, ext_6facc, "", "INTEGER")

# Process: Snap Pour Point
arcpy.gp.SnapPourPoint_sa(Plants_selection, ext_6facc, snp_6_32, "150", "Id")

# Process: Watershed
arcpy.gp.Watershed_sa(ext_6fdir, snp_6_32, ws_6_32, "VALUE")

# Process: Extract by Mask (2)
arcpy.gp.ExtractByMask_sa(all_rasters2__2_, cb100_07_selection_2, extract_7_8)

# Process: Project Raster (2)
arcpy.ProjectRaster_management(extract_7_8, ext_7_8proj,
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]", "NEAREST", "30", "", "",
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]")

# Process: Fill (2)
arcpy.gp.Fill_sa(ext_7_8proj, ext_7_8fill, "")

# Process: Flow Direction (2)
arcpy.gp.FlowDirection_sa(ext_7_8fill, ext_7_8fdir, "NORMAL", Output_drop_raster__2_)

# Process: Flow Accumulation (2)
arcpy.gp.FlowAccumulation_sa(ext_7_8fdir, ext_7_8facc, "", "INTEGER")

# Process: Snap Pour Point (2)
arcpy.gp.SnapPourPoint_sa(Plants_selection_2, ext_7_8facc, snp_7_8, "150", "Id")

# Process: Watershed (2)
arcpy.gp.Watershed_sa(ext_7_8fdir, snp_7_8, ws_7_8, "VALUE")

# Process: Snap Pour Point (3)
arcpy.gp.SnapPourPoint_sa(Plants_selection_3, ext_7_8facc, snp_9, "300", "Id")
```

```
# Process: Watershed (3)
arcpy.gp.Watershed_sa(ext_7_8fdir, snp_9, ws_9, "VALUE")

# Process: Snap Pour Point (4)
arcpy.gp.SnapPourPoint_sa(Plants_selection_4, ext_7_8facc, snp_8, "300", "Id")

# Process: Watershed (4)
arcpy.gp.Watershed_sa(ext_7_8fdir, snp_8, ws_8, "VALUE")

# Process: Extract by Mask (3)
arcpy.gp.ExtractByMask_sa(all_rasters2__4_, cb100_07_selection_4, extract_10)

# Process: Project Raster (3)
arcpy.ProjectRaster_management(extract_10, ext_10proj,
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]", "NEAREST", "30", "", "",
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]")

# Process: Fill (3)
arcpy.gp.Fill_sa(ext_10proj, ext_10fill, "")

# Process: Flow Direction (3)
arcpy.gp.FlowDirection_sa(ext_10fill, ext_10fdir, "NORMAL", Output_drop_raster__3_)

# Process: Flow Accumulation (3)
arcpy.gp.FlowAccumulation_sa(ext_10fdir, ext_10facc, "", "INTEGER")

# Process: Snap Pour Point (5)
arcpy.gp.SnapPourPoint_sa(Plants_selection_5, ext_10facc, snp_10, "350", "Id")

# Process: Watershed (5)
arcpy.gp.Watershed_sa(ext_10fdir, snp_10, ws_10, "VALUE")

# Process: Snap Pour Point (6)
arcpy.gp.SnapPourPoint_sa(Plants_selection_7, ext_10facc, snp_11, "350", "Id")

# Process: Watershed (6)
arcpy.gp.Watershed_sa(ext_10fdir, snp_11, ws_11, "VALUE")

# Process: Snap Pour Point (7)
arcpy.gp.SnapPourPoint_sa(Plants_selection_8, ext_10facc, snp_18, "350", "Id")

# Process: Watershed (7)
arcpy.gp.Watershed_sa(ext_10fdir, snp_18, ws_18, "VALUE")
```

Watershed ID # 24, 14

```
# -*- coding: utf-8 -*-
# ---------------------------------------------------------------------------
# 2.py
# Created on: 2013-02-12 13:46:40.00000
#   (generated by ArcGIS/ModelBuilder)
# Description:
# ---------------------------------------------------------------------------

# Import arcpy module
import arcpy

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")

# Set Geoprocessing environments
arcpy.env.outputCoordinateSystem = ""
arcpy.env.snapRaster = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\Users\\fh41\\Documents\\ArcGIS\\Default.gdb\\Extract_all_1"
arcpy.env.extent = "cb100_07 selection 5"
arcpy.env.cellSize = "30"
arcpy.env.geographicTransformations = ""
arcpy.env.mask = "cb100_07 selection 5"


# Local variables:
all_rasters2 = "all_rasters2"
cb100_07_selection_3 = "cb100_07 selection 3"
Plants_selection_9 = "Plants selection 9"
Plants_selection_10 = "Plants selection 10"
all_rasters2__2_ = "all_rasters2"
cb100_07_selection_5 = "cb100_07 selection 5"
Plants_selection_12 = "Plants selection 12"
Plants_selection_13 = "Plants selection 13"
Plants_selection_14 = "Plants selection 14"
ext_19 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_19"
ext_19prj = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_19prj"
ext_19fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_19fill"
ext_19fdir = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_19fdir"
Output_drop_raster = ""
ext_19facc = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_19facc"
snp_19 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_19"
ws_19 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_19"
snp_24 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_24"
ws_24 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_24"
Extract_all_1 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\Users\\fh41\\Documents\\ArcGIS\\Default.gdb\\Extract_all_1"
```

```
ext_14prj = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_14prj"
ext_14fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_14fill"
ext_14fdir = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_14fdir"
Output_drop_raster__2_ = ""
ext_14facc = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_14facc"
snp_14 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_14"
ws_14 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_14"
snp_1 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_1"
ws_1 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_1"

# Process: Extract by Mask
arcpy.gp.ExtractByMask_sa(all_rasters2, cb100_07_selection_3, ext_19)

# Process: Project Raster
arcpy.ProjectRaster_management(ext_19, ext_19prj, "PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_American_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAMETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]", "NEAREST", "30", "", "", "PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_American_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAMETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]")

# Process: Fill
arcpy.gp.Fill_sa(ext_19prj, ext_19fill, "")

# Process: Flow Direction
arcpy.gp.FlowDirection_sa(ext_19fill, ext_19fdir, "NORMAL", Output_drop_raster)

# Process: Flow Accumulation
arcpy.gp.FlowAccumulation_sa(ext_19fdir, ext_19facc, "", "INTEGER")

# Process: Snap Pour Point
arcpy.gp.SnapPourPoint_sa(Plants_selection_9, ext_19facc, snp_19, "400", "Id")

# Process: Watershed
arcpy.gp.Watershed_sa(ext_19fdir, snp_19, ws_19, "VALUE")

# Process: Snap Pour Point (2)
arcpy.gp.SnapPourPoint_sa(Plants_selection_10, ext_19facc, snp_24, "400", "Id")

# Process: Watershed (2)
arcpy.gp.Watershed_sa(ext_19fdir, snp_24, ws_24, "VALUE")

# Process: Extract by Mask (2)
arcpy.gp.ExtractByMask_sa(all_rasters2__2_, cb100_07_selection_5, Extract_all_1)
```

```
# Process: Project Raster (2)
arcpy.ProjectRaster_management(Extract_all_1, ext_14prj,
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]", "NEAREST", "30", "", "",
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]")

# Process: Fill (2)
arcpy.gp.Fill_sa(ext_14prj, ext_14fill, "")

# Process: Flow Direction (2)
arcpy.gp.FlowDirection_sa(ext_14fill, ext_14fdir, "NORMAL", Output_drop_raster__2_)

# Process: Flow Accumulation (2)
arcpy.gp.FlowAccumulation_sa(ext_14fdir, ext_14facc, "", "INTEGER")

# Process: Snap Pour Point (3)
arcpy.gp.SnapPourPoint_sa(Plants_selection_12, ext_14facc, snp_14, "400", "Id")

# Process: Watershed (3)
arcpy.gp.Watershed_sa(ext_14fdir, snp_14, ws_14, "VALUE")

# Process: Snap Pour Point (4)
arcpy.gp.SnapPourPoint_sa(Plants_selection_14, ext_14facc, snp_1, "400", "Id")

# Process: Watershed (4)
arcpy.gp.Watershed_sa(ext_14fdir, snp_1, ws_1, "VALUE")
```

Watershed ID # 2, 11, 21, 12, 4

```
# -*- coding: utf-8 -*-
# ---------------------------------------------------------------------------
# 3.py
# Created on: 2013-02-12 13:46:57.00000
#   (generated by ArcGIS/ModelBuilder)
# Description:
# ---------------------------------------------------------------------------

# Import arcpy module
import arcpy

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")

# Set Geoprocessing environments
arcpy.env.outputCoordinateSystem =
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
```

```
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]"
arcpy.env.snapRaster = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_4_1"
arcpy.env.extent = "124002.673 10664.688 930397.63425 318097.6925"
arcpy.env.cellSize = "30"
arcpy.env.geographicTransformations = ""
arcpy.env.mask = "cb100_07 selection"


# Local variables:
all_rasters2 = "all_rasters2"
cb100_07_selection = "cb100_07 selection"
Plants_selection = "Plants selection"
Plants_selection_2 = "Plants selection 2"
Plants_selection_3 = "Plants selection 3"
Plants_selection_3__2_ = "Plants selection 3"
all_rasters2__2_ = "all_rasters2"
cb100_07_selection__2_ = "cb100_07 selection"
Plants_selection__2_ = "Plants selection"
cb100_07_selection__3_ = "cb100_07 selection"
Plants_selection__3_ = "Plants selection"
extract_1 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\extract_1"
ext_1prj = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_1prj"
ext_1fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_1fill"
ext_1fdir = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_1fdir"
Output_drop_raster = ""
ext_1facc = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_1facc"
snp_1_1 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_1_1"
ws_11_2 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_11_2"
snp_12 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_12"
ws_12 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_12"
snp_21 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_21"
ws_21 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_21"
ext_4 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_4"
ext_4prj = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_4prj"
ext_4fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_4fill"
ext_4fdir = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_4fdir"
Output_drop_raster__2_ = ""
ext_4facc = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_4facc"
snp_4 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_4"
ws_4 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_4"
```

```
ext_4_1 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_4_1"
ext_4_1prj = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_4_1prj"
ext_4_1fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_4_1fill"
ext_4_1fdir = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_4_1fdir"
Output_drop_raster__3_ = ""
ext_4_1facc = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ext_4_1facc"
snp_4_1 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\snp_4_1"
ws_4_1 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project- CWMTF\\DEMS\\December_02\\Dec_02_WS\\ws_4_1"

# Process: Extract by Mask
arcpy.gp.ExtractByMask_sa(all_rasters2, cb100_07_selection, extract_1)

# Process: Project Raster
arcpy.ProjectRaster_management(extract_1, ext_1prj, "PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_American_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAMETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]", "NEAREST", "30", "", "", "PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_American_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAMETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]")

