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A Watershed Classification System Based on Headwater Catchments in Great Smoky Mountains National Park, Tennessee-North Carolina

Martin Dietrich Lafrenz
University of Tennessee - Knoxville

To the Graduate Council:

I am submitting herewith a dissertation written by Martin Dietrich Lafrenz entitled "A Watershed Classification System Based on Headwater Catchments in Great Smoky Mountains National Park, Tennessee-North Carolina." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Geography.

Carol P. Harden, Major Professor

We have read this dissertation and recommend its acceptance:

Kenneth H. Orvis, Edmund Perfect, Shih-Lung Shaw

Accepted for the Council:

Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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Acceptance for the Council:

Anne Mayhew________
Vice Chancellor and Dean of Graduate Studies

(Original signatures are on file with official student records.)

A WATERSHED CLASSIFICATION SYSTEM BASED ON HEADWATER CATCHMENTS IN GREAT SMOKY MOUNTAINS NATIONAL PARK, TENNESSEE-NORTH CAROLINA

A Dissertation
Presented for the
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Degree
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Martin Dietrich Lafrenz
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ABSTRACT

Headwater areas in the southeastern U.S., as well as elsewhere, have received little attention from researchers, even though headwater catchments comprise over 70% of the land area in the southeastern highlands. The small, low-order streams that drain these catchments are greatly affected by hillslope processes within their watersheds. As such, there exists a strong link between upland landscape history and a headwater stream's condition, including its channel morphology, habitat, and water quality. I employ this tight connection between landscape-scale attributes and reach-scale morphology in order to develop a headwater catchment classification system for Great Smoky Mountains National Park that describes the variation in stream channel morphology explicitly as a function of catchment characteristics. When developing a classification system, I test two separate classification techniques. First, I assess whether a 'top-down' statistical clustering approach, based exclusively on landscape-scale attributes, will distinguish groups of catchments that have significantly distinct types of stream channel morphology. In the second approach, the 'bottom-up' technique, I test whether catchments grouped by their respective distinct types of stream channels show any significant relationships between stream channel morphology and landscape-scale attributes.

For the top-down technique, I use a geographic information system (GIS) and a digital elevation model (DEM) to delineate 862 headwater catchments in the study area; I then use a two-step clustering procedure to create six groups based on catchment area, circularity, resultant aspect, mean elevation, mean slope, and the percentages of burned area, pristine area, small-scale logging, extensive logging, settled areas, weak rocks, medium-strength rocks, strong rocks, and very strong rocks. Based on a stratified random sample, I use these groups to select 51 catchments for the collection of channel morphology information, which includes bankfull width, depth, and cross-sectional area, reach slope, median particle size, and the stored

sediment in a riffle. These data are used to test the efficacy of the top-down technique in creating catchment groups with different types of stream channels based on an analysis of variance (ANOVA) procedure. For the bottom-up classification, I use the stream channel morphology data in a principal components analysis (PCA) and a two-step cluster procedure to create five groups of catchments based on the similarity of stream channel morphology information. I then use a multinomial logistic regression analysis to test how well the bottom-up classified catchment group membership is predicted when using the landscape-scale attributes as independent variables. Finally, I test if either headwater classification technique creates catchment groups with significantly different stream water chemistry.

The top-down classification creates groups of catchments with different combinations of landscape-scale attributes, but these groups do not have significantly different types of stream channels. This is largely because the top-down approach is not a purely process-driven model; rather, it mathematically clusters groups according to a few dominant and shared landscape-scale attributes. As a result, some catchments have one or more statistically important but trivial attributes that offset the geomorphic influence of the dominant attribute on stream channel morphology. The top-down approach also does not account for convergence, where different combinations of attributes produce similar channel morphology. In contrast, the bottom-up approach is driven by geomorphic process; specifically, the catchment groups represent transitional states in the expected response to anthropogenic hillslope disturbances (logging intensity and settlement) of stream channels that are either aggrading, degrading, or in dynamic equilibrium. Bottom-up catchment group membership is predicted with better than 80% accuracy using the relationship between stream type and landscape-scale attributes. This occurs even though several bottom-up catchment groups share a few important landscape-scale attributes. Thus, various types of stream channels can form in similar catchments that differ only in disturbance intensity. Stream water chemistry does not differ between the top-down

classified groups. However, with respect to the bottom-up classification, a significant difference exists between catchment groups regarding total nitrogen; catchment groups with high percentages of pristine forest have correspondingly high total nitrogen values as a result of nitrogen saturation in those areas.

Landscape sensitivity, the degree of change in discharge and sediment flux following disturbance, is also possibly captured by the bottom-up watershed classification technique. As such, this more process-driven watershed classification serves as a metric in identifying the landscape-scale attributes that are most important in maintaining a particular type of stream channel morphology. Therefore, this classification allows researchers and land managers to anticipate possible changes in stream channel habitat as a function of proposed land use changes. It can also be used to identify areas that are particularly vulnerable to landscape change, as well as areas that might be somewhat resilient to various hillslope disturbance processes.

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CHAPTER I
INTRODUCTION

Headwater areas exist in all watersheds, regardless of elevation or ecoregion. Small streams can be found draining steep mountain slopes, low hills on the Coastal Plain, and the back yards of sprawling suburbs. The small rivulets and ephemeral waterways that coalesce into perennial streams are not simply the hydrologic beginnings of larger rivers, but rather, they drain dynamic environments where hillslope processes are intimately linked with the biological integrity and habitat condition of the stream. These low-order streams, being tightly coupled to their contributing areas, can undergo dramatic geomorphic and ecological modification from both natural and anthropogenic disturbance within their respective watersheds.

Unlike larger, high-order rivers, the cause and consequence of disturbance in headwater contributing areas is often quite apparent in these small stream channels. The relatively short transport distances and generally steeper hillslopes in small watersheds can cause rapid delivery of water and sediment to the stream channel; however, the low actual discharge from small contributing areas may not be capable of quickly mobilizing the large amounts of accumulating sediment. Hence, the size and shape of low-order stream channels are directly affected by disturbances in their watersheds, and these changes in channel morphology may persist long after the actual disturbance events. In this manner, headwater stream channels act as long-term records of past disturbance events on the landscape.

Unfortunately, headwater streams have received little attention in past research (Meyer and Wallace 2001), with forested headwaters being the most neglected (Dunne 2001), even though the opportunities are greater for linking stream condition, including channel morphology, habitat, and water quality, to the upland landscape history in headwater contributing areas. In fact, the tight connection between

hillslopes and streams in small watersheds may allow for fixing problems in stream channels through actual changes in management schemes within the headwater catchment. In order for this to occur, it is necessary to develop a metric or classification that describes the relationship between hillslopes and stream channels as well as the relative impact of various disturbances on the condition of headwater streams. The goal of this dissertation research was to develop such a classification procedure.

Geomorphologists have long been fascinated with the connection between rivers and hillslopes. Playfair, in 1802 (p. 19), noted that every river flows in a valley “proportional to its size,” implying that valleys are formed by their rivers. Gilbert (1877) introduced the concept of the *graded* condition, in which sediment transport in a stream is in equilibrium with sediment supply from the hillslopes, and Davis (1899) described the evolution of drainage basins and landscapes as a function of denudation by flowing water over time. The idea that rivers form their own channels was formalized by Leopold and Maddock (1953). Finally, Schumm (1977) described the fluvial system as the area and processes that transfer water and sediment from drainage divides through stream channels, and ultimately to depositional areas such as coasts.

More recently, fluvial geomorphologists and ecologists have focused on processes operating within the stream channel, although these researchers usually recognize that water and sediment are delivered to that particular reach as a function of broader-scale watershed processes. The driver for much of this research has been the emphasis placed by federal and state governments on stream and wetland restoration in areas affected by human activity (National Research Council 1992) and the high levels of funding that have followed (Giller 2005). The cumulative impacts of development, agriculture, and industry caused decreased water quality, decreased water storage, loss of habitat for fish and wildlife, and a lowering of aesthetic value

(National Research Council 1992), with sedimentation and excess nutrients being cited as the most pervasive causes of stream degradation (USEPA 1997). Although several organizations have argued that land use practices throughout a watershed will affect stream channel habitat (USEPA 1996, Federal Interagency Stream Restoration Working Group 2001), most stream restoration activities are limited to isolated reaches.

Often, stream restoration efforts seek to control the form and function of a stream through the use of engineered bank stabilization and grade control (Niezgoda and Johnson 2005) or through more ecologically based solutions (Palmer et al. 2005). In either case, workers normally attempt to ‘re-build’ a stream reach according to an *a priori* assumption of how that reach should function under ‘natural’ conditions. Often the reaches undergoing restoration are aggrading or degrading because of disturbances on the adjacent hillslopes or upstream in the watershed; if the sediment or discharge conditions originating from adjacent hillslopes and upvalley sites are not remediated, then the ‘restored’ reach will either revert to its pre-restoration condition or transfer the problem to another reach in the watershed. In both cases, the problem will persist and require additional, and costly, remediation or, in the latter case, lead to legal action by the newly affected landowner. A better understanding of how landscape-scale processes influence stream channel dynamics would better inform these types of restoration efforts.

Even with the long history of research into the intimate association between hillslopes and stream channels, few studies specifically and quantitatively assess the relationship between landscape-scale watershed attributes and reach-scale stream channel morphology. This type of research is important in several ways. It seeks to identify the landscape-scale attributes that are most important in maintaining a particular type of stream channel morphology, and therefore, it allows researchers and land managers to anticipate possible changes in stream channel function and

morphology as a consequence of proposed land use changes. This research also aids in identifying areas that are particularly vulnerable to landscape change as well as areas that might be somewhat resilient to catchment disturbances. Finally, this type of effort permits the testing of hypotheses regarding the relationship between hillslope attributes and stream channel morphology.

Incorporating the landscape-scale to reach-scale relationship into a watershed classification scheme may allow for prediction of stream channel habitat condition, as a function of landscape-scale attributes, in areas with similar types of watersheds. Such a classification could then provide a possible means for locating populations of rare flora and fauna, suggest areas for the re-introduction of extirpated species, and allow for monitoring adjustments in stream channel morphology following disturbance events.

Anthropogenic alterations in land use and land cover over the last century have dramatically altered the flux of water and sediment to rivers in nearly all inhabited watersheds in the United States (Paul and Meyer 2001). Meanwhile, dams, weirs, diversions, and channelization have disrupted the sediment transport regime and morphology of many streams in these same watersheds. The result is a fragmented system of patchy landscapes, with a variety of land uses, in various stages of vegetation succession, where streams are adjusting to past or ongoing disturbances both within the stream channel and in their catchments.

While terrestrial species can often migrate away from disturbed areas, aquatic species are confined to the stream network. When channel habitat conditions become intolerable, aquatic species often cannot relocate because of instream impediments or unfavorable habitat conditions either upstream or downstream (Johnson et al. 1995). Species adapted to a headwater environment are the least able to migrate following habitat alteration, as they may not be able to withstand higher downstream

temperatures, they are often subject to increased predation downstream, and they have the longest distance to travel in order to find another suitable area of habitat—even if they just travel to the headwaters in an adjacent drainage basin (Miller et al. 1989, Rieman and McIntyre 1995).

The extent of habitat fragmentation became particularly apparent with the advent of remote sensing techniques and landscape classification. Both Omernik (1987) and Bailey (1976) used remotely sensed data and small-scale maps to classify, respectively, North American and U.S. landscapes into ecoregions with similar climates, soil types, landforms, and natural vegetation. Research has shown that both water quality (Robertson and Saad 2003) and macro-invertebrate assemblages (Mykra et al. 2004) differ significantly across ecoregion boundaries. This has led to increased interest in classifying landscapes at various scales. In the late 1980s, the USEPA began the Environmental Monitoring and Assessment Program (EMAP) in order to "develop the tools necessary to monitor and assess the status and trends of national ecological resources" with a particular emphasis on monitoring aquatic ecosystems (USEPA 2005a). Toward better understanding the linkage between watershed processes and stream channel habitats, in 2001, USEPA solicited proposals for the "development of watershed classification systems for diagnosis of biological impairment in watersheds and their receiving water bodies" (USEPA 2005b). That request for proposals inspired this dissertation, as I recognized that a classification linking landscape-scale attributes with reach-scale stream channel morphology could appreciably enhance research efforts seeking to identify landscape processes that alter stream channel habitat; it could also support efforts to protect and sustain headwater species and help in predicting possible fluvial response to future development in a particular watershed.

Objectives

The primary objective of this research was to develop a new classification system for watersheds of low-order streams that specifically links landscape-scale attributes and reach-scale stream channel morphology values. This research used Great Smoky Mountains National Park (GSMNP) as a study area. In GSMNP, and in other humid mountainous landscapes, land surfaces and stream channels are most closely connected in the watersheds of low-order streams (Sidle et al. 2000). Headwater catchments comprise 70% to 80% of total catchment area in many steep regions (Meyer and Wallace 2001), and it is likely that they are equally important in GSMNP. These headwater systems play a key role in determining the flow, water chemistry, nutrients, sediment, and organic matter that reach downstream systems (Gomi et al. 2002). It is thus evident that an effective watershed classification system in such regions, and maybe all regions, should be based on characteristics of headwater catchments.

This classification process also provided an opportunity for testing how successfully we can link processes across scale. Using two primary techniques for classifying headwater catchments, I evaluated both a 'top-down' and a 'bottom-up' approach to catchment classification. With the top-down approach, catchments are partitioned into a finite number of groups based on the similarity of their respective landscape-scale attributes. The advantage to this technique is that it can be done relatively quickly using available digital data, a geographical information system (GIS), and statistical software. The disadvantage is that determining whether the stream channel morphology is truly different in each of the classified groups requires actually collecting channel morphology data for comparison.

In the bottom-up approach, a sample of stream reaches is first classified into groups with similar stream channel morphologies. By assessing the suite of landscape-scale

attributes associated with streams in each group, it is then possible to extrapolate the classification to all remaining catchments in the study area. Using statistically developed clusters based on the initial sample of reaches assures that stream channel morphology will be different in each group of catchments. However, it is time intensive to collect the stream channel morphology information. Additionally, this approach assumes some consistent relationship between reach-scale channel morphology and landscape-scale attributes, although such a relationship can be determined and quantified with a GIS and statistical software.

Working Hypotheses

My development of the headwater catchment classification system was guided by two hypotheses:

> H_1: A statistical classification (clustering) based on landscape-scale attributes, a 'top-down' approach, will distinguish groups of catchments that have significantly distinct types of stream channel morphology.
>
> H_2: Catchments grouped by their respective distinct types of stream channels, a 'bottom-up' approach, will show significant relationships between stream channel morphology and landscape-scale attributes.

I expected GSMNP to contain a limited number of catchment types, and I expected to represent and model the interaction between landscape-scale attributes and channel type based on individual variables and combinations of variables. Being able to easily map process- and disturbance-related classes of catchments should facilitate efforts to target watersheds or stream channels for restoration, as well as promote efforts to explain the role of disturbance in patterns of the distribution of aquatic species or changes in water quality. Statistically relating land and channel characteristics to reference and disturbed conditions should provide a new, objective

framework for documenting ways in which a given watershed differs from or is similar to others in the region.

Background

Research efforts in the past decade have yielded ways to classify streams at the level of reaches based on stream channel morphology alone (Rosgen 1994) and with additional information about the location of the reach within the watershed (Whiting and Bradley 1993, Montgomery and Buffington 1997). At broad scales, remotely sensed data and geographic information systems have been used to classify reaches (Snelder and Biggs 2002) and watersheds (Lipscomb 1998, Jensen et al. 2001, Heinimann et al. 2005) by integrating information about their physical characteristics, and to visualize regional patterns of factors, such as land cover or road location, expected to affect aquatic habitat and water quality (Jones et al. 1997). What remains lacking in watershed research is a process-oriented watershed classification that connects the physical characteristics and geomorphic/hydrologic processes of the land surface, including land surfaces modified by human activity, with those of the fluvial system (National Research Council, 1999). The next crucial step, which I take with this project, is to develop a classification that extends to a finer scale and accounts for the dynamic nature of landscapes.

The recent wave of interest in headwater stream environments (e.g., Rice et al. 2001, Zimmerman and Church 2001, Gomi et al. 2002, Halwas and Church 2002) stems from the areal importance of headwater streams, the frequency with which endemic species are found in headwater streams, and the recognition that a high proportion of the flow, nutrients, and other chemical constituents of rivers originates in headwater regions. Headwater catchments have a large cumulative impact on downstream aquatic resources. The idea that low-order watersheds affect downstream habitat was formalized in the river continuum concept, in which a longitudinal gradient of aquatic

communities represents systematic changes in downstream conditions from the headwaters to the large floodplain of a river system (Vannote et al. 1980). Montgomery (1999) noted that the river continuum concept does not account for discreet local perturbations that may disrupt any gradient in a fluvial system. The patchy nature of disturbance, introduced by Forman and Godron (1978), creates habitat patches of various size and persistence. Montgomery's (1999) process domain concept applied the spatially variable nature of disturbance to watersheds, arguing that the spatial variability of geomorphic processes controls spatial and temporal patterns of disturbances, which influence terrestrial and aquatic ecosystem structure and dynamics. His examples illustrate the possibility of using process domains to identify different habitat-controlling disturbance regimes, and for comparing these across watersheds.

Streams adjust constantly to material and energy inputs. Hydrogeomorphic adjustment reflects annual, decadal, and millennial changes in sediment and peak discharge, and can involve alterations of width, depth, slope, and roughness of the channel (Leopold et al. 1964). Aquatic environments can recover, or be successfully restored to pre-disturbance conditions, only if the catchment-scale hydrogeomorphic processes affecting the stream channel allow for fluvial adjustment to pre-disturbance conditions. A fluvial system pushed beyond a threshold may never return to pre-disturbance conditions (Coates and Vitek 1980). In one Southern Appalachian example, a massively disturbed area in the Copper Basin, Tennessee, where both the A and B soil horizons were eroded, has not recovered hydrologically following 50 years of reforestation (Harden and Mathews 2000). This type of lag time to recovery is likely to exceed the generational life cycle of many species, which can lead to extirpation. Headwaters are often areas of endemism (Gomi et al. 2002) and of small and threatened populations. Terrestrial species may be able to migrate from a disturbed region, but aquatic species are confined to the fluvial system; if a

disturbance effectively decouples the headwaters from downstream refugia, the species will be extirpated.

The typical stream classification technique is based on reach-level geomorphic data (Rosgen 1994, Montgomery and Buffington 1997); however, most watershed classification studies are not concerned with stream channel morphology. Watershed classifications typically use remotely sensed landscape-scale data to place watersheds into relatively homogenous groups based on categories such as drainage area, land use, land cover, geology, and soil type. The groupings can be classified manually, formed by statistical methods such as clustering, or distinguished using a correlation-type procedure between landscape-scale and reach-scale data. Almost without exception, the interest is less with the watershed itself than with a particular stream-related parameter such as water quality (Momen and Zehr 1998, Robertson and Saad 2003), aquatic biological condition (Wardrop et al. 2005), or discharge (Lipscomb 1998, Detenbeck et al. 2005).

The study objectives for each watershed classification effort tend to guide both the classification methodology as well as any attempts to verify the utility of the classification scheme. Heinimann et al. (2005) created a GIS-based watershed classification focusing on the sensitivity of a particular watershed to soil erosion in the Lower Mekong Basin. They manually assigned watersheds into one of five groups according to slope steepness and agricultural or forestry land use. As they were only concerned with identifying sensitive watersheds, they did not incorporate any measures of sedimentation into their classification, nor did they test whether watersheds in the different groups actually had differing amounts of sediment flux from the hillslopes. For watersheds in the Mid-Atlantic region of the U.S., Wardrop et al. (2005) used a hierarchical agglomerative clustering method to classify watersheds based on land use and watershed slope information. Although the focus of this project was on aquatic ecosystems, no values of stream habitat were used in

the classification and the results were not evaluated using any type of aquatic parameter. These studies are typical of watershed classifications that seek only to describe the landscape, which is a necessary first step in any classification scheme. However, these types of classifications do not specifically link hillslope processes to stream channel dynamics.

An assumption in all watershed classification efforts is that the landscape-scale data will have some measurable influence on an environmental parameter in the stream channel. In order to assess the efficacy of any classification, it is necessary to examine a stream parameter and to test whether it differs between the classified watersheds. Lipscomb (1998) clustered sub-basins in central Idaho by stream order using climate, geology, and land cover and assessed the discharge for gauged streams in the study area. Bar graphs show differences in both the annual and monthly discharge regimes between the classified watersheds. However, no statistical test of significant differences between groups with respect to discharge is reported, which would have made this a more complete classification procedure. Libscomb's (1998) Central Idaho classification only tested for discharge; however, the methodology could be easily replicated to examine for differences in channel morphology or water quality.

A contrasting method for creating groups of watersheds is to allow a stream variable to drive the classification. This can be done using *a priori* classified watersheds that fall into natural groups or by allowing a regression-type model to select class membership. Momen and Zehr (1998) used discriminant function analysis (Jennrich 1977) to determine the lakewater chemical constituents that best classify watersheds into one of six previously determined lake types, which are believed to be representative of their watersheds. Discriminant function analysis is used to determine which independent variables can discriminate between one or more naturally occurring or user-specified groups. An issue with the technique, in this

instance, is that it assumes the original categories of watersheds are based on some process-driven criteria related to the water quality phenomena of interest. The authors assumed that the chemical constituents measured in a lake represented hydrogeomorphic conditions in that lake's watershed, although they did not actually assess any landscape-level characteristics.

Detenbeck et al. (2005) used discriminant function analysis to show that several different combinations of streamflow metrics could discriminate between various watershed classes mapped from landscape-scale data. The authors tested how well 32 different flow metrics could delineate groups based on one of two hydrogeomorphic regions, mature or immature forest, a threshold for watershed storage (wetlands and lakes), and combinations of each landscape-level category. Their technique produced classification error rates ranging from 17% to 55%; this was a satisfactory result as the study objective was to verify that thresholds, such as percent mature forest, affected certain flow metrics rather than to create a predictive watershed classification. The results of discriminant function analysis are robust, and significant results can indicate a strong relationship between landscape-scale attributes and reach-scale data; however, the original groups must be carefully designed in order to achieve this successful relationship. In addition, the technique requires nearly equal group sizes, which may be difficult to achieve in watershed and landscape studies.

Another common objective of watershed classification is to predict an environmental parameter of stream condition for unknown areas based on sampled stream values; this is best accomplished using regression equations. Robertson and Saad (2003) used a modified regression-tree analysis (Breiman et al. 1984) to classify watersheds according water quality parameters. With this technique, a water quality parameter (e.g. total phosphorous) is a dependent variable and a suite of landscape attributes serve as independent variables. The model creates two groups using the most highly significant independent variable and then splits each group again using the next most

significant variable. This creates a tree-like structure based on regression equations, hence the term regression-tree analysis. In the Robertson and Saad (2003) study, the authors classified watersheds into one of four groups based on landscape-scale thresholds. For instance, with total phosphorous as the dependent variable, the first split created a group with greater than 30% forest cover and a group with less forest cover. The forested group was subsequently divided into two additional groups with greater or less than 312 mm/year runoff; the less forested group was divided into groups with soil clay content above or below 26%. This process was repeated for nitrogen and for sediment, leading to three different classifications according to the water quality parameter of interest.

The regression-tree analysis successfully detects relationships between landscape-scale and reach-scale attributes, and the thresholds identified can be used to classify watersheds with unknown stream value parameters. However, regression trees have a tendency to create complex trees with more branches than can be justified by the causality of the data (Long et al. 1993), and some cutting points, such as 312 mm/year runoff, may seem arbitrary and may not represent actual physical processes on the landscape. In addition, the trees can be difficult to interpret as slight changes in the branching values can lead to grouping changes that cascade through the tree and alter the resultant classification. These issues can be remedied by using a sufficiently large dataset such that the model can be trained with a subset of data and validated using the remaining data. Hence, regression trees generally perform best with at least 100 cases in the model, while other regression-based classification techniques, such as logistic regression, perform better with smaller datasets (Perlich et al. 2003).

In only one previous paper of watershed classification was stream channel morphology addressed. Jensen et al. (2001) used Rosgen stream types in a canonical correspondence analysis (ter Braak 1986); this direct gradient analysis ordination technique seeks to determine the optimum set of predictor variables that best explain

variation in the canonical variable. Like multiple regression, the model assumes a linear correlation between some combination of predictor values and the canonical variable. The authors used topographic maps to classify stream reaches into level I Rosgen stream types (Rosgen 1994) for 500 sub-basins of the Interior Columbia River Basin. Using the Rosgen stream types as a canonical variable, they identified 15 (out of a possible 54) significant "direct biophysical environment variables," including watershed slope, average daily precipitation for summer months, and average daily air temperature for July (Jensen et al. 2001, p 1160). Again, using Rosgen stream types as the canonical variable, they separately selected 19 (out of a possible 99) significant "indirect biophysical environment variables," including forestlands, loess, and lake sediments. Arguing that both sets of data were significantly related to Rosgen stream type distribution, the authors then clustered all 7,462 sub-basins into in the study area into 84 groups using the more easily mapped 19 indirect biophysical variables.

A critique of canonical correspondence analysis is that, like multiple regression, increasing the number of independent variables will increase the significance of the model, as noisy or irrelevant variables will contribute some explanation of variance to the model (McClune 1997). In addition, the response of the dependent variable must be unimodal (ter Braak 1986). In the Jensen et al. (2001) example, it may not be true that a particular Rosgen type stream will be found in only one specific type of landscape or that one suite of landscape-scale variables will produce only one type of stream channel. In a response to the Jensen et al. paper, Caratti et al. (2004) showed that a random assemblage of many environmental variables could also significantly explain variation in Rosgen stream types within the Interior Columbia River Basin. This indicates that canonical correspondent analysis may not be suited for classifying watersheds at this scale; however, it may also indicate that Rosgen stream types do not correlate well with landscape-scale watershed process attributes.

Although each of these classification techniques showed some success at delineating groups of watersheds with relatively homogenous distributions of landscape-scale attributes, several remaining issues that need to be addressed in order to construct an efficient process-oriented watershed classification. First, a classification using hierarchical clustering must assess whether any difference exists between the classified groups with respect to a reach-scale environmental variable. Second, any watershed classification intended for predictive modeling must demonstrate a significant causal relationship between the selected landscape-scale attributes and the measured reach-scale values. Third, a watershed classification that is focused on aquatic habitat must incorporate actual physical measurements from a representative sample of all aquatic habitats within the study area. The classification undertaken in this dissertation addresses these issues and is one of the few studies, for any region, to bridge scales from the site-specific to the regional and to specifically correlate field-collected stream habitat data, including channel geometry, sediment size, and water quality, with landscape characteristics and disturbance history to classify watersheds into meaningful habitat types.

Study Location

In order to assess the impact of landscape characteristics and disturbance history on headwater streams, it is necessary to examine the channel morphology and water quality of streams that have undergone natural and anthropogenic disturbance at various scales, frequencies, and magnitudes. Because of its location, diversity of landscapes, availability of data, and long history of being studied, Great Smoky Mountains National Park provides an excellent natural laboratory for measuring the impacts of disturbance and the influence of landscapes on stream channel morphology and habitat condition.

The main unit of the national park is just over 2000 km^2 in size and lies almost equally in eastern Tennessee and western North Carolina (Figure 1). The park itself is located on the western edge of the Blue Ridge physiographic province within the southern portion of Appalachian Highlands geologic province (Fenneman and Johnson, 1946). Local relief is considerable and ranges from 260 m just outside the far western boundary of the park to 2025 m on Clingman's Dome, the second highest point in the Eastern United States. Slopes can be quite steep and river valleys are deeply incised. However, extensive areas throughout the range are relatively flat. Average annual precipitation varies from 1600 mm at the lower elevations to 2160 mm above 1800 m in elevation (National Park Service 2005). Temperatures are typically 10 C° cooler on Mt. LeConte (elevation 1950 m) compared with the park headquarters (elevation 488 m) (Gaffin et al. 2002). This produces a humid subtropical climate with mild winters, hot summers, and moisture in all seasons at lower elevations, and a humid continental climate at higher elevations where winters can be severe, summers are cool, and the area receives ample moisture in all seasons (Köppen and Geiger 1936).

