DEVELOPMENT OF AN INTEGRATED, WATERSHED-SCALE, PLANNING TOOL FOR STORMWATER MANAGEMENT IN VERMONT

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ABSTRACT

An Investigative Docket process was initiated in 2004 by the Vermont Water Resources Board to explore options for designing and implementing effective cleanup plans for stormwater-impaired waters. This Docket concluded that the primary cause of stream impairment by stormwater is excessive runoff from impervious surfaces. The Docket also decided that the primary objective of stormwater management should be to return the hydrologic characteristics of impaired streams to a regime that closely parallels the hydrologic characteristics of streams that are not currently impaired. However, there was no agreed protocol or framework to identify these targets or to prioritize specific locations where stormwater reductions would provide the greatest benefits. This project was initiated to develop a framework that could be used to address these needs. We used a set of 12 stormwater-impaired streams and 15 unimpaired (or "attainment) streams. Only a few of these streams had flow-gauging records and so we estimated flow with a simple stormwater hydrologic model (P-8) and used the output from this model to generate 'synthetic' flow duration curves (FDC) for comparison. Statistical clustering methods were used to identify groupings of stormwater impaired and attainment watersheds. A hierarchical cluster analysis of inherent watershed characteristics identified watershed groupings that included both impaired and attainment streams. For these groupings, we used the mean one–day estimated flow values for the attainment watersheds as flow targets for the corresponding impairment watersheds. These flow values satisfy the target setting requirements for assessments of Total Maximum Daily Loads (TMDLs). A risk assessment methodology was developed to address the TMDL pollutant load allocation requirement. Binary logistic regression methods were used to estimate the probability that a watershed is impaired as a function of watershed characteristics. The areas with higher impairment probabilities can be targeted for priority management actions. This approach utilizes readily available data, employs simple models, is acceptable to a wide array of stakeholders and is amenable to adaptive management.

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CHAPTER 1: PROJECT INTRODUCTION

In 2004, seventeen streams in Vermont's urbanizing communities were impaired by stormwater runoff. Vermont law requires that stormwater cleanup plans must either reasonably assure compliance within five years or be based on a Total Maximum Daily Load (TMDL), which involves estimating how much stormwater reduction is needed to meet state Water Quality Standards (Nicholls, 2004). The traditional TMDL approach is based on single pollutant loading and is problematic for stormwater management, as stormwater runoff is known to comprise multiple pollutants and sources. These pollutants move either with the water flow or attached to sediment particles in the water (Gray, 2004; USEPA, 2003; VTDEC, 2004; Walsh, et al., 2005). An alternative stormwater-based TMDL approach that is simple to employ, objective, quantitative, and defensible is desirable.

Managing water flow (hydrology) would be expected to help control the multiple pollutants in runoff and was investigated in this study. Hydrologic and sediment targets can be used to estimate assimilative capacities of the receiving waters and to estimate the loads of stormwater pollutants that must be reduced to meet the targets (Gray, 2004; Nicholls, 2004). The State of Vermont defines assimilative capacity as the amount of a particular pollutant a water body can receive while meeting Water Quality Standards (VTWRB, 2003). In this study, we reinterpreted this definition for flow as the amount of water a stream was "designed" to carry. The methodology described in this study uses the surrogate of stormwater runoff volume rather than the traditional single pollutant approach. This surrogate is appropriate because the pollutant load discharged to a watershed is a function of the volume of stormwater runoff. The above-described TMDL approach utilizing watershed scale hydrologic targets is a promising candidate for a stormwater-based TMDL.

In addition, identification of contributing sources is necessary if targets are to be achieved. Stormwater is a diffuse pollutant, so identifying individual contributors can be difficult. An alternative approach is to devise a statistically sound risk assessment methodology to predict the likelihood of impairment for subcatchments within impaired watersheds. Subcatchments with higher probabilities of impairment could be targeted for priority permitting actions and Best Management Practices (BMPs), within constraints dictated by budgets, policy decisions and other feasibility measures.

This study addresses one of three of Vermont Department of Environmental Conservation's priority management concerns for 2004, most notably the "improvement of stormwater management within the Lake Champlain drainage from developed areas or areas undergoing development". This research is specifically designed to help restore all waters in Vermont listed as impaired by stormwater.

The goal of this research was to develop a TMDL framework with the objective to restore stormwater impaired watersheds to attain a natural hydrologic regime. By achieving this "normal" regime, the biotic health in streams should improve. Vermont uses biocriteria as a measure of whether a stream is meeting Water Quality Standards. Therefore, this research supports a larger State goal of attaining Water Quality Standards and ultimately, healthy streams. To achieve these standards, it was essential to establish objective and defensible targets so the regulated community would know what was expected of them. This information can be used to prioritize where permit actions are necessary and I will provide an example of how this can be done.

The objectives of this research were 1) to identify differences in the flow regime and landscape characteristics of both impaired and attainment watersheds, 2) to prioritize subwatersheds for management actions and 3) to develop a framework for TMDL development. The following Chapter 2 provides a review of relevant literature that sets the context for these objectives. They are further investigated and discussed in detail in Chapter 3.

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CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

In 2004, seventeen Vermont streams were identified by the Environmental Protection Agency (EPA) as being stormwater "impaired", meaning they did not meet Vermont state Water Quality Standards as a result of chemical, physical and/or biological degradation from stormwater runoff (VTDEC, 2004). Vermont law states that stormwater cleanup plans must reasonably assure compliance within five years or be based on a Total Maximum Daily Load (TMDL) (VTWRB, 2004a; VTWRB, 2004b). The following review discusses the science and policy behind stormwater management in Vermont.

This chapter reviews the information currently known about the science and policy behind stormwater management in Vermont. It discusses stormwater runoff, rainfall-runoff modeling and flow duration curves to provide a background for the flow modeling and model input parameters. A review of Vermont stormwater policy, TMDL development and land use as a planning tool will provide a basis for the target setting and permitting structure. The overall purpose of this chapter is to introduce the factors that control and result from stormwater runoff, and the policy tools we have to address the problem.

2.2. Stormwater Runoff

Stormwater pollution is of growing concern across the country and throughout Vermont. Polluted stormwater runoff is the leading cause of impairment to the 40% of the United States water bodies that do not meet water quality standards (USEPA, 2004). It is estimated that almost 90% of the miles and acres of Vermont's impaired surface waters are the result of non-point source pollution or runoff (VTDEC, 2004). Many of Vermont's streams are being adversely affected by stormwater runoff. Seventeen of these have been listed by the state as water quality impaired from stormwater (VTDEC, 2004). Stormwater runoff, as defined in Vermont Agency of Natural Resources' 1997 Stormwater Management Procedures is:

Natural precipitation that does not infiltrate into the soil, including any material dissolved or suspended in such water. Stormwater runoff does not include wastes from combined sewer outflows (VTDEC, 1997).

Recent studies suggest that instream condition is significantly impaired by adverse hydrological conditions (Booth, et al., 2004; Olden and Poff, 2003; Roy, et al., 2003a). Flow extremes resulting from stormwater runoff can increase erosion and disturb habitat. Bankfull or channel forming flows occur once every 1 to 2 years in pristine streams, and between three and five times per year in urban streams (Finkenbine, et al., 2000). These flows can erode banks; scour channels, re-suspend sediments and infill pools. The relationship to lower base flows is not as clear (Roy, et al., 2005).

Not only can stormwater alter the physical characteristics of the stream, a variety of pollutants and other nuisance characteristics may be carried by the runoff into streams, lakes, or other surface water bodies and groundwater. In Vermont, stormwater-related pollutants of concern include: fertilizers, herbicides, and insecticides from agricultural and residential areas; petroleum products and other toxic substances from urban areas;

sediment from development sites and eroding stream banks; road salt; nitrogen and phosphorous form agricultural lands (USEPA, 2003).

2.2.1. Urbanization and Increased Imperviousness

Stormwater runoff is especially prevalent in more urbanized communities where pavement, roofs, sidewalks or other impervious surfaces cover large areas and prevent infiltration (VTWRB, 2004b). In addition, residential lawns and agricultural land can be partially impervious, contributing to runoff in developed areas (VTWRB, 2004b). If infiltration is diminished due to development, then increased runoff volume, peak flow, peak flow duration, stream temperature and sediment loading, and decreased base flows result (Allan, 2004; Finkenbine, et al., 2000; Roy, et al., 2003b; Trauth, 2004; USEPA, 2003; Walsh, et al., 2005). These factors may lead to flooding, habitat loss, erosion, channel widening and streambed alteration (VTDEC, 2004).

Impervious area or percent impervious cover is often used as a measure of watershed development or urbanization. Studies have shown a positive correlation between imperviousness and frequency of storm flows and flashiness (Roy, et al., 2005; Schueler, 1994). Depending on the amount of impervious coverage, the annual volume of stormwater runoff can increase anywhere from 2 to 16 times the predevelopment amount (Schueler, 1994). EPA reviewed the literature for nine case studies that quantitatively examined the relationship between increased impervious surfaces and stream impacts (USEPA, 1997). A resulting table illustrates the many ways that altered hydrology as a result of stormwater runoff can affect the receiving streams (Table 1).

Impervious surface coverage as low as ten percent can destabilize a stream channel, raises water temperature, and reduces water quality and biodiversity (Schueler, 1994). At greater than ten percent imperviousness there is a notable response in erosion, flow and biological condition (Allan, 2004). Others suggest threshold ranges may be higher, between 10 to 20 percent impervious. Some argue that the problem is too complex to address with a threshold. Allan (2004) cites a study in which the relationship between biotic integrity and imperviousness exhibits a linear decline as impervious cover increases.

2.2.2. Biotic Response

Ecologically harmful conditions have resulted in a need for expertise in analyzing and predicting development impacts on the instream environment (Santos-Román, et al., 2003). Walsh, et al. (2005) describe urbanization as having numerous effects on instream biota. Urbanization or other human activities that affect flow, sediments or stability will ultimately affect aquatic ecosystems (Booth, et al., 2004; Roy, et al., 2003b).

Benthic macroinvertebrates may be the most studied aspect of urban streams and have traditionally been used as an indicator of stream health (Walsh, et al., 2005). Macroinvertebrate assemblages show consistent shifts in urban streams, and therefore are often used as indicators of change in urban land use (Roy, et al., 2003a; Roy, et al., 2003b; Walsh, et al., 2005). Urban streams are dominated by disturbance-tolerant macroinvertebrates and fewer species overall. Studies show a similar response in the fish communities including reduction of sensitive species, increase in disturbance-tolerant species, and at times, a decrease in species richness and abundance (Roy, et al., 2005; Walsh, et al., 2005).

Researchers traditionally linked water quality parameters to biological health (Booth, et al., 2004). Booth, et al. (2004) argue that there is little relationship between these two in light to moderately urbanized watersheds, so other factors such as flow likely impact biological health. There are many studies linking flow properties to stream biota characteristics and impacts (Booth, et al., 2004; Clausen and Biggs, 2000; Santos-Román, et al., 2003). Hydrologic effects over time are expected to have the greatest effects on instream biota (Booth, et al., 2004; Olden and Poff, 2003). Using flow attributes as a tool to assess biologic integrity provides a more accurate understanding of the causes of biological degradation because it is more representative of the different processes that are occurring in streams (Booth, et al., 2004).

2.2.3. Best Management Practices (BMPs)

In the past, structural BMPs were the preferred approach to manage stormwater runoff. However, an effective approach to bring stormwater impaired waters into compliance with water quality standards should evaluate approaches other than the end-of-the pipe treatment and control structures that form the centerpiece of most stormwater management programs (VTDEC, 2004). Nonstructural treatments for urban streams might include stream bank stabilization, restoration of riparian zones, the removal of on-stream ponds and the use of municipal stormwater utilities to finance the management of stormwater runoff (VTDEC, 2004). The consideration of nonstructural stormwater management approaches in the development of cleanup plans for urban watersheds may provide additional pollutant load reductions over and above those provided by structural treatment-and control BMPs.

Existing landscape features can provide natural treatment for stormwater runoff. Forest stands in a watershed are critical for mediating other land use impacts on stream habitats (Richards, et al., 1996). The permanent establishment of a riparian buffer can effectively treat stormwater by capturing runoff from pervious and impervious areas adjacent to a stream (VTDEC, 2004). Wetlands in the stream network can also mitigate sediment, nutrients and temperature (Richards, et al., 1996). The Vermont Agency of Natural Resources currently has a program in effect to encourage the use of riparian buffers in its projects (VTDEC, 2001). According to this program, buffers will continue to be used to promote infiltration and treatment, as well as other non-stormwater functions (VTDEC, 2001). In addition, it recognizes the need to site stormwater facilities in a way that they are not in conflict with buffer protection.

2.3. Rainfall Runoff Modeling

Hydrologic modeling was an essential component of this project. My research used the output from a rainfall-runoff model called The Program for Predicting Polluting Particles Passage through Pits, Puddles, and Ponds, Urban Catchment Model (P8). To devise flow targets for permitting we utilized the flow output from this model.

A rainfall-runoff model is a simplified model of real world processes that are far too complex to predict in their entirety (Wagener and Gupta, 2005). Beven (2001) suggests that the two main reasons we model hydrologic systems is to predict what is happening in ungauged watersheds and extrapolate into the future to predict impacts. Rainfall-runoff models can simulate flows when we have little or no stream flow data. There are a number of reasons that streamflow information is needed including flood prediction, water supply planning and water quality improvement.

A model parameter "defines the characteristics of the catchment area or flow domain" (Beven, 2001). Parameters represent natural processes in a watershed (Wagener and Gupta, 2005). Usually, a number of parameters are estimated to convert rainfall to runoff for the watershed (Garg, et al., 2003). It is unlikely that one parameter set is the only one that will work for a model. This is important and should be considered because the results of modeling with different parameter sets will produce different predictions (Beven, 2001; Yu and Yang, 2000). It is usually difficult to closely match all parameters in a model parameter set with appropriate catchment characteristics (Yu and Yang, 2000). There is also the prevalent issue of scaling where the spatial scales of the model-defined parameters are different than what can be measured in the field, effectively "diluting" the parameters (Wagener and Gupta, 2005).

Parameters are difficult to predict and are often calibrated through a process of adjustments between model predictions and observations (Beven, 2001). Traditionally parameter values were optimized in the calibration process through repeated simulations adjusted to actual observations (Beven, 2001; Vogel and Sankarasubramanian, 2003). The problem with this is that the data quality may not support a good optimization of the parameter values (Beven, 2001). Two important assumptions in optimization of parameters are that the model accurately represents the watershed conditions and that the observations are accurate. In addition, parameter adjustment can be very time consuming. “If the process equations are valid, …the parameters should be strongly related to the physical characteristics being represented (Beven, 2001).”

In most cases, it is not possible to derive parameters from direct measurement; therefore, calibration or optimization techniques are generally used. Optimization of parameter values assumes that the model and observations are error free (Beven, 2001). Models of natural systems are based on observations that are typically dynamic over time and space, and so it is unlikely that this assumption is ever completely true. Calibration is the process that adjusts the parameter to synchronize the simulated and natural system. For this reason, parameter values determined by calibration are best used within a specific model and are generally not directly transferable to other models or modeled environments (Beven, 2001; Wagener and Gupta, 2005).

It is difficult to calibrate hydrologic models for ungauged sites. If a watershed used for calibration is not the same as the one to which the model will be applied, then uncertainty or errors in model outputs result (Garg, et al., 2003). As with any scientific study data uncertainty or error is always a concern. In this case, it can result from equipment or human error. Wagener and Gupta (2005) suggest that model uncertainty is introduced the moment we choose the conceptual representation of the study watershed because these are complex systems that we may not completely understand.

Runoff is a spatially and temporally complex process influenced by many factors (Garg, et al., 2003). Spatial scale can vary greatly and may be represented as levels such as cell, field, catchment, sub watershed, and watershed (Beven, 2001). Topography, soils and precipitation are other aspects of a watershed that have spatial characteristics. Other aspects that can be exceedingly difficult to model include time scale, continuous or event-based, land use and water quality indicator or pollutants.

There are multiple model types that we can choose from, each having benefits and limitations. Lumped models calculate based on whole watershed inputs and parameters that have been generalized across the watershed. A limitation with lumped models is that a watershed is a heterogeneous landscape that is being greatly generalized. On the other hand, distributed models calculate runoff on a smaller scale, such as a grid or subcatchment system and therefore can be much more detailed. These details introduce errors through increased parameters and more intensive calibration and validation requirements. One can also choose between deterministic and stochastic models where the deterministic model processes response from a single set of inputs and parameter values. Stochastic models have some uncertainty in inputs or parameter values and therefore have uncertainty in the output (Beven, 2001). Most rainfall-runoff models are deterministic though there is often some crossover between the two.

2.4. Flow Duration Curves

Hydrologic metrics reflecting stream flows provide a direct link between stream health and watershed characteristics (Booth, et al., 2004). A range of streamflow characteristics should be incorporated into studies of the biological impacts of flow regimes, as streams exhibit a multitude of hydrologic conditions (Clausen and Biggs, 2000; Olden and Poff, 2003). Flow duration curves (FDCs) characterize a range of flow conditions and are appropriate for studies of impairments caused by nonpoint source pollution or stormwater runoff (Bonta and Cleland, 2003). An FDC can capture the flashiness of added stormwater runoff caused by increased imperviousness in a watershed.

FDCs have been used for water resource management since the late 1800s to characterize stream flows (Bonta and Cleland, 2003). A FDC summarizes the flow frequency regime of a river. It represents the proportion of time that a given discharge is equaled or exceeded and it represents watershed response to precipitation (Bonta and Cleland, 2003; Leboutillier and Waylen, 1993). Mean daily flows are often used and the results graphed on a log scale. Graphing on a log scale simply highlights the characteristics of the flow regime by linearizing the curve (Holmes, et al., 2002). The more vertical a FDC is, the more "flashy" the watershed is considered to be (Bonta and Cleland, 2003; Holmes, et al., 2002).

Booth, et al. (2004) used regression relationships to compare FDCs with load (sediment) duration curves and concentration (water quality) duration curves. It has been suggested that in a stable watershed, there should be a statistically significant correlation between water quality and flow rate (Bonta and Cleland, 2003). A positive correlation implies that the largest concentrations occur at high flow rates. A negative correlation implies that the chemical concentrations are limiting and/or dilution occurs at high rates and indicates that concentrations are highest at lower flow rates. Frequent high flows were found to destabilize channels, negatively affecting stream health, and biologic integrity was found to be highest in the most stable, least flashy streams (Booth, et al., 2004).

2.4.1. Hydrologic Metrics

Most FDCs in the literature comprise hundreds to thousands of data points. Although FDCs have been widely used for a long time, very little literature is available that describes techniques that compare whole FDCs. Generally, researchers choose a number of "significant" metrics that are helpful to their study and statistically sound. Limitations in analysis techniques for whole FDCs have resulted in a number of studies that have identified a wide range of flow metrics that are significant for geomorphology, ecology and hydrology, among others. If comparing two different watersheds, the standard procedure is to normalize the flows by drainage area, as flows are significantly influenced by watershed area. Onema, et al. (2006) suggested dividing a given quantile value by average daily flow to obtain dimensionless flows that do not reflect impacts from the size of the catchment.

Normally specific points along the FDC are used to explain the whole curve. Following this practice, the first step in comparing two FDCs would be to choose a number of metric or quantiles that one would like to investigate. Researchers recognize that there are different components of the flow regime that regulate ecological processes in rivers and streams. Studies have been conducted to determine which hydrologic metrics best represent those ecological processes (Baker, et al., 2004; Clausen and Biggs, 2000; Sanborn and Bledsoe, 2006; Smakhtin, 2000). Many different hydrologic indices or metrics are published and often used in describing the hydrologic condition of streams and rivers (Booth, et al., 2004; Clausen and Biggs, 2000; Olden and Poff, 2003). These indices range from standard peak and low flows to indices of flashiness. One could fit a regression line on the FDC or visually compare key segments at a fine scale. Clausen and Biggs (2000) recommend the use of multiple indices of flow in ecological studies with at least one index from each of these groups (low flow, high flow and general flow) to appropriately represent the different flow regimes. The options are nearly endless, but don't entirely get at the issue of comparing the whole FDC.

The literature is limited on how one could effectively compare two whole FDCs and determine if significant differences exist. Three studies described briefly below are not entirely adequate, but hold promise as a way to compare two different watersheds or the same watershed at two time steps.

Bonta and Cleland (2003) presented an expression of a load rate (LRE%) TMDL in which E% is percent of time a given load (E) is exceeded. It incorporates a confidence level (N) for uncertainty with a lower limit (LRlow) and upper limit (LRhigh) and therefore accounts for variability. The expression is:

$$\text{LRlow N\%} \leq \text{LR E\%} \leq \text{LRhigh N\%} \qquad \text{Equation 1}$$

Another option that Bonta and Cleland (2003) propose is to calculate a time-weighted average (l/s) for flow rate and multiply it by a given duration of time to get a volume of water for that given duration. They suggest that this could be used as a target or baseline, by which to measure a watershed against itself over time.

Lane, et al. (2006) conducted a study which compared two watersheds before and after a forest fire. To look at changes in FDCs before and after an event (fire), they developed regression models that were fitted to quantiles on the pre-event FDCs with annual rainfall as the independent variable. For example, this method matched the Q95% flow for 1995 with the annual mean daily rainfall for the same year. They then took the rainfall data from the post-event years and applied it to the pre-event equations to get predicted quantiles on the FDC. All but the first percentile on the resultant FDCs produced good prediction models. The study showed that there was not a notable change in the storm flow relative to total flow. Rather, the whole curve shifted up, indicating that normal runoff processes did not scale as expected.

Finally, the approach developed by Onema, et al. (2006) addresses the challenge of comparing two whole watersheds, not just sets of watersheds or a compilation of FDCs over a period of years. Onema, et al. (2006) utilized the Kolmogorov-Smirnov test for normality to compare whole FDCs for upstream and downstream reaches of dams. Typically, the Kolmogorov-Smirnov test provides a comparison between the sample cumulative distribution and the hypothesized cumulative distribution (StatSoft, 2004). In the study conducted by Onema, et al. (2006) the test was used to compare two cumulative frequency distributions and a significant difference was found between the FDCs of the upstream and downstream sides of the dams.

2.4.2. FDC Confidence Intervals

A confidence interval is the range around the predicted mean in which the true mean is expected to lie (StatSoft, 2004). Generally, confidence intervals are constructed around given quantiles on the FDC, not the FDC itself. Dunne and Leopold (1978) described an approach that could be applied across the range of a probability distribution function, in this case a FDC, but this approach has not been referenced in more recent literature. Confidence intervals around FDCs can vary in magnitude and cause, as streams are dynamic and variable systems, even in an undeveloped state.

Generally, sample size and variation influence the width of a confidence interval. Small sample size reduces the statistical significance of the analysis because the influence of potential outliers could have a much greater influence on results than a dataset containing many samples. Variation in the data can also influence the confidence interval. In the case of flow duration curves developed over multiple years, climatologic variation such as dry or wet years, snowfall amounts and temperature can affect stream flow values. Flows on the extreme ends of a FDC tend to have the greatest variation and will therefore have the greatest confidence interval width. In general, interannual variation of low flow (90% exceedence flow) and general flow (mean and median flow) indices are low, while the high flows tend to have greater variation (Clausen and Biggs, 2000). The reason for this is that the lowest lows and the highest highs occur infrequently and are due to extreme climatological events that are not predictable.

The time step may be important because, for example, a FDC developed based on daily values will not capture the smaller hourly variations (Bonta and Cleland, 2003). This factor is usually less evident in large watersheds than small ones, in which flows are generally more variable over a day. Another temporal factor is seasonality. Climate, ground cover and snowmelt are all influenced by the seasonality of the study area and factor into variability.

Additional factors apply when one is using a synthetic or modeled flow duration curve constructed from multiple watersheds. Watershed characteristics such as size, land cover, geology and slope are fed into the rainfall-runoff model that produces the FDCs. If there is a wide range of soil types or land cover types, this variation may be reflected in wider confidence intervals for the FDCs. Quality of the stream flow data, which can be measured or modeled, can affect confidence intervals. Modeled flow data is subject to the accuracy of the input data as previously described and measured data is affected largely by the quality of the gauging equipment and user error.

2.5. Vermont Stormwater Policy

The Vermont Agency of Natural Resources is working to address concerns about stormwater impacts from a diverse group of stakeholders including local, state and government agencies, statewide and regional business groups, environmental advocates, professional engineers, the academic community and the agricultural community (VTWRB, 2004b). These groups have different interests in the outcome ranging from resource conservation to recreation/tourism to economic growth (VTWRB, 2004b). Vermont needs a viable stormwater management plan to protect receiving waters while allowing for economic development (VTWRB, 2004b).

The Vermont Agency of Natural Resources Stormwater Division has been responsible since the 1970's for managing stormwater runoff through a statewide individual permitting program (VTDEC, 2002). As of 2004, there are approximately 2000 state stormwater permits and about half of these were located in the more urbanized areas of the state (VTDEC, 2001). The individual permits must be renewed every five years. Until recently the workload required to process these permit applications created a backlog of expired permits that left little time to monitor existing discharges or assess the health of the receiving streams (VTDEC, 2001).

