DISSERTATION

HYDROGEOMORPHIC CHARACTERIZATION AND CLASSIFICATION OF PACIFIC NORTHWEST MOUNTAIN STREAMS FOR BIOMONITORING

Submitted by

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WE HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER OUR SUPERVISION BY CHRISTOPHER O. CUHACIYAN ENTITLED HYDROGEOMORPHIC CHARACTERIZATION AND CLASSIFICATION OF PACIFIC NORTHWEST MOUNTAIN STREAMS FOR BIOMONITORING BE ACCEPTED AS FULFILLING IN PART REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY.

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ABSTRACT OF DISSERTATION

HYDROGEOMORPHIC CHARACTERIZATION AND CLASSIFICATION OF PACIFIC NORTHWEST MOUNTAIN STREAMS FOR BIOMONITORING

Biomonitoring using benthic macroinvertebrates has become the prevailing technique for assessing stream health in the United States. Because pre-disturbance biological conditions are rarely known, a reference site approach is often used to determine the extent of stream degradation. Ecoregions are the predominant spatial units within which stream reference conditions are developed, but they neglect important valley- and reach-scale influences on stream habitats. Few existing classifications integrate hydrologic and geomorphic (i.e., hydrogeomorphic) typologies and none explicitly describe physical processes and boundary conditions of relevance to stream biotic assemblages.

I used a geographical information system (GIS) to describe hydrologic regimes and geomorphic boundary conditions at 222 minimally-disturbed U. S. Environmental Protection Agency biomonitoring sites in mountainous ecoregions of the Pacific Northwest. Innovative models were developed to predict mountain channel stream types and median substrate size. I applied these multi-scale metrics to develop *a priori* (without biological calibration) and *a posteriori* (biologically calibrated) classifications of biomonitoring sites and compared them to geographically-dependent classifications including Level III ecoregions. Field-measured metrics were included in a set of *a posteriori* models to test for potentially important reach-scale habitat characteristics not accounted for in the GIS-developed metrics. Cluster analyses provided a basis for spatially-neutral classifications based on biological data. Similarity in stream insect assemblages within and among classes was used to develop quantitative measures of classification strength for comparing classification performance.

A priori classifications outperformed ecoregions in 11 of 18 comparisons, indicating that hydrologic and geomorphic classifications can partition biological variability better than ecoregions, often with fewer classes. Classification tree models resulted in classification strengths as high as 90% of the maximum attainable. Valley-scale metrics describing floodplain presence, specific stream power, peak flows, and low flows were consistently strong predictors in classification trees.

The hydrogeomorphic classifications developed provide a framework for identifying relatively homogeneous habitat types sustaining comparable stream insect assemblages and support stream-habitat restoration by providing hydrologic and geomorphic habitat endpoints to target for ecological restoration. GIS-derived hydrologic and geomorphic metrics provide a basis for mapping multi-scaled hydrogeomorphic settings and putative habitat types across entire landscapes, and a framework for process-based stratification in biomonitoring designs.

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LIST OF SYMBOLS AND ABBREVIATIONS

Symbols

–	Dimensionless
A	watershed area
adjusted R^2	coefficient of determination adjusted for the number of predictors
b	Exponent
$\overline{B}$	between-class similarity
β	an adjustable space-distorting/conserving parameter in flexible clustering
c	proportion of a value of the dependent variable in the class
C_p	Mallow's Cp; an estimate of the total standardized expected squared prediction error
d	Exponent
d	bankfull channel depth
D_{50}	median channel substrate size
g	specific weight of water and sediment mixture
Interdecile_CV	interdecile coefficient of variation
n	sample size
Q	stream discharge
r	Pearson correlation coefficient
R^2	coefficient of determination
R_c	relative cost

S	Slope
$SA^{0.4}$	slope times area$^{0.4}$, a surrogate for specific stream power and shear stress
S_f	friction slope
w	specific stream power
w	width of the channel
$\overline{W}$	within-class similarity

Abbreviations

A	watershed area
°C	degrees Celsius
AML	Arc macro language
B-IBI	benthic index of biological integrity
C++	programming language
CART	Classification and Regression Trees
cm	centimeter(s)
cms	cubic meter(s) per second
CS	classification strength
CT	classification tree
DEM	digital elevation model
EMAP	Environmental Monitoring and Assessment Program
EPT	Ephemeroptera, Plecoptera, Trichoptera
ESRI	Environmental Systems Research Institute, Inc.
GIS	geographic information system
kJ	kilojoule(s)

km	kilometer(s)
LiDAR	light detection and ranging
LULC	land use/land cover
LWD	large woody debris
m	meter(s)
mm	millimeter(s)
MRPP	multi-response permutation procedure
MSE	mean square error
NLCD	National Land Cover Dataset
OR-EMAP	Oregon Environmental Monitoring and Assessment Program
OWEB	Oregon Watershed Enhancement Board
PHab	USEPA field-measured physical habitat attributes
PRESS	prediction sum of squares
PRISM	parameter-elevation regressions on independent slopes model
SSE	sum of square errors
SSP	specific stream power
TMDL	total maximum daily load
μeq/L	microequivalents per liter
μg/L	micrograms per liter
US	United States
USEPA	United States Environmental Protection Agency
USGS	United States Geological Survey
W-EMAP	Western Environmental Monitoring and Assessment Program

CHAPTER 1

BIOMONITORING, STREAM CLASSIFICATION, AND MULTI-SCALE GEOSPATIALLY-DERIVED DESCRIPTORS OF STREAM HABITATS: AN INTRODUCTION

The Clean Water Act of 1972 requires that states monitor, maintain, and restore the ecological integrity and aquatic life uses of waters in the United States (US). Biomonitoring and bioassessments (hereafter referred to as *biomonitoring*) are general terms used to describe the examination of environmental condition and ecological integrity using field monitoring of aquatic biota to assess whether 1) a departure from reference or least-disturbed conditions has occurred, and 2) the water bodies of interest (streams in this study) are supporting designated uses (Barbour et al. 1999, Karr 1999, Bonada et al. 2006). The use of biological measures to infer stream and river condition started as early as the 19th century in Europe (Bonada et al. 2006). Biomonitoring has evolved into the prevailing, standard technique for detecting and quantifying anthropogenic degradation of fresh waters in the US.

Stream insects and other benthic macroinvertebrates are the most commonly used organisms for biomonitoring (Bonada et al. 2006). Aquatic insects provide explicit benefits over other taxa including ubiquity in most streams, high species richness providing a large suite of functional characteristics that can be associated with an array of environmental stressors, relatively sedentary behavior compared to fish, and relatively low sampling costs (Norris and Norris 1995, Barbour et al. 1999, Bonada et al. 2006).

Biomonitoring typically involves comparing observed biotic assemblages to those expected if ecological integrity is intact (Barbour et al. 1999, Karr 1999, Bonada et al. 2006). This is no trivial task as there is often little or no available information regarding the pre-disturbance condition (Hawkins and Norris 2000a). Regional or geographic classifications are commonly used as frameworks for developing reference conditions and conducting comparisons of streams of presumably similar ecological potential (Hawkins and Norris 2000a, Stoddard 2005). Such classifications often take into account several landscape characteristics such as topography, geology, vegetation, climate, and soils (Stoddard 2005). There is little consensus among scientists and managers regarding how geographic classifications should be delineated and applied in monitoring design and bioassessment. As a result, physiographic provinces (Fenneman 1946), biogeographical provinces (Hocutt and Wiley 1986), hydrologic units (i.e., watersheds), and ecoregions (Bailey 1983, Omernik 1987) are regularly applied by state biomonitoring programs. Ecoregions have been traditionally recommended by the U.S. Environmental Protection Agency (USEPA), and are arguably the most widely used geographic classification.

Many studies suggest that ecoregion classifications are reasonable and useful for landscape studies of aquatic organisms (Hawkins and Norris 2000b, Stoddard 2005). However, ecoregions and other geographic landscape classifications may lack the spatial resolution necessary for identifying sharp gradients in important physical processes and boundary conditions of known biological significance, especially hydrologic regimes (Resh et al. 1988, Poff and Allan 1995, Power et al. 1995, Poff et al. 1997, Richards et al. 1997) and geomorphic character (Parsons et al. 2003). Regions used in ecoregions and other geographic classifications are typically large (e.g., 10^3-10^5 km^2, Hawkins and

Norris 2000a) and, therefore, do not account for intermediate- (e.g., valley) or small-scale (e.g., reach) habitat characteristics which also play an important role in influencing stream biota. Thus, the strong gradients and spatial heterogeneity in hydrologic, climatic, and lithotopographic characteristics occurring in some regions of this scale can confound bioassessments. This issue is perhaps most relevant to mountainous regions that encompass a variety of precipitation regimes, geologic contexts, and vegetation zones (e.g., the Cascades ecoregion of Oregon and Washington).

There are many geomorphic classifications for characterizing stream environments at intermediate and reach scales including Nanson and Croke (1992), Whiting and Bradley (1993), Rosgen (1994, 1996), Montgomery and Buffington (1997), and Montgomery (1999). These classifications were developed with an emphasis on valley and channel form as they relate to fluvial processes, and were not explicitly developed for delineating changes in form and process of greatest relevance to stream organisms. Although many stream types may be necessary to explain physical processes in stream channels, the number of biological types will not necessarily match because ecological characteristics are likely not exclusive to each stream type (Karr 1999). Hydrologic classifications also exist (e.g., Poff and Ward 1989, Poff 1996, Sanborn and Bledsoe 2006), but both geomorphic and hydrologic classifications remain untested as tools for explaining landscape variability in stream insect assemblages. Furthermore, few classifications integrate hydrologic and geomorphic characteristics into a unified typology (but see Snelder and Biggs 2002, Poff et al. 2006).

A better understanding of how multi-scale hydrologic and geomorphic characteristics influence and constrain biological potential could provide significant improvement in our understanding of spatial and temporal patterns in stream insect assemblages and other stream communities. The development of an integrated hydrologic and geomorphic (hereafter referred to as *hydrogeomorphic*) approach to classification has already proven to be a powerful tool for partitioning wetlands into relatively homogeneous classes (Smith et al. 1995) and may be similarly applicable to the classification and partitioning of stream habitats and associated stream assemblages. A landscape-scale stream classification based on influential physical habitat characteristics could prevent spurious biological comparisons among streams with critical differences in physical processes and improve our ability to detect water-quality impairment in a defensible manner.

In this study, I developed landscape-scale hydrogeomorphic classifications of 222 Pacific Northwest stream biomonitoring sites using geospatial data, and examined the efficacy of these classifications in explaining variation in biomonitoring data among and within 7 heterogeneous ecoregions of Oregon and Washington. Chapter 2 focuses on the need and rationale for developing multi-scale hydrologic and geomorphic metrics that better represent stream processes and boundary conditions at multiple scales. Towards this end, statistical models were used to create new and innovative Geographical Information System (GIS) tools for predicting Montgomery and Buffington (1997) stream type and median channel substrate size (D_{50}) across the study regions without reliance on field data. New climatic and land-cover metrics were also developed, including topographic wetness- and distance-weighted land-cover metrics. All metrics were derived using readily-available geospatial data. Chapters 3 and 4 are intended to be stand-alone journal manuscripts. In Chapter 3, a select subset of the hydrologic and geomorphic metrics was employed to construct several *a priori* (without biological calibration) hydrologic, geomorphic, and hydrogeomorphic classifications of stream habitats. Measures of classification strength based on similarity of stream insect assemblages were used to explicitly quantify the relative strength of these classifications in partitioning variation of stream insect assemblages and to compare against commonly used *a priori* geographic classifications such as ecoregions. In Chapter 4, classification tree modeling was used to directly relate hydrologic and geomorphic metrics to observed stream insect data (*a posteriori*). For comparison, classification trees were also generated using reach-scale physical characteristics measured in the field by USEPA crews. The classification strengths of *a posteriori* classifications were then quantitatively compared to the *a priori* classifications (presented in Chapter 3) to assess how well the two approaches partition variability in aquatic insects across and within these diverse regions of the Pacific Northwest. Finally, Chapter 5 summarizes the major findings and discusses the implications of this work.

Although some of the GIS metrics I have developed and present in Chapter 2 were not used in the analyses presented in Chapters 3 and 4, my colleagues and I have used them in other research associated with this USEPA-funded project. Peer-reviewed journal articles, theses, short papers/posters, and presentations involving the development and/or application of these metrics, or early predecessors to these metrics, include Bledsoe et al. (2003a, 2003b), Cuhaciyan et al. (2003a, 2003b, 2004, 2005a, 2005b, 2006), Poff et al. (2004), Holburn et al. (2005, *In preparation*), Hurst (2005), Olson et al. (2005a, 2005b, *In preparation*), Flores et al. (2006), Olden et al. (2006), and Sanborn and Bledsoe (2006).

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CHAPTER 2

CHARACTERIZING PHYSICAL STREAM HABITATS WITH GEOSPATIAL DATA TO EXPLAIN LANDSCAPE-SCALE VARIATION IN STREAM BIOTA

2.1 INTRODUCTION

Characterizing hydrologic, geomorphic, and other small- to large-scale (e.g., channel cross section to watershed) properties and processes is central to understanding and predicting water quality, water quantity, and the physical structure (i.e., habitat) influencing stream communities. A GIS may be used to extract essential hydrologic, geomorphic, topographic, climatic, and other descriptors from geospatial data. Such an approach could increase understanding of spatial relationships between habitat and aquatic assemblages and support the mapping of improved landscape-scale classifications of stream habitats for biomonitoring. This provides a basis for spatially-explicit modeling of watershed processes and a technique for understanding ecologically important physical characteristics in a watershed context.

Readily available geospatial data and the prevalence of GISs have led to a corresponding increase in landscape-scale studies of stream processes and ecological conditions (Van Sickle 2003). Associated with this growth is a demand for environmental descriptors that appropriately describe upstream contexts that influence physical habitat and biological conditions observed at field-monitoring sites. Many studies have focused on relatively coarse sets of easily computed metrics that represent aspects of climate (e.g., average annual precipitation), topography (e.g., watershed area and slope), percent geologic type, and percent land use/land cover (LULC). Although such metrics have proven useful in a number of studies (e.g., Jennings et al. 1994, Pitlick 1994, Davies et al. 2000, Kearns et al. 2005), particularly those which utilize LULC to assess human influences on water quality and biological conditions (e.g., Richards and Host 1994, Roth et al. 1996, Allan et al. 1997, Kennen 1999, Pan et al. 2004), these metrics often fall short of adequately describing underlying natural variability in water quality, water quantity, stream habitats, or biological communities.

This chapter describes the development of an innovative set of ecologically relevant metrics characterizing watershed- and intermediate- (valley-) scale processes and boundary conditions of Pacific Northwest streams, as well as more common metrics with demonstrated utility such as channel slope, watershed area, and percent LULC. Several of the general types of metrics discussed here were developed collaboratively. This includes the re-classification of geology by Sable (2004) and hydrologic metrics from Sanborn and Bledsoe (2006). Other metrics were developed based on existing stream classification systems (e.g., Whiting and Bradley 1993, Montgomery and Buffington 1997), a literature review of previous works (e.g., Frissell et al. 1986, Poff and Allan 1995, Parsons et al. 2003, 2004), and using knowledge of important and potentially-important physical properties and processes influencing stream habitats and associated stream assemblages. This extensive set of metrics was developed with the explicit consideration of scale as a primary impetus.

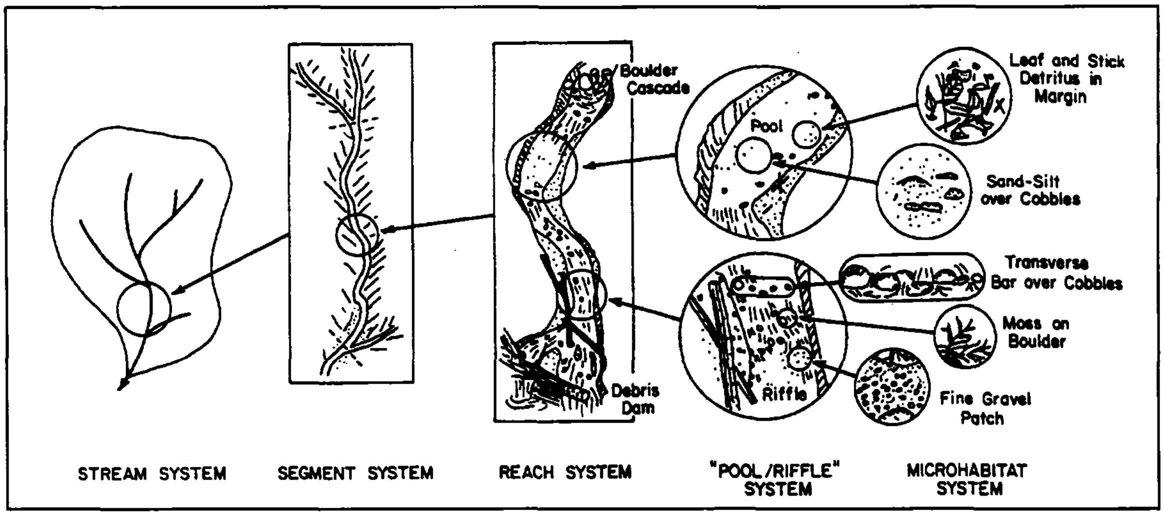

Figure 2.1. Hierarchical stream organization (from Frissell et al. (1986)).

Streams are shaped by processes occurring at many spatial and temporal scales, and can be viewed as hierarchical systems (Figure 2.1, Schumm and Lichty 1965, Frissell et al. 1986, Davies et al. 2000, Parsons et al. 2003, 2004). Local-scale (e.g., reach) stream form and function are constrained by large-scale (e.g., regional- and watershed-scale) influences including climate, geology, topography, and vegetation (e.g., Frissell 1986, Poff et al. 1997, Parsons et al. 2003, 2004). These large-scale influences shape water, sediment, wood, temperature, and nutrient regimes that constrain ecosystem structure and function (e.g., Poff et al. 1997). The resulting habitat becomes the template upon which adapted species combine to structure biological assemblages (Southwood 1977, Townsend and Hildrew 1994). The influence of geomorphic and hydrologic stream characteristics is well established in stream ecology (e.g., Poff and Ward 1989, Poff and Allan 1995, Clausen and Biggs 1997, Poff et al. 1997, McGarrell 1998, Parsons et al. 2003, 2004), yet the development of process-based metrics that can be computed in a GIS and used in predicting the biological condition of streams has lagged behind scientific understanding.

2.1.1 Objectives

This chapter is intended to introduce and provide background information on the geospatially-derived metrics used in subsequent chapters that describe the development of novel physical classifications for explaining landscape variability in stream biota. In this chapter, I describe a large set of innovative metrics that I developed to characterize multi-scale stream processes and boundary conditions. Hydrologic metrics are briefly reviewed here as well. These were generated based on the work of Sanborn and Bledsoe (2006) to support this study.

The metrics described here were ultimately developed to support USEPA Environmental Monitoring and Assessment Program (EMAP) objectives, which include better understanding of multi-scale physical influences with respect to stream monitoring, assessment, and future vulnerability (http://www.epa.gov/emap/index.html). The USEPA EMAP program includes probabilistic site selection for developing a field-monitoring network. During site visits, a thorough assessment of local stream and riparian zone conditions and characteristics is conducted including physical (e.g., slope, width, large woody debris counts, and canopy cover), chemical (e.g., total phosphorus and pH), and biological data (e.g., benthic macroinvertebrate samples and fish counts, Kaufmann et al. (1999)).

Although EMAP field crews methodically describe the local settings of stream reaches, regional- (e.g., ecoregions and hydrologic units), watershed- (e.g., watershed area and precipitation), and intermediate- (e.g., hill-slope connectivity and floodplain presence) scales are not examined. At the outset of this study, I was particularly interested in developing better descriptors of the valley-scale context of streams.

Previous studies that have examined associations between valley-scale descriptors and stream macroinvertebrates have concluded that little association exists (Maridet et al. 1998, Snelder et al. 2004, Parson et al. 2004). This may be a result of valley metrics that were not measured at an appropriate grain, or which simply have little association with stream macroinvertebrates. Valley configuration, however, is clearly an important control on stream forms and processes (e.g., Hynes 1975, Whiting and Bradley 1993, Nanson and Croke 1992, Montgomery and Buffington 1998), which create physical stream habitats. Valley-scale descriptors are challenging to derive and identifying how best to measure them can be difficult.

I hypothesize that classifications of stream insect assemblages based upon multi-scale influences of stream habitats will attain higher classification strengths than classifications based solely on geographically-dependent classifications or reach-scale metrics. This hypothesis is tested in Chapter 4 using classification trees (Breiman et al. 1984) to predict stream insect assemblages. Further, I expect that the valley-scale is important for predicting relatively homogeneous stream biological assemblages. The efficacy of predicting median substrate size (D_{50}) at sites across a large mountainous region using only geospatial data is also examined in this chapter. A further goal of this project was to develop metrics applicable to USEPA research initiatives (e.g., anthropogenic disturbance, natural variation, hydrology, and stream habitat), and this effort ultimately resulted in an initial pool of more than 900 metrics. Many of these metrics were simple variations on a single type of descriptor (e.g., land cover with different distance-weighting schemes). In this chapter, I highlight a small subset of innovative metrics developed in this study with specific emphasis on metrics that proved important in the hydrologic and geomorphic classifications described in Chapters 3 and 4.

2.2 THE METRICS

As a first step in developing multi-scale physical metrics for 222 EMAP monitoring sites in Oregon and Washington, site coordinates were imported into a GIS and used to delineate contributing watersheds. This was no trivial task as site coordinates typically did not match stream-channel locations derived from 10-m digital elevation models (DEMs). Therefore, the first step in the delineation process involved adjusting site coordinates to correspond to the nearest DEM-derived stream channel. This step was followed by the delineation of the contributing watersheds and calculation of watershed areas. The resulting watershed areas and planforms were then compared to watersheds delineated manually by the USEPA. When necessary, site locations were adjusted to maximize correspondence between USEPA and digitally delineated watersheds. The USEPA-delineated watersheds were not used because of differences in map scale and the desire to have digitally-delineated watersheds congruent with 10-m DEMs.

As part of the watershed delineation process, several common hydrologic layers were created using basic ArcInfo™ (ESRI 2004) functionality. These layers include a "filled" DEM where pits (local low spots) are adjusted vertically to allow for the creation of flow accumulation, flow direction, and stream network grids. These grids are the foundation for many of the metrics calculated, including geomorphic and topographic metrics, as well as all of the hydrologic distance weighted metrics. When existing GIS functions were not suitable for the computation of metrics, C++ programs were developed and linked to ArcInfo™ (ESRI 2004) via Arc Macro Language scripts.

An extensive set of metrics describing geomorphic, hydrologic, climatic, and geologic characteristics and LULC was computed at several spatial scales ranging from watershed to local stream segments. These included several innovative metrics based solely on readily available geospatial data: Montgomery and Buffington (1997) stream type (Flores et al. 2006), median channel substrate size (D_{50}), several tributary descriptors, and a surrogate for specific stream power. The following sections describe the development of GIS algorithms and statistical models upon which selected metrics are based.

2.2.1 Geomorphic Metrics

Eighty-two measures of geomorphic character were calculated from 10-m DEMs (Table 2.1). The metrics include measures of median substrate size, valley form, stream type, stream network character, upstream tributary character, and watershed topography character. An important foundation for several geomorphic metrics is the use of $SA^{0.4}$ as a surrogate for specific stream power where S is a measure of channel (bed) slope and A is watershed area. Following Flores et al. (2006), specific stream power (ω) can be written as:

$$\omega = \frac{\gamma Q S_f}{w} \tag{2.1}$$

where γ is the specific weight of the water and sediment mixture, Q is stream discharge, S_f is the friction slope, and w is the width of the channel. Steady uniform discharge is typically assumed so that bed slope (S) can be assumed to equal S_f. Assuming that γ is constant and substituting a hydraulic geometry equation relating channel width to discharge and a watershed area to discharge relationship, it can be shown that:

$$\omega \propto S_0 A^{d(1-b)} \tag{2.2}$$

where the exponent (b) commonly has a value near 0.5 (Hey and Thorne 1986, Knighton 1998) and d can vary from 0.6 and 1.0 (Cathcart 2001, Eaton et al. 2002, Jennings et al. 1994, Knighton 1987). If we assume that $d = 0.8$, then:

$$\omega \propto SA^{0.4} \tag{2.3}$$

This surrogate measure of specific stream discharge is straightforward to implement in a GIS, needing only a DEM from which to estimate watershed area and channel slope.

Table 2.1. Geomorphic metrics and descriptions.