The Great Smoky Mountains are an area of transition from the younger and relatively unaltered Paleozoic sedimentary rocks of the Appalachian Valley in the northwest and Pre-Cambrian metamorphic and granitic rocks to the southeast in the Blue Ridge (King et al. 1968, Hatcher, 1978). The present day structure of the mountains was constructed during the late Carboniferous and into the Permian during the Alleghanian orogeny (Hatcher et al. 1986). The collision of North America with Africa pushed the Blue Ridge-Piedmont thrust sheet northwest along the Appalachian fold-thrust belt exposing Pre-Cambrian metamorphic rocks and sending faults throughout the older sedimentary layers (Hatcher et al. 1986). Based on crosscut relationships, many of the folds in this region pre-date the Alleghanian orogen, which leads to a complex arrangement of terranes and surface ages in this section of the Southern Appalachians (Hatcher et al. 1986).

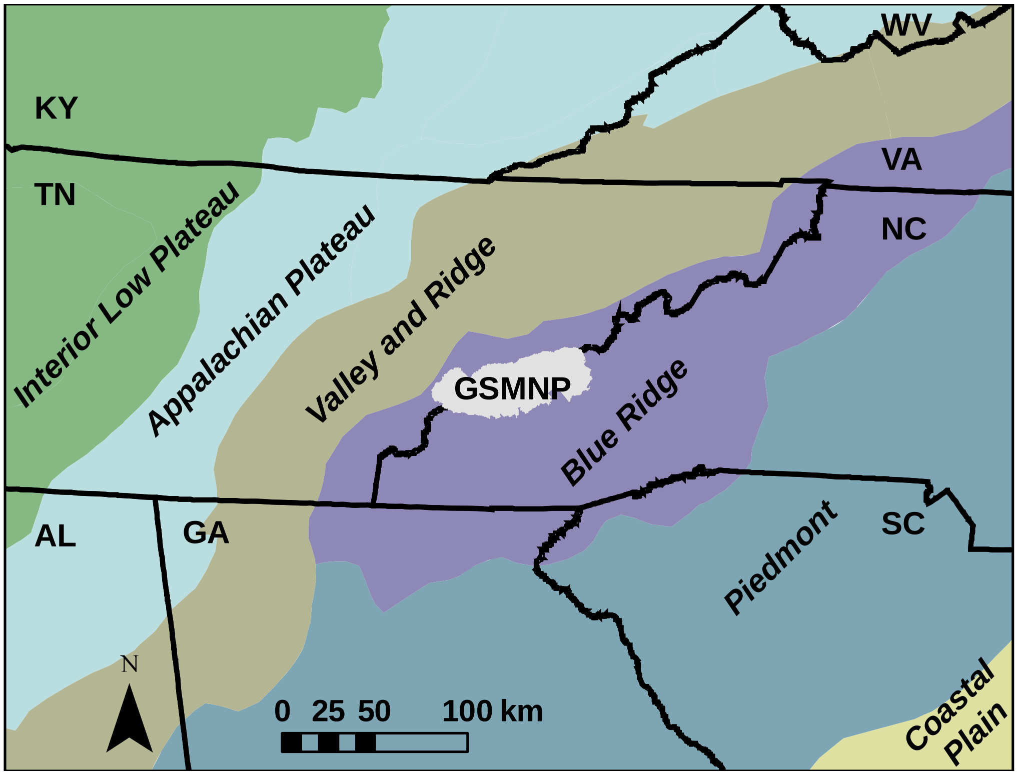

Figure 1. Location of Great Smoky Mountains National Park. The park is plotted with reference to physiographic provinces defined for the surrounding region by Fenneman and Johnson (1946).

The bedrock units in the Great Smoky Mountains have been folded, faulted, and eroded to varying degrees, exposing three primary units (Hatcher 1978). The oldest of these, the Basement Complex, is the highly altered crystalline foundation of the entire region, which dates to the Pre-Cambrian. It has only limited surface exposure in the far southeastern section of the national park. Within the Basement Complex are the most resistant rock types, including gneisses and schists of both sedimentary and igneous origin (King et al. 1968). The next oldest group of rock units, the Ocoee Series, is the most prominent of the bedrock types in the park and represents the true transitional unit from old to young and complexly folded to relatively unaltered rock units. Formations in the Ocoee Series are composed of late Pre-Cambrian sedimentary rocks ranging from phyllitic layers and fine-grained sandstones, near its contact with the Basement Complex, to coarse-grained sandstones and pebbly conglomerates near the upper position of this series. However, several silty and argillaceous rock units are interbedded throughout the Ocoee Series; most notable of these is the dark, silty Anakeesta Formation, which is particularly prone to mass wasting (Henderson 1997) where it intertongues with the ubiquitous coarse-grained Thunderhead Sandstone.

During the Alleghanian uplift, rocks of the Ocoee Series were superposed onto the younger Paleozoic rocks along the regional Great Smoky fault complex (Hatcher et al. 1986). Subsequent faulting in the northwest portion of the park created long parallel ridges with resistant quartzite outcrops that form the present boundary between the high-relief topography of the park and the low-relief adjacent Appalachian Valley (King et al. 1968). Erosion of the overthrust Ocoee rocks has created ‘windows’ that expose the younger, underlying limestones and shales, which constitute the cove landscapes in the park. These relatively flat and fertile areas were actively farmed and settled by both Native Americans and then by European settlers until the time of park establishment in 1934 (Pyle 1988).

Soils in the park are quite varied due to the heterogeneity of vegetation, aspect, elevation, and rock types in this region. Detailed soil mapping of the park began in 1998 and is expected to be concluded in 2007; however, some preliminary summary information was provided by Anthony Khiel (NRCS, Sevierville, TN, personal communication). In the northern section of the park, moderately deep to shallow upland soils and rock outcrops cover most of the area, with small patches of thin colluvial soils. These soils are low in nutrients and morphology is greatly affected by aspect. Soils on the Anakeesta formation are very low in plant nutrients and tend to be unstable as a function of steep slopes and highly weathered conditions. Cades Cove has the only mapped alluvial soils in the northern portion of the park, although alluvial conditions do occur elsewhere. Soil morphology in the southern portion of the park is less affected by differences in aspect, but nutrients are also relatively low. Upland soils and rock outcrops also comprise much of the soil landscape, but overall the soils tend to be somewhat thicker than soils in the northern section of the park. Alluvial soils near Smokemont and along the Oconaluftee River are much better drained and deeper than the alluvial soils around Cades Cove.

Land cover in the park is currently over 90% forested (National Park Service 2005), although nearly 60% of the park had been logged prior to the establishment of the national park (Lambert 1958). After colonization by European settlers, GSMNP had been actively logged, farmed, and inhabited for 100 years prior to achieving protected status (Pyle 1988). Disturbance patterns in the park are better documented than those in the surrounding region. Historic natural disturbances in the park include fire (Harmon 1981), insect outbreak (Allen and Kupfer 2001), and large mass wasting events (Henderson 1997). In the last few decades of the 1800s, the principal form of anthropogenic disturbance was small-scale logging by farmers who cut and sold a few trees each year, and commercial cutting of selected trees over small areas (Lambert 1958). This scale of disturbance stands in sharp contrast to the intensive, mechanized logging that began at the turn of the 20th century when 'corporate' logging companies

purchased large tracts of land at higher elevations in Tennessee and throughout North Carolina, and removed all trees on the hillslopes (Pyle 1988). Several intense fires were caused by logging activities, and after removal of the trees, many of these areas were purposely burned (Harmon 1981).

Before park establishment, many smaller fires were either set by humans to clear land and open travel routes through the dense tree canopy (Harmon 1981) or by lightning strikes. After park establishment, fire has occurred less frequently, with the larger fires happening along the park's boundary adjacent to settled areas and roads. The most extensive disturbance event has been the near elimination of all chestnut trees since the 1930s because of a chestnut blight (Arends 1981). The chestnut had been a prominent tree in nearly every forest type of the park (Miller 1938); hence, its decline has dramatically affected forest structure throughout the park.

Along with the wealth of information concerning vegetation disturbance history in the park, research has been ongoing in several other scientific fronts. Numerous researchers have been inventorying and monitoring the occurrence and ecological significance of as many species as has been practical as part of the All Taxa Biodiversity Inventory (ATBI). This effort, in addition to attempting to catalog every species in the park, provides a fertile setting for researchers from diverse backgrounds to study the flora, fauna, soils, geology, air quality, and water quality of the region. Some fluvial geomorphology research has been conducted in the park (Hart 2002), but most stream research has focused on losses in native fish populations (Strange and Habera 1998) and water quality (Robinson et al. 2002). The water chemistry of park streams is actually much better known than that of streams in the surrounding region. Water quality samples have been collected and analyzed in the park since 1993. Biannual synoptic sampling of 367 streams from 1993-1995 was changed to monthly sampling of 160 streams and later to quarterly sampling of 90 streams

(Robinson et al. 2002). In sum, GSMNP is a data-rich environment with a high diversity of both species and landscapes.

Organization of This Dissertation

Beginning in chapter II of this dissertation, I describe, in more detail, the type of landscape-scale data that I used in designing both my top-down and bottom-up catchment classifications. In addition, I describe the hydrologic modeling necessary to delineate the headwater catchments and extract the specific landscape-scale data for each catchment. In chapter III, I present the methodology and results for the top-down classification, which is based entirely on landscape-scale data. In contrast with the top-down approach is the bottom-up approach, which is driven by reach-scale data and presented in chapter IV.

Having presented both classification techniques, I proceed, in chapter V, to test the efficacy of each classification in creating groups with significantly different stream channel types that are also significantly related to landscape-scale processes. With chapter VI, I discuss the merits and limitations of each classification and place the results in context of existing geomorphic theory. In addition, I propose that this approach could transcend the park boundaries, suggest possible applications for this work, and finally, propose the direction in which this, and possibly other, watershed classifications should proceed.

CHAPTER II
DIGITAL DATA ACQUISITION AND PROCESSING

Watershed classification efforts normally seek to discover and document patterns on the landscape that may influence stream channels and water quality. This exercise requires spatially-explicit landscape-scale data that are of good quality and represent phenomena that are likely to influence discharge and sediment flux to stream channels. A growing cache of digital spatial information is available for research and analysis of watershed processes. Broad-scale digital elevation models (DEMs) have been created for most of the continental United States; in addition, many state and federal agencies have created extensive digital datasets of land use, land cover, geology, soils, vegetation, and transportation. With this array of data, it is possible to assess both the spatial correlation of various landscape attributes and the relationship between landscape-scale attributes and stream channel morphology.

In this chapter, I describe the methods used to collect and process the landscape-scale digital data used to create and validate each watershed classification procedure. I begin by describing the digital watershed-scale data available for this study area and the processing steps necessary to get these datasets into a usable format. I then discuss the modeling steps I used to extract hydrologic patterns from the GSMNP 10-m DEM. Using the DEM-derived watersheds, I present the method for determining the landscape-scale attributes for each watershed.

Landscape-Scale Attributes

Great Smoky Mountains National Park has an unusually extensive amount of digital spatial data. The GIS consultant for the park, Michael Kunze, has assembled and digitized several different GIS layers, including park boundaries, roads and trails, vegetation disturbance history, fire history and frequency, and bedrock geology. The

boundaries and transportation layers were digitized from 1:24,000 USGS topographic maps and corrected with GPS measurements. The vegetation disturbance history layer is an approximately 1:24,000 dataset that has been digitized from the Pyle (1988) study on anthropogenic vegetation disturbance in the park from European settlement through the 1940s; the fire history and fire frequency layers are of a similar scale and are based on documented fires in the park from the 1940s through the 1970s (Harmon, 1981). The geology layer is a digitized version of a 1:125,000 USGS geologic map of the park (King et al. 1968). For the elevation, slope, and aspect data, I used the 7.5' USGS level 2 DEMs with 10-m resolution. With this suite of digital data, I constructed six GIS layers–land use, burned areas, rock strength, elevation, slope, and aspect–for further watershed analysis.

Land Use

The vegetation disturbance history of Great Smoky Mountains National Park prior to park establishment in 1934 was mapped using existing maps, photos, and archival reports by Pyle (1985) in a special report for the National Park Service. The objective of this report was to map human-induced disturbance that happened in the park prior to park establishment and to speculate about the resulting changes in vegetation dynamics. The digital version of this report, with amendments from Pyle (1988), maps into five categories: settlement, heavily disturbed, lightly disturbed, selective cutting, and undisturbed. Based on Pyle's original report and the needs of this study, I renamed categories and reclassified some of the polygons to reflect the working hypotheses of hillslope and stream channel interactions.

Polygons mapped as settled in the digital disturbance map represent areas of concentrated settlement. These include cleared fields for farming, homesteads, the small pre-park towns, such as Elkmont and Cataloochee, and roads. This category is the smallest in terms or mapped area, but it represents the greatest magnitude and most extensive duration of human disturbance. In addition, these areas are nearly

always adjacent to streams. The heavily cut polygons are regions where corporate logging occurred. This logging involved large tracts of land and the use of mechanized equipment and skidding, where cut logs were dragged across the ground with winches and cables. The extent of logging varied, but always included cutting along the creeks and in the riparian area; large fires often followed logging when entire hillslopes were cut (Pyle, 1985). By the time of park establishment in 1934, over half the park area had been heavily logged. In the new land use layer that I created, I maintained these category names and their mapped boundaries.

Lightly disturbed polygons are areas of diffuse disturbance associated with settlement; these disturbance activities included cutting for home building and firewood, setting small fires, and grazing. I maintain both Pyle's (1988) name and boundaries for this category. The selectively cut mapped polygons represent areas with big trees and diffuse human activity. Two small tracts classified as selectively cut. The first is the area around Cataloochee Valley. This area was not logged by corporate logging because of the numerous small home sites surrounding the valley. The farmers could not remove many of the larger trees but did some logging for building and firewood; I reclassified this area as lightly disturbed. The second region is in the western area of the park that was formerly dominated by chestnuts, which were decimated by a chestnut blight, but was never logged. This area was digitized as selectively cut because it was "lacking in a wholly undisturbed appearance" (Pyle 1985, p.11). However, the area is only slightly affected by anthropogenic disturbance; thus, I reclassified this area as pristine. The undisturbed category was described by Pyle as being "high in virgin forest attributes" (1985, p. 21), although she recognized that the vegetation in these areas had likely been affected by human activity. I renamed this category as 'pristine' to reflect the limited anthropogenic as well as natural disturbance in these areas, and I kept the mapped boundaries (Figure 2).

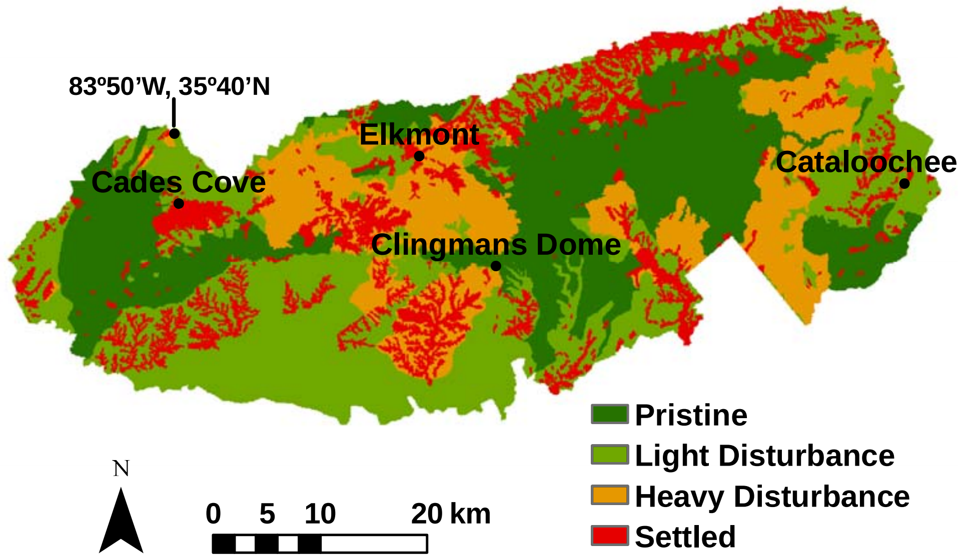

Figure 2. Land use in GSMNP.

Burned Area

The fire history layer maps the most recent fire for a particular area in the park as determined by Harmon (1981), and the fire frequency layer denotes the number of fires at a particular location since the 1940s. Most studies indicate that the effect of fire on streams does not persist longer than 15 years (Gresswell 1999, Minshall 2003). As it had already been longer than 15 years since the burned areas were digitized, I collapsed all burned-area information into one layer with the single binary attribute of burned (Figure 3). Most fires in the park since 1940 have occurred along the periphery of the park near areas of current settlement.

Rock Strength

The geology of the park was mapped by King et al. (1968) with the exception of the Hazel Creek area in the southwest portion of the park. This map was subsequently digitized to represent the 25 distinct types of bedrock geology that occur in the park. Given that geologic names are often type localities rather than descriptions of spatial processes, I reclassified each geologic unit into one of five classes (Table 1) based on rock strength and cohesiveness as very weak, weak, medium-strength, strong, and very strong, as suggested by Attewell and Farmer (1976). Their classification is based on reported values for unconfined fracture strength of rocks as measured in megapascals (MPa). I used this measurement of cohesiveness as an indicator of a rock unit's resistance to both physical and chemical weathering. With my watershed classification, I was interested in the production of sediment on hillslopes, as well as the delivery of material directly to a stream channel via mass wasting processes. As such, a rock unit was classified as relatively strong if it was either resistant to weathering or unlikely to produce high magnitude mass wasting events, such as debris flows or avalanches. In contrast, rock units were classified as relatively weak if they were prone to extensive weathering (e.g., chemical weathering of carbonates), or if inclined to generate periodic, high magnitude mass wasting events. Thus, this

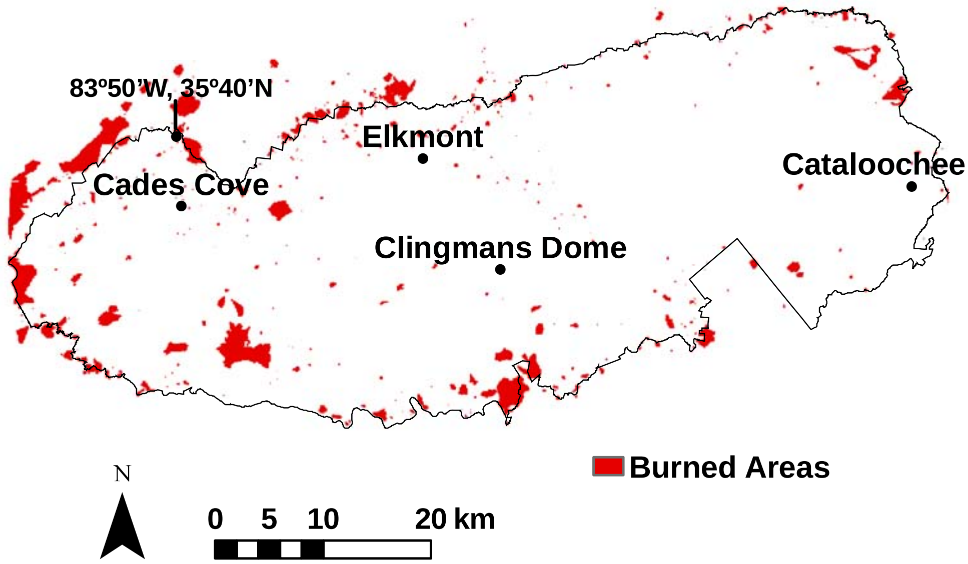

Figure 3. Burned area in and near GSMNP.

Table 1. Classification of rock strength and resistance to erosion. Strength ranges and descriptions are from Attewell and Farmer (1976).

Rock Strength Classification	*Class Description*	*Range of Strength Failure (MPa)*	*Rock Types*
1	Very weak	5-20	Weathered and weakly-compacted sedimentary rocks
2	Weak	20-40	Weakly-cemented sedimentary rocks; schists
3	Medium	40-80	Competent sedimentary rocks; some low density, coarse igneous rocks
4	Strong	80-160	Competent igneous, metamorphic rocks and some fine-grained sandstones
5	Very strong	160-320	Quartzites; dense fine-grained igneous rocks

rock strength classification served as a proxy for a combined set of hillslope geomorphic processes related to the flux of sediment to a stream channel.

I used the descriptions in King et al. (1968) to classify each rock unit into one of the five rock strength classifications (Table 2). For instance, the Anakeesta formation is described as “consist(ing) mainly of dark silty and argillaceous rocks altered to slate, phyllite, or schist,” (King et al. 1968) and is thus classified as weak. Even though the Anakeesta formation is found in some of the highest and steepest portions of the park, this rock unit is classified as weak, because it has produced several high magnitude mass wasting events (Henderson 1997). The stronger and cohesive Roaring Fork Sandstone is reclassified as strong based on its fine-grained, strongly cemented sandstone matrix. The most common geologic unit is the Thunderhead Sandstone, which covers nearly half the study area; it is classified as having medium rock strength because it is coarse-grained and is intertongued throughout its distribution with layers of the Anakeesta formation. Several of the resistant bedrock outcrops in the park are composed of Thunderhead Sandstone, yet, the coarse-grained sedimentary composition, combined with the interbedded silty and argillaceous layers found in this formation, produce a net classification of a medium level of resistance to erosion.

Largely because of the ubiquitous presence of Thunderhead Sandstone, medium-strength rocks are the most common rock types in the park, followed by strong, fine-grained sandstones (Figure 4). Relatively small units of limestone in Cades Cove are classified as weak, as is the somewhat extensive unit of Metcalf Phyllite. The remaining geologic units in the park are small and discontinuous, with classifications ranging from weak unclassified formations of sedimentary rock to the very strong Longarm Quartzite. No rock units in the park are classified as being very weak. The Great Smoky Group is not classified because it is a general term for the Hazel Creek

Table 2. Rock strength classification for each type of geology in the study area. Also reported is the percent of the original geology unit in the park.

Geologic Unit	*Percent of Study Area*	*Rock Strength Class*
Anakeesta Formation	7.8	Weak
Basement Complex	1.9	Weak
Blockhouse Shale	0.0	Weak
Cades Sandstone	5.9	Medium
Cochoran Formation	0.1	Very Strong
Elkmont Sandstone	9.3	Strong
Great Smoky Group	-	NA
Hesse Quartzite	0.1	Very Strong
Lenoir Limestone	< 0.1	Weak
Limestone/Dolomite	0.8	Weak
Longarm Quartzite	2.7	Very Strong
Metadiorite	< 0.1	Very Strong
Metcalf Phyllite	3.2	Weak
Murray Shale	< 0.1	Weak
Nebo Quartzite	0.1	Very Strong
Nichols Shale	0.1	Weak
Pigeon Siltstone	3.3	Weak
Rich Butt Sandstone	1.8	Medium
Roaring Fork Sandstone	8.6	Strong
Shields Formation	< 0.1	Strong
Thunderhead Sandstone	48.7	Medium
Unnamed Sandstone	0.6	Medium
Wading Branch Formation	0.2	Weak
Wilhite Formation Coarse	3.0	Medium
Wilhite Formation	1.9	Weak

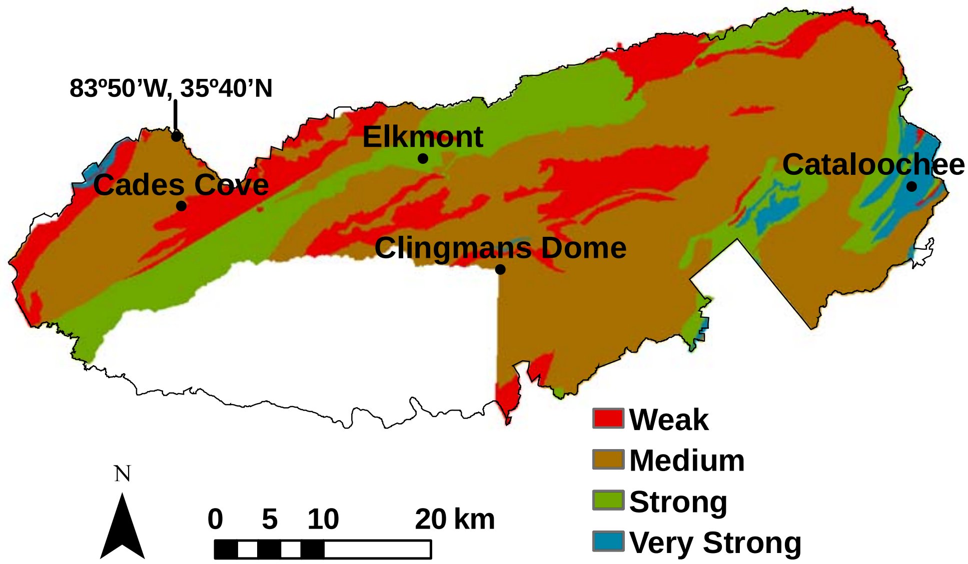

Figure 4. Rock strength classes in GSMNP. Missing area in southwest portion has no geologic data.

area in the southwestern portion of the park for which no descriptive geologic information is available.

Elevation

The elevation attribute layer was created using USGS 7.5 minute level 2 DEMs. USGS created the original raster datasets, which cover the same area as a standard USGS 7.5 minute quadrangle; the elevation information is recorded along a regularly spaced profile, which is a 10-m interval for these DEMs. The level 2 DEMs have been edited by USGS to remove systematic errors, and to increase the accuracy of the linear interpolation procedure by incorporating hypsographic and hydrographic data. The resulting level 2 DEMs for GSMNP have a maximum vertical error of 6 m (USGS 1993).

In order to create a seamless elevation layer, I mosaicked the individual DEM files together using ArcGIS version 8.3 software (ESRI 2003). The level 2 files have much better accuracy along their edges than the original level 1 DEMs; hence, the edges of each paired DEM fit well together. However, some areas still had no data either along an edge or within each individual DEM layer. For each pixel lacking an elevation value, I assigned the mean of the surrounding eight pixels; this is the 3x3 cell neighborhood window in raster analysis (Franke 1982). I then buffered a boundary layer of the park by 1 km to produce a shape that is slightly larger than the actual park boundary. I clipped the seamless DEM to produce the elevation layer for the park with values ranging from 265-2028 m (Figure 5) with a mean value of 1147 m.

Slope and Aspect

The slope and aspect layers were both created using the Spatial Analyst extension for ArcGIS 8.3. Conceptually, the algorithm fits a plane to the values of the 3x3 cell neighborhood around the pixel of interest; the average maximum vertical change

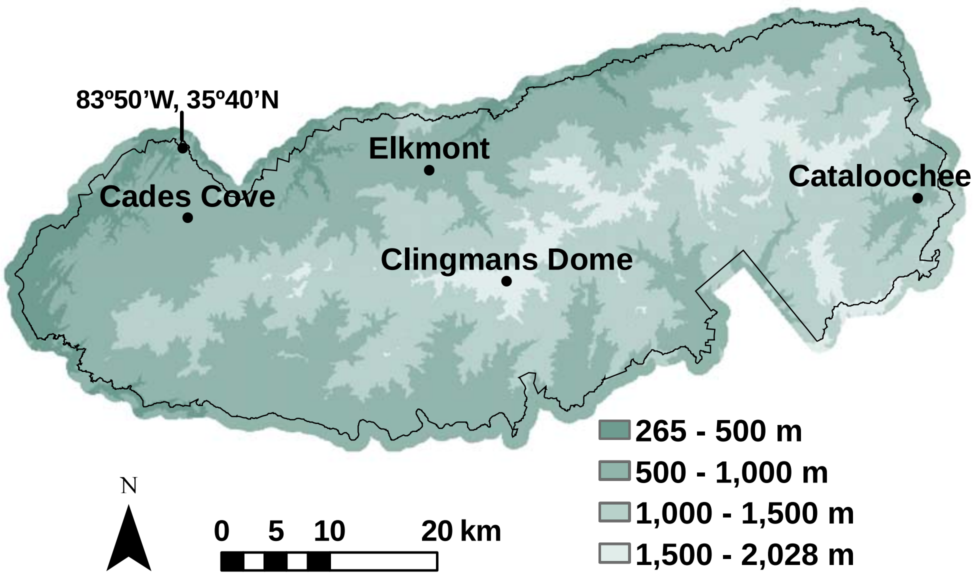

Figure 5. Elevation in GSMNP grouped into elevation classes.

across this plane, divided by the distance and multiplied by 100, is used to calculate the percent slope of the center pixel (Burrough 1986). The direction this plane faces is the aspect of the center pixel. This method can produce anomalous results at the edges of DEMs or where data are missing. However, I had already corrected for missing data values, and I had eliminated edge effects by extending the seamless DEM 1 km past the boundary of the study area.