Based partly on recommendations in the Center for Watershed Protection's Technical Support Documents and the passage of Act 109 in 2002, the Agency of Natural Resources drafted new permitting rules that would move towards the use of general permits. These general permits would be specific to an individual watershed as a way to implement the stormwater program's cleanup plan (VTDEC, 2001). The general permits placed the responsibility of system design certification on the permit applicant using a licensed professional (VTDEC, 2002). Under this scheme, the Agency of Natural Resources would be responsible for conducting random audits on a percentage of the systems (VTDEC, 2002). These general permits were more fully developed in 2001 and 2002 and on July 1, 2002, Watershed Improvement Permits were issued for four impaired streams (VTWRB, 2003). These were general permits, specific to a specific impaired watershed, which outlined BMPs to be applied to new and existing discharges (VTWRB, 2003). The Watershed Improvement Permit methodology was described by the state as the "principle means for water quality remediation in stormwater affected areas" (VTDEC, 2004). State law is such that impaired receiving waters should comply with state Water Quality Standards within five years (VTWRB, 2003). Shortly after they were issued the initial four Watershed Improvement Plans were appealed by the Conservation Law Foundation and the Vermont Natural Resources Council and ultimately rejected because they could not “reasonably assure compliance” within this 5-year regulatory timeframe (VTWRB, 2003).

In 2004, seventeen Vermont streams were placed on the Environmental Protection Agency’s Section 303.d list as a result of stormwater impairments (VTDEC, 2004). Vermont Natural Resources Council and Conservation Law Foundation petitioned the Water Resources Board stating that stormwater discharges into five stormwater-impaired streams (Potash, Englesby, Morehouse, Centennial, and Bartlett Brooks) are violations of the Vermont Water Quality Standards and are therefore required to be permitted under Federal National Pollutant Discharge Elimination System permits (VTWRB, 2004a). If this petition were upheld, it would have been the first ruling of its kind in the country. No one, including the Agency of Natural Resources and the Environmental Protection Agency, issues such a permit for stormwater discharges (VTDEC, 2004). On October 14, 2004, the Vermont Water Resources Board issued a Memorandum of Decision in response to this petition and a subsequent denial from the Agency of Natural Resources (VTWRB, 2004a). This decision placed the National Pollutant Discharge Elimination System permitting authority on the State and stated that the Agency of Natural Resources would establish minimum thresholds and permit conditions (VTWRB, 2004a).

With the passage of Act 140, the Agency of Natural Resources was required to develop and implement long-term cleanup plans for the 17 stormwater-impaired streams on the 303(d) list by September 30, 2007 (LaFlamme, 2004). The state decided to investigate the application of a TMDL to serve the watershed plan function.

2.6. TMDL Development

A TMDL is a cleanup plan that includes an assessment of the pollutant assimilative capacity of a receiving water and an allocation of portions of that assimilation capacity among the various pollutant sources in the watershed. It includes a margin of error to accommodate unknown and future demands on the assimilative capacity (CWA, § 303(d)). Hydrologic targets can be used to estimate assimilative capacities of the receiving waters and to estimate the loads of stormwater pollutants that must be reduced to achieve water quality standards (Gray, 2004; Nicholls, 2004). This methodology uses the surrogate of stormwater runoff volume rather than the traditional single pollutant approach. This surrogate is appropriate because the pollutant load discharged to a watershed is a function of the volume of stormwater runoff.

Researchers and regulators are challenged when conducting water quality investigations and setting TMDLs or cleanup targets for streams due to their flow variability. Some researchers have been looking into the use of FDCs to set targets for TMDLs (Booth, et al., 2004). Historically, the targets were a single discharge value that didn't accurately represent the range of flows affecting the impaired water body (Bonta and Cleland, 2003; Olden and Poff, 2003).

The Environmental Protection Agency issued TMDL regulations in 1985 and amended them in 1992 to implement section 303(d) of the Clean Water Act (§§ 130.7). TMDLs are developed by individual states for each impaired water body and are submitted to the Environmental Protection Agency for approval (USEPA, 2003). Under section 303(d) of the Clean Water Act, states are required to identify impaired waters that do not meet state Water Quality Standards (USEPA, 2003). They are the foundation of the state's water pollution control and water quality protection efforts, and are the responsibility of the Board (VTDEC, 2004). The Water Quality Standards provide the specific criteria and policies for the management and protection of Vermont's surface waters (VTDEC, 2004).

The current Vermont Water Quality Standards were adopted on June 10, 1999 and became effective July 2, 2000 (VTDEC, 2004). Every two years, each state must submit a list to the Environmental Protection Agency of those waters within its boundaries that do not comply with the State's Water Quality Standards and for which TMDLs are required (CWA, § 303(d)). Vermont law states impaired receiving waters should comply with state WQSs within five years (VTWRB, 2003). However, when a TMDL is developed, there is no required timeframe, in federal law, in which the waterbody must meet Water Quality Standards (VTWRB, 2004b). The reasoning is that a properly designed TMDL creates reasonable assurance that, with implementation, Water Quality Standards will be met (VTWRB, 2004b).

To date, one of Vermont's 17 stormwater impaired streams has an approved TMDL based on the target setting methodology described in the next chapter and four others are pending approval. Once plans are developed, an associated General Permit for each watershed will be issued to implement the plan (LaFlamme, 2004). The following subchapters provide background on the aspects of the TMDL framework that are investigated in the next chapter.

2.6.1. Target Setting

Vermont law requires that stormwater cleanup plans must either reasonably assure compliance within five years or be based on a TMDL, which involves estimating how much stormwater reduction is needed to meet Water Quality Standards (VTWRB, 2004b). Although stormwater runoff is a complex mixture of pollutants, these pollutants move either with the water flow or are attached to sediment particles in the water (VTDEC, 2004). Therefore, addressing water flow (hydrology) and sediment loading would be expected to help control the other pollutants as well. Flow can be considered a single concentration surrogate for all the pollutants associated with stormwater.

Using a single concentration value for TMDLs does not account for frequency, duration or risk associated with flow rates or uncertainty in concentration-flow rate relationships in natural streams. Regression relations can be used to address uncertainty by setting confidence limits for the FDCs (Bonta and Cleland, 2003). These confidence limits when applied to TMDL implementation can account for uncertainty, natural variations and landscape changes due to development (Bonta and Cleland, 2003). Once a target has been set, the contributing sources in the watershed need to be identified. The following section reviews a risk assessment technique that can be used as a basis for source identification and prioritization.

2.6.2. GIS-based Risk Assessment

Mitchell (2005) developed a GIS-based planning and assessment model for non-point source pollution for application in more urbanized watersheds. The intended model application is for watershed areas that are already built out, though the authors recognized that the model could also evaluate the impact of land use changes. The Mitchell (2005) study was not a full risk assessment because it did not address acute or short-term effects. Rather, it serves as a screening tool to characterize subwatershed areas for further consideration and investigation (Mitchell, 2005; Trauth, 2004).

2.6.3. Adaptive Management

Because the proposed TMDL framework is an innovative and untested methodology, the accuracy of the targets must be verified through a comprehensive monitoring program (VTWRB, 2004b). The Environmental Protection Agency supports the use of hydrologic and sediment targets as set forth in the docket, but they agreed that the correlations being drawn must be evaluated and adjusted over time (VTWRB, 2004b). To this end, the docket suggested an adaptive management component of the plan that allows for adjustments to the plan over time (VTWRB, 2004b). A simple schematic of a typical adaptive management process is depicted in Figure 1.

The use of adaptive management for resource management originated in the 1970's (Holling, 1978). Though it has not been explicitly incorporated into the TMDL process, components of adaptive management have been, and the results have been both lauded and criticized (Freedman, 2004). Adaptive management allows for the implementation of a TMDL and avoids overly strict targets or a lack of water quality improvement while targets are under debate (Freedman, 2004). It recognizes that models used for decision-making are approximations, not absolutes (Dilks and Freedman, 2004; Freedman, 2004). It also recognizes that changes targeted at improving one resource may have unintended consequences or unexpected outcomes. It allows for additional investigation to detect these consequences and address them in a timely manner (Freedman, 2004). Watershed analysis should be viewed as an 'evolving process' that should allow for improvements as our knowledge increases over time (Kohm and Franklin, 1997).

2.7. Land Use as a Planning Tool

Numerous factors affect the flow regime of a river or stream. On the broadest scale, there are natural factors that cannot be controlled, including rainfall, evaporation and temperature (Holmes, et al., 2002). On a local scale, flow is affected by physical properties such as geology, topology and land cover (Bonta and Cleland, 2003; Booth, et al., 2004; Holmes, et al., 2002; Leboutillier and Waylen, 1993; Santos-Román, et al., 2003; Young, et al., 2005). Of these, the land cover characteristics related to development seem to play the largest role on the flow regime and water quality (Booth, et al., 2004; Santos-Román, et al., 2003). Increased development, as defined by urban land cover and total impervious area, leads to more frequent high flows (Booth, et al., 2004). It is important to understand how different land cover characteristics, i.e. land use type and percent impervious cover affect the stream. There are a number of statistical techniques used for this research (Bonta and Cleland, 2003; Booth, et al., 2004; Santos-Román, et al., 2003).

Water quality or other stream characteristics such as flow can be used to group like watersheds (Santos-Román, et al., 2003). In watersheds where stream flow data are not available, watershed characteristics may be used to predict water quality (Santos-

Román, et al., 2003). Biologic integrity has been found to be significantly correlated with land use and as total impervious area increased, biological condition generally declined (Booth, et al., 2004). Land cover characteristics important in determining biotic indices, although land cover relationships have been found to be weaker predictors than reach scale variables (Lammert and Allan, 1999; Roy, et al., 2003a; Sutherland, et al., 2002). For this reason studies in gauged watersheds should still use the variety of techniques discussed previously, but the methods described by (Booth, et al., 2004; Santos-Román, et al., 2003) would provide a reasonable surrogate for stormwater.

Roy, et al. (2003b) identified a threshold of water quality, which indicates that in areas with greater than 15-20% urban land cover the water quality was bad enough to negatively affect macroinvertebrates. In addition to an urban land cover threshold, one relating to non-forested land was found. Sutherland, et al. (2002) suggested that a threshold might exist between 10% and 20% non-forested land cover beyond which benthic crevice and gravel fish species cannot survive. This threshold was also supported by the fact that above 20% non-forested land cover, suspended sediment and bedload transport increased dramatically. Roy, et al. (2003b) found that land cover was correlated to specific geomorphic and water quality variables. Increases in urban land and decreases in forestland were found to produce larger substrate sizes, lower slope and lower local relief. Increased agricultural and increased urban land was related to higher nutrient levels and turbidity (Roy, et al., 2003b; Schueler, 2003).

The next chapter will describe a protocol to address the target setting and subwatershed cleanup priorities as the basis for a TMDL for stormwater-impaired streams.

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CHAPTER 3: SETTING OBJECTIVE WATERSHED LEVEL TARGETS FOR STORMWATER MANAGEMENT

3.1. Introduction

The objectives of this research were to identify differences in the flow regime and landscape characteristics of stormwater impaired and reference watersheds, to prioritize subwatersheds for Best Management Practices (BMP) implementation, and to develop a framework for Total Maximum Daily Load (TMDL) development. This research was necessary to support a protocol that had been designed by the state to objectively identify targets for stormwater reduction and locations for priority permit actions relevant to the new Vermont state stormwater rules enacted in 2004. Reference watersheds were defined as watersheds that had some level of development (urban or agricultural) but still attained the Vermont water quality biocriteria standards. For the purposes of this report, these areas will be referred to as "attainment" watersheds rather than reference watersheds, to emphasize that the attainment watersheds were not necessarily in a totally unimpaired or pristine condition as is often intended when using the term "reference stream" (VTWRB, 2004b).

3.1.1. Background

Since 2001, the key stumbling block in Vermont stormwater management – as in other states – has been an ongoing problem of how to regulate the public in a scientifically, technically and economically acceptable way, while protecting water resources. In 2002, the Vermont Agency of Natural Resources developed Watershed Improvement Plans (WIPs) that were to be the basis of the stormwater permitting program. However, the WIPS were appealed by environmental advocacy groups and ultimately rejected because they successfully argued that the WIPs could not "reasonably assure compliance" within the five year regulatory timeframe dictated by the Clean Water Act and Vermont law (VTWRB, 2003).

As a result of the appeal, an Investigative Docket process was initiated by the Vermont Water Resources Board to explore options for designing and implementing effective cleanup plans for impaired waters (VTDEC, 2004). The Docket was a technical advisory group that researched and developed an innovative approach to stormwater management that would satisfy the scientific requirements, while addressing some of the limitations of previous attempts. The docket committee agreed that hydrologic and sediment targets could be used to create stormwater pollutant loading reduction estimates as the basis for a TMDL (VTWRB, 2004b). The outcome of the Docket was a suggested stormwater cleanup framework that is the basis of this research.

The framework aimed to restore the stormwater impaired watersheds and to achieve water quality standards through implementation of a TMDL. The TMDL process is well established and has a defined framework. The process relies on scientific research outcomes to feed a preexisting policy model. In this case, the policy or standard TMDL framework was not flexible enough to address the results of the scientific study. The issue was that the TMDL framework was originally established to address the impacts from a single pollutant. In the case of stormwater runoff, there are potentially many pollutants involved and it was not realistic to devise separate TMDLs for each pollutant.

An innovative conceptual approach was developed that used a more holistic target or surrogate – flow regime – as the indicator.

3.2. Project Setting

This study was based on technical data created by Tetra Tech, Inc. who had been contracted by the Vermont Agency of Natural Resources to produce simulated flow data from a simple catchment-based rainfall-runoff stormwater model. Simulated data were needed because no historical flow data existed for the watersheds of concern. In the following sections I describe the physical setting of the study watersheds and the technical data used and generated by the Tetra Tech, Inc. initiative. Both of these are necessary precursors to the methods used in this study and results that were generated.

3.2.1. Study watersheds

The project area comprised a suite of 27 stormwater impaired and "attainment" watersheds in non-mountainous areas of Vermont (largely in Chittenden County). For the purposes of this study, impaired watersheds are those watersheds that have been identified by the state as having biotic characteristics that have been degraded by stormwater runoff and are reported as such on the Vermont state "303.d" list of impaired waters. For this study I used 12 of the 17 streams in the state that have been listed for stormwater impairment (Table 2). Attainment watersheds are watersheds, also identified by the state, that have been developed to some degree but currently attain the state's biocriteria standards. I used 15 attainment watersheds in this study (Table 2).

3.2.2. Technical Background

This study used only input parameters that were readily available through Geographic Information Systems (GIS). The independent variables in these analyses were the variables used to define the hydrologic model input (Table 3). These variables were watershed area, land use/land cover, impervious cover, average slope and hydrological soil group. Table 3 provides an explanation of the watershed variables.

The GIS database is comprised of land use, soils, slope, hydrography and orthoimagery. Natural Resource Conservation Service digital soil survey "SSURGO" data were used to map and calculate areas for the four standard Hydrologic Soil Groups. Land use characteristics were obtained from Vermont Center for Geographic Information 1992 land use\land cover data. Slope data were derived from United States Geological Survey National Elevation Dataset (7.5' DEM Slope24) data. Streams and tributaries were derived from the Vermont Hydrography Dataset of surface waters. 1:5000 digital orthophotograph quadrangles were obtained through the Vermont Mapping Project.

Data errors associated with GIS data and processing could affect the confidence associated with the results reported here. Two observations in particular deserve mention. The metadata for the soil data indicated that the data for Chittenden County had not been through Quality Assurance/Quality Control for accuracy. Thus, there may some uncertainty with respect to the Soil Hydrogroup designations (A, B, C, or D). In addition, the land use/land cover data were originally developed in 1992 with some minor updates in 1997. However, impairment designations were made in 2004. Thus, there is a notable timing discrepancy between the land use/land cover data and the impairment designations. It is likely that development increased between 1992/1997 and 2004 with the effect that impairment predictions based on older, less-developed land use/land cover data might be somewhat conservative. When newer land use/land cover is available, the models could be updated to reflect these changes.

The hydrologic data used in this study were derived from the output of a model called The Program for Predicting Polluting Particles Passage through Pits, Puddles and Ponds, Urban Catchment Model (P8) (Walker, 1990). The P8 model is a simple rainfall-runoff model based on land use/land cover. It was appropriate for the limited input and validation data available in Vermont (TetraTech, 2005). Input parameters for hydrologic simulation included climatological data, percent imperviousness, pervious curve number, and time of concentration for ground water base flow and surface runoff. The model was parameterized and run by Tetra Tech, Inc. and the model output was provided for use in this study.

For this study, the modelers used a lumped watershed approach, though one of the reasons P8 was chosen was because it has capabilities to be used as a distributed model with multiple subcatchments as well. The model used continuous hourly rainfall and daily air temperature series data for a period from 1992 to 1994 as input and base flow based on an effective watershed time of concentration. The effective watershed time of concentration was derived from a simple relationship between watershed area and watershed slope TetraTech (2005), that is functionally similar to slope/area index used in many hillslope models (e.g., TOPMODEL) (Beven and Kirkby, 1979; Beven, et al., 1984). A simple linear reservoir model was added to more realistically estimate groundwater inputs. Pervious runoff was computed using the Soil Conservation Service curve number approach. Antecedent moisture conditions were based on 5-day antecedent precipitation. Runoff estimates considered both rainfall and snowmelt, which is important in Vermont where snow accumulation can be significant.

The P8 model was calibrated for two New York watersheds in the Lake Champlain basin where accurate and concurrent precipitation and flow data were available. The calibrated model was validated against observed rainfall and runoff data for June to July 2004 in Potash Brook, the only stream in our study set for which real flow data were available at the time of this study. The calibrated and validated model was then used to develop simulated time-series flow records for our ungauged study streams based on ten years of precipitation and temperature data (1990 to 1999). The same climatological data were used for each watershed simulation; only the watershed characteristics changed. The simulated 10-year flow record for each watershed was used to produce a flow duration curve (FDC) and flow metrics were then extracted from these simulated flow duration curves.

3.3. Methods

3.3.1. Flow Metrics

Based on the literature, eight simulated flow values were chosen for comparison between the impaired and attainment streams. The flows (Q_{95}, Q_{80}, Q_{50}, Q_{20}, Q_5, Q_1, $Q_{0.3}$, $Q_{0.1}$) for each stream, as simulated by TetraTech, were supplied to the University of

Vermont by the Agency of Natural Resources (Table 4). Qx refers to the simulated flow level that is exceeded X% of the time (annually).

Data sets (impaired and attainment separately, at a flow level) that passed normality were tested for equality of variance. Groups that passed this test were subjected to an unpaired *t*-test. The null hypothesis of this test was that the flow means of the two groups were the same. The minimum criterion for rejecting the null hypothesis was P=0.05. However, more stringent probabilities (P=0.01 and P=0.001) were noted where appropriate.

If the data failed the test for normality, they were analyzed by the nonparametric Mann-Whitney Rank Sum test. The null hypothesis of this test is that the flow *medians* of the two groups are the same. The data are ranked from low to high, regardless of what group (impaired or attainment) it came from. The ranks were summed for each group and these sums (rank sums) were compared. Identical criteria for significance were used for the Mann-Whitney and t-test results.

3.3.2. Hydrologic Targets

The dependent variable in most of the following tests was the $Q_{0.03}$ or the 1 day (P=0.03%) discharge from the model generated FDC's. This variable was selected because it was easily understood, it is related to fundamental channel-forming processes and it was a variable that key stakeholders were likely to agree was important. The independent variables in the following analyses were the variables used to define the P8 input. These variables were the watershed area, land use/land cover percentages, impervious cover, average slope, soil hydrological group. Systat® 11 software was used to conduct the statistical testing. It is a user-friendly program with a Windows® interface that can be run on any computer with a Microsoft Windows® based system.

Descriptive statistics were computed for the watershed variables. The Shapiro-Wilks W test was used to test the normality of the independent watershed variables for both impaired and attainment watersheds. SoilD and Forest were the only variables that resulted in normal distributions. Normality is not required for the tests used in this study, so untransformed variables were used throughout.

Scatterplot matrix plots show correlations among all possible pairs of variables and between the impaired and attainment watersheds. Correlation matrices were produced for both the impaired and attainment watersheds. Variables that passed the normality test were subjected to an unpaired two sample *t*-test. The null hypothesis of this test was that the watershed variable means of the two groups were the same. The minimum criterion for rejecting the null hypothesis was P=0.05. However, more stringent probabilities (P=0.01 and P=0.001) were noted where appropriate. If the data failed the test for normality, they could not be analyzed appropriately by a *t*-test. In these cases, the nonparametric Mann-Whitney Rank Sum test was used. The null hypothesis of this test is that the watershed variable *medians* of the two groups are the same. The data are ranked from low to high, regardless of what group (impaired or attainment) it came from. The ranks were summed for each group and these sums (rank sums) were compared. Identical criteria for significance were used for the Mann-Whitney and the *t*-test results.

As a complement the paired tests described above, a Kruskal-Wallace MANOVA was performed on the non-normal data only. This test provides information about which variables in the data set differ between the impaired and attainment watersheds. The Kruskal-Wallace MANOVA is non-parametric and so does not make any assumptions about the underlying distribution of the data. It is best suited to data that are known to be non-normal.

Cluster analysis is a method used to identify natural groupings in datasets through correlation. The most common use is when the number and members of groups in a dataset are not known. Cluster analysis can also be used to see how members aggregate when groupings are hypothesized.

I used a K-means cluster analysis for two groups to test if there was a natural separation of impaired and attainment watersheds based on their watershed characteristics. The K-means clustering method is one way to calculate cluster similarities that clarifies which variables are responsible for the clustering. Successive removal of the lowest ranking variables was conducted to see if there was any influence on the resulting clusters. The minimum set of variables determined in this way were considered the most influential variables affecting impairment.

The purpose of the hierarchical clustering was to identify natural groupings of impaired and attainment watersheds that would otherwise be similar if it were not for the influential variables that caused degradation of the impaired watershed. Two different hierarchical cluster analyses were conducted using the average linking method, which clusters cases based on average Euclidian distances. The first hierarchical cluster analysis used the most influential variables determined by the K-means clustering and resulted in clustering based on the dominant watershed variables. A second hierarchical cluster analysis used the *lowest ranking* variables from the k-means clustering results to examine whether and how the watersheds clustered on the basis of variables that did not strongly distinguish the watersheds. The attainment watersheds in a group could then serve as a target for the impaired watersheds in a group. Therefore, the flow targets for the impaired watersheds were based on the flow characteristics of complementary attainment watersheds.

3.3.3. Subwatershed Prioritization

All 12 impaired and 15 attainment watersheds from Vermont were used in the calibration and validation of the model. Following model selection, a more detailed application focused on Centennial Brook subcatchments and the Potash Brook subcatchments, both located in Burlington and South Burlington, Vermont. Subcatchment boundaries based on topography and stormwater infrastructure drainage networks were delineated by Pioneer Environmental, a consultant to Vermont Agency of Natural Resources.

Logistic regression is a type of generalized linear model that can predict group membership from a set of variables. Binary logistic regression is a model used to predict the probability that the response variable will assume one of the two binary responses (Smith, et al., 2001). In logistic regression, there is no distribution assumption, that is, the independent variables do not have to be normally distributed or have equal variance within each group. The analysis was limited by the number of watersheds with simulated flow values (12 impaired and 15 attainment). In this case the dependent variable is binary: impaired (1) or attainment (0). The independent (or predictor) variables of interest are the watershed characteristics that were provided as the input variables to the P8 hydrologic models (Table 3).

A correlation matrix was produced and initial variable selection/exclusion was conducted based on significance of correlations. Variables that were highly correlated with the dependent binary variable (impairment) were the first ones investigated, as they would likely produce the best predictive model. Variable pairs with high correlations ($>\pm0.600$) were not considered in the same model, as this autocorrelation would likely reduce the significance of the model if both variables in the pair were included. Variable pairs with little correlation ($<\pm0.300$) are better candidates to consider in the same model.

A combination of two statistical software packages was used to complete the full logistic regression analysis. Systat® has the capabilities to perform stepwise regressions within the logistic analysis, but is limited to 15 iterations for the regression. Minitab® can select best subsets outside of the regression analysis and the user can select any number of iterations for logistic regression. As many of the logistic combinations required more than 15 iterations, Minitab was the preferred software package for this part of the analysis.

All potential watershed variables were investigated using forward and backward stepwise selection and best subset selection to determine the variables with the greatest explanatory power. Various models were built introducing new variables and new combinations of variables. Appropriateness of each model was evaluated by examining the statistical significance of the model terms. A level of significance of 0.05 for p-values was used for variable inclusion in equations selected for further evaluation.

The general equation for a binary logistic regression is:

$$P = \frac{\exp(b_0 + b_1x_1 + \ldots + b_nx_n)}{1 + \exp(b_0 + b_1x_1 + \ldots + b_nx_n)} \qquad \text{Equation 2}$$

where P is the probability of the condition (impaired) being true, exp is the exponential function e^x (natural log), b_0 is the constant or intercept, b_n is the variable coefficient and x_n is the variable value for variables 1 to n. The output of a logistic regression is the equation log(odds) = $b_0 + b_1x_1$. To compute probability from this output, I calculated the odds ratio (odds) by taking the exponential function of log(odds). The probability is odds/(1+odds).