Class	Code	Description	Units
Channel substrate	CCD_{50}	Predicted median substrate size	mm
Valley form	CVMCon	Coefficient of variation in MCon	m
	CVentCC	Coefficient of variation in MentCC	m
	CVentDR	Coefficient of variation in MentDR	-
	MCon	Average hill-slope connectivity	m
	MentCC	Average valley entrenchment (difference between local land surface elevation and stream elevation)	m
	MentDR	Average valley entrenchment (floodprone width to bankfull width)	-
Stream type	MnB	Montgomery and Buffington stream type	-
	Pct_C	Percent cascade	%
	Pct_lt4	Percent cells less than 4% slope	%
	Pct_lt7	Percent cells less than 7% slope	%
	Pct_PB	Percent plane bed	%
	Pct_PR	Percent pool riffle	%
	Pct_SP	Percent step pool	%
Stream network	Chan_slp	Average channel slope	m/m
	Drainden	Drainage density	m^{-1}
	DWsp1	Distance weighted stream power ($w = 1/x^2$)	$km^{0.8}$
	DWsp2	Distance weighted stream power ($w = \exp(-x/X_{Max})$)	$km^{0.8}$
	Link_SA	Outlet link mean *SA* product	km^2
	Link_SA4	Outlet link mean $SA^{0.4}$	$km^{0.8}$
	Link_slope	Outlet link mean slope	-
	Out_sa	*SA*	km^2
	Out_sa4	$SA^{0.4}$	$km^{0.8}$
	Shrev_area	Shreve per area	#/km^2
	Shreve	Shreve stream order	#
	Strah_area	Strahler per area	#/km^2
	Strahler	Strahler stream order	#
Tributary	A1	Tributary 1 to main-stem area ratio	-
	A2	Tributary 2 to main-stem area ratio	-
	Area_1	Tributary 1 area	km^2
	Area_2	Tributary 2 area	km^2
	Aspect	Average aspect	degrees
	Dist_1	Distance to tributary 1	m
	Dist_2	Distance to tributary 2	m
	DW_a1_025	Distance weighted (-0.025) tributary 1 to main-stem area ratio	-
	DW_a1_1	Distance weighted (-0.1) tributary 1 to main-stem area ratio	-
	DW_a1_25	Distance weighted (-0.25) tributary 1 to main-stem area ratio	-
	DW_a2_025	Distance weighted (-0.025) tributary 2 to main-stem area ratio	-
	DW_a2_1	Distance weighted (-0.1) tributary 2 to main-stem area ratio	-
	DW_a2_25	Distance weighted (-0.25) tributary 2 to main-stem area ratio	-
	DW_sa1_025	Distance weighted (-0.025) tributary 1 to main-stem SA ratio	-
	DW_sa1_1	Distance weighted (-0.1) tributary 1 to main-stem *SA* ratio	-
	DW_sa1_25	Distance weighted (-0.25) tributary 1 to main-stem *SA* ratio	-

Class	Code	Description	Units
	DW_sa10.4_025	Distance weighted (-0.025) tributary 1 to main-stem $SA^{0.4}$ ratio	-
	DW_sa10.4_1	Distance weighted (-0.1) tributary 1 to main-stem $SA^{0.4}$ ratio	-
	DW_sa10.4_25	Distance weighted (-0.25) tributary 1 to main-stem $SA^{0.4}$ ratio	-
	DW_sa2_025	Distance weighted (-0.025) tributary 2 to main-stem SA ratio	-
	DW_sa2_1	Distance weighted (-0.1) tributary 2 to main-stem SA ratio	-
	DW_sa2_25	Distance weighted (-0.25) tributary 2 to main-stem SA ratio	-
	DW_sa20.4_025	Distance weighted (-0.025) tributary 2 to main-stem $SA^{0.4}$ ratio	-
	DW_sa20.4_1	Distance weighted (-0.1) tributary 2 to main-stem $SA^{0.4}$ ratio	-
	DW_sa20.4_25	Distance weighted (-0.25) tributary 2 to main-stem $SA^{0.4}$ ratio	-
	MDW_a_025	Distance weighted (-0.025) maximum tributary to main-stem area ratio	-
	MDW_a_1	Distance weighted (-0.1) maximum tributary to main-stem area ratio	-
	MDW_a_25	Distance weighted (-0.25) maximum tributary to main-stem area ratio	-
	MDW_sa_025	Distance weighted (-0.025) maximum tributary to main-stem SA ratio	-
	MDW_sa_1	Distance weighted (-0.1) maximum tributary to main-stem SA ratio	-
	MDW_sa_25	Distance weighted (-0.25) maximum tributary to main-stem SA ratio	-
	MDW_sa0.4_025	Distance weighted (-0.025) maximum tributary to main-stem $SA^{0.4}$ ratio	-
	MDW_sa0.4_1	Distance weighted (-0.1) maximum tributary to main-stem $SA^{0.4}$ ratio	-
	MDW_sa0.4_25	Distance weighted (-0.25) maximum tributary to main-stem $SA^{0.4}$ ratio	-
	MA	Maximum Tributary to main-stem area ratio	-
	Msa	Maximum Tributary to main-stem SA ratio	-
	Ma_0.4	Maximum Tributary to main-stem $SA^{0.4}$ ratio	-
	MSarea_1	Main steam area above tributary 1	km^2
	MSarea_2	Main steam area above tributary 2	km^2
	MSsslope_1	Slope for main stem above tributary 1	-
	MSslope_2	Slope for main stem above tributary 2	-
	SA1	Tributary 1 to main-stem SA ratio	-
	SA1_0.4	Tributary 1 to main-stem $SA^{0.4}$ ratio	-
	SA2	Tributary 2 to main-stem SA ratio	-
	SA2_0.4	Tributary 2 to main-stem $SA^{0.4}$ ratio	-
	Slope_1	Slope for tributary 1	-
	Slope_2	Slope for tributary 2	-
Watershed	Avg_elev	Average basin elevation	m
	DA	Drainage area	km^2
	Min_elev	Minimum basin elevation	m
	Relief_r	Basin relief divided by its length	-
	Shed_slp	Average slope of the basin	m/m
	Slp_elon	Ratio of the slope of the basin to the elongation of the basin	m^{-1}
	Store_p	Percentage of basin that is lakes or other water storage	-
	Topo_wet	Average topographic wetness	-

2.2.1.1 Channel Substrate

A best subsets regression routine was developed in SAS© 9.1 (2004; Version 9.1, The SAS Institute, Inc., Cary) to evaluate and rank all possible equations given a set of potential independent variables. The program was designed to retain and display the ten "best" equations with one to six variables. The "best" equations, as considered here, were those with the lowest Mallow's C_P values. Mallow's C_P is an estimate of the total standardized expected squared prediction error. Choosing models with the lowest values of Mallows C_P is akin to choosing models with the lowest mean squared prediction errors, which is reasonable if the goal of the study is prediction (Neter et al. 1996). Model validation was performed using the prediction sum of squares (PRESS) statistic. The PRESS statistic is calculated the same way as the sum of square errors (SSE), with one important exception: each sample is left out once and the regression completed on the remaining data. The PRESS statistic was then compared to the SSE for the model. As PRESS values approach the value of SSE, it is suggested that the mean square error (MSE) better represents the true error and the model is cross-validated for new observations (Neter et al. 1996). Final model selection was performed by evaluating models using knowledge of physical processes affecting bed-material size to ensure equations chosen are physically intuitive.

All of the independent variables used in the regression analysis were derived from geospatial data and are described in this chapter. The median channel substrate (D_{50}) data used to train the model was field-measured by USEPA EMAP field crews (Kaufmann et al. 1999). The final equation, with an *adjusted* R^2 of 0.36 is:

$$D_{50} = 1.227 S^{1.12} Mx7d^{0.4} MentCC^{0.858} Ma3^{-0.955} Ma41^{0.432} - 1 \quad (2.4)$$

where S is a measure of channel slope, $Mx7d$ is the average annual maximum 7-day discharge, $MentCC$ is a measure of valley entrenchment, $Ma3$ is the coefficient of variation of daily discharges, and $Ma41$ is a measure of water yield per unit watershed area.

The model suggests that D_{50} increases with increasing slope, peak discharge, near-channel hill slope and floodplain elevations, and flow yield, while decreasing with daily flow variation. The slope-discharge product in the model is similar to the Hack (1957) model and may be interpreted as a surrogate for shear stress and specific stream power. The valley entrenchment metric suggests that D_{50} is smaller in stream channels with large energy dissipating floodplains and where hill slopes are less likely to be contributing colluvial materials. This metric may also be acting as a surrogate for other correlated metrics such as slope or stream type. Flow yield may be acting as a surrogate for discharge or variables related to elevation, precipitation, network position, or similar related physical influences. Variation in discharge was shown by Tague and Grant (2004) to be inversely related to substrate size in the Pacific Northwest, as suggested by the model developed in this study.

2.2.1.2 Valley Form

Three valley-form metrics were computed using 10-m DEMs to estimate the presence and extent of floodplains versus the potential for hill slopes directly connected to the stream channel. Three more metrics characterize the variability in these metrics for a distance of 100 m (or ten grid cells) upstream of the watershed outlet (biomonitoring site).

I developed the MentCC metric to be a measure of valley entrenchment. The algorithm calculates the average ground surface elevation in a circular area, with a diameter of approximately one meander belt width, relative to the stream-channel elevation. A meander belt width was estimated as 5.5 times the channel width (Zeller 1967 as cited in Julien 2002). Bankfull channel width was predicted with a downstream hydraulic geometry equation I developed using field data (n = 433) from USEPA biomonitoring sites (Kaufmann et al. 1999) in Oregon and Washington. The resulting equation, contingent upon watershed area in lieu of discharge is:

$$w = 3.02A^{0.325} \tag{2.5}$$

where w is channel width, and A is watershed area in km^2.

A second measure of valley entrenchment (MentDR) was developed to measure entrenchment similar to the entrenchment ratio used by Rosgen (1996). This algorithm computes a ratio of an estimate of floodprone width to estimated bankfull channel width. An estimate of maximum channel depth is required to estimate the elevation at which to compute floodprone width. I used USEPA field data (n = 433, Kaufmann et al. 1999) to develop a hydraulic geometry equation for predicting bankfull channel depth. The equation, based on watershed area is:

$$d = 0.17A^{0.35} \tag{2.6}$$

where d is bankfull channel depth in m and A is watershed area in km^2. The final entrenchment metric is calculated as the ratio of the floodprone width, measured as the width between the valley walls at an elevation of two times the depth plus 1 m (to make up for vertical DEM resolution) to channel width. Typically, bankfull widths and floodprone widths are measured in the field, whereas the use of hydraulic geometry equations and the coarse resolution of DEMs, relative to field measurements, render this metric clearly incomparable to Rosgen's entrenchment ratio. Regardless, this metric suggests an estimate of the cross-sectional shape of the valley bottom.

Hill-slope connectivity (MCon) was developed to detect hill slopes that have a direct influence on the stream channel. A key difference between the aforementioned valley metrics and MCon is how they handle cases where a floodplain is only present on one side of a stream. MCon was developed based on the Whiting and Bradley (1993) process-based headwater stream classification. Their classification was used to predict the potential for debris flows to reach the stream channel and, therefore, influence stream channel morphology. Following the work of Ikeya (1981), they measured the surface elevation 25 m from the stream to serve as the basis for prediction. Given the resolution of the DEMs used here (10 m), a distance of two cells (20 m) was chosen to measure the ground surface elevation. The algorithm was designed to return the difference between the adjacent hill slope and the stream elevation for the higher of two hill slopes perpendicular to stream flow.

2.2.1.3 Stream Type

I developed a classification tree (Breiman et al. 1984) to predict Montgomery and Buffington (1997) stream type using data collected from 270 field sites in California, Colorado, Washington, and Montana (see Flores et al. (2006)). The ten-fold cross-validated model (Figure 2.2) has a relative cost of 0.36 (model fit improves as R_C approaches 0) and a 76% correct classification rate.

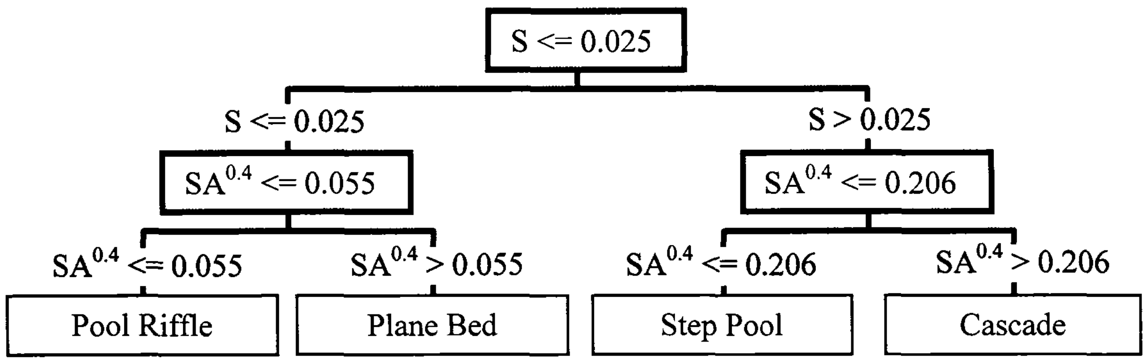

Figure 2.2. Classification tree for predicting Montgomery and Buffington stream type (from Flores et al. (2006)).

In this model, S is channel slope and $SA^{0.4}$ is a surrogate measure of specific stream power. The channel slopes used to develop this model are field measured, whereas the prediction of stream type in this study utilized DEM-derived slope measures. It is likely that this further decreases correct classification rates. Although this would be of value to quantify, detailed site locations were not available for much of the model building data.

2.2.1.4 Stream Network

Stream network metrics included estimates of drainage density, channel slope, stream order, and stream power. Two measures of channel slope were calculated, one based on a 3-cell average (Chan_slp) and one based on a link average (Link_slope), where a link is defined as a stream reach between two tributaries. The vertical resolution of DEMs can falsely indicate that there is no slope in low gradient areas. To prevent false zero slopes, the Chan_slp algorithm locates the nearest upstream and downstream elevation changes. The channel length between these two points is determined and a reach-averaged channel slope calculated.

Two distance-weighted specific stream power ($SA^{0.4}$) metrics were calculated for the entire upstream channel network. Specific stream power was calculated for each link in the network as well as the mean hydrologic distance of the link to the outlet. Finally, two decay rates (Table 2.1) were calculated and applied based on the distance from the centroid of each channel link to watershed outlet to compute a mean distance-weighted estimate of specific stream power.

2.2.1.5 Tributary

Tributary metrics were calculated using a C++ program developed in association with an Arc macro language (AML) script. The values returned in this program include channel slope and watershed area for the nearest upstream tributaries as well as the main-stem channel where the tributary enters. The distance from the watershed outlet to each tributary junction was calculated to derive distance-weighted tributary to main-stem ratios of specific stream power and watershed areas. These metrics allow for the determination of tributary junctions that can have significant geomorphic effects (Rhoads 1987, Rice 1998, Benda et al. 2004), including changes in channel substrate size distributions (Rice 1994, 1998) and stream assemblages (Rice et al. 2001).

2.2.1.6 Watershed Topography

All watershed topography metrics were calculated from 10-m DEMs with the exception of the water storage metric (Store_p), which was computed using the National Land Cover Dataset (NLCD, http://erg.usgs.gov/isb/pubs/factsheets/fs10800.html).

2.2.2 Hydrologic Metrics

Discriminant functions were used to classify biomonitoring sites by similarity in high-flow, low-flow, monthly-flow, and all-flow characteristics. These flow regime types allowed for the discrimination of sites into snow melt, snow and rain, rain, and variable regimes. Multiple regression equations unique to each flow regime type were then applied to derive the remaining metrics. Several climatic, physiographic, and geologic metrics described herein are used as the independent variables (Sanborn and Bledsoe 2006). These metrics (Table 2.2) describe ecologically important hydrograph characteristics including peak flows, low flows, variability, rates of change, and durations (Poff and Ward 1989, Richter et al. 1996, Poff et al. 1997).

Table 2.2. Hydrologic metrics and descriptions (after Sanborn and Bledsoe (2006)).

Class	Code	Description	Units
Flow Classes	All4pca	Flow classification based on all-flow metrics	-
	Hi4pca	Flow classification based on high flows	-
	Lo4pca	Flow classification based on low flows	-
	Month4_f5	Flow classification based on monthly flows	-
Peak flow	DatMx	Julian date of the maximum flow	-
	Dh12	Mean annual 7-day maximum divided by median discharge	-
	Dh13	Mean annual 30-day maximum divided by median discharge	-
	Fh11	Mean number of discrete flood events per year	-
	Mh1	Maximum monthly flow for October	cms
	Mh8	Maximum monthly flow for May	cms
	Mx1d	Average annual 1-day maximum flow	cms
	Mx30d	Average annual 30-day maximum flow	cms
	Mx3d	Average annual 3-day maximum flow	cms
	Mx7d	Average annual 7-day maximum flow	cms
	Mx90d	Average annual 90-day maximum flow	cms
Low flow	BaseQ	7-day minimum flow divided by mean flow for that year	-
	DatMn	Julian date of the minimum flow	-
	Dl13	Mean annual 30-day minimum divided by median discharge	-
	Fl3	Total number of low-flow spells (threshold equal to 5% of mean daily flow) divided by record length in years	-
	Ml14	Mean of lowest annual daily flow divided by median annual daily flow averaged across all years	-
	Ml22	Mean annual minimum flows divided by watershed area	cms/km^2
	Mn1d	Average annual 1-day minimum flow	cms
	Mn30d	Average annual 30-day minimum flow	cms
	Mn3d	Average annual 3-day minimum flow	cms
	Mn7d	Average annual 7-day minimum flow	cms
	Mn90d	Average annual 90-day minimum flow	cms
	Th3	Maximum proportion of the year (num days / 365) during which no floods have ever occurred over the period of record	-
	ZeroD	Number of days per year with zero flow	-
Variability	Flash	Mean annual 1-day maximum / average flow over all years	-
	Ma3	Coefficient of variation of daily flows	-
	Ma40	(Mean monthly flow - median monthly flow) / median monthly flow	-
	Ma44bs	Average variability in daily flows divided by median daily flows for each year, where variability is calculated as 90th to 10th percentile	-
	Ml13	CV in minimum monthly flows	-
	NHiPl	Average number of low pulses, low pulse defined as 1 standard deviation below the mean	-
	NLoPl	Average number of low pulses, low pulse defined as 1 standard deviation above the mean	-
	Revs	Number of flow reversals	-
	Skew	Skewness of daily flows	-
Duration	DHiPl	Average duration of high pulses	-
	DLoPl	Average duration of low pulses	-

Class	Code	Description	Units
	Mh17	Mean of 25th percentile from the flow duration curve divided by median daily flow across all years	-
Rate of change	FallR	Fall rate – mean of all negative differences	cms/day
	RiseR	Rise rate – mean of all positive differences	cms/day
Mean flow	Ma41	Mean annual runoff divided by watershed area	cm
	MAR	Mean annual runoff	cms
	Avg_Oct	Average October flow	cms
	Avg_Nov	Average November flow	cms
	Avg_Dec	Average December flow	cms
	Avg_Jan	Average January flow	cms
	Avg_Feb	Average February flow	cms
	Avg_Mar	Average March flow	cms
	Avg_Apr	Average April flow	cms
	Avg_May	Average May flow	cms
	Avg_Jun	Average June flow	cms
	Avg_Jul	Average July flow	cms
	Avg_Aug	Average August flow	cms
	Avg_Sep	Average September flow	cms

2.2.3 Climate

Climate metrics (Table 2.3) are relatively straightforward, generally being computed as watershed averages of each characteristic by monthly averages. Precipitation and snowfall metrics were computed from PRISM data sets (Daly et al. 1994), whereas evapotranspiration, temperature, and solar radiation metrics were computed using data from Hobbins et al. (2001a, 2001b).

Table 2.3. Climate metrics and descriptions.

Class	Code	Description	Units
Temperature	Avgt_apr	Average temperature in April	°C
	Avgt_aug	Average temperature in August	°C
	Avgt_dec	Average temperature in December	°C
	Avgt_feb	Average temperature in February	°C
	Avgt_jan	Average temperature in January	°C
	Avgt_jul	Average temperature in July	°C
	Avgt_jun	Average temperature in June	°C
	Avgt_mar	Average temperature in March	°C
	Avgt_may	Average temperature in May	°C
	Avgt_nov	Average temperature in November	°C
	Avgt_oct	Average temperature in October	°C
	Avgt_sep	Average temperature in September	°C
	Mint_apr	Minimum temperature in April	°C
	Mint_aug	Minimum temperature in August	°C
	Mint_dec	Minimum temperature in December	°C
	Mint_feb	Minimum temperature in February	°C
	Mint_jan	Minimum temperature in January	°C
	Mint_jul	Minimum temperature in July	°C
	Mint_jun	Minimum temperature in June	°C
	Mint_mar	Minimum temperature in March	°C
	Mint_may	Minimum temperature in May	°C
	Mint_nov	Minimum temperature in November	°C
	Mint_oct	Minimum temperature in October	°C
	Mint_sep	Minimum temperature in September	°C
	Nt_ndjfm	Minimum November-March temperature	°C
Precipitation	Prcp_apr	Average precipitation in April	mm
	Prcp_aug	Average precipitation in August	mm
	Prcp_dec	Average precipitation in December	mm
	Prcp_feb	Average precipitation in February	mm
	Prcp_jan	Average precipitation in January	mm
	Prcp_jul	Average precipitation in July	mm
	Prcp_jun	Average precipitation in June	mm
	Prcp_mar	Average precipitation in March	mm
	Prcp_may	Average precipitation in May	mm
	Prcp_nov	Average precipitation in November	mm
	Prcp_oct	Average precipitation in October	mm
	Prcp_sep	Average precipitation in September	mm
	Precip_t	Total precipitation	mm
	Precipr1	Ratio of precipitation in wettest month to the driest month	-
	Precipr2	Ratio of precipitation in wettest three months to driest three months	-
	Snow_apr	Average snow fall in April	mm
	Snow_aug	Average snow fall in August	mm
	Snow_dec	Average snow fall in December	mm
	Snow_feb	Average snow fall in February	mm

Class	Code	Description	Units
	Snow_jan	Average snow fall in January	mm
	Snow_jul	Average snow fall in July	mm
	Snow_jun	Average snow fall in June	mm
	Snow_mar	Average snow fall in March	mm
	Snow_may	Average snow fall in May	mm
	Snow_nov	Average snow fall in November	mm
	Snow_oct	Average snow fall in October	mm
	Snow_sep	Average snow fall in September	mm
	Snow_ppt	Percent precipitation as snow	-
	Snow_t	Average annual snow fall	mm
Solar radiation	Srad_apr	Solar radiation in April	$kJ/m^2/day$
	Srad_aug	Solar radiation in August	$kJ/m^2/day$
	Srad_dec	Solar radiation in December	$kJ/m^2/day$
	Srad_feb	Solar radiation in February	$kJ/m^2/day$
	Srad_jan	Solar radiation in January	$kJ/m^2/day$
	Srad_jul	Solar radiation in July	$kJ/m^2/day$
	Srad_jun	Solar radiation in June	$kJ/m^2/day$
	Srad_mar	Solar radiation in March	$kJ/m^2/day$
	Srad_may	Solar radiation in May	$kJ/m^2/day$
	Srad_nov	Solar radiation in November	$kJ/m^2/day$
	Srad_oct	Solar radiation in October	$kJ/m^2/day$
	Srad_sep	Solar radiation in September	$kJ/m^2/day$
	Srad_t	Yearly total solar radiation	$kJ/m^2/day$
Evapotranspiration	Et_apr	Evapotranspiration in April	mm
	Et_aug	Evapotranspiration in August	mm
	Et_dec	Evapotranspiration in December	mm
	Et_feb	Evapotranspiration in February	mm
	Et_jan	Evapotranspiration in January	mm
	Et_jul	Evapotranspiration in July	mm
	Et_jun	Evapotranspiration in June	mm
	Et_mar	Evapotranspiration in March	mm
	Et_may	Evapotranspiration in May	mm
	Et_nov	Evapotranspiration in November	mm
	Et_oct	Evapotranspiration in October	mm
	Et_sep	Evapotranspiration in September	mm
	Et_t	Yearly total evapotranspiration	mm

2.2.4 Geology

Geology metrics (Table 2.4) were based on the reclassification of parent geologic materials to provide an expectation of the type of sediment that would be produced (Sable 2004). The metrics were calculated as a percent of the watershed area with a specified sediment class. Four distance-weighted versions of each metric were also calculated using exponential decay rates of -0.0001, -0.0001, -0.0005, and -0.001. Twelve landslide potential metrics were also calculated in addition to the metrics shown in the table.

Table 2.4. Geologic metrics and descriptions.

Class	Code	Description	Units
Rock type	Uncons	Unconsolidated geology	%
	Sedim	Sedimentary geology	%
	Volcan	Volcanic geology	%
	Cryst	Crystalline geology	%
Sediment producing class 1	Uncon_f	Unconsolidated, fine sediment	%
	Uncon_c	Unconsolidated, coarse sediment	%
	Sed_f	Sedimentary, fine sediment	%
	Sed_c	Sedimentary, coarse sediment	%
	Sp1_coarse	Coarse sediment producing	%
	Sp1_volcan	Extrusive volcanics	%
Sediment producing class 2	Sp2_uncons	Unconsolidated	%
	Fine_gs	Fine grain soft sediment producing	%
	Fine_gh	Fine grain hard sediment producing	%
	Sp2_course	Coarse grain sediment producing	%
Other	Lndslide	Quaternary landslide deposits	%
	Buffer	Calcareous rocks	%
	Coal	Coal	%
	Shale	Shale	%

2.2.5 Land Cover/Land Use

Land cover/land use metrics (Table 2.5) were based on the U.S. Geological Survey (USGS) and USEPA cooperative NLCD (http://erg.usgs.gov/isb/pubs/factsheets/fs10800.html). Metrics were calculated based on the percent LULC in the watershed. Additional metrics used two different exponential decay-weighting schemes; one based on hydrologic distance (along the flow accumulation pathway) and the other based on topographic wetness and hydrologic distance. Four exponential decay coefficients were used in each case (-0.0001, -0.0001, -0.0005, and -0.001).

Table 2.5. Land-cover metrics and descriptions.

Class	Code	Description	Units
Individual	11	Open water	%
	12	Perennial ice, snow	%
	21	Low-intensity residential	%
	22	High-intensity residential	%
	23	Commercial, industrial, transportation	%
	31	Bare rock, sand, clay	%
	32	Quarries, strip mines, gravel pits	%
	33	Transitional, changing	%
	41	Deciduous	%
	42	Evergreen	%
	43	Mixed	%
	51	Shrubland	%
	61	Orchards, vineyards, other	%
	71	Grasslands, herbaceous	%
	72	Alpine, tundra	%
	81	Pasture, hay	%
	82	Row crops	%
	83	Small grains	%
	84	Fallow	%
	85	Urban, recreational grasses	%
	91	Woody wetlands	%
	92	Emergent herbaceous wetlands	%
Combined	20	Residential	%
	30	Bare rock, mines, pits, transitional	%
	40	Forest	%
	70	Grasslands, herbaceous, alpine, tundra	%
	80	Agriculture	%
	90	Wetlands	%
	8061	Agriculture, orchards, vineyards	%

2.3 SYNTHESIS

Many of the metrics presented here, as well as some earlier versions of these metrics, have successfully described physical processes and boundary conditions in landscape-scale studies (e.g., Holburn 2005, Hurst 2005, Olson 2005, Flores et al. 2006, Olden et al. 2006, Sanborn and Bledsoe 2006). Hydrologic and geomorphic metrics were used in Chapters 3 and 4 to explain variability in stream insect assemblages at reference sites in the Pacific Northwest. As shown in these chapters, classifications based on these metrics can significantly outperform ecoregion and other geographically-dependent classifications. The models explained as much as 90% (compared to 41% for ecoregions) of the best attainable classification strengths indicated by classifications that were calibrated purely to biological data.

The application of classification trees for predicting Montgomery and Buffington (1997) stream type proved to be a powerful method that demonstrated important relationships between stream type, slope, and a surrogate for specific stream power. Although slope is associated with stream type (Montgomery and Buffington 1997), this model indicates that scaling slope by watershed area can better predict stream types within sediment transport- and supply-limited systems.

A novel model for predicting and mapping D_{50} was developed based on geospatially-derived metrics describing geomorphic and hydrologic character. The successful development of a process-based substrate predictor in a GIS holds promise for future models.

As high-resolution geospatial data become more prevalent, the capacity to map key habitat features across landscapes will increase. Light Detecting and Ranging (LiDAR) data for developing high vertical and horizontal resolution DEMs will be particularly useful, especially as the resolution approaches the scale-important geomorphic features for small streams. The advent of Green LiDAR, which can penetrate water surfaces (Lillycrop and Banic 1992, Brock et al. 2001, 2004), will further improve geomorphic and related stream studies.