# Process: Fill
arcpy.gp.Fill_sa(ext_1prj, ext_1fill, "")

# Process: Flow Direction
arcpy.gp.FlowDirection_sa(ext_1fill, ext_1fdir, "NORMAL", Output_drop_raster)

# Process: Flow Accumulation
arcpy.gp.FlowAccumulation_sa(ext_1fdir, ext_1facc, "", "INTEGER")

# Process: Snap Pour Point
arcpy.gp.SnapPourPoint_sa(Plants_selection, ext_1facc, snp_1_1, "300", "Id")

# Process: Watershed
arcpy.gp.Watershed_sa(ext_1fdir, snp_1_1, ws_11_2, "VALUE")

# Process: Snap Pour Point (2)
arcpy.gp.SnapPourPoint_sa(Plants_selection_2, ext_1facc, snp_12, "500", "Id")

# Process: Watershed (2)
arcpy.gp.Watershed_sa(ext_1fdir, snp_12, ws_12, "VALUE")

# Process: Snap Pour Point (3)
arcpy.gp.SnapPourPoint_sa(Plants_selection_3__2_, ext_1facc, snp_21, "500", "Id")
```

```
# Process: Watershed (3)
arcpy.gp.Watershed_sa(ext_1fdir, snp_21, ws_21, "VALUE")

# Process: Extract by Mask (2)
arcpy.gp.ExtractByMask_sa(all_rasters2__2_, cb100_07_selection__2_, ext_4)

# Process: Project Raster (2)
arcpy.ProjectRaster_management(ext_4, ext_4prj,
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]", "NEAREST", "30", "", "",
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]")

# Process: Fill (2)
arcpy.gp.Fill_sa(ext_4prj, ext_4fill, "")

# Process: Flow Direction (2)
arcpy.gp.FlowDirection_sa(ext_4fill, ext_4fdir, "NORMAL", Output_drop_raster__2_)

# Process: Flow Accumulation (2)
arcpy.gp.FlowAccumulation_sa(ext_4fdir, ext_4facc, "", "INTEGER")

# Process: Snap Pour Point (4)
arcpy.gp.SnapPourPoint_sa(Plants_selection__2_, ext_4facc, snp_4, "500", "Id")

# Process: Watershed (4)
arcpy.gp.Watershed_sa(ext_4fdir, snp_4, ws_4, "VALUE")

# Process: Extract by Mask (3)
arcpy.gp.ExtractByMask_sa(all_rasters2__2_, cb100_07_selection__3_, ext_4_1)

# Process: Project Raster (3)
arcpy.ProjectRaster_management(ext_4_1, ext_4_1prj,
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]", "NEAREST", "30", "", "",
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]")

# Process: Fill (3)
arcpy.gp.Fill_sa(ext_4_1prj, ext_4_1fill, "")

# Process: Flow Direction (3)
```

```
arcpy.gp.FlowDirection_sa(ext_4_1fill, ext_4_1fdir, "NORMAL", Output_drop_raster__3_)

# Process: Flow Accumulation (3)
arcpy.gp.FlowAccumulation_sa(ext_4_1fdir, ext_4_1facc, "", "INTEGER")

# Process: Snap Pour Point (5)
arcpy.gp.SnapPourPoint_sa(Plants_selection__3_, ext_4_1facc, snp_4_1, "500", "Id")

# Process: Watershed (5)
arcpy.gp.Watershed_sa(ext_4_1fdir, snp_4_1, ws_4_1, "VALUE")
```

Watershed ID # 10, 11, 12, 13, 14, 15

```
# -*- coding: utf-8 -*-
# ---------------------------------------------------------------------------
# 4.py
# Created on: 2013-02-12 13:47:17.00000
#   (generated by ArcGIS/ModelBuilder)
# Description:
# ---------------------------------------------------------------------------

# Import arcpy module
import arcpy

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\Users\\fh41\\Documents\\ArcGIS\\Default.gdb"
arcpy.env.outputCoordinateSystem = "PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_American_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAMETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]"
arcpy.env.snapRaster = "grdn37w078_1"
arcpy.env.extent = "-78.00166666667 35.99833333333 -76.9983333333359 37.0016666666641"
arcpy.env.cellSize = "30"
arcpy.env.geographicTransformations = ""
arcpy.env.mask = "grdn37w078_1"
arcpy.env.workspace = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\Users\\fh41\\Documents\\ArcGIS\\Default.gdb"


# Local variables:
v37_80_prj = "37_80_prj"
Plants_selection = "Plants selection"
e_35_80_prj = "e_35_80_prj"
Plants_selection_2 = "Plants selection 2"
e_36_79_prj = "e_36_79_prj"
Plants_selection_3 = "Plants selection 3"
e_36_80_prj = "e_36_80_prj"
Plants_selection_4 = "Plants selection 4"
e_37_79_prj = "e_37_79_prj"
Plants_selection_5 = "Plants selection 5"
```

```
e_37_78_prj = "e_37_78_prj"
Plants_selection_6 = "Plants selection 6"
v37_80_fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\37_80_fill"
flowdir_37_80 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowdir_37_80"
Output_drop_raster = ""
flowacc_37_80 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowacc_37_80"
snp_10 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\snp_10"
watershed_10 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Watersheds\\watershed_10"
v35_80_fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\35_80_fill"
flowdir_35_80 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowdir_35_80"
Output_drop_raster__2_ = ""
flowacc_35_80 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowacc_35_80"
snp_11 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\snp_11"
watershed_11 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Watersheds\\watershed_11"
v36_79_fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\36_79_fill"
flowdir_36_79 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowdir_36_79"
Output_drop_raster__3_ = ""
flowacc_36_79 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowacc_36_79"
snp_12 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\snp_12"
watershed_12 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Watersheds\\watershed_12"
v36_80_fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\36_80_fill"
flowdir_36_80 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowdir_36_80"
Output_drop_raster__4_ = ""
flowacc_36_80 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowacc_36_80"
snp_13 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\snp_13"
watershed_13 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Watersheds\\watershed_13"
v37_79_fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\37_79_fill"
flowdir_37_79 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowdir_37_79"
Output_drop_raster__5_ = ""
flowacc_37_79 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowacc_37_79"
snp_14 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\snp_14"
watershed_14 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Watersheds\\watershed_14"
```

```
fill_test = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\fill_test"
flowdir_37_78 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowdir_37_78"
Output_drop_raster__6_ = ""
flowacc_37_78 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\flowacc_37_78"
snp_15 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\Dec_01_Mosaic\\Hydro_analysis\\snp_15"
watershed_15 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\Dec_01_Mosaic\\Watersheds\\watershed_15"

# Process: Fill
arcpy.gp.Fill_sa(v37_80_prj, v37_80_fill, "")

# Process: Flow Direction
arcpy.gp.FlowDirection_sa(v37_80_fill, flowdir_37_80, "NORMAL", Output_drop_raster)

# Process: Flow Accumulation
arcpy.gp.FlowAccumulation_sa(flowdir_37_80, flowacc_37_80, "", "INTEGER")

# Process: Snap Pour Point
arcpy.gp.SnapPourPoint_sa(Plants_selection, flowacc_37_80, snp_10, "150", "Id")

# Process: Watershed
arcpy.gp.Watershed_sa(flowdir_37_80, snp_10, watershed_10, "VALUE")

# Process: Fill (2)
arcpy.gp.Fill_sa(e_35_80_prj, v35_80_fill, "")

# Process: Flow Direction (2)
arcpy.gp.FlowDirection_sa(v35_80_fill, flowdir_35_80, "NORMAL", Output_drop_raster__2_)

# Process: Flow Accumulation (2)
arcpy.gp.FlowAccumulation_sa(flowdir_35_80, flowacc_35_80, "", "INTEGER")

# Process: Snap Pour Point (2)
arcpy.gp.SnapPourPoint_sa(Plants_selection_2, flowacc_35_80, snp_11, "150", "Id")

# Process: Watershed (2)
arcpy.gp.Watershed_sa(flowdir_35_80, snp_11, watershed_11, "VALUE")

# Process: Fill (3)
arcpy.gp.Fill_sa(e_36_79_prj, v36_79_fill, "")

# Process: Flow Direction (3)
arcpy.gp.FlowDirection_sa(v36_79_fill, flowdir_36_79, "NORMAL", Output_drop_raster__3_)

# Process: Flow Accumulation (3)
arcpy.gp.FlowAccumulation_sa(flowdir_36_79, flowacc_36_79, "", "INTEGER")

# Process: Snap Pour Point (3)
arcpy.gp.SnapPourPoint_sa(Plants_selection_3, flowacc_36_79, snp_12, "150", "Id")

# Process: Watershed (3)
arcpy.gp.Watershed_sa(flowdir_36_79, snp_12, watershed_12, "VALUE")

# Process: Fill (4)
```

```
arcpy.gp.Fill_sa(e_36_80_prj, v36_80_fill, "")

# Process: Flow Direction (4)
arcpy.gp.FlowDirection_sa(v36_80_fill, flowdir_36_80, "NORMAL", Output_drop_raster__4_)

# Process: Flow Accumulation (4)
arcpy.gp.FlowAccumulation_sa(flowdir_36_80, flowacc_36_80, "", "INTEGER")

# Process: Snap Pour Point (4)
arcpy.gp.SnapPourPoint_sa(Plants_selection_4, flowacc_36_80, snp_13, "150", "Id")

# Process: Watershed (4)
arcpy.gp.Watershed_sa(flowdir_36_80, snp_13, watershed_13, "VALUE")

# Process: Fill (5)
arcpy.gp.Fill_sa(e_37_79_prj, v37_79_fill, "")

# Process: Flow Direction (5)
arcpy.gp.FlowDirection_sa(v37_79_fill, flowdir_37_79, "NORMAL", Output_drop_raster__5_)

# Process: Flow Accumulation (5)
arcpy.gp.FlowAccumulation_sa(flowdir_37_79, flowacc_37_79, "", "INTEGER")

# Process: Snap Pour Point (5)
arcpy.gp.SnapPourPoint_sa(Plants_selection_5, flowacc_37_79, snp_14, "150", "Id")

# Process: Watershed (5)
arcpy.gp.Watershed_sa(flowdir_37_79, snp_14, watershed_14, "VALUE")

# Process: Fill (6)
arcpy.gp.Fill_sa(e_37_78_prj, fill_test, "")

# Process: Flow Direction (6)
arcpy.gp.FlowDirection_sa(fill_test, flowdir_37_78, "NORMAL", Output_drop_raster__6_)

# Process: Flow Accumulation (6)
arcpy.gp.FlowAccumulation_sa(flowdir_37_78, flowacc_37_78, "", "INTEGER")

# Process: Snap Pour Point (6)
arcpy.gp.SnapPourPoint_sa(Plants_selection_6, flowacc_37_78, snp_15, "150", "Id")

# Process: Watershed (6)
arcpy.gp.Watershed_sa(flowdir_37_78, snp_15, watershed_15, "VALUE")
```

Watershed ID # 23, 9

```
# -*- coding: utf-8 -*-
# ---------------------------------------------------------------------------
# 5.py
# Created on: 2013-02-12 13:47:38.00000
#   (generated by ArcGIS/ModelBuilder)
# Description:
# ---------------------------------------------------------------------------