Good modeling practice dictates that data used to calibrate a model should not be used subsequently in predictions to validate that the model is working well , to avoid circularity. Consequently, we divided the original whole watershed dataset of 12 impaired and 15 attainment watersheds into two subsets, a calibration set and a validation set. The calibration set comprised 10 impaired and 12 attainment watersheds. The validation set consisted of five randomly selected watersheds from the original 27 watersheds, two impaired and three attainment. The calibration set was used to generate the models, while the purpose of the validation set was to verify the results against a different sample set. Once a potentially appropriate model was identified, it was applied to the validation set for confirmation.

The final logistic models provided an estimate of the probability of impairment based on watershed-scale variables. I made an assumption that these watershed-scale variables would have the same impact at the sub-watershed level. I then applied the watershed-scale logistic regression to the sub-watersheds within a given watershed. The result was a sub-watershed map of probability of impairment which could be used to evaluate priorities for management. This approach was applied to two of the 12 impaired watersheds (Centennial Brook and Potash Brook) as a demonstration.

3.4. Results

3.4.1. Flow Metrics

The Q_{95}, Q_{80}, Q_{50}, Q_{20}, Q_5, and $Q_{0.3}$ metrics all passed the normality and equal variance tests and were analyzed with *t*-tests (Table 5). The differences in means for the Q_{95} and Q_{80} metrics were found to be extremely significant ($P<0.001$), the difference in means for the Q_{50} metric was found to be highly significant ($P<0.01$), and the difference in means for the $Q_{0.3}$ metric was found to be significant ($P<0.05$). The differences in means for the Q_{20} and Q_5 metrics were not significant. The power for the Q_{95} and Q_{80} metrics was above my limit of 0.8, while the power for the remaining metrics was below that limit. The Q_1 and $Q_{0.1}$ metrics did not pass the normality test, so the Mann-Whitney test was used (Table 5). The difference of medians for the Q_1 metric was found to be extremely significant ($P<0.001$), while the difference in medians for the $Q_{0.1}$ metric was found to be non-significant.

3.4.2. Hydrologic Targets

Scatter plot matrices were constructed to visualize the data from the attainment and impaired watersheds (Figure 2). Tables 6 and 7 provide the Pearson correlation coefficients for these same data. There are a number of strong internal correlations in the data. In the attainment watersheds, Urban positively correlated with SoilC and with Impervious Cover, as should be expected. Agriculture was negatively correlated with Forest, again as should be expected. SoilA and SoilD were inversely correlated and Impervious Cover tended to be lowest where SoilD is high. Of note, Water was strongly associated with SoilA (the most permeable hydroclass). Urban areas were negatively correlated with Forest, Agriculture and Wetland and positively correlated with Impervious Cover, which was expected. In both impaired and attainment watersheds, Forest was associated with higher Slope. In the attainment watersheds, Water, Urban, SoilA and Impervious Cover were consistently low and appeared to be unaffected by the other watershed variables. Within the impaired watersheds Water, Wetland, SoilA and Slope appeared to be unaffected by the other watershed variables. A number of the variables for both attained and impaired had outliers, though these were not attributed to any particular watershed trend.

The Kruskal-Wallis MANOVA test identified statistically significant differences between impaired and attainment watersheds for the Urban, Forest, Impervious Cover and Slope variables (Table 8). Several things should be noted about these variables, however. First, Urban and Impervious Cover are clearly auto-correlated. In addition, the Urban and Forest variables are negatively correlated.

All watershed variables were included in the first K-means cluster analysis (k=2) as illustrated in Figure 3. Area disproportionately influenced the clustering, reducing the influence of the remaining variables. The F-ratio for Area was 93, while the F-ratio for the next most influential variable was three. The specific watersheds assigned to each cluster were a mix of attainment and impaired watersheds that were clustered based on size (small versus large watersheds). Including the Area variable obscured the more interesting and useful underlying structure of the data and is logically not a useful variable for this analysis

When the Area variable was removed, the influence of the remaining variables increased (Figure 4). In addition, clustering without Area produced a better split of attainment and impaired watersheds. Impervious Cover was also removed as it is highly correlated with Urban. Cluster 1 contained 15 cases, 12 of which were attainment watersheds. Cluster 2 contained 12 cases, nine of which were impaired watersheds. SoilD, Urban and Forest were the most influential variables in this clustering.

The k-means clustering was repeated 4 more times, each time removing the lowest ranking variable in the previous test (Water, SoilC, SoilB, and Wetland). This resulted in a final clustering based on the most influential watershed variables (Figure 5). The final clustering was based on (in order of significance) SoilD, Urban, Forest, SoilA, Slope, Agriculture and Wetland. SoilD had an F-ratio of 45.054, twice that of Urban with a value of 22.731. Forest and SoilA had F-ratios of approximately 12. The remaining three variables had less disparate means and therefore, less influence on the clustering. The final watersheds included in each cluster are noted in Table 9.

The final k-means clustering of the most influential variables (SoilD, Urban, Forest, SoilA, Slope, Agriculture and Wetland) were used in the hierarchical cluster analysis. The resulting permuted data matrix is shown in Figure 6. This permuted data matrix was the hierarchical clustering of all the watershed variables (columns) crossed with all the watershed cases (rows). Distances between clusters are noted as different colors in the matrix. The "cooler" blue colors are less distant while "hotter" red colors are more distant. The more distant clusters are stronger relationships. This provided an easy way to visualize how the different cases (watersheds) cluster and upon which variables (columns). The hierarchical cluster analysis of the most influential variables from the k-means test identifies which watershed characteristics are driving the two clusters.

Figure 6 shows that SoilD and Forest formed a distinct cluster. Slope and Wetland clustered together and both are more distantly related to Urban, SoilA and Agriculture. Nine attainment watersheds clustered out on the basis of SoilD and Forest as illustrated in the red cluster on the bottom right of Figure 6. Four impaired watersheds clustered loosely based on Urban and SoilA. Another more distantly connected group of 10 mixed watersheds clustered out on the basis of Urban, Agriculture, SoilD and Wetland combined as illustrated in the light green cluster in Figure 6.

A second hierarchical cluster analysis was performed with Area and the next *most* influential variables (based on k-means clustering results) removed from the analysis (Figure 7). The resulting matrix identified five distinctive clusters that are primarily influenced by SoilA, Agriculture and SoilC.

Each of the five clusters identified in Figure 7 contained both impaired and attainment watersheds. These clusters represent groupings of impaired and attainment watersheds that have similar watershed characteristics, based on variables that have little influence on whether the watersheds are impaired or not. The attainment watersheds within a cluster can, therefore, be used as targets for the impaired watersheds in the same cluster. To accomplish this, the mean and standard deviation for the Q 0.3% flow and Q 95% flow of the attainment watersheds in each cluster were calculated and are included in Table 10. The Q 0.3% attainment means were lower and the Q 95% attainment means were higher than the calculated values for each impaired watershed in a given cluster. It should be noted that for Indian Brook the Q 95% flow exceeds and the Q 0.3% flow is below the attainment average with the standard deviation taken into account.

3.4.3. Subwatershed Prioritization

Whole watershed data were provided by Agency of Natural Resources and are provided in Table 2. Impervious cover was calculated by urban land use subtype and summed in the last column. The Urban land use category was comprised of five subcategories that included Residential, Commercial, Industrial, Transportation and Other Urban uses. Commercial, Industrial and Transportation were consolidated into a sixth subcategory called "Hard Urban". Five watersheds were set aside for the purpose of validation: Allen Brook (A), Malletts Creek (A), Sheldon Spring (A), Englesby (I) and Monroe (I). The remaining watersheds comprised the calibration set.

A correlation matrix provided the Pearson correlation coefficients and associated p-values for the whole watershed calibration data (Table 11). The relationships between the basic variables have been discussed previously in this article. In addition to these variables, the binary variable (impaired) is highly positively correlated to Urban, Residential, Transportation, Hard Urban and Impervious Cover, and highly negatively correlated to Forest.

Numerous variable combinations were investigated based on correlations, step-wise analysis and best subsets analysis (Table 12). All multi-variable equations resulted in non-significant p-values, large coefficients and/or large standard errors, all of which degrade the quality of prediction. Of the P8 input variables, only Urban land use produced a significant ($p \leq 0.05$) model. This model is as follows:

$$-5.05 + (19.44*URBAN) \qquad \text{Equation 3}$$

When applied to the whole watershed calibration dataset, the Urban model classified the watersheds with 91 percent accuracy (Table 13). At a statistical test level of α=0.05 it is reasonable to expect that 1 or 2 of the 27 total watershed would be misclassified and so a classification accuracy of 91 percent is not unexpected. When applied to the validation dataset, the Urban model classified the watersheds with 100 percent accuracy. This model was then applied to the Centennial watershed and the probability of impairment for each subcatchment was calculated (Table 14 and Figure 8). For Centennial, 28 of the 38 subcatchments were assigned an impairment probability of 100 percent. Two more subcatchments were assigned a 98 percent probability of impairment. The remaining eight subcatchments (21 percent) were assigned values between 1 and 34 percent.

To further delineate the 30 subcatchments with very high probabilities of impairment, the Urban category was decomposed into its five component subcategories: Residential, Commercial, Industrial, Transportation/Utilities and Other Urban. Three significant models were identified and selected for further analysis (Table 12). These models included the variables Residential, Commercial and "Hard Urban" (a combination of commercial, transportation/utilities and industrial). These models and associated p-values are provided in Table 15.

When applied to the whole watershed calibration dataset, the Residential, Commercial and Hard Urban models classified the watersheds with 82 to 86 percent accuracy (Table 13). At a statistical test level of α=0.5 it is reasonable to expect that 1 or 2 of the 27 total watershed would be misclassified and so the observed classification accuracy is somewhat lower than might be expected. When applied to the validation dataset, these three models classified the watersheds with 80 to 100 percent accuracy (Table 13), which is acceptable.

As a demonstration, the models were applied to the Centennial and Potash data and probabilities were calculated (Tables 14 and 16 respectively). Maps of the impairment probability of Residential, Commercial and Hard Urban for subcatchments in the Centennial Brook catchment are provided in Figures 9-11 respectively. Similar maps of the impairment probability of Urban, Residential, Commercial and Hard Urban for subcatchments in the Potash Brook catchment are provided in Figures 12-15.

3.5. Discussion

The conceptual framework described in this document is outlined in a flow diagram in Figure 16. The framework provides a visual representation of the progression from hydrologic modeling to subcatchment prioritization. Model inputs and outputs are described as well. The following discussion provides further insight into the various steps described above.

3.5.1. Flow Metrics

The simulated flow duration data supported the hypothesis that the $Q_{0.3}$ or 1-year flow (the highest daily flow of the year) for impaired streams was significantly different from attainment streams. The low power of this test, however, suggested that the ability to identify statistically significant differences when they were real was not high. The $Q_{0.1}$ or ~3-year flow was not significant. Because the $Q_{0.1}$ data did not conform to normality, it was inappropriate to calculate a standard error for this particular mean value pair. Furthermore, it was clear that both the standard error and coefficient of variation (standard deviation/mean*100) increased as the flow duration probability decreased (higher flows). Due to this increase variability, it was not possible to establish significant difference for the largest flow events used in this study.

While the Q_1 flows were highly significant (by a Mann Whitney test), the Q_5 and Q_{20} flows were non-significant. Land use and land cover change had the least effect on middle flow levels. It was notable that the median flow rate (Q_{50}) was significant. The flow metrics below the median flow (Q_{80} and Q_{95}) were highly significant and the t-tests had acceptable power levels. This was consistent with the expectation that stormwater-impaired streams have *lower* low flows than unimpaired streams (Allan, 2004; Finkenbine, et al., 2000; Roy, et al., 2003a; Trauth, 2004; USEPA, 2003; Walsh, et al., 2005). However, this result should be viewed with some caution because the P8 model was not intended to be used as a low flow model. Furthermore, the data used to originally validate the P8 model were based on only a portion of the year (July to November) that would normally include a number of low flow days (although this happened to be a rather wet and rainy period in 2004).

3.5.2. Hydrologic Targets

The Kruskal-Wallis test for non-normal data and the t-test for normal data identified significant differences between the impaired and attainment watersheds for the Urban, Forest and Impervious Cover variables. The Kruskal-Wallis test also identified Slope as having significant differences between the impaired and attainment watersheds. These watershed data supported the hypothesis that urban land use and percent impervious cover are the key factors driving the differences between impaired and attainment watersheds. Forest was generally an inverse function of Urban extent and exhibited a significant difference in means between impaired and attainment watersheds. Although more refined and complex watershed variables could be suggested, in most cases data for these variables did not exist. However, if in the future new hydrologic data become available, these same tests could be used with an extended set of field-derived independent variables.

The final watershed variables included in the k-means two cluster analysis resulted in very good separations of impaired and attainment watersheds. The most influential variables for both analyses were Urban, SoilD and Forest. The means for these variables were consistently different between the attainment and impaired watersheds, making these variables good indicators of watershed status. Sand Hill Brook, Teney Brook, and Youngman Brook clustered in the predominantly impaired

Cluster 2. These may be good watersheds to evaluate as attainment targets, as they comprise similar influential watershed characteristics as the majority of the impaired watersheds.

The hierarchical clustering resulted in SoilD and Forest clustering together with higher values generally corresponding with attainment watersheds. Agriculture and Wetlands clustered together with Slope. This might be expected as Wetlands and Agriculture are generally associated with flat lands. Urban was clustered with Wetlands and Agriculture at a greater distance indicating that the relationship was less significant, but likely still associated with the Slope factor.

The hierarchical matrix of the highest ranked variables from the k-means test clustered the watersheds in small groupings. The result is two impaired clusters, three attainment clusters and two mixed clusters. This indicated that the chosen variables resulted in meaningful clusters, though this did not address the goal of matching attainment watersheds with impaired watersheds. Both matrices also indicated three larger clusters, though these too were generally skewed toward impaired or attainment.

The clusters in the matrix of lowest ranking variables from the k-means clustering resulted in better within-cluster mixing of attainment and impaired watersheds than the clusters based on the most influential variables (Area, IC, Urban, SoilD and Forest). All six resultant clusters contained both impaired and attainment watersheds. This was a good way to group impaired watersheds with appropriate attainment watersheds.

3.5.3. Subwatershed Prioritization

The four land use-based binary logistic models predicted the whole watershed validation and development watersheds well. Adding other variables to the logistic model reduced the significance and predictive qualities of the equation. I made a fundamental assumption that the probability models developed for the whole watersheds on the basis of whole watershed characteristics were equally applicable to the subwatersheds, given their particular subwatershed characteristics. In other words, the influences of impairment are universal and independent of scale (e.g., high impervious cover is likely to cause impairment at both the whole watershed and subwatershed scale). There is, however, an important consequence of this assumption that should be recognized. When applied to subwatersheds, the results of the probability models should be interpreted to suggest the likelihood that these areas *contribute* to impairment of stream reaches within the whole watershed. The specific stream reaches within subwatersheds that the model identifies as "impaired" may or may not be impaired, but the subwatershed is one that has been identified by the model as having characteristics that may lead to impairment somewhere (downstream) in the watershed.

When the Urban model was applied to Centennial and Potash watersheds, the large majority of subcatchments had impairment probabilities of 100 percent. Because probabilities were needed as a guidance tool for regulatory action, a more refined discrimination among these areas was required. Breaking out the Urban land use variable into five subcategories provided more detail and a better understanding of factors affecting impairment. The Residential- and Hard Urban-based models had the highest significance. The Hard Urban model resulted in the most representation between the extreme probability values and could be helpful in prioritizing the mid-range subcatchments.

This analysis did not include a consideration of the drainage infrastructure or on-site BMPs. Leaving these out of the initial risk assessment provided an overview of the watershed in an “unmanaged” condition. Information about drainage infrastructure and effectiveness of on-site BMP’s can and should be added to this assessment later to refine the choice of subcatchments that should receive priority attention for stormwater runoff abatement.

3.5.4. TMDL issuance and implementation

In October 2006, the Vermont Agency of Transportation submitted a TMDL for Potash Brook which was accepted on December 19, 2006. The TMDL submittal and approval documents described this hydrologic modeling methodology and outcomes in direct reference. Both included a report titled “University of Vermont Stormwater Project – Statistical Analysis of Watershed Variables” which we submitted to ANR in October 2005. Sixteen more TMDL documents are to be prepared for each of the remaining stormwater impaired watersheds. Of these, TMDLs for Centennial Brook, Bartlett Brook, Englesby Brook and Morehouse Brook have been developed and released for public comment. As the first was approved by the Environmental Protection Agency, it is assumed that the remainder will follow the same form, and will include our hydrologic modeling framework. The Agency of Natural Resources is currently working on the General Permit language based on these TMDLs.

Although not explicitly required in the TMDL process, the Agency of Natural Resources has followed the Docket recommendation for an adaptive management component. The State has committed to using the results of required watershed monitoring to determine if the implementation of the TMDL is moving toward or achieving the target. If goals are not being met, there is a plan to revisit the science and policies that make up the TMDL.

3.6. Conclusions and Recommendations

Flows for impaired and attainment streams were found to be significantly different. The $Q_{0.3}$ and Q_{95} metrics were found to be statistically and hydrologically significant when assessing stormwater impacts. The $Q_{0.3}$ flow is the 1-day or annual flow level and is generally thought to be consistent with the 'channel forming' flow. The Q_{95} flow represents a low flow metric comparable to baseflow.

The method of watershed grouping based on k-means clustering combined with hierarchical clustering is a statistically defensible way to identify groupings of impaired and attainment watersheds to set hydrologic targets. In conducting a hierarchical cluster analysis on the lowest ranking watershed variables, natural groupings of watersheds were identified that included both impaired and attainment streams. With the exception of Sunderland Brook watershed in the transformed dataset, the Q 0.3% attainment means were lower and the Q 95% attainment means were higher than the calculated values for each impaired watershed in a given cluster group. Using these groupings, the attainment means could be used as flow targets for the corresponding impairment watersheds. Care should be taken when applying this methodology to the transformed data, as it accounts for fewer watershed variables than the clustering based on the untransformed data.

All four logistic regression models investigated would provide important information about impairment probabilities by subcatchment. The Urban model did not discriminate well in the mid-range of probabilities, but it gave a good overview of the whole watershed and spatial trends in potential impairment. Though it was not a highly specific model, the Hard Urban model predicted impairment for the areas most influenced by the land uses (commercial, industrial and transportation) that are the greatest contributors to runoff in a watershed. Although many of these contributors are currently covered under another existing permit system (i.e.; Multisector General Permit or National Pollutant Discharge Elimination System), the remainder would be good candidates for priority cleanup actions. Subcatchments predicted to be impaired on the basis of Residential land use are less likely to fall within the jurisdiction of the current permit program due to the requirement that such properties have a minimum of 1-acre of impervious cover. A more detailed analysis of these properties would be required to identify those that qualify for permits. Prioritizing subcatchments with a combination of the Hard Urban and Commercial models provided useful information about transportation and industrial, commercial and other urban contributions. These models could be used individually or in tandem to make decisions about permitting and BMP implementation. It would be a policy decision by the State as to which models are used and how.

The analysis protocol reported here provides an objective way to rank subcatchments from those most likely to be impaired to those least likely to be impaired.

The priority or rank level at which action should be taken to abate stormwater runoff is not a fixed or quantitative value. Rather, this level will have to be determined by some combination of engineering analysis (i.e.; to quantify the likely reduction in stormwater runoff achievable for each subcatchment), economic analysis (i.e.; to determine benefit:cost within the constraints of available budgets), and expediency (e.g.; to take advantage of opportunities that will return large benefits on small investments). An optimal prioritization might be determined analytically. Alternatively, it might be beneficial to optimize this prioritization through a stakeholder-driven process of adaptive management. The prioritization tool is a good way to rapidly assess the likely conditions within a watershed to assist investigation and remedial efforts.

These methodologies and associated outcomes are statistically sound and can objectively set hydrologic targets and prioritize permitting actions for stormwater-impaired watersheds. These models can easily be applied to other watersheds in the state and provide an unbiased approach to support TMDL development or other regulatory needs. The overall approach utilizes readily available data, employs simple models, is acceptable to a wide array of stakeholders and is amenable to adaptive management.

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APPENDIX A - TABLES

Table 1. Impacts from increases in impervious surfaces (USEPA 1997).

Increases Imperviousness Leads to:	Resulting Impacts				
	Flooding	Habitat Loss	Erosion	Channel Widening	Streambed Alteration
Increased Volume	•	•	•	•	•
Increased Peak Flow	•	•	•	•	•
Increased Peak Duration	•	•	•	•	•
Increased Stream Temperature		•			
Decreased Base Flow		•			
Sediment Loading Changes	•	•	•	•	•

Table 2. The watershed data used in this analysis. Area values are in acres. All other values are in decimal percent. Note that watersheds marked with asterisks are validation watersheds.

Table 2a. Percent land use calculated by watershed.

Watersheds	Status	Total Area (Acres)	Land Use (% by area)							
			Residential	Commercial	Industrial	Transport	Other Urban	Forest	Wetland/ Water	Agriculture
Alder Brook	A	6571	15%	0%	0%	6%	2%	40%	7%	29%
Allen Brook (A)*	A	2475	9%	0%	0%	6%	0%	49%	3%	33%
Bump School Brook	A	670	0%	0%	0%	0%	0%	92%	6%	2%
Hubbardton River	A	10825	1%	0%	0%	3%	0%	69%	14%	12%
Laplatte River	A	1651	6%	0%	0%	3%	1%	59%	4%	26%
Little Otter Creek	A	7368	2%	0%	0%	3%	0%	46%	7%	41%
Malletts Creek*	A	9318	7%	0%	0%	5%	1%	59%	6%	22%
Milton Pond Trib	A	1515	2%	1%	0%	4%	0%	74%	6%	13%
Muddy Branch	A	8382	0%	0%	0%	2%	0%	68%	6%	24%
Rock River	A	1225	0%	0%	0%	2%	0%	86%	6%	7%
Sand Hill Brook	A	685	3%	0%	10%	5%	0%	76%	5%	1%
Sheldon Spring*	A	1886	1%	0%	0%	5%	0%	76%	4%	13%
Teney Brook	A	2987	21%	1%	0%	7%	0%	59%	4%	7%
Willow Brook	A	1478	0%	0%	0%	2%	0%	83%	5%	10%
Youngman Brook	A	672	0%	0%	0%	5%	0%	57%	6%	31%
Allen (I)	I	6635	15%	1%	0%	9%	1%	35%	4%	33%
Bartlett	I	736	42%	6%	0%	14%	0%	10%	7%	21%
Centennial	I	887	27%	20%	0%	20%	4%	18%	7%	4%
Englesby *	I	605	40%	17%	0%	22%	17%	0%	4%	0%
Indian	I	4582	15%	3%	0%	10%	11%	37%	6%	18%
Moon	I	5546	34%	2%	1%	11%	0%	44%	6%	1%
Morehouse	I	263	46%	3%	17%	22%	0%	4%	7%	1%
Munroe*	I	3492	17%	2%	1%	6%	3%	26%	7%	39%
Potash	I	4561	22%	10%	1%	16%	4%	11%	6%	30%
Rugg	I	1831	11%	0%	0%	9%	0%	38%	6%	37%
Stevens	I	2136	31%	0%	0%	16%	0%	26%	5%	23%
Sunderland	I	1320	22%	37%	0%	17%	0%	11%	9%	4%

Table 2b. Calculations of hydrologic soil groups, average slope and impervious cover for each watershed.

Watersheds	Status	Total Area (Acres)	Hydrologic Soil Group (% by area)				Average Slope (% by area)	Impervious Cover (% by area)
			A	B	C	D		
Alder Brook	A	6571	9%	19%	30%	41%	7%	6%
Allen Brook (A)*	A	2475	0%	0%	46%	54%	7%	4%
Bump School Brook	A	670	0%	0%	13%	87%	13%	0%
Hubbardton River	A	10825	4%	0%	19%	62%	13%	2%
Laplatte River	A	1651	19%	6%	6%	69%	12%	3%
Little Otter Creek	A	7368	27%	16%	19%	31%	9%	2%
Malletts Creek*	A	9318	15%	4%	23%	57%	10%	4%
Milton Pond Trib	A	1515	7%	0%	7%	87%	16%	3%
Muddy Branch	A	8382	12%	39%	9%	31%	15%	1%
Rock River	A	1225	0%	0%	15%	85%	16%	1%
Sand Hill Brook	A	685	86%	0%	14%	0%	8%	8%
Sheldon Spring*	A	1886	9%	9%	27%	55%	11%	3%
Teney Brook	A	2987	12%	21%	55%	3%	12%	7%
Willow Brook	A	1478	0%	0%	19%	81%	14%	1%
Youngman Brook	A	672	83%	0%	0%	17%	5%	3%
Allen (I)	I	6635	7%	7%	34%	51%	7%	7%
Bartlett	I	736	25%	25%	25%	25%	6%	17%
Centennial	I	887	62%	0%	0%	25%	6%	31%
Englesby *	I	605	17%	17%	17%	33%	5%	27%
Indian	I	4582	12%	4%	17%	60%	6%	8%
Moon	I	5546	14%	11%	53%	16%	13%	13%
Morehouse	I	263	25%	50%	0%	0%	6%	32%
Munroe*	I	3492	0%	14%	16%	68%	6%	4%
Potash	I	4561	28%	10%	14%	48%	5%	22%
Rugg	I	1831	14%	0%	71%	14%	11%	7%
Stevens	I	2136	0%	4%	75%	21%	8%	11%
Sunderland	I	1320	86%	14%	0%	0%	6%	11%

Table 3. Independent variables used in the hydrologic modeling.