By applying this method, I determined that most slope values in the study area range from 0% to 165%, with just a few pixels having much higher values on overhanging cliff faces; the mean slope value is 83%. Most flat areas with 0% slope occur on Fontana Lake in the southwest portion of the park and on the flooded creeks that drain into other impoundments just beyond the park boundary. Aspect values range from 0 to 359 degrees. In flat areas, all eight-neighborhood aspect pixels have the same value, resulting in no true aspect; in these areas, the pixel was coded with a value of negative one, and excluded from the analysis.

Hydrologic Modeling

Traditionally, watershed delineation and stream network mapping have been accomplished by tracing polygons and lines directly from a topographic map. With the expanded coverage of DEMs and the development of raster modeling tools in GIS software, the process of mapping hydrologic features can be automated. This permits more rapid watershed and stream mapping and allows the researcher to conduct analyses on larger areas. With changes in software and user interface design following the advent of GIS, the precise steps involved in delineating hydrologic features have evolved through many forms. However, the concept behind watershed derivation has remained the same: a DEM is pre-processed, and several new grids are created in an iterative fashion that leads to the partitioning of the landscape into internally-drained hydrologic units based on a user defined scale.

The gridded matrix of a DEM provides a useful mechanism for modeling surface drainage flow paths with a modification of the raster 3x3 neighborhood analysis, the D-8 model (Fairfield and Leymarie 1991). With this model, the 'downhill' direction from a particular cell, and hence, its flow direction due to gravity, can be determined as the software looks at each of the eight cells that surround the selected cell and models the flow to the cell that has the lowest elevation. This method has difficulties in flat areas where each of the eight cells has the same value, in regions of karst terrain where sinkholes interrupt the drainage network, and where sampling during DEM creation produces slightly higher elevation pixels that block or divert drainage. Each of these scenarios must be assessed and solved by pre-processing the DEM before proceeding with the hydrological extraction techniques.

Three tasks must be accomplished when pre-processing a DEM for watershed modeling. The first and second tasks are to check for obvious elevation value errors and then to assign values through linear interpolation to missing data cells, which I did while creating the elevation GIS layer. The third task is to create a new grid with all or some of the 'sinks' filled in. A sink is an area on the grid with internal drainage or no outlet, meaning each of the surrounding cells in the D-8 model has a higher elevation value than the sink cell. Sinks most often occur because of errors in the creation of the DEM through interpolation. However, in karst landscapes, these internally draining areas could be real geomorphic features such as sinkholes and karst valleys. Each of these scenarios was evaluated by identifying true sinks that impact stream flow and then creating a new grid with the anomalous sinks filled in using a *fill sinks* command; this process raises the elevation value of a sink cell until it drains into another cell. The user can set a threshold for the size of a sink that will be filled based on the difference between adjacent elevation values; this allows the user to accept some large sinks that may be sinkholes.

I found several small sinks in the GSMNP DEM. I determined through analysis of topographic maps that only one sink, near Cades Cove, drains an area large enough to produce a perennial channelized flow into the sink. Hence, I filled all other sinks such that they are part of a larger catchment for modeling purposes. To achieve this, I instructed the *fill sinks* process to fill any sink except those deeper than 20 m. Following this step, the resulting DEM was ready for watershed delineation and stream channel extraction.

The first step in extracting hydrologic features from a processed DEM is to determine the flow direction and flow accumulation area for the grid. Using the filled sinks grid, I created a new grid that shows the flow direction for all cells on the grid. This was done, again, using the D-8 model. Then, a flow accumulation grid was created from the flow direction grid; the flow accumulation grid stores, for each cell, the number of cells that drain into it. At this point the user selects the scale of watershed size that is of interest to the model. It is important to note that there exists a minimum size of watershed that can be delineated based on the original DEM data; for instance, a DEM cannot model a real feature that is the same size as the resolution of the DEM. A general rule for hydrology is to model features that are a minimum of one order of magnitude larger than the resolution of the original DEM (Garbrecht and Martz 1994). Based on this rule, and on my observations of the minimum watershed size needed to produce perennial channelized flow in GSMNP, I set the minimum threshold for watershed size at 0.5 km^2.

I next created a new grid that identified each cell in the flow accumulation grid meeting the minimum threshold for flow—it drained an area at least 0.5 km^2; this grid represented the likely location of streams on the modeled landscape. Once a pixel had been identified as draining the minimum area specified, it was labeled as a stream pixel. The stream then built downstream until it encountered another pixel that drained an area of at least 0.5 km^2. Where these two pixels met became a stream

junction, a point that drained two separate headwater areas. The model continued building a stream network downstream to the edge of the DEM. This stream grid was then converted into a vector layer and used for further network analysis of stream functions (Figure 6). As a pixel is not defined as being a 'stream' pixel until it meets the minimum drainage area, streams in my modeled network do not extend as close to the divide as streams on most USGS 7.5' topographic maps for this area. However, being that most valleys are rather narrow, the actual location of each stream was quite close to the USGS mapped location. Finally, I created a watershed grid from the stream grid (Figure 6); this assured that each streamline (now a reach) would have an associated catchment. These watersheds were converted into vector polygons for overlay analysis; however, I retained the watershed grid so that larger watersheds could be modeled from the nested features that I created.

In this project, I was only concerned with evaluating headwater catchments, as these are the areas hypothesized to show the strongest relationship between hillslope processes and stream channel morphology. Therefore, the next step was to select only headwater drainage areas, defined as the catchments draining all first-order modeled streams. To obtain this group of watersheds, I assigned the Strahler stream order to all the model streams. I then created a new watershed grid based on the stream order grid; in this manner, I had first-order, second-order, third-order, etc. catchments. From this grid I selected only the first-order catchments for further analysis. In addition, I removed the watersheds in the Hazel Creek area because that region lacked geologic information; finally, I eliminated any of the watersheds that drained large areas outside of the park boundary because the land use data did not extend beyond the park border. The final headwater catchment layer consisted of 862 individual first-order catchments that ranged in size from 0.5 to 6.0 km^2 with a mean of 1.2 km^2 (Figure 7); this was the data set used for all future stream channel sampling and modeling.

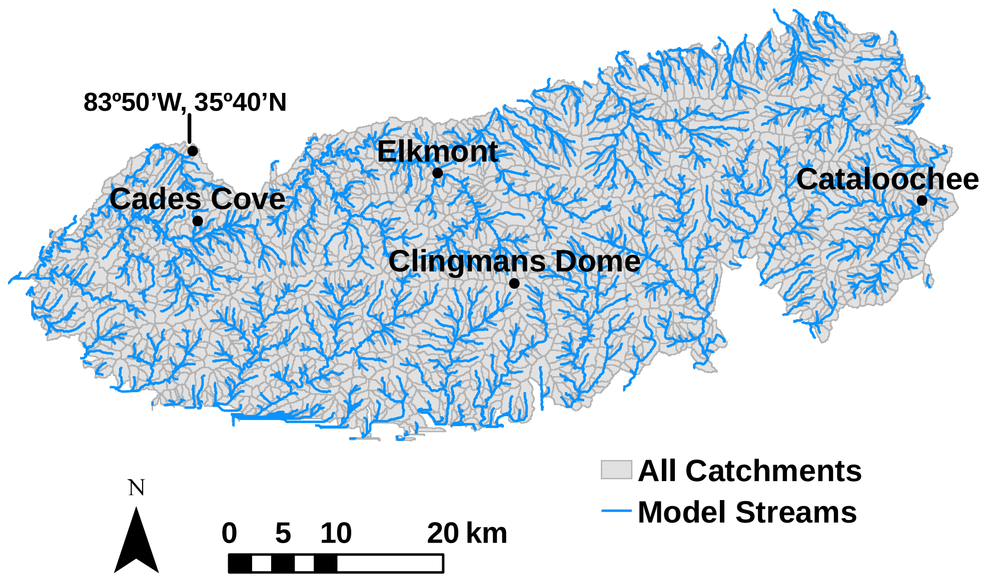

Figure 6. Delineated watersheds and the extracted stream network in GSMNP. The minimum drainage area is 0.5 km^2.

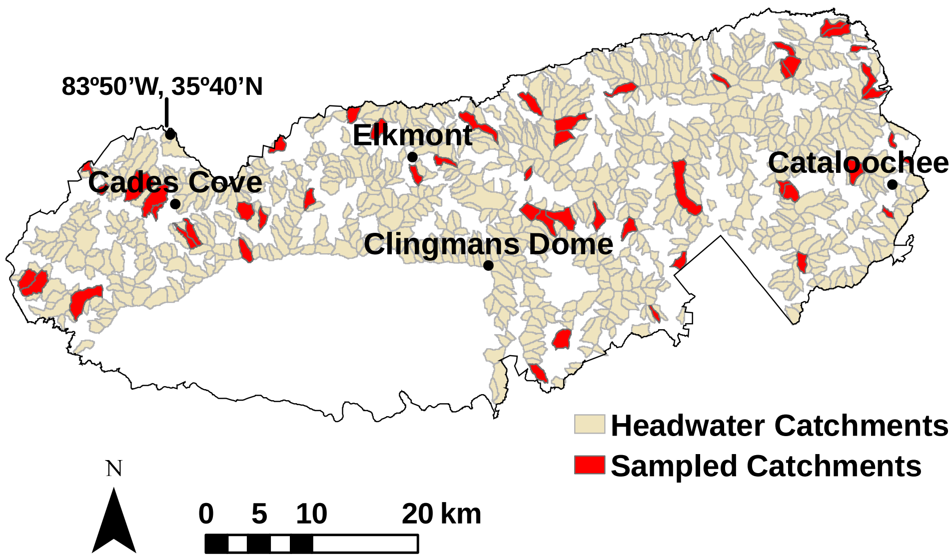

Figure 7. All first-order catchments used in this study and the 51 catchments that were sampled for stream channel morphology.

Landscape-Scale Attributes by Catchment

Having extracted 862 headwater catchments with a GIS-based hydrologic model, I then overlaid this catchment layer on each of the landscape-scale attribute GIS layers to determine the mean elevation, mean slope, resultant aspect (equivalent of mean aspect), and circularity for each catchment as well as the percent coverage of each different land use type, rock strength classification, and burned area. Each of these processes was done using ArcGIS, version 8.3, and the information was exported to tabular format in order to calculate summary statistics and to conduct statistical classification procedures.

Zonal Statistics

In the GIS environment, zonal statistics are the summary statistics for any given layer within a specified zone. I used the headwater catchments as the zonal layer to determine mean elevation, mean slope, and resultant aspect by catchment. Determining mean elevation and mean slope is a one-step process. I simply extracted the summary statistics for each catchment in tabular form, which was saved as a table in the GIS database. Mean catchment elevations ranged from 388 m to 1741 m, with the average elevation of all catchment means being 1103 m. The highest mean slope value for a catchment was 84%, and the lowest mean value was 10%; the average slope value for all catchments was 48%. Typically, catchments with high mean elevations had correspondingly high mean slope values, and the opposite was also true. I noted that this correlation was more pronounced with smaller catchments, those less than 1.5 km^2, than with larger catchments.

Calculating the resultant aspect of each catchment was a more involved process. The resultant aspect is the sum of all vectors within a given set. It is necessary to use vector addition to determine an average, instead of a typical mean calculation, because aspect is not a linear dataset. For instance, the 'average' aspect of 359° and

1°, which are both nearly true north is (359 + 1) / 2 = 180°, which is true south, a completely illogical result. The solution to this example can be determined by making a scaled drawing of the vectors, with equal magnitudes, and using the 'head to tail' method to get a value of 360° as a resultant vector. However, this method is computationally difficult with many vectors, and the smallest catchment in this study had over 500,000 pixels, with an equal number of aspect vectors to draw.

In order to more quickly compute the resultant vector, I calculated the arctangent of the sum of the sine values divided by the sum of the cosine values within each catchment (Curray 1956). The value of the resultant vector will fall between the range of -180° and 180°. Positive values represent the resultant vector in the range of 0° through 180°; negative values represent the resultant vector in the range of 181° through 359°, as the sine of these values is negative. I determined the resultant vector for each catchment by first creating two new grids, the sine and cosine of each aspect pixel respectively. I then extracted the summary statistics from the sine and cosine grids, for each catchment, and calculated the resultant vectors using a spreadsheet. A northern resultant aspect was the most common, occurring in 285 of the 862 catchments. An eastern resultant aspect was the least common, 168 catchments; 219 catchments had a western resultant aspect, and 190 catchments showed a resultant southern exposure.

Along with the summary statistics by zone, I extracted the area of each catchment for later analysis and the perimeter for calculating circularity. Circularity is a basin shape measurement, which is determined through dividing the area of a catchment by the area of a circle having the same perimeter as the catchment (Miller 1953, p. 51). Values approaching one are more circular catchments, which tend to have a more peaked flood hydrograph. Catchments with values approaching zero are either irregular in shape or are oblong; in either case runoff following storm events is spread over a longer period of time than with a similar sized circular watershed, resulting in

relatively lower peak discharge values. Catchment circularity values ranged from 0.13 to 0.55 with an overall mean of 0.35.

Categorical Attributes by Area

For the landscape-scale categorical attributes of land use, rock strength, and burned area, I determined the percentage of each value by catchment. This is similar to a zonal statistics function; however, it was accomplished using the *tabulate area* command. This process returns a table with the same number of columns as attributes in the GIS layer; for instance, tabulating the area of land use with catchment as the zone layer returns a table with the percent of each type of land use within each catchment. Most catchments had only one or two of the possible classes for each categorical attribute, and the remaining values were 0%. Descriptive statistics are not informative for this type of data as the minimum summary value by attribute will always be 0% because at least one catchment will not bound that particular attribute (e.g. no pristine forest); likewise, the maximum summary value will always be 100%, where at least one catchment is entirely composed of a particular landscape-scale categorical attribute (e.g., entirely underlain by medium-strength rocks).

Having delineated and selected all of the headwater catchments in my study area, determined the area, circularity, mean elevation, mean slope, and resultant aspect for each catchment, extracted the percentage of each catchment that was burned, pristine forest, lightly cut, heavily cut, or settled, as well as the percentage that was composed of weak, medium-strength, strong, or very strong rocks, I was prepared to begin the top-down classification procedure. In this chapter, I emphasized the care and detail that was necessary in order to construct GIS layers and statistical tables of good quality as all future tests and conclusions would be based on this landscape-scale dataset. In the following chapter, I first describe the methodology for conducting the top-down watershed classification procedure, which is based entirely on this landscape-scale data, and then I present the results of that exercise. With these two

chapters, I take the initial step toward assessing my first hypothesis, which states that a statistical classification based on landscape-scale attributes, the ‘top-down’ approach, will distinguish groups of catchments that have significantly distinct types of stream channel morphology. In subsequent chapters, I test this hypothesis.

CHAPTER III
CATCHMENT CLASSIFICATION USING LANDSCAPE-SCALE DATA

By far, the most common method of classifying watersheds is to use manual or statistical techniques in grouping watersheds with similar landscape-scale attributes. This approach assumes that watersheds sharing a related suite of characteristics are likely to have similar types of stream channel habitat conditions. In this chapter, I describe the methods I used to classify headwater catchments in Great Smoky Mountains National Park according to my first hypotheses, which states that a 'top-down' statistical classification based on landscape-scale attributes will distinguish groups of catchments that have significantly distinct types of stream channel morphology. This type of classification is an iterative effort; I first describe the method for the entire procedure, and I then present results from each iteration. Finally, I show a map displaying the completed top-down classification for GSMNP and describe the landscape-scale attributes that contributed most heavily toward delineating the study area into discrete groups of watersheds. In subsequent chapters, I evaluate the effectiveness of this effort.

Top-Down Classification Procedure

Statistical clustering is a relatively objective means of creating groups with similar attributes. Unlike manual methods, in which the user places entities into groups based on a particular criterion, statistical clustering employs a user-specified similarity metric to create groups with similar attributes in an unsupervised manner. Mathematical clustering using statistical software also allows for rapid classification of data sets that have a large number of samples, several different attributes, or both. Watershed classification is well suited to statistical clustering as a particular region will have many watersheds that can be clustered based on a variety of different landscape-scale parameters. The technique can create watershed groups with similar

geology (Lipscomb 1998) or similar land use (Wardrop et al. 2005), and, with the technique presented in this chapter, with both geology and land use, as well as with additional parameters.

Landscape-scale attributes have historically tended to be descriptive, and rarely have the groupings been tested to determine whether different groups correlate with different watershed processes. In the previous chapter, I described the process that I used to transform the categorical landscape-scale attribute information, such as geology, into classes that may influence hillslope processes, such as rock strength. This, hopefully, will more effectively produce clustered groups that reflect watershed processes, and possibly show variation in stream channel morphology values. To create groups of catchments in my top-down approach, I used hierarchical cluster analysis (Tryon 1939) followed by a non-agglomerative clustering technique, k-means clustering (Hartigan 1975), in a two-step procedure that formed groups of watersheds with similar landscape-scale attributes.

Hierarchical Cluster Analysis

Hierarchical cluster analysis, like any clustering algorithm, seeks to create groups of similar cases such that the variance within groups is minimized and the between-group variance is maximized (Tryon 1939). Hierarchical clustering begins with n clusters (with n being the number of cases); two clusters are merged (individual cases in the first round of clustering), and then either a third case is added or two additional cases are joined. This process is repeated until only one large cluster contains all cases. Once a case has been put into a cluster it cannot be moved to another cluster; hence, this is an agglomerative technique. I clustered all 862 headwater catchments, based on their standardized attribute values (z scores) for circularity, mean elevation, mean slope, resultant aspect, and the percent coverage for each type of land use and rock strength class, using the statistical software SPSS (version 13.0). I did not use the attribute catchment area, because percent land use and rock strength were

normalized by total catchment area; if I had included area as an attribute, it is likely that the clustering algorithm would have generated redundant groups that were different in size but otherwise similar in terms of attribute distribution.

As I had several different attributes (columns of data) and I wished to minimize within-group variation, I used Ward's minimum variance method for linking clusters (Ward 1963) with squared Euclidian distance as the distance measurement. This method uses an ANOVA (Fisher 1954) type technique for combining clusters, such that at each stage of clustering, this method adds one cluster to whichever existing cluster will have the lowest resulting within-group sum of squares or scatter around the group centroid.

Each step of hierarchical clustering produces fewer clusters, and the variance within those clusters increases. Choosing where to stop the clustering procedure involved analyzing the cluster dendrogram and the agglomeration schedule table. The dendrogram is a tree-like diagram that displays the linkages between groups from the initial cases to the final all-inclusive cluster; along one axis is the list of cases, and along the other axis is the scaled distance between cluster centroids (Figure 8). As the clustering proceeds, the number of groups decreases and the distance between group centroids increases. Generally, a stage is reached at which the distances between clusters become large, which means further joining of groups would result in relatively large within-group variance; this is a logical stage at which to stop the clustering process. It is also helpful to analyze the agglomeration schedule table to determine a stopping point for clustering. This table shows the clusters being combined at each stage and the resulting within-group sum of squares from that join. By locating large changes in the sum of squares value, one can determine stages that are also likely stopping points for clustering.

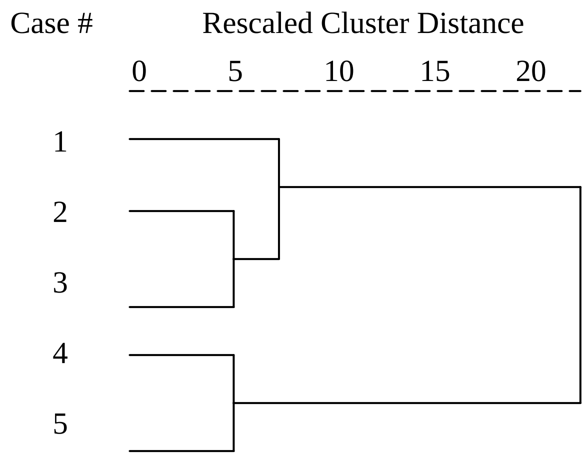

Figure 8. Example of a dendrogram from a hierarchical clustering procedure with five cases. The optimum cluster solution here is three groups.

Refining Clusters

A disadvantage to hierarchical clustering is that once a case has been assigned to a cluster, it cannot be removed and reassigned to a different cluster. This means that near the final cluster solution some cases may be quite different than the means of their respective clusters. The solution given by hierarchical clustering can be refined using a k-means clustering technique (Hartigan 1975). The technique requires an *a priori* decision as to the number of groups in the model. Beginning with *k* number of groups, the data are partitioned with *k* centroids, and each observation is grouped with its most similar centroid point based on having the lowest calculated sum of squares. New centroids are calculated and observations are re-assigned if they are more similar to another group. In an iterative fashion, the algorithm continues, moving cases from one group to another until no further improvement in the sum of squares within each cluster can be achieved.

To refine the clusters of headwater catchments, I selected the number of groups based on the result from the hierarchical clustering. In addition, I used the cluster centroids from the hierarchical clustering solution as 'seed points' for the k-means clustering process. In this manner, cases that were misclassified in the hierarchical procedure were re-assigned to groups with more similar attributes. The k-means clustering procedure produces an ANOVA-type output comparing the attribute data distribution within each cluster; the F statistics should all be large and significant, because the clustering procedure is attempting to reduce within-group sum of squares. The magnitude of any given F statistic can be used to assess the relative importance of a particular attribute in creating a cluster. Finally, I examined the cases in each cluster to note any general patterns with respect to landscape-scale data, and, using the respective F statistics, I described the composition of each cluster.

Top-Down Classification Results

I used hierarchical cluster analysis to cluster all 862 catchments based on their standardized attribute values for circularity, mean elevation, mean slope, resultant aspect, and percent coverage for each type of land use and rock strength class. Based on the dendrogram and the agglomeration schedule table (Table 3), I found several possible stopping points for the clustering procedure. The first relatively large gap in cluster distances occurs at stage 849, which would be a 13-cluster solution. The distances between clusters increase at each successive stage, but get substantially larger at stage 855, a seven-cluster solution; the largest distance occurs where the final clusters join. Any stopping point at stage 855 or above would be a suitable stopping point, based on the occurrence of relatively large gaps in cluster distances. I stopped the clustering at stage 856, a six-cluster solution. Group sizes do not change dramatically between stage 855 and stage 856; however, stage 857 joins two very large groups that should likely remain separate.

The k-means cluster procedure produced an ANOVA-type table showing that the attributes used for clustering had significantly different means in each group (Table 4). This is expected because the groups were created to maximize attribute differences between groups. The magnitude of the F statistic indicates the importance of a particular attribute in the clustering procedure. Rock strength was the most important attribute in the clustering process; in particular, the percentages of very strong rocks and strong rocks were essential for creating groups. The percentage of burned area was also a significant attribute for clustering followed by medium and weak rock strength. The lightly disturbed land use designation and mean elevation of the catchment were the remaining important attributes in this process. Mean aspect appeared to contribute significantly to group assignment, but it was the least valuable attribute in this clustering process.

Table 3. Final 20 stages of clustering in the hierarchical cluster analysis of all 862 catchments. The distance column is the distance between cluster centers; the bold row, stage 856, is the stopping point chosen in this analysis.

	Clusters Combined			*Stage Cluster First Appears*		
Stage	Cluster 1	Cluster 2	Distance	Cluster 1	Cluster 2	Next Stage
842	90	712	3435	830	769	851
843	2	4	3525	839	832	853
844	7	84	3615	808	825	854
845	12	324	3709	831	822	847
846	130	137	3812	826	833	852
847	12	244	3950	845	841	854
848	71	129	4092	824	816	852
849	1	5	4244	837	836	856
850	542	549	4398	838	819	857
851	90	93	4619	842	820	857
852	71	130	4854	848	846	859
853	2	123	5134	843	834	856
854	7	12	5415	844	847	855
855	7	242	5902	854	827	860
856	**1**	**2**	**6468**	**849**	**853**	**858**
857	90	542	7046	851	850	859
858	1	95	7822	856	840	861
859	71	90	8611	852	857	860
860	7	71	9672	855	859	861
861	1	7	11193	858	860	0

Table 4. ANOVA table from top-down k-means cluster procedure. The results show that attribute means differ between the six groups. The magnitude of the F statistic indicates the importance of that attribute in the clustering procedure.

	Cluster		*Error*			
	Mean Square	df	Mean Square	df	*F*	*Sig.*
Circularity	16.4	5	0.91	856	18.1	0.00
Resultant Aspect	2.9	5	0.99	856	3.0	0.01
Mean Elevation	66.5	5	0.62	856	107.7	0.00
Mean Slope	39.6	5	0.78	856	51.1	0.00
Burned Area	129.6	5	0.25	856	520.3	0.00
Lightly Disturbed	90.1	5	0.48	856	187.9	0.00
Heavily Disturbed	7.4	5	0.96	856	7.6	0.00
Pristine	54.5	5	0.69	856	79.3	0.00
Settled Area	46.2	5	0.74	856	62.9	0.00
Weak Rocks	78.7	5	0.55	856	144.3	0.00
Medium Rocks	112.3	5	0.35	856	320.8	0.00
Strong Rocks	144.9	5	0.16	856	909.5	0.00
Very Strong Rocks	151.8	5	0.12	856	1273.8	0.00

The six groups created by the k-means clustering procedure had a fairly unequal number of cases in each group (Table 5). By observing the final cluster centers and examining the attribute values in each case, I described the typical suite of variables for each group. Catchments in the top-down classification group three (TD-3) were mostly found in pristine areas at high elevations and had medium-strength rocks. This was the largest of all groups, accounting for nearly half of all cases. The classified groups TD-5 and TD-6 each had 152 cases. TD-5 catchments had strong rocks, a low mean elevation, and low mean slopes; catchments that were lightly disturbed with high percentages of medium-strength rocks were likely to be classified into TD-6. The next most frequently occurring catchments were in group TD-1 and are found in areas with weaker rocks at low elevation, with high percentages of settled land. TD-2 and TD-4 had the fewest catchments in this study area. TD-2 catchments have very strong rocks, theoretically the most important attribute in the clustering procedure, light disturbance, and a low mean slope. TD-4 is essentially composed of the catchments with a high percentage of burned area.

The distribution of catchments across the study area reflects the importance of a few attributes in classifying each of the cases (Figure 9). The two most striking spatial patterns can be seen with the location of catchments in TD-5 and TD-3. The geologic variable ‘strong rock strength’ was clearly driving the classification of catchments into TD-5 (refer to Figure 4, Chapter II). Most TD-5 catchments lay on the east side of the northeast/southwest trending Greenbrier Fault that separates strong rocks from weak and medium-strength rocks. TD-4, the largest group, created two large contiguous clusters around each of the contiguous pristine areas in the park. Geology and land use are also important in creating TD-1; notably, this group captured many of the catchments in Cades Cove, which had large areas of limestone and experienced a high degree of settlement. TD-2 was heavily influenced by the infrequent occurrence of very strong rocks, resulting in few catchments being classified into this group. The burned areas in the park were small and discontinuous; however, the few

Table 5. Number of cases in each top-down classified group and the prominent attributes in each group.