# Import arcpy module
import arcpy
```

```
# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\Users\\fh41\\Documents\\ArcGIS\\Default.gdb"
arcpy.env.outputCoordinateSystem =
"PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_America
n_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],P
ROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETE
R['Central_Meridian',-
79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAM
ETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]"
arcpy.env.snapRaster = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\extract_7"
arcpy.env.extent = "cb100_07 selection 2"
arcpy.env.cellSize = "All_rasters2"
arcpy.env.geographicTransformations = ""
arcpy.env.mask = "cb100_07 selection 2"
arcpy.env.workspace = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\Users\\fh41\\Documents\\ArcGIS\\Default.gdb"


# Local variables:
All_rasters2 = "All_rasters2"
cb100_07_selection = "cb100_07 selection"
Plants_selection = "Plants selection"
All_rasters2__2_ = "All_rasters2"
cb100_07_selection_2 = "cb100_07 selection 2"
Plants_selection__2_ = "Plants selection"
Plants_selection_selection = "Plants selection selection"
ext_id23 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\Watersheds\\ext_id23"
id23_prj = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\id23_prj"
id23_fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\id23_fill"
id23_fdir = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\id23_fdir"
Output_drop_raster = ""
id23_facc = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\id23_facc"
snp_23 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\snp_23"
ws_id23 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\ws_id23"
extract_7 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\extract_7"
extract_7_ProjectRaster = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\Users\\fh41\\Documents\\ArcGIS\\Default.gdb\\extract_7_ProjectRaster"
id7_9_fill = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\id7_9_fill"
id7_9fdir = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\id7_9fdir"
Output_drop_raster__2_ = ""
id7_9facc = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-
CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\id7_9facc"
```

```
snp_9 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\snp_9"
ws_id9 = "Y:\\MP_CWMTF\\Master's Project- CWMTF\\Master's Project-CWMTF\\DEMS\\Dec_01_Mosaic\\WS_hydro_analysis\\ws_id9"

# Process: Extract by Mask
arcpy.gp.ExtractByMask_sa(All_rasters2, cb100_07_selection, ext_id23)

# Process: Project Raster
arcpy.ProjectRaster_management(ext_id23, id23_prj, "PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_American_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAMETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]", "NEAREST", "30", "", "", "PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_American_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAMETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]")

# Process: Fill
arcpy.gp.Fill_sa(id23_prj, id23_fill, "")

# Process: Flow Direction
arcpy.gp.FlowDirection_sa(id23_fill, id23_fdir, "NORMAL", Output_drop_raster)

# Process: Flow Accumulation
arcpy.gp.FlowAccumulation_sa(id23_fdir, id23_facc, "", "INTEGER")

# Process: Snap Pour Point
arcpy.gp.SnapPourPoint_sa(Plants_selection, id23_facc, snp_23, "90", "Id")

# Process: Watershed
arcpy.gp.Watershed_sa(id23_fdir, snp_23, ws_id23, "VALUE")

# Process: Extract by Mask (2)
arcpy.gp.ExtractByMask_sa(All_rasters2__2_, cb100_07_selection_2, extract_7)

# Process: Project Raster (2)
arcpy.ProjectRaster_management(extract_7, extract_7_ProjectRaster, "PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_American_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAMETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]", "NEAREST", "30", "", "", "PROJCS['NAD_1983_StatePlane_North_Carolina_FIPS_3200',GEOGCS['GCS_North_American_1983',DATUM['D_North_American_1983',SPHEROID['GRS_1980',6378137.0,298.257222101]],PRIMEM['Greenwich',0.0],UNIT['Degree',0.0174532925199433]],PROJECTION['Lambert_Conformal_Conic'],PARAMETER['False_Easting',609601.22],PARAMETER['False_Northing',0.0],PARAMETER['Central_Meridian',-79.0],PARAMETER['Standard_Parallel_1',34.33333333333334],PARAMETER['Standard_Parallel_2',36.16666666666666],PARAMETER['Latitude_Of_Origin',33.75],UNIT['Meter',1.0]]")

# Process: Fill (2)
arcpy.gp.Fill_sa(extract_7_ProjectRaster, id7_9_fill, "")
```

```
# Process: Flow Direction (2)
arcpy.gp.FlowDirection_sa(id7_9_fill, id7_9fdir, "NORMAL", Output_drop_raster__2_)

# Process: Flow Accumulation (2)
arcpy.gp.FlowAccumulation_sa(id7_9fdir, id7_9facc, "", "INTEGER")

# Process: Snap Pour Point (2)
arcpy.gp.SnapPourPoint_sa(Plants_selection_selection, id7_9facc, snp_9, "300", "Id")

# Process: Watershed (2)
arcpy.gp.Watershed_sa(id7_9fdir, snp_9, ws_id9, "VALUE")
```

APPENDIX IV: STATA OUTPUTS

(a) Correlations between explanatory variables

```
. corr watershedsize forestcover imperviousness agriculturalcover
(obs=31)

             | water~ze forest~r imperv~s agricu~r
-------------+------------------------------------
watersheds~e |   1.0000
 forestcover |  -0.2217   1.0000
impervious~s |   0.3074  -0.6284   1.0000
agricultur~r |   0.1363  -0.7595   0.1585   1.0000


. corr watershedsize forestcover300 imperviousness300 agriculturalcover300
(obs=31)

             | water~ze fore~300 impe~300 agri~300
-------------+------------------------------------
watersheds~e |   1.0000
forestco~300 |  -0.2351   1.0000
impervio~300 |   0.3068  -0.6672   1.0000
agricult~300 |   0.2650  -0.4092   0.0620   1.0000


. corr watershedsize forestcover100 imperviousness100 agriculturalcover100
(obs=31)

             | water~ze fore~100 impe~100 agri~100
-------------+------------------------------------
watersheds~e |   1.0000
forestco~100 |  -0.1747   1.0000
impervio~100 |   0.2331  -0.6008   1.0000
agricult~100 |   0.3001  -0.1245  -0.0727   1.0000


. corr forestcover forestcover300 forestcover100
(obs=31)

             | forest~r fore~300 fore~100
-------------+---------------------------
 forestcover |   1.0000
forestco~300 |   0.9013   1.0000
forestco~100 |   0.7628   0.9440   1.0000


. corr imperviousness imperviousness300 imperviousness100
(obs=31)

             | imperv~s impe~300 impe~100
-------------+---------------------------
impervious~s |   1.0000
impervio~300 |   0.9077   1.0000
impervio~100 |   0.8219   0.9452   1.0000

. corr agriculturalcover agriculturalcover300 agriculturalcover100
(obs=31)

             | agricu~r agri~300 agri~100
-------------+---------------------------
agricultur~r |   1.0000
agricult~300 |   0.9426   1.0000
agricult~100 |   0.8194   0.9500   1.0000
```

(b) Examination of possible transformations for all variables

```
. ladder turbidity

Transformation         formula               chi2(2)       P(chi2)
------------------------------------------------------------------
cubic                  turbid~y^3             33.77         0.000
square                 turbid~y^2             28.12         0.000
identity               turbid~y               13.73         0.001
square root            sqrt(turbid~y)          3.57         0.168
log                    log(turbid~y)           1.14         0.565
1/(square root)        1/sqrt(turbid~y)       11.15         0.004
inverse                1/turbid~y             24.85         0.000
1/square               1/(turbid~y^2)         41.46         0.000
1/cubic                1/(turbid~y^3)         46.76         0.000


. ladder toc

Transformation         formula               chi2(2)       P(chi2)
------------------------------------------------------------------
cubic                  toc^3                   6.41         0.041
square                 toc^2                   5.41         0.067
identity               toc                     8.58         0.014
square root            sqrt(toc)               8.12         0.017
log                    log(toc)                2.04         0.360
1/(square root)        1/sqrt(toc)             8.39         0.015
inverse                1/toc                  19.16         0.000
1/square               1/(toc^2)              32.08         0.000
1/cubic                1/(toc^3)              37.64         0.000


. ladder watershedsize

Transformation         formula               chi2(2)       P(chi2)
------------------------------------------------------------------
cubic                  waters~e^3             39.78         0.000
square                 waters~e^2             35.42         0.000
identity               waters~e               22.66         0.000
square root            sqrt(waters~e)          8.57         0.014
log                    log(waters~e)           1.33         0.514
1/(square root)        1/sqrt(waters~e)       39.02         0.000
inverse                1/waters~e             47.76         0.000
1/square               1/(waters~e^2)         48.53         0.000
1/cubic                1/(waters~e^3)         48.53         0.000