Variable Name	Description
Area	Watershed area (acres)
Agriculture	% Agricultural landuse in watershed
Forest	% Forest in watershed
Urban	% Urban landuse in watershed
Water	% Open water in watershed
Wetland	% Wetland in watershed
Soil_A	% Hydrologic soil group A
Soil_B	% Hydrologic soil group B
Soil_C	% Hydrologic soil group C
Soil_D	% Hydrologic soil group D
IC	% Impervious cover
Slope	Average % slope of watershed

Table 4. Flow data from the P-8 model for selected flow probability levels. Data generated by TetraTech and supplied by ANR. Both non-normalized and normalized data are shown.

		Non-normalized flows								Normalized flows							
Stream	Status	Q95	Q80	Q50	Q20	Q5	Q5	Q0.3	Q0.1	NQ95	NQ80	NQ50	NQ20	NQ5	NQ5	NQ0.3	NQ0.1
Allen Brook (impaired)	I	0.20	0.55	1.15	2.08	3.61	6.18	11.74	22.67	0.926	0.935	0.942	0.953	0.965	1.034	1.047	1.105
Bartlett Brook	I	0.20	0.55	1.16	2.15	3.78	7.10	11.35	18.23	0.919	0.939	0.951	0.985	1.011	1.189	1.013	0.888
Centenniel Brook	I	0.19	0.52	1.13	2.13	4.11	9.17	16.04	24.27	0.862	0.890	0.925	0.979	1.099	1.535	1.431	1.182
Englesby Brook	I	0.19	0.52	1.11	2.08	3.96	8.83	15.46	24.29	0.875	0.887	0.913	0.955	1.059	1.477	1.380	1.183
Indian Brook	I	0.21	0.57	1.20	2.17	3.79	6.37	11.64	22.70	0.969	0.978	0.986	0.997	1.013	1.065	1.039	1.106
Moon Bk	I	0.20	0.55	1.17	2.15	3.70	6.43	9.96	16.66	0.933	0.947	0.964	0.988	0.990	1.076	0.889	0.812
Morehouse Brook	I	0.19	0.51	1.12	2.14	4.14	9.47	16.88	25.94	0.896	0.876	0.921	0.983	1.106	1.586	1.506	1.264
Munroe Brook	I	0.20	0.54	1.14	2.05	3.56	6.04	12.01	23.93	0.926	0.932	0.936	0.942	0.951	1.011	1.072	1.166
Potash Brook	I	0.20	0.54	1.15	2.16	3.91	7.41	12.24	20.41	0.903	0.918	0.946	0.991	1.044	1.240	1.092	0.994
Rugg	I	0.20	0.55	1.14	2.07	3.61	5.99	11.32	21.57	0.932	0.934	0.940	0.949	0.965	1.003	1.010	1.051
Stevens	I	0.20	0.54	1.14	2.08	3.65	6.55	11.91	23.12	0.909	0.929	0.936	0.956	0.976	1.096	1.063	1.127
Sunderland Brook	I	0.22	0.60	1.26	2.29	3.81	6.53	8.25	11.01	1.025	1.030	1.036	1.049	1.019	1.093	0.736	0.537
Allen Brook (attained)	A	0.22	0.58	1.22	2.17	3.75	6.07	11.21	21.15	0.998	0.997	0.999	0.996	1.002	1.016	1.000	1.030
Alder Brook	A	0.22	0.60	1.26	2.25	3.88	6.25	11.33	20.53	1.029	1.031	1.035	1.033	1.036	1.047	1.012	1.000
Bump School Brook	A	0.21	0.56	1.16	2.09	3.63	5.97	12.53	24.72	0.965	0.965	0.958	0.959	0.969	1.000	1.118	1.204
Hubbardton River	A	0.21	0.57	1.18	2.12	3.67	6.11	11.96	23.68	0.973	0.972	0.971	0.971	0.980	1.023	1.068	1.154
LaPlatte River	A	0.21	0.57	1.18	2.11	3.64	5.89	11.52	22.81	0.980	0.970	0.969	0.969	0.973	0.985	1.028	1.111
Little Otter Creek	A	0.22	0.60	1.25	2.23	3.79	5.92	9.02	15.54	1.034	1.030	1.030	1.021	1.013	0.991	0.805	0.757
Malletts Creek	A	0.22	0.58	1.22	2.18	3.75	6.04	10.92	19.11	1.000	1.000	1.003	1.000	1.002	1.011	0.975	0.931
Milton Pond Trib	A	0.20	0.54	1.13	2.04	3.52	5.86	12.09	23.99	0.932	0.934	0.927	0.936	0.941	0.981	1.079	1.169
Muddy Branch New Haven	A	0.22	0.58	1.22	2.18	3.66	5.75	8.14	13.64	1.000	1.002	1.000	1.000	0.978	0.962	0.727	0.665
Rock River	A	0.20	0.54	1.12	2.03	3.51	5.75	11.99	23.34	0.936	0.930	0.923	0.931	0.938	0.963	1.070	1.137
Sand Hill Brook	A	0.23	0.62	1.29	2.33	3.81	6.38	8.02	9.10	1.073	1.056	1.060	1.067	1.018	1.068	0.716	0.443
Sheldon Spring Trib	A	0.22	0.60	1.24	2.20	3.77	5.90	9.24	18.22	1.029	1.029	1.021	1.011	1.007	0.987	0.825	0.888
Teney Brook	A	0.24	0.64	1.35	2.42	4.11	6.58	9.34	16.16	1.103	1.101	1.110	1.112	1.098	1.102	0.833	0.787
Willow Brook	A	0.21	0.57	1.17	2.10	3.63	5.89	11.95	24.04	0.975	0.972	0.965	0.963	0.969	0.985	1.067	1.171
Youngman Brook	A	0.23	0.61	1.29	2.29	3.74	6.18	7.90	8.90	1.050	1.044	1.057	1.048	1.000	1.034	0.705	0.434

Table 5. Summary to statistical analysis for flow metrics. Mean values are shown in normal text. Median values are italicized for Q1 and Q0.1 flows. The coefficient of variation (CV%) is the standard deviation divided by the mean, expressed as a percentage. Normality was tested using the Kolmogorov-Smirnov test.

Metric	Impaired			Attainment		
	Mean (Median if normality fails)	Standard Error	Number	Mean (Median if normality fails)	Standard Error	Number
Q0.1	22.687	NA	12	*20.526*	NA	15
Q0.3	12.400	0.726	12	10.479	0.431	15
Q1	*6.541*	NA	12	*5.975*	NA	15
Q5	3.804	0.056	12	3.724	0.038	15
Q20	2.131	0.019	12	2.183	0.028	15
Q50	1.155	0.012	12	1.218	0.016	15
Q80	0.545	0.007	12	0.585	0.007	15
Q95	0.201	0.003	12	0.219	0.003	15

Metric	Normality	Equal Variance	Parametric *t* -Test				Nonparametric Mann-Whitney	
			t	df	Power	P	T	P
Q0.1	Failed	NA					190	Not Significant
Q0.3	Y (P=0.721)	Y (P=0.733)	2.379	25	<0.80	0.05-0.01		
Q1	Failed	NA					236	<0.001
Q5	Y (P=0.567)	Y (P=0.395)	1.221	25	<0.80	Not Significant		
Q20	Y (P=0.249)	Y (P=0.071)	-1.463	25	<0.80	Not Significant		
Q50	Y (P=0.099)	Y (P=0.062)	-3.013	25	<0.80	<0.01		
Q80	Y (P=0.431)	Y (P=0.286)	-3.991	25	?0.80	<0.001		
Q95	Y (P=0.463)	Y (P=0.350)	-4.626	25	?0.80	<0.001		

Table 6. Correlation matrix of attainment watershed variables. Correlations greater than ±0.6 are considered significant.

	Area	Water	Urban	Agri	Forest	Wetland	Soil_A	SoilB	Soil_C	Soil_D	IC	Slope
AREA	1.000											
WATER	0.511	1.000										
URBAN	0.031	-0.171	1.000									
AGRI	0.352	-0.238	0.057	1.000								
FOREST	-0.427	0.136	-0.561	-0.839	1.000							
WETLAND	0.196	-0.408	-0.155	0.409	-0.269	1.000						
SOIL_A	-0.242	-0.104	0.158	0.080	-0.150	0.056	1.000					
SOIL_B	0.446	-0.113	0.249	0.297	-0.362	0.052	-0.126	1.000				
SOIL_C	0.122	-0.167	0.697	-0.001	-0.352	-0.075	-0.364	0.192	1.000			
SOIL_D	-0.121	0.124	-0.608	-0.195	0.489	-0.028	-0.686	-0.438	-0.270	1.000		
IC_FINAL	-0.061	-0.100	0.911	-0.042	-0.442	-0.199	0.453	0.076	0.477	-0.693	1.000	
SLOPE	0.008	0.181	-0.449	-0.528	0.662	-0.144	-0.595	0.092	-0.204	0.598	-0.527	1.000

Table 7. Correlation matrix of impaired watershed variables. Correlations greater than ±0.6 are considered significant.

	Area	Water	Urban	Agri	Forest	Wetland	Soil_A	SoilB	Soil_C	Soil_D	IC	Slope
AREA	1.000											
WATER	-0.615	1.000										
URBAN	-0.668	0.427	1.000									
AGRI	0.418	-0.302	-0.840	1.000								
FOREST	0.697	-0.478	-0.827	0.394	1.000							
WETLAND	0.635	-0.190	-0.604	0.344	0.628	1.000						
SOIL_A	-0.413	0.738	0.515	-0.511	-0.410	-0.021	1.000					
SOIL_B	-0.414	0.320	0.574	-0.375	-0.597	-0.312	0.037	1.000				
SOIL_C	0.253	-0.565	-0.582	0.408	0.624	0.160	-0.580	-0.433	1.000			
SOIL_D	0.576	-0.427	-0.497	0.577	0.254	0.241	-0.499	-0.367	-0.090	1.000		
IC_FINAL	-0.558	0.327	0.819	-0.658	-0.703	-0.665	0.362	0.478	-0.511	-0.379	1.000	
SLOPE	0.313	-0.350	-0.447	0.038	0.739	0.465	-0.265	-0.284	0.740	-0.327	-0.373	1.000

Table 8. Results from the Kruskal-Wallis MANOVA and difference of means testing.

Dependent Variable	Rank Sums		M-W		Chi^2
	A	I	U	P(U)	1 df
Area	224.0	154.0	104.0	0.495	0.5
Water	178.5	199.5	58.5	0.124	2.4
Urban	124.0	254.0	4.0	0.000	17.6
Agriculture	214.0	164.0	94.0	0.845	0.0
Forest	299.0	79.0	179.0	0.000	18.9
Wetland	230.5	147.5	110.5	0.315	1.0
Soil A	184.5	193.5	64.5	0.211	1.6
Soil B	179.0	199.0	59.0	0.121	2.4
Soil C	204.5	173.5	84.5	0.788	0.1
Soil D	250.0	128.0	130.0	0.051	3.8
IC	127.0	250.0	7.5	0.000	16.3
Slope	271.0	107.0	151.5	0.003	9.0

Table 9. Table of k-means clustering results for the untransformed watershed variables.

Cluster 1 (15 cases)		
Case	**Watershed**	**Status**
1	Alder	Attainment
2	Allen_A	Attainment
3	BumpSchool	Attainment
4	Hubbardton	Attainment
5	Laplatte	Attainment
6	LittleOtter	Attainment
7	Malletts	Attainment
8	MiltonPond	Attainment
9	MuddyBranch	Attainment
10	Rock	Attainment
12	SheldonSpr	Attainment
14	Willow	Attainment
16	Allen_I	Impaired
20	Indian	Impaired
23	Monroe	Impaired

Cluster 2 (12 cases)		
Case	**Watershed**	**Status**
11	SandHill	Attainment
13	Teney	Attainment
15	Youngman	Attainment
17	Bartlett	Impaired
18	Centennial	Impaired
19	Englesby	Impaired
21	Moon	Impaired
22	Morehouse	Impaired
24	Potash	Impaired
25	Rugg	Impaired
26	Stevens	Impaired
27	Sunderland	Impaired

Table 10. Hierarchical clustering results for the raw, untransformed data.

Table 10a. Individual Q 0.3% flow values and mean attainment flow values are identified for each cluster. Note that the Q 0.3% flow for Indian Brook watershed is below the attainment average plus the standard deviation.

Cluster	Case #	Watershed	Status	Q 0.3%	Avg A Q 0.3%	Std Dev	Q0.3% + SD
1	18	Centennial	I	16.0399	7.9636	0.0849	8.0485
	27	Sunderland	I	8.2525			
	11	SandHill	A	8.0236			
	15	Youngman	A	7.9035			
2	22	Morehouse	I	16.8777	8.1448	--	--
	9	Muddy Branch	A	8.1448			
3	19	Englesby	I	15.4649	11.5276	1.1173	12.6449
	20	Indian	I	11.6373			
	3	BumpSchool	A	12.5317			
	4	Hubbardton	A	11.9623			
	7	Malletts	A	10.9241			
	8	MiltonPond	A	12.0885			
	10	Rock	A	11.9923			
	12	SheldonSpr	A	9.2432			
	14	Willow	A	11.9511			
4	17	Bartlett	I	11.3478	10.2719	1.7680	12.0399
	24	Potash	I	12.2374			
	5	Laplatte	A	11.5221			
	6	LittleOtter	A	9.0217			
5	16	Allen_I	I	11.7358	11.2695	0.0912	11.3607
	23	Munroe	I	12.0108			
	1	Alder	A	11.3340			
	2	Allen_A	A	11.2050			
6	21	Moon	I	9.9587	9.3369	--	--
	25	Rugg	I	11.3195			
	26	Stevens	I	11.9120			
	13	Teney	A	9.3369			

Table 10b. Individual Q 95% flow values and mean attainment flow values are identified for each cluster. Note that the Q 95% flow for Indian Brook watershed exceeds the attainment average plus the standard deviation.

Cluster	Case #	Watershed	Status	Q 95%	Avg A Q 95%	Std Dev	Q95% - SD
1	18	Centennial	I	0.1875	0.2310	0.0035	0.2275
	27	Sunderland	I	0.2229			
	11	SandHill	A	0.2335			
	15	Youngman	A	0.2285			
2	22	Morehouse	I	0.1948	0.2176	--	--
	9	Muddy Branch	A	0.2176			
3	19	Englesby	I	0.1903	0.2116	0.0074	0.2042
	20	Indian	I	0.2108			
	3	BumpSchool	A	0.2100			
	4	Hubbardton	A	0.2116			
	7	Malletts	A	0.2177			
	8	MiltonPond	A	0.2027			
	10	Rock	A	0.2036			
	12	SheldonSpr	A	0.2239			
	14	Willow	A	0.2121			
4	17	Bartlett	I	0.2000	0.2190	0.0083	0.2107
	24	Potash	I	0.1964			
	5	Laplatte	A	0.2132			
	6	LittleOtter	A	0.2249			
5	16	Allen_I	I	0.2015	0.2206	0.0048	0.2158
	23	Munroe	I	0.2016			
	1	Alder	A	0.2240			
	2	Allen_A	A	0.2172			
6	21	Moon	I	0.2030	0.2399	--	--
	25	Rugg	I	0.2027			
	26	Stevens	I	0.1977			
	13	Teney	A	0.2399			

Table 11. Correlation matrix of watershed variables and the binary (impairment) variable. Correlations greater than ±0.600 are considered significant.

Table 11a. Correlation matrix for urban land use.

	URBAN	Residential	Commercial	Industrial	Transport	Other Urban	Hard Urban
Residential	0.923						
Commercial	0.692	0.427					
Industrial	0.337	0.332	-0.063				
Transportation	0.969	0.891	0.644	0.325			
Other Urban	0.502	0.356	0.335	-0.112	0.460		
Hard Urban	0.925	0.735	0.856	0.366	0.908	0.373	
AGRI	-0.348	-0.244	-0.346	-0.342	-0.261	-0.149	-0.406
FOREST	-0.885	-0.847	-0.580	-0.190	-0.893	-0.446	-0.788
SOIL_A	0.290	0.069	0.542	0.263	0.294	-0.033	0.515
SOIL_B	0.437	0.509	0.101	0.488	0.371	0.017	0.351
SOIL_C	-0.061	0.173	-0.336	-0.236	0.010	-0.158	-0.252
SOIL_D	-0.545	-0.534	-0.347	-0.409	-0.564	0.056	-0.560
IC	0.911	0.842	0.532	0.453	0.932	0.444	0.845
SLOPE	-0.635	-0.545	-0.432	-0.212	-0.657	-0.425	-0.601
BINARY (impaired)	0.799	0.784	0.496	0.140	0.813	0.408	0.691

Table 11b. Correlation matrix for remaining, non-land use variables.

	AGRI	FOREST	SOIL_A	SOIL_B	SOIL_C	SOIL_D	IC	SLOPE
FOREST	-0.121							
SOIL_A	-0.199	-0.226						
SOIL_B	-0.067	-0.432	-0.026					
SOIL_C	0.252	-0.027	-0.435	-0.154				
SOIL_D	0.127	0.514	-0.608	-0.441	-0.208			
IC	-0.352	-0.789	0.294	0.394	-0.138	-0.492		
SLOPE	-0.227	0.785	-0.450	-0.168	0.105	0.456	-0.578	
BINARY (impaired)	-0.008	-0.837	0.103	0.214	0.162	-0.371	0.694	-0.571

Table 12. The logistic regression models tested for suitability of impairment probability prediction.

Variables	Model	p-value (constant)	p-value (variable)	Significance of Model
Com	-1.78358 + (159.129 * Com)	0.022	0.050 Com	Significant
Com, SOIL_D	-0.812368 + (148.175 * Com) + (-2.3450 * SOIL_D)	0.479	0.066 Com 0.332 SOIL_D	Not Significant
FOREST	15.0618 + (-35.3841 * FOREST)	0.144	0.153 FOREST	Not Significant
FOREST, SOIL_D, SLOPE	--	--	--	Exceeded Max Iterations
Hard Urban	-4.78811 + (46.0652 * Hard Urban)	0.02	0.022 Hard Urban	Significant
IC	-8.29780 + (115.612 * IC)	0.153	0.150 IC	Not Significant
Res	-3.86238 + (25.3452 * Res)	0.021	0.021 Res	Significant
Res, AGRI	-8.08043 + (37.0340 * Res) + (12.3330 * AGRI)	0.118	0.073 Res 0.220 AGRI	Not Significant
Res, Com	-3.35032 + (17.8641 * Res) + (61.0792 * Com)	0.022	0.078 Res 0.477 Com	Not Significant
Res, FOREST	--	--	--	Exceeded Max Iterations
Res, Hard Urban	-6.24845 + (16.7065 * Res) + (38.3946 * Hard Urban)	0.096	0.216 Res 0.167 Hard Urban	Not Significant
Res, Indus	-3.44036 + (24.7771 * Res) + (-15.9117 * Indus)	0.026	0.014 Res 0.788 Indus	Not Significant
Res, OtherUrb	--	--	--	Exceeded Max Iterations
Res, SLOPE	-0.0502975 + (22.3791 + Res) + (-36.7624 * SLOPE)	0.986	0.029 Res 0.232 SLOPE	Not Significant
Res, SOIL_A	-3.65121 + (24.8626 * Res) + (0.710943 * SOIL_A)	0.031	0.015 Res 0.815 SOIL_A	Not Significant
Res, SOIL_B	--	--	--	Exceeded Max Iterations
Res, SOIL_C	-3.65173 + (24.7489 * Res) + (0.593643 * SOIL_C)	0.042	0.017 Res 0.862 SOIL_C	Not Significant
Res, SOIL_D	-4.72151 + (28.2491 * Res) + (1.89827 * SOIL_D)	0.114	0.028 Res 0.596 SOIL_D	Not Significant
Res, Trans	--	--	--	Exceeded Max Iterations
Trans	-10.7878 + (150.298 * Trans)	0.053	0.075 Trans	Not Significant
Trans, OtherUrb	--	--	--	Exceeded Max Iterations
Trans, SOIL_A	--	--	--	Exceeded Max Iterations
Trans, SOIL_B	--	--	--	Exceeded Max Iterations
URBAN	-5.05257 + (19.4422 * URBAN)	0.040	0.047 URBAN	Significant
URBAN, SLOPE	-3.43831 + (18.8229 * URBAN) + (-16.2464 * SLOPE)	0.398	0.064 URBAN 0.652 SLOPE	Not Significant
URBAN, SOIL_D	-6.22586 + (21.4385 * URBAN) + (2.20556 * SOIL_D)	0.077	0.056 URBAN 0.579 SOIL_D	Not Significant
URBAN, SOIL_D, SLOPE	-4.76466 + (20.0660 * URBAN) + (1.90401 * SOIL_D) + (-11.0349 * SLOPE)	0.385	0.074 URBAN 0.641 SOIL_D 0.757 SLOPE	Not Significant
WETLAND	0.432917 + (-61.9462 * WETLAND)	0.505	0.238 WETLAND	Not Significant

Table 13. Development watersheds with land use characteristics and predicted probabilities by land use category.

Table 13a. Development watersheds with land use characteristics and predicted probabilities for Urban and Hard Urban models.

Watershed	Status	Total Area (Acres)	Urban				Hard Urban			
			% by Area	Log Odds	Odds	Probability	% by Area	Log Odds	Odds	Probability
Alder	A	6571	23%	-0.53	5.86E-01	37%	7%	-1.79	1.67E-01	14%
Allen_A	A	2475	15%	-2.13	1.19E-01	11%	6%	-2.03	1.31E-01	12%
BumpSchool	A	670	0%	-5.04	6.46E-03	1%	0%	-4.79	8.33E-03	1%
Hubbardton	A	10825	4%	-4.31	1.34E-02	1%	3%	-3.44	3.21E-02	3%
Laplatte	A	1651	10%	-3.04	4.76E-02	5%	3%	-3.20	4.09E-02	4%
LittleOtter	A	7368	6%	-3.93	1.96E-02	2%	3%	-3.20	4.08E-02	4%
Malletts	A	9318	13%	-2.53	7.96E-02	7%	5%	-2.31	9.94E-02	9%
MiltonPond	A	1515	6%	-3.86	2.10E-02	2%	5%	-2.67	6.90E-02	6%
Muddy Branch	A	8382	3%	-4.53	1.08E-02	1%	2%	-3.70	2.48E-02	2%
Rock	A	1225	2%	-4.71	9.00E-03	1%	2%	-4.00	1.83E-02	2%
SandHill	A	685	18%	-1.58	2.05E-01	17%	15%	2.00	7.42E+00	88%
SheldonSpr	A	1886	7%	-3.79	2.26E-02	2%	6%	-2.24	1.07E-01	10%
Teney	A	2987	30%	0.76	2.14E+00	68%	9%	-0.87	4.20E-01	30%
Willow	A	1478	2%	-4.61	1.00E-02	1%	2%	-3.81	2.22E-02	2%
Youngman	A	672	5%	-3.99	1.84E-02	2%	5%	-2.41	8.99E-02	8%
Allen_I	I	6634.9	26%	0.00	1.00E+00	50%	10%	-0.18	8.34E-01	45%
Bartlett	I	735.6	62%	7.01	1.10E+03	100%	20%	4.50	8.97E+01	99%
Centennial	I	887.1	71%	8.72	6.13E+03	100%	40%	13.52	7.45E+05	100%
Englesby	I	605.3	96%	13.58	7.91E+05	100%	39%	13.16	5.17E+05	100%
Indian	I	4582.4	39%	2.53	1.26E+01	93%	13%	1.20	3.32E+00	77%
Moon	I	5545.6	49%	4.41	8.21E+01	99%	14%	1.86	6.41E+00	86%
Morehouse	I	262.7	88%	12.06	1.72E+05	100%	42%	14.56	2.10E+06	100%
Munroe	I	3491.7	29%	0.59	1.80E+00	64%	9%	-0.64	5.26E-01	34%
Potash	I	4561.1	53%	5.16	1.74E+02	99%	27%	7.63	2.06E+03	100%
Rugg	I	1830.7	20%	-1.16	3.12E-01	24%	9%	-0.64	5.26E-01	34%
Stevens	I	2136.1	47%	4.09	5.95E+01	98%	16%	2.58	1.32E+01	93%
Sunderland	I	1320.3	76%	9.72	1.67E+04	100%	54%	20.09	5.29E+08	100%

Table 13b. Development watersheds with land use characteristics and predicted probabilities for Urban and Hard Urban models.