Top-down Group	*Count*	*Important Attributes*	*# Sampled*
TD-1	94	Weak rocks, low elevation, high settlement	6
TD-2	28	Very strong rocks, light disturbance, low mean slope	5
TD-3	419	Pristine, high elevation, medium-strength rocks	15
TD-4	17	Burned area	5
TD-5	152	Strong rocks, low elevation, low mean slope	10
TD-6	152	Light disturbance, medium-strength rocks	10
Total	*862*		*51*

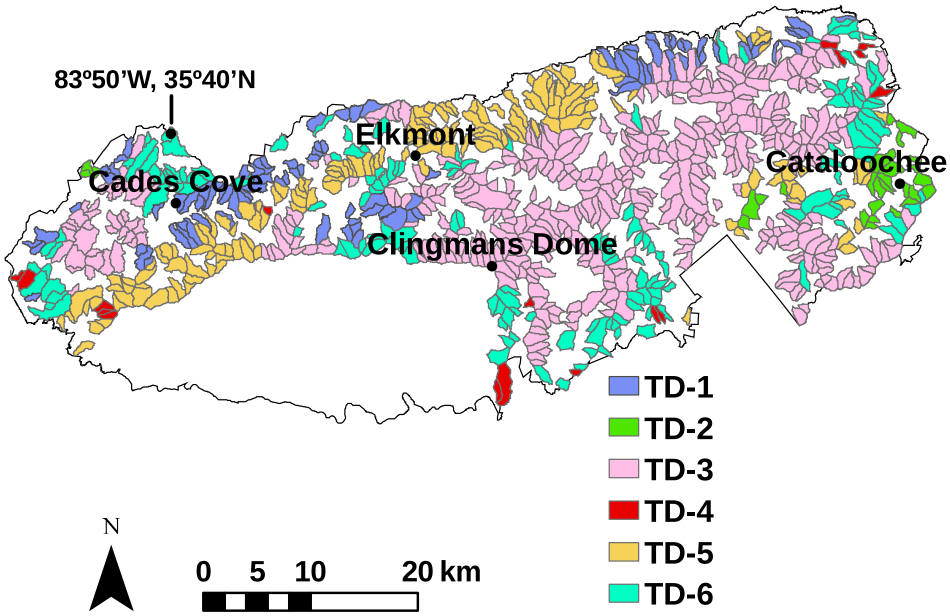

Figure 9. Results from the top-down classification procedure.

relatively large patches, found mostly near the park boundary, dominated the TD-4 classification.

The top-down classification technique created groups with distinct spatial patterns. This indicated that the clustering algorithm worked well at delineating groups that had at least one dominant landscape-scale attribute in common. It was also reassuring to note that the salient grouping attributes were geology and land use, which were likely to represent different types and magnitudes of watershed processes. For instance, it is a logical step to presume that TD-3 catchments, which consist of predominantly pristine areas, should have lower sediment loadings than more disturbed catchments. Additionally, TD-2 and TD-5 were composed of catchments with low mean slopes; I anticipated that streams in these catchments should have wider channels because of increased meandering and more stored sediment.

Most watershed classification schemes stop at this juncture and predict that stream channels will be different in each of the classified catchments. In this study, I collected channel morphology data from a sample of catchments; thus, I could directly test how much variation in stream channel morphology existed between these classified groups as well as evaluate other techniques of watershed classification. According to my first hypothesis, this top-down statistical classification, based entirely on landscape-scale attributes, will have distinguished groups of headwater catchments that have significantly distinct types of stream channel morphology. After presenting an alternative classification procedure in the next chapter, the bottom-up approach, I use the channel morphology data that I collected to test the top-down hypothesis.

CHAPTER IV
CATCHMENT CLASSIFICATION BASED ON REACH-SCALE DATA

The process of classifying watersheds typically involves grouping catchments exclusively on the basis of a suite of landscape-scale attributes. However, because I wished to create groups with distinctly different types of channel morphology, it seemed reasonable to first sort the streams into groups of similar channel types and then to assess whether group membership could be predicted by the landscape-scale information associated with each group. This alternative technique for catchment classification is based on my second working hypothesis, that catchments grouped by their respective distinct types of stream channels, a 'bottom-up' approach, will show significant relationships between stream channel morphology and landscape-scale attributes. In this chapter, I describe the procedure for classifying a sample of stream channels based on reach-scale channel morphology values and discuss the role of fluvial processes in guiding group membership.

Reach-Scale Data

In order to compare the relationships between landscape-scale attributes and reach-scale data, it was necessary to collect channel measurements and water quality samples in the field. I used the dataset of 862 classified headwater catchments, generated by the top-down classification procedure (Chapter III, Figure 9), to select 51 catchments for the collection of channel morphology information. The catchments were chosen in a stratified random manner such that each classified group was represented by a minimum of five sample catchments (Chapter III, Table 5). Using the top-down classification, which created groups with differing combinations of landscape-scale attributes, to select the 51 sample catchments, ensured a broad representation of the study area (Chapter III, Figure 7).

I followed modified guidelines for the establishment of a reference reach (Harrelson et al. 1994; Bunte and Abt 2001) and the collection of water samples (Tennessee Department of Environmental Quality protocols) in collecting channel morphology information and water quality samples. I measured and recorded bankfull width and depth, the reach water surface slope, the median particle size of the bed, the stored fines in a riffle, and collected a water sample for the analysis of water chemistry. I photo-documented the reach and installed a local datum with a 90-cm (three-foot) section of rebar; I marked the monument with a brass tag stamped with the study and reach numbers. At or near the monument, I recorded a GPS point, to be differentially corrected using Pathfinder software, version 2.90. Unfortunately, when plotting these GPS points, I determined that four sample reaches were not actually located in one of the 862 headwater catchments; therefore, I removed them from any subsequent analyses, leaving 47 sampled reaches (Table 6).

Channel Morphology

In the field, I visited each catchment during low flow conditions and chose a representative reach approximately 100 m upstream from the mouth; if necessary, I traveled farther upstream in order to get above any geomorphic influence from the trunk stream. This reference reach extended upstream for a distance of at least 20 times the active channel width. With a stadia rod and a rotating laser level that provided a level datum, I mapped five to seven channel-cross-sections along the reach. Based on these data and my observations, I selected an additional cross-section that I felt best represented the channel conditions for the reach. I established the monument near this location, being careful to place it outside of the active floodplain.

Using standard survey techniques for small wadeble streams (Harrelson et al. 1994), I mapped the channel cross- section at 0.1 m intervals or where I found a channel morphological feature of interest, including the bankfull positions, the water surface,

Table 6. The 51 sample catchments used to collect channel morphology information. The coordinates mark the monumented piece rebar adjacent to the surveyed channel cross-section. Asterisks mark catchments surveyed but not used for further analysis because of problems with sampling.

Reach #	*Stream Name*	*Latitude (N*)*	*Longitude (W)**
1	Rush Branch	35.667070	83.717412
2	Laurel Cove Creek	35.609103	83.736351
3	Cooper Branch	35.587997	83.812853
4	Dry Branch	35.744071	83.198369
5	Trib. of Cosby Creek	35.758137	83.207816
6	Leatherwood Branch	35.756639	83.105076
7	Indian Camp Branch	35.708354	83.470890
8	Little Brier Branch*	35.680936	83.642704
9	Trib. of Bradley Fork	35.565567	83.308709
10	Smith Branch	35.587158	83.359275
11	Bunches Creek*	35.553969	83.164887
12	Janey Whank Branch	35.465639	83.434528
13	Bearpen Hollow*	35.636958	83.462208
14	Road Prong	35.610916	83.459849
15	Tulip Branch	35.646233	83.582536
16	Copperhead Branch	35.730864	83.271448
17	Wilson Branch	35.610056	83.877747
18	Long Branch	35.689935	83.395265
19	Palmer Branch	35.621083	83.089352
20	Baxter Creek	35.742169	83.113938
21	Trib. of Mingus Creek	35.518201	83.319884
22	Laurel Creek	35.608708	83.748038
23	Big Holler	35.624242	83.682632
24	Beech Flats Prong	35.601166	83.409331
25	Trib. Of Little Cataloochee Creek	35.673510	83.077286
26	Ball Branch	35.718694	83.090492
27	Carolina Prong	35.775671	83.130716
28	Bird Branch	35.712571	83.381761
29	Trib. of Cataloochee Creek	35.662875	83.072235
30	Shop Creek	35.531410	83.982642

Table 6. Continued.

Reach #	*Stream Name*	*Latitude (N*)*	*Longitude (W*)*
31	Blacksmith Branch	35.531843	83.983789
32	Arrowhead Branch	35.646370	83.554838
33	Ledge Creek	35.628907	83.193308
34	Trib. of Ledge Creek	35.628914	83.194012
35	Baumgardner Branch	35.493324	83.425899
36	Mill Branch	35.615165	83.906766
37	Enloe Creek*	35.614109	83.270578
38	Jack Bradley Branch	35.595472	83.386174
39	Poplar Branch	35.669125	83.624395
40	Deep Creek	35.589928	83.428027
41	Parsons Branch	35.506777	83.925479
42	Trib. of Abrahms Creek	35.593877	83.845312
43	Cosby Creek	35.744168	83.197721
44	Davidson Creek	35.639785	83.120473
45	Tobes Creek	35.776880	83.131464
46	Left Fork Anthony Creek	35.579104	83.758637
47	Arbutus Branch	35.597171	83.859102
48	Cades Branch	35.590859	83.825702
49	Trillium Branch	35.674195	83.415359
50	Twomile Branch	35.691683	83.531579
51	Kingfisher Creek	35.630259	83.914070

*Positional error is less than 2 meters.

and the thalweg position (Figure 10). While surveying each cross-section along the reach, I used leveling techniques, with the rotating laser, to determine the water surface slope along the reach. I always began and ended this longitudinal survey with the water surface elevation on similar channel features such as a riffle or a pool.

I used the Wolman (1954) pebble count method to determine the median particle size (D_{50}) of the bed material. At each cross-section surveyed along the reach, I walked heel-to-toe across the reach, picking up the first particle I touched just in front of my toe; using a gravelometer capable of determining 18 size classes ranging from 2 mm to 362 mm, I recoded the b-axis size class of the each randomly selected particle. I did this across the entire cross-section and made sure to measure a minimum of 100 particles for the entire reach. I then calculated the median particle size in a spreadsheet using linear interpolation (Bunte and Abt 2001).

I estimated the amount of stored fines in a riffle by directly sampling the bed using the ‘quorer’ method (NIWA 2005, Quinn and Cooper 1997). This method assumes that much of the near-surface fines stored in a riffle are mobilized as suspended sediment during flood conditions; hence, this technique attempts to replicate sampling suspended sediment concentrations during bankfull conditions. I began by taking a background sample of the flowing water near the edge of a riffle. Then, I pushed a 15 cm (6 inch) diameter PVC coupling into the bed sediments until I felt the sediment size get abruptly larger. I recorded the depth of the water inside the coupling at five scattered locations. Then, using a piece of rebar, I stirred the sediment and water inside the tube for one minute and collected a sample of the slurry. I re-stirred the sediment and measured the depth of disturbed sediment at five scattered locations in the cylinder. Back in the lab, I determined the suspended sediment concentration of the slurry sample and the background sample using a hand-operated vacuum pump, which filters the sediment from the slurry sample (ASTM 2002). I subtracted the

Figure 10. Surveying a monumented cross section.

background concentration from the slurry concentration, multiplied this value by the water depth in the cylinder, and divided that value by the depth of stirred sediment to arrive at an estimate of stored fines for that location (NIWA 2005). This result tends to overestimate the probable suspended sediment concentration during bankfull discharge, but it is an effective technique for comparing the accumulation of fines between different streams. Finally, the stored sediment value was reported as g/m^3, which is directly equivalent to mg/l, in order to follow the convention established by Quinn and Cooper (1997).

During the field-survey process, I measured the bankfull width and depth for five to seven cross-sections along each reach. I used this information to assist in choosing a representative reach for the establishment of a monumented cross-sectional survey. Choosing a representative reach is a rather subjective procedure. Therefore, I compared the mean values from all of the surveyed cross-sections in a reach to the width and depth values from the monumented reach. In five instances (reaches 3, 5, 17, 39, and 43), the monumented reach values differed by more than two standard deviations from the mean value for that reach. Each of these cases was also an outlier for width and depth. Therefore, in each of those cases, I used the mean reach values for width and depth calculations rather than the monumented reach values.

The largest channel used in this analysis, reach 17, had a bankfull cross-sectional area of 1.82 m^2; this reach also had the widest channel, measuring 6.13 m, and quite nearly the deepest at 0.30 m (Table 7). Reach 48 had the smallest channel, 0.14 m^2 in cross-section, and was both narrow and shallow. Otherwise stream channels tended to be wide and shallow or narrow and deep; the mean bankfull width of all surveyed channels was 3.19 m and the mean bankfull depth was 0.23 m (Table 7). The average reach slope for the surveyed reaches that I used for further analysis was 8.4%, with reach 21 being the steepest (19%) and reach 42 having the most shallow slope (<1%). Median particle sizes range from fine gravel in reach 42 (4.0 mm), where sand and

Table 7. Results of channel morphology measurements from the 51 sampled reaches. Reaches marked with an asterisk were not used for further analysis because of problems with sampling.

Reach #	*Width (m)*	*Depth (m)*	*Cross-sectional Area (m^2)*	*Reach Slope %*	*Median Particle Size (mm)*	*Stored Sediment (g/m^3)*
1*	3.50	0.21	0.73	6	30.4	12,347
2*	2.80	0.16	0.46	10*	30.0	75,902
3*	2.92	0.19	0.54	5	21.9	6,137
4*	1.80	0.14	0.25	17*	33.7	13,954
5*	4.88	0.16	0.76	6	12.5	8,138
6*	2.10	0.13	0.27	4	10.1	27,722
7*	4.00	0.13	0.53	9	15.1	16,024
8*	3.70	0.21	0.79	3	13.2	35,669
9*	2.30	0.16	0.37	12*	23.7	11,816
10*	3.40	0.19	0.63	6	8.4	20,085
11*	2.25	0.13	0.30	10*	6.9	30,604
12*	2.30	0.19	0.44	11*	15.3	26,677
13*	3.60	0.33	1.17	26*	42.8	16,612
14*	4.20	0.17	0.71	6	21.0	6,405
15*	3.00	0.20	0.60	11*	8.1	28,254
16*	3.40	0.24	0.83	18*	18.5	4,029
17*	6.13	0.30	1.82	9	8.9	3,585
18*	3.30	0.26	0.87	7	11.6	25,591
19*	2.20	0.24	0.52	3	6.4	52,215
20*	3.30	0.28	0.93	14*	22.1	6,307
21*	2.30	0.18	0.41	19*	9.3	11,476
22*	3.25	0.27	0.87	2	10.9	33,372
23*	3.60	0.19	0.67	7	21.9	45,393
24*	3.85	0.20	0.76	6	20.2	12,275
25*	1.90	0.21	0.39	13*	12.9	5,524
26*	2.55	0.20	0.52	10*	13.1	1,195
27*	2.50	0.08	0.20	7	14.0	62,339
28*	3.45	0.15	0.52	3	10.3	16,395
29*	2.60	0.14	0.37	18*	23.1	138,532
30*	3.15	0.30	0.93	7	10.5	11,806

Table 7. Continued.

Reach #	*Width (m)*	*Depth (m)*	*Cross-sectional Area (m^2)*	*Reach Slope %*	*Median Particle Size (mm)*	*Stored Sediment (g/m^3)*
31*	3.75	0.23	0.85	3	12.5	3,410
32*	2.45	0.26	0.63	13*	9.4	16,537
33*	2.10	0.20	0.41	7	11.1	39,359
34*	1.80	0.11	0.19	10*	9.7	43,709
35*	3.35	0.19	0.63	6	10.1	16,907
36*	2.33	0.22	0.53	7	17.4	6,292
37*	5.35	0.39	2.11	6	31.1	13,146
38*	3.05	0.31	0.94	7	18.1	24,774
39*	3.19	0.39	1.25	15*	34.8	14,493
40*	3.85	0.21	0.79	5	32.9	21,327
41*	2.90	0.24	0.69	4	27.2	25,866
42*	1.30	0.18	0.24	0	4.0	79,779
43*	4.30	0.32	1.36	13*	37.3	3,996
44*	3.50	0.20	0.70	5	14.7	108,713
45*	3.70	0.19	0.72	9	15.1	74,389
46*	3.75	0.33	1.23	15*	34.1	6,710
47*	4.05	0.34	1.37	5	6.2	14,486
48*	1.10	0.13	0.14	1	7.0	4,921
49*	3.60	0.36	1.30	10*	38.4	4,540
50*	3.25	0.26	0.84	6	11.7	44,081
51*	3.10	0.23	0.71	8	19.9	25,434
Means	3.19	0.23	0.80	8.4	17.4	26,876

silt were prevalent, to coarse gravel in streams with numerous boulders such as reach 49 (42.8 mm); the mean size of 17.35 mm falls between the medium and coarse gravel size classes. The mean value for stored fines is 26,876 g/m^3; however, more than an order of magnitude difference occurs between the minimum of 1,195 g/m^3 in reach 26 and the maximum in reach 29 of 138,532 g/m^3. Note that the quorer method tends to overestimate suspended sediment during bankfull discharge but acts as a good comparative value between sites.

Stream Water Chemistry

Several water monitoring stations in GSMNP are used in ongoing studies of water chemistry in the park. However, few of these stations are located on the small streams that I sampled in this project. Therefore, I collected water samples for analysis by the EPA-certified Tennessee Department of Environmental Quality laboratory in Knoxville. In an attempt to control for different flows and seasonal effects, I collected all water quality samples during a two-week period of low flow conditions in early December 2003. As I only collected one sample from each stream, these single samples cannot represent any temporal or seasonal trend, and it is not possible to determine whether the results fall within the typical values for each stream. However, the results could possibly be used to compare the general differences in stream water chemistry between all catchments because the samples were taken within a few days of each other.

At 40 of the 47 streams, I recorded temperature and pH, and then collected two liters of stream water using the grab method. The samples were transported, in ice, to the Tennessee Department of Environment and Conservation Water Quality laboratory in Knoxville, TN within 24 hours. Following EPA guidelines, each sample was analyzed for total dissolved solids (TDS), which is the sum of the major ions calcium (Ca^{+2}), potassium (K^{+}), chloride (Cl^{-}), and sulfate ($SO4^{-2}$), and for the indices of

biological productivity total nitrogen (TN), total phosphorous (TP), and total organic carbon (TOC).

Stream temperatures, which were only successfully recorded at 30 streams, were quite low, as would be expected for December, with a relatively large difference between the minimum of 3.0° C in reach 14 and the maximum temperature of 9.7° C in reach 41 (Table 8). I found little difference between pH values; however, total dissolved solids showed a large amount of variation, ranging from 2.34 mg/l in reach 32 to 11.96 mg/l in reach 31; this was largely due to different levels of calcium and sulfate ions in the sampled streams. Nutrient levels were low; several streams had no detectable levels of total nitrogen, and only five streams actually had any detectable levels of total phosphorous. Total organic carbon was generally low, averaging 2.11 mg/l, and showed very little variation between the sampled streams.

Classification of Stream Reaches

At this point, my GIS database contained a suite of landscape-scale attribute information layers, including elevation, slope, aspect, land use, and rock strength for the study area, delineated headwater catchments, an extracted digital stream network, tables of landscape-scale data within each catchment, channel morphology information for 47 different reaches, and stream water chemistry data for 40 different streams. Thus, I could proceed with the second classification procedure, the bottom-up approach.

Watershed classification is normally done by grouping catchments with similar landscape-scale attributes and then comparing discharge, water chemistry, or more infrequently, channel types in order to evaluate the success of the classification procedure (e.g., Jones et al. 1997, Lipscomb 1998). Given that it is the actual channel habitat that is often of interest in these classification schemes, I developed a method

Table 8. Stream water chemistry results from the sampled catchments. The hyphen (-) indicates that no sample was collected for that stream.

Reach #	*Temperature (Celsius)*	*pH*	*Total Dissolved Solids (mg/l)*	*Total Nitrogen (µg/l)*	*Total Phosphorous (µg/l)*	*Total Organic Carbon (mg/l)*
1	6.0	6.98	7.53	110	5	2.11
2	-	6.87	5.82	130	0	1.63
3	6.7	6.92	5.91	0	0	1.82
4	7.8	6.81	7.29	370	0	1.50
5	-	6.93	5.97	450	0	1.52
6	-	6.96	7.20	140	0	1.49
7	-	7.08	4.82	0	0	1.59
8	-	-	-	170	0	-
9	8.5	6.95	6.18	70	0	2.06
10	-	7.07	4.13	-	-	1.75
11	-	-	-	580	0	-
12	-	-	-	310	0	-
13	-	-	-	670	0	-
14	3.0	6.37	4.69	50	6	1.82
15	6.4	6.65	4.76	310	0	1.96
16	-	6.01	6.07	-	-	1.63
17	5.1	6.54	7.21	660	0	2.53
18	7.9	6.70	5.79	80	0	1.50
19	-	-	-	0	0	-
20	-	6.58	5.83	340	14*	1.47
21	8.4	6.74	4.53	550	38*	1.61
22	6.2	6.65	7.30	-	-	1.84
23	6.5	6.73	5.15	-	-	1.69
24	5.2	6.51	10.13	300	0	1.59
25	-	-	-	60	0	-
26	-	-	-	-	.	-
27	-	7.03	6.07	0	0	1.48
28	7.1	7.13	5.95	0	0	1.46
29	-	-	-	70	0	-
30	7.1	6.70	10.56	80	0	2.03

Table 8. Continued.

Reach #	*Temperature (Celsius)*	*pH*	*Total Dissolved Solids (mg/l)*	*Total Nitrogen (µg/l)*	*Total Phosphorous (µg/l)*	*Total Organic Carbon (mg/l)*
31	7.9	6.79	11.96	290	0	1.81
32	7.5	6.96	2.34	-	-	1.84
33	-	6.94	5.41	0	0	1.61
34	-	6.75	5.38	110	0	2.02
35	-	-	-	70	0	-
36	7.1	6.89	7.16	360	0	1.94
37	-	-	-	230	0	-
38	6.2	6.97	4.35	90	0	1.70
39	7.7	6.85	4.46	490	0	1.85
40	8.0	6.83	5.08	-	-	1.87
41	9.7	7.60	9.52	90	0	1.92
42	5.9	7.52	8.42	450	0	2.55
43	7.7	7.44	5.66	0	0	1.46
44	-	-	-	20	0	-
45	9.5	7.10	5.77	410	0	1.61
46	4.0	7.01	5.49	170	24*	1.65
47	4.9	6.97	6.23	0	0	2.46
48	6.7	6.99	5.87	110	5	1.70
49	5.0	6.66	4.60	130	0	1.54
50	9.1	7.03	8.43	0	0	2.20
51	5.9	6.90	7.32	370	0	1.77
Means	6.9	6.9	6.3	207	2	1.8

for classifying the 862 catchments in this study based directly on the variability in stream channel morphology. This bottom-up approach involved first reducing the channel morphology data using principal components analysis (PCA) (ter Braak 1987). I then clustered the PCA scores using the same two-step approach as described for the top-down approach for catchment classification.

Principal Components Analysis

Channel morphology values are often highly auto-correlated with each other. For instance, channel width and depth both tend to increase with increasing catchment size; in addition, reach slope angle and median particle size both tend to decrease with decreasing average slope in a drainage basin. Therefore, it is helpful to account for this auto-correlation by reducing the number of attributes before attempting to classify the stream channels into distinct groups. Principal Components Analysis (PCA) is well suited to this data reduction task. PCA is also used to identify underlying factors or processes that may explain the variance in a large data matrix. The analysis seeks to collect the common variance among many variables into one factor. The process helps to identify independent variables with common variance, which is likely measuring the same phenomenon, in order to combine those variables into uncorrelated new variables. This indirect gradient analysis creates groupings, called principal components, by maximizing the variance among the *variables* (columns of data); in this manner, it differs from the cluster analysis process, which creates groups of *cases* (rows of data).

The PCA process is similar to regression in that PCA attempts to capture the variability in a dataset. The first principal component is considered a new variable that explains as much linear variation in all of the original variables as is possible; the second component explains as much of the remaining variation as is possible, and so on. The model will calculate as many principal components as the number of columns in the dataset; however, normally only the first few components explain any

significant amount of variation in the original data. The eigenvalue refers to the magnitude of the component vector; larger eigenvalues explain more variation. In general, eigenvalues should be at least greater than 1.0 because the principle component should be at least as important to the model as the original variable (ter Braak 1987). With PCA, I could calculate the percentage of variation that each component explains in the model as well as determine which axis best explained certain variables based on the component 'loadings,' values that indicate the strength of correlation between an original variable and a principal component.

I conducted PCA on the channel morphology data in order to collapse highly correlated variables into the same principal component. When constructing the components, I used a varimax rotation in order to make each component orthogonal and thus, not correlated with the other components. In addition, I saved the component scores, which can be thought of as the coordinates of each original channel morphology value in principal component space, using the Anderson-Rubin method (Anderson and Rubin 1956), a technique that standardizes the component scores to a mean of zero with a standard deviation of one.

Using the component loadings and the component scores, I described each principal component and graphed the location of each stream channel relative to the component axes. Based on the spatial distribution of each measured stream channel in principal component space, I was able to detect underlying physical processes represented by the principal components that aided in explaining the distribution of channel morphology values.

Stream Channel Clustering

In order to organize the stream channels into groups with similar channel morphology, I ran a two-step clustering procedure similar to that used in the catchment clustering process. I used Ward's method for hierarchical cluster analysis

(Ward 1963) to group the 47 reaches based on the standardized PCA scores rather than the raw channel morphology values. I selected the stopping point for clustering using the dendrogram and by finding large gaps in the distance measurement of the agglomeration schedule table. I then refined the group assignments using k-means clustering (Hartigan 1975).

Bottom-Up Classification Results

Prior to running to running the PCA, I tested whether the sample distribution of stream channel morphology was similar to a normal distribution. I evaluated the Shaprio-Wilk test statistic (Shapiro et al. 1968), which is used when sample sizes are relatively small. If the statistic is not significant, at the 0.05 level, then no difference between the sample distribution and a normal distribution is detected. I also examined a histogram of the sample data to evaluate the shape of the distribution, a boxplot to note any outliers, and a normal probability plot to check for a linear pattern as predicted by normally distributed data. If a category did not fit a normal distribution, I log-transformed the data and re-tested for normality.

Bankfull width and depth were the only channel morphology values that appeared to follow a normal distribution, as their Shaprio-Wilk statistics were not significant (Table 9). However, an examination of the box plots for both width and depth showed several outliers from the distribution. In fact, each variable had several outliers that were much larger than the mean. This indicated that a log transformation of the variables would better approximate a normal distribution, as log transforming tends to reduce the impact of extremely large values.

I log-transformed all of the variables and evaluated the Shaprio-Wilk statistic for normality (Table 10). All of the log-transformed variables followed a normal distribution, except for the log of reach slope. By examining the histograms, I

Table 9. Test for normality of stream channel morphology variables. Significant Shaprio-Wilk statistics indicate the distribution is different from a normal distribution.

	Shaprio-Wilk		
	Statistic	df	Sig.
Width	0.09	48	0.23*
Depth	0.16	48	0.25*
X-Area	0.22	48	0.01*
Reach Slope	0.14	48	0.10*
d50	0.17	48	0.01*
SS	0.23	48	0.01*

*Significant at 0.05 level

Table 10. Test for normality of log-transformed stream channel morphology variables. Significant Shaprio-Wilk statistics indicate the distribution is different from a normal distribution.

	Shaprio-Wilk		
	Statistic	df	Sig.
Log Width	0.12	47	0.06*
Log Depth	0.11	47	0.63*
Log X-Area	0.11	47	0.20*
Log Reach Slope	0.14	47	0.01*
Log d50	0.07	47	0.40*
Log SS	0.08	47	0.86*

*Significant at 0.05 level

determined that the original reach slope values more closely approximated a normal distribution. Thus, I used the log-transformed values for all channel morphology variables, except for reach slope, in all further analyses.

Having run the principal components analysis using the logs of bankfull width, depth, and cross-sectional area, reach slope, and the logs of median particle size and stored sediment, I retained the first two principal components (PC1 and PC2) as these were the only components with eigenvalues greater than 1.0 (Table 11). The first component captured 46.1% of the variation in the original data, and the second component accounted for 21.7% for a cumulative total of 67.8% variation explained with this model. The third component added another 14.5% explained variation to the model but had an eigenvalue less than 1.0, so was not retained.

The rotated component matrix table is helpful for explaining the meaning of a particular component. The table shows how each variable 'loads' on each component. Higher absolute values indicate that more variation is captured by that component; the sign of the loading indicates the direct or inverse relationship between the component and the variable. For instance, the logs of bankfull width, depth, and cross-sectional area all loaded highly on PC1, and the sign of each loading was positive (Table 12). This means that PC1 explained the combined variation of these three variables, and that higher component scores were related to relatively wider, deeper, and larger stream channels. PC2 captured the variation in reach slope and the log of median particle size; it was also a direct relationship, meaning that streams with high PC2 scores were likely to have steep water surface slopes and large particles in the bed material. The log of stored sediment had split loadings between both components. It is likely that this variable would load on a third component; however, it is not useful to have a component that explains only one variable. This variable was negatively loaded on each component, indicating that low PC1 or PC2 scores may be indicative of streams with high amounts of stored sediment.