. ladder forestcover

Transformation         formula               chi2(2)       P(chi2)
------------------------------------------------------------------
cubic                  forest~r^3              5.48         0.065
square                 forest~r^2              5.66         0.059
identity               forest~r                6.93         0.031
square root            sqrt(forest~r)          7.78         0.020
log                    log(forest~r)           8.39         0.015
1/(square root)        1/sqrt(forest~r)        8.31         0.016
inverse                1/forest~r              7.26         0.027
1/square               1/(forest~r^2)          3.23         0.199
1/cubic                1/(forest~r^3)          1.53         0.466
```

. ladder forestcover300

Transformation	formula	chi2(2)	P(chi2)
cubic	fore~300^3	8.36	0.015
square	fore~300^2	5.50	0.064
identity	fore~300	2.36	0.308
square root	sqrt(fore~300)	0.86	0.649
log	log(fore~300)	0.05	0.976
1/(square root)	1/sqrt(fore~300)	0.57	0.753
inverse	1/fore~300	3.45	0.178
1/square	1/(fore~300^2)	11.57	0.003
1/cubic	1/(fore~300^3)	21.00	0.000

. ladder forestcover100

Transformation	formula	chi2(2)	P(chi2)
cubic	fore~100^3	6.44	0.040
square	fore~100^2	1.94	0.379
identity	fore~100	1.41	0.493
square root	sqrt(fore~100)	5.25	0.073
log	log(fore~100)	9.99	0.007
1/(square root)	1/sqrt(fore~100)	15.29	0.000
inverse	1/fore~100	20.43	0.000
1/square	1/(fore~100^2)	29.03	0.000
1/cubic	1/(fore~100^3)	35.26	0.000

. ladder imperviouscover

Transformation	formula	chi2(2)	P(chi2)
cubic	imperv~r^3	29.40	0.000
square	imperv~r^2	19.42	0.000
identity	imperv~r	6.48	0.039
square root	sqrt(imperv~r)	2.28	0.320
log	log(imperv~r)	.	.
1/(square root)	1/sqrt(imperv~r)	.	.
inverse	1/imperv~r	.	.
1/square	1/(imperv~r^2)	.	.
1/cubic	1/(imperv~r^3)	.	.

. ladder imperviouscover300

Transformation	formula	chi2(2)	P(chi2)
cubic	impe~300^3	18.62	0.000
square	impe~300^2	11.48	0.003
identity	impe~300	4.25	0.119
square root	sqrt(impe~300)	3.89	0.143
log	log(impe~300)	.	.
1/(square root)	1/sqrt(impe~300)	.	.
inverse	1/impe~300	.	.
1/square	1/(impe~300^2)	.	.
1/cubic	1/(impe~300^3)	.	.

. ladder imperviouscover100

Transformation	formula	chi2(2)	P(chi2)
cubic	impe~100^3	16.41	0.000
square	impe~100^2	8.38	0.015
identity	impe~100	4.76	0.092
square root	sqrt(impe~100)	4.94	0.084
log	log(impe~100)	.	.
1/(square root)	1/sqrt(impe~100)	.	.
inverse	1/impe~100	.	.
1/square	1/(impe~100^2)	.	.
1/cubic	1/(impe~100^3)	.	.

. ladder agriculturalcover

Transformation	formula	chi2(2)	P(chi2)
cubic	agricu~r^3	11.33	0.003
square	agricu~r^2	4.59	0.101
identity	agricu~r	9.24	0.010
square root	sqrt(agricu~r)	5.56	0.062
log	log(agricu~r)	13.24	0.001
1/(square root)	1/sqrt(agricu~r)	25.18	0.000
inverse	1/agricu~r	28.83	0.000
1/square	1/(agricu~r^2)	32.15	0.000
1/cubic	1/(agricu~r^3)	33.21	0.000

. ladder agriculturalcover300

Transformation	formula	chi2(2)	P(chi2)
cubic	agri~300^3	5.13	0.077
square	agri~300^2	9.15	0.010
identity	agri~300	10.59	0.005
square root	sqrt(agri~300)	4.76	0.092
log	log(agri~300)	11.48	0.003
1/(square root)	1/sqrt(agri~300)	31.45	0.000
inverse	1/agri~300	44.12	0.000
1/square	1/(agri~300^2)	48.34	0.000
1/cubic	1/(agri~300^3)	48.53	0.000

. ladder agriculturalcover100

Transformation	formula	chi2(2)	P(chi2)
cubic	agri~100^3	4.91	0.086
square	agri~100^2	10.32	0.006
identity	agri~100	10.38	0.006
square root	sqrt(agri~100)	5.29	0.071
log	log(agri~100)	.	.
1/(square root)	1/sqrt(agri~100)	.	.
inverse	1/agri~100	.	.
1/square	1/(agri~100^2)	.	.
1/cubic	1/(agri~100^3)	.	.

(c) Simple linear regression models

```
. reg logturbidity forestcover [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =   14.56
                                                       Prob > F      =  0.0007
                                                       R-squared     =  0.3534
                                                       Root MSE      =  .40793

------------------------------------------------------------------------------
             |               Robust
logturbidity |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 forestcover |  -.0151011   .0039582    -3.82   0.001    -.0231965   -.0070058
       _cons |    1.62115   .2839793     5.71   0.000     1.040347    2.201953
------------------------------------------------------------------------------


. reg logturbidity forestcover300 [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    6.00
                                                       Prob > F      =  0.0206
                                                       R-squared     =  0.2016
                                                       Root MSE      =  .45329

--------------------------------------------------------------------------------
               |               Robust
  logturbidity |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
forestcover300 |  -.0140998    .005758    -2.45   0.021    -.0258763   -.0023233
         _cons |   1.571266   .4281234     3.67   0.001     .6956557    2.446877
--------------------------------------------------------------------------------


. reg logturbidity forestcover100 [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    1.59
                                                       Prob > F      =  0.2174
                                                       R-squared     =  0.0837
                                                       Root MSE      =  .48563

--------------------------------------------------------------------------------
               |               Robust
  logturbidity |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
forestcover100 |  -.0082388   .0065344    -1.26   0.217    -.0216032    .0051257
         _cons |   1.172592   .4738596     2.47   0.019     .2034408    2.141744
--------------------------------------------------------------------------------
```

```
. reg logturbidity imperviouscover [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    4.09
                                                       Prob > F      =  0.0526
                                                       R-squared     =  0.1459
                                                       Root MSE      =  .46883

------------------------------------------------------------------------------
                |               Robust
   logturbidity |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
imperviouscover |   .0478077   .0236517     2.02   0.053    -.0005654    .0961808
          _cons |   .4280547    .126843     3.37   0.002     .1686315    .6874778
------------------------------------------------------------------------------


. reg logturbidity imperviouscover300 [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    3.25
                                                       Prob > F      =  0.0820
                                                       R-squared     =  0.0903
                                                       Root MSE      =  .48387

------------------------------------------------------------------------------
                |               Robust
   logturbidity |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
imperviousco~300 |   .0684754    .038011     1.80   0.082    -.0092659    .1462166
           _cons |    .433701   .1409197     3.08   0.005      .145488    .7219141
------------------------------------------------------------------------------


. reg logturbidity imperviouscover100 [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    0.26
                                                       Prob > F      =  0.6149
                                                       R-squared     =  0.0139
                                                       Root MSE      =  .50377

------------------------------------------------------------------------------
                |               Robust
   logturbidity |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
imperviousco~100 |   .0337497   .0663541     0.51   0.615    -.1019597     .169459
           _cons |   .5242637   .1607783     3.26   0.003     .1954352    .8530923
------------------------------------------------------------------------------
```

```
. reg logturbidity agriculturalcover [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =   25.96
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.4817
                                                       Root MSE      =  .36521

------------------------------------------------------------------------------
             |               Robust
logturbidity |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
agriculturalco~r |   .028587   .0056105     5.10   0.000     .0171122    .0400618
       _cons |   .2202624     .11134     1.98   0.057    -.0074536    .4479783
------------------------------------------------------------------------------


. reg logturbidity agriculturalcover300 [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =   49.69
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6371
                                                       Root MSE      =  .30559

------------------------------------------------------------------------------
             |               Robust
logturbidity |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
agricultural~300 |   .0506429   .0071845     7.05   0.000     .0359489    .0653369
       _cons |   .1109082   .0997445     1.11   0.275    -.0930923    .3149087
------------------------------------------------------------------------------

. reg logturbidity agriculturalcover100 [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =   61.95
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6586
                                                       Root MSE      =  .29644

------------------------------------------------------------------------------
             |               Robust
logturbidity |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
agricultural~100 |   .0719326    .009139     7.87   0.000     .0532412     .090624
       _cons |   .1314223   .0823134     1.60   0.121    -.0369276    .2997721
------------------------------------------------------------------------------
```

```
. reg logturbidity logsize [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =   43.79
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.4949
                                                       Root MSE      =  .36055

------------------------------------------------------------------------------
             |               Robust
logturbidity |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     logsize |   .1466055   .0221557     6.62   0.000      .101292     .191919
       _cons |  -.8432276   .2372893    -3.55   0.001    -1.328539   -.3579165
------------------------------------------------------------------------------


. reg logtoc forestcover [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =   11.17
                                                       Prob > F      =  0.0023
                                                       R-squared     =  0.3196
                                                       Root MSE      =  .20959

------------------------------------------------------------------------------
             |               Robust
      logtoc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 forestcover |  -.0120005     .00359    -3.34   0.002    -.0193429   -.0046581
       _cons |   1.266635   .2318223     5.46   0.000     .7925048    1.740764
------------------------------------------------------------------------------


. reg logtoc forestcover300 [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =   13.64
                                                       Prob > F      =  0.0009
                                                       R-squared     =  0.3374
                                                       Root MSE      =  .20684

------------------------------------------------------------------------------
             |               Robust
      logtoc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
forestcov~300 |  -.0177468   .0048054    -3.69   0.001    -.0275748   -.0079187
       _cons |   1.693542   .3155873     5.37   0.000     1.048094     2.33899
------------------------------------------------------------------------------
```

```
. reg logtoc forestcover100 [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    6.67
                                                       Prob > F      =  0.0151
                                                       R-squared     =  0.2043
                                                       Root MSE      =  .22666

------------------------------------------------------------------------------
             |               Robust
      logtoc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
forestcov~100 |  -.0103359   .0040029    -2.58   0.015    -.0185227   -.0021492
       _cons |    1.26931    .257813     4.92   0.000      .742023    1.796596
------------------------------------------------------------------------------

. reg logtoc imperviouscover [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    9.77
                                                       Prob > F      =  0.0040
                                                       R-squared     =  0.1894
                                                       Root MSE      =  .22877

------------------------------------------------------------------------------
             |               Robust
      logtoc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
imperviousc~r |   .0275966   .0088296     3.13   0.004      .009538    .0456551
       _cons |   .4786329   .0786193     6.09   0.000     .3178383    .6394275
------------------------------------------------------------------------------

. reg logtoc imperviouscover300 [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    2.49
                                                       Prob > F      =  0.1252
                                                       R-squared     =  0.0938
                                                       Root MSE      =  .24188

------------------------------------------------------------------------------
             |               Robust
      logtoc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
imperviou~300 |   .0351978   .0222918     1.58   0.125     -.010394    .0807895
       _cons |   .5180785   .0875547     5.92   0.000     .3390091    .6971479
------------------------------------------------------------------------------
```

```
. reg logtoc imperviouscover100 [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    0.34
                                                       Prob > F      =  0.5615
                                                       R-squared     =  0.0196
                                                       Root MSE      =  .25158
```

logtoc	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
imperviou~100	.0221329	.0376851	0.59	0.562	-.0549418	.0992075
_cons	.5737617	.0957532	5.99	0.000	.3779246	.7695989

```
. reg logtoc agriculturalcover [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    0.18
                                                       Prob > F      =  0.6762
                                                       R-squared     =  0.0104
                                                       Root MSE      =  .25276
```

logtoc	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
agricultura~r	.0020706	.0049074	0.42	0.676	-.0079663	.0121074
_cons	.5798978	.1301402	4.46	0.000	.3137312	.8460644

```
. reg logtoc agriculturalcover300 [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    0.15
                                                       Prob > F      =  0.7038
                                                       R-squared     =  0.0071
                                                       Root MSE      =  .25318
```

logtoc	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
agricultu~300	.0028902	.0075268	0.38	0.704	-.0125038	.0182842
_cons	.5811946	.139591	4.16	0.000	.2956989	.8666903

```
. reg logtoc agriculturalcover100 [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    0.07
                                                       Prob > F      =  0.7981
                                                       R-squared     =  0.0024
                                                       Root MSE      =  .25379
```

logtoc	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
agricultu~100	-.002555	.0098962	-0.26	0.798	-.022795	.0176851
_cons	.6513603	.1188515	5.48	0.000	.4082816	.894439