Future studies could benefit from sensitivity and uncertainty analyses relating horizontal and vertical DEM resolution to the metrics developed. Valley bottom widths, for instance, may be overly coarse in narrow valleys with widths on the same order as the horizontal resolution. In narrow valleys, DEM stream cells may partially include adjacent hillslopes thereby artificially increasing stream channel elevations. This could bias channel slope estimates in headwater and canyon reaches, whereas low vertical accuracy may be biasing slope estimates in reaches where the actual slope is near or less than the vertical DEM resolution. Alternative LULC and geology classifications could also potentially improve regional classifications used in water quality assessment. The work presented here seeks only to elucidate patterns in how physical metrics relate to stream insect assemblages at regional scales. The use of GISs in landscape-scale studies of aquatic resources will continue to grow as geospatial data become more prevalent, as data better represent finer spatial scales, and as studies, such as presented here, illustrate their potential.

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CHAPTER 3
HYDROGEOMORPHIC CLASSIFICATIONS OF MOUNTAIN STREAMS FOR BIOMONITORING I: AN *A PRIORI* APPROACH

Abstract

Existing classifications used to stratify stream biotic communities do not explicitly describe spatial variability in coupled hydrologic and geomorphic (hydrogeomorphic) processes. I used multi-scale hydrologic and geomorphic descriptors to develop hierarchical physical classifications of 222 minimally disturbed U. S. Environmental Protection Agency (USEPA) biomonitoring sites in mountainous regions of Oregon and Washington. Level III ecoregions and geospatially-derived descriptors of watershed-scale flow regime, valley-scale geomorphology, and local-scale stream substrate were used individually and in combination to classify sites. I compared the relative strengths of *a priori* geographically-independent (hydrogeomorphic) classifications and geographically-dependent (ecoregion, physiographic province, and hydrologic unit) classifications against a spatially-neutral classification based on cluster analyses of insect taxa. Classification strengths were assessed by comparing average between-class similarity ($\overline{B}$) to average within-class similarity ($\overline{W}$) of insect taxa using the Sorensen distance measure. Results indicate that non-geographic hydrologic and geomorphic classifications can partition biological variability better than geographic classifications with fewer classes. Classifications based on low flow and valley characteristics performed particularly well, whereas those based solely on substrate characteristics (both predicted and field-measured values) did not perform well. Non-geographic classifications outperformed ecoregions in 11 out of 18 comparisons of

classification strength. This has important implications for *a priori* stratification of stream habitats and suggests that an *a posteriori* approach to creating classifications is advisable. Geographic Information System (GIS)-based hydrogeomorphic classifications support the determination of regional environmental drivers, provide a basis for mapping multi-scaled hydrogeomorphic settings and putative habitat types, and a framework for process-based stratification in bioassessments and monitoring designs.

3.1 INTRODUCTION

Hydrologic and geomorphic processes create the physical structure and disturbance characteristics that form instream habitat. Species preferentially select habitats for which they have developed compatible life strategies (Southwood 1977, Townsend and Hildrew 1994). To ensure the health of freshwater ecosystems, the best possible classification systems must be developed and implemented (Hawkins and Norris 2000). Such classifications should be based, in part, on the hydrologic regime and geomorphic characteristics that form the physical habitat contributing to community composition establishment (Parsons et al. 2003). Improvements in our ability to stratify aquatic habitats across landscapes will facilitate understanding of biological variation across landscapes and linkages between biotic and physical stream diversity (Hawkins and Norris 2000).

Landscape classifications may aid interpretation of biotic spatial distributions (Hawkins et al. 2000, Stoddard 2005) and frequently become a framework for defining reference sites in bioassessments (Hawkins and Norris 2000). Regional geographic classifications are attractive because they are user friendly. For example, ecoregions

(Omernik 1987) are widely used for the purpose of comparing freshwater biota (Hawkins et al. 2000, Stoddard 2005). Ecoregions are based on multiple physical landscape features reflected in stream habitat and associated biotic communities; therefore, it is reasonable to compare them to insect communities constrained by the physical environment they inhabit (Stoddard 2005). Ecoregions have proven valuable in accounting for differences in biological communities (Hughes 1995), especially when compared to a random or null model (Van Sickle and Hughes 2000, Hawkins et al. 2000, Gerritsen et al. 2000). However, it is not well understood how heterogeneity in physical drivers influences aquatic biota within and among ecoregions. Whether threshold values used for discretizing ecoregions represent appropriate ecological thresholds in physiographically similar areas is an additional concern.

Many studies, however, have found that ecoregions are relatively strong classifiers of benthic invertebrate assemblages. In a study of 44 reference streams in Missouri, Rabeni and Doisy (2000) computed classification strengths of 0.70 for both Bailey ecoregions (Bailey 1995) and Omernik ecoregions (Omernik 1987). They also tried an aquatic faunal regionalization (Pflieger 1989) that scored 0.69. Although Rabeni and Doisy's classification strengths were high, their data set was relatively small and their study had a strong physiographic gradient that included mountains, prairies, and lowland river valleys. The rivers were also selected to be of similar size and have similar habitats, thus developing a data set of relatively homogenous streams with strong physiographic differences accounted for by ecoregions. In the Mid-Atlantic Highlands, Waite et al. (2000) compared geographic and non-geographic classification of 88 minimally impacted sites across piedmont, plains, and mountainous ecoregions.

Ecoregion and catchment classifications were relatively low (0.011 and 0.01, respectively) compared to *a priori* physical classifications based on stream order (0.036) and slope (0.028). A cluster analysis of benthic macroinvertebrate taxa gave a classification strength of 0.076. A study of 30 reference streams spread over much of Alabama, Georgia, and parts of Tennessee (Feminella 2000) found ecoregions (Omernik 1987) and catchments to be strong classifiers of benthic macroinvertebrates (0.782 and 0.793, respectively). Here there was also a strong physiographic gradient (mountains and piedmont) and relatively few biomonitoring sites. In a Wyoming study of 85 minimally disturbed sites, ecoregions (Omernik 1987) were a strong classifier of sites (0.087), whereas a cluster analysis (0.13) showed that stronger classifications were still possible (Gerritsen et al. 2000). A study of 428 minimally disturbed sites in Sweden found that ecoregions were a strong classifier (0.06), but were relatively weak compared to the potential shown by cluster analysis (0.127, Sandin and Johnson 2000). In California, 254 minimally disturbed biomonitoring sites were classified by Hawkins and Vinson (2000) using ecoregions (0.06), hydrologic units (0.074), and cluster analysis (0.123). All of these studies demonstrated that ecoregions are a statistically significant classification scheme. Further, cluster analysis results consistently illustrated that better classifications are possible. Only the study by Waite et al. (2000) attempted to expand beyond *a priori* geographical classifications of the landscape and it showed promise for partitioning the landscape for benthic macroinvertebrate assemblages.

There are several physical classifications of streams that can be used for selecting sites expected to have similar biotic communities. These include the river continuum concept (Vannote et al. 1980), the patch dynamics concept (Frissell et al. 1986, Naiman et al. 1988, Townsend 1996, Poff 1997), the Rosgen (1994, 1996) stream classification (McGarrell 1998), and the Montgomery and Buffington (1997) stream classification. A shortcoming common to each classification is the explicit lack of consideration of many important ecological drivers, such as the interacting influences of hydrologic regime and geomorphic processes and boundary conditions. Moreover, these classifications are generally limited to the local, or reach scale. Landscape-scale classifications such as hydrologic units, biogeographical provinces (Hocutt and Wiley 1986), and physiographic provinces (Fenneman 1946) do not define insect assemblages adequately (Gerritsen et al. 2000), nor do they provide a process-based understanding of biological patterns.

The ability to detect water-quality impairment in bioassessments relies largely on our ability to properly define reference conditions (Karr and Chu 1999, Chessman and Royal 2004) yet existing landscape and stream classifications, with insufficient aquatic habitat context, are commonly used to define reference conditions. Biological potential is limited by the regional availability of species and the quality, quantity, spatial arrangement, and variability of physical habitats that form the habitat template (Poff and Ward 1990, Townsend and Hildrew 1994). Mountainous regions have large deviations in hydrologic and geomorphic characteristics that are likely to develop distinct habitat types. Channel gradients, valley morphology, bedrock control, and other geomorphic variables that influence biotic communities are spatially patchy and may occur at scales intermediate to local- and regional-scales. Including intermediate-scale (i.e., valley-scale) metrics in stream classification may substantially improve the strengths of habitat and biotic classifications in mountainous and other topographically heterogeneous regions. Many important physical stream habitat forms and processes to which stream insects may respond are strongly constrained by valley-scale boundary conditions (e.g., Hynes 1975, Whiting and Bradley 1993, Nanson and Croke 1992, Montgomery and Buffington 1998).

Hydrology, often considered a "master variable" in stream ecology (Resh et al. 1988, Poff et al. 1997), is also highly variable in the mountains of Oregon and Washington (Tague and Grant 2004, Sanborn and Bledsoe 2006). Heterogeneity in hydrology and hydraulics has direct effects on channel characteristics and associated aquatic communities (Hynes 1975, Statzner et al. 1988, Poff and Ward 1989, Naiman 1995, Miller and Ritter 1996, Townsend et al. 1997, Poff et al. 1997, Knighton 1998). Hydrologic differences result from variations in geology (Tague and Grant 2004), geomorphology, and climate. Because these influential factors occur in spatially disconnected patterns across mountainous landscapes, it is likely that explicitly non-geographical hydrogeomorphic classifications will outperform geographically-dependent ecoregions in describing stream insect assemblages.

Combining hydrologic regime and geomorphic character is a powerful predictor of wetland habitats (Smith et al. 1995) and is expected to be a similarly powerful predictor of instream habitats and putative insect assemblages. A major impetus of this study is to determine whether physically-based, *a priori* hydrogeomorphic classifications of stream insect assemblages based on geospatial data can outperform and/or refine predictions made from geographically-dependent ecoregions. The ability to identify stream hydrogeomorphic types and disturbance characteristics from readily available digital geospatial data would represent an important methodological advance for stratifying aquatic habitats within ecoregions to more effectively explain patterns of biological variation and facilitate understanding of linkages between biotic and hydrogeomorphic diversity. GIS-based descriptors also provide a basis for mapping multi-scaled hydrogeomorphic settings and putative habitat types. The ability to predict channel substrate character from geospatial data would also be an important advance for stratifying aquatic habitats.

Channel substrate characteristics influence the composition of macroinvertebrate communities (e.g., Minshall 1984, Rice et al. 2001, Hall and Killen 2005) and are often measured during bioassessments (Plafkin et al. 1989). Fine sediment accumulation on the streambed can have severe negative effects on stream biota (Waters 1995). Deposited fine sediments reduce the suitability of channel substrates for macroinvertebrates (Erman and Ligon 1988, Richards and Bacon 1994, Hurst 2005), and can reduce oxygen supplies (Eriksen 1966) and respiration for certain taxa (Lemly 1982). Herlihy et al. (2005) found that percent sand and fines (<2 mm) was negatively correlated with benthic index of biological integrity (B-IBI, Oregon Watershed Enhancement Board (OWEB) 1999) scores for small streams in western Oregon. Zweig and Rabeni (2001) found a negative correlation between fine sediments and Ephemeroptera, Plecoptera, and Trichoptera (EPT) taxa in Appalachian streams. Increases in fine sediments have also been associated with shifts in community structure to more tolerant taxa (Wood and Armitage 1997, Waters 1995, Ryan 1991, Cordone and Kelley 1961).

Median channel substrate effects on stream benthic communities are less well understood than effects of fine materials. A study of macroinvertebrate communities on the Fraser River in British Columbia, Canada, found that mean substrate diameter was positively correlated with taxa richness, but not with invertebrate densities (Rempel et al.

2000). Collector-gatherers and shredders were influenced principally by larger substrate materials, which may result from lower shear stresses from the larger roughness elements (Rempel et al. 2000). In the Taieri River Basin of New Zealand, Brosse et al. (2003) reported that D_{50} (median substrate size) was the most influential bedform (local) scale metric for predicting invertebrate species richness. Another study of several New Zealand streams found that relative abundance of invertebrates increased with substrate size (Jowett 2003). These studies suggest that integrating D_{50}, or a similar measure of substrate size, may provide a means for stratifying insect communities.

Biological processes such as predation and recruitment can account for much of the spatial and temporal variabilities in communities (Bunn and Davies, 2000). Natural chemical and biological aspects influencing insect communities, such as buffer capacity and predator/prey interactions, were not explicitly considered here, but are known to be important (Peckarsky 1983, Naiman et al. 2000). This study assimilates knowledge of stream insects, hydrology, and geomorphology to develop *a priori* landscape-level classifications of stream environments expected to have similar stream insect communities. Olden et al. (2006) argue that *a priori* ecological knowledge should be incorporated into ecoinformatics. Geographically independent, fluvial geomorphic and hydrologic metrics are used to classify sites of known biological composition. Such a classification system, developed using least disturbed settings, provides a base condition against which to test the biological integrity of streams.

3.1.1 Objectives

This study tests hypotheses regarding the spatial distribution of stream insect communities using "minimally disturbed" biomonitoring sites. First, I expect that ecoregions will provide a relatively weak stratification of insect communities within the mountains of the Pacific Northwest. Thus, I hypothesize that *a priori* classifications of stream insect communities, based on prior research and knowledge of regional environmental gradients, will stratify insect communities with stronger class separation than ecoregions. These *a priori* classifications will be based on geospatially-derived descriptors of hydrologic and geomorphic character. Second, I expect classifications combining hydrology and geomorphology to outperform classifications based on either individually. Classifications that include metrics at multiple scales, especially those at the valley-scale, are likely to result in higher classification strengths than those focused on a single scale. The overall objective of this study is to determine the hydrogeomorphic drivers that influence the gradient of insect assemblages in least disturbed stream reaches of the Pacific Northwest. Specific objectives are to:

- develop *a priori* landscape classifications of the mountainous ecoregions of the Pacific Northwest for stream insect communities using prior research, judgment, and geospatially-derived hydrologic and geomorphic metrics; and
- test the classification strengths of geospatially-derived hydrologic and geomorphic metrics compared to geographic classifications for explaining variation in stream communities.

3.2 METHODS

The mountains of the Pacific Northwest are heterogeneous environments with large hydroclimatic, geologic, and geomorphic gradients. Elevations range from near sea level to over 2000 m. Oregon and Washington have predominantly maritime climates, with mean annual precipitation ranging from 25 cm in the eastern deserts to nearly 500 cm on the western slopes of the high mountains. High precipitation rates in the west are driven by orographic lift, whereas desert conditions in the east exist in rain shadows cast by the Cascade Mountain Range that runs north-south through both states.

Two sets of USEPA biomonitoring data were analyzed in parallel as a proof of concept. The sites were randomly selected for sampling and are generally first- through fourth-order streams (Kaufmann et al. 1999). One data set consists of 165 USEPA Western Environmental Monitoring and Assessment Program (W-EMAP) sites distributed throughout the mountainous ecoregions of Washington and Oregon. The second data set is comprised of 97 USEPA Oregon Environmental Monitoring and Assessment Program (OR-EMAP) pilot study sites located in mountainous ecoregions of Oregon.

I screened biomonitoring sites using field-measured water quality and riparian disturbance characteristics (Kaufmann et al. 1999, Table 3.1) to remove those highly influenced by anthropogenic disturbance. Many forms of human influence are likely present in the data, including forestry practices (Herlihy et al. 2005) and other current and historic land uses (Harding et al. 1998). Site screening was simply intended to create a "minimally disturbed" data set.

Table 3.1. Criteria for screening sites to develop a "minimally disturbed" data set.

Code	Description	Threshold	Units
PHSTVL	pH	< 6	--
PTL	Total Phosphorus	> 100	µg/L
SO4	Sulfate	> 1000	µeq/L
CL	Chloride	> 1000	µeq/L
NTL	Total Nitrogen	> 1500	µg/L

W1_HALL	Riparian Disturbance – Sum All Types (Proximity Weighted)	> 3	%
PCT_FN	Substrate Fines – Silt/Clay/Muck	> 50	%

The W-EMAP sample sites included 223 macroinvertebrate taxa, mostly identified to the genus level. OR-EMAP sample sites contained 173 macroinvertebrate taxa. I removed non insects (oligochetes, bivalves, etc.), rare taxa (found at less than 5% of sites), and transformed both data sets into presence/absence matrices (McCune and Grace 2002). The final biological data set contained 140 W-EMAP sites with 140 insect taxa and 82 OR-EMAP sites with 83 insect taxa (Figure 3.1). Together, the data sets have a maximum urban landcover of 2.9% in the contributing watersheds with an average of 0.06%. One W-EMAP site retained was 21.3% agriculture. Including this site, average agricultural landcover was 0.36%.

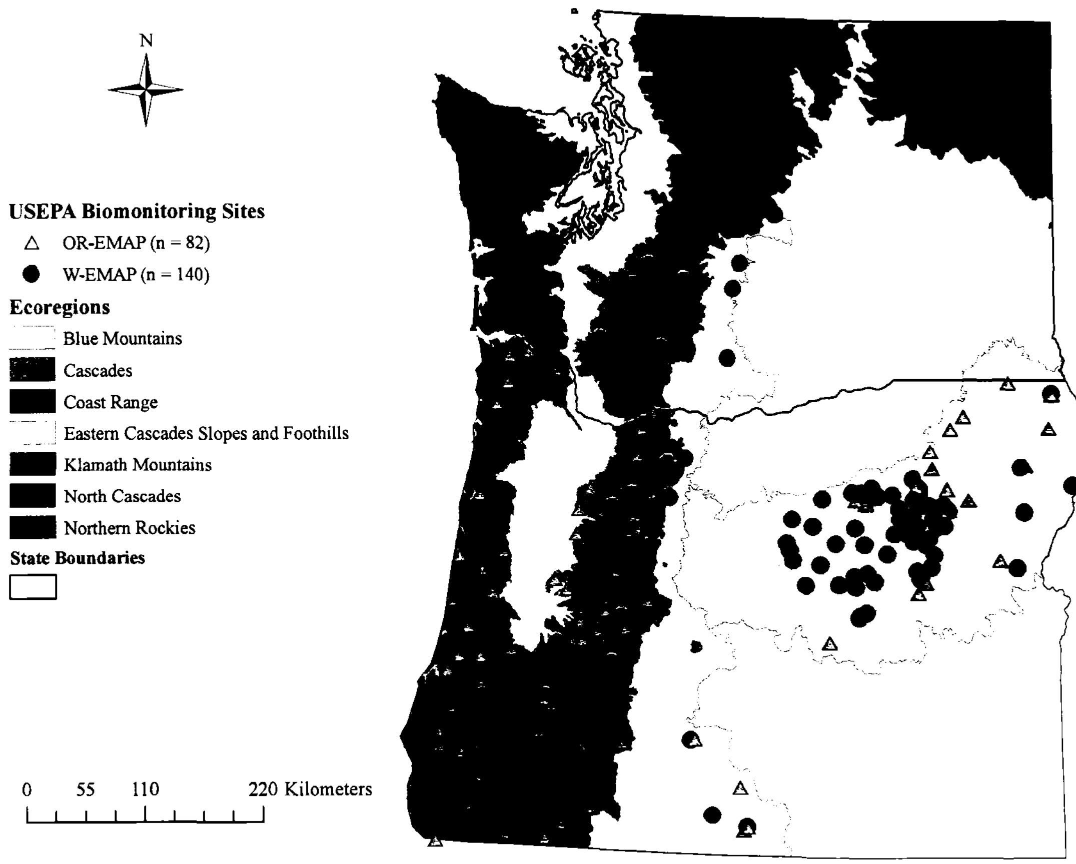

Figure 3.1. USEPA OR-EMAP and W-EMAP biomonitoring sites.

3.2.1 GIS-derived Hydrogeomorphic Metrics

I used hydrologic and geospatial data to physically describe the 222 biomonitoring sites and analyze landscape-level biological variation as it relates to flow regime, geomorphic boundary conditions, channel substrate, and geographic landscape classifications (e.g., ecoregions). The USEPA provided latitude and longitude coordinates for mapping of biomonitoring sites using a GIS. The delineation of site-specific watersheds and computation of geospatially-derived descriptive metrics followed.

3.2.1.1 Hydrology

Most of the EMAP sites reside in ungauged streams far from representative gauges; therefore, I developed hydrologic regime metrics following an extrapolation technique for ungauged streams (Sanborn and Bledsoe 2006). GIS-computed climate and physical watershed characteristics were used in discriminant functions to group sites into one of four classes using three different classifications: high-flow, low-flow, and all-flow hydrograph characteristics. Each classification included four types of flow regimes to which a site may be assigned. Plotting average monthly discharge divided by mean annual runoff for each of the four types suggests that the "all-flow" classification may be described as snow melt, snow and rain, rain, and variable hydrologic regimes (Figure 3.2).

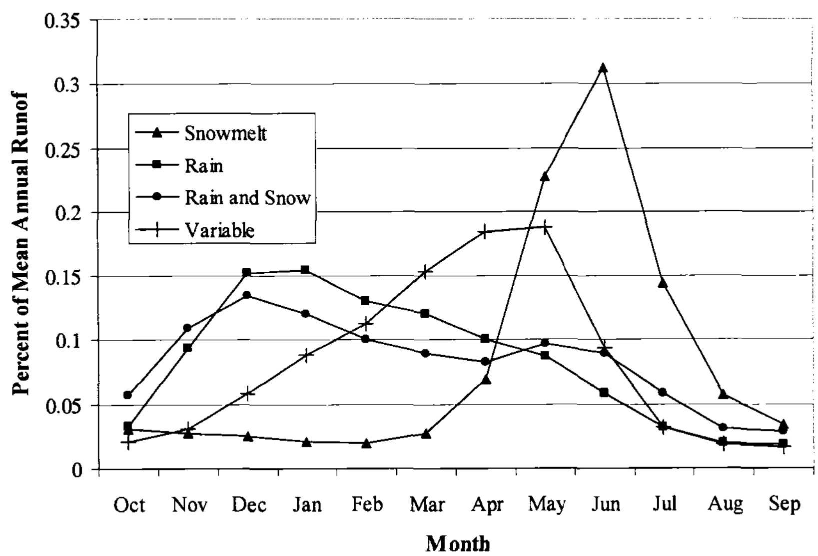

Figure 3.2. Flow regime hydrographs based on average monthly flows as a proportion of mean annual runoff (from Sanborn and Bledsoe (2006)).

3.2.1.2 Geomorphology

Geomorphic characteristics used in the physical classifications included estimates of Montgomery and Buffington (1997) channel type (Flores et al. 2006) and three measures of valley form, all of which were computed using Arc Macro Language scripts and 10-m digital elevation models (DEMs). Montgomery and Buffington channel type predictions required the estimation of channel slope from a DEM and a surrogate measure of specific stream power (*SSP*) defined as:

$$SSP = SA^{0.4} \tag{3.1}$$

where S is slope (m/m) of the channel and A is watershed area (km^2). These values were then entered in a ten-fold cross-validated classification tree (Figure 3.3) to determine probable stream type classification with 76% accuracy (Flores et al. 2006).

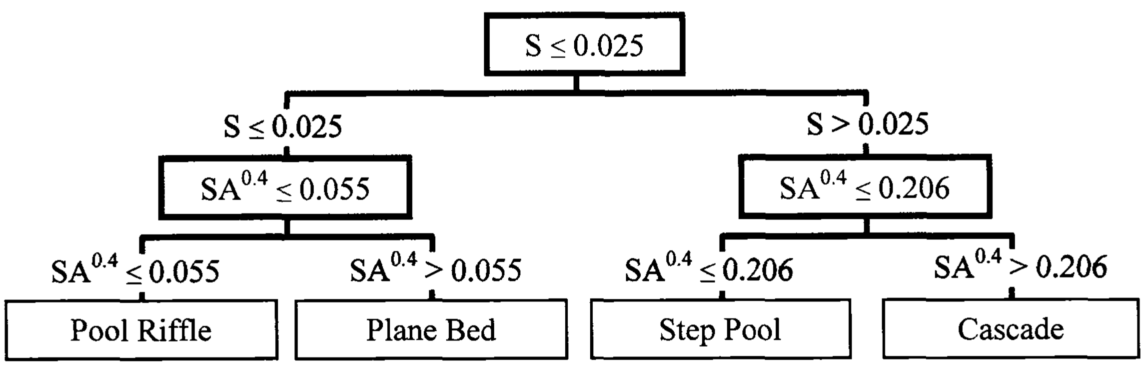

Figure 3.3. Ten-fold cross validated classification tree for predicting Montgomery and Buffington (1997) stream type with 76% accuracy (from Flores et al. (2006)).

Valley form has a strong ecological influence on streams (Hynes 1975). Valley form, including floodplain presence and extent, can influence channel slope, sinuosity, channel roughness, channel substrate and other geomorphic characteristics that have the potential to drive stream community composition. Floodplain presence and extent are strongly associated with stream types (Nanson and Croke 1992, Rosgen 1996) and valley type is a dominant geomorphic boundary condition. Previous research on associations between scaled geomorphic features and macroinvertebrates (e.g., Parsons et al. 2003) suggests that valley form could provide a noteworthy stratification of insect assemblages.

Given the potential influence of valley form on insect assemblages, three metrics were developed to characterize valley bottom characteristics. The first metric describing valley form (MentCC) measures elevations of the local ground surfaces relative to the stream channel. One meander belt width is estimated as 5.5 times the channel width and is used as the boundary within which the metric is calculated. Channel width is estimated from downstream hydraulic geometry using watershed area from flow accumulation models. The mean elevation difference between all DEM cells within a radius of one half a meander belt width from the stream cell and the elevation of stream cell is calculated.

The second metric describing the valley, valley entrenchment (MentDR), is similar to the Rosgen (1994, 1996) entrenchment ratio because it compares an estimate of floodprone width to estimated channel width. However, the relatively coarse DEM resolution and lack of field-measured bankfull width render this estimate not directly comparable to Rosgen's entrenchment ratio. The resulting metric is a predictor of the cross-sectional shape of the valley bottom. The final metric is calculated as the ratio of the floodprone width, measured as the width between the valley walls at an elevation of two times the depth plus 1 m (to account for vertical DEM resolution), to channel width (from downstream hydraulic geometry).

The final valley metric, hill-slope connectivity (MCon), was modeled after the process-based headwater stream classification of Whiting and Bradley (1993). The elevation of the land at a distance of 25 m from the channel was used as a basis for predicting if hill-slope debris flows will enter (Ikeya 1981), and thereby influence stream channel morphology. A distance of two cells, measured perpendicular to the stream channel, was used here as this was the best approximation possible given 10-m DEM resolution. The highest elevation of two cells, one on either side of the stream, is determined and the difference in elevation between the highest cell and the stream channel is returned.

Developing classifications based on valley form, valley entrenchment, and hill-slope connectivity metrics required prediction of the best continuous variable splits with respect to stream insect assemblages. Because these metrics have not been previously compared to insect assemblages, making *a priori* splits from the literature was challenging. Metrics were split for the *a priori* physical classification based on a fundamental understanding of their development, the distributions of values, and on judgment based on knowledge of channel hydraulics that tend to be associated with different valley contexts, the goal being to separate reaches with adjacent hill slopes versus floodplain. To create two classes for each metric, valley form was split at 2 m, valley entrenchment at 10, and hill-slope connectivity at 3 m.