Watershed	Status	Total Area (Acres)	Residential				Commercial			
			% by Area	Log Odds	Odds	Probability	% by Area	Log Odds	Odds	Probability
Alder	A	6571	15%	0.27	1.31E+00	57%	0%	-1.11	3.29E-01	25%
Allen_A	A	2475	9%	-1.25	2.86E-01	22%	0%	-1.78	1.68E-01	14%
BumpSchool	A	670	0%	-3.50	3.02E-02	3%	0%	-1.78	1.68E-01	14%
Hubbardton	A	10825	1%	-3.29	3.73E-02	4%	0%	-1.77	1.71E-01	15%
Laplatte	A	1651	6%	-2.05	1.29E-01	11%	0%	-1.74	1.76E-01	15%
LittleOtter	A	7368	2%	-2.93	5.31E-02	5%	0%	-1.76	1.72E-01	15%
Malletts	A	9318	7%	-1.84	1.58E-01	14%	0%	-1.37	2.55E-01	20%
MiltonPond	A	1515	2%	-3.13	4.38E-02	4%	1%	-0.60	5.50E-01	35%
Muddy Branch	A	8382	0%	-3.43	3.23E-02	3%	0%	-1.78	1.69E-01	14%
Rock	A	1225	0%	-3.50	3.03E-02	3%	0%	-1.78	1.68E-01	14%
SandHill	A	685	3%	-2.74	6.46E-02	6%	0%	-1.78	1.68E-01	14%
SheldonSpr	A	1886	1%	-3.27	3.81E-02	4%	0%	-1.72	1.79E-01	15%
Teney	A	2987	21%	1.82	6.17E+00	86%	1%	0.36	1.43E+00	59%
Willow	A	1478	0%	-3.47	3.13E-02	3%	0%	-1.73	1.77E-01	15%
Youngman	A	672	0%	-3.44	3.20E-02	3%	0%	-1.64	1.95E-01	16%
Allen_I	I	6634.9	15%	0.23	1.26E+00	56%	1%	-0.19	8.25E-01	45%
Bartlett	I	735.6	42%	6.93	1.02E+03	100%	6%	7.57	1.94E+03	100%
Centennial	I	887.1	27%	3.24	2.54E+01	96%	20%	30.19	1.29E+13	100%
Englesby	I	605.3	40%	6.48	6.49E+02	100%	17%	25.17	8.54E+10	100%
Indian	I	4582.4	15%	0.23	1.26E+00	56%	3%	2.99	1.99E+01	95%
Moon	I	5545.6	34%	5.02	1.52E+02	99%	2%	1.63	5.12E+00	84%
Morehouse	I	262.7	46%	7.96	2.86E+03	100%	3%	2.99	1.99E+01	95%
Munroe	I	3491.7	17%	0.73	2.07E+00	67%	2%	1.40	4.05E+00	80%
Potash	I	4561.1	22%	1.89	6.60E+00	87%	10%	13.77	9.52E+05	100%
Rugg	I	1830.7	11%	-0.77	4.64E-01	32%	0%	-1.78	1.68E-01	14%
Stevens	I	2136.1	31%	4.22	6.80E+01	99%	0%	-1.78	1.68E-01	14%
Sunderland	I	1320.3	22%	1.98	7.21E+00	88%	37%	57.09	6.25E+24	100%

Table 14. Centennial subcatchments with land use characteristics and predicted probabilities by land use category.

Table 14a. Centennial subcatchments with land use characteristics and predicted probabilities for Urban and Hard Urban land use models.

Subcatchment ID	Total Area (Acres)	Urban				Hard Urban			
		% by Area	Log Odds	Odds	Probability	% by Area	Log Odds	Odds	Probability
A01	5	77%	9.91	2.00E+04	100%	77%	30.65	2.05E+13	100%
A02	12	98%	14.06	1.27E+06	100%	98%	40.49	3.83E+17	100%
A03	2	77%	9.90	2.00E+04	100%	77%	30.65	2.04E+13	100%
A04	37	84%	11.31	8.18E+04	100%	72%	28.33	2.01E+12	100%
A05	6	100%	14.32	1.66E+06	100%	100%	41.12	7.24E+17	100%
A06	4	100%	14.39	1.78E+06	100%	69%	27.01	5.36E+11	100%
A07	7	18%	-1.48	2.28E-01	19%	1%	-4.37	1.26E-02	1%
A08	7	72%	8.89	7.22E+03	100%	2%	-4.04	1.76E-02	2%
A09	26	89%	12.34	2.28E+05	100%	17%	3.12	2.26E+01	96%
A10	61	9%	-3.37	3.45E-02	3%	9%	-0.79	4.52E-01	31%
A11	17	100%	14.39	1.78E+06	100%	100%	41.17	7.59E+17	100%
A12	81	94%	13.28	5.83E+05	100%	72%	28.30	1.96E+12	100%
A13	14	98%	13.92	1.11E+06	100%	95%	38.83	7.30E+16	100%
A14	23	84%	11.28	7.90E+04	100%	20%	4.34	7.64E+01	99%
A15	39	100%	14.39	1.78E+06	100%	100%	41.26	8.34E+17	100%
A16	49	84%	11.31	8.14E+04	100%	17%	3.23	2.52E+01	96%
A17	63	100%	14.35	1.70E+06	100%	38%	12.51	2.72E+05	100%
A18	30	14%	-2.24	1.07E-01	10%	14%	1.61	5.00E+00	83%
A19	55	23%	-0.65	5.21E-01	34%	12%	0.87	2.39E+00	70%
A20	13	100%	14.39	1.78E+06	100%	51%	18.55	1.14E+08	100%
A21	10	100%	14.39	1.78E+06	100%	83%	33.63	4.04E+14	100%
A22	36	100%	14.39	1.78E+06	100%	67%	26.03	2.02E+11	100%
A23	27	99%	14.17	1.43E+06	100%	75%	29.58	7.01E+12	100%
A24	21	17%	-1.69	1.84E-01	16%	10%	-0.33	7.16E-01	42%
A25	54	46%	3.98	5.37E+01	98%	7%	-1.60	2.02E-01	17%
A26	26	100%	14.39	1.78E+06	100%	45%	16.03	9.16E+06	100%
A27	2	100%	14.39	1.78E+06	100%	78%	5.30	2.01E+02	100%
A28	15	47%	4.17	6.47E+01	98%	32%	10.18	2.63E+04	100%
A29	52	61%	6.80	9.01E+02	100%	12%	0.70	2.01E+00	67%
A30	4	3%	-4.46	1.16E-02	1%	3%	-3.38	3.41E-02	3%
A31	34	97%	13.88	1.06E+06	100%	97%	40.06	2.50E+17	100%
A32	18	21%	-1.04	3.54E-01	26%	20%	4.31	7.47E+01	99%
A33	1	56%	5.87	3.52E+02	100%	56%	21.08	1.43E+09	100%
A34	1	77%	9.85	1.89E+04	100%	77%	30.51	1.78E+13	100%
A35	3	87%	11.89	1.46E+05	100%	44%	15.37	4.74E+06	100%
A36	11	100%	14.39	1.78E+06	100%	29%	8.74	6.23E+03	100%
A37	14	65%	7.67	2.15E+03	100%	13%	1.19	3.29E+00	77%
A38	5	18%	-1.49	2.25E-01	18%	18%	3.65	3.86E+01	97%

Table 14b. Centennial subcatchments with land use characteristics and predicted probabilities for Residential and Commercial land use models.

Subcatchment	Total Area	Residential				Commercial			
ID	(Acres)	% by Area	Log Odds	Odds	Probability	% by Area	Log Odds	Odds	Probability
A01	5	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A02	12	0%	-3.51	2.99E-02	3%	55%	85.57	1.45E+37	100%
A03	2	0%	-3.51	2.99E-02	3%	77%	120.63	2.44E+52	100%
A04	37	12%	-0.45	6.39E-01	39%	58%	90.47	1.95E+39	100%
A05	6	0%	-3.51	2.99E-02	3%	70%	109.83	4.99E+47	100%
A06	4	31%	4.21	6.76E+01	99%	0%	-1.78	1.68E-01	14%
A07	7	17%	0.85	2.34E+00	70%	0%	-1.78	1.68E-01	14%
A08	7	70%	13.96	1.15E+06	100%	0%	-1.78	1.68E-01	14%
A09	26	72%	14.51	2.00E+06	100%	0%	-1.78	1.68E-01	14%
A10	61	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A11	17	0%	-3.45	3.17E-02	3%	69%	107.82	6.71E+46	100%
A12	81	16%	0.38	1.46E+00	59%	52%	80.87	1.32E+35	100%
A13	14	3%	-2.79	6.15E-02	6%	93%	146.15	2.97E+63	100%
A14	23	64%	12.49	2.66E+05	100%	15%	21.77	2.85E+09	100%
A15	39	0%	-3.50	3.01E-02	3%	80%	124.91	1.77E+54	100%
A16	49	67%	13.13	5.04E+05	100%	0%	-1.78	1.68E-01	14%
A17	63	62%	12.01	1.64E+05	100%	1%	-0.36	7.00E-01	41%
A18	30	1%	-3.36	3.47E-02	3%	11%	15.48	5.26E+06	100%
A19	55	10%	-0.93	3.95E-01	28%	0%	-1.01	3.63E-01	27%
A20	13	49%	8.79	6.58E+03	100%	11%	16.43	1.37E+07	100%
A21	10	17%	0.63	1.87E+00	65%	83%	130.18	3.43E+56	100%
A22	36	22%	1.85	6.37E+00	86%	35%	53.15	1.20E+23	100%
A23	27	24%	2.54	1.27E+01	93%	51%	78.58	1.34E+34	100%
A24	21	8%	-1.61	2.00E-01	17%	4%	4.67	1.07E+02	99%
A25	54	40%	6.35	5.75E+02	100%	0%	-1.78	1.68E-01	14%
A26	26	55%	10.15	2.57E+04	100%	11%	15.38	4.77E+06	100%
A27	2	22%	1.95	7.04E+00	88%	0%	-1.78	1.68E-01	14%
A28	15	15%	0.22	1.24E+00	55%	0%	-1.78	1.68E-01	14%
A29	52	16%	0.39	1.48E+00	60%	0%	-1.15	3.18E-01	24%
A30	4	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A31	34	0%	-3.51	2.99E-02	3%	40%	61.33	4.33E+26	100%
A32	18	1%	-3.29	3.73E-02	4%	14%	20.11	5.39E+08	100%
A33	1	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A34	1	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A35	3	43%	7.31	1.50E+03	100%	0%	-1.78	1.68E-01	14%
A36	11	71%	14.10	1.33E+06	100%	0%	-1.78	1.68E-01	14%
A37	14	52%	9.57	1.44E+04	100%	5%	6.40	6.00E+02	100%
A38	5	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%

Table 15. The final logistic regression models used for impairment probability prediction.

Model	p-Value (Constant)	p-Value (Variable)
-5.05257 + (19.4422 * URBAN)	0.040	0.047
-3.50976 + (24.9319 * Residential)	0.023	0.014
-1.78358 + (159.129 * Commercial)	0.022	0.050
-4.78811 + (46.0652 * HardUrban)	0.020	0.022

Table 16. Potash subcatchments with land use characteristics and predicted probabilities for Urban and Hard Urban land use models.

Table 16a. Potash subcatchments with land use characteristics and predicted probabilities for Urban and Hard Urban land use models.

Subcatchment	Total Area	Urban				Hard Urban			
ID	(Acres)	% by Area	Log Odds	Odds	Probability	% by Area	Log Odds	Odds	Probability
A01	121	7%	-3.68	2.52E-02	2%	5%	-2.54	7.92E-02	7%
A02	56	6%	-3.98	1.87E-02	2%	0%	-4.60	1.00E-02	1%
A03	78	21%	-0.95	3.86E-01	28%	21%	4.93	1.38E+02	99%
A04	41	70%	8.60	5.46E+03	100%	25%	6.50	6.66E+02	100%
A05	19	61%	6.82	9.13E+02	100%	49%	17.86	5.72E+07	100%
A06	18	96%	13.71	8.96E+05	100%	96%	39.66	1.67E+17	100%
A07	18	36%	1.92	6.84E+00	87%	0%	-4.79	8.33E-03	1%
A08	98	9%	-3.34	3.53E-02	3%	8%	-1.31	2.69E-01	21%
A09	39	89%	12.21	2.01E+05	100%	69%	26.91	4.87E+11	100%
A10	79	97%	13.89	1.08E+06	100%	31%	9.45	1.27E+04	100%
A11	9	65%	7.59	1.97E+03	100%	17%	3.07	2.15E+01	96%
A12	5	68%	8.11	3.34E+03	100%	7%	-1.54	2.15E-01	18%
A13	25	100%	14.39	1.78E+06	100%	11%	0.38	1.46E+00	59%
A14	30	98%	13.94	1.14E+06	100%	57%	21.53	2.24E+09	100%
A15	137	28%	0.43	1.53E+00	61%	15%	1.92	6.84E+00	87%
A16	99	5%	-4.17	1.55E-02	2%	2%	-3.71	2.44E-02	2%
A17	58	65%	7.54	1.88E+03	100%	30%	8.93	7.57E+03	100%
A18	44	4%	-4.26	1.42E-02	1%	4%	-2.90	5.49E-02	5%
A19	13	25%	-0.27	7.67E-01	43%	25%	6.55	7.02E+02	100%
A20	55	36%	1.88	6.58E+00	87%	22%	5.21	1.83E+02	99%
A21	8	75%	9.61	1.48E+04	100%	71%	27.74	1.11E+12	100%
A22	29	33%	1.40	4.06E+00	80%	26%	7.31	1.50E+03	100%
A23	12	100%	14.35	1.71E+06	100%	78%	30.96	2.79E+13	100%
A24	8	100%	14.39	1.78E+06	100%	31%	9.69	1.62E+04	100%
A25	22	97%	13.72	9.05E+05	100%	97%	39.68	1.71E+17	100%
A26	10	100%	14.39	1.78E+06	100%	100%	41.28	8.44E+17	100%
A27	40	100%	14.39	1.78E+06	100%	51%	18.64	1.24E+08	100%
A28	5	99%	14.26	1.56E+06	100%	99%	40.97	6.23E+17	100%
A29	14	257%	44.85	3.02E+19	100%	257%	113.46	1.87E+49	100%
A30	27	2%	-4.71	9.04E-03	1%	2%	-3.97	1.89E-02	2%
A31	95	94%	13.28	5.87E+05	100%	29%	8.50	4.92E+03	100%
A32	19	100%	14.39	1.78E+06	100%	0%	-4.79	8.33E-03	1%
A33	9	100%	14.38	1.77E+06	100%	100%	41.26	8.32E+17	100%
A34	9	77%	10.00	2.20E+04	100%	77%	30.88	2.57E+13	100%
A35	73	74%	9.39	1.20E+04	100%	74%	29.14	4.51E+12	100%
A36	69	13%	-2.45	8.66E-02	8%	13%	1.24	3.44E+00	77%
A37	20	90%	12.37	2.36E+05	100%	90%	36.49	7.06E+15	100%
A38	4	100%	14.39	1.78E+06	100%	100%	41.28	8.44E+17	100%
A39	8	100%	14.39	1.78E+06	100%	100%	41.28	8.44E+17	100%
A40	6	100%	14.32	1.65E+06	100%	98%	40.57	4.14E+17	100%
A41	49	43%	3.31	2.75E+01	96%	37%	12.44	2.52E+05	100%
A42	27	100%	14.34	1.69E+06	100%	97%	39.71	1.75E+17	100%
A43	8	80%	10.42	3.34E+04	100%	74%	29.41	5.90E+12	100%
A44	26	98%	14.09	1.31E+06	100%	54%	19.99	4.82E+08	100%
A45	11	6%	-3.82	2.19E-02	2%	6%	-1.87	1.54E-01	13%
A46	118	28%	0.37	1.45E+00	59%	21%	4.90	1.34E+02	99%
A47	12	8%	-3.41	3.29E-02	3%	8%	-0.91	4.04E-01	29%
A48	2	24%	-0.48	6.18E-01	38%	24%	6.04	4.21E+02	100%
A49	8	60%	6.64	7.65E+02	100%	59%	22.27	4.71E+09	100%
A50	58	0%	-5.05	6.39E-03	1%	0%	-4.79	8.33E-03	1%
A51	42	99%	14.18	1.44E+06	100%	8%	-0.87	4.17E-01	29%
A52	4	52%	5.10	1.64E+02	99%	47%	17.09	2.64E+07	100%
A53	2	96%	13.56	7.71E+05	100%	36%	11.75	1.27E+05	100%
A54	5	94%	13.31	6.04E+05	100%	74%	29.43	6.03E+12	100%
A55	22	90%	12.51	2.71E+05	100%	76%	30.00	1.07E+13	100%
A56	5	100%	14.39	1.78E+06	100%	22%	5.41	2.23E+02	100%
A57	2	79%	10.39	3.26E+04	100%	73%	28.67	2.83E+12	100%
A58	18	100%	14.39	1.78E+06	100%	66%	25.56	1.26E+11	100%
A59	1	100%	14.39	1.78E+06	100%	98%	40.45	3.70E+17	100%
A60	13	91%	12.63	3.06E+05	100%	16%	2.60	1.34E+01	93%
A61	52	73%	9.17	9.58E+03	100%	36%	12.00	1.62E+05	100%
A62	17	100%	14.39	1.78E+06	100%	29%	8.46	4.73E+03	100%
A63	38	52%	4.98	1.45E+02	99%	23%	6.00	4.04E+02	100%
A64	9	72%	8.98	7.96E+03	100%	7%	-1.78	1.69E-01	14%
A65	13	28%	0.48	1.62E+00	62%	16%	2.62	1.38E+01	93%
A66	16	32%	1.22	3.40E+00	77%	14%	1.77	5.89E+00	85%

Subcatchment	Total Area	Urban				Hard Urban			
ID	(Acres)	% by Area	Log Odds	Odds	Probability	% by Area	Log Odds	Odds	Probability
A67	6	99%	14.14	1.38E+06	100%	12%	0.52	1.67E+00	63%
A68	15	100%	14.34	1.68E+06	100%	35%	11.18	7.16E+04	100%
A69	11	100%	14.39	1.78E+06	100%	48%	17.47	3.88E+07	100%
A70	18	77%	9.97	2.13E+04	100%	39%	13.20	5.40E+05	100%
A71	1	100%	14.39	1.78E+06	100%	100%	41.28	8.44E+17	100%
A72	18	99%	14.28	1.60E+06	100%	99%	41.02	6.55E+17	100%
A73	6	71%	8.79	6.56E+03	100%	71%	28.01	1.46E+12	100%
A74	1	55%	5.72	3.04E+02	100%	0%	-4.79	8.33E-03	1%
A75	5	22%	-0.77	4.62E-01	32%	7%	-1.34	2.61E-01	21%
A76	1	74%	9.29	1.08E+04	100%	36%	11.93	1.52E+05	100%
A77	2	4%	-4.33	1.32E-02	1%	4%	-3.07	4.64E-02	4%
A78	13	100%	14.39	1.78E+06	100%	43%	15.18	3.93E+06	100%
A79	17	99%	14.15	1.40E+06	100%	42%	14.43	1.84E+06	100%
A80	9	100%	14.39	1.78E+06	100%	6%	-2.05	1.29E-01	11%
A81	16	20%	-1.23	2.92E-01	23%	8%	-1.24	2.89E-01	22%
A82	14	0%	-5.05	6.39E-03	1%	0%	-4.79	8.33E-03	1%
A83	3	0%	-5.05	6.39E-03	1%	0%	-4.79	8.33E-03	1%
A84	58	1%	-4.94	7.16E-03	1%	0%	-4.79	8.33E-03	1%
A85	41	79%	10.25	2.83E+04	100%	24%	6.05	4.26E+02	100%
A86	5	100%	14.39	1.78E+06	100%	56%	21.06	1.40E+09	100%
A87	28	82%	10.82	5.00E+04	100%	12%	0.66	1.94E+00	66%
A88	4	81%	10.67	4.32E+04	100%	49%	17.98	6.46E+07	100%
A89	4	100%	14.39	1.78E+06	100%	26%	7.42	1.67E+03	100%
A90	11	13%	-2.60	7.46E-02	7%	12%	0.86	2.35E+00	70%
A91	56	40%	2.76	1.58E+01	94%	13%	1.41	4.11E+00	80%
A92	35	83%	11.13	6.84E+04	100%	21%	4.91	1.36E+02	99%
A93	10	100%	14.39	1.78E+06	100%	12%	0.69	2.00E+00	67%
A94	48	77%	9.97	2.14E+04	100%	31%	9.55	1.41E+04	100%
A95	24	0%	-5.05	6.39E-03	1%	0%	-4.79	8.33E-03	1%
A96	25	1%	-4.78	8.43E-03	1%	1%	-4.13	1.61E-02	2%
A97	27	30%	0.76	2.15E+00	68%	8%	-0.99	3.71E-01	27%
A98	35	12%	-2.63	7.20E-02	7%	12%	0.56	1.75E+00	64%
A99	31	87%	11.88	1.44E+05	100%	16%	2.78	1.61E+01	94%
B01	25	95%	13.48	7.16E+05	100%	20%	4.32	7.52E+01	99%
B02	165	16%	-2.04	1.30E-01	12%	5%	-2.69	6.77E-02	6%
B03	36	76%	9.81	1.82E+04	100%	11%	0.06	1.06E+00	51%
B04	15	83%	11.05	6.30E+04	100%	83%	33.37	3.09E+14	100%
B05	2	100%	14.39	1.78E+06	100%	100%	41.28	8.44E+17	100%
B06	4	81%	10.67	4.31E+04	100%	81%	32.47	1.26E+14	100%
B07	7	91%	12.59	2.92E+05	100%	91%	37.00	1.17E+16	100%
B08	15	83%	11.09	6.52E+04	100%	83%	33.45	3.36E+14	100%
B09	21	100%	14.39	1.78E+06	100%	100%	41.26	8.33E+17	100%
B10	8	100%	14.39	1.78E+06	100%	100%	41.28	8.44E+17	100%
B11	22	52%	5.12	1.68E+02	99%	16%	2.71	1.51E+01	94%
B12	4	0%	-4.98	6.85E-03	1%	0%	-4.62	9.82E-03	1%
B13	10	29%	0.55	1.74E+00	63%	28%	8.02	3.05E+03	100%
B14	1	51%	4.87	1.31E+02	99%	51%	18.73	1.36E+08	100%
B15	2	100%	14.39	1.78E+06	100%	21%	4.82	1.24E+02	99%
B16	16	93%	13.05	4.65E+05	100%	93%	38.10	3.53E+16	100%
B17	2	100%	14.39	1.78E+06	100%	100%	41.28	8.44E+17	100%
B18	5	89%	12.23	2.05E+05	100%	89%	36.16	5.04E+15	100%
B19	30	89%	12.18	1.95E+05	100%	85%	34.25	7.49E+14	100%
B20	42	92%	12.75	3.45E+05	100%	78%	31.11	3.26E+13	100%
B21	3	100%	14.39	1.78E+06	100%	100%	41.28	8.44E+17	100%
B22	66	55%	5.58	2.64E+02	100%	27%	7.52	1.85E+03	100%
B23	6	100%	14.39	1.77E+06	100%	100%	41.27	8.35E+17	100%
B24	23	51%	4.79	1.20E+02	99%	51%	18.53	1.11E+08	100%
B25	11	99%	14.15	1.39E+06	100%	19%	3.83	4.59E+01	98%
B26	19	98%	13.96	1.16E+06	100%	38%	12.50	2.69E+05	100%
B27	35	52%	5.11	1.66E+02	99%	4%	-2.86	5.75E-02	5%
B28	40	0%	-5.05	6.39E-03	1%	0%	-4.79	8.33E-03	1%
B29	50	5%	-4.12	1.62E-02	2%	0%	-4.77	8.44E-03	1%
B30	3	100%	14.39	1.78E+06	100%	50%	18.13	7.51E+07	100%
B31	37	88%	12.02	1.65E+05	100%	30%	8.90	7.31E+03	100%
B32	16	95%	13.35	6.25E+05	100%	95%	38.80	7.12E+16	100%
B33	5	30%	0.86	2.36E+00	70%	9%	-0.62	5.40E-01	35%
B34	2	100%	14.39	1.78E+06	100%	75%	29.55	6.84E+12	100%
B35	5	80%	10.42	3.35E+04	100%	6%	-1.94	1.44E-01	13%