```
. reg logtoc logsize [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  1,    29) =    0.09
                                                       Prob > F      =  0.7695
                                                       R-squared     =  0.0022
                                                       Root MSE      =  .25381
```

logtoc	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
logsize	.0064822	.0219143	0.30	0.769	-.0383376	.0513019
_cons	.5535309	.2407837	2.30	0.029	.0610728	1.045989

(d) Multiple linear regression models

```
. reg logturbidity forestcover imperviouscover agriculturalcover logsize reservoir
> lake river [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   23.09
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7592
                                                       Root MSE      =  .27951
```

logturbidity	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover	.0067711	.0073556	0.92	0.367	-.0084452	.0219873
imperviouscover	.0163412	.0231634	0.71	0.488	-.031576	.0642584
agriculturalco~r	.0237568	.0092695	2.56	0.017	.0045814	.0429321
logsize	.0902766	.0242857	3.72	0.001	.0400379	.1405153
reservoir	-.4214367	.1683594	-2.50	0.020	-.7697146	-.0731588
lake	-.0191765	.1753516	-0.11	0.914	-.3819188	.3435659
river	.0618585	.2054735	0.30	0.766	-.3631958	.4869128
_cons	-1.052195	.6818639	-1.54	0.136	-2.462738	.3583477

```
. vif
```

Variable	VIF	1/VIF
forestcover	6.13	0.163024
agricultur~r	3.47	0.288481
impervious~r	3.39	0.295376
river	2.65	0.377702
lake	2.23	0.448768
logsize	2.06	0.486190
reservoir	1.56	0.641145
Mean VIF	3.07	

```
. reg logturbidity forestcover300 imperviouscover300 agriculturalcover300 logsize r
> eservoir lake river [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   20.02
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.8061
                                                       Root MSE      =  .25085
```

logturbidity	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover300	.0024078	.0043275	0.56	0.583	-.0065443	.0113599
imperviousco~300	.0226246	.0252933	0.89	0.380	-.0296985	.0749477
agricultural~300	.0356987	.0084178	4.24	0.000	.0182851	.0531122
logsize	.0754923	.0244332	3.09	0.005	.0249484	.1260362
reservoir	-.3907342	.153186	-2.55	0.018	-.7076237	-.0738448
lake	-.0964332	.1378109	-0.70	0.491	-.3815166	.1886503
river	-.0191508	.168654	-0.11	0.911	-.3680381	.3297366
_cons	-.6047724	.4139601	-1.46	0.158	-1.461114	.2515693

```
. vif
```

Variable	VIF	1/VIF
river	2.55	0.392462
forestco~300	2.50	0.400460
lake	2.09	0.478544
impervio~300	2.08	0.480843
logsize	2.05	0.487998
agricult~300	1.76	0.567489
reservoir	1.63	0.615175
Mean VIF	2.09	

```
. reg logturbidity forestcover100 imperviouscover100 agriculturalcover100 logsize r
> eservoir lake river [aweight= weightturbidity], robust
(sum of wgt is   7.8132e+02)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   23.52
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7981
                                                       Root MSE      =  .25599
```

logturbidity	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover100	.0004143	.0031765	0.13	0.897	-.0061569	.0069854
imperviousco~100	.0244765	.0330151	0.74	0.466	-.0438204	.0927734
agricultural~100	.0516679	.0129327	4.00	0.001	.0249146	.0784212
logsize	.0688031	.0255979	2.69	0.013	.0158497	.1217565
reservoir	-.3786172	.156253	-2.42	0.024	-.7018511	-.0553833
lake	-.1500946	.14437	-1.04	0.309	-.4487466	.1485574
river	-.0366901	.1775831	-0.21	0.838	-.4040487	.3306685
_cons	-.3731441	.3748235	-1.00	0.330	-1.148526	.4022375

```
. vif
```

Variable	VIF	1/VIF
logsize	2.51	0.398389
river	2.38	0.420511
lake	2.02	0.495484
agricult~100	1.93	0.517569
forestco~100	1.79	0.558945
reservoir	1.56	0.640907
impervio~100	1.46	0.683189
Mean VIF	1.95	

```
. reg logtoc forestcover imperviouscover agriculturalcover logsize reservoir lak
> e river [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =    8.81
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.4295
                                                       Root MSE      =   .2155
```

logtoc	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover	-.0168959	.005676	-2.98	0.007	-.0286376	-.0051543
imperviousc~r	-.0020623	.0192777	-0.11	0.916	-.0419413	.0378167
agricultura~r	-.0075725	.0057776	-1.31	0.203	-.0195244	.0043794
logsize	.0102687	.0253246	0.41	0.689	-.0421193	.0626568
reservoir	.0207836	.2108221	0.10	0.922	-.4153352	.4569023
lake	-.0006134	.1326498	-0.00	0.996	-.2750203	.2737936
river	.0818565	.1865784	0.44	0.665	-.3041104	.4678233
_cons	1.572823	.4667592	3.37	0.003	.6072579	2.538388

```
. vif
```

Variable	VIF	1/VIF
agricultur~r	5.00	0.199893
forestcover	4.80	0.208523
impervious~r	4.54	0.220092
river	4.33	0.230837
lake	4.29	0.233122
reservoir	2.71	0.368872
logsize	1.39	0.717749
Mean VIF	3.87	

```
. reg logtoc forestcover300 imperviouscover300 agriculturalcover300 logsize rese
> rvoir lake river [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =    6.57
                                                       Prob > F      =  0.0003
                                                       R-squared     =  0.3852
                                                       Root MSE      =  .22371
```

logtoc	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcov~300	-.0177348	.0045499	-3.90	0.001	-.027147	-.0083227
imperviou~300	.0005428	.0414493	0.01	0.990	-.0852017	.0862872
agricultu~300	.0045267	.0058819	0.77	0.449	-.0076409	.0166943
logsize	.0029471	.0254494	0.12	0.909	-.0496989	.0555932
reservoir	-.0090018	.188391	-0.05	0.962	-.3987184	.3807147
lake	-.0000577	.1308562	-0.00	1.000	-.2707543	.270639
river	.1020674	.2155173	0.47	0.640	-.3437642	.547899
_cons	1.572269	.3509168	4.48	0.000	.846342	2.298195

```
. vif
```

Variable	VIF	1/VIF
river	4.22	0.237193
lake	4.12	0.242735
reservoir	2.91	0.344210
impervio~300	2.49	0.401808
agricult~300	1.53	0.654462
forestco~300	1.51	0.661661
logsize	1.40	0.716735
Mean VIF	2.59	

```
. reg logtoc forestcover100 imperviouscover100 agriculturalcover100 logsize rese
> rvoir lake river [aweight=weighttoc], robust
(sum of wgt is   2.3062e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =    9.85
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.3342
                                                       Root MSE      =   .2328

------------------------------------------------------------------------------
             |               Robust
      logtoc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
forestcov~100 |  -.0150508   .0037876    -3.97   0.001    -.0228861   -.0072155
imperviou~100 |  -.0333094   .0560766    -0.59   0.558    -.1493127    .0826938
agricultu~100 |   .0091542   .0138561     0.66   0.515    -.0195093    .0378177
     logsize |   .0012273   .0271276     0.05   0.964    -.0548903    .0573449
   reservoir |   .1456373   .1542521     0.94   0.355    -.1734574    .4647321
        lake |   .0998367   .1539153     0.65   0.523    -.2185613    .4182346
       river |   .2824982     .22105     1.28   0.214    -.1747785    .7397749
       _cons |   1.401467   .3996796     3.51   0.002     .5746668    2.228267
------------------------------------------------------------------------------

. vif

    Variable |       VIF       1/VIF
-------------+----------------------
        lake |      4.26    0.234635
       river |      4.16    0.240430
   reservoir |      3.05    0.327464
impervio~100 |      1.97    0.506427
agricult~100 |      1.78    0.560565
forestco~100 |      1.57    0.635276
     logsize |      1.40    0.713369
-------------+----------------------
    Mean VIF |      2.60
```

(e) Multiple linear regression models for seasons

```
. reg logturbiditywinter forestcover imperviouscover agriculturalcover logsize r
> eservoir lake river [aweight= weightturbiditywinter], robust
(sum of wgt is   1.5111e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   21.51
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7635
                                                       Root MSE      =  .21995
```

logturbid~ter	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover	.0131925	.0046612	2.83	0.009	.0035502	.0228349
imperviousc~r	.0373701	.0174204	2.15	0.043	.0013333	.0734068
agricultura~r	.0254269	.0065908	3.86	0.001	.0117929	.0390609
logsize	.1022304	.0222517	4.59	0.000	.0561993	.1482615
reservoir	-.3188935	.1166144	-2.73	0.012	-.5601288	-.0776583
lake	-.0514917	.1215016	-0.42	0.676	-.3028369	.1998535
river	.0140809	.1628732	0.09	0.932	-.322848	.3510099
_cons	-1.810281	.4878217	-3.71	0.001	-2.819417	-.8011449

```
. vif
```

Variable	VIF	1/VIF
forestcover	5.65	0.176868
impervious~r	4.06	0.246083
agricultur~r	3.33	0.300599
lake	2.21	0.453445
river	1.74	0.575607
logsize	1.69	0.592402
reservoir	1.45	0.688402
Mean VIF	2.88	

```
. reg logturbiditywinter forestcover300 imperviouscover300 agriculturalcover300 logs
> ize reservoir lake river [aweight= weightturbiditywinter], robust
(sum of wgt is   1.5111e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   40.46
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.8277
                                                       Root MSE      =  .18775

------------------------------------------------------------------------------
                  |               Robust
logturbiditywin~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+-----------------------------------------------------------
   forestcover300 |   .0065525   .0020091     3.26   0.003     .0023965    .0107086
imperviouscov~300 |   .0510429   .0139363     3.66   0.001     .0222134    .0798724
agriculturalc~300 |    .033011   .0068825     4.80   0.000     .0187735    .0472486
          logsize |   .0693272   .0204793     3.39   0.003     .0269625    .1116919
        reservoir |  -.2924635   .1017928    -2.87   0.009    -.5030379   -.0818891
             lake |  -.0783296   .0852069    -0.92   0.367    -.2545935    .0979343
            river |  -.0218108   .1232101    -0.18   0.861    -.2766904    .2330688
            _cons |   -.989813   .2757612    -3.59   0.002    -1.560268   -.4193576
------------------------------------------------------------------------------


. vif

    Variable |       VIF       1/VIF
-------------+----------------------
forestco~300 |      2.20    0.454204
impervio~300 |      2.00    0.500691
     logsize |      1.84    0.542214
        lake |      1.80    0.556181
agricult~300 |      1.74    0.574101
       river |      1.57    0.638666
   reservoir |      1.44    0.694291
-------------+----------------------
    Mean VIF |      1.80


. reg logturbiditywinter forestcover100 imperviouscover100 agriculturalcover100 logs
> ize reservoir lake river [aweight= weightturbiditywinter], robust
(sum of wgt is   1.5111e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   28.62
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.8097
                                                       Root MSE      =  .19731