3.2.1.3 Channel Substrate

I developed models to predict median channel substrate size (D_{50}) for characterizing channel substrate. The equation was developed using best subsets regression and field-measured D_{50} (in mm) from the USEPA (Kaufmann et al. 1999). The resulting equation uses geospatially-derived metrics that can be mapped in a GIS. The resulting equation (adjusted $R^2 = 0.36$) is:

$$D_{50} = 1.227 S^{1.12} Mx7d^{0.4} MentCC^{0.858} Ma3^{-0.955} Ma41^{0.432} - 1 \tag{3.2}$$

where S is slope (dimensionless), *MentCC* is a measure of valley morphology (m), *Ma*3 is the predicted coefficient of variation in daily flows over the period of record (Sanborn and Bledsoe 2006, dimensionless), *Ma*41 is the predicted flow yield per watershed area (Sanborn and Bledsoe 2006, cm), and *Mx7d* is the predicted average maximum 7-day flow (Sanborn and Bledsoe 2006, m^3/s). The result is a predictor of D_{50} (mm) that relies on a term similar to Hack's (1957) model based on slope and watershed area—a surrogate for specific stream power. The model suggests that D_{50} increases with specific stream power, valley entrenchment (*MentCC*), and flow yield (*Ma*41). The model also includes flow variability, suggesting that high variability results in a lower D_{50}. The resulting D_{50} prediction makes physical sense and is solely a product of GIS-derived watershed-scale hydrologic and valley-scale geomorphic metrics.

Two field-measured descriptions of channel substrate, D_{50} and percent sand and fines (Pct_SAFN, < 2 mm), were also used to develop classifications. These data were taken from the physical habitat metrics measured in the field by EMAP field crews (Kaufmann et al. 1999). In a field study and with EMAP data from streams in Colorado, Hurst (2005) found that fine sediments (<2 mm) diminished EPT taxa richness with as little as 10% fines covering the stream bottom. A study of 562 stream reaches in Idaho, Wyoming, Washington, and Oregon, found several species of stream insects absent from reaches with more than 30 to 40% fines less than 2 mm (Relyea et al. 2000). The same study found that %EPT and EPT/Chironomidae metrics declined sharply when fine sediments increased by more than 20%. In a study of Western Cascade streams in Oregon and Washington, unimpaired habitats were estimated to have less than 12% sand

and fines, whereas poor habitat had more than 16% sand and fines (Hayslip et al. 2004). Substrate porosity, which is positively correlated with macroinvertebrates, may approach zero as the percent sand and fines (<1 mm) approached 30% (Maridet and Phillippe, 1993). Accordingly, two *a priori* classifications were developed using Pct_SAFN based on a review of the literature: one with two classes (split at 30% sand and fines) and one with three classes (split at 10% and 30% sand and fines). Both field-measured and GIS-predicted D_{50} were split at 8 mm for a two-class typology and at 8 mm and 64 mm for a three-class typology of dominant bed material.

3.2.2 Classification, the Spatially-neutral Model, and Similarity Analysis

Grouping channel reaches and sampling sites that are similar to one another is a useful technique and a necessity for determining reference sites in bioassessments. A scientifically defensible classification offers a sensible foundation for management decisions involving aquatic resources (Barbour et. al 1999). I created physical classifications of channel habitat by delineating hydrologic processes and geomorphic boundary conditions that have the potential to influence insect community structure. A total of 40 physical classifications were tested. All metrics developed were used individually and in combination with other metrics to create a total of 21 *a priori* classifications. Given the emphasis on geographically-dependent classifications in bioassessments, sites were also grouped by ecoregion for comparison. Five hybrid *a priori* classifications were developed by stratifying ecoregions by hydrologic, geomorphic, and channel substrate metrics. These five models are hereafter referred to as stratified ecoregions. Four classifications were developed from field-measured substrate data and nine classifications were developed using taxonomic data.

A spatially-neutral model (Van Sickle and Hughes 2000) was developed to provide a benchmark for assessing the performance of physical and geographic classifications in partitioning biological variability. It was developed using cluster analysis on the biological data in PC-Ord™ software (McCune and Mefford 1999; Version 4.0, MjM Software Design, Gleneden Beach) to group sites of similar insect community composition. The result is a taxonomic classification of biomonitoring sites where sites are grouped by optimizing within-class similarity of taxa. The model was developed using the Sorenson distance measure with a flexible β of -0.25. Sorenson distance is a measure of shared taxa divided by the mean total of taxa at two sites. The result may be understood as the proportion of the community assemblage shared by two sites (Van Sickle and Hughes 2000). By grouping sites that are similar to one another in a step-wise process, cluster analysis estimates the optimal groupings of two through n classes, where n is the total number of sites. Cluster models with 2 to 18 clusters (classes) were retained for analysis. Resulting cluster analysis dendrograms are presented in Appendix A.

For each classification I calculated the similarity of insect taxa within a class (e.g., pool-riffle) versus the similarity of insect taxa between classes (e.g., pool-riffle vs. step-pool). Because the similarity of taxa should be more similar within a class and less similar between classes, these measures can be used to provide a measure of classification strength. The Multi-response Permutation Procedure (MRPP) function in PC-Ord™ (McCune and Mefford 1999) and MEANSIM6 (Van Sickle 1997, Van Sickle and Hughes 2000; Version 6, USEPA, Corvallis) were used in succession to perform similarity analyses to develop measures of classification strength (CS). Classification schemes were assessed by dividing the average within-class assemblage similarity ($\overline{W}$) by the average between-class assemblage similarities ($\overline{B}$) and by subtracting $\overline{B}$ from $\overline{W}$ based on the Sorensen distance measure (Van Sickle 1997, Van Sickle and Hughes 2000).

3.3 RESULTS

I tested a total of 40 classifications, including 26 based on novel GIS-based descriptors of hydrologic and/or geomorphic character (Table 3.2). MRPP results were used to quantify classification strengths. Classification strengths are plotted against the number of clusters in Figures 3.4 and 3.5 for OR-EMAP and W-EMAP studies, respectively. Several *a priori* classifications outperformed ecoregions. The most significant *a priori* classification was a two-class measure of floodplain presence (MentCC) with a CS of 1.147 for OR-EMAP data and 1.13 for W-EMAP data (Figure 3.6). Other measures of floodplain presence (MentDR) and hill-slope connectivity (MCon) had relatively weak CS values. Bed material classifications performed poorly for both data sets regardless of whether field-measured or GIS-predicted values were used (CS of 1.031). Hydrologic regime classes performed well, especially given the low number of classes in each. In both studies, classifications based on low-flow metrics outperformed high-flow and all-flow metrics. The Montgomery and Buffington stream type CS was high (1.082) using OR-EMAP data, performing as well as ecoregions (1.083) with half as many classes. Using W-EMAP data, it was not as strong (1.035), with a weaker CS than ecoregions (1.09).

Table 3.2. Classification (n = 40) descriptions and results classification strengths for 26 GIS-based descriptions of hydrologic and geomorphic character.

			W-EMAP			OR-EMAP		
Class Type	**Class Name**	**Class Description**	**Number of Classes**	$CS = \overline{B}/\overline{W}$	$CS = \overline{W} - \overline{B}$	**Number of Classes**	$CS = \overline{B}/\overline{W}$	$CS = \overline{W} - \overline{B}$
Geographic	Ecoregions	Omernick ecoregions	6	0.914	0.044	5	0.942	0.034
	Physiographic Provinces	Fenneman and Johnson physiographic provinces (section level)	12	0.912	0.048	9	0.956	0.033
	Hydrologic Units	U. S. Geological Survey (USGS) 6-digit hydrologic units	11	0.907	0.045	5	0.945	0.026
Hydrologic	Allflow	Flow regime based on all-flow metrics	4	0.969	0.015	4	0.942	0.034
	Hiflow	Flow regime based on high-flow metrics	4	0.954	0.023	4	0.950	0.029
	Loflow	Flow regime based on low-flow metrics	4	0.939	0.031	3	0.937	0.037
Geomorphic	MentCC	Valley form	2	0.860	0.068	2	0.890	0.063
	MentDR	Valley entrenchment	2	0.924	0.036	2	0.983	0.010
	MCon	Hill-slope connectivity	2	0.988	0.006	2	0.985	0.008
	MnB	Montgomery and Buffington stream type	4	0.962	0.018	3	0.942	0.034
Channel Substrate	CCD50-2	Predicted median substrate	2	0.966	0.016	2	0.986	0.008
	CCD50-3	Predicted median substrate	3	0.974	0.013	3	0.998	0.001
	Pct_SAFN-2	% sand and fines (<2 mm)	2	0.953	0.022	2	0.963	0.021
	Pct_SAFN-3	% sand and fines (<2 mm)	3	0.978	0.011	3	0.982	0.010
	D50-2	Field-measured median substrate	2	0.970	0.014	2	0.977	0.013
	D50-3	Field-measured median substrate	3	0.966	0.016	3	0.986	0.008
Hydro-geomorphic	Hillcon-all	Hill-slope connectivity and all-flow regime	8	0.971	0.014	10	0.945	0.033
	D50-2-all	Median substrate and all-flow regime	8	0.955	0.022	8	0.939	0.036
	MentCC-all	Valley form and all-flow regime	6	0.944	0.028	9	0.935	0.039
	MentCC-lo	Valley form and low-flow regime	8	0.909	0.046	4	0.931	0.041
	MentDR-all	Valley entrenchment and all-flow regime	8	0.956	0.022	5	0.942	0.034

			W-EMAP			OR-EMAP		
Class Type	**Class Name**	**Class Description**	**Number of Classes**	$CS = \overline{B}/\overline{W}$	$CS = \overline{W} - \overline{B}$	**Number of Classes**	$CS = \overline{B}/\overline{W}$	$CS = \overline{W} - \overline{B}$
	Pct_SAFN-2-all	% sand and fines and all-flow regime	8	0.953	0.023	4	0.929	0.042
	MB-all	Montgomery and Buffington and all flow	13	0.951	0.024	8	0.923	0.046
	MB-hi	Montgomery and Buffington and high flow	14	0.927	0.037	7	0.920	0.048
	MB-lo	Montgomery and Buffington and low flow	13	0.918	0.043	7	0.918	0.050
Geomorphic-Substrate	D50-2-MB	Median substrate and Montgomery and Buffington	7	0.960	0.020	6	0.944	0.033
	MB-Pct_SAFN-2	% sand and fines, and Montgomery and Buffington	7	0.959	0.020	4	0.943	0.034
	MentCC-MB	Valley form and Montgomery and Buffington	7	0.952	0.024	4	0.939	0.036
Stratified Ecoregions	Eco-D50-2	Ecoregions and median substrate	10	0.908	0.048	6	0.928	0.043
	Eco-MentCC	Ecoregions and valley form	9	0.890	0.058	9	0.939	0.036
	Eco-lo	Ecoregions and low-flow regime	14	0.915	0.045	8	0.939	0.036
	Eco-MB	Ecoregions and Montgomery and Buffington	17	0.907	0.049	6	0.934	0.040
	Eco-Pct_SAFN	Ecoregions and % sand and fines	11	0.908	0.048	13	0.937	0.037
Spatially-neutral Models	2 Cluster	Insect cluster analysis	2	0.697	0.154	2	0.812	0.110
	4 Cluster	Insect cluster analysis	4	0.816	0.098	4	0.842	0.099
	6 Cluster	Insect cluster analysis	6	0.804	0.107	6	0.828	0.110
	8 Cluster	Insect cluster analysis	8	0.808	0.107	8	0.821	0.116
	10 Cluster	Insect cluster analysis	10	0.804	0.112	10	0.824	0.117
	12 Cluster	Insect cluster analysis	12	0.796	0.118	12	0.821	0.120
	14 Cluster	Insect cluster analysis	14	0.793	0.121	N/A	N/A	N/A
	16 Cluster	Insect cluster analysis	16	0.791	0.123	N/A	N/A	N/A
	18 Cluster	Insect cluster analysis	18	0.786	0.128	N/A	N/A	N/A

N/A – not applicable

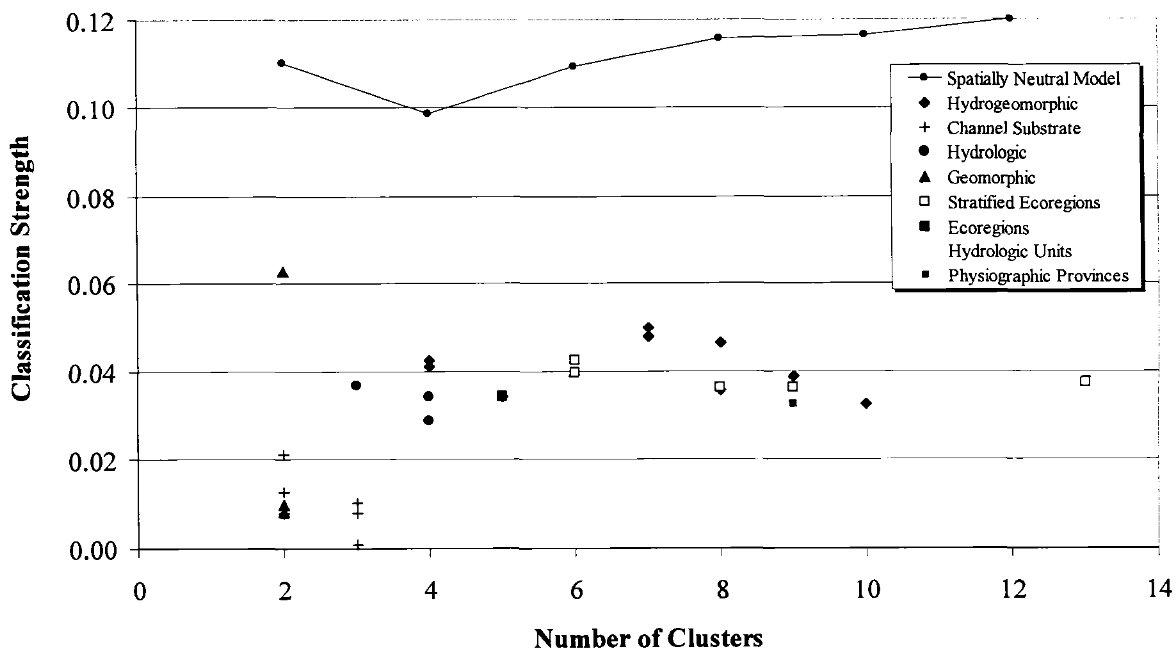

Figure 3.4. OR-EMAP classification strengths ($CS = \overline{W} - \overline{B}$).

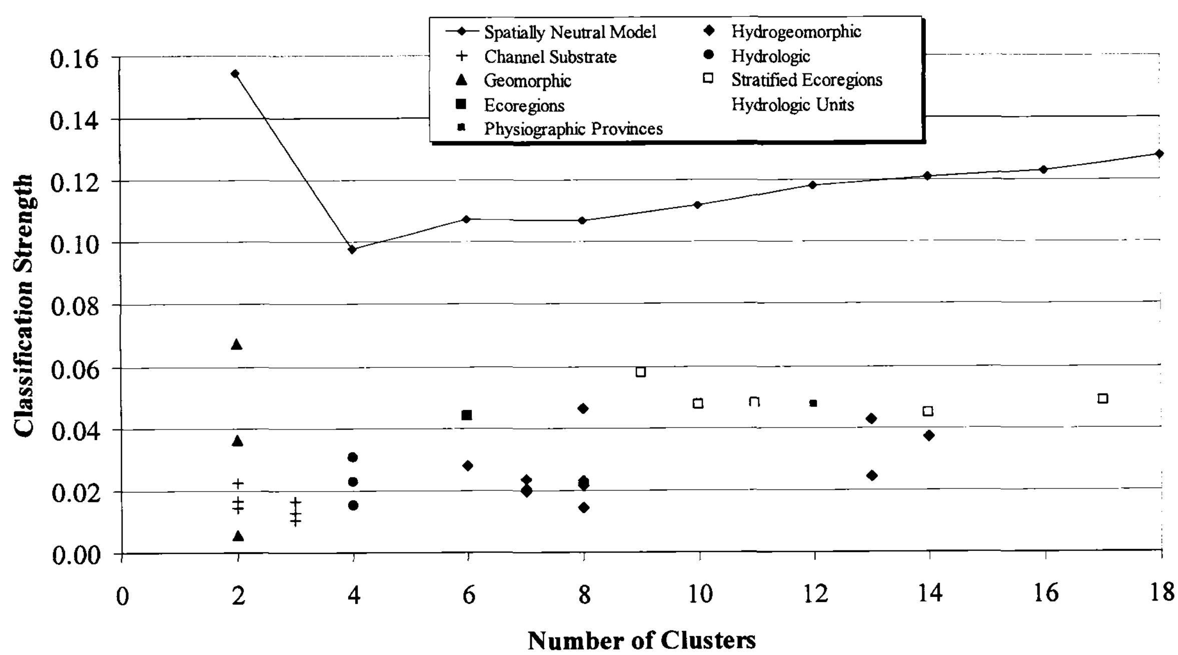

Figure 3.5. W-EMAP classification strengths ($CS = \overline{W} - \overline{B}$).

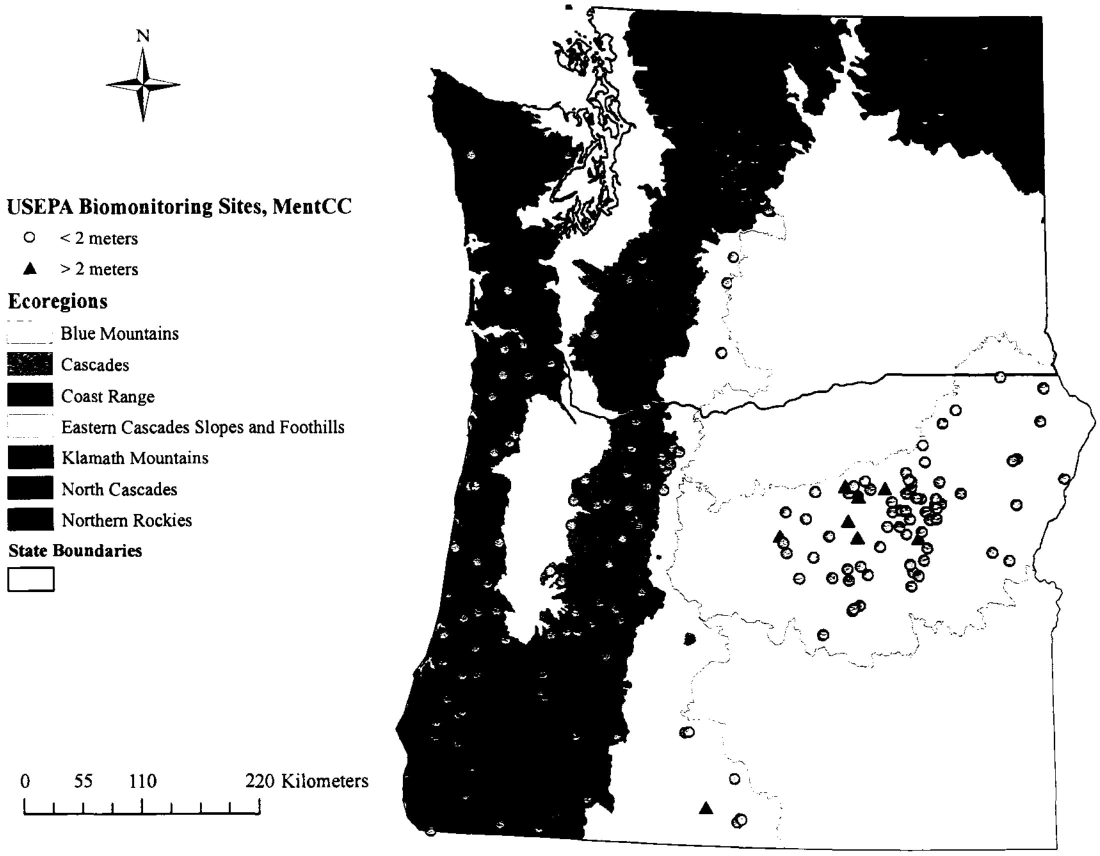

Figure 3.6. OR-EMAP and W-EMAP sites classified by MentCC. MentCC is the mean ground height above the stream channel in a circular area with a diameter of approximately one meander belt width.

Thirteen classifications outperformed ecoregions using the OR-EMAP data set. The best performing classifications were combinations of Montgomery and Buffington stream type and hydrologic classifications, with the low-flow regime performing the best (CS = 1.128). Montgomery and Buffington stream type and hydrologic classifications similarly combined to make the better classifications of W-EMAP sites except that a classification combining MentCC and low flow performed best and was the only hydrogeomorphic classification to surpass ecoregions.

Stratified ecoregions outperformed level III ecoregions in every case, but patterns between the two data sets were inconsistent, with a two-class D_{50} split (CS = 1.104) performing the best for the OR-EMAP study and a two class MentCC split (CS = 1.122) performing the best in the W-EMAP study. Regardless, classification strengths for stratified ecoregions were quite low given the number of classes required and in each case the gain in CS was relatively small compared to ecoregions. Further, no hybrid ecoregion classification resulted in a CS value higher than MentCC with only two classes.

Cluster models were mapped to visually analyze patterns resulting from the cluster analyses (Figure 3.7). The four-cluster model illustrates the geographically-independent nature of an optimal classification scheme resulting directly from insect assemblage data.

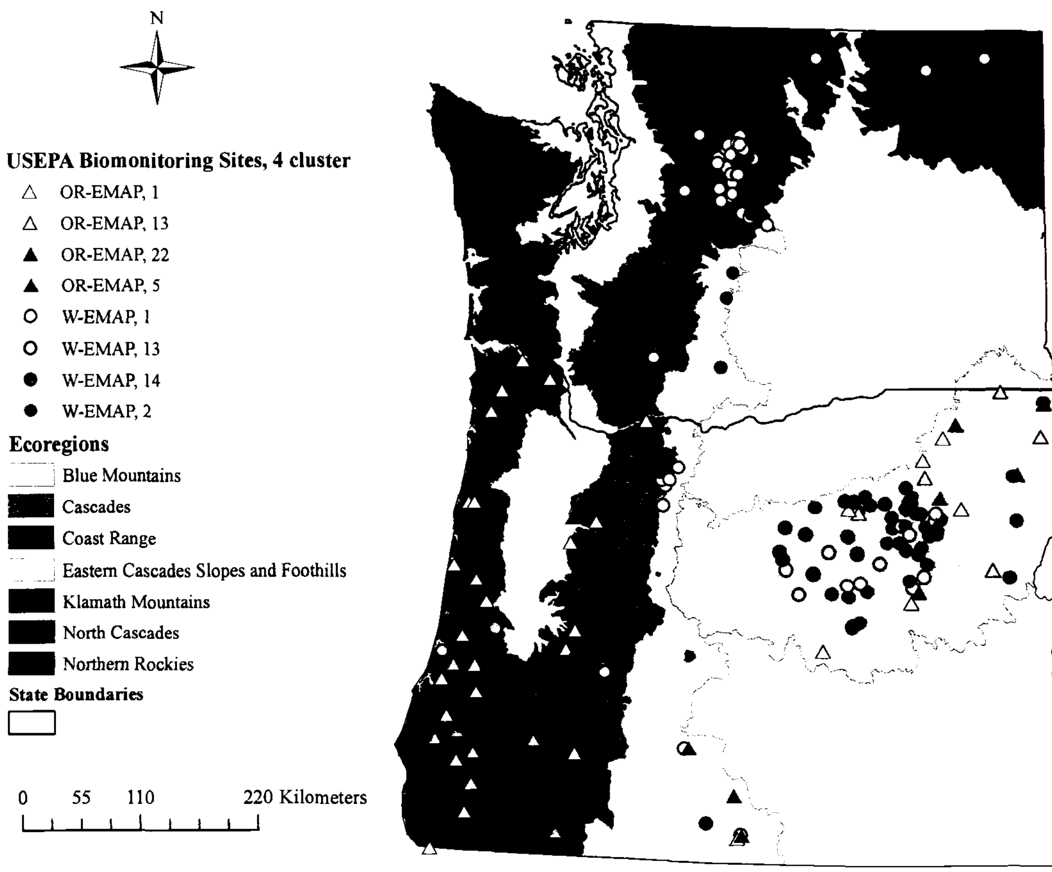

Figure 3.7. Cluster analysis results showing four-cluster models for both W-EMAP (Oregon and Washington) and OR-EMAP (Oregon) data.

3.4 DISCUSSION AND CONCLUSIONS

The spatially-neutral models used here as the base line for comparing classification strengths not only contain signals from hydrologic, geomorphic, physical disturbance (i.e., bed-load movement) influences, but also water quality, predation, competition, and other biotic controls. Nonetheless the hydrologic and geomorphic classifications presented here have shown promise for partitioning the landscape in a manner that facilitates understanding of spatial variation in stream insect communities. Improvements in the understanding of insect community filters may also reduce the reliance on reference sites when conducting bioassessments (Chessman and Royal 2004). This study developed techniques and suggestions for stratifying stream habitats to support bioassessments, biomonitoring, and other stream ecology studies.

3.4.1 Geographically-dependent Classifications

Hawkins et al. (2000) acknowledge the common use of ecoregions in bioassessments and suggest that they may continue to be a useful framework because of the physical factors used in their development. Many studies have found that ecoregions are relatively strong classifiers of benthic invertebrate assemblages that typically outperform other geographic classifications (Feminella 2000, Gerritsen et al. 2000, Hawkins and Vinson 2000, Rabeni and Doisy 2000, Sandin and Johnson 2000, Waite et al. 2000, Snelder et al. 2004). In these studies, ecoregion classification strengths ranged from 13.2% to 66.9% of the "optimized" clusters based on taxonomic data. Results presented here are comparable, with ecoregions outperforming hydrologic units and physiographic provinces, with classification strengths of 31.3% (OR-EMAP) and 40.9% (W-EMAP) of taxonomic cluster analyses.

Ecoregions were combined with hydrologic, geomorphic, and bed-material metrics to determine whether within-ecoregion stratification would develop powerful classifications. Such a classification could take habitat patchiness into consideration, while building upon the strength of ecoregions. However, this study used one metric at a time to stratify within all the ecoregions—a potential oversimplification. Previous work, on data sets not screened for highly disturbed sites, suggests that the physical metrics (and the scale of those metrics) that are best for predicting taxonomic metrics vary by ecoregion (Holburn et al. *In preparation*). This implies that ecoregion stratification requires an understanding of the most heterogeneous filters of insect communities inherent to that ecoregion. Still, when ecoregions were combined with smaller-scale metrics, there was an improvement in 7 out of 10 classifications. Ecoregions and within-ecoregion stratifications consistently classified W-EMAP data better than OR-EMAP data. This suggests that larger extent studies across strong environmental gradients (i.e., mountains and plains) could particularly benefit from ecoregions and a multi-scale approach to stratification.