Subcatchment	Total Area	Urban				Hard Urban			
ID	(Acres)	% by Area	Log Odds	Odds	Probability	% by Area	Log Odds	Odds	Probability
B36	14	95%	13.44	6.85E+05	100%	61%	23.46	1.54E+10	100%
B37	26	54%	5.53	2.53E+02	100%	16%	2.51	1.23E+01	92%
B38	10	28%	0.37	1.45E+00	59%	0%	-4.79	8.33E-03	1%
B39	16	65%	7.53	1.85E+03	100%	16%	2.65	1.41E+01	93%
B40	68	63%	7.13	1.25E+03	100%	20%	4.28	7.25E+01	99%
B41	18	27%	0.13	1.13E+00	53%	19%	4.14	6.27E+01	98%
B42	3	100%	14.39	1.78E+06	100%	76%	30.34	1.49E+13	100%
B43	15	96%	13.53	7.51E+05	100%	59%	22.45	5.60E+09	100%
B44	22	66%	7.83	2.51E+03	100%	55%	20.67	9.44E+08	100%
B45	2	64%	7.32	1.51E+03	100%	64%	24.52	4.46E+10	100%
B46	1	18%	-1.47	2.30E-01	19%	18%	3.70	4.06E+01	98%
B47	1	87%	11.93	1.52E+05	100%	0%	-4.79	8.33E-03	1%
B48	0	46%	3.83	4.62E+01	98%	46%	16.27	1.16E+07	100%
B49	8	100%	14.39	1.78E+06	100%	56%	20.98	1.29E+09	100%
B50	10	91%	12.57	2.87E+05	100%	35%	11.29	7.98E+04	100%
B51	20	22%	-0.85	4.28E-01	30%	21%	4.66	1.06E+02	99%
B52	9	100%	14.39	1.78E+06	100%	34%	10.91	5.45E+04	100%
B53	51	79%	10.30	2.97E+04	100%	26%	7.05	1.15E+03	100%
B54	4	100%	14.39	1.78E+06	100%	43%	15.00	3.28E+06	100%
B55	124	28%	0.42	1.52E+00	60%	20%	4.53	9.29E+01	99%
B56	5	71%	8.78	6.51E+03	100%	11%	0.43	1.53E+00	61%
B57	10	100%	14.39	1.78E+06	100%	49%	17.90	5.95E+07	100%
B58	5	31%	1.01	2.74E+00	73%	16%	2.67	1.44E+01	94%
B59	66	13%	-2.45	8.60E-02	8%	13%	1.13	3.10E+00	76%
B60	16	100%	14.39	1.78E+06	100%	100%	41.28	8.44E+17	100%
B61	32	99%	14.10	1.33E+06	100%	52%	18.94	1.68E+08	100%
B62	29	16%	-1.85	1.57E-01	14%	16%	2.79	1.63E+01	94%
B63	52	93%	13.08	4.80E+05	100%	36%	11.88	1.45E+05	100%
B64	4	95%	13.46	7.00E+05	100%	8%	-1.07	3.44E-01	26%
B65	14	80%	10.57	3.90E+04	100%	19%	3.88	4.86E+01	98%
B66	19	91%	12.71	3.32E+05	100%	30%	9.24	1.03E+04	100%
B67	62	16%	-1.86	1.56E-01	14%	10%	-0.16	8.48E-01	46%
B68	34	10%	-3.05	4.72E-02	5%	9%	-0.83	4.37E-01	30%
B69	6	64%	7.42	1.68E+03	100%	2%	-3.74	2.39E-02	2%
B70	11	82%	10.80	4.91E+04	100%	21%	4.83	1.25E+02	99%
B71	4	37%	2.19	8.91E+00	90%	37%	12.37	2.35E+05	100%
B72	1	94%	13.27	5.80E+05	100%	91%	37.29	1.57E+16	100%
B73	13	97%	13.77	9.54E+05	100%	48%	17.15	2.81E+07	100%
B74	88	61%	6.84	9.37E+02	100%	6%	-1.92	1.46E-01	13%
B75	11	100%	14.39	1.78E+06	100%	27%	7.82	2.50E+03	100%
B76	1	63%	7.11	1.22E+03	100%	63%	24.02	2.71E+10	100%
B77	5	70%	8.57	5.28E+03	100%	31%	9.66	1.57E+04	100%
B78	26	92%	12.78	3.56E+05	100%	26%	7.22	1.36E+03	100%
B79	1	73%	9.08	8.82E+03	100%	63%	24.28	3.52E+10	100%
B80	6	37%	2.05	7.75E+00	89%	20%	4.61	1.00E+02	99%
B81	19	93%	13.00	4.43E+05	100%	31%	9.43	1.24E+04	100%
B82	2	100%	14.33	1.68E+06	100%	97%	40.06	2.51E+17	100%
B83	40	97%	13.74	9.32E+05	100%	67%	26.11	2.19E+11	100%
B84	23	64%	7.45	1.72E+03	100%	25%	6.70	8.09E+02	100%
B85	2	76%	9.78	1.77E+04	100%	76%	30.35	1.52E+13	100%
B86	1	100%	14.39	1.78E+06	100%	97%	39.69	1.73E+17	100%
B87	8	100%	14.39	1.78E+06	100%	48%	17.51	4.01E+07	100%
B88	17	67%	8.05	3.14E+03	100%	17%	3.13	2.30E+01	96%
B89	3	91%	12.64	3.10E+05	100%	53%	19.68	3.51E+08	100%

Table 16b. Potash subcatchments with land use characteristics and predicted probabilities for Residential and Commercial land use models.

Subcatchment ID	Total Area (Acres)	Residential				Commercial			
		% by Area	Log Odds	Odds	Probability	% by Area	Log Odds	Odds	Probability
A01	121	1%	-3.19	4.11E-02	4%	0%	-1.78	1.68E-01	14%
A02	56	5%	-2.23	1.07E-01	10%	0%	-1.78	1.68E-01	14%
A03	78	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A04	41	41%	6.63	7.61E+02	100%	0%	-1.78	1.68E-01	14%
A05	19	12%	-0.55	5.78E-01	37%	0%	-1.78	1.68E-01	14%
A06	18	0%	-3.51	2.99E-02	3%	78%	122.35	1.37E+53	100%
A07	18	36%	5.43	2.29E+02	100%	0%	-1.78	1.68E-01	14%
A08	98	1%	-3.36	3.47E-02	3%	0%	-1.78	1.68E-01	14%
A09	39	20%	1.47	4.35E+00	81%	57%	88.96	4.31E+38	100%
A10	79	67%	13.08	4.80E+05	100%	10%	14.65	2.31E+06	100%
A11	9	48%	8.45	4.65E+03	100%	0%	-1.78	1.68E-01	14%
A12	5	54%	10.07	2.37E+04	100%	1%	-0.03	9.67E-01	49%
A13	25	47%	8.26	3.88E+03	100%	0%	-1.75	1.74E-01	15%
A14	30	1%	-3.38	3.39E-02	3%	22%	33.24	2.72E+14	100%
A15	137	14%	-0.11	8.93E-01	47%	2%	2.06	7.82E+00	89%
A16	99	2%	-2.95	5.22E-02	5%	0%	-1.78	1.68E-01	14%
A17	58	35%	5.21	1.83E+02	99%	2%	1.56	4.76E+00	83%
A18	44	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A19	13	0%	-3.51	2.99E-02	3%	6%	7.53	1.86E+03	100%
A20	55	14%	-0.03	9.74E-01	49%	0%	-1.78	1.68E-01	14%
A21	8	5%	-2.32	9.86E-02	9%	71%	110.57	1.04E+48	100%
A22	29	7%	-1.78	1.68E-01	14%	3%	3.39	2.97E+01	97%
A23	12	22%	2.02	7.56E+00	88%	8%	10.75	4.67E+04	100%
A24	8	69%	13.58	7.93E+05	100%	17%	25.87	1.72E+11	100%
A25	22	0%	-3.51	2.99E-02	3%	73%	113.63	2.23E+49	100%
A26	10	0%	-3.51	2.99E-02	3%	32%	48.85	1.64E+21	100%
A27	40	49%	8.74	6.23E+03	100%	26%	39.41	1.30E+17	100%
A28	5	0%	-3.51	2.99E-02	3%	59%	91.83	7.61E+39	100%
A29	14	0%	-3.51	2.99E-02	3%	171%	269.64	1.27E+117	100%
A30	27	0%	-3.51	2.99E-02	3%	2%	1.05	2.87E+00	74%
A31	95	6%	-2.04	1.30E-01	11%	14%	19.83	4.11E+08	100%
A32	19	0%	-3.51	2.99E-02	3%	99%	155.36	2.96E+67	100%
A33	9	0%	-3.51	2.99E-02	3%	100%	157.30	2.06E+68	100%
A34	9	0%	-3.51	2.99E-02	3%	53%	82.64	7.80E+35	100%
A35	73	1%	-3.35	3.50E-02	3%	2%	1.36	3.90E+00	80%
A36	69	0%	-3.43	3.25E-02	3%	0%	-1.78	1.68E-01	14%
A37	20	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A38	4	0%	-3.51	2.99E-02	3%	99%	156.27	7.38E+67	100%
A39	8	0%	-3.51	2.99E-02	3%	95%	150.04	1.45E+65	100%
A40	6	1%	-3.22	4.01E-02	4%	53%	82.14	4.69E+35	100%
A41	49	6%	-2.10	1.22E-01	11%	34%	52.79	8.41E+22	100%
A42	27	3%	-2.72	6.58E-02	6%	65%	101.65	1.40E+44	100%
A43	8	5%	-2.18	1.13E-01	10%	39%	59.96	1.09E+26	100%
A44	26	45%	7.62	2.04E+03	100%	15%	22.27	4.71E+09	100%
A45	11	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A46	118	7%	-1.79	1.66E-01	14%	6%	7.26	1.42E+03	100%
A47	12	0%	-3.51	2.99E-02	3%	1%	-0.41	6.62E-01	40%
A48	2	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A49	8	1%	-3.16	4.24E-02	4%	0%	-1.78	1.68E-01	14%
A50	58	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A51	42	6%	-1.91	1.48E-01	13%	0%	-1.78	1.68E-01	14%
A52	4	5%	-2.34	9.67E-02	9%	0%	-1.78	1.68E-01	14%
A53	2	60%	11.40	8.95E+04	100%	0%	-1.78	1.68E-01	14%
A54	5	20%	1.52	4.58E+00	82%	20%	30.74	2.25E+13	100%
A55	22	15%	0.18	1.20E+00	55%	53%	82.15	4.74E+35	100%
A56	5	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A57	2	7%	-1.81	1.63E-01	14%	10%	13.82	1.00E+06	100%
A58	18	34%	5.00	1.48E+02	99%	50%	77.65	5.28E+33	100%
A59	1	2%	-3.06	4.67E-02	4%	9%	12.57	2.89E+05	100%
A60	13	75%	15.17	3.88E+06	100%	0%	-1.78	1.68E-01	14%
A61	52	61%	11.66	1.15E+05	100%	9%	12.29	2.17E+05	100%
A62	17	67%	13.26	5.73E+05	100%	0%	-1.78	1.68E-01	14%
A63	38	13%	-0.38	6.82E-01	41%	6%	7.81	2.46E+03	100%
A64	9	55%	10.20	2.69E+04	100%	0%	-1.78	1.68E-01	14%
A65	13	12%	-0.42	6.55E-01	40%	0%	-1.78	1.68E-01	14%
A66	16	18%	0.99	2.68E+00	73%	0%	-1.78	1.68E-01	14%

Subcatchment ID	Total Area (Acres)	Residential				Commercial			
		% by Area	Log Odds	Odds	Probability	% by Area	Log Odds	Odds	Probability
A67	6	87%	18.23	8.23E+07	100%	0%	-1.78	1.68E-01	14%
A68	15	65%	12.71	3.31E+05	100%	0%	-1.78	1.68E-01	14%
A69	11	52%	9.37	1.18E+04	100%	1%	-0.92	4.00E-01	29%
A70	18	38%	6.01	4.09E+02	100%	13%	19.30	2.40E+08	100%
A71	1	0%	-3.51	2.99E-02	3%	73%	114.76	6.91E+49	100%
A72	18	22%	1.96	7.09E+00	88%	80%	125.63	3.65E+54	100%
A73	6	0%	-3.51	2.99E-02	3%	71%	111.51	2.68E+48	100%
A74	1	55%	10.30	2.98E+04	100%	0%	-1.78	1.68E-01	14%
A75	5	15%	0.11	1.12E+00	53%	0%	-1.78	1.68E-01	14%
A76	1	37%	5.83	3.41E+02	100%	36%	55.98	2.05E+24	100%
A77	2	0%	-3.51	2.99E-02	3%	4%	4.15	6.33E+01	98%
A78	13	57%	10.61	4.06E+04	100%	12%	17.98	6.44E+07	100%
A79	17	57%	10.72	4.52E+04	100%	0%	-1.78	1.68E-01	14%
A80	9	94%	19.94	4.56E+08	100%	0%	-1.78	1.68E-01	14%
A81	16	12%	-0.53	5.89E-01	37%	0%	-1.78	1.68E-01	14%
A82	14	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A83	3	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A84	58	1%	-3.36	3.46E-02	3%	0%	-1.78	1.68E-01	14%
A85	41	54%	9.90	1.99E+04	100%	0%	-1.78	1.68E-01	14%
A86	5	44%	7.43	1.69E+03	100%	45%	70.51	4.18E+30	100%
A87	28	13%	-0.25	7.80E-01	44%	1%	-0.26	7.72E-01	44%
A88	4	5%	-2.21	1.10E-01	10%	32%	49.03	1.97E+21	100%
A89	4	74%	14.82	2.72E+06	100%	5%	6.25	5.20E+02	100%
A90	11	0%	-3.41	3.29E-02	3%	0%	-1.78	1.68E-01	14%
A91	56	27%	3.15	2.33E+01	96%	0%	-1.78	1.68E-01	14%
A92	35	62%	12.00	1.62E+05	100%	0%	-1.78	1.68E-01	14%
A93	10	88%	18.46	1.04E+08	100%	0%	-1.78	1.68E-01	14%
A94	48	46%	7.99	2.96E+03	100%	0%	-1.49	2.25E-01	18%
A95	24	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A96	25	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
A97	27	22%	1.90	6.66E+00	87%	0%	-1.78	1.68E-01	14%
A98	35	1%	-3.30	3.69E-02	4%	0%	-1.78	1.68E-01	14%
A99	31	71%	14.11	1.34E+06	100%	0%	-1.78	1.68E-01	14%
B01	25	76%	15.33	4.54E+06	100%	0%	-1.78	1.68E-01	14%
B02	165	9%	-1.35	2.60E-01	21%	0%	-1.78	1.68E-01	14%
B03	36	66%	12.93	4.11E+05	100%	0%	-1.78	1.68E-01	14%
B04	15	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
B05	2	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
B06	4	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
B07	7	0%	-3.51	2.99E-02	3%	91%	142.58	8.34E+61	100%
B08	15	75%	15.15	3.79E+06	100%	75%	117.44	1.01E+51	100%
B09	21	0%	-3.50	3.01E-02	3%	74%	116.63	4.48E+50	100%
B10	8	0%	-3.51	2.99E-02	3%	99%	156.34	7.86E+67	100%
B11	22	36%	5.48	2.40E+02	100%	10%	13.71	9.04E+05	100%
B12	4	0%	-3.44	3.20E-02	3%	0%	-1.78	1.68E-01	14%
B13	10	1%	-3.26	3.85E-02	4%	4%	3.85	4.70E+01	98%
B14	1	0%	-3.51	2.99E-02	3%	49%	76.24	1.29E+33	100%
B15	2	79%	16.22	1.11E+07	100%	0%	-1.78	1.68E-01	14%
B16	16	0%	-3.51	2.99E-02	3%	22%	32.92	1.99E+14	100%
B17	2	0%	-3.51	2.99E-02	3%	67%	104.32	2.03E+45	100%
B18	5	0%	-3.51	2.99E-02	3%	73%	113.67	2.32E+49	100%
B19	30	4%	-2.54	7.90E-02	7%	79%	124.20	8.72E+53	100%
B20	42	14%	-0.11	8.94E-01	47%	61%	95.55	3.15E+41	100%
B21	3	0%	-3.51	2.99E-02	3%	81%	126.66	1.02E+55	100%
B22	66	28%	3.46	3.17E+01	97%	1%	-0.87	4.19E-01	30%
B23	6	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
B24	23	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
B25	11	80%	16.45	1.39E+07	100%	0%	-1.78	1.68E-01	14%
B26	19	60%	11.51	1.00E+05	100%	0%	-1.78	1.68E-01	14%
B27	35	48%	8.48	4.80E+03	100%	0%	-1.78	1.68E-01	14%
B28	40	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
B29	50	5%	-2.32	9.82E-02	9%	0%	-1.78	1.68E-01	14%
B30	3	50%	9.02	8.23E+03	100%	0%	-1.78	1.68E-01	14%
B31	37	35%	5.33	2.06E+02	100%	0%	-1.78	1.68E-01	14%
B32	16	0%	-3.51	2.99E-02	3%	51%	78.63	1.41E+34	100%
B33	5	21%	1.81	6.14E+00	86%	0%	-1.78	1.68E-01	14%
B34	2	25%	2.84	1.70E+01	94%	0%	-1.78	1.68E-01	14%
B35	5	73%	14.79	2.64E+06	100%	0%	-1.78	1.68E-01	14%

Subcatchment ID	Total Area (Acres)	Residential				Commercial			
		% by Area	Log Odds	Odds	Probability	% by Area	Log Odds	Odds	Probability
B36	14	34%	4.91	1.36E+02	99%	35%	53.60	1.90E+23	100%
B37	26	39%	6.11	4.52E+02	100%	0%	-1.78	1.68E-01	14%
B38	10	28%	3.45	3.14E+01	97%	0%	-1.78	1.68E-01	14%
B39	16	49%	8.60	5.41E+03	100%	0%	-1.78	1.68E-01	14%
B40	68	43%	7.20	1.34E+03	100%	0%	-1.78	1.68E-01	14%
B41	18	7%	-1.70	1.82E-01	15%	0%	-1.78	1.68E-01	14%
B42	3	24%	2.41	1.12E+01	92%	76%	119.01	4.85E+51	100%
B43	15	36%	5.58	2.65E+02	100%	6%	7.30	1.48E+03	100%
B44	22	11%	-0.77	4.64E-01	32%	51%	79.50	3.34E+34	100%
B45	2	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
B46	1	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
B47	1	87%	18.27	8.62E+07	100%	0%	-1.78	1.68E-01	14%
B48	0	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
B49	8	44%	7.48	1.77E+03	100%	21%	32.00	7.89E+13	100%
B50	10	56%	10.39	3.24E+04	100%	0%	-1.78	1.68E-01	14%
B51	20	1%	-3.23	3.94E-02	4%	0%	-1.78	1.68E-01	14%
B52	9	66%	12.93	4.12E+05	100%	0%	-1.78	1.68E-01	14%
B53	51	53%	9.77	1.76E+04	100%	0%	-1.78	1.68E-01	14%
B54	4	57%	10.71	4.48E+04	100%	0%	-1.78	1.68E-01	14%
B55	124	3%	-2.82	5.95E-02	6%	10%	13.51	7.40E+05	100%
B56	5	60%	11.41	8.99E+04	100%	4%	5.33	2.06E+02	100%
B57	10	51%	9.14	9.34E+03	100%	13%	18.63	1.23E+08	100%
B58	5	15%	0.23	1.25E+00	56%	0%	-1.78	1.68E-01	14%
B59	66	0%	-3.49	3.06E-02	3%	0%	-1.10	3.32E-01	25%
B60	16	0%	-3.51	2.99E-02	3%	72%	113.20	1.45E+49	100%
B61	32	47%	8.21	3.68E+03	100%	0%	-1.78	1.68E-01	14%
B62	29	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
B63	52	57%	10.72	4.54E+04	100%	3%	2.26	9.59E+00	91%
B64	4	87%	18.21	8.14E+07	100%	0%	-1.78	1.68E-01	14%
B65	14	16%	0.59	1.80E+00	64%	0%	-1.78	1.68E-01	14%
B66	19	61%	11.68	1.18E+05	100%	0%	-1.78	1.68E-01	14%
B67	62	6%	-1.91	1.48E-01	13%	0%	-1.78	1.68E-01	14%
B68	34	2%	-3.09	4.55E-02	4%	0%	-1.78	1.68E-01	14%
B69	6	62%	11.92	1.50E+05	100%	0%	-1.78	1.68E-01	14%
B70	11	61%	11.62	1.11E+05	100%	0%	-1.78	1.68E-01	14%
B71	4	0%	-3.51	2.99E-02	3%	33%	50.00	5.20E+21	100%
B72	1	3%	-2.79	6.15E-02	6%	0%	-1.78	1.68E-01	14%
B73	13	49%	8.75	6.32E+03	100%	0%	-1.78	1.68E-01	14%
B74	88	55%	10.19	2.67E+04	100%	0%	-1.78	1.68E-01	14%
B75	11	73%	14.60	2.18E+06	100%	1%	0.02	1.02E+00	50%
B76	1	0%	-3.51	2.99E-02	3%	0%	-1.78	1.68E-01	14%
B77	5	39%	6.14	4.64E+02	100%	0%	-1.78	1.68E-01	14%
B78	26	66%	12.87	3.87E+05	100%	0%	-1.78	1.68E-01	14%
B79	1	10%	-1.12	3.28E-01	25%	3%	2.43	1.14E+01	92%
B80	6	16%	0.51	1.67E+00	62%	0%	-1.78	1.68E-01	14%
B81	19	62%	11.95	1.54E+05	100%	0%	-1.76	1.73E-01	15%
B82	2	2%	-2.92	5.37E-02	5%	0%	-1.78	1.68E-01	14%
B83	40	30%	3.87	4.79E+01	98%	5%	6.15	4.69E+02	100%
B84	23	39%	6.30	5.47E+02	100%	11%	15.35	4.65E+06	100%
B85	2	0%	-3.51	2.99E-02	3%	40%	61.43	4.76E+26	100%
B86	1	3%	-2.65	7.05E-02	7%	42%	65.42	2.57E+28	100%
B87	8	52%	9.36	1.16E+04	100%	9%	13.18	5.30E+05	100%
B88	17	50%	9.01	8.16E+03	100%	0%	-1.78	1.68E-01	14%
B89	3	38%	5.94	3.81E+02	100%	0%	-1.78	1.68E-01	14%

APPENDIX B – FIGURES

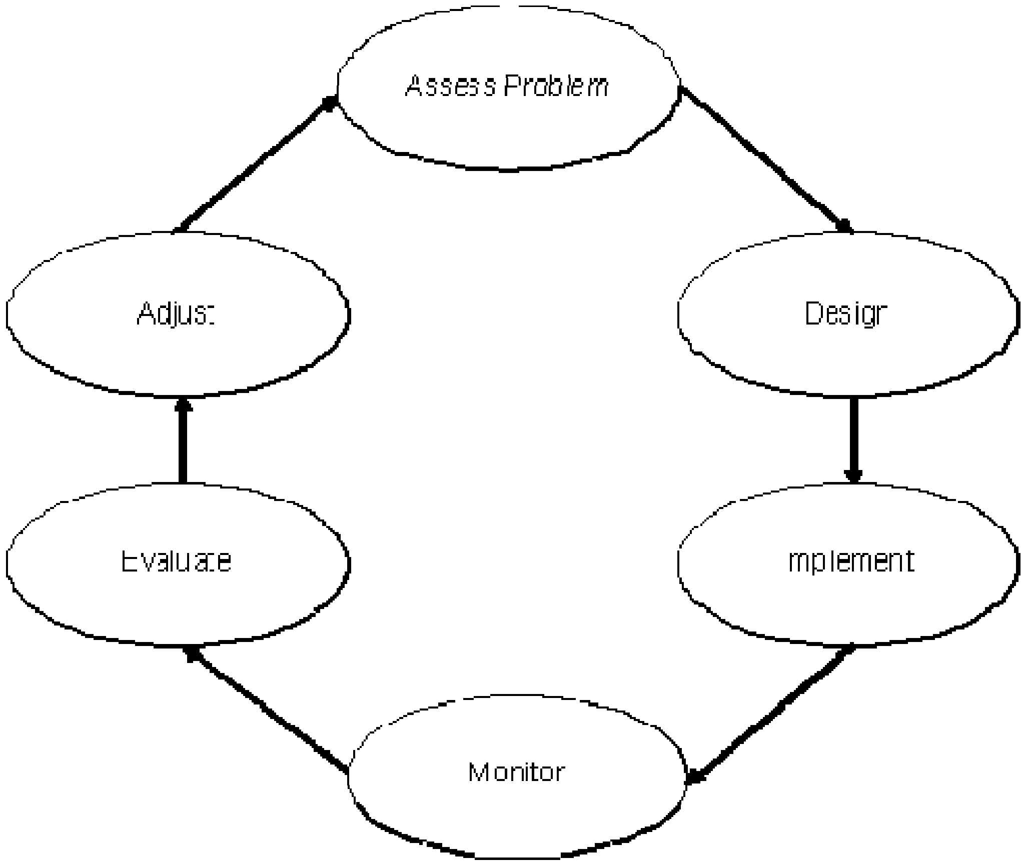

Figure 1. An example of a typical adaptive management process (Freedman 2004).

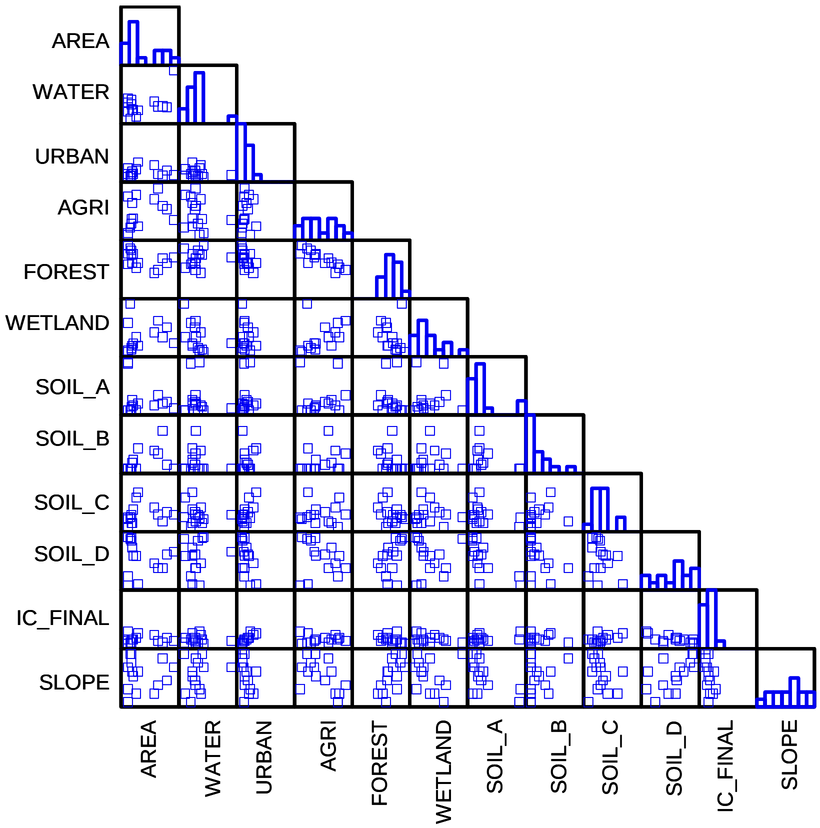

Figure 2. Scatterplot matrices of watershed variables for attainment and impaired streams.