------------------------------------------------------------------------------
                  |               Robust
logturbiditywin~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+-----------------------------------------------------------
   forestcover100 |   .0042267   .0017766     2.38   0.026     .0005516    .0079018
imperviouscov~100 |   .0440264   .0241452     1.82   0.081    -.0059218    .0939746
agriculturalc~100 |    .041086   .0109931     3.74   0.001      .018345     .063827
          logsize |   .0779777    .020945     3.72   0.001     .0346496    .1213057
        reservoir |  -.2720251   .1134058    -2.40   0.025     -.506623   -.0374272
             lake |  -.0522434   .0906527    -0.58   0.570    -.2397728     .135286
            river |  -.0072549   .1452236    -0.05   0.961    -.3076727    .2931629
            _cons |  -.8592896   .2747531    -3.13   0.005     -1.42766   -.2909196
------------------------------------------------------------------------------
```

```
. vif

    Variable |       VIF       1/VIF
-------------+----------------------
agricult~100 |      1.91    0.522900
forestco~100 |      1.91    0.524678
     logsize |      1.87    0.534540
        lake |      1.78    0.562017
impervio~100 |      1.54    0.649944
       river |      1.50    0.665025
   reservoir |      1.39    0.721625
-------------+----------------------
    Mean VIF |      1.70

. reg logtocwinter forestcover imperviouscover agriculturalcover logsize reservoir l
> ake river [aweight= weighttocwinter], robust
(sum of wgt is   4.9204e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =    6.52
                                                       Prob > F      =  0.0003
                                                       R-squared     =  0.4906
                                                       Root MSE      =   .2254

------------------------------------------------------------------------------------
                  |               Robust
     logtocwinter |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
      forestcover |  -.0161277     .007103    -2.27   0.033    -.0308213    -.001434
  imperviouscover |  -.0108805    .0359686    -0.30   0.765    -.0852873    .0635263
agriculturalcover |   -.008873    .0075738    -1.17   0.253    -.0245405    .0067945
          logsize |   .0127454    .0241735     0.53   0.603    -.0372612     .062752
        reservoir |   .1427657    .1814071     0.79   0.439    -.2325036     .518035
             lake |  -.0100042    .1987312    -0.05   0.960    -.4211111    .4011027
            river |   .0910663    .3121066     0.29   0.773    -.5545754    .7367081
            _cons |   1.509901    .6919179     2.18   0.040     .0785601    2.941243
------------------------------------------------------------------------------------


. vif

    Variable |       VIF       1/VIF
-------------+----------------------
 forestcover |      9.94    0.100625
agricultur~r |      8.33    0.120024
impervious~r |      5.11    0.195546
        lake |      4.75    0.210534
       river |      3.84    0.260312
   reservoir |      3.70    0.270440
     logsize |      2.52    0.397337
-------------+----------------------
    Mean VIF |      5.46
```

```
. reg logtocwinter forestcover300 imperviouscover300 agriculturalcover300 logsize re
> servoir lake river [aweight= weighttocwinter], robust
(sum of wgt is   4.9204e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   16.28
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5295
                                                       Root MSE      =  .21662
```

logtocwinter	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover300	-.0198058	.004364	-4.54	0.000	-.0288334	-.0107783
imperviouscov~300	-.050627	.0556277	-0.91	0.372	-.1657017	.0644477
agriculturalc~300	.0018463	.0067512	0.27	0.787	-.0121196	.0158122
logsize	.0149212	.0232967	0.64	0.528	-.0332717	.0631141
reservoir	.1325227	.1357962	0.98	0.339	-.1483931	.4134385
lake	.0015848	.1387057	0.01	0.991	-.2853497	.2885194
river	.2128303	.242157	0.88	0.389	-.2881095	.7137702
_cons	1.642877	.4552922	3.61	0.001	.701033	2.584721

```
. vif
```

Variable	VIF	1/VIF
lake	4.30	0.232551
reservoir	3.83	0.261155
river	3.22	0.310238
logsize	2.60	0.385307
agricult~300	2.53	0.394491
impervio~300	2.25	0.444207
forestco~300	1.77	0.564309
Mean VIF	2.93	

```
. reg logtocwinter forestcover100 imperviouscover100 agriculturalcover100 logsize re
> servoir lake river [aweight= weighttocwinter], robust
(sum of wgt is   4.9204e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   17.75
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6049
                                                       Root MSE      =  .19851
```

logtocwinter	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover100	-.014976	.0023747	-6.31	0.000	-.0198884	-.0100637
imperviouscov~100	-.0664609	.046692	-1.42	0.168	-.1630507	.0301289
agriculturalc~100	.0096201	.0117061	0.82	0.420	-.0145958	.0338361
logsize	-.0054517	.0257024	-0.21	0.834	-.0586212	.0477178
reservoir	.1283615	.1292342	0.99	0.331	-.1389797	.3957028
lake	-.0364432	.1359	-0.27	0.791	-.3175739	.2446874
river	.211594	.1941468	1.09	0.287	-.1900293	.6132172
_cons	1.574493	.3327063	4.73	0.000	.8862379	2.262749

```
. vif

    Variable |       VIF       1/VIF  
-------------+----------------------
        lake |      4.69    0.213296
   reservoir |      4.08    0.245263
agricult~100 |      3.88    0.257496
     logsize |      3.07    0.326009
       river |      2.91    0.343818
impervio~100 |      1.88    0.532479
forestco~100 |      1.41    0.706919
-------------+----------------------
    Mean VIF |      3.13


. reg logturbidityspring forestcover imperviouscover agriculturalcover logsize reser
> voir lake river [aweight= weightturbidityspring], robust
(sum of wgt is   1.2793e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   49.81
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.8979
                                                       Root MSE      =  .22097

------------------------------------------------------------------------------
             |               Robust
logturbidityspr~g |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      forestcover |   .0134059   .0056719     2.36   0.027     .0016727    .0251392
  imperviouscover |   .0349652   .0214124     1.63   0.116    -.0093298    .0792602
agriculturalcover |   .0380886   .0083199     4.58   0.000     .0208775    .0552996
          logsize |   .0775366   .0264347     2.93   0.007     .0228524    .1322209
        reservoir |  -.5594349   .1373576    -4.07   0.000    -.8435808    -.275289
             lake |   .0708316   .1777967     0.40   0.694    -.2969689     .438632
            river |   .0591647   .2195344     0.27   0.790    -.3949768    .5133062
            _cons |  -1.606447   .5925055    -2.71   0.012    -2.832138    -.380756
------------------------------------------------------------------------------


. vif

    Variable |       VIF       1/VIF  
-------------+----------------------
 forestcover |      7.86    0.127204
impervious~r |      3.64    0.274837
agricultur~r |      3.58    0.279658
     logsize |      3.26    0.306456
       river |      3.19    0.313714
   reservoir |      2.46    0.406680
        lake |      2.14    0.468067
-------------+----------------------
    Mean VIF |      3.73
```

```
. reg logturbidityspring forestcover300 imperviouscover300 agriculturalcover300 logs
> ize reservoir lake river [aweight= weightturbidityspring], robust
(sum of wgt is   1.2793e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   72.17
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.9286
                                                       Root MSE      =  .18476

------------------------------------------------------------------------------
                  |               Robust
logturbidityspr~g |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+-----------------------------------------------------------
   forestcover300 |   .0052215    .004151     1.26   0.221    -.0033656    .0138085
imperviouscov~300 |   .0434224   .0241503     1.80   0.085    -.0065364    .0933812
agriculturalc~300 |   .0497222   .0075802     6.56   0.000     .0340415     .065403
          logsize |   .0652152   .0252196     2.59   0.017     .0130446    .1173859
        reservoir |  -.5006445   .1522452    -3.29   0.003    -.8155876   -.1857014
             lake |  -.0975362   .1268926    -0.77   0.450    -.3600336    .1649612
            river |   -.102347   .1732638    -0.59   0.560    -.4607706    .2560765
            _cons |  -.8060954   .4314448    -1.87   0.075    -1.698607    .0864161
------------------------------------------------------------------------------


. vif

    Variable |       VIF       1/VIF
-------------+----------------------
forestco~300 |      4.28    0.233467
       river |      3.34    0.299603
     logsize |      3.04    0.328927
   reservoir |      2.86    0.350156
impervio~300 |      2.69    0.372278
agricult~300 |      2.22    0.451204
        lake |      2.13    0.470517
-------------+----------------------
    Mean VIF |      2.93
```

```
. reg logturbidityspring forestcover100 imperviouscover100 agriculturalcover100 logs
> ize reservoir lake river [aweight= weightturbidityspring], robust
(sum of wgt is   1.2793e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   63.35
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.9184
                                                       Root MSE      =  .19752
```

logturbidityspr~g	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover100	.0022265	.003354	0.66	0.513	-.0047118	.0091648
imperviouscov~100	.0593673	.0314007	1.89	0.071	-.00559	.1243246
agriculturalc~100	.0677228	.0135552	5.00	0.000	.0396818	.0957639
logsize	.0732364	.024851	2.95	0.007	.0218281	.1246447
reservoir	-.4394198	.1666248	-2.64	0.015	-.7841095	-.09473
lake	-.1850595	.1338403	-1.38	0.180	-.4619292	.0918103
river	-.1399156	.1907578	-0.73	0.471	-.5345282	.2546969
_cons	-.637981	.3697484	-1.73	0.098	-1.402864	.1269019

```
. vif
```

Variable	VIF	1/VIF
logsize	3.56	0.281248
forestco~100	3.40	0.293855
river	3.16	0.316911
reservoir	2.89	0.346363
agricult~100	2.40	0.417018
impervio~100	2.01	0.498578
lake	1.98	0.505520
Mean VIF	2.77	

```
. reg logtocspring forestcover imperviouscover agriculturalcover logsize reservoir l
> ake river [aweight= weighttocspring], robust
(sum of wgt is   3.4114e+03)

Linear regression                                      Number of obs =      30
                                                       F(  7,    22) =   14.26
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6649
                                                       Root MSE      =  .17271

------------------------------------------------------------------------------
                  |               Robust
     logtocspring |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+-----------------------------------------------------------
      forestcover |  -.0136544   .0054121    -2.52   0.019    -.0248785   -.0024304
  imperviouscover |   .0137497   .0195983     0.70   0.490    -.0268947    .0543942
agriculturalcover |  -.0038439   .0064214    -0.60   0.556    -.0171611    .0094733
          logsize |   .0292024   .0175787     1.66   0.111    -.0072537    .0656585
        reservoir |   .1307794   .1100768     1.19   0.247     -.097506    .3590648
             lake |  -.1052702   .1431515    -0.74   0.470    -.4021482    .1916078
            river |  -.0229126   .1984853    -0.12   0.909    -.4345459    .3887207
            _cons |   1.086705   .5027976     2.16   0.042     .0439661    2.129443
------------------------------------------------------------------------------