However, results from this study suggest that there are influential hydrologic and geomorphic drivers that occur in patches across the landscape which are not represented in ecoregions. Stream insect communities also do not occur in discrete regions; rather, they form inconsistent, spatially disconnected patches across the landscape (Figure 3.7, Poole 2002). This partially explains the inferior performance of geographically-dependent landscape scale classifications such as ecoregions (Detenbeck et al. 2000) in comparison to the geographically-independent classification presented here and in the River Environment Classification (Snelder and Biggs 2002).

3.4.2 Geographically-independent Hydrogeomorphic Classifications

These results contribute to the physical understanding of drivers influencing stream insect assemblage composition in the mountains of the Pacific Northwest. Process-oriented metrics describing the hydrologic and geomorphic characteristics of biomonitoring sites provided a basis for developing physically-based classifications of the landscape. This research demonstrates the superior ability of geographically-independent physical classifications of streams to partition biological variability with fewer classes than ecoregion classifications.

Classifications based on low flows performed better than other hydrologic classifications on both data sets, when used individually and when used in combination with geomorphic variables. Low flows are biological constraints that reduce the areal extent of habitat available to aquatic biota and apply strong selective forces on stream biota (Lytle and Poff 2004) through numerous effects. They may also be associated with elevated stream temperatures and increased pollutant concentrations.

Measures of valley morphology had a wide range of classification strengths, with interesting implications for stream habitat classification aided by GIS. For practical purposes, both metrics (MentDR and MentCC) attempted to answer the same question: Is the area adjacent to the stream channel a low elevation, energy dissipating, and water storage area, or are hill slopes in close proximity to the channel? The metrics addressed this question with a different algorithm. The channel depth requirement in the MentDR metric likely reduced its classification strength. The data set consists of wadeable streams with bankfull depths less than or near the level of vertical accuracy in the DEMs. Floodprone width measurements suffer as well because DEM channel widths are in increments of 10 m, or 14.1 m in diagonal, making values somewhat insensitive relative to the channel sizes in this study. However, MentCC only uses channel width to calculate meander belt width and define the area where further calculations are made.

These results indicate that valley-scale descriptors are perhaps the most important metrics in describing stream habitat and putative insect assemblages. Many have suggested the importance of valleys (Hynes 1975, Frissell et al. 1986, Parsons et al. 2003, 2004), but it is difficult to determine appropriate valley-scale measures or metrics. Valley descriptors, as computed here, have relationships to many physical processes and boundary conditions known to be important to stream biota. MentCC for instance, was developed to be a measure of floodplain vs. hill slope presence and may be the first valley-scale metric to outperform watershed and local scales of measure. The presence and extent of floodplains adjacent to the channel can have a profound influence on both hydrologic and geomorphic processes that combine to form the local habitat and disturbance regimes, including energy dissipation, riparian vegetation, and colluvial inputs. Such a valley measure is expected to be correlated with, and therefore may be a surrogate for, many other physical habitat related variables such as slope, network position, hyporheic exchange potential, stream type (such as Montgomery and Buffington (1997)), large woody debris, elevation, and adjacent riparian communities.

Montgomery and Buffington (1997) stream type was not a strong classifier of insect assemblages in the larger extent, W-EMAP data set. However, it was similar in strength to ecoregions for the OR-EMAP data with half as many classes. This suggests that channel morphology may be a significant indicator of habitat types at scales for stream insect assemblages. Results here are similar to those of Parsons et al. (2003), who suggested that spatial patterns in macroinvertebrates may follow predictable, hierarchical patterns in geomorphic characteristics where larger-scale processes confine processes at progressively smaller scales (Schumm and Lichty 1965, Schumm 1977, Knighton 1998, Frissell et al. 1986, de Boer 1992). The predictor of Montgomery and Buffington (1997) stream type from Flores et al. (2006) is an example of a local-scale (i.e., reach) geomorphic form that is constrained by larger-scale (i.e., watershed area) geomorphic boundary conditions. Stream type was a powerful classifier of insect communities using the OR-EMAP data, an example of the biological significance of geomorphology. The weaker CS resulting from W-EMAP data suggests that there are large-scale regional patterns within the study extent that are not being accounted for with valley-scale geomorphic descriptors. A tiered approach, as suggested by Hawkins et al. (2000), where large-scale descriptors are used to refine the smaller-scale classification, may be appropriate here and would likely improve classifications strengths.

Bed-material descriptors based on EMAP field data classified insect communities poorly. When combined with other metrics to create hybrid classes, bed-material metrics improved CS but gains were relatively small, especially given the increases in the number of classes necessary. Interestingly, field-measured D_{50} did not outperform the regression equation predictions. This may result from the inclusion of significant watershed and valley-scale descriptors included in the regression equation used to predict D_{50} even though the regression equation does not have a particularly high R^2 value. Other studies have found significant relationships between macroinvertebrates and substrate size using measures of abundance (e.g., Brosse et al. 2003, Jowett 2003, Sandin and Johnson 2004). However, the generally low CS values and the use of presence/absence data suggest that insect assemblages are not strongly associated with bed-material size at the scales examined here, although some individual taxa may be dependent on bed-material size.

3.4.3 Scale

Regional-scale patterns emerged from both taxonomic data sets. The cluster analyses (Figure 3.7) illustrate the presence of all four clusters in southwestern Oregon and the Blue Mountain ecoregion in eastern Oregon, whereas other regions contain only two insect clusters from the four-cluster model. This self-emerging pattern (O'Neil et al. 1986, O'Neil and King 1998, Parsons et al. 2003) may have important implications for future regional-scale stratifications. Discovering the cause of this large-scale pattern may provide important insight as to the regionally available pool of species or significant physical drivers influencing insect community composition. The use of this pattern in subsequent classifications could improve the explanatory power of insect assemblage predicting models.

3.4.4 Practical Implications

The practical implications of this study, especially when considered in light of previous work on landscape classification for bioassessment, suggest that there is spatial heterogeneity in important physical drivers that influence stream insect and other macroinvertebrate communities. Additionally, there may be many ways to partition the landscape, because of correlations in important habitat characteristics, that provide moderately acceptable classifications for biomonitoring. Numerous classifications tested here and in other studies have proven to be significant with respect to stream biota. because all of these classifications are *a priori* classifications, we may be able to assume that we can use professional judgment and regional knowledge of potential physical drivers to develop relatively successful classifications (Barbour et al. 1999). Hydrology and Montgomery and Buffington (1997) stream type, for instance, may be useful and relatively straightforward techniques for stratifying stream environments for bioassessments and biomonitoring. The simplified Rosgen (1994, 1996) classification might also be a reasonable way to stratify sites as the classes therein are associated with valley types (Rosgen 1996), although characterizing bed sediments may be an unnecessary step, as demonstrated here. A slightly modified Rosgen classification has previously been shown to correlate with benthic macroinvertebrate communities in

Pennsylvania (McGarrell 1998). A further benefit of valley-scale (and other geomorphic) metrics, as calculated here, are that they are simpler to calculate and map than hydrologic data using only DEMs and simple algorithms.

3.4.5 Synthesis

The need for measuring stream health is becoming more important worldwide (Bunn and Davies, 2000). Karr and Chu (1997, 1999) suggest that the development of multimetric biological indices requires the classification of homogeneous regions as a prerequisite step. This work demonstrates how geospatial data may be used to map hydrologic and geomorphic variables together to create hydrogeomorphic classifications of the landscape to improve understanding and assessments of aquatic ecosystems. The use of geospatially-derived metrics in stream classification has potential to improve bioassessment success by integrating hydrogeomorphic contexts occurring in mosaics across the landscape. The ability to readily map relevant physical drivers of biological variability in a GIS makes their use in bioassessments possible, although not as simple as the implementation of geographically-dependent classifications. However, this study suggests that the benefits in understanding and improved accuracy in habitat classification may well be worth the additional effort required.

This *a priori* approach to hydrogeomorphic classification shows promise as a way of partitioning complex mountain landscapes into homogeneous patches where aquatic assemblages may be expected to be similar, thereby preventing spurious comparisons of dissimilar biomonitoring sites. However, cluster analyses based on taxonomic data have resulted in high classification strengths, to which *a priori* landscape-scale classifications have not been able to come close. An *a posteriori* approach to determining landscape-scale classifications for biomonitoring may be required to provide a boost in classification strength and mechanistic understanding of the interactions between physical habitat and stream insect assemblages.

Refinement of this approach (i.e., determining the best hydrogeomorphic metrics to use, scale(s) to best view them, and optimal classes within them) will continue to provide additional insight into physical features and processes affecting community composition. The increased prevalence of high-resolution geospatial data (e.g., Light Detection and Ranging (LiDAR)) will help as the scale of the data approaches the scale of the processes and boundary conditions being estimated. Such refinement will likely require regional calibration to determine the most important influences on stream insect assemblage composition. The ability to map reach-scale habitat with watershed- and valley-scale metrics would be a powerful tool for bioassessments and study designs. Randomly selected stream sites, as commonly used in similar studies, may neglect rare habitat types (Hawkins et al. 2000) given the spatial patchiness of stream habitats. The results presented here support this assertion, as the distribution of sites was not consistent throughout the taxonomic clusters nor were sites consistently distributed within classes that yielded at least moderate classification strengths. Further, the results of the spatially-neutral models are not evenly distributed across the landscape. A better understanding of the physical contexts of these rare habitat types requires further study of the associations between habitat types and stream communities on a region-by-region basis. With better landscape classifications in place, other environmental filters at smaller scales could be tested within this framework to develop a hierarchical understanding of stream insect and other aquatic assemblages.

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CHAPTER 4

HYDROGEOMORPHIC CLASSIFICATIONS OF MOUNTAIN STREAMS FOR BIOMONITORING I: AN *A POSTERIORI* APPROACH

Abstract

An essential part of assessing the biological condition of streams (and rivers) is making appropriate comparisons among systems of similar biological potential. Hydrologic processes and geomorphic boundary conditions, at multiple scales, combine to form relatively homogeneous patches of habitat that constrain the structure of stream insect assemblages. The large geographic extent and potential habitat heterogeneity of ecoregions and many other landscape classifications renders them unlikely candidates for developing strong, physically-based landscape-scale classifications. A geographical information system (GIS) was used to create geospatially-derived metrics describing hydrologic regime, geomorphic context, and stream substrate for developing classification tree models of stream insect assemblages at 222 minimally disturbed U.S. Environmental Protection Agency (USEPA) biomonitoring sites. Geographically dependent classifications (e.g., ecoregions), field-measured stream characteristics, and "spatially-neutral" optimal classifications based on biological data were also developed. The strength of classifications for partitioning variation in stream insect assemblages was measured using average between-class similarity ($\overline{B}$) versus average within-class similarity ($\overline{W}$). Spatially-neutral models developed using cluster analyses provided "optimal"

classification strengths against which to compare other models. Hydrogeomorphic classifications developed in this study substantially outperformed previous classifications with an average classification strength of 74% of "optimal" and a maximum of 90%. Metrics that consistently emerged as robust predictors included measures of valley form, channel slope, watershed area, minimum elevation, peak discharge, low flow characteristics, canopy cover, woody debris, and wetted (low flow) channel width to depth ratio. Median channel substrate and percent sand and fines had low association with stream insect assemblages. In particular, the results suggest that spatial scales intermediate to watersheds and reaches (valley segment) and low flow regimes are important influences on aquatic insect assemblages in the Pacific Northwest and should therefore be included in classifications. The results also have important implications for assessing water quality, design of biomonitoring networks, and stream restoration.

4.1 INTRODUCTION

An essential part of assessing the biological condition of streams (and rivers) is making appropriate comparisons among waterbodies where the biological potential is expected to be similar. Typically, the biological potential of degraded streams is not directly known from historical data, making comparisons to other streams necessary (Hawkins and Norris 2000a). Although biotic and abiotic aspects of streams are continuous in nature, it is necessary to classify stream reaches in ways that will maximize within-class similarity of stream biota and minimize similarity between classes. This would provide classes within which reasonable comparisons of biota could be made. Given that biological communities used in biomonitoring are not known in advance, other characteristics (e.g., ecoregions, stream type, and geology) anticipated to be associated with that community type are typically used to stratify reference sites.

Physically-based and easy to compute metrics calculated in a GIS may provide a powerful method for determining physical characteristics associated with relatively homogeneous biological assemblages. Classification of homogeneous stream environments is a prerequisite step to the development and implementation of biological indices (Karr and Chu 1997, 1999). Classifications must be practical and scientifically valid (Wasson et al. 2002) for the effective stream assessment, protection, and restoration. Our ability to identify degraded streams relies heavily upon the strength of the classification used (Karr and Chu 1999).

The water quality of streams in the United States (US) has been declining since 1998, after marked improvements following the Clean Water Act of 1972 (Palmer and Allan 2006). At the same time, the US population, which relies on rivers for municipal water supplies, irrigated farming, waste removal, and recreation (Karr 1999), is increasing (U.S. Census Bureau 2006), and applying ever-more stress to already stressed stream environments. To fulfill anti-degradation policies, the ability to detect human-induced impairment must, at minimum, be a step ahead of our ability to cause impairment. It is also important to understand which physical processes and boundary conditions are critical for the successful restoration of impaired streams. This underscores the need to develop the best possible, most physically meaningful classifications of stream environments.

A priori knowledge is typically used to select streams which are believed to be comparable to the potentially degraded streams under evaluation, although *a posteriori* classifications have also been deemed acceptable (Barbour et al. 1999, Newell and Wells 2000). These streams become the base line against which to test measures of biological integrity. Ecoregions (Omernik 1987), hydrologic units, and physiographic provinces (Fenneman 1946) are commonly suggested, *a priori* geographic landscape classifications within which streams historically sharing the same influences and constraints on regional biota are located. Several studies have focused on identifying strata within ecoregions in an attempt to improve their ability to partition biological variability (Gerritsen et al. 2000, Wasson et al. 2002, Ferréol et al. 2005).

The geographic large scale and environmental heterogeneity of some ecoregions, and many other landscape classifications, renders them unlikely candidates for developing strong, physically-based landscape-scale classifications of stream biota, especially in mountainous regions with strong hydro-climatic gradients (Chapter 3). Ecoregions have been used with moderate to little success in partitioning the landscape for studies of stream biotic communities (Hawkins and Norris 2000b). There is, however, a growing awareness that relatively homogeneous stream environments occur as patches across the landscape (Pringle et al. 1988, Townsend 1989, Poole 2002, Chapter 3). These patches are hierarchical in nature, occurring at various scales across the landscape (Frissell et al. 1986, Townsend 1996, Parsons et al. 2003, 2004).

The desire for greater understanding of the importance of patchiness and scaled geomorphic and hydrologic characteristics of streams have encouraged the development of *a priori* landscape classifications which take into account the physical drivers that influence stream community composition (Snelder and Biggs 2002, Chapter 3). These physically-based, landscape-scale classifications more directly account for drivers of stream community assemblages: However, as they are *a priori* classifications, they have not been calibrated and tested with biological data. It is unlikely that variation in stream biotic assemblages is best partitioned purely on expert judgment. This study develops landscape-scale, physical classifications, based on geomorphic and hydrologic characteristics of stream channels using *a posteriori* techniques to test several commonly used *a priori* classifications. This study will also examine whether *a priori* classifications of stream channels are strong relative to *a posteriori* classifications for determining stream reaches where stream insect assemblages are expected to be similar.

4.1.1 Conceptual Framework

Fluvial landscape ecology encompasses several basic fields of knowledge including ecology, hydrology, and fluvial geomorphology (Figure 4.1, from Poole (2002)). Ecoregions only vaguely capture the important influences of fluvial geomorphology and hydrology, the dominant physical constituents of stream habitat. Hydrologic processes and geomorphic boundary conditions are increasingly recognized as key influences on spatial patterns of stream biota. However, with the exception in Chapter 3 herein, no classification has been developed that combines hydrologic and geomorphic drivers into a unified hydrogeomorphic classification (Poff et al. 2006, *In press*). Such a classification is highly desirable and would facilitate significant advances in biomonitoring and bioassessments, and provide watershed managers with improved decision-making tools. Hydrologic regimes interact with geomorphic boundary conditions to determine characteristic patterns of disturbance and habitat, the template upon which stream biotic communities develop (Pringle et al. 1988, Resh et al. 1988, Poff and Ward 1989, 1990, Poff et al. 1997, Townsend and Hildrew 1994, Poole 2002, Benda et al. 2004). Disturbances of many types are known to ecologists to impose substantial influence on community composition as species have many complex and diverse ways of coping with disturbances.

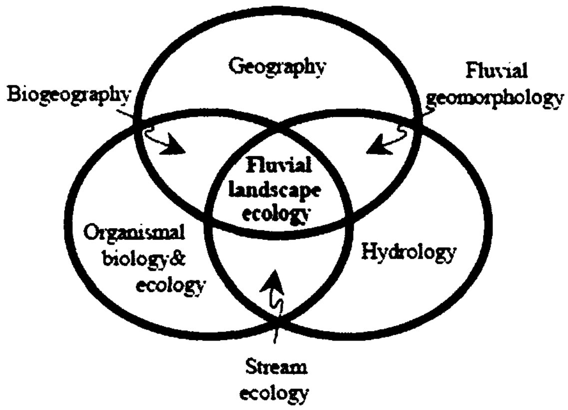

Figure 4.1. Foundations of fluvial landscape ecology (from Poole 2002).

4.1.1.1 Fluvial Geomorphology

Stream communities are directly tied to upstream contributing watersheds and valley form (Hynes 1975) and vary spatially within watersheds (Vannote et al. 1980, Benda et al. 2004). Much of the stream heterogeneity observed occurs at multiple scales that are hierarchical in nature (Schumm and Lichty 1965, Frissell et al. 1986, Davies et al. 2000). Parsons et al. (2003) have suggested that patterns in macroinvertebrate assemblages likely follow these scaled patterns of geomorphic processes, which are further determined by patterns in the regionally available pool of species.

Floodplain presence and extent are strongly associated with valley and stream types (Nanson and Croke 1992, Whiting and Bradley 1993, Rosgen 1996), and floodplains themselves are a dominant geomorphic feature of stream environments. Valley form influences floodplain presence and extent, channel slope, sinuosity, channel roughness, channel substrate, and other geomorphic boundary conditions that have the potential to constrain stream community composition. This indicates that valley form could provide a noteworthy stratification of insect assemblages. The results of Chapter 3 substantiate this connection between valley form and stream insect assemblages.

4.1.1.2 Hydrology

Flow regime has been shown to strongly influence stream ecosystems (Poff and Allan 1995, Power et al. 1996, Richards et al. 1997, Chapter 3) and may be considered a "master variable" in stream ecology (Resh et al. 1988, Poff et al. 1997). Relating stream flow patterns to stream communities may provide substantial insight into biological patterns observed in stream ecology (Poff and Allan 1985, Poff and Ward 1989, Clausen and Biggs 1997, Poff et al. 1997) because hydrology imposes limits on riverine species. Using appropriate flow descriptions could provide a means for delineating relatively distinct physical environments for riverine habitats (Poff and Ward 1989). To elucidate the most influential flow regime characteristics, researchers have begun characterizing flow regimes using ecologically-relevant metrics (Poff and Ward 1989, Poff 1996, Richter et al. 1996, Olden and Poff 2003, Sanborn and Bledsoe 2006) describing magnitude, duration, frequency, timing, and rate of change of flows, all of which may be important to ecological processes. Variation in key flow regime metrics may be able to explain spatial patterns in stream biotic assemblages (Richter et al. 1996, Poff et al. 1997).

4.1.1.3 Hydrogeomorphic Classification

Given the spatially heterogeneous pattern (i.e., patchiness) of hydrologic and geomorphic stream habitat-forming processes and boundary conditions, it is unlikely that geographically-dependent classifications, such as watersheds and ecoregions, provide adequate resolution for detecting human influences on stream biotic communities. Physical classifications based on scaled hydrologic and geomorphic influences, however, have potential to yield more robust classifications that provide significant insight regarding the physical controls that constrain and regulate stream communities. Numerous stream environment classifications exist, including hydrologic (e.g., Poff and Ward 1989, Sanborn and Bledsoe 2006) and geomorphic (e.g., Rosgen 1996, Montgomery and Buffington, 1997) classifications. These classifications, however, were not intended for or optimized by stream biotic communities. Classifications that include both hydrologic and geomorphic characteristics are more challenging to consider and relatively few attempts have been made to develop such a typology (Snelder and Biggs 2002, Chapter 3).

4.1.2 Objectives

Hydrologic and geomorphic stream characteristics have been neglected or over-simplified in many previous studies. Although the importance of scaled processes and boundary conditions to ecological processes is widely recognized, previous research has not yielded models that clearly support this view because of the challenge presented by derivation and computation of robust hydrologic and geomorphic metrics at watershed- and valley-scales. Metrics, and the explanatory power of the scales they represent, are only as good as our ability to describe them. Here, a rigorous set of new and descriptive metrics was developed in a GIS to provide a platform upon which to compute and subsequently map ecologically-relevant metrics for a large set of biomonitoring sites. A major impetus of this study was the use of an extensive list of multi-scale, process-based metrics, coupled with advanced statistical techniques, to develop *a posteriori* physical classifications based on variation in stream insect assemblages. Furthermore, I was interested in developing innovative GIS-based descriptors of the valley context of streams because it is a central control of stream forms and processes (e.g., Hynes 1975, Whiting and Bradley 1993, Nanson and Croke 1992, Montgomery and Buffington 1998).

I hypothesize that *a posteriori* hydrogeomorphic classifications will stratify insect communities with substantially stronger class separation than previously obtained in *a priori* classifications. Thus, classifications developed here will attain a greater proportion of "optimized" classification strengths of stream insect assemblages. Further, I hypothesize that hydrogeomorphic classifications will considerably outperform hydrologic classifications and geomorphic classifications individually. Specific objectives of this study were to:

- develop cross-validated classification trees of stream habitats in the mountains of the Pacific Northwest related to stream insect assemblages using geospatially-derived hydrologic and geomorphic metrics;
- test the classification strengths of *a posteriori* classifications compared to *a priori* geographic classifications (ecoregions, hydrologic units, and physiographic provinces);

- compare *a posteriori* classifications developed using the same limited set of metrics tested in Chapter 3 to the *a priori* classifications developed in Chapter 3;
- compare *a posteriori* classifications developed using all of the metrics presented here to the *a priori* classifications developed in Chapter 3;
- demonstrate the importance of valley context in identifying relatively homogeneous stream habitats for stream insect assemblages; and
- identify potentially important physical influences on stream habitats that are not represented in the GIS-derived metrics.

4.2 METHODS

4.2.1 Biological Data

USEPA biomonitoring data were used to develop and test hydrogeomorphic classifications of stream insect communities. The sites are distributed throughout mountainous ecoregions of the Pacific Northwest (Figure 4.2). The sites are on first- through fourth-order wadeable streams and were randomly selected for sampling (Kaufmann et al. 1999). Two separate data sets are used: a set of 165 USEPA Western Environmental Monitoring and Assessment Program (W-EMAP) sites in Washington and Oregon, and 97 USEPA Oregon Environmental Monitoring and Assessment Program (OR-EMAP) Pilot Study sites in Oregon.

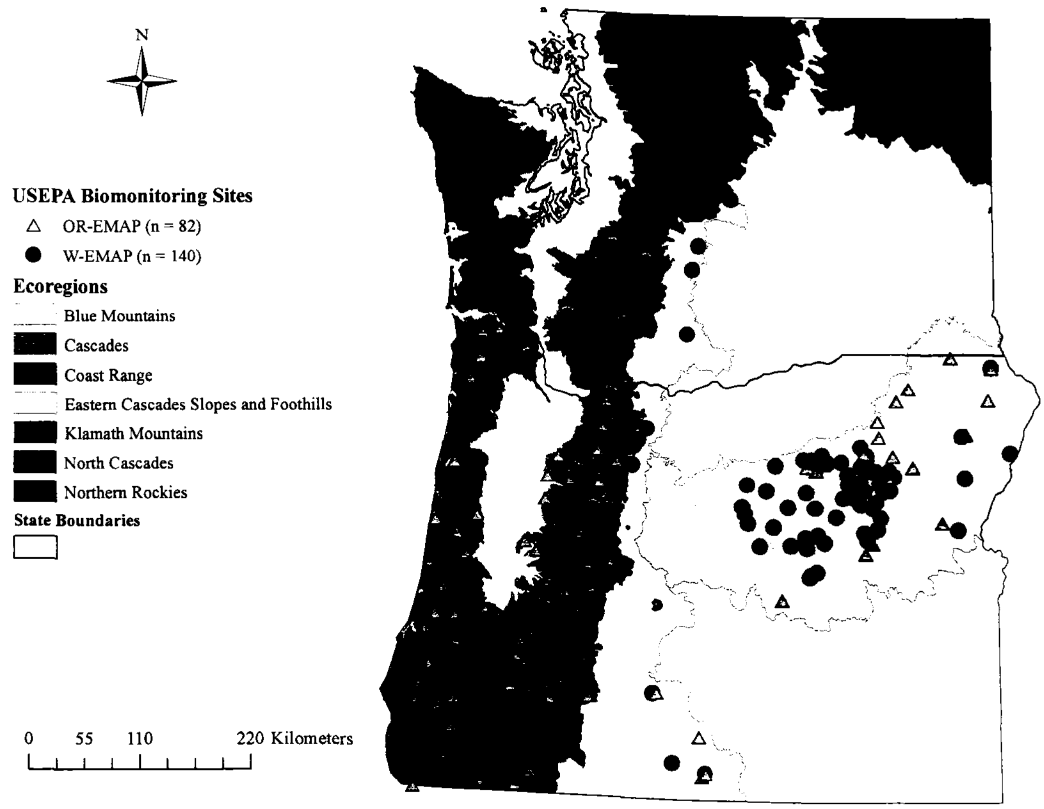

Figure 4.2. USEPA Western and Oregon EMAP biomonitoring sites.

I screened the biomonitoring sites using reach-specific water quality and riparian disturbance characteristics that were measured by EMAP field crews (Kaufmann et al. 1999, Table 4.1). Site screening was intended to remove sites that were heavily impacted by human influence, while not removing so many sites that the data set becomes too small for analysis. Human influences are still present in the data sets and may include forestry practices (Herlihy et al. 2005) and legacy effects (Harding et al. 1998). Although land cover / land use was not used to screen sites, the distribution of land cover in the final data sets was analyzed to give an understanding of the general character of remaining *minimally disturbed sites*. The maximum urban land cover was 2.9%, with an average of 0.06%. The average agricultural land cover was 0.36%, with one W-EMAP site being 21.3% agriculture.

Table 4.1. Criteria for site screening.