Figure 2a. Scatterplot matrix for attainment streams.

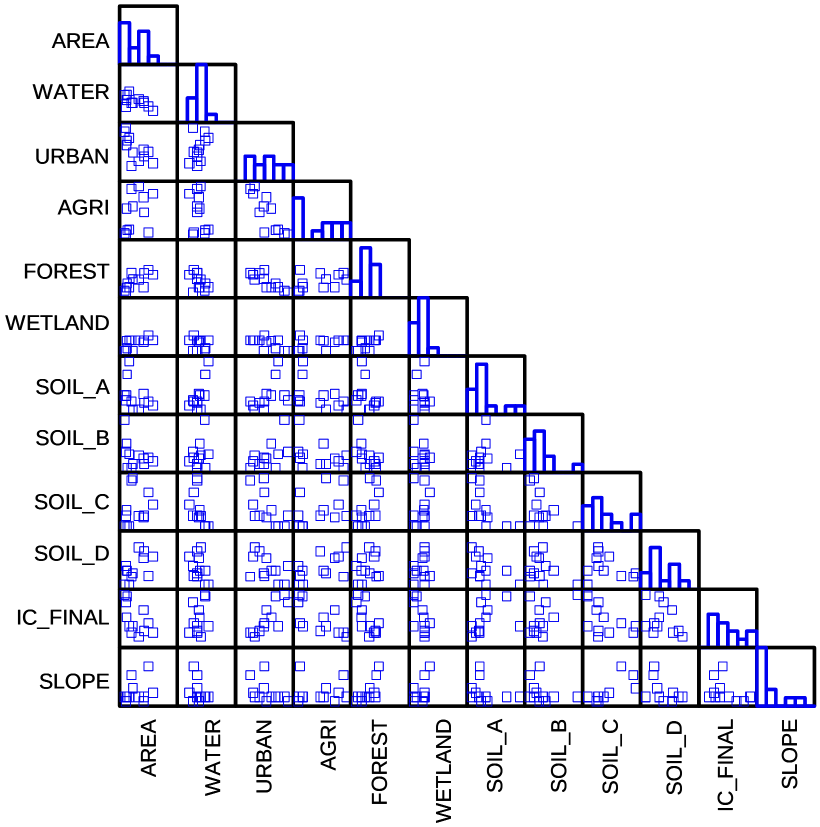

Figure 2b. Scatterplot matrices (SPLOM) of watershed variables for impaired streams.

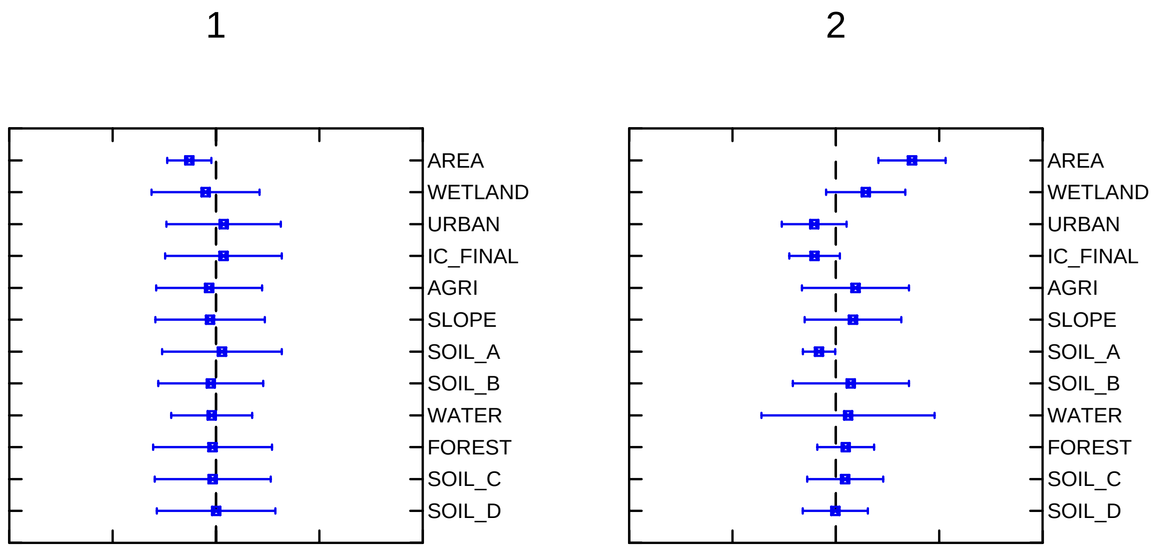

Figure 3. Cluster profile plot of watershed variables from the K-means analysis for 2 clusters. Note the influence of the Area variable.

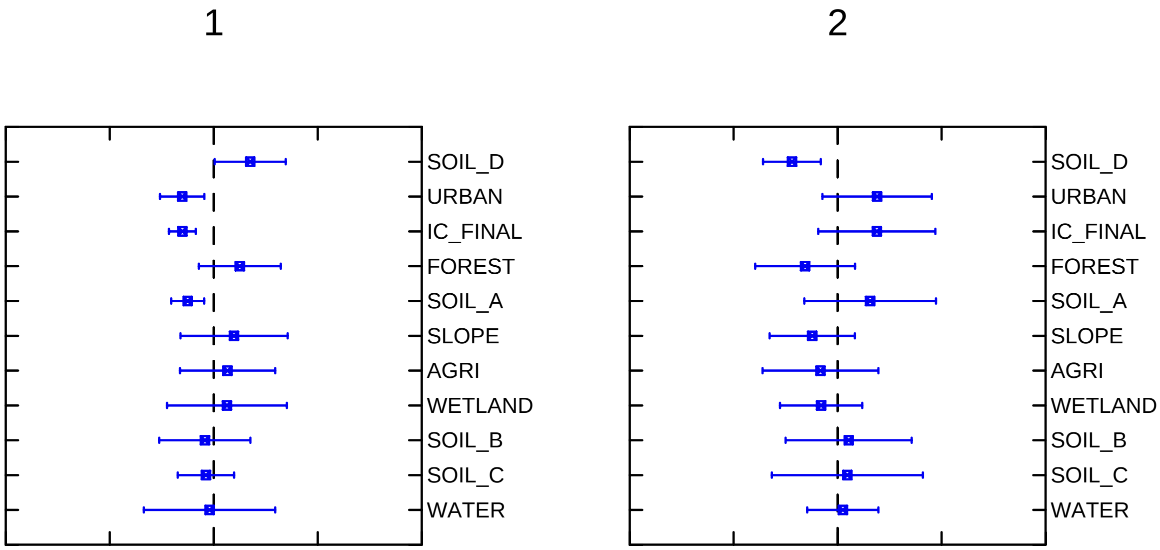

Figure 4. K-means cluster profile plot of watershed variables for K=2 with the Area variable removed.

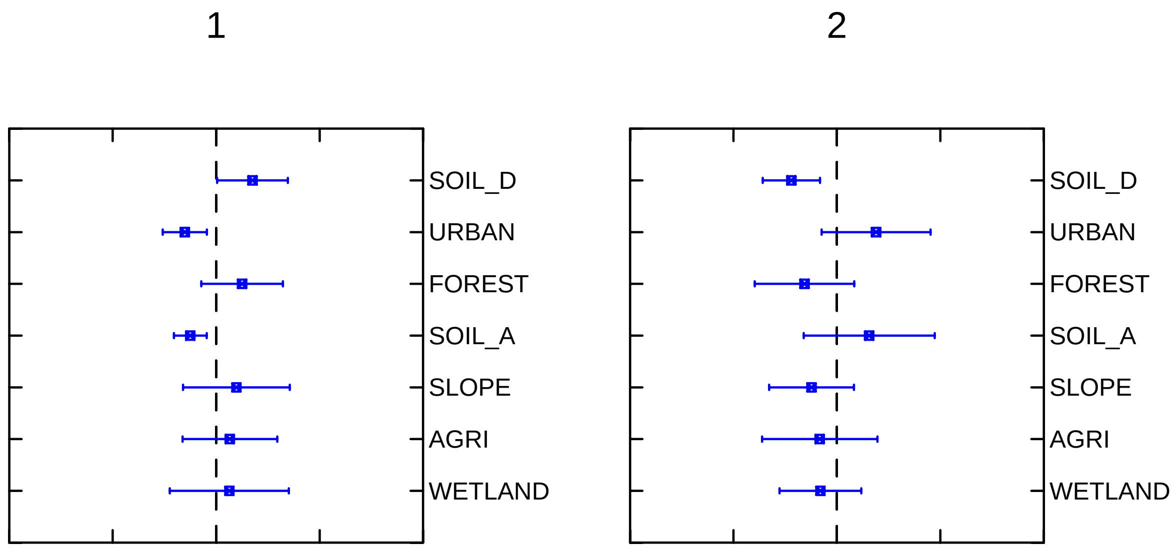

Figure 5. Final K-mean cluster profile plot of watershed variables for K=2.

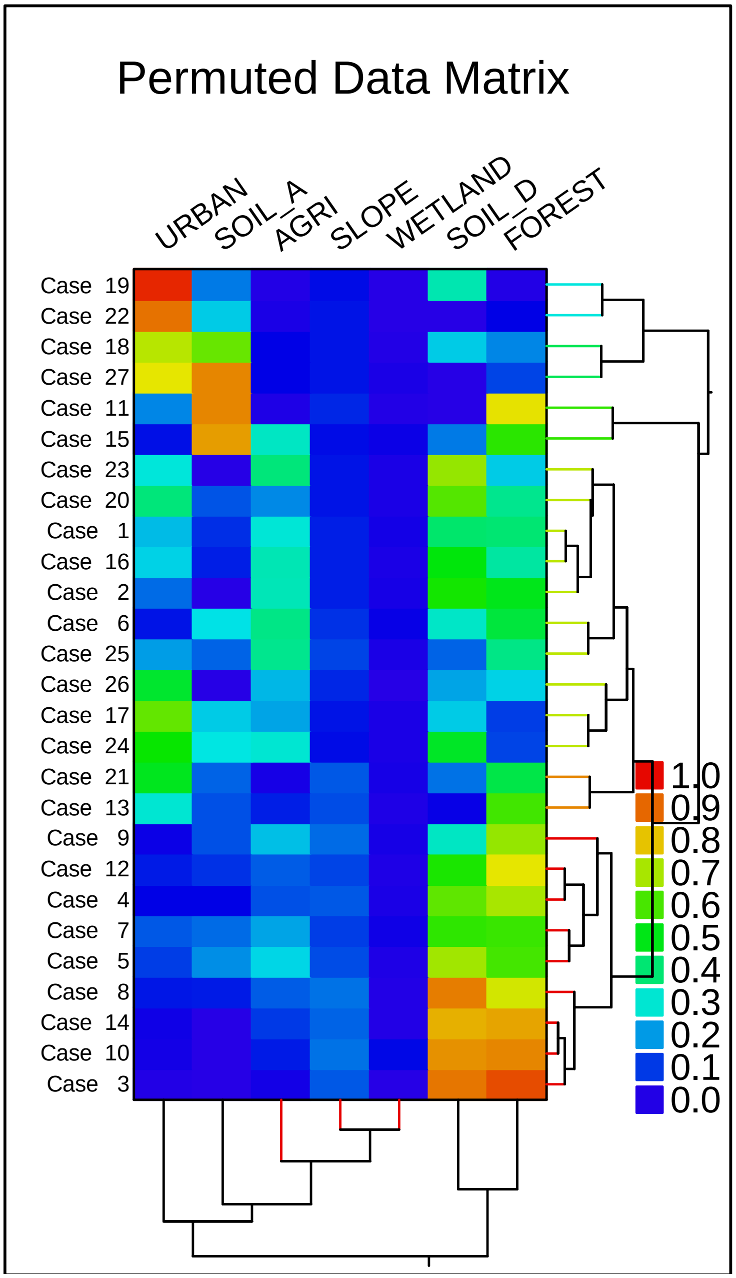

Figure 6. Hierarchical cluster matrix using average linkage method. Input variables are the final cluster variables from the k-means clustering.

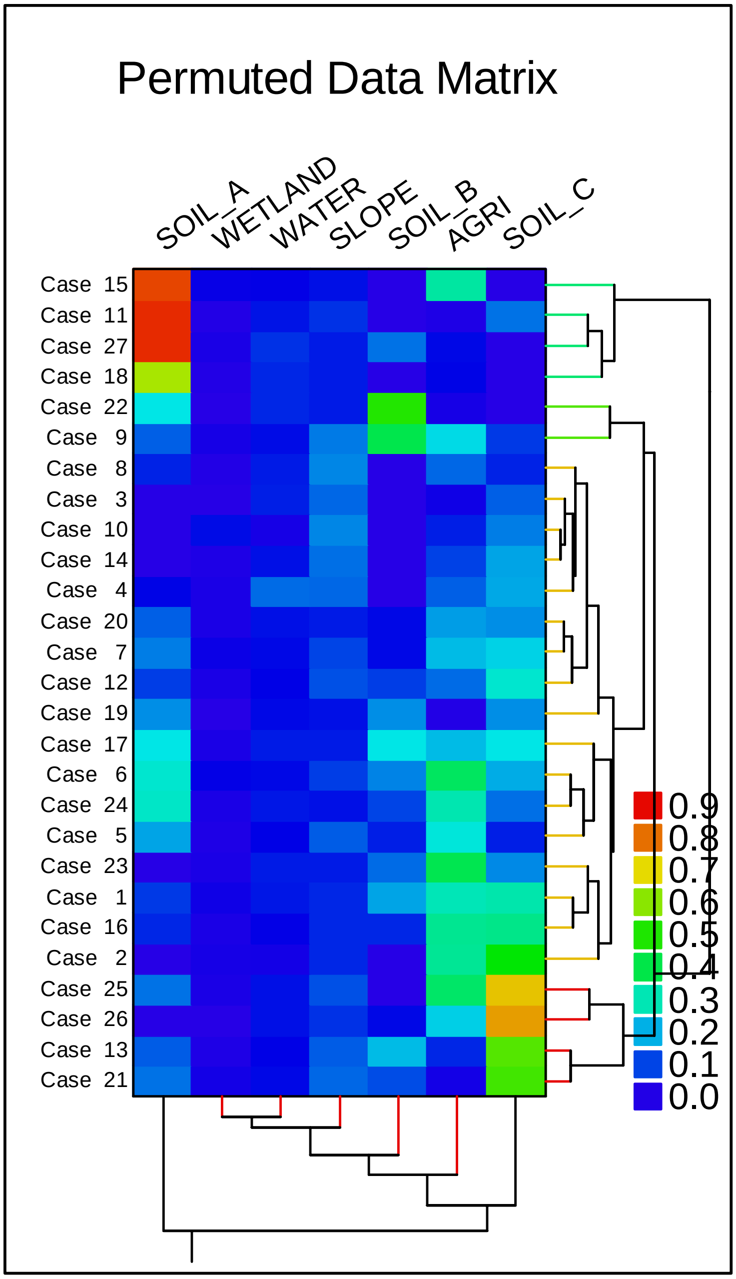

Figure 7. Hierarchical cluster matrix using average linkage method. Input variables are the lowest ranking variables from the k-means clustering.

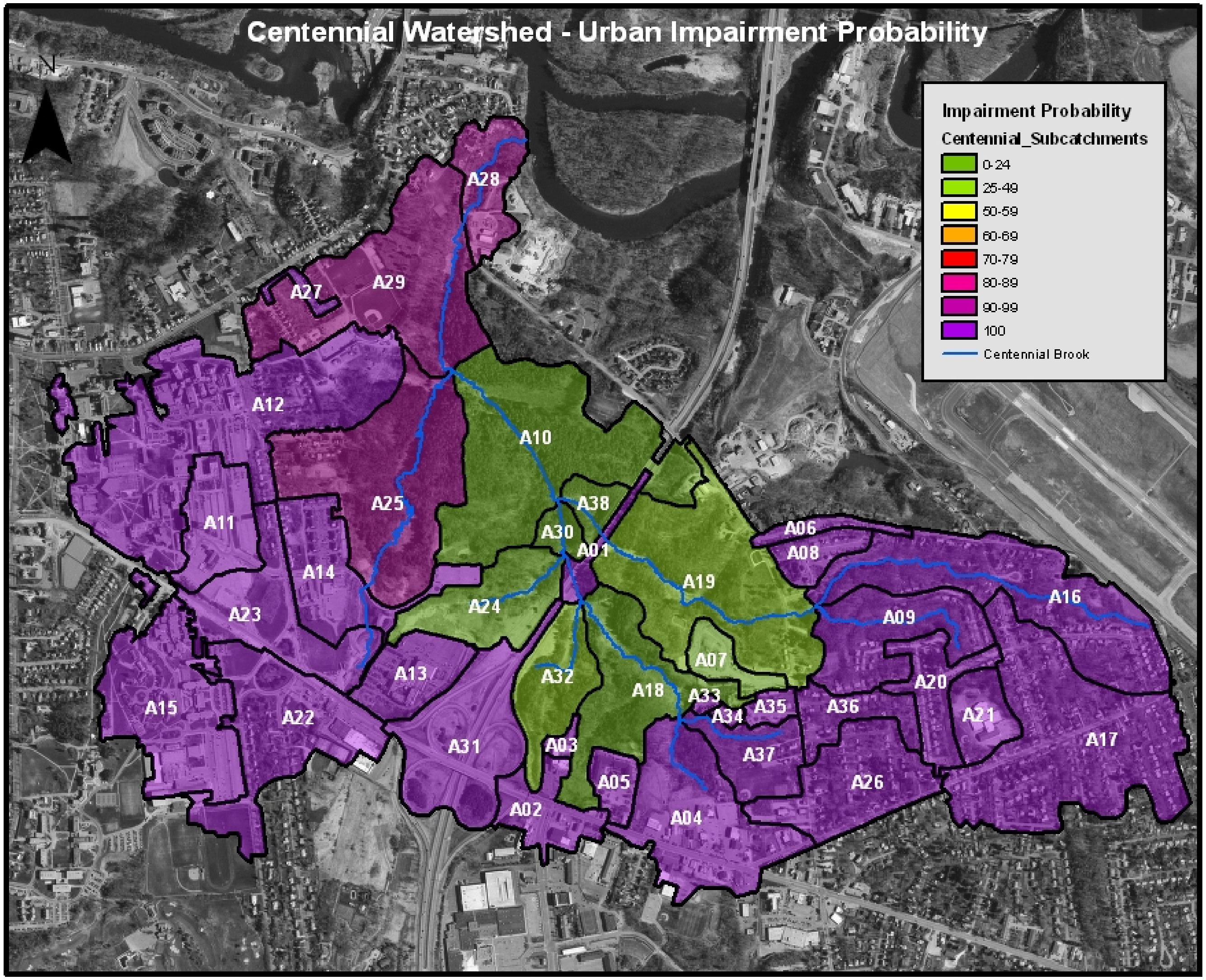

Figure 8. The impairment probabilities calculated for each Centennial Brook subcatchment based on the Urban model.

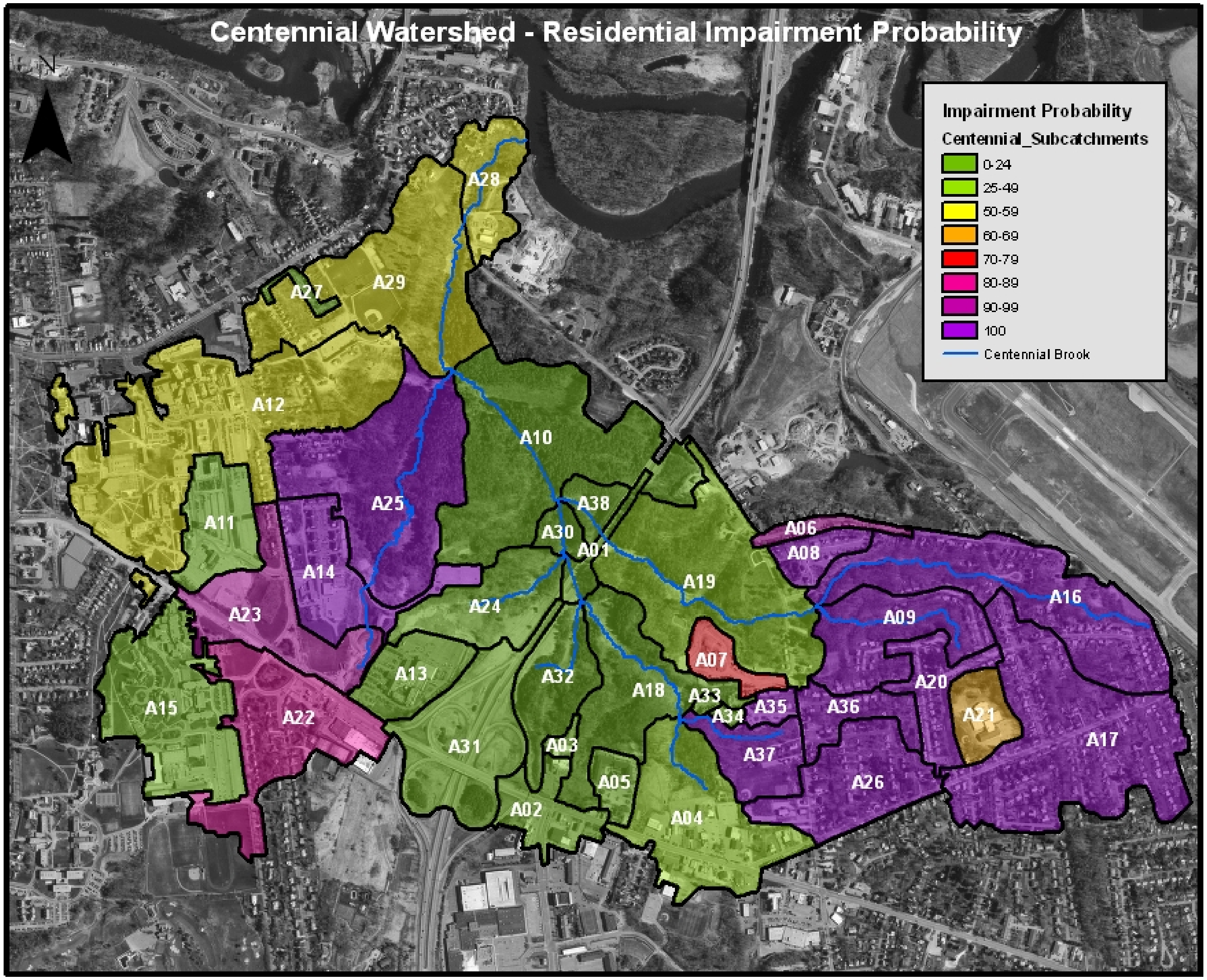

Figure 9. The impairment probabilities calculated for each Centennial Brook subcatchment based on the Residential model.