. vif

    Variable |       VIF       1/VIF
-------------+----------------------
agricultur~r |      4.87    0.205523
impervious~r |      4.47    0.223804
        lake |      4.31    0.231770
 forestcover |      4.18    0.238963
       river |      3.84    0.260272
   reservoir |      3.46    0.288873
     logsize |      1.77    0.565112
-------------+----------------------
    Mean VIF |      3.84

. reg logtocspring forestcover300 imperviouscover300 agriculturalcover300 logsize re
> servoir lake river [aweight= weighttocspring], robust
(sum of wgt is   3.4114e+03)

Linear regression                                      Number of obs =      30
                                                       F(  7,    22) =   12.01
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5780
                                                       Root MSE      =  .19381

------------------------------------------------------------------------------
                  |               Robust
     logtocspring |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+-----------------------------------------------------------
   forestcover300 |  -.0170183   .0054184    -3.14   0.005    -.0282555   -.0057812
imperviouscov~300 |   .0197314   .0392345     0.50   0.620    -.0616359    .1010987
agriculturalc~300 |   .0071686   .0060895     1.18   0.252    -.0054602    .0197975
          logsize |   .0339252    .023721     1.43   0.167    -.0152692    .0831195
        reservoir |    .115654   .1005428     1.15   0.262     -.092859    .3241671
             lake |   -.070091   .1370632    -0.51   0.614    -.3543427    .2141607
            river |  -.0020293   .2275427    -0.01   0.993    -.4739239    .4698653
            _cons |   1.126417   .4806391     2.34   0.029     .1296328    2.123202
------------------------------------------------------------------------------
```

```
. vif

    Variable |       VIF       1/VIF  
-------------+----------------------
        lake |      4.14    0.241326
   reservoir |      4.06    0.246425
       river |      3.90    0.256351
agricult~300 |      2.47    0.404661
impervio~300 |      2.43    0.410845
     logsize |      1.88    0.531828
forestco~300 |      1.40    0.716801
-------------+----------------------
    Mean VIF |      2.90


. reg logtocspring forestcover100 imperviouscover100 agriculturalcover100 logsize re
> servoir lake river [aweight= weighttocspring], robust
(sum of wgt is   3.4114e+03)

Linear regression                                      Number of obs =      30
                                                       F(  7,    22) =   46.28
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5019
                                                       Root MSE      =  .21055

------------------------------------------------------------------------------
             |               Robust
logtocspring |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
forestcover100 |  -.011662   .0034545    -3.38   0.003    -.0188263   -.0044978
imperviouscov~100 | .0050188 .0588324    0.09   0.933    -.1169922    .1270298
agriculturalc~100 | .0096742 .0138723    0.70   0.493    -.0190952    .0384437
     logsize |   .0319154   .0342996     0.93   0.362    -.0392175    .1030484
   reservoir |   .2218013   .1095386     2.02   0.055    -.0053679    .4489705
        lake |   -.018532   .1695477    -0.11   0.914    -.3701524    .3330885
       river |   .1228138   .2519087     0.49   0.631    -.3996128    .6452404
       _cons |   .8400076   .4491954     1.87   0.075    -.0915667    1.771582
------------------------------------------------------------------------------


. vif

    Variable |       VIF       1/VIF  
-------------+----------------------
        lake |      4.52    0.221131
   reservoir |      4.11    0.243331
       river |      4.04    0.247415
agricult~100 |      3.47    0.288223
impervio~100 |      2.36    0.422974
     logsize |      2.20    0.454106
forestco~100 |      1.50    0.668512
-------------+----------------------
    Mean VIF |      3.17
```

```
. reg logturbiditysummer forestcover imperviouscover agriculturalcover logsize reser
> voir lake river [aweight= weightturbiditysummer], robust
(sum of wgt is   2.4608e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =    7.53
                                                       Prob > F      =  0.0001
                                                       R-squared     =  0.7158
                                                       Root MSE      =  .30111
```

logturbiditysum~r	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover	-.0000458	.0100564	-0.00	0.996	-.020849	.0207573
imperviouscover	-.0047059	.0328006	-0.14	0.887	-.072559	.0631473
agriculturalcover	.011952	.0130595	0.92	0.370	-.0150635	.0389676
logsize	.1072853	.0366124	2.93	0.008	.0315467	.1830239
reservoir	-.6737363	.1762894	-3.82	0.001	-1.038419	-.3090539
lake	-.158956	.2070388	-0.77	0.450	-.5872484	.2693363
river	-.0504583	.2044755	-0.25	0.807	-.4734482	.3725315
_cons	-.3966324	.909725	-0.44	0.667	-2.278542	1.485277

```
. vif
```

Variable	VIF	1/VIF
forestcover	7.53	0.132856
agricultur~r	4.16	0.240243
impervious~r	3.83	0.260782
logsize	2.44	0.409974
river	2.39	0.418054
lake	1.97	0.508875
reservoir	1.47	0.679606
Mean VIF	3.40	

```
. reg logturbiditysummer forestcover300 imperviouscover300 agriculturalcover300 logs
> ize reservoir lake river [aweight= weightturbiditysummer], robust
(sum of wgt is   2.4608e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =    7.35
                                                       Prob > F      =  0.0001
                                                       R-squared     =  0.7354
                                                       Root MSE      =  .29052
```

logturbiditysum~r	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover300	-.0009358	.0075664	-0.12	0.903	-.0165881	.0147165
imperviouscov~300	-.0060755	.0446586	-0.14	0.893	-.0984589	.0863079
agriculturalc~300	.0223595	.0137837	1.62	0.118	-.0061542	.0508732
logsize	.0942986	.038473	2.45	0.022	.0147112	.1738861
reservoir	-.6503842	.1612589	-4.03	0.001	-.9839738	-.3167947
lake	-.1864652	.1958446	-0.95	0.351	-.5916005	.2186702
river	-.0724728	.1921052	-0.38	0.709	-.4698728	.3249272
_cons	-.2574969	.7146112	-0.36	0.722	-1.735783	1.220789

```
. vif

    Variable |       VIF       1/VIF  
-------------+----------------------
forestco~300 |      3.54    0.282354
impervio~300 |      2.75    0.363322
     logsize |      2.37    0.421098
       river |      2.35    0.424808
agricult~300 |      2.14    0.467364
        lake |      1.87    0.534868
   reservoir |      1.52    0.658423
-------------+----------------------
    Mean VIF |      2.36

. reg logturbiditysummer forestcover100 imperviouscover100 agriculturalcover100 logs
> ize reservoir lake river [aweight= weightturbiditysummer], robust
(sum of wgt is   2.4608e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =    8.76
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7475
                                                       Root MSE      =  .28379

------------------------------------------------------------------------------
                  |               Robust
logturbiditysum~r |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+-----------------------------------------------------------
   forestcover100 |  -.0025869   .0057766    -0.45   0.658    -.0145367    .0093628
imperviouscov~100 |  -.0236579   .0431564    -0.55   0.589    -.1129337    .0656179
agriculturalc~100 |   .0397194   .0173299     2.29   0.031     .0038697    .0755691
          logsize |   .0681714   .0351352     1.94   0.065    -.0045114    .1408541
        reservoir |  -.6382539   .1527504    -4.18   0.000    -.9542422   -.3222657
             lake |  -.2059806   .2015445    -1.02   0.317     -.622907    .2109459
            river |  -.0337097   .1800437    -0.19   0.853    -.4061584    .3387389
            _cons |   .1071362   .6188642     0.17   0.864    -1.173082    1.387354
------------------------------------------------------------------------------

. vif

    Variable |       VIF       1/VIF  
-------------+----------------------
     logsize |      3.13    0.319423
forestco~100 |      2.37    0.422044
agricult~100 |      2.17    0.461886
       river |      2.15    0.464795
        lake |      1.80    0.555701
impervio~100 |      1.68    0.594446
   reservoir |      1.47    0.679837
-------------+----------------------
    Mean VIF |      2.11
```

```
. reg logtocsummer forestcover imperviouscover agriculturalcover logsize reservoir l
> ake river [aweight= weighttocsummer], robust
(sum of wgt is   3.7583e+03)

Linear regression                                      Number of obs =      30
                                                       F(  7,    22) =    5.24
                                                       Prob > F      =  0.0013
                                                       R-squared     =  0.4990
                                                       Root MSE      =  .21831

------------------------------------------------------------------------------
             |               Robust
logtocsummer |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 forestcover |  -.0132497   .0048901    -2.71   0.013    -.0233911   -.0031083
imperviousc~r|    .008156   .0192241     0.42   0.675    -.0317123    .0480243
agricultura~r|    -.00413   .0060102    -0.69   0.499    -.0165943    .0083343
     logsize |   .0161329   .0203051     0.79   0.435    -.0259774    .0582431
   reservoir |   .0688291   .1444512     0.48   0.638    -.2307444    .3684025
        lake |  -.0939487   .1588471    -0.59   0.560    -.4233774    .2354801
       river |  -.0553708   .2168969    -0.26   0.801    -.5051874    .3944458
       _cons |    1.26337   .4111973     3.07   0.006     .4105992    2.116141
------------------------------------------------------------------------------
```

Note: the row labels in the table above are printed in full on the page as `imperviouscover` and `agriculturalcover`:

logtocsummer	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover	-.0132497	.0048901	-2.71	0.013	-.0233911	-.0031083
imperviouscover	.008156	.0192241	0.42	0.675	-.0317123	.0480243
agriculturalcover	-.00413	.0060102	-0.69	0.499	-.0165943	.0083343
logsize	.0161329	.0203051	0.79	0.435	-.0259774	.0582431
reservoir	.0688291	.1444512	0.48	0.638	-.2307444	.3684025
lake	-.0939487	.1588471	-0.59	0.560	-.4233774	.2354801
river	-.0553708	.2168969	-0.26	0.801	-.5051874	.3944458
_cons	1.26337	.4111973	3.07	0.006	.4105992	2.116141

```
. vif
```

Variable	VIF	1/VIF
agricultur~r	5.56	0.179994
forestcover	5.15	0.194361
lake	4.48	0.222995
impervious~r	4.32	0.231509
river	3.51	0.284718
reservoir	3.41	0.293323
logsize	1.64	0.611146
Mean VIF	4.01	

```
. reg logtocsummer forestcover300 imperviouscover300 agriculturalcover300 logsize re
> servoir lake river [aweight= weighttocsummer], robust
(sum of wgt is   3.7583e+03)

Linear regression                                      Number of obs =      30
                                                       F(  7,    22) =    3.86
                                                       Prob > F      =  0.0069
                                                       R-squared     =  0.4054
                                                       Root MSE      =  .23785
```

logtocsummer	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover300	-.0149504	.004879	-3.06	0.006	-.0250688	-.0048319
imperviouscov~300	-.0049435	.0497579	-0.10	0.922	-.1081351	.0982481
agriculturalc~300	.0026332	.0062809	0.42	0.679	-.0103926	.015659
logsize	.0194072	.0256926	0.76	0.458	-.0338759	.0726904
reservoir	.15727	.1506864	1.04	0.308	-.1552346	.4697745
lake	.0186924	.1655693	0.11	0.911	-.3246773	.3620621
river	.0797376	.2472404	0.32	0.750	-.4330076	.5924828
_cons	1.240483	.439861	2.82	0.010	.3282668	2.152698