Table 11. Eigenvalues for the six principal components extracted from the channel morphology variables.

Component	*Eigenvalues*		
	Total	% of Variance	Cumulative %
1	2.76	46.07	46.07
2	1.30	21.74	67.81
3	0.87	14.51	82.32
4	0.61	10.24	92.56
5	0.45	7.44	100.00
6	<0.01	<0.01	100.00

Table 12. Rotated component matrix for the two principal components used in the analysis. Higher absolute values indicate to what degree each variable is explained by a particular component.

	Component 1	*Component 2*
Log Width	0.83	0.09
Log Depth	0.83	0.08
Log X-area	0.99	0.10
Reach Slope	-0.06	0.87
Log d50	0.23	0.78
Log SS	-0.39	-0.34

I used the standardized component scores for each of the 47 reaches to group streams using the aforementioned two-step classification procedure. In the first step, Ward's method for hierarchical clustering (Ward 1963), I found five distinct groups of stream channels based on the dendrogram and the agglomeration schedule (Table 13). The first large gap in cluster distances occurred at stage 39, which would be an eight-cluster solution. However, by moving only a little distance to the right in the dendrogram, I encountered a large gap beginning with the five-cluster solution. A pronounced change in the agglomeration schedule occurred at stage 43, a four-cluster solution; yet, that stage combined two large groups creating a new group that contained over half the reaches. Thus, I selected the five-cluster solution as being most likely to represent small within-group variation and high between-group differences of means.

For the second step of the reach clustering procedure, I used the cluster centroids from the hierarchically clustered groups as the beginning point for k-means clustering into five groups. Only two cases changed group membership in the k-means procedure. The ANOVA result from the k-means clustering (Table 14) showed that each of the components made a significant contribution to the model. In addition, Table 15 also showed that the actual channel morphology values differed significantly between the groups, with the exception of stored sediment.

Table 16 shows the case count and description of each bottom-up classified group (BU-1 through BU-5) based on the range of channel morphology values in each group. In order to aid in describing the type of channel morphology of each group as well as to explain any underlying processes captured by the PCA procedure, it was helpful to plot the catchments into principal component space (Figure 11). The largest group of catchments, with 16 cases, was BU-5, which had mid-range values for all the channel morphology measurements; all of the component scores are near zero. Relative to this group, the 13 reaches in BU-2 had roughly the same size

Table 13. Agglomeration schedule for hierarchical clustering of stream reaches based on channel morphology variables.

Stage	*Clusters Combined*		*Coefficients*	*Stage Cluster First Appears*		*Next Stage*
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	29	30	0.003	0	0	27
2	27	28	0.006	0	0	22
3	19	23	0.012	0	0	13
4	20	21	0.020	0	0	9
5	36	37	0.029	0	0	35
6	3	5	0.038	0	0	14
7	8	10	0.054	0	0	18
8	15	17	0.070	0	0	10
9	16	20	0.088	0	4	16
10	15	18	0.106	8	0	17
11	40	43	0.126	0	0	19
12	6	9	0.152	0	0	21
13	19	22	0.177	3	0	23
14	3	7	0.204	6	0	20
15	11	12	0.235	0	0	26
16	16	24	0.277	9	0	25
17	13	15	0.342	0	10	26
18	4	8	0.408	0	7	21
19	40	41	0.480	11	0	28
20	2	3	0.581	0	14	33
21	4	6	0.705	18	12	37
22	25	27	0.839	0	2	32
23	19	26	0.984	13	0	31
24	39	42	1.133	0	0	34
25	14	16	1.287	0	16	36
26	11	13	1.454	15	17	31
27	29	31	1.663	1	0	32
28	38	40	1.887	0	19	34
29	34	35	2.127	0	0	39
30	1	44	2.474	0	0	37

Table 13. Continued.

Stage	*Clusters Combined*		*Coefficients*	*Stage Cluster First Appears*		*Next Stage*
	Cluster 1	Cluste r 2		Cluster 1	Cluster 2	
31	11	19	2.982	26	23	36
32	25	29	3.684	22	27	40
33	2	47	4.387	20	0	42
34	38	39	5.107	28	24	45
35	33	36	5.862	0	5	39
36	11	14	6.815	31	25	43
37	1	4	8.000	30	21	38
38	1	45	9.557	37	0	42
39	33	34	11.150	35	29	41
40	25	32	13.148	32	0	44
41	33	46	16.025	39	0	44
42	1	2	19.051	38	33	43
43	1	11	27.566	42	36	45
44	25	33	41.065	40	41	46
45	1	38	59.574	43	34	46
46	1	25	92.000	45	44	0

Table 14. ANOVA table from the stream channel k-means cluster procedure. The results show that each component made a significant contribution to the model. The magnitude of the F statistic indicates the importance of that attribute in the clustering procedure.

	Cluster		*Error*			
	Mean Square	df	Mean Square	df	*F*	*Sig.*
PC1	9.106	4	.228	42	39.934	0.00
PC2	9.164	4	.222	42	41.187	0.00

Table 15. ANOVA results showing that channel morphology values differ between the five catchment groups.

		Sum of Squares	*df*	*Mean Square*	*F*	*Sig.*
Log Width	Between Groups	0.53	4	0.13	14.70	0.00
	Within Groups	0.37	42	0.01		
	Total	0.90	46			
Log Depth	Between Groups	0.55	4	0.14	16.08	0.00
	Within Groups	0.36	42	0.01		
	Total	0.92	46			
Log X-area	Between Groups	2.08	4	0.52	40.95	0.00
	Within Groups	0.53	42	0.01		
	Total	2.62	46			
Reach Slope	Between Groups	0.06	4	0.01	21.28	0.00
	Within Groups	0.03	42	0.01		
	Total	0.09	46			
Log D50	Between Groups	1.42	4	0.35	13.49	0.00
	Within Groups	1.10	42	0.02		
	Total	2.52	46			
Log Stored Sediment	Between Groups	1.70	4	0.42	2.33	0.07
	Within Groups	7.67	42	0.18		
	Total	9.38	46			

Table 16. Number of cases in each reach cluster and cluster descriptions.

Bottom-up Groups	*Count*	*Description*
BU-1	5	Narrow, shallow, small channel, low slope, small particle size, and high stored sediment
BU-2	13	Relatively wide, relatively deep, relatively deep channel, relatively low slope, relatively small particle size, and mid-range of stored sediment
BU-3	7	Relatively narrow, relatively shallow, relatively small channel, relatively large particle size, relatively high stored sediment
BU-4	6	Wide, deep, large channel, relatively steep, large particle size, low stored sediment
BU-5	16	Mid-sized width, depth, and channel, moderate slope, relatively low stored sediment
Total	47	

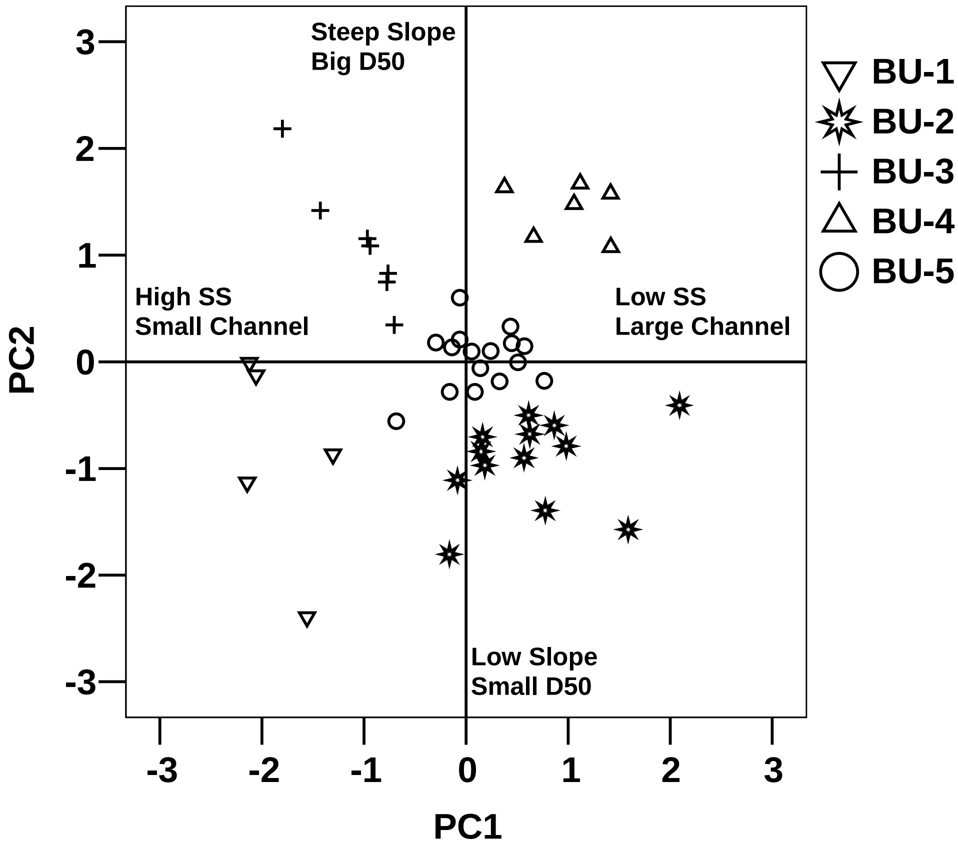

Figure 11. Bottom-up catchment groups plotted by first and second principal component score. (SS, stored sediment)

channels but had shallower slopes, smaller median particle sizes and higher amounts stored sediment. Reaches in BU-1 and BU-4 were mirror opposites. BU-1 had the smallest stream channels, high levels of stored sediment, and low reach slopes while BU-4 reaches had the largest channels, low stored sediment, and steep slopes. Finally, BU-3 reaches were relatively small and steep, but had both large median particle sizes and large amounts of stored sediment.

Each of the five groups had good clustering in principal component space. In fact, no single case overlapped spatially on any one component with more than two other groups. Hence, only one group dominated each quadrant of the graph. For instance, with respect to PC2, reaches in BU-3 and BU-4 had values similar to each other but did not overlap with reach values in either BU-1 or BU-2. However, BU-3 and BU-4 were quite different from each other with respect to scores on PC1. Reaches in BU-5 had moderate values for both components, while each of the other groups had relatively high values on at least one component. This was convenient for modeling each stream channel, as BU-5 reaches could serve as a reference group for comparing each of the other types of stream channels.

Using the component loadings with respect to the original channel morphology data, I detected two drivers in fluvial processes, discharge and sediment flux, represented by each of the principal components. Channels get larger with increasing PC1 scores, indicating a likely increase in discharge along this axis. This is also supported by the fact that stored sediment decreases with increasing PC1 scores, indicating increased possible scour and capacity in the larger channels. High PC2 scores represented steeper channels with larger median particle sizes, which can be interpreted as decreased transport of fines and possible degradation. Low PC2 scores likely represent streams that are aggrading, because they have lower slopes, smaller median particle sizes, and high levels of stored sediment.

Classifying each catchment based on its respective stream channel's grouping completed the bottom-up catchment classification procedure. In view of the fact that the groupings are based on stream channel morphology, I expected that the ANOVA analysis, which tests the difference of mean channel morphology values between catchments, would be highly significant, as the clustering process is based on minimizing within-group variation while maximizing between group variation. This does not mean that this second approach is better at delineating catchments with different channel morphologies, because I had really only classified the sampled reaches themselves at this point. In order to test the efficacy of this bottom-up catchment classification procedure, I needed to, first, determine whether any relationship was evident between the reach-scale channel morphology data and the landscape-scale data, and, second, assess the success of predicting group membership based solely on the landscape-scale attribute data within each catchment.

CHAPTER V
ASSESSING THE CLASSIFICATION TECHNIQUES

The top-down classification of catchments using landscape-scale attributes resulted in six groups with distinctly different combinations of landscape attributes; however, whether each of these groups has significantly different stream channel morphology remains to be seen. In other words, can the top-down procedure create combinations of landscape-scale attributes that actually represent watershed-scale processes, and will differences between groups be reflected by different stream channel characteristics? The bottom-up approach to catchment classification organized reaches into five groups with distinctly different types of stream channels. These groups appeared to reflect various magnitudes of discharge and sediment flux, resulting in different types of stream channels; but whether this variability is directly related to any watershed-scale processes has not been shown. Hence, the question remains, can landscape-scale attributes, in any way, predict stream channel habitat?

It is important to test the efficacy of each classification and especially to quantify the relationships between landscape-scale attributes and reach-scale values in order to link landscape processes to stream channel morphology. In this chapter, I explore the relationship between landscape-scale attributes and stream channel morphology; then, I test the effectiveness of each classification method for linking these two scales of data with the goal of accurately predicting reach-scale channel morphology values throughout all headwater systems in Great Smoky Mountains National Park.

Relationship Between Landscape and Reach-Scale Data

In order to achieve a successful top-down or bottom-up catchment classification, a causal relationship between the landscape-scale information and reach-scale data must exist. In other words, I wished to determine if any of the landscape-scale

attributes and channel morphology values co-varied in a linear fashion. To assess this covariance, I used bivariate correlation analysis (Sokal and Rohlf 1995), which pairs each variable with every other variable in a *p* x *p* matrix (where *p* is an independent predictor variable). The standardized extent to which the two variables are proportionate to each other in a linear fashion, that is to which they co-vary either directly or inversely, is described by the correlation coefficient; these coefficient values range from –1.00 (perfect inverse correlation) to 1.00 (perfect direct correlation), with a value near zero indicating no relationship between the two variables.

Given that the landscape-scale attributes have several 0% values in the land use and rock strength categories, these variables do not follow a normal distribution as is required when calculating the Pearson's R correlation coefficient (Sokal and Rohlf 1995). Therefore, I calculated the nonparametric Spearman's *rho* (r_s) as the rank correlation coefficient (Siegel and Castellan 1988). Spearman's *rho* is less sensitive than Pearson's R; however, the interpretation of the coefficient and its significance level is the same.

An evaluation of the Spearman's *rho* correlation coefficients (Table 17) showed that the log of catchment area was highly correlated with the logs of bankfull width, depth, and cross-sectional area, as would be expected based on the established relationship between watershed size and bankfull stream channel dimensions (Dunne and Leopold 1978). Circularity of a catchment's shape was directly related to the log of median particle size, which suggests the higher peak flows in circular watersheds led to relatively higher bedload transport capacities. The mean elevation and mean slope of a catchment were positively correlated with reach slope; hence, high elevation, steeply inclined reaches had steep longitudinal profiles. Mean catchment slope was also positively related to the median particle size in a streambed,

Table 17. Correlation coefficients between stream channel morphology values and landscape-scale attributes.

		Log Width	*Log Depth*	*Log X-area*	*Reach Slope*	*Log d50*	*Log SS*
Log Area	rho	0.58*	0.43*	0.62*	-0.25	0.09	-0.08
	Sig.	0.00	0.00	0.00	0.09	0.54	0.60
Circularity	rho	0.22	0.19	0.20	0.08	0.30*	-0.02
	Sig.	0.15	0.21	0.18	0.57	0.04	0.88
Resultant Aspect	rho	-0.01	-0.02	0.00	0.21	0.05	-0.22
	Sig.	0.96	0.91	0.99	0.15	0.74	0.15
Mean Elevation	rho	0.09	-0.02	0.02	0.38*	0.29	-0.04
	Sig.	0.56	0.90	0.90	0.01	0.05	0.78
Mean Slope	rho	0.13	-0.08	0.03	0.32*	0.42*	-0.27
	Sig.	0.40	0.59	0.86	0.03	0.00	0.07
Burned Area	rho	-0.07	0.05	0.02	0.24	0.14	-0.13
	Sig.	0.62	0.76	0.87	0.11	0.34	0.39
Lightly Disturbed	rho	-0.14	-0.18	-0.19	-0.09	-0.29	0.06
	Sig.	0.36	0.22	0.19	0.56	0.05	0.69
Heavily Disturbed	rho	-0.25	-0.05	-0.12	0.25	0.05	.31*
	Sig.	0.09	0.74	0.41	0.09	0.73	0.03
Pristine	rho	0.32*	0.21	0.28	-0.09	0.24	-0.28
	Sig.	0.03	0.16	0.06	0.55	0.11	0.06
Settled Area	rho	0.03	-0.11	0.00	-0.43*	-0.36*	0.17
	Sig.	0.83	0.45	0.99	0.00	0.01	0.27
Weak Rocks	rho	0.14	-0.18	0.00	-0.43*	-0.01	-0.09
	Sig.	0.36	0.22	0.99	0.00	0.93	0.55
Medium Rocks	rho	0.07	0.22	0.21	0.18	-0.07	-.29*
	Sig.	0.66	0.14	0.16	0.22	0.65	0.05
Strong Rocks	rho	-0.15	-0.11	-0.18	-0.07	-0.07	0.27
	Sig.	0.33	0.48	0.22	0.63	0.65	0.07
Very Strong Rocks	rho	-.32*	-0.11	-0.28	0.15	-0.07	0.23
	Sig.	0.03	0.48	0.06	0.32	0.62	0.13

*Correlation is significant at the 0.05 level, n = 47.

confirming that reaches with low slopes are more likely to store fine sediments (Schumm 1977).

The land use categories of burned area and light disturbance did not show a significant relationship with any of the channel morphology values; however, the other land use categories did show strong correlations. Catchments with high percentages of heavily disturbed areas had high values for stored sediment indicating storage of eroded material. The settled area attribute was inversely related to reach slope; this may be a function of aggradation in the stream channel, but is more likely related to people building settlements in less steep places. Catchments that were largely pristine tended to have wider stream channels; this is consistent with other findings both in the park (Hart 2002) and in other temperate regions (Davies-Colley 1997), which demonstrated that old-growth forests contribute coarse woody debris to streams leading to channel scour and widening.

The rock strength category produced both expected and counterintuitive correlation results with stream channel morphology. The percent coverage of weak rocks was inversely correlated with reach slope, indicating that the more easily weathered material was efficiently transported to stream channels possibly leading to an accumulation of fines. However, the medium-strength rocks category was inversely related to median particle size, which suggests catchments with these relatively easily weathered rocks were not delivering abundant fines to the stream channels. Matmon et al. (2003) found that deep soils in Southern Appalachian mountains restricted rates of bedrock erosion; hence, it may be that soils happen to be thicker in the sampled catchments with medium strength rocks, which would restrict the transport of fines from the hillslopes.

With respect to rock strength, it may also be true that catchments with weak rocks have generally lower slopes throughout the catchment; thus, the correlation between

weak rocks and reach slope would be a function of drainage basin evolution rather than an indication of sediment accumulating in the stream channels. The very strong rocks category was inversely correlated with channel width, meaning catchments with this type of geology tended to have narrow stream channels; this, also, is consistent with observations showing that more resistant rock inhibits lateral erosion of the stream channel (Duval et al. 2004).

Based on these relationships, ten landscape-scale attributes—catchment area and circularity, mean slope and elevation, pristine, heavily disturbed, and settled land uses, weak, medium, and very strong rocks—appeared to be good candidates for use in further modeling of the relationship between landscape processes and stream channel morphology. Having established this set of significant relationships, I proceeded to test the effectiveness of each classification technique in creating distinct groupings that reflected these significant relationships between landscapes and stream channels.

Assessment of the Top-Down Approach

Using a top-down approach, I had classified all 862 catchments into a discrete number of groups based on landscape-scale attribute information (Chapter III). To determine whether these groups differed from each other with respect to channel morphology, I used analysis of variance (ANOVA) (Fisher 1954) and analysis of covariance (ANCOVA) (Sokal and Rohlf 1995) to test for significant differences in bankfull width, depth, and cross-sectional area, reach slope, median particle size, and stored sediment between the various groups of classified catchments. I first assessed any difference between groups based on un-weighted data, and then I assessed for differences between the groups while controlling for the size of each catchment.

Comparison of Group Means

I used ANOVA to test for the equality of group means in channel morphology between the six top-down classified groups. This test actually compares the variation within each group to the variation between all of the other groups. If the variation between the groups is large relative to the within-group variation of a particular group, then the groups are considered to be quite different. This test requires that observations in each category be normally distributed and that population variances be equal or homoscedastic (Sokal and Rohlf 1995). To assess homoscedasticity, I applied Levene's (1960) test; if the Levene statistic is not significant, at the 0.05 level, then homogeneity of variance can be assumed. Although it is optimal to have homoscedasticity, the ANOVA technique is still quite robust if this assumption is not met.

Having already log-transformed the channel morphology data in order to achieve a normal distribution, I ran an ANOVA test to determine whether channel morphology values differed significantly with each classified group. If I found a significant difference between the groups for any particular category, I assessed the results of a *post hoc* test to determine which groups were significantly different from any of the others. I used the Bonferroni *post hoc* test (Sokal and Rohlf 1995) to compare groups that had equal variance (they do not have a significant Levene's test statistic); this Bonferroni method computes a t statistic for each combination of the groups, but the significance levels are adjusted based on the total number of groups. For groups with unequal variance, I used Tamhane's T2 *post hoc* test, which also compares groups based on a t statistic (Sokal and Rohlf 1995).

Comparison of Group Means Controlling for Area

In humid temperate regions, it is often the case that stream channels get larger as the drainage area of the catchment increases (Dunne and Leopold 1978). Therefore, it may be necessary to account for the size of a catchment when comparing channel

morphology values. I used catchment area as a covariate in an ANCOVA procedure to compare differences between mean channel morphology values for each group while controlling for differences in drainage area. ANCOVA is a technique for reducing within-group variability when a covariate is related to a dependent variable the same way in each group (Sokal and Rohlf 1995). With ANCOVA, a regression of the dependent variable on the covariate is done for each group, and the residuals are used for an analysis of variance procedure. Like ANOVA, if the within-group variation around the mean, which in this case is a regression line, is less than the between-group variation, then at least some of the groups differ significantly from the others.

This test requires that the dependent variable be normally distributed, that the relationship between the dependent variable and the covariate is linear, and that the slope of the within-group regression is the same across all groups. Having previously determined that the dependent variables follow a normal distribution, and transforming variables as necessary, I regressed each channel morphology value on catchment area looking for a linear relationship. To evaluate homogeneity of slopes across groups, I ran the ANCOVA procedure using the dependent variable, the covariate, and the interaction between the two variables. If the interaction term is not significant in this model, then the slopes are considered to be equal in each group. Having checked the assumptions of the ANCOVA model, I proceeded to test for any significant difference in channel morphology values between the classified groups while controlling for catchment size.

Top-Down Assessment: Results and Further Tests

I proceeded to conduct an ANOVA, with *post hoc* tests, to assess for any difference in channel morphology values between the classified catchments. Two variables, reach slope and the log of stored sediment, showed significant differences between the catchment groups. The log of bankfull width was the only variable that did not

show homogeneity of variance across all groups; however, its *F* statistic was not significant, so it was not necessary to examine the *post hoc* test for this variable (Table 18). Nor was it necessary to look for group differences based on the log of depth, log of cross-sectional area, or the log median particle size. Although reach slope had a significant ANOVA result, TD-1 and TD-3 were the only catchment groups that were significantly different from each other according to the *post hoc* test. With respect to the log of stored sediment, TD-5 was significantly different from both TD-3 and TD-4; however, TD-3 and TD-4 were not different from each other. For all other variables and all other cases, I found no significant difference in channel morphology values between the top-down classified catchment groups.

The first step in the ANCOVA analysis was to determine if a linear relationship existed between catchment size and each of the channel morphology variables. I used the log of catchment area in this analysis because the relationship between drainage area and bankfull dimensions has been shown to have a log-linear relationship (Dunne and Leopold 1978). The logs of bankfull width, depth, cross-sectional area and the un-transformed reach slope values showed a significant linear relationship with the log of catchment area (Table 19 and Figures 12-17). However, values for the log of median particle size and the log of stored sediment were not affected by catchment size, so I did not run an ANCOVA analysis for these two variables.

The next step in the ANCOVA process was to test for homogeneity of slopes between the groups. I ran the ANCOVA and evaluated the interaction between catchment area and each channel morphology variable; a significant interaction would indicate that the slopes were different in some groups. The interaction term, *Groups*Log area*, was not significant for any of the four variables tested (Table 20); therefore, the slopes were considered to be similar in each catchment group.

Table 18. Results of ANOVA testing for differences in channel morphology between the six top-down classified catchments.

		Sum of Squares	*df*	*Mean Square*	*F*	*Sig.*
Log Width	Between Groups	0.13	5	0.03	1.36	0.26*
	Within Groups	0.78	41	0.02		
	Total	0.91	46			
Log Depth	Between Groups	0.12	5	0.02	1.05	0.40*
	Within Groups	0.82	41	0.02		
	Total	0.92	46			
Log X-area	Between Groups	0.44	5	0.09	1.65	0.17*
	Within Groups	2.18	41	0.05		
	Total	2.62	46			
Reach Slope	Between Groups	0.02	5	0.01	2.50	0.04*
	Within Groups	0.08	41	0.01		
	Total	0.09	46			
Log D_{50}	Between Groups	0.46	5	0.09	1.80	0.13*
	Within Groups	2.07	41	0.05		
	Total	2.52	46			
Log SS	Between Groups	3.031	5	0.61	3.91	0.01*
	Within Groups	6.351	41	0.16		
	Total	9.383	46			

*The mean difference is significant at the 0.05 level

Table 19. Regression results from testing the linear relationship between the log of catchment area and each of the channel morphology variables.

Log Area &	*R Square*	*Std. Error of the Estimate*	*Sig.*
Log Width	0.30	0.11	0.00*
Log Depth	0.12	0.13	0.01*
Log X-area	0.30	0.19	0.00*
Reach Slope	0.07	0.04	0.04*
Log d50	-0.01	0.23	0.53
Log SS	-0.01	0.45	0.47

*Significant at the 0.05 level

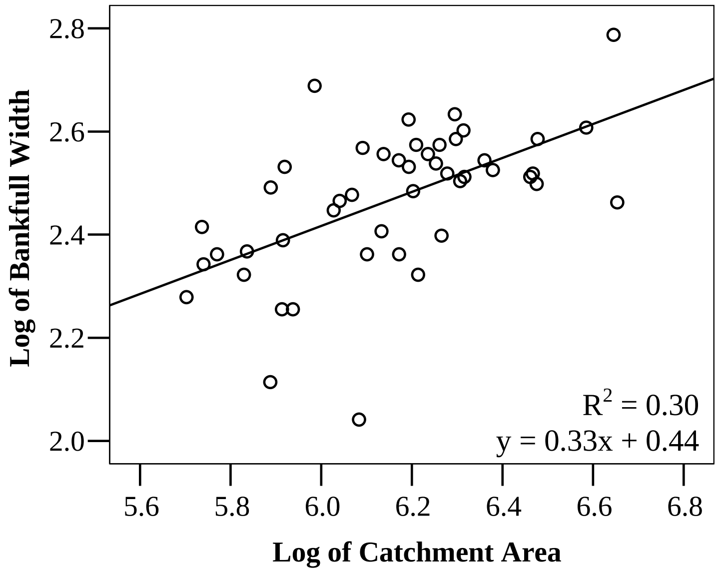

Figure 12. Scatter plot showing the linear relationship between the log of catchment area and the log of bankfull width.