Code	Description	Threshold	Units
PHSTVL	pH	< 6	–
PTL	Total phosphorus	> 100	µg/L
SO4	Sulfate	> 1000	µeq/L
CL	Chloride	> 1000	µeq/L
NTL	Total nitrogen	> 1500	µg/L
W1_HALL	Riparian disturbance, sum of all types (proximity weighted)	> 3	%
PCT_FN	Substrate fines – silt/clay/muck	> 50	%

Macroinvertebrate taxa at the biomonitoring sites were mostly identified to genus. The initial W-EMAP set had 223 macroinvertebrate taxa and the OR-EMAP set had 173 macroinvertebrate taxa. Taxa that were found at less than 5% of the sites and non-insects were removed from the study. The remaining stream insects were used to create presence/absence matrices (McCune and Grace 2002). The W-EMAP matrix contained 140 sites and 140 insect taxa, whereas the OR-EMAP matrix contained 82 sites and 83 insect taxa.

4.2.2 Hydrogeomorphic Characterization

I used GIS to develop measures of the hydrologic and geomorphic character of each minimally-disturbed USEPA biomonitoring site. Site locations were used to delineate watersheds and stream networks using 10-m digital elevation models (DEMs). Geospatially-derived, descriptive metrics of sites were then computed to investigate the influence of flow regime, geomorphic boundary conditions, channel substrate, and ecoregions on landscape-level biological variation.

Few, if any, of the biomonitoring sites were located on gauged stream reaches, making direct calculation of hydrologic metrics impossible. Hydrologic metrics were, therefore, extrapolated from U.S. Geological Survey (USGS) stream gauges with relatively unaltered flow regimes using the equations and techniques of Sanborn and Bledsoe (2006). This required the computation of several climate and physical watershed characteristics that were used to group sites into one of four general flow-regime classes; snow melt, rain, snow and rain, and variable flow regimes. Multiple regression models unique to each of these flow regimes were then used to calculate 29 ecologically-relevant metrics describing hydrograph characteristics (Figure 4.2, Sanborn and Bledsoe 2006).

Table 4.2. Hydrologic metric descriptions.

Code	Description	Units
Hi4pca	High-flow regime type	–
Lo4pca	Low-flow regime type	–
Month4f5	Monthly-flow regime type	–
All4pca	All-flows flow regime type	–
Avg_Jun	Mean June flow	cubic meters per second (cms)
Avg_Nov	Mean November flow	cms
Avg_Oct	Mean October flow	cms
BaseQ	7-day minimum flow divided by mean flow for that year	–
Dh12	Mean annual 7-day maximum divided by median discharge	–
DHiPl	Mean duration of high pulses	day
FallR	Fall rate – mean of all negative differences	cms/day
Fh11	Mean number of discrete flood events per year	–
Flash	Mean annual 1-day maximum / mean flow over all years	–
Ma3	Coefficient of variation of daily flows	–
Ma41	Mean annual runoff divided by watershed area	cm
Ma44	Mean variability in daily flows divided by median daily flows for each year, where variability is calculated as 90th to 10th percentile	–
MAR	Mean annual runoff	cms
Mh1	Maximum monthly flow for October	cms
Ml13	Coefficient of variation in minimum monthly flows	–
Ml22	Mean annual minimum flows divided by watershed area	cms/km^2
Mn1d	Mean annual 1-day minimum flow	cms
Mn30d	Mean annual 30-day minimum flow	cms
Mn3d	Mean annual 3-day minimum flow	cms
Mn7d	Mean annual 7-day minimum flow	cms
Mx1d	Mean annual 1-day maximum flow	cms
Mx3d	Mean annual 3-day maximum flow	cms
Mx7d	Mean annual 7-day maximum flow	cms
NHiPl	Mean number of low pulses, low pulse defined as 1 standard deviation below the mean	–
RiseR	Rise rate – mean of all positive differences	cms/day

The geomorphic character of biomonitoring sites was computed in a GIS with a combination of linked C++ programs and Arc Macro Language scripts using 10-m DEMs as the basis for computation. A total of 29 watershed-, network-, and valley-scale metrics were developed to characterize major geomorphic boundary conditions with the potential to influence stream insect community composition (Table 4.3). The metrics include an estimate of Montgomery and Buffington (1997) channel type (Flores et al. 2006), three measures of valley bottom morphology, several measures of tributary characteristics for tributaries immediately upstream of the sampling location, channel slope, and several measures of specific stream power (*SSP*) estimated with a surrogate measure defined as:

$$SSP = SA^{0.4} \tag{4.1}$$

where S is channel slope (m/m) and A is watershed area (km^2).

Table 4.3. Geomorphic metric descriptions.

Code	Description	Units
MnB	Predicted Montgomery and Buffington stream type (at watershed outlet)	–
Pct_C	Percent of stream network – cascade	%
Pct_PB	Percent of stream network – plane-bed	%
Pct_PR	Percent of stream network – pool-riffle	%
Pct_SP	Percent of stream network – step-pool	%
D_{50}	Predicted median substrate size (D_{50})	mm
Pct_lt4	Percent of stream network with less than 4% slopes	%
Pct_lt7	Percent of stream network with less than 7% slopes	%
Chan_slp	Slope of channel at outlet	–
Link_slope	Slope of outlet stream link	–
DAkm2	Watershed area	km^2
Link_SA	Slope-area product for outlet stream link	km^2
Link_SA4	$SA^{0.4}$ product of outlet stream link	$km^{0.8}$
DWSP1	Mean distance-weighted link $SA^{0.4}$ ($w = 1/x^2$)	$km^{0.8}$
DWSP2	Mean distance-weighted link $SA^{0.4}$ ($w = \exp(-x/X_{Max})$)	$km^{0.8}$
MCon	Hill-slope connectivity – highest elevation in the second stream cell perpendicular to stream channel	m
MentCC	Valley entrenchment-elevation of the local ground surface relative to stream elevation.	m
MentDR	Valley entrenchment-floodprone width divided by bankfull channel width.	–
MDW_A_025	Distance-weighted tributary to main stem watershed area ratio	–
MDW_A_1	Distance-weighted tributary to main stem watershed area ratio	–
MDW_A_25	Distance-weighted tributary to main stem watershed area ratio	–
MDW_SA_025	Distance-weighted tributary to main stem *SA* ratio	–
MDW_SA_1	Distance-weighted tributary to main stem *SA* ratio	–
MDW_SA_25	Distance-weighted tributary to main stem *SA* ratio	–
MDW_SA0_4_025	Distance-weighted tributary to main stem $SA^{0.4}$ ratio	–
MDW_SA0_4_1	Distance-weighted tributary to main stem $SA^{0.4}$ ratio	–
MDW_SA0_4_25	Distance-weighted tributary to main stem $SA^{0.4}$ ratio	–
Min_elev	Lowest elevation in watershed (outlet elevation)	m
Slp_elon	Ratio of watershed slope to watershed elongation where elongation is the diameter of a circle with the same area as the watershed	m^{-1}

Median channel substrate size (D_{50}) was predicted using a regression equation developed using best subsets multiple regression and D_{50} estimates from pebble counts conducted by EMAP field crews (Kaufmann et al. 1999). All the potential independent variables tested were geospatially-derived metrics, providing a prediction of reach D_{50} based solely on remotely sensed data. The equation with an adjusted $R^2 = 0.36$ is:

$$D_{50} = 0.089 Chan\_slp^{1.12} Mx7d^{0.4} MentCC^{0.858} Ma3^{-0.955} Ma41^{0.432} - 1 \qquad (4.2)$$

The result is a predictor of D_{50} that relies on a term similar to Hack's (1957) model based on slope and watershed area—a surrogate for specific stream power.

Field-measured descriptions (Table 4.5) of biomonitoring sites were also used to develop classifications and provide a means of testing GIS metrics versus field data. A total of 29 USEPA metrics (Kaufmann et al. 1999) were selected, including measures of channel geometry, channel substrate, large woody debris (LWD), riparian characteristics, and various habitat types. These metrics represent the reach scale because the values for these metrics were averaged over 11 transects spaced one bankfull channel width apart.

Table 4.4. USEPA EMAP physical habitat (PHab) metric descriptions (field-measured, Kaufman et al. (1999)).

Code	Description	Units
Bfwd_rat	Mean bankfull width/depth ratio	m/m
Lsub_D50	$Log_{10}\ D_{50}$	Log(mm)
Lsub_D84	$Log_{10}\ D_{84}$	Log(mm)
Lwdtv33	Volume/reach of all LWD	m^3
Pcan_c	Riparian canopy coniferous	%
Pcan_d	Riparian canopy deciduous	%
Pcan_m	Riparian canopy mix coniferous-deciduous	%
Pct_fast	Fast water habitat	%
Pct_org	Substrate wood or detritus	%
Pct_pool	Pools	%
Pct_ri	Riffle	%
Pct_SAFN	Substrate sand and fines (<2 mm)	%
Pct_slow	Slow water habitat	%
Pfc_big	LWD, rock, over hanging brush or human fish cover	%
Pfc_lwd	LWD presence	%
Pfc_ohv	Overhanging vegetation presence	%
V1w	LWD volume in bankfull channel	m^3
V1w_msq	LWD volume in bankfull channel	m^3
V4w	LWD volume in bankfull channel	m^3
Xbkf_H	Mean bankfull height	mm
Xbkf_W	Mean bankfull width	m
XC	Riparian vegetation canopy cover	%
Xcdenbk	Mean bank canopy density	%
Xdepth	Mean thalweg depth	cm
Xfc_big	LWD, rock, undercut bank or human fish cover	m^2
Xpcmg	Riparian canopy cover 3 layers present	%
Xslope	Mean reach channel slope	%
Xwd_rat	Mean width/depth ratio	m/m
Xwidth	Mean wetted width	m

4.2.3 Statistical Analysis

4.2.3.1 The Spatially-neutral Model

Spatially-neutral models were used to provide a benchmark against which to judge classification performance and they were the dependent variables for building explanatory models. These models are *spatially neutral* because they are based solely on taxonomic data and do not directly consider geographical relationships (Van Sickle and Hughes 2000). Models were developed in PC-Ord™ software (McCune and Mefford 1999; Version 4.0, MjM Software Design, Gleneden Beach) by means of cluster analyses on presence/absence matrices of stream insect data using the Sorenson distance measure and a flexible β of -0.25. The resulting dendrograms represent groups of biomonitoring sites optimized by taxonomic similarity. For this study, cluster solutions with 2, 4, and 6 clusters were retained for OR-EMAP data and 2, 4, 6, 8, and 10 cluster solutions were retained for W-EMAP data. In both cases, the maximum number of clusters corresponded with 25% information remaining, a commonly used guideline for deciding the number of clusters to retain (Gauch 1982).

4.2.3.2 Classification Trees

Classification Trees (CTs) were used to develop models for predicting the membership of biomonitoring sites into classes of similar stream insect assemblages. CTs are binary decision trees where values of explanatory variables (metrics) lead to an estimation of a response variable (Breiman et al. 1984). The explanatory, or splitting variable, and the respective split value are chosen by the ability of the split to minimize the within-group sum of squares based on the response variable (De'ath and Fabricus

2000). Each node is a decision that directs the user along a branch, either to another decision node, or to a terminal node. A terminal node, or *leaf*, is a predicted class from the learning data set. CTs have several benefits over other classification techniques: data can be categorical, no assumptions regarding the distributions of the data are necessary (nonparametric), errors have no assumed or required distributions, and they are capable of handling missing data (Breiman et al. 1984).

A significant benefit of the CT model structure is the direct identification of complex variable interactions. This is particularly important with respect to scaling. Variables can be used to split data repeatedly. CTs explicitly define thresholds where a predictor variable may generate an increase or decrease in the dependent variable, depending on scale.

The CTs were created in CART® V6.2 (Salford Systems 2005) using the Gini Index, ten-fold validation, and error shaving. The Gini Index is the only splitting rule that is a direct measure of node impurity. The Gini Index can be written as:

$$1-\sum c^2 \tag{4.3}$$

where c is the proportion of a value of the dependent variable in the class. This value approaches 0 as the purity, or homogeneity, of nodes increases. Ten-fold validation divides the data into 10 groups, creating 10 CTs where 9 of the 10 groups are used as the learning sample and the remaining group is used as the test sample. The CT with the smallest test sample error is retained. Error shaving is an iterative process of CT selection which can potentially improve the resulting tree (model). Typically, CTs are grown by choosing the best split for each node from the top down. Therefore, node splits are maximized in a step-wise process. However, it is quite possible that an inferior split at any node will allow for a better split at a subsequent node, which may provide better overall model results. Error shaving, although it does not develop and test an exhaustive number of models, attempts to improve the final model through an iterative process of removing the poorest predictors sequentially. Each metric is removed from the potential pool of splitting variables once, and a CT is grown. A single metric, that when left in the potential pool of splitting variables resulted in the poorest performing tree, is removed from further consideration. This is repeated until only two metrics are left, at which point the best of all the trees can be retained as the final model.

Relative costs (R_c) and misclassification rates were used to assess CT model performance. The better performing models are those with the lowest R_c and misclassification rates. Perhaps most important is that the classification models make physical sense given expert understanding of the processes affecting stream insect communities.

4.2.3.3 Similarity Analysis and Classification Strengths

The Multi-response Permutation Procedure (MRPP) function in PC-Ord™ (McCune and Mefford 1999) and MEANSIM6 (Van Sickle 1997, Van Sickle and Hughes 2000; Version 6, USEPA, Corvallis) were used in succession to perform similarity analyses to develop measures of classification strength (CS). Classification schemes were assessed by dividing the average between-class assemblage dissimilarities ($\overline{B}$) by the average within-class assemblage dissimilarity ($\overline{W}$) and by subtracting average within-class assemblage dissimilarity ($\overline{W}$) from the average between-class assemblage dissimilarities ($\overline{B}$) based on the Sorensen distance measure (Van Sickle 1997, Van Sickle and Hughes 2000). All the classification schemes developed, including the spatially-neutral models, ecoregions, and CTs, were tested using this procedure.

Taking this extra step beyond examining misclassification rates is quite valuable for determining classification performance. As an example, two classifications may have the same misclassification rates and incorrectly classify one site each. However, because insect assemblages are not distinct groups, but rather are overlapping distributions of taxa, it is important to understand how different the single misclassified site is from the others in the class. The site may be relatively similar, providing a high CS, or it may be quite different, which will tend to reduce the CS. As more sites are incorrectly classified, this influence may be magnified. Hence, classifications strengths provide a more comprehensive basis for scrutinizing classifications than R_c or misclassification rates.

4.2.4 Model Development

Over 100 CTs were developed (i.e., grown) to predict the eight cluster analyses results retained for OR-EMAP and W-EMAP data. The large number of CTs developed is a result of five factors, the simplest of which is the use of two data sets. Additionally, there is no "correct" number of clusters to predict. Predicting several cluster analysis results provides various resolutions (number of clusters) of classification, while providing a measure of confidence for CART results. This is important, given the relatively small sample size used here for CART analysis. The desire to compare tiers of metrics (i.e., hydrologic versus geomorphic), geospatially-derived versus field-measured metrics, and geographic versus non-geographic classifications, further increased the number of CTs required.

Developing different CTs was accomplished by predicating different numbers of taxonomic clusters and by controlling the pool of metrics (Figure 4.3) from which CART selected model predictors. First, CTs were grown to make direct comparisons with single geomorphic and channel substrate metric classifications developed in Chapter 3. These trees were grown using one metric at a time, such as MentCC and CCD_{50}. Second, the limited set of the hydrologic, geomorphic, and USEPA channel substrate metrics were used together to grow limited-metric hydrogeomorphic trees (i.e., the pool of metrics was limited to the pool of metrics used in the *a priori* classifications tested in Chapter 3). These trees allow direct comparisons with the *a priori* hydrogeomorphic classifications from Chapter 3. Results of the models mentioned to this point are presented in the *Limited-metric Model Results*, Section 4.3.1. All of the subsequent trees were grown using the comprehensive set of metrics depicted in Figure 4.3 and described in Tables 4.2 through 4.4. Results of these models are presented in Section 4.3.2, *Comprehensive Metric Model Results*. The third set of classification trees used the comprehensive set of hydrologic, geomorphic, and field-based USEPA PHAb metrics individually. This resulted in hydrologic, geomorphic, and reach-scale classifications. Fourth, the best performing hydrologic and geomorphic metrics from the third set of trees were selected to create a pool of 29 metrics to develop hydrogeomorphic classifications. Fifth, this pool of GIS metrics was reduced to 20 variables and the 10 best PHab metrics were added to create "all-metric" models. Sixth, all of the geomorphic, hydrologic, PHab, hydrogeomorphic, and all-metric models were evaluated a second time. In these analyses, ecoregions were added to the pool of potential splitting variables to determine whether ecoregions improved results. The final CTs were developed as *a posteriori* stratified-ecoregion classifications based on separate cluster analyses within each Level III ecoregion. Classification trees were created to predict each within-ecoregion two-cluster solution using the comprehensive set of hydrologic and geomorphic metrics.

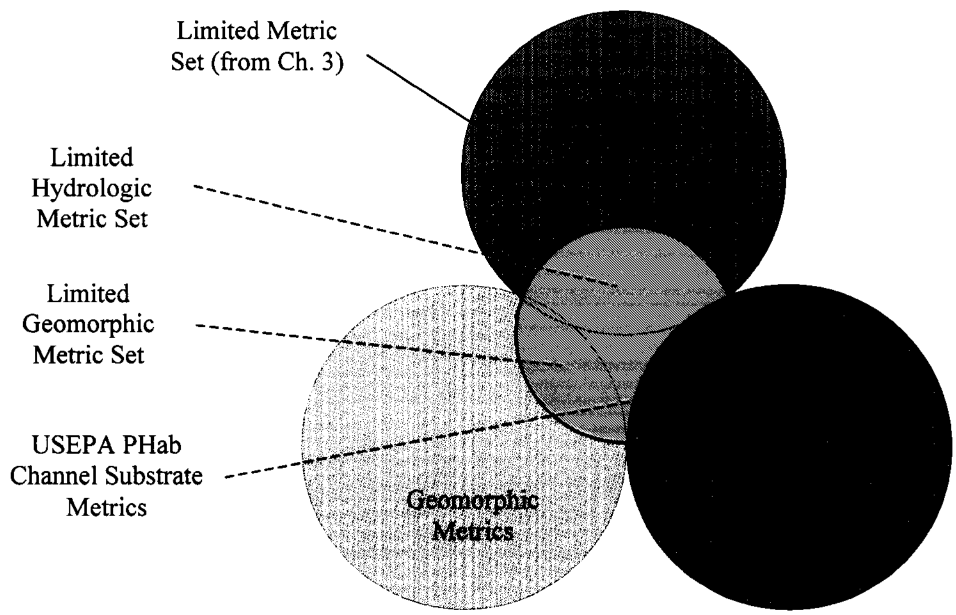

Figure 4.3. Pool of metrics used to create *a posteriori* classifications trees.

4.3 RESULTS

The results of the limited-metric classification trees are presented first. The metrics used in these models were limited to the set of metrics used in the *a priori* models presented in Chapter 3 (Figure 4.3). The pool of metrics used to create *a posteriori* classification trees (Figure 4.3) allowed a direct comparison between the results of *a priori* classifications and the *a posteriori* classifications presented here. This is followed by the results of *a posteriori* models developed using the comprehensive set of metrics described in Tables 4.2 through 4.4. In general, models based on the limited metric set performed similar to the *a priori* and geographic classifications tested in Chapter 3, with maximum CSs reaching 57% of spatially-neutral models. Classifications based on the comprehensive set of metrics substantially outperformed all previous models, with CSs reaching 96% of spatially-neutral models.

4.3.1 Limited-metric Model Results

Classification trees grown using the valley-scale geomorphic metrics were generally powerful models, with a minimum correct classification rate on a test sample of 76.8% and a maximum of 86.6%. An exception was the hill-slope connectivity (Mcon) metric, which did not grow a tree using W-EMAP data. Instances where CART did not identify any split (i.e., grow a tree) were instances where no split resulted in improved node purity. Ideally, the split value should lead to the creation of two nodes where mean heterogeneity of those nodes is less than the heterogeneity of the original, combined data set. Classification trees could not be grown for several individual metrics tested in Chapter 3. This included both median substrate size metrics for OR-EMAP data. Percent sand and fines (Pct_SAFNs) was used to grow a tree, but the R_c was high and the correct classification rates were low. None of the channel substrate metrics provided a basis to grow trees using W-EMAP data. CART results are presented in Appendices B and C, and are summarized in Tables 4.5 and 4.6 for OR-EMAP and W-EMAP data, respectively.

Table 4.5. OR-EMAP classification tree results for models limited to metrics used in *a priori* classifications.

Metric Type	Class Name	Number of Clusters	R_c	Learning % Correct	Test % Correct
Channel Substrate	D_{50}	2	NTG	N/A	N/A
	CCD_{50}	2	NTG	N/A	N/A
	Pct_SAFNs	2	0.928	34.1	32.9
Geomorphic	MentCC	2	0.693	87.8	86.6
	MentDR	2	0.812	86.6	82.9
	Mcon	2	0.883	80.5	76.8
Hydrogeomorphic	Limited metrics	2	0.428^{+}	91.5	82.9
	Limited metrics	4	0.529^{+}	78.0	58.5
	Limited metrics	6	0.500	68.3	50.0

NTG – no tree was grown
N/A – not applicable
$^{+}$ – hydrogeomorphic models with no hydrologic metric splits

Table 4.6. W-EMAP classification tree results for models limited to metrics used in *a priori* classifications.

Metric Type	Class Name	Number of Clusters	R_c	Learning % Correct	Test % Correct
Channel Substrate	D_{50}	2	NTG	N/A	N/A
	CCD_{50}	2	NTG	N/A	N/A
	Pct_SAFNs	2	NTG	N/A	N/A
Geomorphic	MentCC	2	0.764	82.9	82.9
	MentDR	2	0.633	83.6	82.1
	Mcon	2	NTG	N/A	N/A
Hydrogeomorphic	Limited metrics	2	$0.353^{\#}$	79.3	79.3
	Limited metrics	4	0.646	62.9	47.9
	Limited metrics	6	0.672	52.1	37.9
	Limited metrics	8	0.756	47.9	30.0
	Limited metrics	10	0.788	44.3	23.6

NTG – no tree was grown
N/A – not applicable
$^{\#}$ – hydrogeomorphic models with no geomorphic metric splits

Hydrogeomorphic metric models resulted in the lowest R_c of all the limited-metric models grown. All geomorphic and hydrologic metrics used in the *a priori* models were potential explanatory metrics in these models. The 2- and 4-cluster OR-EMAP trees, however, only contained geomorphic metrics (MentCC, Mcon, and MnB), whereas the 2-cluster W-EMAP tree only used hydrologic metrics (All4pca and Lo4pca). For each data set, correct classification rates decreased when more clusters were predicted. This results from increased tree complexity required to predict more clusters, while average within-class sample sizes decreases. In general, OR-EMAP trees had higher correct classification rates than W-EMAP trees.

Classification strength results are plotted in Figure 4.4 and Figure 4.5 for OR-EMAP and WEMAP data, respectively. The *a priori* classification results from Chapter 3 are superimposed to demonstrate departures observed when using *a posteriori* categorical splits with CART.

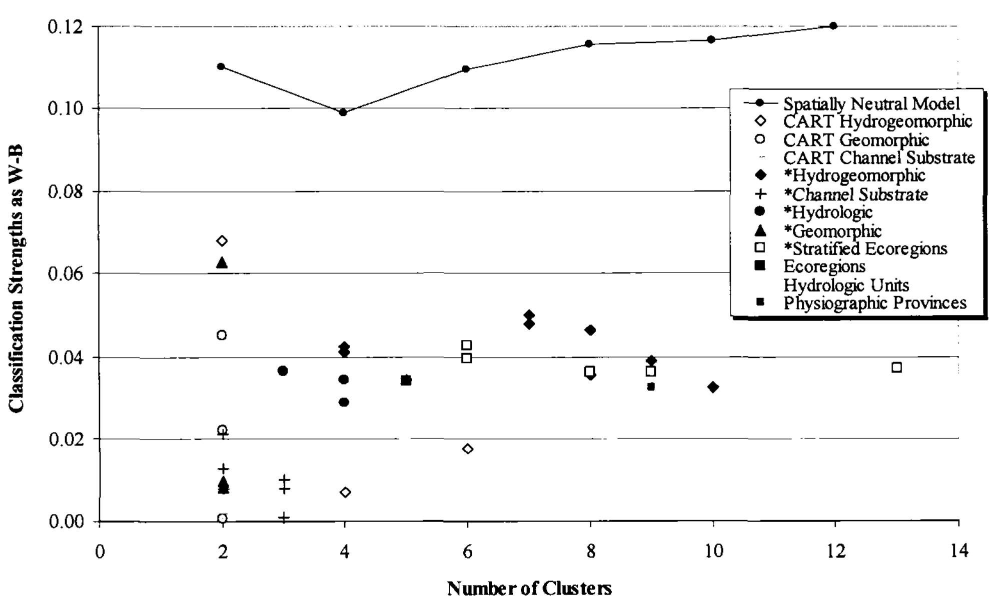

Figure 4.4. OR-EMAP classification strengths for models limited to metrics used in *a priori* classifications (* in figure legend denotes *a priori*-derived classes).

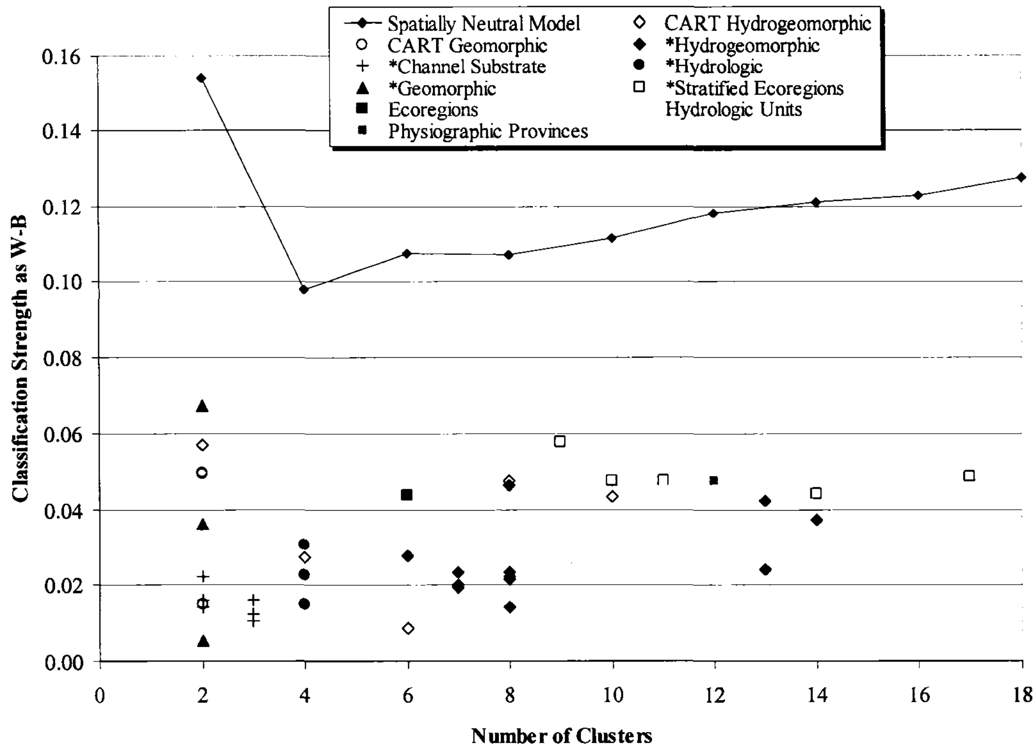

Figure 4.5. W-EMAP classification strengths for models limited to metrics used in *a priori* classifications (* in figure legend denotes *a priori*-derived classes).