```
. vif

    Variable |       VIF       1/VIF  
-------------+----------------------
        lake |      4.02    0.248806
   reservoir |      3.24    0.308756
       river |      3.22    0.310353
impervio~300 |      2.21    0.452192
agricult~300 |      2.01    0.497166
     logsize |      1.72    0.582087
forestco~300 |      1.50    0.665195
-------------+----------------------
    Mean VIF |      2.56

. reg logtocsummer forestcover100 imperviouscover100 agriculturalcover100 logsize re
> servoir lake river [aweight= weighttocsummer], robust
(sum of wgt is   3.7583e+03)

Linear regression                                      Number of obs =      30
                                                       F(  7,    22) =   21.27
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.3991
                                                       Root MSE      =  .23909

------------------------------------------------------------------------------
                  |               Robust
     logtocsummer |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
   forestcover100 |  -.0123281   .0029074    -4.24   0.000    -.0183578   -.0062985
imperviouscov~100 |   -.035249   .0570136    -0.62   0.543    -.1534879    .0829899
agriculturalc~100 |   .0052722   .0129022     0.41   0.687    -.0214853    .0320297
          logsize |   .0113182   .0332178     0.34   0.737    -.0575714    .0802077
        reservoir |   .1977707   .1357788     1.46   0.159    -.0838174    .4793587
             lake |   .0430144   .1632919     0.26   0.795    -.2956324    .3816611
            river |   .1655421   .2138321     0.77   0.447    -.2779185    .6090027
            _cons |   1.214443   .4477098     2.71   0.013     .2859497    2.142936
------------------------------------------------------------------------------

. vif

    Variable |       VIF       1/VIF  
-------------+----------------------
        lake |      4.04    0.247226
   reservoir |      3.12    0.320515
       river |      3.01    0.332711
agricult~100 |      2.10    0.475309
     logsize |      1.94    0.515796
impervio~100 |      1.68    0.595846
forestco~100 |      1.33    0.754108
-------------+----------------------
    Mean VIF |      2.46
```

```
. reg logturbidityautumn forestcover imperviouscover agriculturalcover logsize reser
> voir lake river [aweight= weightturbidityautumn], robust
(sum of wgt is   1.9573e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =    8.77
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5962
                                                       Root MSE      =  .35135

------------------------------------------------------------------------------
                  |               Robust
logturbidityaut~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+-----------------------------------------------------------
      forestcover |   -.006847   .0110118    -0.62   0.540    -.0296266    .0159325
  imperviouscover |  -.0262666   .0338534    -0.78   0.446    -.0962976    .0437645
agriculturalcover |   .0028479   .0129787     0.22   0.828    -.0240006    .0296964
          logsize |   .1032489   .0349341     2.96   0.007     .0309823    .1755155
        reservoir |  -.3289796   .2305687    -1.43   0.167    -.8059472    .1479881
             lake |  -.2057317    .270347    -0.76   0.454     -.764987    .3535237
            river |   .1333704   .2692835     0.50   0.625    -.4236849    .6904257
            _cons |   .1330854   .9648294     0.14   0.891    -1.862816    2.128987
------------------------------------------------------------------------------


. vif

    Variable |       VIF       1/VIF
-------------+----------------------
 forestcover |      9.37    0.106722
agricultur~r |      5.01    0.199769
impervious~r |      4.05    0.246655
       river |      3.49    0.286600
        lake |      3.28    0.304653
     logsize |      2.30    0.435583
   reservoir |      2.06    0.486607
-------------+----------------------
    Mean VIF |      4.22

. reg logturbidityautumn forestcover300 imperviouscover300 agriculturalcover300 logs
> ize reservoir lake river [aweight= weightturbidityautumn], robust
(sum of wgt is   1.9573e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =    8.96
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6181
                                                       Root MSE      =  .34167

------------------------------------------------------------------------------
                  |               Robust
logturbidityaut~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+-----------------------------------------------------------
   forestcover300 |   -.006354   .0082926    -0.77   0.451    -.0235085    .0108006
imperviouscov~300 |  -.0437085   .0487042    -0.90   0.379    -.1444608    .0570438
agriculturalc~300 |   .0141913   .0137998     1.03   0.314    -.0143559    .0427385
          logsize |    .092379   .0383265     2.41   0.024     .0130946    .1716634
        reservoir |  -.3043476   .2153517    -1.41   0.171    -.7498366    .1411413
             lake |  -.2341135   .2546129    -0.92   0.367    -.7608205    .2925934
            river |   .1154988   .2489996     0.46   0.647    -.3995962    .6305938
            _cons |   .1310629   .6864121     0.19   0.850    -1.288889    1.551015
------------------------------------------------------------------------------
```

```
. vif

    Variable |       VIF       1/VIF  
-------------+----------------------
forestco~300 |      3.42    0.291986
       river |      3.24    0.308320
        lake |      3.02    0.331476
     logsize |      2.41    0.415467
impervio~300 |      2.40    0.417082
   reservoir |      2.13    0.469505
agricult~300 |      2.12    0.472681
-------------+----------------------
    Mean VIF |      2.68

. reg logturbidityautumn forestcover100 imperviouscover100 agriculturalcover100 logs
> ize reservoir lake river [aweight= weightturbidityautumn], robust
(sum of wgt is   1.9573e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   11.82
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6300
                                                       Root MSE      =  .33632

------------------------------------------------------------------------------------
                  |               Robust
logturbidityaut~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
   forestcover100 |  -.0048671   .0058025    -0.84   0.410    -.0168704    .0071363
imperviouscov~100 |  -.0414306   .0479065    -0.86   0.396    -.1405328    .0576716
agriculturalc~100 |   .0323183   .0188074     1.72   0.099    -.0065877    .0712243
          logsize |   .0662407   .0416537     1.59   0.125    -.0199266     .152408
        reservoir |   -.346586   .2049285    -1.69   0.104    -.7705129     .077341
             lake |   -.306522   .2590547    -1.18   0.249    -.8424175    .2293735
            river |    .078061   .2454186     0.32   0.753    -.4296262    .5857481
            _cons |   .2403061   .6091219     0.39   0.697    -1.019759    1.500371
------------------------------------------------------------------------------------

. vif

    Variable |       VIF       1/VIF  
-------------+----------------------
       river |      3.03    0.330239
     logsize |      2.99    0.333962
        lake |      2.98    0.335225
forestco~100 |      2.21    0.451531
agricult~100 |      2.16    0.463308
   reservoir |      2.03    0.491873
impervio~100 |      1.65    0.607854
-------------+----------------------
    Mean VIF |      2.44
```

```
. reg logtocautumn forestcover imperviouscover agriculturalcover logsize reservoir l
> ake river [aweight= weighttocautumn], robust
(sum of wgt is   3.3767e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   26.46
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5865
                                                       Root MSE      =  .17249
```

logtocautumn	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover	-.0185313	.0053649	-3.45	0.002	-.0296294	-.0074331
imperviouscover	-.0091898	.0150314	-0.61	0.547	-.0402846	.021905
agriculturalcover	-.0099399	.0049143	-2.02	0.055	-.020106	.0002262
logsize	.0023338	.0237185	0.10	0.922	-.0467316	.0513993
reservoir	.0192244	.2269727	0.08	0.933	-.4503045	.4887532
lake	.1047777	.1004121	1.04	0.308	-.1029404	.3124959
river	.1015081	.1497644	0.68	0.505	-.2083033	.4113194
_cons	1.791794	.3752235	4.78	0.000	1.015586	2.568003

```
. vif
```

Variable	VIF	1/VIF
forestcover	7.46	0.134114
impervious~r	6.05	0.165156
agricultur~r	5.93	0.168715
river	5.10	0.196086
lake	3.87	0.258166
reservoir	1.77	0.563833
logsize	1.62	0.617885
Mean VIF	4.54	

```
. reg logtocautumn forestcover300 imperviouscover300 agriculturalcover300 logsize re
> servoir lake river [aweight= weighttocautumn], robust
(sum of wgt is   3.3767e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =   11.22
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5576
                                                       Root MSE      =  .17843
```

logtocautumn	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover300	-.0164745	.0049014	-3.36	0.003	-.0266138	-.0063352
imperviouscov~300	.0025759	.0300117	0.09	0.932	-.059508	.0646599
agriculturalc~300	.0019285	.0045921	0.42	0.678	-.007571	.0114281
logsize	-.010039	.0226747	-0.44	0.662	-.0569453	.0368672
reservoir	-.0090686	.2175151	-0.04	0.967	-.4590329	.4408956
lake	.0681739	.1012954	0.67	0.508	-.1413716	.2777195
river	.0943021	.17805	0.53	0.601	-.2740225	.4626266
_cons	1.657727	.2481809	6.68	0.000	1.144325	2.171128

```
. vif
```

Variable	VIF	1/VIF
river	4.88	0.205050
lake	3.56	0.280973
impervio~300	3.37	0.297083
forestco~300	2.17	0.460953
reservoir	1.80	0.555869
logsize	1.70	0.589194
agricult~300	1.37	0.730167
Mean VIF	2.69	

```
. reg logtocautumn forestcover100 imperviouscover100 agriculturalcover100 logsize re
> servoir lake river [aweight= weighttocautumn], robust
(sum of wgt is   3.3767e+03)

Linear regression                                      Number of obs =      31
                                                       F(  7,    23) =    6.38
                                                       Prob > F      =  0.0003
                                                       R-squared     =  0.4939
                                                       Root MSE      =  .19083
```

logtocautumn	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
forestcover100	-.0150562	.0040953	-3.68	0.001	-.023528	-.0065844
imperviouscov~100	-.0170692	.0537499	-0.32	0.754	-.1282593	.0941209
agriculturalc~100	.0103921	.0097476	1.07	0.297	-.0097723	.0305564
logsize	-.002125	.0237349	-0.09	0.929	-.0512244	.0469743
reservoir	.0550022	.1980388	0.28	0.784	-.3546724	.4646767
lake	.0671516	.1155065	0.58	0.567	-.1717918	.306095
river	.1742196	.212307	0.82	0.420	-.2649709	.61341
_cons	1.450322	.343903	4.22	0.000	.7389042	2.161739

```
. vif
```

Variable	VIF	1/VIF
river	5.08	0.196861
lake	3.62	0.276255
impervio~100	2.95	0.339344
forestco~100	2.10	0.476515
reservoir	1.98	0.505739
logsize	1.76	0.569498
agricult~100	1.28	0.783640
Mean VIF	2.68	