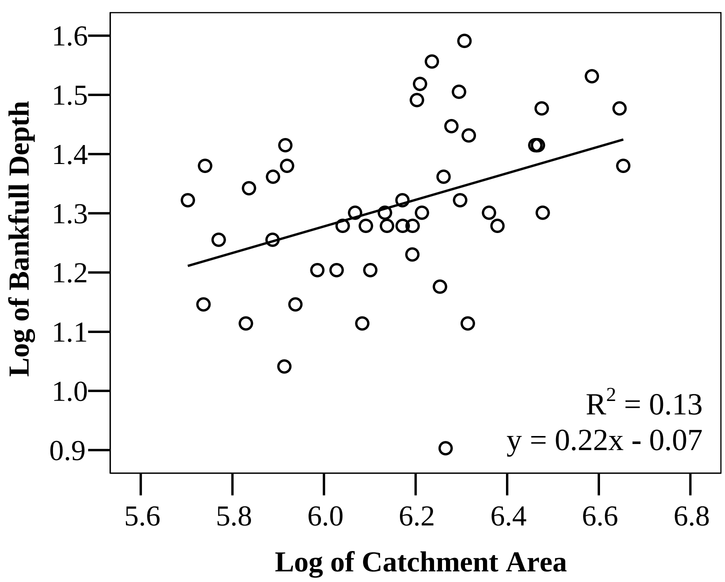

Figure 13. Scatter plot showing the linear relationship between the log of catchment area and the log of bankfull depth.

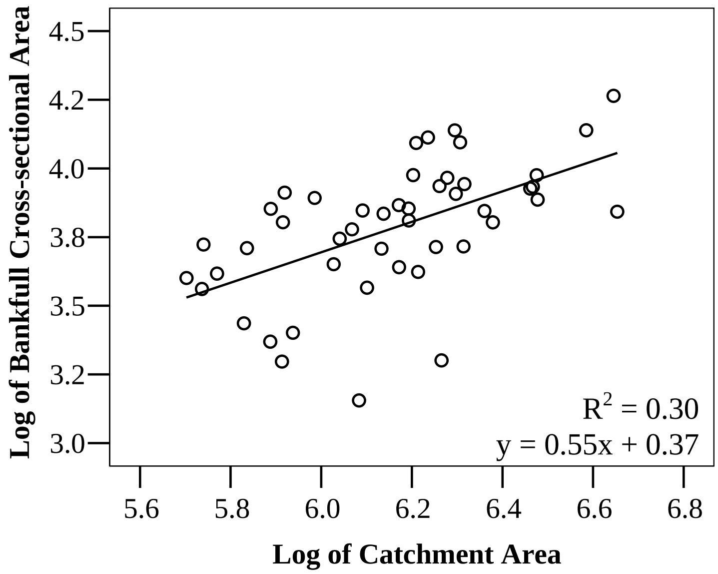

Figure 14. Scatter plot showing the linear relationship between the log of catchment area and the log of bankfull cross-sectional area.

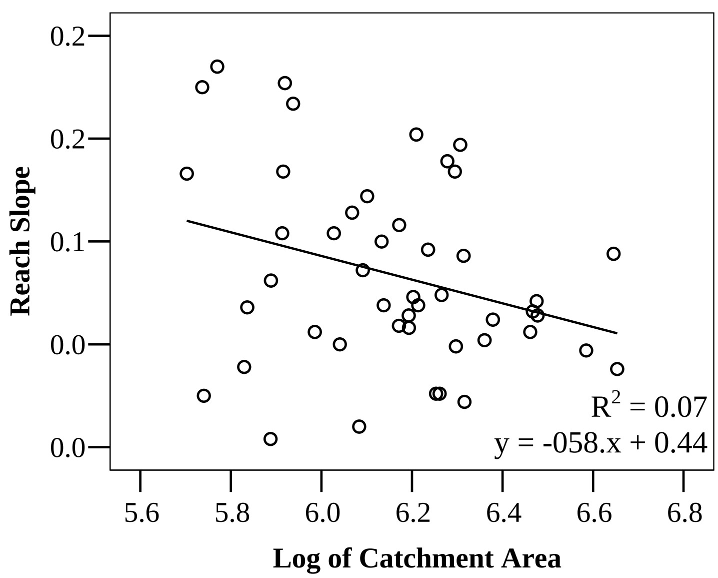

Figure 15. Scatter plot showing the somewhat linear relationship between the log of catchment area and reach slope.

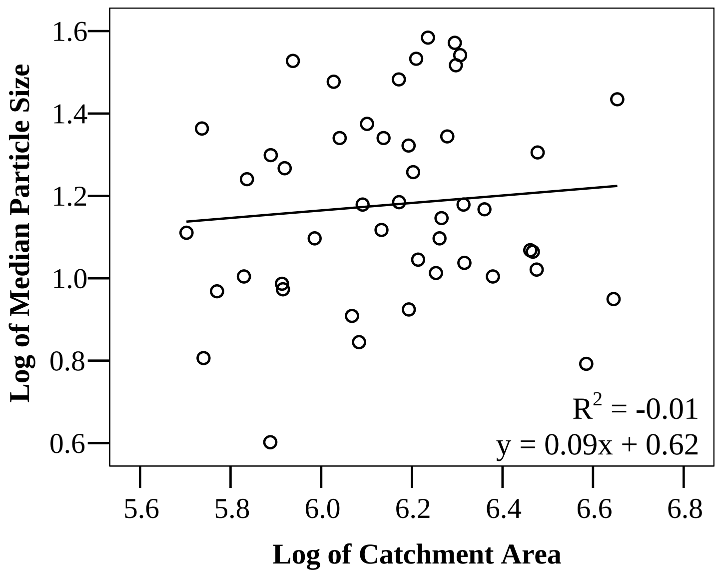

Figure 16. Scatter plot showing no linear relationship between the log of catchment area and the log of median particle size.

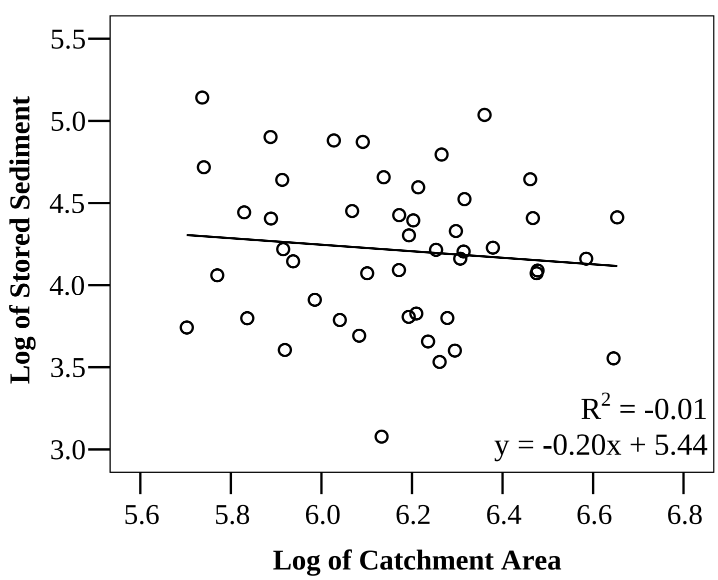

Figure 17. Scatter plot showing no linear relationship between the log of catchment area and the log of stored sediment.

Table 20. ANCOVA analysis run with the classified groups and catchment area set as an interaction term (in bold) in order to assess the homogeneity of slopes.

Source	*Dependent Variable*	*Type III Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Corrected Model	Log width	0.39	11	0.04	2.43	0.02
	Log depth	0.29	11	0.03	1.47	0.19
	Log x-area	1.17	11	0.11	2.55	0.02
	Reach Slope	0.04	11	0.00	2.05	0.05
Intercept	Log width	0.00	1	0.00	0.14	0.71
	Log depth	0.00	1	0.00	0.12	0.73
	Log x-area	0.01	1	0.01	0.21	0.65
	Reach Slope	0.01	1	0.01	3.98	0.05
Groups	Log width	0.04	5	0.01	0.54	0.75
	Log depth	0.05	5	0.01	0.58	0.72
	Log x-area	0.02	5	0.00	0.09	0.99
	Reach Slope	0.00	5	0.00	0.30	0.91
Log of Catchment Area	Log width	0.11	1	0.11	7.14	0.01
	Log depth	0.04	1	0.04	2.00	0.17
	Log x-area	0.27	1	0.27	6.37	0.02
	Reach Slope	0.01	1	0.01	3.01	0.09
Groups*Log area	**Log width**	**0.04**	**5**	**0.01**	**0.56**	**0.73**
	Log depth	**0.05**	**5**	**0.01**	**0.57**	**0.72**
	Log x-area	**0.02**	**5**	**0.00**	**0.10**	**0.99**
	Reach Slope	**0.00**	**5**	**0.00**	**0.30**	**0.91**
Error	Log width	0.52	35	0.02		
	Log depth	0.63	35	0.02		
	Log x-area	1.45	35	0.04		
	Reach Slope	0.06	35	0.00		
Total	Log width	287.40	47			
	Log depth	82.00	47			
	Log x-area	675.00	47			
	Reach Slope	0.43	47			
Corrected Total	Log width	0.91	46			
	Log depth	0.92	46			
	Log x-area	2.62	46			
	Reach Slope	0.10	46			

I then re-ran the ANCOVA without the interaction term in the model to evaluate any differences between the groups while controlling for the effect of the covariate, catchment size. The group variable, in Table 21, showed the effect of interest; I evaluated the significance of the *F* statistic for each stream channel morphology dependent variable to determine if the top-down groups were significantly different for that variable while controlling for the log of catchment area. The group factor was only significant for the reach slope variable, which was similar to the ANOVA results (Table 18). This indicated that the classified groups successfully discriminated between some groups with respect to reach slope and that the differences were not simply a function of catchment size. However, this is not the case for bankfull width, depth, or cross-sectional area. In fact, the addition of top-down group information detracted from the ability of catchment size to explain variation in channel width, depth, and cross-sectional area. For instance, the catchment area to channel width model was stronger when using just catchment area ($r^2 = 0.31$, Table 19) then the model with the added group factor ($r^2 = 0.29$, Table 21, see 'Corrected Model').

Top-Down Assessment: Discussion

The intent of the top-down classification was to create groups of headwater catchments that had significantly different types of stream channels. In the previous section, I showed that several landscape-scale attributes were correlated with stream channel morphology values and that these relationships were consistent with results from other geomorphic studies. However, the groups created in the top-down classification procedure showed few differences between each other with respect to reach-scale values. The technique had some success, which is worth discussing further as it reinforces the influence of hillslopes on stream channel processes. Yet, ultimately, the top-down approach did not fulfill the requirements necessary to support my first hypothesis.

Table 21. ANCOVA analysis run with the classified groups as the contributing factor of interest (in bold) and catchment area as a covariate.

Source	*Dependent Variable*	*Type III Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Corrected Model	Log width	0.35(a)	6	0.06	4.21	0.00*
	Log depth	0.24(b)	6	0.04	2.35	0.05*
	Log x-area	1.15(c)	6	0.19	5.18	0.00*
	Reach Slope	0.04(d)	6	0.01	3.84	0.00*
Intercept	Log width	0.00	1	0.00	0.07	0.79*
	Log depth	0.01	1	0.01	0.59	0.45*
	Log x-area	0.01	1	0.01	0.13	0.72*
	Reach Slope	0.02	1	0.02	10.90	0.00*
Log of Catchment Area	Log width	0.22	1	0.22	16.02	0.00*
	Log depth	0.14	1	0.14	7.92	0.01*
	Log x-area	0.71	1	0.71	19.15	0.00*
	Reach Slope	0.01	1	0.01	8.30	0.01*
Groups	**Log width**	**0.06**	**5**	**0.01**	**0.86**	**0.52***
	Log depth	**0.11**	**5**	**0.02**	**1.23**	**0.32***
	Log x-area	**0.32**	**5**	**0.06**	**1.73**	**0.15***
	Reach Slope	**0.03**	**5**	**0.01**	**3.46**	**0.01***
Error	Log width	0.56	40	0.01		
	Log depth	0.68	40	0.02		
	Log x-area	1.47	40	0.04		
	Reach Slope	0.06	40	0.00		
Total	Log width	287.40	47			
	Log depth	82.00	47			
	Log x-area	675.00	47			
	Reach Slope	0.43	47			
Corrected Total	Log width	0.91	46			
	Log depth	0.92	46			
	Log x-area	2.62	46			
	Reach Slope	0.10	46			

(a) overall $r^2 = 0.29$; (b) overall $r^2 = 0.15$; (c) overall $r^2 = 0.35$; (d) overall $r^2 = 0.27$

*Significant at the 0.05 level

The top-down catchment group TD-5 had the highest mean stored sediment value, and this group was significantly different, according to ANOVA, from groups TD-3 and TD-4, which both had low mean stored sediment values. Headwater catchments classified as TD-5 were found at low elevations and had low mean slope angles (Chapter, III, Table 5); these low energy environments would encourage the accumulation of fines leading to high stored sediment values. In contrast, TD-3 catchments were located at high elevations and had pristine forests. The low levels of disturbance in these catchments would have minimized sediment generation, and the high potential energy in these catchments could easily mobilize sediment that had been transported to the stream channel. Catchments in group TD-4 also had low amounts of stored sediment in their stream channels, which was interesting, as this group was distinguished by having large percentages of burned areas. As it has been more than two decades since a fire occurred in these catchments, this result appears to support other research indicating the impacts from sediment delivery following fire do not persist in stream channels longer than 10-15 years (Gresswell 1999, Minshall 2003), although the increased runoff from fire likely impacted these stream channels in other ways that was not captured by the top-down classification.

With respect to the reach longitudinal profile, the catchments in TD-1, which had weak rocks, high percentages of settled areas, and low mean elevations, had significantly lower reach slope values than catchments in TD-3 (high elevation, pristine catchments). According to my correlation analysis (Table 17), as mean catchment elevation increased, the reach slope also increased. Thus, the top-down classification successfully distinguished these two groups, with respect to reach slope, by creating a low elevation catchment group and a high elevation catchment group. The low elevation catchments in TD-1 also had high percentages of settled areas and weak rocks, both of which were inversely correlated with reach slope. It is likely that the weak rocks and heavy disturbance due to settlement led to aggradation in TD-1 stream channels and subsequent decreases in reach slope. Thus, the top-down

classification did a good job of identifying catchments likely to have the lowest reach slope values. Unfortunately, the technique could only predict low reach slope values; it was not effective at distinguishing groups with moderately sloped stream channels even though the correlation analysis showed a strong positive relationship between catchment mean slope angle and the slope of a stream channel. Hence, several other landscape-scale processes likely confound the ability of the top-down classification procedure to distinguish catchments with varying reach slope angles.

The area of a catchment had a significant linear relationship with the size and slope of a stream channel. However, controlling for catchment size with ANCOVA did not lead to significant differences between the top-down catchment groups with respect to channel dimensions. This effort did identify catchment group TD-1 as having the lowest reach slopes, as had the ANOVA analysis. This reinforced the effectiveness of the top-down classification in identifying landscape-scale attributes that contributed to the development of low reach slope values, regardless of the size of the contributing area. However, the ANCOVA also showed that the top-down approach could not enhance the ability to predict channel width or depth above and beyond the existing relationship between catchment area and channel size. In addition, median particle size and stored sediment did not co-vary with catchment size. Thus, unlike the ANOVA, the ANCOVA did not detect a difference between catchment group TD-5 and both catchment groups TD-3 and TD-4 in terms of stored sediment. This further supported that catchment size is not an important variable for predicting stored sediment in small headwater catchments; in other words, differing sources of sediment from land uses, and the potential energy in systems at higher elevations, likely drive the amount of sediment stored in these stream channels.

Given that larger watersheds can generate higher discharge, the size of a stream channel should increase with increasing basin area. That assumed relationship is supported with my research findings, which showed a significant direct linear

relationship between catchment area and channel size. It follows that watershed attributes affecting the timing of runoff should also have an impact on the size of a stream channel. My correlation analysis (Table 17) showed that channel width increased in catchments with high percentages of pristine area, likely due to the influence of coarse woody debris, and that stream channels were narrower in catchments with highly resistant strata. Therefore, I would anticipate that stream channel width should not only increase with increasing catchment area, but that it should increase in size more rapidly in pristine catchments and less rapidly in catchments with very strong rocks. However, these channel traits were not detected by the ANCOVA procedure even though catchment groups TD-2 and TD-3 had high percentages of very strong rocks and pristine areas, respectively. This example highlights the most serious limitation of the top-down classification approach: hierarchical clustering is not process-driven.

The top-down approach could not take advantage of correlations between landscape-scale attributes and stream channel dimensions because it is primarily an exercise in mathematical clustering rather than a process-oriented approach. By design, the top-down approach has no information on stream channel morphology, or habitat, prior to conducting the clustering procedure that creates catchment groups. It was not my intention to create a model that would be unsuccessful at delineating headwater catchments into discrete groups with significantly different channel morphology. Quite to the contrary, I was careful to use only the landscape-scale datasets that, according to the literature, seemed most likely to represent hillslope processes; for instance, I re-classified the descriptive geology layer into rock strength classes that might represent resistance to erosion. Ultimately, however, the top-down approach could only create clusters that had, at most, a few similar landscape-scale attributes. In a few instances, the top-down clustering led to significant results, including TD-1 having significantly lower reach slopes. Yet, many of the groups included catchments that had attributes with competing hillslope processes. For instance, all of

the catchments in TD-3 have high percentages of pristine area, which should lead to significantly wider stream channels than should be found in catchments of similar size in other groups. However, this is not always the case; for instance, the steep slopes in the catchment for Dry Branch (reach # 4) cause high stream velocity and incision, which causes this channel to have one of the most narrow cross-sections that I surveyed, even though its drainage basin is 99% pristine, leading it to be classified as a TD-3 catchment. In fact, several of the stream channels in TD-3 are narrow as a result of steep slopes, as many pristine areas are found at high elevations in GSMNP. Thus, the hierarchical clustering of the top-down approach, which selects a few important and dominant attributes, cannot anticipate the influence of other, confounding or even complementary, landscape-scale attributes on stream channel morphology.

An examination of the top-down clusters reveals a problem with the commonly invoked assumption that different landscape-scale attributes should create different types of stream channels. This is an interesting limitation because it criticizes the basic tenet of watershed classification and hypothesis one, which both state that different combinations of landscape-scale data will produce different types of stream habitat. The problem with this assumption is in not recognizing the concept of convergence in geomorphology (Schumm 1991). Convergence refers to the situation where different processes can lead to similar landforms. This problem was best exemplified, again, by stream width in this study. Most stream channels in catchment group TD-3 were significantly wider than channels in other groups. This is reflected by the direct correlation between pristine area and channel width. However, stream channels can also be relatively wide in other groups as a function of different landscape-scale processes. In fact, the second widest stream channel surveyed was a tributary of Cosby Creek (reach # 5). The catchment for this reach was top-down classified as TD-1 because it contained a high percentage of weak rocks and settled areas. Thus, in this study, stream channels were relatively wide in both pristine areas

and in settled areas, though for different reasons; stream channels widen in pristine areas because of bank scour around coarse woody debris, and stream channels widen in settled areas because of channel aggradation leading to meandering and bank erosion.

A final issue with the top-down approach relates to scale. Each catchment group was distinguished based on a few dominant landscape-scale attributes, based on the assumption that these attributes would have the greatest cumulative impact on stream channel habitat. Yet, in some instances, the more localized attributes exhibited greater control on channel morphology. Two catchments, in particular, highlight this issue of scale. Cades Branch (reach # 48) and Oliver Branch (reach # 3) are both tributaries of Abrahms Creek in the Cades Cove area of the national park. Each catchment was approximately the same size, had a similar mean elevation and slope, was lightly disturbed, and was composed of roughly half strong rocks and half weak rocks; this led to a top-down catchment classification of TD-1 for both catchments. However, while Oliver Branch had an average stream width for the study area (2.92 m), Cades Branch had the narrowest stream channel surveyed (1.10 m). Both reaches were surveyed at a location of weak rock; the Oliver Branch reach was located in a forested area on the fringe of Cades Cove, and the Cades Branch reach was surveyed in a pasture/meadow within Cades Cove. As has been noted (Davies-Colley 1997), streams tend to be wider in forests than in meadows. Hence, even though Cades Branch only flows through a meadow on its final few hundred meters before joining with Abrahams Creek, the local control of meadow vegetation reduced its channel size much more than would be expected based on the dominant land use and rock strength of its top-down classification.

It is unfortunate that the top-down catchment classification was not more successful at distinguishing groups with significantly different channel morphology, as this has been the most common approach for watershed classification to date. It would

certainly be possible to refine the landscape-scale attributes in order to create a more process-driven model. However, this option exists only because I took the time to gather reach-scale data from the study area. Most watershed classification efforts that use some variation of the top-down approach are not validated in this manner. Therefore, it is highly likely that other watershed classification schemes suffer from similar issues as my top-down approach, that their clustered groups do not truly reflect hillslope processes, that different processes can create similar landforms (convergence), and that local controls may be more influential in dictating channel morphology than any dominant landscape-scale attribute.

My first working hypothesis stated that a statistical classification (clustering) based on landscape-scale attributes, the top-down approach, would distinguish groups of catchments that had significantly distinct types of stream channel morphology. Based on the ANOVA and ANCOVA results presented in this section, I reject this hypothesis, as only minimal differences existed between the six catchment groups classified using the top-down classification method. The reach slopes were significantly different in catchment group TD-1, but otherwise, channel morphology showed no significant variation between any other groups. I found significant correlations between several landscape-scale attributes and reach-scale values, but my top-down classification did not create groups that took advantage of those relationships, even though the landscape-scale attributes were different in each top-down classified catchment group. This implied either that the top-down classification selected the wrong combinations of landscape-scale attributes during the clustering procedure, or possibly that stream channel response to landscape influences was more complex than could be modeled with this technique.

Assessment of the Bottom-Up Approach

I expected to find a significant difference in channel morphology values between the catchments classified by stream type (the bottom-up approach), because the classification is based on stream channel morphology measurements. Therefore, I could not use ANOVA or ANCOVA to test for significant differences in stream channel morphology between the groups, as was down with the top-down assessment. Rather, I evaluated the utility of the reach-scale bottom-up classification by testing how well group membership was predicted based on each group's suite of landscape-scale attribute information using a multinomial logistic regression analysis (Agresti 1996). In this manner, I could assess to what degree, if any, landscape-scale attributes varied among the bottom-up classified groups. With this information, I could evaluate how successfully the bottom-up method, which is based on the sampled catchments, could be extrapolated to all remaining catchments in my study area.

Multinomial Logistic Regression

In simple linear regression, the dependent variable is always continuous. Thus, a one-unit change in a predictor variable results in a predicted change in the dependent variable according to the linear regression equation. However, I wished to examine whether a suite of independent variables could predict membership in a classified group, so I used multinomial logistic regression. This process differs from ordinary least-squares linear regression in that the response variable, group membership, is categorical; however, the objective is still to predict the value of a dependent variable based on a linear combination of independent variables. The multinomial logit model is an extension of the standard logit model, which predicts the probability of a binary outcome based on the independent variables (Agresti 1996). In the multinomial logit model, each case is assigned a probability, calculated as the log odds, that it is a member of a particular category. The case is then assigned to the category with the

highest calculated probability of membership. The independent variables can be either continuous or categorical, although all of my landscape-scale attributes were continuous. Logistic regression works well for small sample sizes (30-100 cases), and it is preferred over discriminant analysis where group sizes have unequal membership (Long et al. 1993), as was the case in this project.

Two calculations are helpful for interpreting the goodness-of-fit for a multinomial logistic regression model, a likelihood ratio test and a pseudo r^2 statistic. The likelihood ratio test calculates a Chi-square statistic, which is the difference between the final model and a null model in which all of the independent variables are set to zero (Agresti 1996). A significant Chi-square statistic suggests the independent variables are likely to perform better than a model using only the intercept in a regression equation. The multinomial logistic regression cannot produce an r^2 value similar to that of ordinary regression. However, it is possible to calculate the Nagelkerke pseudo r^2, which can be interpreted in much the same way as a traditional r^2 value (Nagelkerke 1991).

The most useful output from the multinomial logistic regression model is a summary table of observed and predicted frequencies by category, the percent correct classification by group, and the overall success of the model by percentage. This table related the effectiveness of each model in predicting bottom-up classified group membership based on the landscape-scale attributes. With the statistical software SPSS, version 13.0, I conducted the multinomial logistic regression analysis, using a manual, backward elimination procedure, and assessed the significance of each independent variable in the final model.

Bottom-Up Assessment: Results and Further Tests

I used the ten landscape-scale attributes that I had previously identified as being significantly related to stream channel morphology as independent variables, and

group membership as a categorical dependent variable in building a multinomial logistic regression model. The ten independent predictors were: log of catchment area, catchment shape circularity, mean elevation and mean slope of each catchment, the percent pristine, heavily disturbed, and settled area, and the percent weak, medium-strength, and very strong rocks within each catchment. First, I ran the model with all ten independent variables entered, and then, I iteratively eliminated one variable to evaluate the impact that removal had on successive model runs. If I noted a decrease in the pseudo r^2 or the predictive ability of the model, I added that attribute back to the model and continued with the analysis.

With all ten landscape-scale attributes entered in the model, the Chi-square goodness-of-fit statistic was significant and large, at 85.6, indicating that this model performed well (Table 22). This model also had a pseudo r^2 value of 0.88, which indicated that the independent variables were likely capturing approximately 88% of the variation in the dependent classification variable; this pseudo r^2 was also higher than of any of the subsequent backward-elimination models. By removing circularity from the model, the pseudo r^2 only dropped to 0.87, and the Chi-square statistic remained significant. Each iterative removal of a variable resulted in a model that was significantly better than the null model (intercept only), and most models had only slight decreases in variance explained. The removal of either the log of catchment area (pseudo r^2 = 0.80), the mean catchment slope (pseudo r^2 = 0.81), or weak rocks (pseudo r^2 = 0.82), had the largest impact on goodness-of-fit, which indicated that these variables likely were the more important attributes in the overall model.

The overall predictive success rate for the model with all ten variables was 81%, meaning that these landscape-scale attributes could successfully predict bottom-up group membership in slightly better than eight out of ten instances (Table 23). This model also had good predictive success within each classification group, as the success rate was over 80% for each group except for BU-1 (Table 23). In the

Table 22. Goodness-of-fit results from each multinomial logistic regression model.

	Model	*-2 Log Likelihood*	*Likelihood Ratio Chi-square*	*df*	*Sig.*	*Pseudo r2*
All Ten Variables	Intercept	141.7				
	Full Model	56.0	85.6	40	0.01	0.88
After removing:						
Circularity	Intercept	141.7				
	Full Model	58.2	83.5	36	0.01	0.87
Very Strong Rocks	Intercept	141.7				
	Full Model	58.3	83.4	36	0.01	0.87
Mean Elevation	Intercept	141.7				
	Full Model	58.8	82.9	36	0.01	0.87
Heavily Disturbed	Intercept	141.7				
	Full Model	62.0	79.6	36	0.01	0.86
Medium Rocks	Intercept	141.7				
	Full Model	62.6	79.1	36	0.01	0.86
Pristine	Intercept	141.7				
	Full Model	63.0	78.6	36	0.01	0.85
Settled Areas	Intercept	141.7				
	Full Model	63.6	78.1	36	0.01	0.85
Weak Rocks	Intercept	141.7				
	Full Model	70.8	70.9	36	0.01	0.82
Mean Slope	Intercept	141.7				
	Full Model	72.4	69.3	36	0.01	0.81
Log of Area	Intercept	141.7				
	Full Model	74.2	67.5	36	0.01	0.80

Table 23. Classification success for each multivariate logistic regression model both within each catchment group and overall.

	BU-1	*BU-2*	*BU-3*	*BU-4*	*BU-5*	*Overall*
All Ten Variables	60%	85%	86%	83%	81%	81%
After removing						
Circularity	40%	85%	86%	100%	88%	83%
Mean Slope	60%	77%	71%	83%	88%	79%
Very Strong Rocks	40%	77%	86%	83%	81%	77%
Pristine	20%	85%	57%	83%	88%	74%
Heavily Disturbed	40%	77%	71%	83%	81%	74%
Weak Rocks	40%	92%	71%	67%	75%	74%
Medium Rocks	60%	85%	71%	83%	69%	74%
Mean Elevation	40%	77%	71%	83%	75%	72%
Log of Area	40%	77%	57%	83%	81%	72%
Settled Areas	40%	69%	57%	100%	69%	68%

bottom-up classification procedure, BU-5 was the largest group, having 16 of the 47 classified reaches (Chapter IV, Table 14); hence, there exists a one in three chance that any particular catchment could be classified as BU-5. Any multinomial logistic regression model run that could not predict a particular group membership better than 34% of the time was thus functioning worse than chance alone and was considered a poor model. The removal of circularity actually increased the overall success rate of the model (83%), but it decreased the predictive ability for BU-1 to 40%. This is only slightly better than classification by chance. Each other model performed worse overall than the model with all ten variables, and most of the models were particularly ill-suited for classifying BU-1 catchments. As with the goodness-of-fit tests (Table 22), removal of log of catchment area had the greatest negative impact on the model.