The poor classification strength of Pct_SAFNs decreased further with the CART-derived split. This can occur because CART only reduces misclassification rates and does not consider taxonomic similarity. No substrate metrics were able to discriminate insect assemblages within the W-EMAP study.

The valley-scale geomorphic metrics in general, and the MentCC metric in particular, performed well as predictors of insect assemblages. MentCC continued to outperform other valley metrics, with the exception of MentDR, which increased to match the CS of MentCC with the W-EMAP data set. Hill-slope connectivity (Mcon) had the lowest CS of the valley-scale metrics, although it increased relative to the *a priori* split.

Hydrogeomorphic classifications produced mixed results and varied with the number of clusters predicted. The OR-EMAP 2-cluster hydrogeomorphic classification, which included only geomorphic metrics, outperformed all other limited-metric classifications. The 4- and 6-cluster models were relatively poor classifications, which resulted in the low test sample correct classification rates. The W-EMAP 2-cluster solution produced a relatively strong classification despite an absence of geomorphic metrics in the CT. Only the 2- and 8-cluster solutions (0.057 and 0.048, respectively) outperformed ecoregions. Classification strengths for the remainder of the hydrogeomorphic models varied from 0.009 to 0.044, showing no improvement over ecoregions.

4.3.2 Comprehensive Metrics Model Results

Classification trees (Appendices D and E) developed using geomorphic, hydrologic, and USEPA PHab metrics (from Tables 4.2 through 4.4) correctly classified 56 to 96% of OR-EMAP validation sites and 46 to 92% of WEMAP sites (Table 4.7 and Table 4.8, respectively). Models that predicted more classes tended to benefit the most from combining hydrologic and geomorphic metrics. For OR-EMAP models, the performance of a single type of metric varied with the number of clusters predicted. Hydrologic models outperformed geomorphic and PHab (field data) metrics in 3 out of 5 models with the W-EMAP data. Hydrogeomorphic models generally outperformed models that were strictly hydrologic- or geomorphic-based. Although PHab metrics typically resulted in the models with the highest misclassification rates, hydrogeomorphic models benefited from their addition in the all-metric models. The PHab metrics that most frequently occurred in the all-metric models were measures of LWD (V1w_msq and V1w), channel width (Xwidth), width/depth ratio (Xwd_rat), and canopy cover (XC).

Ecoregion was added to CART as a potential explanatory variable, but did not improve model performance in any of the OR-EMAP models (Table 4.7). Ecoregion did, however, improve several of the W-EMAP models (Table 4.8). Most notable were the Phab models, nearly all of which benefited from the addition of ecoregion as a predictor variable. Ecoregions improved PHab model test sample classification rates by up to 10.7%.

Table 4.7. OR-EMAP classification tree performance.

Metric Type	Number of Clusters	R_c	Learning % Correct	Test % Correct	Ecoregions improve model?
Geomorphic	2	0.211	81.7	81.7	no
	4	0.427	81.7	70.7	no
	6	0.493	74.4	56.1	no
Hydrology	2	0.196	98.8	96.3	no
	4	0.504	84.1	63.4	no
	6	0.445	74.4	65.9	no
Hydrogeomorphic	2	0.210	98.8	95.1	no
	4	0.356	84.1	72.0	no
	6	0.421	81.7	74.4	no
USEPA PHab	2	0.280	91.5	89.0	no
	4	0.427	68.3	62.2	no
	6	0.453	68.3	58.5	no
All Metrics	2	0.196	98.8	96.3	no
	4	0.347	92.7	80.5	no
	6	0.354	63.4	56.1	no

Table 4.8. W-EMAP classification tree performance.

Metric Type	Number of Clusters	R_c	Learning % Correct	Test % Correct	Ecoregions improve model?	R_c	Learning % Correct	Test % Correct
Geomorphic	2	0.826	90.7	86.4	no			
	4	0.527	80.0	72.1	no			
	6	0.595	76.4	68.6	no			
	8	0.556	77.9	60.7	yes	0.500	83.8	69.4
	10	0.661	57.9	47.1	yes	0.643	55.0	48.6
Hydrology	2	0.565	93.6	92.1	no			
	4	0.554	89.3	70.7	yes	0.514	84.3	72.9
	6	0.581	73.6	69.3	no			
	8	0.475	74.3	66.4	no			
	10	0.581	77.9	58.6	no			
Hydro-geomorphic	2	0.522	94.3	91.4	no			
	4	0.527	80.0	70.7	no			
	6	0.581	77.9	69.3	no			
	8	0.475	74.3	66.4	no			
	10	0.563	76.4	55.0	no			
USEPA PHab	2	0.478	94.3	92.1	no			
	4	0.676	77.1	64.3	yes	0.473	87.9	75.0
	6	0.730	87.1	61.4	yes	0.554	82.1	70.7
	8	0.687	83.6	51.4	yes	0.576	69.3	59.3
	10	0.679	76.4	45.7	yes	0.625	72.9	50.0
All Metrics	2	0.478	93.6	92.1	no			
	4	0.500	79.3	73.6	no			
	6	0.568	82.1	70.0	yes	0.362	80.8	67.6
	8	0.475	74.3	66.4	no			
	10	0.580	80.0	53.6	no			

Growing CTs to develop models of stream insect assemblage with the full suite of metrics substantially improved classification strengths for both data sets (Figure 4.6 and Figure 4.7), and considerably outperformed the *a priori* and geographic classifications. Geomorphic models attained consistently high classification strengths for both data sets, but were particularly high when applied to the OR-EMAP data. Models based on other metrics, including hydrogeomorphic and all-metric models, did not provide stronger classifications, although several models (2- and 6-cluster) were equivalent.

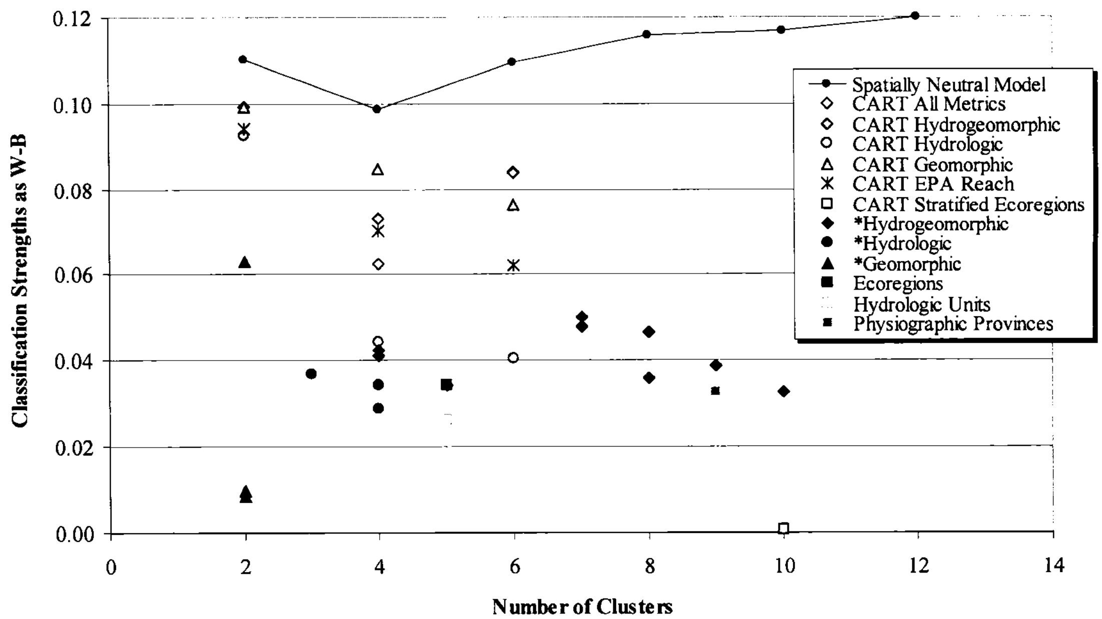

Figure 4.6. OR-EMAP classification strengths using complete metric set (* in figure legend denotes *a priori*-derived classes (from Chapter 3)).

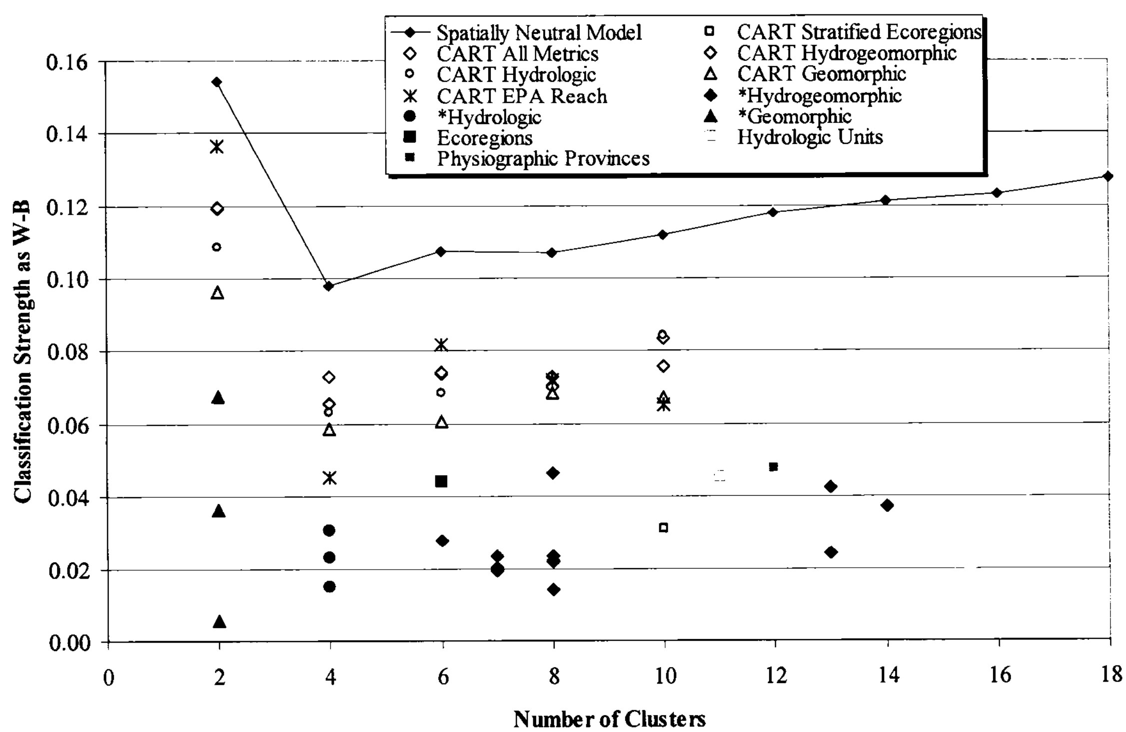

Figure 4.7. W-EMAP classification strengths using complete metric set (* in figure legend denotes *a priori*-derived classes (from Chapter 3)).

The W-EMAP models tended toward a slightly different pattern. Here, the geomorphic models often resulted in the lowest classification strengths, followed by hydrologic models. PHab models were inconsistent, sometimes being the weakest *a posteriori* classification strength (4-cluster) and sometimes the strongest (2- and 6-cluster). Hydrogeomorphic models consistently resulted in high classification strengths, as did all-metric models.

The stratified-ecoregion classification was comprised of three CTs (Appendix F) for OR-EMAP data. CART did not grow ten-fold validated CTs for the Klamath (n = 9) and Eastern Cascades and Foothills (n = 4) ecoregions because of the small sample sizes. No stratification was done within these ecoregions, leaving the OR-EMAP stratified-ecoregion classification with eight classes. The W-EMAP stratified-ecoregion classification had 11 classes for six ecoregions as no tree could be grown for the Northern Rockies ecoregion (n = 4). The resulting classification was comprised of five CTs (Appendix G) and had 23 misclassified sites and four sites which were not stratified. Classification strengths with these models were low, especially the OR-EMAP model, which differed little from a randomly generated classification. The W-EMAP model was stronger, performing similar to many *a priori* models. However, the CS was lower than other *a posteriori* models and was lower than ecoregion and other geographic classifications.

4.4 DISCUSSION AND CONCLUSIONS

Classification trees based on GIS-derived hydrologic and geomorphic characteristics appear to be an attractive, physically-based technique for developing *a* *posteriori* stream habitat classifications of insect assemblages in heterogeneous mountain landscapes. Furthermore, classification trees are straightforward to interpret and are readily transferred into a GIS for mapping expected stream habitat types and associated biotic assemblages. Many of the geospatial data used in deriving these classifications are readily available online, at no cost (e.g., http://seamless.usgs.gov/). Together, these attributes satisfy the important requirements of a sound classification tool for biomonitoring and assessments (Barbour et al. 1999, Wasson et al. 2002).

Although many studies emphasize hierarchical, multi-scale processes and boundary conditions in relation to stream ecological processes, previous research has generally relied on relatively coarse surrogates for watershed hydrology and valley morphology (but see Olden et al. 2006). The explanatory power of metrics is commensurate with the fidelity of those metrics to actual physical processes. Similarly, the explanatory power of a particular spatial scale (e.g., valley segments) depends on how completely and accurately the relevant characteristics occurring at that scale are described with surrogate variables. Thus, a lack of emphasis on describing valley scale influences in previous studies may have led to spurious conclusions regarding the explanatory power of metrics characterizing spatial scales intermediate to watersheds and reaches. This study provides an innovative suite of GIS-based physical metrics that are arguably more representative of watershed- and valley-scale characteristics that control habitat structure and dynamics.

Several geographic, *a posteriori* CART, and stratified-ecoregion classifications were developed. The following sections compare and contrast these approaches and physically interpret the resulting models.

4.4.1 Geographic classifications

Classification strengths of the geographic classifications examined in this study averaged 34% of "optimal" (spatially-neutral) classifications, with a maximum of 41%. Similarly, ecoregion classifications were 31% of maximum using OR-EMAP data and 41% using W-EMAP data. Previous studies classifying stream habitats for benthic macroinvertebrates found comparable classifications strengths. The River Environment Classification (Snelder et al. 2004) achieved 55% in New Zealand, outperforming ecoregions (45%) and a proximity-based classification (47%). Ecoregions were 47% of optimal classifications in a Swedish study (Sandin and Johnson 2000) and 67% in a Wyoming study (Gerritsen et al. 2000). In a study of biomonitoring sites in the western US, Hawkins and Vinson (2000) found that ecoregions and hydrologic units attained 49% and 60%, respectively. A study in the Mid-Atlantic attained 15% for ecoregions, whereas slope and stream order attained 37% and 47%, respectively (Waite et al. 2000). Stratified-ecoregion classifications were examined to determine whether appreciably stronger classifications could be developed by partitioning stream habitats within ecoregions, thus characterizing patchiness in stream habitat types within ecoregions. Ten stratified-ecoregion classifications were developed in Chapter 3, all of which, not surprisingly, resulted in higher classification strengths than ecoregions alone. However, the stratifications were created by selecting a single metric for stratification within each ecoregion. Based on the findings of Holburn et al. (*In preparation*), this may be a gross oversimplification as dominant stream community influences likely vary substantially among ecoregions. Accordingly, unique classification trees were developed within each ecoregion. The individual within-ecoregion CTs were then combined into one classification by forcing ecoregion as the initial level in deciding class membership, followed by applying the appropriate CT for that ecoregion. The resulting CS from this classification was unexpectedly low, as it was lower than ecoregions. This was largely a result of small within-ecoregion sample sizes relative to what is typically required for CART analysis, which led to a final classification with a high misclassification rate. A 2-cluster solution was predicted within each ecoregion, but the average class sample size was only 12 for W-EMAP data and 8 for OR-EMAP (actual sample sizes were 4 to 58 per ecoregion), making the growth of robust, ten-fold validated trees nearly impossible. A much larger within-ecoregion sample size would remedy this problem; however, the success of other classifications presented here, for partitioning biological variation in stream insect assemblages, may suggest this is a moot point.

4.4.2 Limited-metric physical classifications

Physical classifications developed using biological data and the limited set of metrics from Chapter 3 were used to provide some understanding of the benefits of using classifications calibrated with biological data (*a posteriori*) versus *a priori* classifications. It is important to understand how statistically-optimized partitions differ from partitions based on judgment and prior knowledge and whether more classification potential exists within the limited metrics set than was achieved with *a priori* classifications; i.e., could *a priori* classifications using those same metrics have led to much stronger classifications through selection of class thresholds with greater relevance to stream insect assemblages? Interestingly, although the limited-metric *a posteriori* classifications were calibrated with biological data, the resulting classifications strengths were quite similar to *a priori* results.

Many of the classification-tree metric splits were similar to those used in the *a priori* study. Valley-scale geomorphic classifications were similar in classification strengths and were still among the stronger classifications. Classification trees based on channel substrate metrics were consistently weak classifications, implying that there is little relationship between those metrics and presence- or absence-based stream insect assemblages at the scales studied. *A posteriori* hydrogeomorphic classifications, with simple categorized flow types, inconsistently predicted various numbers of taxa clusters of stream insect assemblages. This suggests that although there is some relationship between the stream insect assemblages and the flow types used, specific flow regime characteristics (e.g., base flow and duration) could provide more explanatory power. The complexity of *a posteriori* classification trees further suggests that *a priori* classifications are typically too simple to explain more than 40 to 50% of the biological variation across the study regions examined.

Although *a posteriori* classifications using the limited metric set were on par with the *a priori* classifications, their generally weak classification strength, relative to the "optimally" classified assemblages (7 to 62% of optimal), suggested that stronger classifications could be possible. Models developed with comprehensive sets of metrics greatly improved resulting classification strengths. Further, it was shown that stream insect assemblages are responding to many interacting factors and that relatively complex sets of physical habitat descriptors are likely needed to describe those relationships. Deriving these complex relationships based on prior knowledge has proven difficult to this point. The strengths of the *a posteriori* classifications developed in this study (up to 90%) indicate that much improvement can be made over *a priori* landscape classifications for the stream insect assemblages of the Pacific Northwest. The moderate success of both geographic and non-geographic *a priori* classifications suggests that both approaches may be reasonable for initially partitioning the landscape. However, the complex association of physical habitat attributes illustrated in the classification trees suggests that geographic classifications lead to comparisons of rather dissimilar stream types, and that achieving higher resolution requires development and iterative refinement of *a posteriori* classifications.

4.4.3 Comprehensive classifications

Geomorphic metrics provided the strongest classifications for the OR-EMAP data set, whereas hydrologic metrics provided the strongest W-EMAP classifications. This could potentially reflect the geographic extent of the data sets relative to the scale of the metrics. It is plausible that hydrologic variation, which is predominantly controlled by watershed to regional scale climatic, geologic, and vegetative characteristics, may better explain differences in biological variation across larger geographic extents than the geomorphic metrics I examined. The W-EMAP data set has a much greater spatial extent than does the OR-EMAP data set (Figure 4.2), and there are 57 more taxa present in the data.

To further explore this hypothesis, a measure of the variability (interdecile coefficient of variation) in the hydrologic and geomorphic metrics that appear in classifications trees was computed as:

$$Interdecile\_CV = \left(\left(90^{th}\ percentile - 10^{th}\ percentile \right) \Big/ median \right) \quad (4.4)$$

to compare heterogeneity between the two data sets. The geomorphic metrics across both data sets have a similar range of variability. Values for 8 of 12 metrics were within 80% of one another and all were within 48%. Hydrologic variability, however, was greater in the W-EMAP data set as 7 of 12 metrics had more variability than OR-EMAP data. There were three OR-EMAP metrics with as little as 29% of the variability of W-EMAP, whereas only one W-EMAP metric was as low as 34% of OR-EMAP variability. Furthermore, all four classes of each of the four hydrologic classifications are present in the W-EMAP set, whereas the OR-EMAP set only has three classes present for two of four classifications. This supports the expectation that there is less hydrologic variability in OR-EMAP data (Oregon) than there is in the W-EMAP data (Oregon and Washington), but a more similar degree of geomorphic variability between datasets.

Geomorphic metrics may be excellent for discriminating habitats within small regions, but such a classification may not be extendable across large regions without the inclusion of hydrologic metrics that encompass climatic and lithotopographic variability. To illustrate, Montgomery and Buffington (1997) stream types may be a powerful way to classify stream environments for biomonitoring within regions that are relatively homogeneous hydroclimatically; however, as the regional extent of the study expands, pool-riffle sequences throughout the larger area may become less comparable in terms of thermal and disturbance regimes. Similarly, large-scale (e.g., hydrology) metrics may be too gross to account for influential small-scale (e.g., valley-scale geomorphology) variation in habitats for small regions. The relatively poor performance of USEPA Phab metric CTs based solely on reach-scale field data further underscores the need for multiple-scale descriptors in large spatial extent studies.

Within the OR-EMAP study, USEPA PHab metrics performed reasonably well with relative costs of 0.45 to 0.28. The addition of ecoregions did not improve these model results. However, ecoregions improved the PHab metric model R_c by as much as 0.20 (11% improvement in correct classification rate) in the larger geographic extent W-EMAP study. Studies that do not span relatively sharp hydroclimatic gradients may produce reasonable models of expected habitats using only reach- or valley-scale metrics, whereas studies that do overlap strong hydroclimatic gradients should include watershed- or regional-scale metrics.

The hydrogeomorphic classifications presented here had, on average, classification strengths of 74% of the "optimal" (spatially-neutral) classifications derived from cluster analysis. The maximum percentage achieved was 90%, substantially higher than previous classifications. Combining both hydrologic and geomorphic metrics to grow CTs improved classification strengths in 5 of 8 models as compared to trees with either hydrologic or geomorphic metrics. Surprisingly, CTs grown using only geomorphic or hydrologic metrics attained classification strengths that were within more than 90% of the hydrogeomorphic classification trees. It was expected that hydrogeomorphic trees would have substantially and consistently outperformed trees based on either hydrologic or geomorphic metrics alone. The small difference in classification strengths may be attributable to correlations among geomorphic and hydrologic descriptors. Indeed, the flow of water erodes, transports, and deposits sediment, wood, and other debris, forming many of the geomorphic features found in rivers. This includes floodplains (e.g., Nanson and Croke 1992) and stream-bed topography (Montgomery and Buffington 1997). Moreover, comparable or inferior classification strengths in some instances may simply result from the lack of a "best" tree search in CART or the absence of a metric to describe an important hydrogeomorphic process or boundary condition.

Metrics that commonly emerge as first splits in CTs included measures of channel slope, peak discharge, watershed area, minimum elevation, and valley form. The general downstream trend of several of these metrics may initially suggest that stream insect assemblages are conforming to the river continuum concept (Vannote et al. 1980). However, placed in the context of the data, this is obviously not the case. The biomonitoring sites presented here are randomly selected and are very rarely distributed longitudinally along streams. To further study this point, watershed area was used a surrogate for downstream distance. Correlation analyses indicated low to moderate correlations linking these metrics to drainage area (Appendices H and I for OR-EMAP and W-EMAP Pearson (r) correlations, respectively). Strong climatic variation within the study region explains, in part, the low discharge-watershed area correlation. Further, the geographically independent classifications developed in this study suggest that relatively homogeneous stream habitats occur in discontinuous valley contexts that form mosaics across the landscape, as noted by others (Pringle et al. 1988, Townsend 1989, Poole 2002, Benda et al. 2004).

The addition of USEPA field-measured physical habitat metrics produced interesting results. Overall classifications strengths increased in only 2 out of 8 models, suggesting that the GIS-based hydrologic and geomorphic metrics were rather thorough in describing instream physical habitat in the study region. The PHab metrics used in the two improved models included measures of canopy cover, LWD, and wetted (low flow) channel width to depth ratio. Although these metrics only improved two models, future research could benefit from developing such metrics in a GIS with Light Detection and Ranging (LiDAR) or other high-resolution data. Canopy cover could be estimated by identifying riparian vegetation type and seral stage, whereas LWD estimates could be obtained using techniques similar to Buckley et al. (2000) or Lunetta et al. (1997). Low-flow channel width-depth ratio could be estimated using regionally-calibrated hydraulic geometry equations.

4.4.4 Synthesis

Classification trees validated several *a priori* classification results, including the importance of intermediate-scale valley metrics (i.e., MentCC) and hydrologic character (especially low flows), for discerning relatively homogeneous stream habitats. Further, CTs confirmed that median channel substrate and percent sand and fines calculated using reach pebble counts ($n \approx 100$) have unexpectedly low association with stream insect assemblages in minimally-disturbed mountain streams of the Pacific Northwest.

Previous studies using multi-scale metrics to make predictions at a site along a stream network have emphasized a simple set of easily calculated metrics. Some common metrics used include: watershed area, average annual precipitation, slope, stream order, and regions such as ecoregion and hydrologic units. This study illustrates the substantial improvements gained through the use of GIS to develop more detailed, physically-based metrics which better describe hydrogeomorphic processes and boundary conditions at watershed- and valley-scales. Not only does this improve physical understanding and the predictive accuracy of models, but it also provides a platform for mapping stream habitat classifications.

Geographically-dependent classifications were clearly inferior to *a posteriori*-derived physical classifications, which included models based on hydrologic, geomorphic, and physical habitat (field-measured) metrics. This may be attributable to several factors. First, the use of an *a posteriori* classification technique, which uniquely adjusts the model to the target variable (stream insect assemblages), will almost always outperform, or at least perform equivalent to, the *a priori* technique of placing thresholds using judgment and prior knowledge. Second, the metrics used here are more directly associated with instream habitat. An individual ecoregion, for instance, may be relatively homogeneous with respect to climate, geology, and topography, all of which are known to influence hydrologic regimes. However, this study goes a step further and directly applies expected hydrologic regime characteristics such as base flows and fall rates. Finally, stream biotic assemblages are known to occur in patches across the landscape (Poole 2002, Chapter 3), which cannot be taken into account given the scale of ecoregion classifications.

Existing hydrologic and geomorphic classifications, although not explicitly tested with the exception of Montgomery and Buffington (1997), may partition homogeneous insect assemblages given the high classification strengths of valley and hydrologic metrics presented here. Several geomorphic classifications provide a measure of valley context including Whiting and Bradley (1993), Rosgen (1994, 1996), and Montgomery (1999). The Rosgen (1994, 1996) classifications showed association with stream macroinvertebrates in Pennsylvania, although a much simplified version with fewer classes performed best (McGarrell 1998). The hydrologic classification of Poff and Ward (1989) may also partition stream insect assemblages, but, in this study *a posteriori* classifications partitioned biological variability better than statistically generated flow regime classifications.