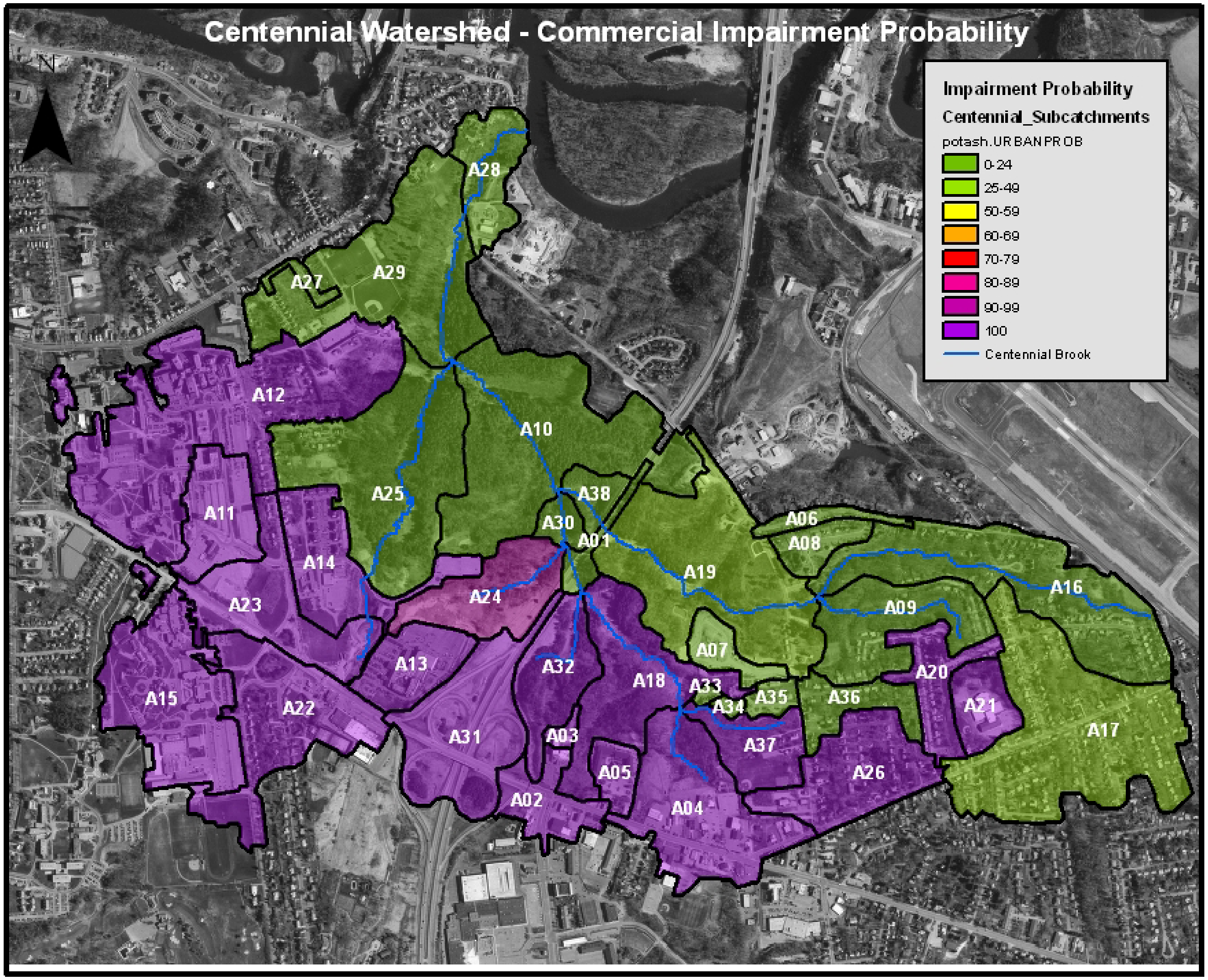

Figure 10. The impairment probabilities calculated for each Centennial Brook subcatchment based on the Commercial model.

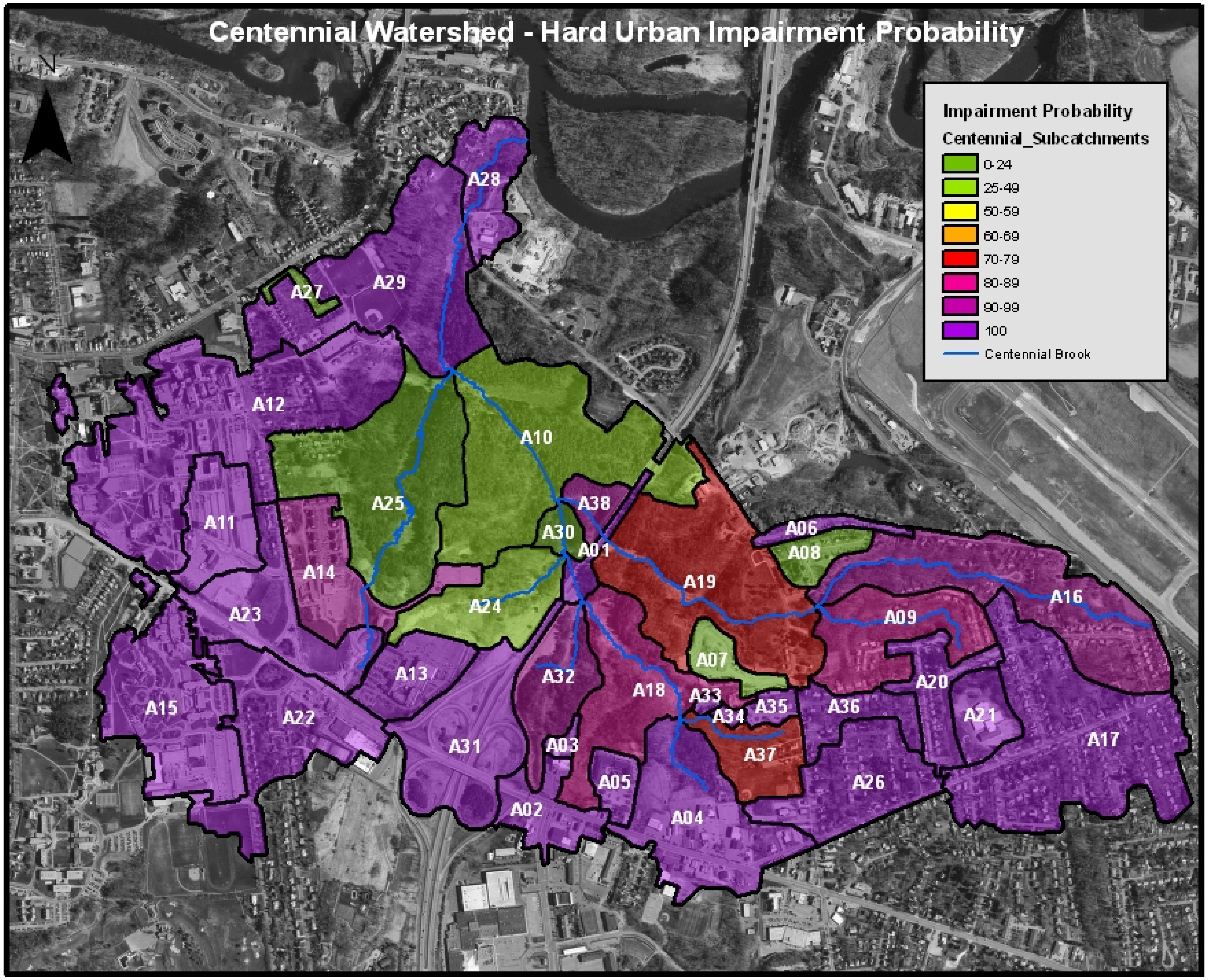

Figure 11. The impairment probabilities calculated for each Centennial Brook subcatchment based on the Hard Urban model.

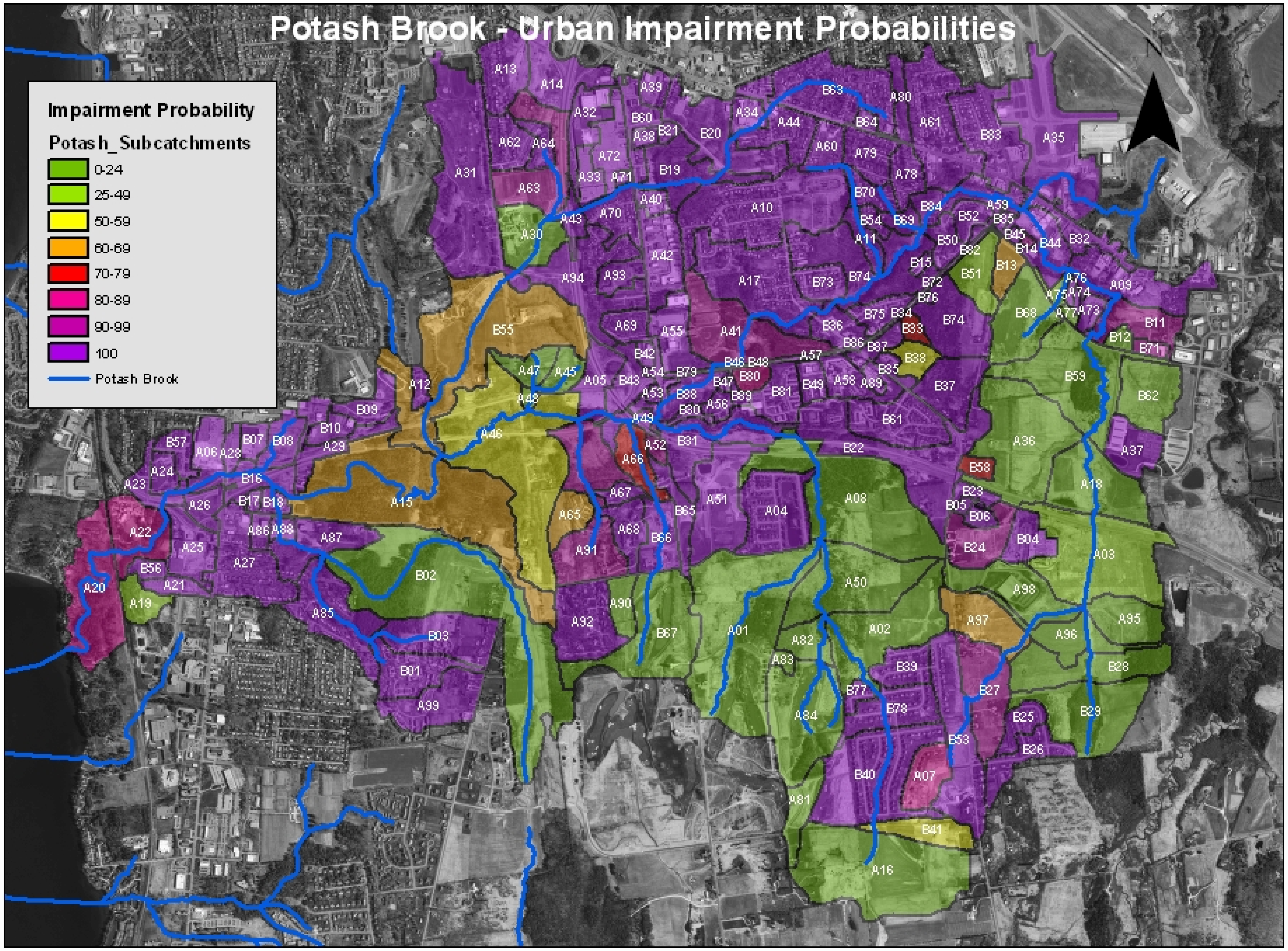

Figure 12. The impairment probabilities calculated for each Potash Brook subcatchment based on the Urban model.

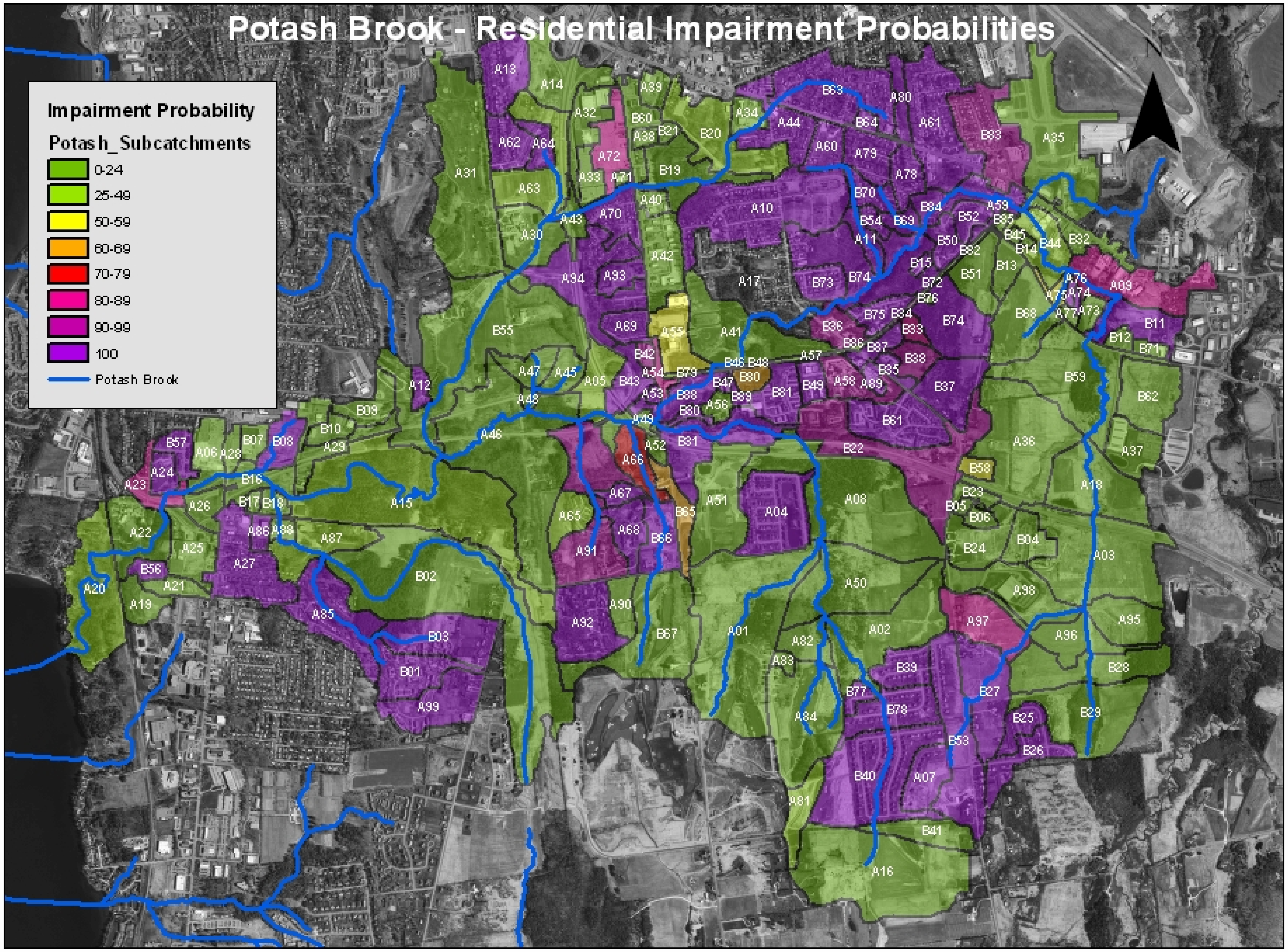

Figure 13. The impairment probabilities calculated for each Potash Brook subcatchment based on the Residential model.

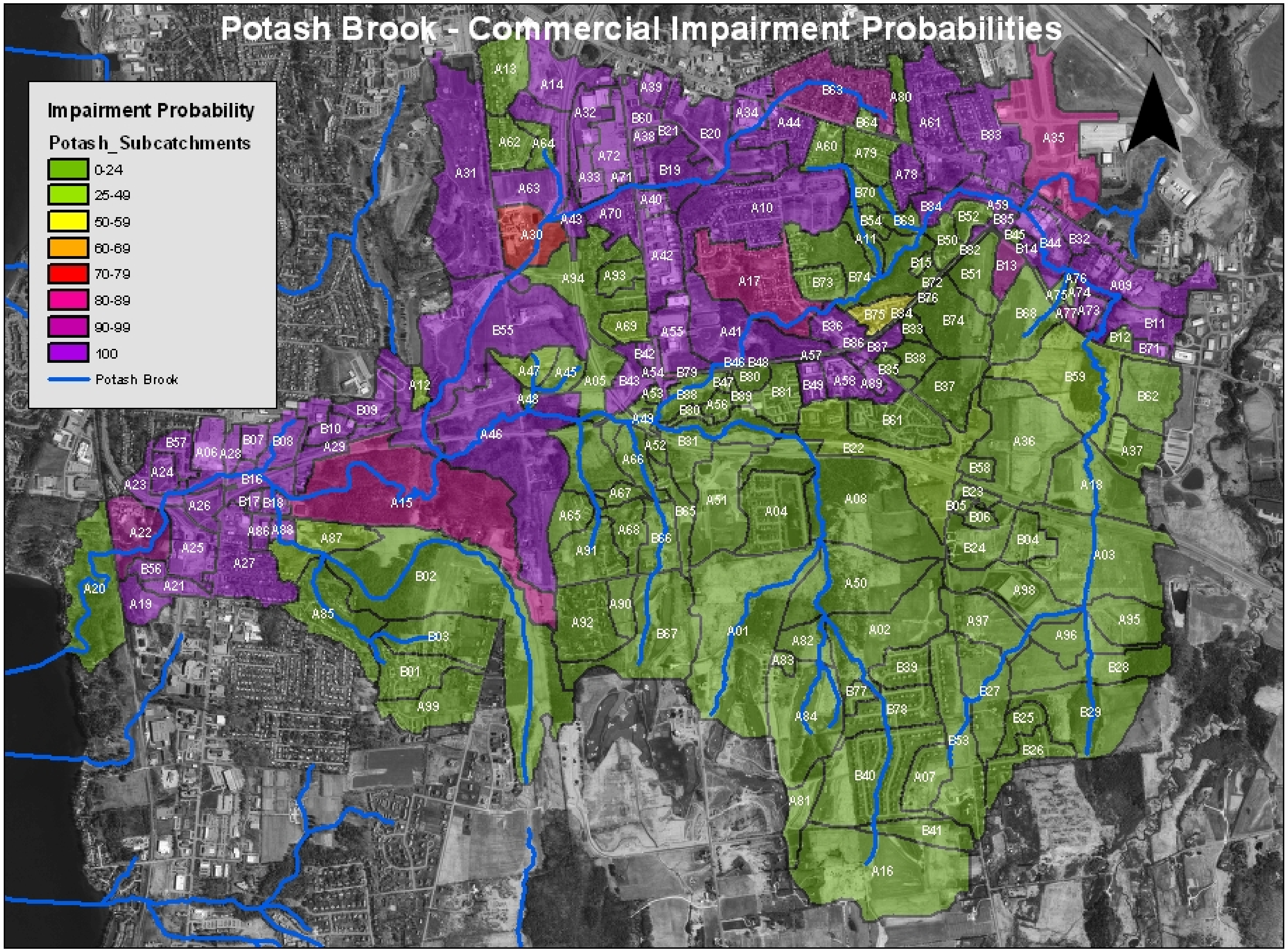

Figure 14. The impairment probabilities calculated for each Potash Brook subcatchment based on the Commercial model.

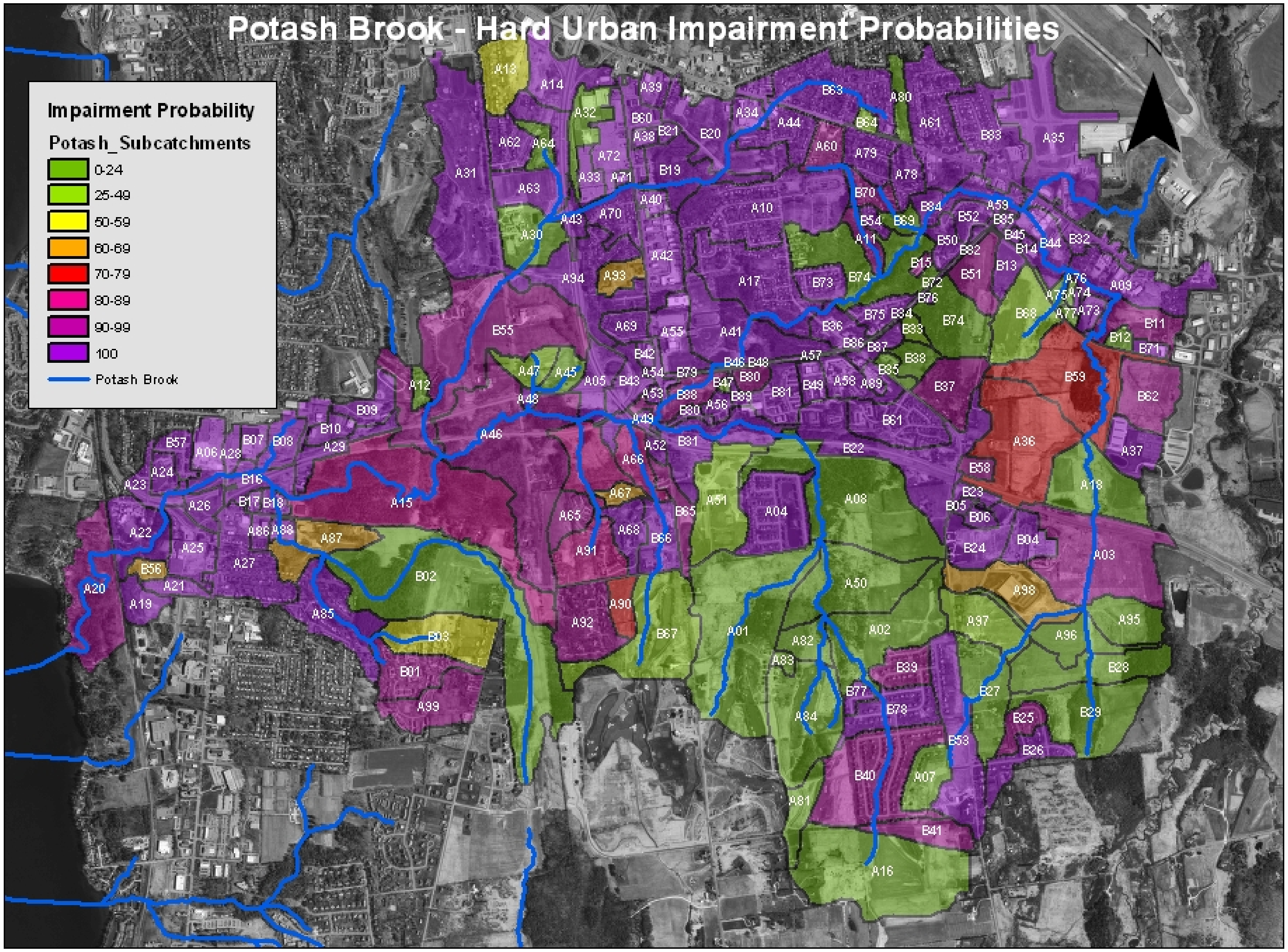

Figure 15. The impairment probabilities calculated for each Potash Brook subcatchment based on the Hard Urban model.

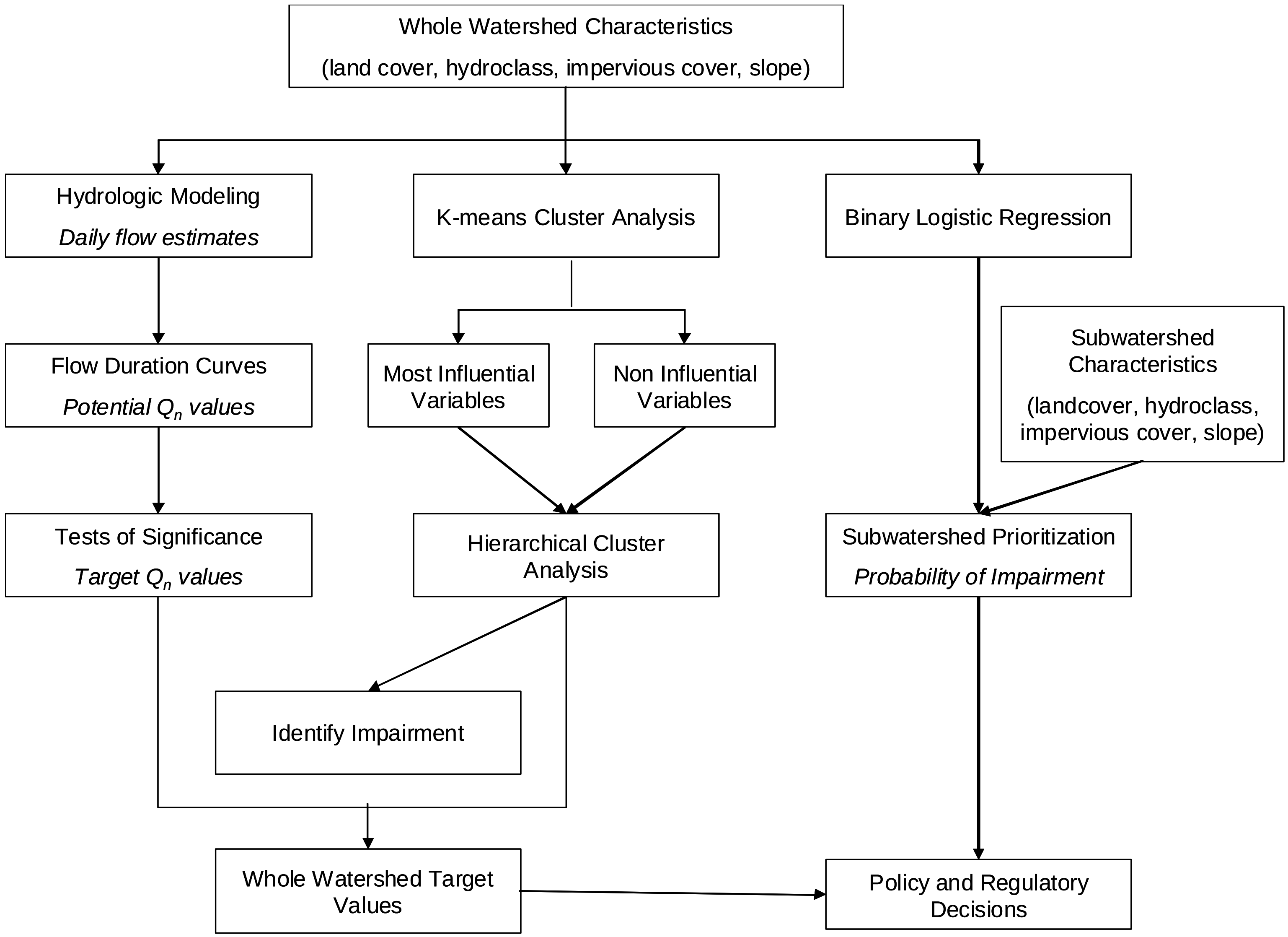

Figure 16. The conceptual framework of the modeling used in this study.