Each multinomial logistic regression model was significantly better than a null model, and each had good success in predicting bottom-up catchment classification group membership based on its particular combination of landscape-scale attributes. This confirmed that these landscape attributes were highly correlated with reach-scale channel morphology values, and suggested that the bottom-up catchment groups could be accurately predicted using landscape-scale information. Based on its goodness-of-fit, overall classification rate, and success rate at predicting membership within each catchment group, I used the combined model, with all ten landscape-scale attributes, for predicting group membership in all remaining headwater catchments in the study area.

Similar to ordinary regression, multinomial logistic regression produces a set of parameter estimates (Table 24) with which I could extract regression equations for predicting the dependent variable of group membership. The logit coefficients (‘B’ in Table 24) were the natural logs of the odds, or probability, that an event occurred as opposed to the reference event (Agresti 1996); the Wald statistic was a measure of the contribution each attribute made to the model, with higher values being more

Table 24. Parameter estimates for the multinomial logistic regression model using all ten landscape-scale attributes.

Catchment Group		B	Std. Error	Wald Statistic	df	Sig.
BU-1	Intercept	96.3	51.0	3.6	1	0.06
	Circularity	-19.9	22.6	0.8	1	0.38
	Mean Elevation	0.0	0.0	0.2	1	0.66
	Mean Slope	0.1	0.2	0.3	1	0.60
	Pristine	-0.1	4.4	0.0	1	0.98
	Heavily disturbed	-1.5	3.2	0.2	1	0.65
	Settled areas	16.2	8.6	3.6	1	0.06
	Weak rocks	-11.4	6.5	3.0	1	0.08
	Medium rocks	-1.4	2.4	0.3	1	0.56
	Very strong rocks	-6.0	10.8	0.3	1	0.58
	Log of area	-15.4	8.4	3.3	1	0.07
BU-2	Intercept	-49.9	36.1	1.9	1	0.17
	Circularity	5.7	9.7	0.3	1	0.56
	Mean Elevation	0.0	0.0	1.0	1	0.32
	Mean Slope	-0.3	0.2	2.9	1	0.09
	Pristine	-5.1	3.7	1.9	1	0.16
	Heavily disturbed	-21.6	19.3	1.2	1	0.26
	Settled areas	12.2	7.6	2.5	1	0.11
	Weak rocks	0.5	4.3	0.0	1	0.91
	Medium rocks	4.9	3.2	2.3	1	0.13
	Very strong rocks	5.3	6.2	0.7	1	0.39
	Log of area	8.9	6.1	2.1	1	0.14
BU-3	Intercept	106.7	61.1	3.0	1	0.08
	Circularity	2.4	23.1	0.0	1	0.92
	Mean Elevation	0.0	0.0	0.1	1	0.75
	Mean Slope	0.4	0.3	1.9	1	0.16
	Pristine	-3.8	5.0	0.6	1	0.44
	Heavily disturbed	-1.1	2.8	0.1	1	0.71
	Settled areas	16.9	9.6	3.1	1	0.08
	Weak rocks	-10.0	7.9	1.6	1	0.21
	Medium rocks	-2.3	3.4	0.4	1	0.50
	Very strong rocks	1.1	7.5	0.0	1	0.89
	Log of area	-20.9	12.1	3.0	1	0.08

Table 24. Continued.

Catchment Group		B	Std. Error	Wald Statistic	df	Sig.
BU-4	Intercept	-20.1	74.3	0.1	1	0.79
	Circularity	6.3	11.5	0.3	1	0.58
	Mean Elevation	0.0	0.0	1.1	1	0.30
	Mean Slope	-0.2	0.3	0.4	1	0.54
	Pristine	4.4	3.8	1.3	1	0.25
	Heavily disturbed	-1.5	5.0	0.1	1	0.76
	Settled areas	-4.3	16.1	0.1	1	0.79
	Weak rocks	-152.9	6494.1	0.0	1	0.98
	Medium rocks	5.9	4.4	1.8	1	0.18
	Very strong rocks	-70.6	0.0	.	1	0.54
	Log of area	1.2	10.4	0.0	1	0.91
BU-5	*Reference category*	-	-	-	-	-

p (BU-1) = exp (a1 + b1x) / [1 + exp (a1 + b1x) + exp (a2 + b2x)…+ exp (a_n + b_nx)]
p (BU-2) = exp (a2 + b2x) / [1 + exp (a1 + b1x) + exp (a2 + b2x)…+ exp (a_n + b_nx)]
p (BU-3) = exp (a3 + b3x) / [1 + exp (a1 + b1x) + exp (a2 + b2x)…+ exp (a_n + b_nx)]
p (BU-4) = exp (a4 + b4x) / [1 + exp (a1 + b1x) + exp (a2 + b2x)…+ exp (a_n + b_nx)]
p (BU-5) = 1 / [1 + (a1 + b1x) + (a2 + b2x)…+ (a_n + b_nx)]

important. The resulting regression equations produced the probabilities that a catchment would be classified to a particular group (BU-1 through BU-4), based on the set of independent landscape-scale attributes, as opposed to having been classified to the reference category (BU-5). As the logits were natural logs, it was necessary to take the exponent of each expression as suggested by Agresti (1996), in order to calculate a percentage probability that a catchment should be classified as BU-1 or BU-2, etc. The equations are shown at the bottom of Table 24.

I exported the landscape-scale attributes for all 862 catchments into a spreadsheet and calculated the probability of a catchment being classified as belonging to a particular group using the multinomial logistic regression logit coefficients and the above equations. The number of cases for each group is given in Table 25 and is graphically shown in Figure 18; the assignment of catchments to each bottom-up classification group was more evenly distributed than for the top-down classification (Chapter III, Table 5). The smallest group is BU-2 with 93 catchments and the largest group is BU-4 with 250 catchments. The logit coefficients in Table 24 were also helpful for determining the importance of an independent variable in classifying catchments to a particular group. The higher the log odds for an independent variable, the greater is its contribution toward classifying a catchment into that group rather than the reference group. As the logits are natural logs, large positive values represented high probabilities of classification, while negative values and logits approaching a value of one indicated the variable was not important in distinguishing between that catchment group and the reference group.

Based on the logits in Table 24, the 98 catchments in group BU-1 were distinguished from the reference group (BU-5) by the presence of settled areas and the mean slope in the catchments (Table 25). The directional influence for an attribute, such as mean slope, was determined by comparing the mean values for a particular group to the

Table 25. Number of catchments and descriptions for the extrapolated bottom-up catchment classification in GSMNP.

Bottom-up Group	*Count*	*Important Attributes*
BU-1	98	Settled areas, low mean slopes
BU-2	93	Settled areas, large catchment area, high circularity, absence of very strong rocks, medium rocks
BU-3	194	Limited settled area, low circularity, very strong rocks
BU-4	250	High circularity, medium rocks, pristine areas, log of area
BU-5	227	High mean elevation, heavily disturbed, weak rocks
Total	862	

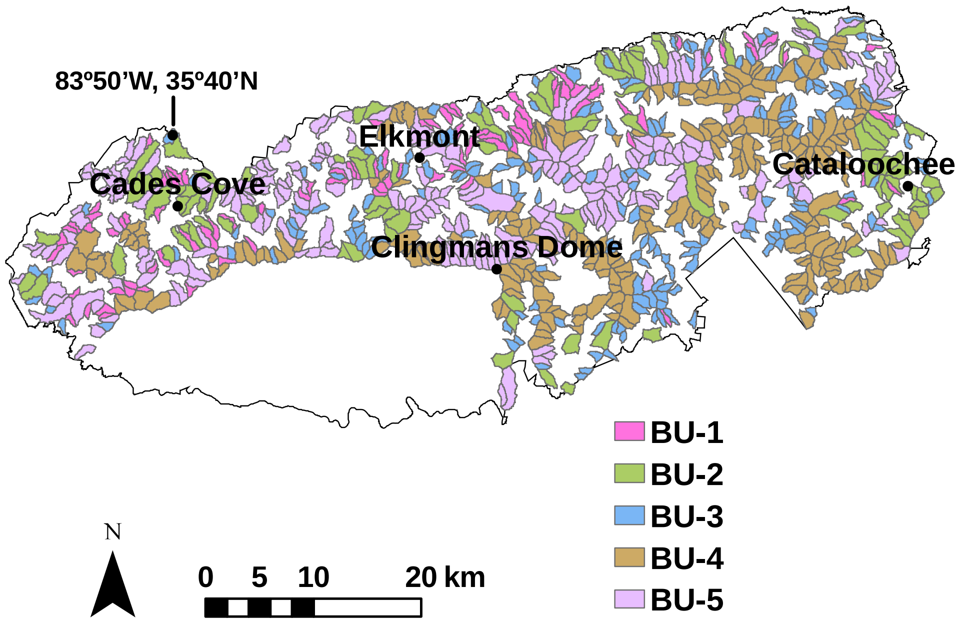

Figure 18. Results of the bottom-up extrapolated catchment classification.

overall mean and by overlaying the bottom-up classified catchments (Figure 18) onto the landscape-scale attributes in a GIS. For instance, in catchment group BU-1, low mean slopes were the distinguishing attribute. The 93 catchments in BU-2 also had settled areas, as well as large catchment areas, high circularity, medium rocks, and an absence of very strong rocks. A lack of settled areas was important to discriminating catchment groups in BU-3, as were low circularity and large coverage by very strong rocks. Catchments in group BU-4 were all large, highly circular, mostly covered in pristine area, and composed of medium-strength rocks. Lastly, BU-5, the reference category group, was distinguished by those attributes that did not otherwise contribute toward the first four groups; thus, the important attributes for BU-5 were high mean elevations, heavily disturbed areas, and weak rocks.

Bottom-Up Assessment: Discussion

The bottom-up classification procedure, which was based on different types of stream channels, was quite successful at creating catchments groups with strong correlations between landscape-scale attributes and reach-level values. This was evident by the better than 80% group membership prediction rate using the landscape data.

The combination of important landscape-scale attributes is different between the top-down (Chapter III, Table 5) and bottom-up (Table 25) classifications; however, the variables themselves are quite similar. Even though the top-down approach used several more attributes for its clustering procedure, the most important attributes were similar to the important attributes identified in the bottom-up procedure. Unlike the top-down classified groups, many of the bottom-up catchment groups shared the same important landscape-scale attributes; this was true despite the fact that the channel morphology was significantly different in each of the bottom-up classified groups. This suggested that different types of stream channels could form in catchments with similar landscape-scale attributes; thus, it is likely that the combination of different landscape elements, as well as the intensity of disturbance in the watershed, is more

important to stream channel morphology than any one particular type of watershed attribute.

The bottom-up classified reaches from Chapter IV (Figure 11) appeared to group according to expected fluvial response with reference to changes in discharge and sediment flux (Schumm 1977). For instance, BU-4 catchments had the largest stream channels and low amounts of stored sediment. This was likely a function of relatively high discharge as the important attributes of this group were high circularity, which can increase peak discharge, and having a large drainage basin, which increases overall discharge. The BU-4 catchments also had high percentages of pristine area, which can lead to wider stream channels (Davies-Colley 1997). This group is also strongly supported by the correlations between individual landscape-scale attributes and reach-scale values. For instance, catchment area and pristine area are both directly correlated with stream width (Table 17).

The BU-2 catchments also had some of the widest stream channels, but unlike the BU-4 catchments, they had relatively shallow reach slopes and small median particle sizes (Chapter IV, Figure 11). This is probably related to increased sediment loads as these catchments have high percentages of settled areas (high disturbance) and low mean catchment slope angles, which results in decreased potential energy for the removal of fines. The response of stream channel widening in both BU-2 and BU-4 catchments is another example of convergence (Schumm 1991). Stream channels will widen with increases in discharge; however, they will also widen with increases in sediment loading as the channel will aggrade, the reach slope will decrease, and the stream will meander, causing bank failure and channel widening (Schumm 1977). The primary difference between these two catchment groups was the land use, pristine for BU-4 and settled areas for BU-2. Thus, these catchments both had relatively wide channels, but as a result of different processes, although each stream channel was adjusting according to expected fluvial response.

In figure 11, note that several BU-5 catchments plotted between BU-2 and BU-4 catchments with respect to reach slope and median particle size (PC2) but had approximately the same size channels (they plotted on the same location with respect to PC1). The BU-5 catchments are distinguished as having large areas that were heavily disturbed by mechanical logging. The catchments that plotted closer to BU-4 (pristine) were high elevation catchments that were logged and abandoned; the catchments that fell closer to BU-2 (settled areas) were areas that had a mix of logging and settlement and thus, experienced longer sustained disturbance. Therefore, with respect to reach slope and median particle size, these three bottom-up catchment groups represented a gradient of fluvial response to disturbance intensity within their respective watersheds from intensive disturbance, aggrading channels in settled areas, to channels in dynamic equilibrium with their environments in pristine areas. It is interesting that the bottom-up procedure would detect this type of response; yet, it also points toward a drawback to this particular type of exercise in that this model represents a single point in time. Hence, it is unclear if, for instance, the most intensively disturbed catchments, BU-2, are adjusting toward the BU-5 catchments, or if they are still aggrading as a response to former disturbance regimes.

The catchments in BU-1 also had large percentages of settled areas and low mean catchment slope angles, which led to lower reach slopes and relatively small median particle sizes as a function of aggradation and low energy in the fluvial system. However, this catchment group had the lowest success rate of prediction (60%, Table 23) based on the landscape-scale attributes. This low success rate is partially due to the low number of samples in this group. However, an additional issue involves the role of local controls on stream channel morphology. Of the five sampled catchments that were classified as BU-1, two catchments (a tributary of Abrahams Creek, reach # 42; Cades Branch, reach # 48) were surveyed in meadow riparian conditions, which led to narrow and deep stream channels. The other three catchments were even more problematic; each of these catchments had a perfect suite of landscape-scale attributes

for disrupting the fluvial system through hillslope disturbance. In addition to having large amounts of settled areas and low catchment slope angles, these three catchments were relatively small and had large areas that had been mechanically logged. Nearly half of each catchment had burned within the last 70 years, the bedrock was largely of medium strength or weak rocks, and these catchments had low circularity. The combination of these attributes led to massive and sustained sediment generation in watersheds with both low competence and limited capacity. As such these stream channels have been slow to adjust following historic disturbance.

Because the catchments in BU-1 were so heavily disturbed, along with being quite vulnerable to disturbance, these stream channels exhibited a complex response with respect to the bottom-up classification. Essentially, these catchments are currently incising into the stored alluvium in their stream channels in an attempt to re-establish dynamic equilibrium conditions. Thus, the landscape-scale attributes that predict wide stream channels in other catchments, particularly settled areas, actually have produced relatively narrow channels in these catchments. Again, this is only a temporary condition as these stream channels are still adjusting to past disturbance events. An example will help to illustrate this point. Leatherwood Branch (reach # 6), a tributary of Cosby Creek, is currently degrading and incising into the alluvium that was deposited in its floodplain over the past in the early 20th century. This area was logged and intensively settled until shortly after the creation of the park. The current bed material matches the coarse sands and gravels in the pre-disturbance floodplain, which is overlain by one meter of accumulated silts and sand (Figure 19). The fine material accumulated as a result of the 20th century disturbance events; the vegetation at the top of the image represents the floodplain following the intensive disturbance. At some point, the stream channel ceased aggrading and began to incise into the stored alluvium, leading to channel narrowing and deepening. As such, this stream is currently disconnected from its historic floodplain. Although it has probably finished degrading, based on the nature of the current bed material, this

Figure 19. The floodplain sediments stored in the banks of Leatherwood Branch. The pre-disturbance floodplain has been exposed as the stream incised into the stored alluvium.

stream will continue to erode its banks and mobilize stored sediment until it either re-connects to its former floodplain or establishes a new floodplain within the current steam channel.

Much like the gradient for reach slope and median particle size that was represented by the transitional catchments BU-2 to BU-5 to BU-4 (along PC2, Chapter IV, Figure 11), a gradation in adjustment exists from BU-1 (narrow channels) to BU-2 (wide channels) along PC1 (Chapter IV, Figure 11). This gradient is best detected by observing a catchment that was misclassified in the bottom-up approach. Recall that the catchment group BU-1 had the poorest success with classification (60%). This was partially a function of local controls on channel morphology but also a result of BU-1 catchments going through adjustment following massive disturbance. The catchment for Carolina Prong (reach # 27), in the Cosby Creek drainage, was bottom-up classified as BU-1 based on its stream channel being narrower than all stream channels in BU-2 catchments and having both low reach slopes and a small median particle size of bed material; however, it had the widest stream channel measurement of the all BU-1 catchments. The Carolina Prong catchment had settled areas and relatively low mean catchment slopes, but it was also relatively circular and as large as most BU-2 catchments. Hence, this catchment had sufficient discharge to mobilize the sediment generated from the massive disturbance associated with BU-1 catchments. As such, it has nearly established a new floodplain within its current channel; it seems unlikely, based on the height of the banks, that it will re-connect to its pre-disturbance floodplain in the foreseeable future. However, if this channel were to be re-surveyed in the next few decades, it is likely that it would re-classify as a BU-2 catchment, according to this classification system, based on its widening stream channel. This again emphasizes the ultimate limitation involved in bottom-up classification— stream channels will continue to change after they have been surveyed and classified, particularly in reaches that exhibit a complex or counterintuitive response to catchment classification. Yet, this could also be an

advantage for long-term research, as it allows for monitoring the change from one type of catchment to another over time.

The BU-3 catchments had small channels with steep slopes and large median particle sizes. Most of these catchments were quite small, had relatively strong rocks, low circularity, and little disturbance. Most appear to be smaller versions of BU-4 catchments, with the exception that rock strength is somewhat higher. One BU-3 catchment, Ledge Creek in the Raven's Fork drainage (reach # 33), was misclassified in the multinomial logistic regression procedure as a BU-2 catchment (settled areas). This catchment experienced intensive disturbance, but only near the ridge and not down by the mouth where I surveyed the cross-section. The channel itself was relatively small, although it did have the highest stored sediment amounts for its group. Hence, the disturbance may have contributed sediment down the stream system, but it either did not affect channel form, or the channel has adjusted to pre-disturbance conditions.

In analyzing the different bottom-up classified groups, it was also helpful to overly the top-down classification on the bottom-up classification and extract a table that compares the distribution of top-down classified catchments within each bottom-up category (Table 26). I did not expect to find a perfect correlation between the groups, and in fact, each bottom-up catchment group contained several different top-down categories. Yet, several interesting correlations did emerge. For instance, the BU-1 group contained at least one catchment from every top-down category; however, the TD-5 group occurred most frequently. Recall that the BU-1 catchments tend to have large amounts of settled areas and low mean catchment slopes (Table 25); the TD-5 catchments were also described as having low mean elevations and low mean slopes, although the dominant landscape-scale attribute forming the TD-5 group was the presence of strong rocks (Chapter III, Table 5). Nevertheless, each of these groups seemed to have much in common with respect to their catchment characteristics.

Table 26. Comparison of the frequency of top-down and bottom-up catchments with respect to each classification.

	TD-1	*TD-2*	*TD-3*	*TD-4*	*TD-5*	*TD-6*	*Total*
BU-1	8	1	16	4	51	18	*98*
BU-2	27	13	5	1	16	31	*93*
BU-3	15	9	77	5	30	58	*194*
BU-4	0	0	206	1	16	27	*250*
BU-5	44	5	115	6	39	18	*227*
Total	*94*	*28*	*419*	*17*	*152*	*152*	*862*

Yet, no clear patterned emerged with catchment groups BU-2 and BU-3, as the distribution of top-down groups was relatively uniform across each of these categories. Both BU-4 (medium-strength rocks, pristine) and BU-5 (high elevation, heavily disturbed, weak rocks) were most highly correlated with TD-3 catchments (pristine, high elevation, medium-strength rocks). This again showed the limited ability of the top-down approach in handling competing landscape-scale attributes. As most pristine areas occurred at high elevations, the TD-3 group captured nearly all of the high elevation catchments, even though some heavily disturbed catchments could be found at high elevations. However, the bottom-up classification split these catchments into two groups, disturbed and pristine, and allowed both to occur at high elevations.

The bottom-up classification procedure was successful on two fronts. First, the stream channels grouped into types that reflected variability in both discharge and sediment flux. Second, the landscape-scale attributes were able to predict group membership in eight out of ten cases, which implies that these attributes are good indicators of hillslope processes and that those processes largely control stream channel morphology. In addition, the bottom-up classification procedure identified gradients of stream channel adjustment to disturbance. As such, it can act as a first step toward predicting how landscapes may respond to future disturbances, as well as give some indication of the time needed for recovery to disturbance. However, this technique is limited in that it was only a snapshot of fluvial conditions at the time the stream channels were surveyed. Many of these channels are in adjustment, and it is not necessarily clear whether they are aggrading or degrading. The landscape-scale datasets are not well designed in a temporal sense. For instance, settled areas were settled at one time, but it is not always clear how long a particular area was settled, how intensive the actual land use was, and when the settlement activity ended. Nevertheless, GSMNP achieved national park status in 1934 and has been protected from logging and most settlement activity since that time, which has allowed for the

establishment and of new vegetation and stabilization of soils. This gives us a marker for time since most disturbance activities occurred and provides an excellent laboratory for detecting the impact of different intensities of disturbance on stream channel habitat. Hence, in spite of the its limitations, the bottom-up approach was successful in creating a metric that reflects which combinations of landscape attributes had the greatest impact on stream channel morphology.

The final model of the multinomial logistic regression predicted bottom-up group membership with better than 80% accuracy. Hence, I do not reject my second hypothesis, which states that catchments grouped by their respective distinct types of stream channels, the ‘bottom-up’ approach, would show significant relationships between stream channel morphology and landscape-scale attributes. As depicted in Figure 18, the bottom-up classified catchments in GSMNP did not show nearly as much of an influence from one dominant landscape-scale attribute as was seen with the top-down classification (Chapter III, Figure 9). This suggests that processes operating within a headwater catchment may have a greater impact on stream channel morphology than could be detected with more regional-scale landscape attributes. Ultimately, the significant results from the bottom-up classification showed that hillslope processes had a considerable influence on variation in reach-scale values and that we can predict reach stream channel morphology based on this relationship in GSMNP.

Assessment of Classifications Using Stream Water Chemistry Values

Authors of several of the classification schemes I discussed in Chapter I were interested in creating watershed classifications that explained variation in stream water chemistry (Jones et al. 1997, Momen and Zehr 1998, Robertson and Saad 2003). In fact, most research into the relationship between landscape-scale attributes and stream channel habitat has focused on water quality (e.g., Baker et al. 2001, Gove

et al. 2001). In these projects, researchers typically collect water quality samples at regular intervals throughout the year, in order to account for changes in discharge and seasonality when modeling the landscape influence on stream water quality. I was only able to obtain one water quality analysis from my sample catchments, from grab samples collected within two weeks of each other, in early December, under similar flow conditions. However, Robinson et al. (2002) have collected hundreds of water quality samples in GSMNP over the past decade and have found correlations between landscape attributes and water quality (Harwell 2001). Hence, while my water quality data lacked statistical power, having only one sample per catchment, I could imply a stronger association if either of my classification techniques suggested a difference in water quality parameters, by catchment, which was consistent with established landscape to stream water quality relationships in GSMNP.

For both the top-down and bottom-up classifications, I examined the distribution of stream water chemistry data (pH, total dissolved solids, total nitrogen, total phosphorous, and total organic carbon from my water quality samples) using box plots, which showed the maximum, minimum, and median values, as well as the upper and lower quartiles of water quality data within each catchment group. I then transformed the data, where necessary to achieve a normal distribution, and tested for significant water quality differences between the catchments in both the top-down and bottom-up classifications using ANOVA.

The box plots (Figure 20) showed little difference between the top-down catchment groups with respect to stream water chemistry. TD-3 did show higher variation in both pH and total nitrogen, and its median value for total nitrogen was much larger than those of other groups. Catchments in TD-3 tend to have large amounts of pristine area and high mean elevations; the relatively high nitrogen levels in this group are consistent with results reported by Nodvin et al. (1995), who determined that soils located in old growth forests of the national park were nitrogen saturated, leading to

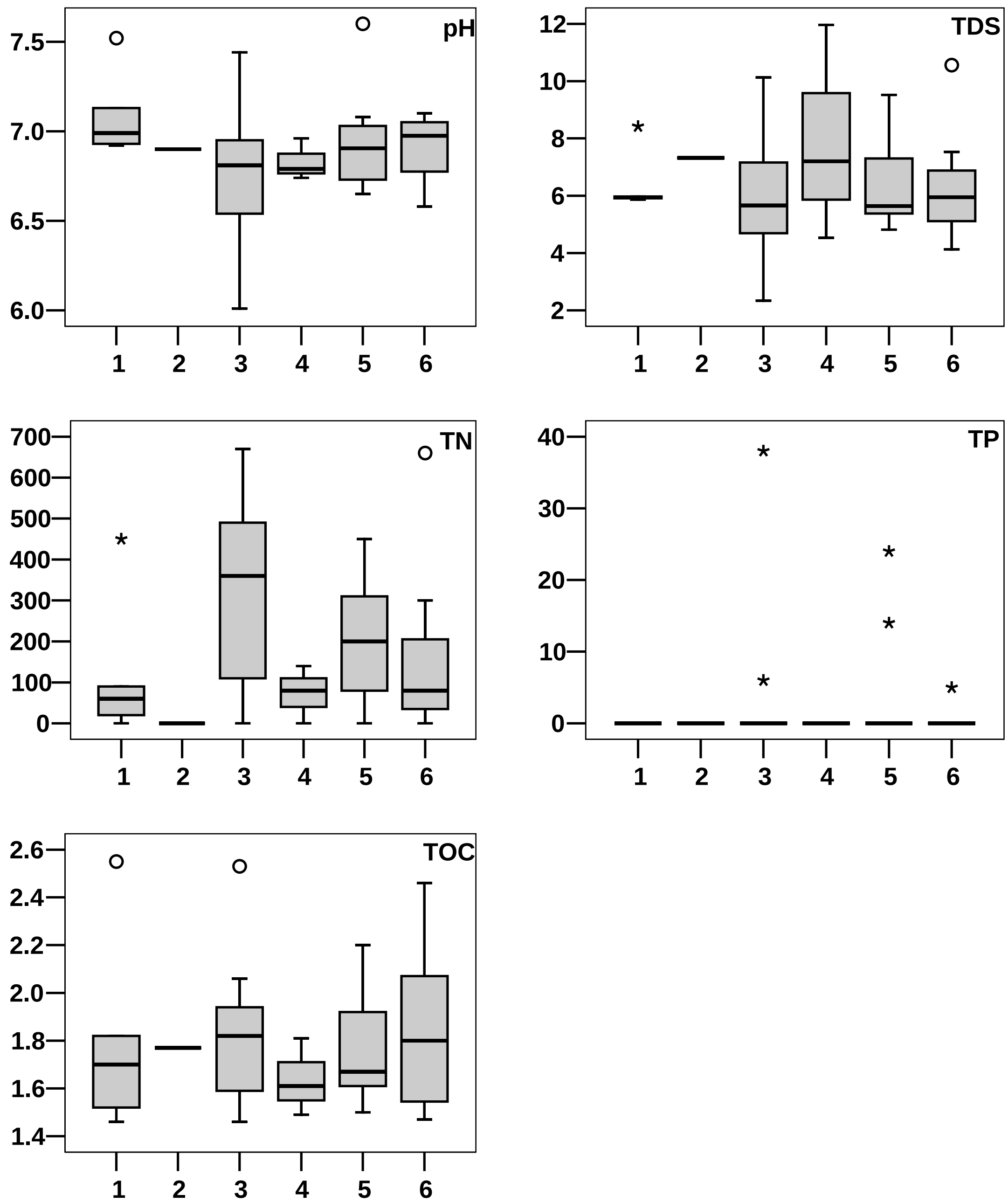

Figure 20. Box plots of stream water chemistry for each top-down classified catchment group. Circles denote outliers and stars are extreme values. TDS, total dissolve solids in mg/l; TN, total nitrogen in (µg/l); TP, total phosphorous in (µg/l); TOC, total organic carbon in mg/l.

high nitrogen loading in streams draining areas of pristine forest. Harwell (2001) also reported that pH levels in streams decreased with increasing elevation. Although some TD-3 catchments had high pH values, the median for that group was slightly lower than most of the other groups. Total dissolved solids were slightly elevated in TD-4 catchments, which were distinguished by having large amounts of burned areas. Total organic carbon values were quite similar, and total phosphorous values were difficult to assess as only five streams had recorded levels of phosphorous.

With respect to the bottom-up classified catchments, the box plots (Figure 21) suggested a large in difference total nitrogen for catchment group BU-4. This group was composed of catchments with large amounts of pristine area, and, as such, is consistent with the proposed old-growth nitrogen saturation model (Nodvin et al. 1995). Total dissolved solids are highest in BU-2 catchments, which had settled areas and medium-strength rocks. Unlike the case of catchment TD-4, no bottom-up group was distinguished by having burned areas. The pH and total organic carbon values were relatively consistent between catchment groups, and again, total phosphorous differences were inconclusive because I had too few samples for comparison.

I then ran the ANOVA analysis to test if either catchment classification created groups with significantly different stream water chemistry values, having first log-transformed the total dissolved solids data and square-root transformed the total nitrogen and total phosphorous data in order to better approximate a normal distribution. I used the catchment classes as the factor variable and stream water chemistry values as the dependent variables. The variables were not significant for Levene's test, and thus showed homogeneity of variance. In the top-down classification, none of the catchment groups were significantly different from each other based on water chemistry values (Table 27). However, in the bottom-up classification, a significant difference existed between catchments groups regarding total nitrogen (Table 28). A *post hoc* test showed that BU-4 and BU-2 had

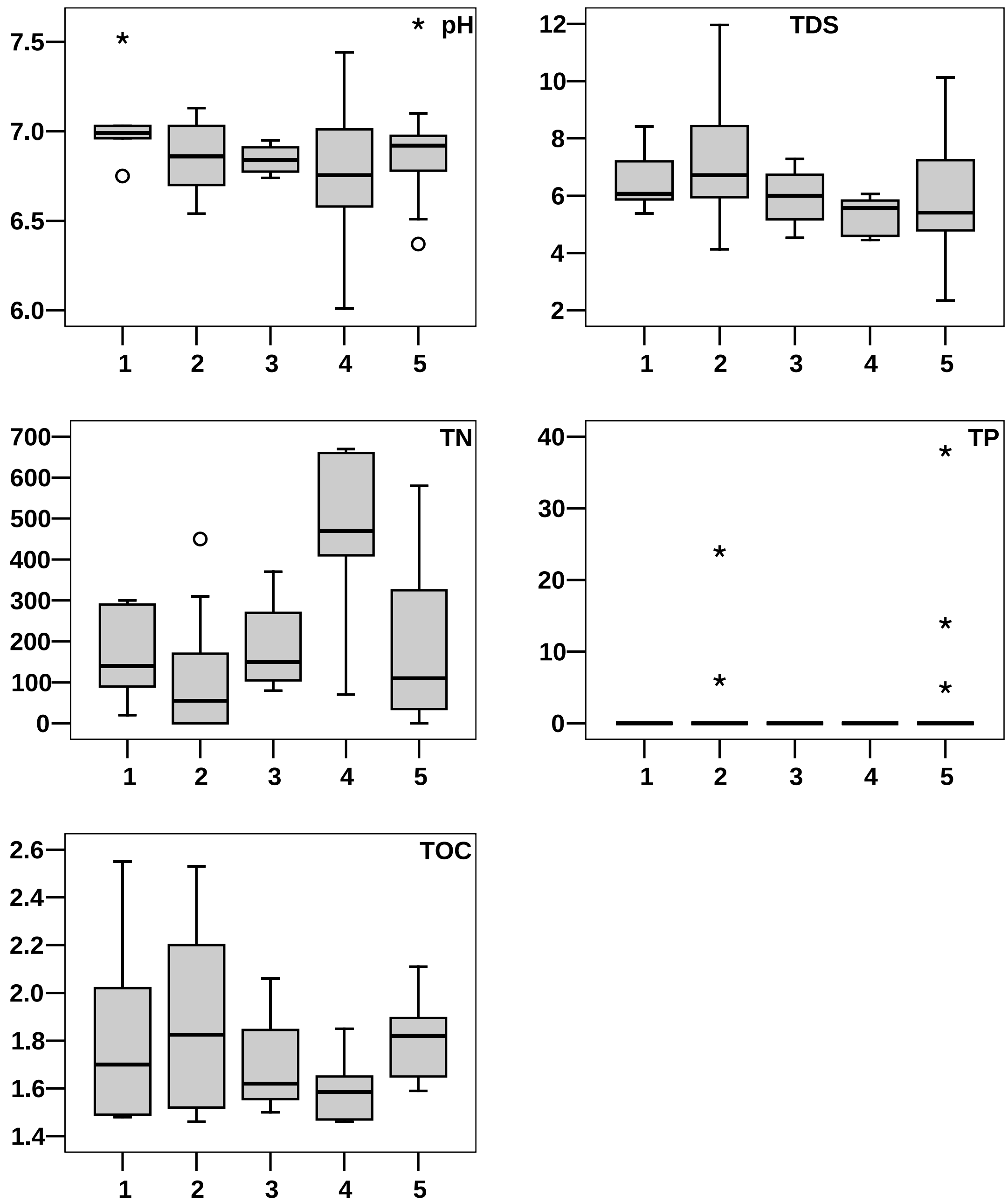

Figure 21. Box plots of stream water chemistry for each bottom-up classified catchment group. Circles denote outliers and stars are extreme values. TDS, total dissolved solids in mg/l; TN, total nitrogen in (µg/l); TP, total phosphorous in (µg/l); TOC, total organic carbon in mg/l

Table 27. ANOVA for the test of differences in stream water chemistry between the top-down classified groups.

		Sum of Squares	*df*	*Mean Square*	*F*	*Sig.*
pH	Between Groups	0.55	5	0.11	1.40	0.25
	Within Groups	2.66	34	0.08		
	Total	3.21	39			
TDS	Between Groups	0.05	5	0.01	0.59	0.70
	Within Groups	0.59	34	0.02		
	Total	0.64	39			
TN	Between Groups	542.49	5	108.50	1.80	0.14
	Within Groups	2053.19	34	60.39		
	Total	2595.68	39			
TP	Between Groups	4.30	5	0.86	0.40	0.85
	Within Groups	73.20	34	2.15		
	Total	77.50	39			
TOC	Between Groups	0.11	5	0.02	0.23	0.95
	Within Groups	3.09	34	0.09		
	Total	3.20	39			

Table 28. ANOVA for the test of differences in stream water chemistry between the bottom-up classified groups.

		Sum of Squares	*df*	*Mean Square*	*F*	*Sig.*
pH	Between Groups	0.25	4	0.06	0.74	0.57
	Within Groups	2.96	35	0.08		
	Total	3.21	39			
TDS	Between Groups	0.08	4	0.02	1.24	0.31
	Within Groups	0.56	35	0.02		
	Total	0.64	39			
TN	Between Groups	663.95	4	165.99	3.01	0.03*
	Within Groups	1931.73	35	55.19		
	Total	2595.68	39			
TP	Between Groups	5.73	4	1.43	0.70	0.60
	Within Groups	71.77	35	2.05		
	Total	77.50	39			
TOC	Between Groups	0.41	4	0.10	1.29	0.29
	Within Groups	2.79	35	0.08		
	Total	3.20	39			

*Significant at the 0.05 level

significantly different mean values of total nitrogen; BU-4 catchments (high in pristine areas) had the highest values, and BU-2 catchments (mostly settled area) had the lowest values. This further suggested that catchments with large areas of pristine forest were nitrogen saturated. The chances of finding large differences in water quality using only one sample per catchment were remote, which is why most research efforts use many samples collected over long periods of time. Hence, finding a significant difference in total nitrogen between two catchment groups emphasized the potential effectiveness of the bottom-up classification technique.

Based on the comparative results, I could assess how well each classification technique fared at supporting my hypotheses. I concluded that hypothesis one, a statistical classification (clustering) based on landscape-scale attributes, a 'top-down' approach, will distinguish groups of catchments that have significantly distinct types of stream channel morphology, was not supported. The top-down approach did create groups with distinctively different suites of landscape-scale attributes; however, stream channel morphology values showed little difference between the different groups. In contrast, I concluded that hypothesis two, that catchments grouped by their respective distinct types of stream channels, a 'bottom-up' approach, will show significant relationships between stream channel morphology and landscape-scale attributes, was supported based on the goodness-of-fit and prediction success rate of the multinomial logistic regression procedure. In addition, stream water chemistry values were not significantly different between the top-down catchments, although a correlation between pristine forest and high nitrogen levels was suggested. However, nitrogen levels were significantly different between two of the bottom-up classified catchments, which both supports the premise that landscape-scale attributes are related to reach-level processes and partially validates the strength of the bottom-up classification procedure.

CHAPTER VI
APPLICATIONS AND CONCLUSIONS

My goal with this dissertation was to present a metric, in this case a watershed classification, which both described the relationship between hillslopes and stream channels and assessed the relative impact of various disturbances on the condition of headwater streams. Both of these goals were achieved with the bottom-up classification procedure. This classification created five catchment groups that had significantly different types of channel morphology, as determined from variations in bankfull width, depth, cross-sectional area, reach slope, median particle size, and amount of stored sediment. A multinomial logistic regression analysis showed that membership of these catchment groups could be successfully predicted based on ten landscape-scale attributes: catchment area and circularity; mean slope and elevation; pristine, heavily disturbed, and settled land uses; and weak, medium, and very strong rocks, which represented hillslope processes. Finally, I demonstrated that these groups were capable of identifying catchments that drained streams in various stages of adjustment to disturbance, from incision to dynamic equilibrium.

The data set I created is rich in many aspects. Park managers and scientists can use this database in order to find stream habitat in the park that was most affected by anthropogenic disturbance, locations that were more resilient, and catchments that might be negatively affected by future disturbance, including the disappearance of the eastern hemlock. In addition, the technique itself, although not the exact classification, would be useful for locating highly impacted streams, monitoring stream restoration projects, and possibly modeling total maximum daily loads (TMDL) for sediment. A particularly noteworthy aspect of this type of classification is that it allows for the prediction of probable change in stream channel function and morphology as a direct consequence of landuse change. Toward elucidating the utility of this research, I conclude this dissertation by proposing a few applications of

that may be useful both within the park boundaries as well as in the greater Southern Appalachian region, and I discuss where this research fits within the broader scope of geomorphological inquiry.

In this project, I determined that GSMNP contained a limited number of catchment types, and I was able to model the interaction between landscape-scale attributes and channel type based on both individual attributes and combinations of attributes. I identified, for instance, that the bottom-up classified BU-1 catchments had sustained the greatest intensity of disturbance and that stream channels in these catchments were still incising into the stored alluvium that had been transported from hillslopes in the early 20th century. In contrast, many catchments classified into the BU-5 catchment group are likely adjusting back toward pre-disturbance conditions, which are represented by the BU-4 catchments. The BU-5 catchments represent areas that should be targeted for restoration, as they appear to be adjusting toward a stable condition.

Stream channels in the BU-5 catchments would likely respond most directly to enhancements in their catchments; at a minimum, no further disturbance, such as road building, should be permitted within these catchments as they represent the best chance for achieving pre-disturbance conditions. These catchments are also the best choices for species re-introduction efforts. Many BU-5 stream channels have likely stabilized in terms of stream width, although stored sediment will remain high for some time. Nevertheless, these stream channels represent areas that are most like the pristine conditions found in the park, and barring any further human or natural catastrophic disturbance event, they are likely to remain that way. For the re-introduction of aquatic species, researchers should locate BU-5 catchments that differ only in past disturbance regimes from BU-4 catchments; these represent locations most likely to succeed with stream restoration, as the stream channel habitat should continue to adjust toward BU-4 conditions.

The highly disturbed BU-1 catchments are not good candidates for species re-introduction or stream restoration activities. Many of these stream channels will continue to incise for some time. As such, these stream channels may become even narrower and deeper. Hence, these stream channels will adjust away from pre-disturbance conditions until such time as they re-connect to their former floodplain. Many streams in these catchments will likely re-establish a new floodplain within their current stream channels; therefore, these catchments will have a narrower riparian area. Logging and settlement in these catchments removed trees that were adjacent to the stream channels. Thus, it will take some time before these streams benefit from the addition of coarse woody debris, which assists in excavating bank material and widening the stream. Short of excavating alluvium directly from the floodplain, these catchments will not benefit greatly from stream restoration activities. Unfortunately, these catchments have low discharge, which is the only process capable of mobilizing the sediment stored in these channels. In sum, restoration activities in BU-1 catchments would be expensive and would show poor success rates.

It is worth noting that BU-5 catchments were the reference category in the multinomial logistic regression procedure. This does not imply that these catchments have 'reference' streams (Harrelson et al. 1994). A reference stream is a stream channel occurring in relatively undisturbed conditions; as such, the stream channel should be in dynamic equilibrium with inputs from its drainage basin, and the habitat should be representative of the native flora and fauna. Reference streams can be determined for water quality (Hampson et al. 2000), fish or macro-invertebrate communities (Barbour et al. 1999), and even channel morphology (USEPA 2005a), although it is rarely done for morphology. Based on the bottom-up classification, BU-4 and BU-3 catchments represent reference conditions, even though the stream channels in each of these catchment types are much different. BU-4 streams are wide and shallow because they drain large circular catchments with relatively weak rocks;

BU-3 catchments are smaller, more oblong, and contain stronger rocks, which results in narrow, deep stream channels. The stream channels in each of the other catchments are adjusting toward these types of channels. Hence, no one type of catchment can be considered a reference catchment, and no one type of stream can be considered a reference stream in GSMNP. Finally, it is also worth noting that the bottom-up classification system did not predict group membership with 100% accuracy. Hence, some catchments will be misclassified with this system. In fact, some catchments with streams that are in dynamic equilibrium could be mis-construed as having streams in adjustment. This, again, emphasizes the importance of visiting a stream and collecting field measurements prior to making any management decisions regarding land use change that might affect that stream.

Given that landscape-scale attributes have been shown to be highly correlated with stream channel morphology and that GSMNP has a large diversity of landscapes, it is not unexpected that there should be more than one type of 'reference' stream in this study area. Most programs that identify reference streams are aware of the diversity in stream types, and will choose at least one reference stream from each ecoregion in an area (see Arnwine et al. 2000 for an example of reference stream selection by sub-ecoregion in Tennessee). However, at least for GSMNP, the diversity in stream types exceeds the number of ecoregions (Griffith et al. 1997, Griffith et al. 2002); this is likely to be true for other areas as well. Furthermore, with respect to stream channel morphology, the reference stream may be a flawed concept. It is less important to classify a reach as being a particular type of stream channel than it is to determine if that reach is aggrading, degrading, or maintaining dynamic equilibrium. This is best accomplished by surveying the stream channel repeatedly over several decades. However, in lieu of that effort, the bottom-up classification, as presented in this dissertation, maps catchments according to process- and disturbance-related classes by statistically relating land and channel characteristics to reference and disturbed *catchment* conditions. From the resulting groups, I can identify whether the stream in

a given watershed differs from or is similar to others in its class, and whether it should be targeted for restoration efforts, given the likelihood of the stream channel adjusting toward equilibrium as a result of the restoration effort.

In a final note concerning reference streams and reference catchments, recall that the BU-5 catchments, which had been heavily disturbed by corporate logging, served as the reference category in the multinomial logistic regression model. This was an artifact of the clustering procedure, whereby this category had moderate values for all channel morphology variables. Therefore, it served as the most utilitarian group, from a mathematical standpoint, for statistical modeling, as each other group had either higher or lower values than BU-5 for each channel morphology measurement. This may indicate that the typical, and possibly average, stream channel condition in the park is disturbed and adjusting back toward pre-disturbance equilibrium conditions. However, this is also the second largest group and may contain several streams that are in dynamic equilibrium but have values slightly lower than the values for catchment groups BU-1 and BU-3. Nevertheless, many of these streams would likely qualify as 'reference' streams according to the current selection criteria (Arnwine et al. 2000). Yet, many of these stream channels are likely still in adjustment; therefore, stream biota and water quality are likely to change as the stream channel adjusts over time. As such, the 'reference' condition would be a moving target, making it difficult to document whether relative change in a different stream, which was being monitored following restoration, actually represented positive or negative change. This reinforces both the importance of documenting any land use changes that have occurred in a monitored watershed and determining whether the stream channel of interest is still adjusting to those changes.

Although the bottom-up approach was more successful than the top-down approach in creating useful catchment groups in GSMNP, it is worth considering whether the top-down approach would perform better if the differences between landscape-scale

attributes were less subtle. For instance, if I were to include the entire Little River watershed, from the headwaters, which are in GSMNP, to its confluence with the Tennessee River, differences in physiography, climate, vegetation, and land use would increase. The Little River leaves the Blue Ridge physiographic province and flows through the Valley and Ridge as it approaches its confluence with the Tennessee River. Relief decreases in the Valley and Ridge, resulting in headwaters with lower mean elevations and generally lower mean slopes, although the upper reaches of some catchments are still quite steep. The less resistant Paleozoic limestones and shales on the valley floors could provide more sediment and would produce lower reach-slopes. The vegetation is quite different, owing largely to human-induced land use changes. In particular, the Little River flows through areas that continue to be settled, farmed, and logged, which is not the case in GSMNP; hence, disturbance regimes are more pervasive and persistent in headwaters draining into the lower reaches of the Little River and into other drainage basins outside of the park boundaries. As disturbance was the most important landscape attribute in the bottom-up classification, I would expect that increasing the heterogeneity in disturbance processes would actually increase the efficacy of this classification approach. This likely would be the case even though the overall landscape character in GSMNP is somewhat distinctive from the rest of the southeastern U.S.

Because of the more dramatic differences in landscape-scale attributes at broader scales, I would expect the top-down approach to create additional catchment classes across larger regions; yet, these additional classes may not increase the strength of correlations with stream channel morphology, as it is likely that convergence would still be an issue with the top-down approach. Thus, several top-down catchment groups would have similar types of stream channels. For instance, several different combinations of landscape-scale attributes would lead to highly disturbed catchments with highly impacted streams. Once again, the duration and intensity of disturbance, combined with the sensitivity of the catchment to disturbance, would dictate the

degree of fluvial adjustment occurring in the stream channel. What I learned from attempting the top-down approach in GSMNP is that I would need to refine the divisions of landscape-scale attributes into classes that better represent hillslope processes happening over time. In other words, frequency and magnitude of disturbance need to be incorporated into the model. This might not improve the top-down approach in GSMNP, as it has been several decades since disturbance in all catchments; but increasing a temporal component would certainly increase the variability in types of disturbance outside the park.

The top-down catchment classification in GSMNP suggested water quality differences between the catchments, and the bottom-up classification confirmed this variability. Specifically, catchments with large percentages of pristine area had significantly higher levels of nitrogen, as old growth trees uptake less nitrogen than early-successional species. As I used only one grab sample per catchment, the statistical power was quite low for measuring differences between catchments. However, a more intensive sampling scheme would likely reveal additional significant differences. Yet, the next step in investigating the utility of catchment classification in the park, as well as in other regions, should be to assess for differences in aquatic fauna between the catchments. Many state agencies use information regarding both fish and macro-invertebrate assemblages to determine the habitat quality of a particular stream (e.g., Arnwine and Denton 2001), as these biological indices act as reliable indicators of stream condition (Mykra et al. 2004). Therefore, it would be helpful to determine whether catchment types are correlated with aquatic species to better map disturbance-response processes happening in a particular watershed.

Given that stream channel habitat includes geomorphic condition, in addition to water quality and the health of the aquatic flora and fauna, the true biological integrity of a stream must account for any adjustment processes happening in a stream channel as a

function of disturbance. As this adjustment response is variable, being a function of disturbance frequency and magnitude as well as the resiliency of a particular catchment, a watershed classification based on stream channel geomorphic condition and its relationship to hillslope processes, such as the bottom-up approach, would benefit researchers and agencies attempting to assess the condition of any stream. This is not to say that we should stop collecting water chemistry and biological information; rather, we should include geomorphic measurements and assess correlations between all of these data and watershed processes, through the use of bottom-up classification techniques, in an effort to best map and monitor the biological integrity of any watershed.

Toward that effort of including geomorphic data in stream surveys, I offer a brief assessment of the time needed to complete a bottom-up channel survey, as well as suggestions on the more important data that are needed. I was able to survey two stream channels in one day with help from one field assistant, provided both reaches were relatively accessible. More remote streams and channels with dense riparian vegetation took an entire day to survey. This necessarily limits the number of stream reaches that can be surveyed. With the bottom-up approach being predicated on actually having stream channel morphology data, the success of the model will always be driven by resources available for stream surveys. It may be possible to conduct a more limited stream channel survey that achieves similar results to the model that I have presented. For instance, a trained fluvial geomorphologist could select a representative reach rather quickly, rather than surveying seven cross-sections per reach before beginning the monumented cross-section. In addition, stream width was a better indicator of fluvial condition than depth in this study; therefore, a rapid assessment could be done by simply measuring bankfull stream width. The median particle size and reach slope were highly, positively correlated; therefore, a quick stream channel assessment, at least in GSMNP, could forego the leveling techniques necessary to acquire the longitudinal profile, and simply document the median

particle size. Stored sediment was not correlated with any other channel morphology measurement and was quite sensitive to land use; as such, it should be included in any channel survey regardless of the sampling effort. Finally, I did not include any measurement for the presence of coarse woody debris (CWD) in this classification. However, while surveying streams in the park, I noted that CWD was an important contributor to the heterogeneity of stream channel habitat, and that it had a profound local influence on reach-scale channel morphology. As such, some measurement of CWD should also be included in any stream channel sampling effort.

That channel types should reflect hillslope disturbance processes is not surprising. In fact, Montgomery (1999) proposed that one could map areas in a watershed characterized by the different geomorphic processes and disturbance regimes most important to stream channel morphology. Theoretically, these process domains denote portions of a watershed where a dominant disturbance regime directly influences stream channel morphology. In zero-order, colluvial hollows the most important disturbance processes would be fire, wind, and landslides. Debris flows in steep canyons would have the greatest impact on ephemeral and small streams, while flooding would be the most important disturbance process in larger streams. Finally, channel migration would drive channel morphology change in the largest alluvial channels. In practice, these process domains could also be used to predict different types of stream channels (Montgomery and Buffington 1997).

The concept of process domains heavily influenced my study design, as I sought to test to what degree hillslope processes in GSMNP could predict stream channel morphology. Process domains change with increasing stream order and increases in valley width; hillslope processes are most important in headwaters, and alluvial processes dominate in the valley bottoms. All of the catchments classified in this dissertation were headwater contributing areas with perennial flow. As such, each surveyed reach was located near the transition between the debris-flow-dominated

and the flood-dominated process domains, and each should have been exposed to similar disturbance and geomorphic processes. This was done purposefully, so that I could assess the relative importance of different landscape-scale attributes on stream channel morphology while, hopefully, controlling for the expected geomorphic influence. In fact, my classified watersheds could all be mapped as either small, steep-sloped catchments dominated by debris flows (although debris flows are infrequent occurrences in this study area) or larger flood-dominated catchments. The BU-3 group was typical of the former process domain, and the BU-4 group was typical of the latter. However, most of my catchments did not classify into one of these two bottom-up catchment groups. Hence, the additional variation in stream channel morphology that I found was a function of the severity of disturbance, which was largely human-induced, and the sensitivity of each catchment to that disturbance.

In essence, my headwater classification identified three additional catchment classes, each of which represented a transitional catchment with the stream channel adjusting toward equilibrium conditions. Most of the BU-2 catchments are heavily disturbed flood-dominated catchments that are moving toward the BU-4 group. Some of the BU-1 catchments are also flood-dominated catchments moving toward the BU-2 group and ultimately into the BU-4 group. The remaining BU-1 catchments are small, disturbed headwaters that are transitioning toward the BU-3 group. BU-5 catchments have moderate reach-scale values, have experienced moderate disturbance, and have moderate sensitivity to disturbance; these catchments are adjusting toward either BU-3 or BU-4 depending on their size, geometry, and slope steepness. These results indicate that, although the process domain concept is a valid framework for organizing the landscape according to geomorphic processes and disturbance regimes, land-use history, surficial geology, and drainage basin geometry can be used to decrease the variability in prediction of stream channel habitat and to identify the state of adjustment for stream channels in disturbed catchments.

This headwater classification process provided an opportunity for testing how successfully we can link processes across scale. Using two techniques for classifying headwater catchments, I evaluated both a top-down and a bottom-up approach to catchment classification. The top-down approach partitioned catchments into six discrete groups based on the similarity of their respective landscape-scale attributes. This technique was easily done using GIS and statistical software; however, it did not create catchment groups that had significantly different stream channel morphology. Although I attempted to use landscape-scale attributes that represented hillslope processes, the model failed because it was not a true process-driven model. The clustering procedure used in the top-down approach tends to choose one dominant attribute for clustering rather than a combination of attributes. This results in some catchments having one or more statistically trivial attributes that may offset the geomorphic influence of the dominant attribute on stream channel morphology. The top-down approach also could not account for convergence, where different combinations of attributes produce similar channel morphology. Hence, top-down catchments could not effectively take advantage of the correlation between landscape-scale and reach-scale information in order to discriminate among different types of stream channels.

In contrast to the top-down approach, the bottom-up headwater classification technique better modeled the geomorphic processes related to stream channel adjustment. With this approach, a sample of stream reaches was first classified into five types, based on similarities in stream channel morphology. These five types represented transitional states in the expected response of stream channels that were either aggrading, degrading, or in dynamic equilibrium. These stream types ranged from small to large, as a function of discharge, and had steep reach slopes with large median particle sizes or shallow slopes and small bed material as a function of sedimentation. In the bottom-up classification procedure, I classified each catchment into one of five groups based on the type of stream that drained the catchment. Using

a multinomial logistic regression model, I was able to predict catchment group membership, according to the relationship between stream type and landscape-scale attributes, with better than 80% accuracy. I achieved this result even though several bottom-up catchment groups shared a few important landscape-scale attributes. Thus, I found that different types of stream channels could form in similar catchments that differed only in disturbance intensity. This supported my conclusion that land use history was a critical component of this, and possibly any, classification procedure.

Neither my top-down nor my bottom-up analyses would be directly applicable in other physiographic regions, and each would likely require substantial modification in order to be used outside of the park boundaries. Nevertheless, the process of relating landscape-scale attributes to stream channel function and morphology by analyzing relationships between variables at the two scales, particularly the bottom-up technique, is a generally applicable tool and potentially a powerful one. A catchment whose characteristics have been analytically combined into a single metric provides a point of reference in time, such that future changes in stream condition can be documented and quantified as a function of changes in the catchment condition. Additionally, catchment analysis allows for the synthesis of disparate data types, which provides measurable and standardized dependent variables for modeling the multivariate influence of many independent variables. It is true that all data reduction necessarily involves a loss of information when going from the original, sampled components to a single, combined metric. However, if properly modeled, a catchment metric can actually enhance the descriptive power of the original data by representing gradients and emergent properties that would not normally be detected when modeling with only the individual components of the system.

Although it is time-intensive to collect the stream channel morphology information, the ultimate advantage is in directly sampling the habitat of interest with regard to biological integrity. The broader interest in classifying watersheds, and landscapes in

general, is likely to continue as we acquire more sophisticated and accurate remotely-sensed data. However, much as in the early days of remote sensing, it is imperative that we ‘ground-truth’ the data. Thus, we must continue to directly collect stream channel habitat data and correlate these data with landscape-scale attributes in order to better understand how to model the hillslope processes that impact stream channel morphology. My headwater classification effort is one step toward this progression of linking processes across scale and extrapolating those findings throughout landscapes to better predict and protect biological integrity of both streams and the hillslopes that drain to those streams. The bottom-up catchment classification procedure may require more effort to produce than the typical top-down approach, but ultimately, it provides the best template for further research on physical-biological interactions both in the Great Smoky Mountains National Park and throughout the region.

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