Classification trees demonstrated important associations between physical habitat and biological assemblages. The CTs were grown using ten-fold validation to provide a level of confidence and prevent overly optimistic and over-fit models. Although the CTs are often relatively simple to interpret, they do not clearly identify metrics of primary importance (main effects) across the study region. An approach that combines the methods used here with multivariate ordination techniques (e.g., detrended correspondence analysis (Hill and Gauch 1980) or nonmetric multidimensional scaling (Kruskal 1964)), although not yet available for use with categorical data, would be a powerful research tool. CART delineates potential thresholds and can represent complex interactions between predictors and dependent variables. The data become segregated, however, making it difficult to determine underlying patterns as lower level nodes partition a subset of the data.

Changes in stream habitat and processes directly constrain biological communities (Allan 2004). Understanding whether important thresholds for physical habitat change exist, and if so what they are, could maximize stream resources for human and economic needs, while also protecting ecosystem function. CART provides clear thresholds in metrics (physical stream attributes) that are correlated with target variables (insect assemblages in this study), and once crossed, alter the probable biological endpoint. Using such a model with detailed hydrologic and geomorphic metrics allows prediction of shifts in insect assemblages with changes in physical habitat. Although the resulting trees represent associations, not actual cause and effect relationships between stream insects and habitats, they do allow us, within reason, to begin placing potential habitat changes into a biological context. CART models may improve efforts to detect habitat degradation by providing a template against which to compare habitat quality.

These models may also be applicable to stream restoration projects where they could be used as a design tool for emphasis on watershed-scale processes as opposed to the simple application of local project objectives. Classification tree models could be implemented in a GIS to map expected habitat types and biological assemblages to attain realistic expectations of stream form and biological potential. Furthermore, based on the metrics and thresholds in the CTs, it may be possible to determine physical contexts that cannot be controlled (e.g., valley form or certain human-modified flow metrics) and those that can and must be altered (e.g., minimum base flows) to restore stream habitat, processes, and target biotic assemblages. Such an approach would ensure that appropriate, multi-scale hydrologic and geomorphic characteristics are the focus of restoration plans designed to return natural ecological function (Palmer et al. 1997, Booth 2005, Wohl et al. 2005).

The use of a rigorous set of hydrologic and geomorphic metrics in CART to optimize classifications of stream habitats has developed classifications with much more explanatory power than previously achieved by geographic and non-geographic *a priori* classifications. However, classification trees based on geomorphic metrics alone produced classification strengths that explained a considerable part of the variation in stream insect assemblages. Geomorphic metrics are also simpler to calculate than estimates of hydrologic character which, as calculated here, require several geomorphic, geologic, and climate descriptors to satisfy predictive equations (Sanborn and Bledsoe 2006). Geomorphic metrics, however, only require one layer of geospatial data (DEMs), making them relatively straightforward to apply relative to the other classifications. The additional influence of hydrology, canopy cover, and LWD may be easier to use in the field to further refine expected stream habitats. Integrating knowledge of key physical habitat characteristics influencing biological contexts may still be an integral part of searches for streams with comparable habitats (Karr 1987, Karr and Chu 1999, Barbour et al. 1999). As we gain a greater understanding of the physical influences of instream biological communities, the techniques used to determine biological sampling sites will undoubtedly be refined. The sites used in this study, for instance, were chosen using a random sampling design. Hawkins et al. (2000), however, suggest that such sampling designs may overlook rare habitat types. Mapping successful habitat classifications, such as those presented here, could verify and help identify potentially rare habitat types. Further selection of biological sampling sites could then be done using a stratified random sampling design to develop data sets with distributions that better represent regional environmental variability. This type of ongoing refinement and updating will continue to be necessary because the relationships between stream biota and physical habitats are multifaceted and complex.

4.5 LITERATURE CITED

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CHAPTER 5

SUMMARY

Project objectives designated at the onset of this study were met, including the development of an extensive set of multi-scale metrics describing physical processes and boundary conditions at biomonitoring sites in the Pacific Northwest mountains. These were combined to generate novel *a priori* and *a posteriori* hydrogeomorphic classifications of stream environments for explaining variation in stream insect assemblages. These classifications partitioned stream insect assemblages better than existing geographic classifications, while providing a foundation for understanding important stream habitat characteristics that influence stream insect assemblages.

Several *a priori* classifications outperformed ecoregions, including two hydrologic and two geomorphic classifications which had fewer classes than ecoregions, and nine of 18 hydrogeomorphic models, five of which had fewer classes than ecoregions. All ten *a priori* stratified-ecoregion classifications outperformed ecoregions. The relatively high classification strengths and the ease of deriving stratified-ecoregions makes them attractive classifications for determining reference sites *a priori*. The predictive power of CART classifications developed in this study suggests that combining geospatially-derived metrics with classification tree modeling provides a more physically-based yet straightforward and interpretable means of classifying and mapping key physical influences on benthic community structure. *A posteriori* models were robust, explaining as much as 90% of the biological variation indicated by spatially-neutral models, as compared to 57% for *a priori* models. The methods developed here provide a strong underpinning for USEPA and State biomonitoring efforts because they provide scientifically sound and user-friendly classifications.

The best performing *a priori* models were based on a valley-form metric (MentCC) and low-flow classification (Lo4pca). Valley form has a strong influence on stream-channel condition (Hynes 1975), including local habitat and disturbance regimes. The presence and extent of floodplains is correlated with many stream characteristics that could be directly influencing stream assemblages, including energy dissipation, slope, potential for hyporheic exchange, stream type (e.g., Montgomery and Buffington, 1997), large woody debris, and adjacent riparian communities. Low-flow conditions constrain biota by reducing habitat availability and applying strong selective forces on biota (Lytle and Poff 2004). Low flows may also be associated with increased pollutant concentrations and elevated stream temperatures.

The MentCC metric and Montgomery and Buffington (1997) stream type provided the highest classification strengths when used to stratify within ecoregions. Ecoregion stratification by stream type may prove to be a practical option for improving ecoregion classifications as:

1) it is a relatively intuitive and common stream classification that is easy to observe;
2) I developed a technique for estimating and mapping stream type with readily available DEMs;

3) it has demonstrated high classification strengths; and
4) stream types are a process-based typology that, at least intuitively, could be associated with stream insects in many mountainous regions.

Montgomery and Buffington (1997) stream types depict gravel-bed forms that alter near-bed hydraulics. Stream type is also associated with downstream trends in slope and sediment supply and transport (Montgomery and Buffington 1997). Improved models for predicting stream type may reveal that this is a key influence of stream assemblages, although it is likely that optimal geomorphic stratifications for aquatic insects versus fishes may be substantially different. The current model has a 76% correct classification rate using field-measured slopes, whereas this work used DEM-measured slopes. Although a substantial predictor of important habitat types, a large number of sites were incorrectly classified, which could be reducing classification strengths.

Classification trees developed using both hydrologic and geomorphic metrics generally outperformed and were more consistent in attaining high classifications strengths than models using either type of metric alone. Metrics describing the presence and extent of floodplains, channel slope, surrogates for stream power, and watershed area were among the most common geomorphic metrics in models, whereas common hydrologic metrics included those describing peak flows, low flows, and rate of change in flows. Classifications developed using only hydrologic or geomorphic metrics performed better than expected. Given the difficulty in extrapolating hydrologic regime metrics and the relative ease of estimating geomorphic character in a GIS, the development and application of classifications in new regions may benefit from a focus on geomorphic classifications, particularly those describing valley context.

Common first-split metrics in classification trees include channel slope, peak discharge, minimum elevation, and floodplain extent. Many of these metrics have a general downstream trend, which may initially suggest that stream insect assemblages follow downstream trends, as suggested by the river continuum concept (Vannote et al. 1980). In the context of the data presented here, however, this clearly is not the case where sites are randomly distributed across the landscape and are not distributed in a downstream progression along streams. Using watershed area as a surrogate for downstream distance, correlation analyses indicate there is low to moderate correlation between these metrics and drainage area (see Appendices H and I for OR-EMAP and W-EMAP Pearson (r) correlations, respectively). Strong variation in climate across the study region, especially the strong precipitation gradient, explains the low-discharge watershed area correlation and suggests that splits in peak flows could be partitioning hydrologic regimes. The high classification strengths of the geographically-independent classifications developed in this study suggest that stream habitats occur in discontinuous valley contexts and patches across the landscape, as suggested by others (Pringle et al. 1988, Townsend 1989, Poole 2002, Benda et al. 2004).

A posteriori classifications confirmed at least three important results of *a priori* classifications. First, they confirmed that an appropriate measure of valley form such as MentCC is a powerful and robust metric by which to partition relatively homogeneous stream habitats. Second, they confirmed the importance of hydrology as a key influence on aquatic insects, and underscored the importance of metrics describing low flows. Finally, they consistently suggested that substrate characteristics measured as D_{50} or percent sand and fines with reach-wide pebble counts ($n \approx 100$) have surprisingly little association with stream insect assemblages in minimally-disturbed mountain streams of the Pacific Northwest.

Although not directly tested, other existing hydrologic and geomorphic classifications may successfully partition stream habitats and associated insect assemblages given the success of valley and hydrologic metrics presented here. Classifications that provide a measure of valley context such as Whiting and Bradley (1993), Rosgen (1994, 1996), or Montgomery (1999) deserve further attention. McGarrell (1998) found associations between the Rosgen (1994, 1996) classifications and stream macroinvertebrates in Pennsylvania, although a slightly modified classification with fewer classes performed best. The hydrologic classification of Poff and Ward (1989) similarly deserves further study, but, the *a posteriori* classifications partitioned biological variability better in this study than did statistically-generated classes of flow regime.

The classification strengths of models developed in this study have important implications for biomonitoring relative to ecoregions, the stratification unit most commonly used in regional assessments. Ecoregions were a moderately strong and consistent classifier of stream insect assemblages, as demonstrated in other studies (Hawkins and Norris 2000). Ecoregions work well in data sets with large geographic extents (perhaps > 200,000 km^2) and relatively strong physiographic gradients. However, ecoregions provide relatively little understanding of specific relationships between stream communities and key environmental influences, especially when compared to the potential of hydrologic and geomorphic characterizations of habitats. This suggests that thoughtfully constructed *a priori* classifications, including patterns revealed in *a priori* and *a posteriori* classifications presented here, can surpass ecoregion classifications.

The hydrogeomorphic classifications developed in this study may be used to improve biomonitoring network design and reduce spurious comparisons of biomonitoring sites, while providing a scientifically defensible basis for quantifying departures from reference conditions. Randomly selected stream sites may neglect rare habitat types (Hawkins et al. 2000), and the unbalanced distribution of sites among hydrogeomorphic classes in the data sets I examined supports this idea. The results presented here suggest that an iterative process of developing *a priori* classifications, comparing to *a posteriori* classifications, and refining *a priori* models over time, may be necessary to develop representative biomonitoring networks and further understanding of complex stream habitat and biota patterns. Stratifying within influential hydrologic and geomorphic habitat characteristics may prevent missing or underrepresented habitat types.

Although the advantages of using a GIS to develop models were illustrated, the benefits of applying models to stream networks have yet to be fully realized. Mapping habitat types across entire networks would allow comparisons of spatial patterns in stream habitat versus patterns in stream biodiversity. Rare habitat types as well as disconnected habitats could be identified and viewed in a watershed context. Stream-restoration efforts, biomonitoring and bioassessments, water-quality modeling, sediment-transport modeling, and regional stratification and classification of stream habitats could all benefit from large-scale (e.g., watershed) mapping of physically-based metrics.

Classification trees showed associations between physical habitat and biological assemblages, but, they can be somewhat challenging to interpret and do not clearly identify metrics of primary importance to all sites (main effects). Combining the approach presented here with multivariate ordination techniques such as detrended correspondence analysis (Hill and Gauch 1980) or nonmetric multidimensional scaling (Kruskal 1964) would be powerful, but, such techniques are not yet available for use with categorical data. Although CART delineates thresholds that potentially represent complex interactions between predictors and dependent variables, the data become compartmentalized. Splits beyond the initial split are partitioning a subset of the data set, therefore, it can be difficult to interpret underlying patterns and reasons for the split at the sample sizes available in this study. Further, a number of classification trees of similar predictive ability can be grown that use different metrics. Because the classification trees were ten-fold validated, there is a degree of confidence that the results are not overly optimistic and that over-fitting was minimized. Classification strengths computed from taxonomic data provide further confidence in classification-tree results.

The complexity of classification trees, sometimes with twice as many terminal nodes as classes to predict, suggests that physical habitat influences on stream insect assemblages are multifaceted. This is a possible explanation for why *a priori* classifications typically result in low classification strengths relative to models "optimized" by taxa. Future *a priori* models could benefit from the inclusion of metrics (or appropriate surrogates) used in classification-tree models of this study. Refinement of models may also benefit from a forced hierarchical structure where large-scale (e.g., regional or watershed) metrics are used to constrain intermediate-scale (e.g., valley) metrics, which further constrain small-scale (reach or smaller) metrics (Snelder and Biggs 2002, Olden et al. 2006). With improved knowledge of hierarchical patterns of habitat influences on stream assemblages, models could more easily be transferred to new regions and regionally-appropriate *a priori* models could be refined.

The importance of multi-scale processes and boundary conditions to stream assemblages is widely recognized (e.g., Frissell et al. 1986, Parsons et al. 2003, 2004, Snelder et al. 2004) and clearly supported by models developed in this study. The relevance of valley-scale morphology in describing stream insect assemblages is a central finding of this work. Although valley context has long been recognized as a highly influential control on stream character (Hynes 1975), previous studies have generally shown weak correlations between valley-scale morphology and stream benthic macroinvertebrates (Maridet et al. 1998, Parsons et al. 2003, Snelder et al. 2004). Previous studies, however, examined relatively few and simple metrics describing the valley context that may not have been adequate surrogates of important processes and boundary conditions.

Scales of metrics and, therefore, their position in a hierarchy, require further study where scales of importance are allowed to "self-emerge" (Parsons et al. 2004). Scales of geomorphic variables, for instance, have been shown to coincide with patterns in stream macroinvertebrate assemblages (Parson et al. 2003). However, such scaled patterns may be more challenging to elucidate with hydrologic metrics. In this study, hydrologic metrics were considered to be watershed-scale metrics, because watershed area and mean annual precipitation over the watershed are important influences on hydrology. Often these are used as surrogates for peak flows and other hydrologic measures. Yet hydrology is site specific. For example, peak-flow estimates represent flows at a specific location in the channel network. Other studies have taken the view that hydrology is a local-scale process (e.g., Snelder and Biggs 2002). Ultimately, the results are inconclusive regarding the best scale(s) for combining hydrologic and geomorphic metrics for portioning stream insect assemblages.

Streams have inherent combinations of physical influences that result in unique character (Wohl et al. 2005). In fact, the 6th century philosopher Heraclitus noted that one cannot step into the same river twice. This would seem to suggest that stream classification is an unreasonable endeavor in that a continuum of hydrologic and geomorphic processes is artificially divided. Schumm (1963), however, succinctly states the need for stream classification:

> *"Classifications of natural phenomena are of value because they focus attention on the key factors which distinguish the individual phenomena."*

The success of stream-restoration efforts is often based on the return of ecological function and stream communities, including sensitive taxa. For this reason, process-based classifications that indicate key environmental factors, which constrain the regional species pool at monitoring sites, provide a framework for developing (and potentially transferring) restoration strategies (Wohl et al. 2005). The methodology developed as part of this study could provide a platform for the development of such classifications.

The approach presented here could be used for data stratification in fluvial engineering work. For instance, cluster-analysis-derived or *a priori* classifications of physical processes or forms (i.e., bedload transport, shear stress, width to depth ratio) could be predicted with CART using geospatial data. The resulting CTs could then be applied in a GIS to map the expected class membership of stream reaches at watershed or regional scales . This approach could be used to identify candidate analog sites for physical habitat design or to locate study reaches where important physical processes and boundary conditions are held relatively constant among reaches. Hence, this general approach could be used in a wide variety of applications requiring a typology of stream reaches based on physical and/or biological conditions of interest.

Further, this approach could prove valuable for determining habitat types that are resilient or sensitive to human alteration or natural environmental changes. Classification trees that predict important physical or biological characteristics could be developed and used to predict system trajectories associated with anticipated changes human influences or natural forcing. For example, climate change models could be used to predict changes in hydrologic metrics serving as input to CTs that directly quantify thresholds that are likely to lead to alternative physical or biological states. Therefore, this approach could be used as a vulnerability analysis given expected changes in important drivers of biological assemblages and physical boundaries and processes when the drivers that are likely to change occur within the predictive CT model. Similarly, CTs could be used to predict combinations of physical habitat characteristics including channel form, substrate, and woody debris, thereby providing threshold models of stream habitat sensitivity. CTs based on hydrogeomorphic drivers could provide a basis for stratification in research and monitoring designs to identify sensitive and resilient habitat types. Such classifications could also support land use planning, reservoir operation plans, and stream conservation strategies in the face of rapid environmental change.

The approach to stream-habitat characterization and classification presented here will continue to be of value in the future, especially as high-resolution geospatial data become more prevalent. Increased vertical and horizontal resolution DEMs, such as that provided by LiDAR, will provide a basis for increased metric accuracy, especially on small streams that have bankfull widths less than current, widely available 10-m DEMs. Local slope estimates will also benefit from higher resolution data, especially in larger stream channels where low slopes are common. Green LiDAR, with improved ability to penetrate water surfaces (Lillycrop and Banic 1992, Brock et al. 2001, 2004), could provide detailed stream bathymetry, further improving the ability to remotely sense channel form and habitat characteristics. Metrics developed in this study from relatively coarse scale data, provide a foundation for development of more robust metrics and indicate that high classification strengths may be expected from their application.

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APPENDIX A

CLUSTER ANALYSIS DENDROGRAMS

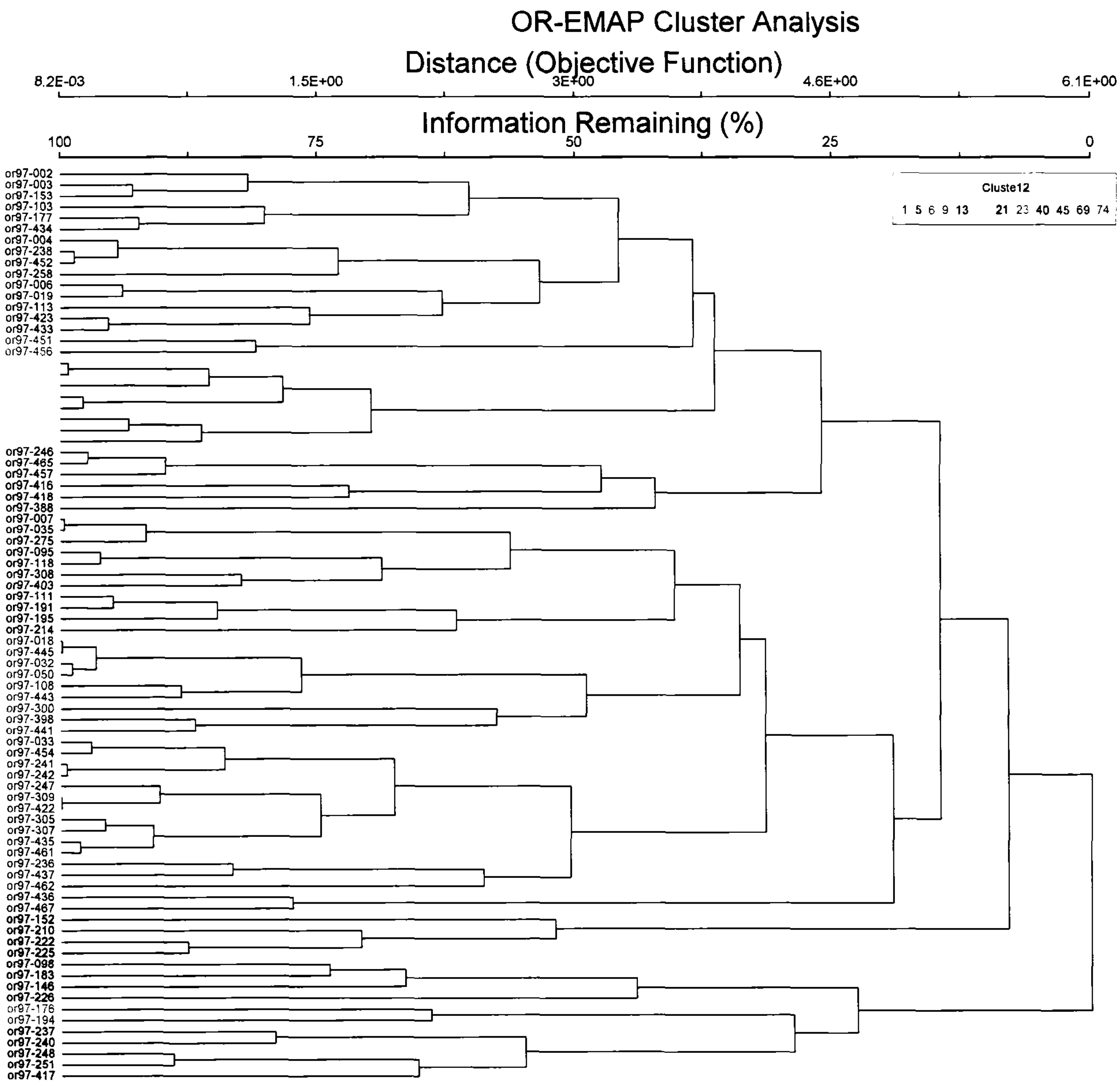


Figure E.1. OR-EMAP cluster analysis dendrogram.

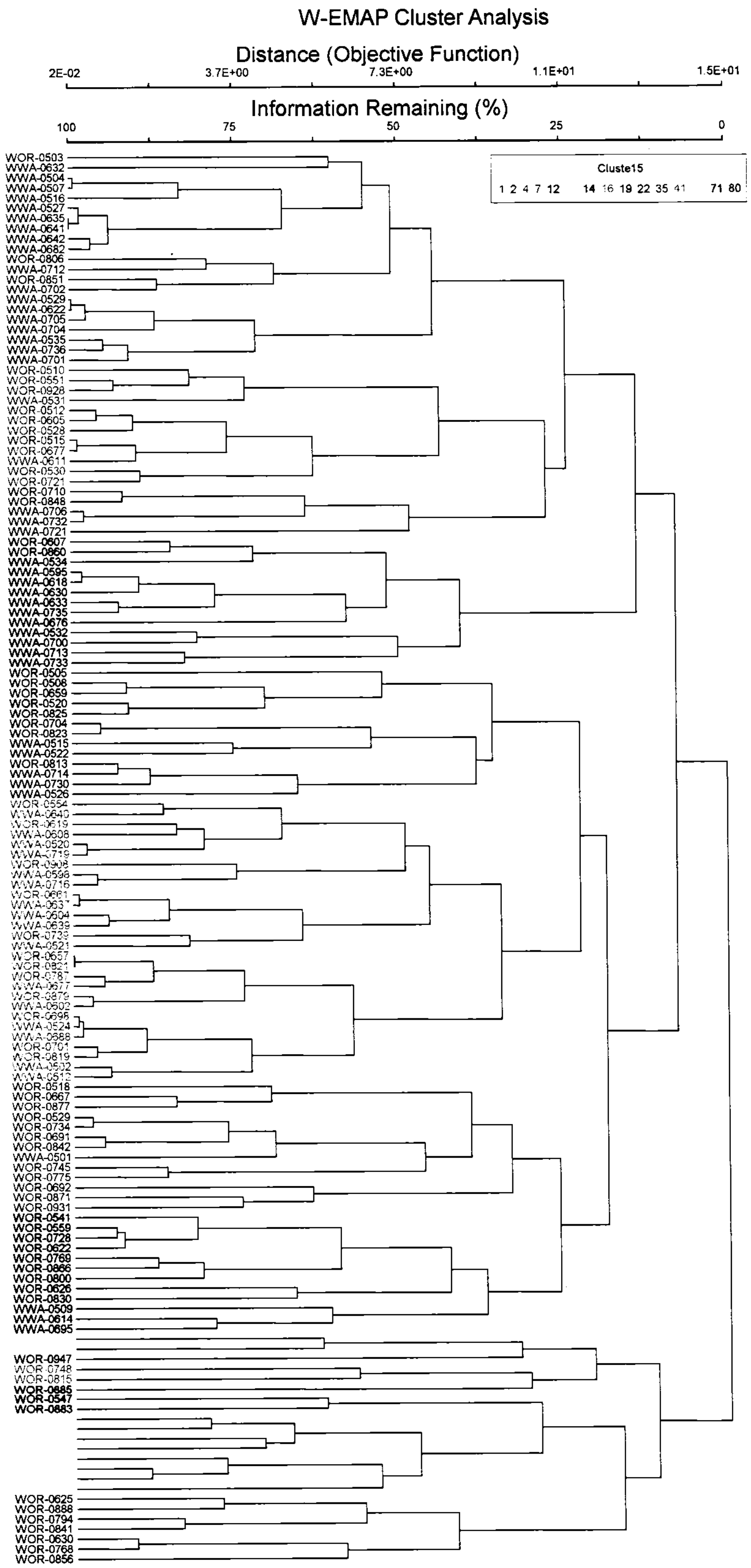


Figure E.2. W-EMAP cluster analysis dendrogram.

APPENDIX B

OR-EMAP LIMITED METRIC CLASSIFICATION TREES

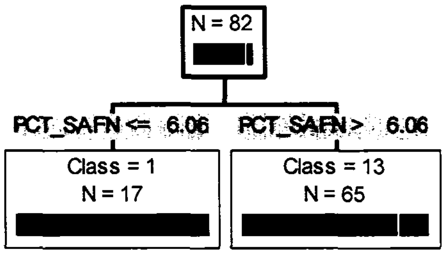
Predicted d_{50}

CART was not able to produce a classification tree.

USEPA Field-measured d_{50}

CART was not able to produce a classification tree.

pSAFN

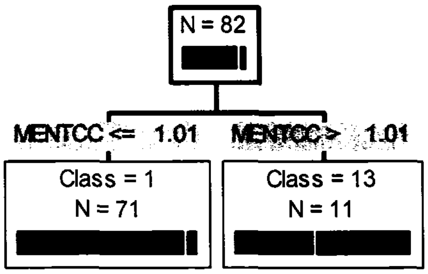


$R_c = 0.928$

MIS-CLASSIFICATION BY CLASS (Cross Validated)						
	Prior	Weight		Weight		
Class	Probability	Count	Count	Mis-classed	Mis-classed	Cost
1	0.50000	71.00	71	54.00	54	0.76056
		(71.00	71	53.00	53	0.74648)
13	0.50000	11.00	11	0.00	0	0.00000
		(11.00	11	2.00	2	0.18182)
Total	1.00000	82.00	82	54.00	54	
		(82.00	82	55.00	55)	

VARIABLE IMPORTANCE	
Metric	Relative Importance
PCT_SAFN	100.00000

MentCC

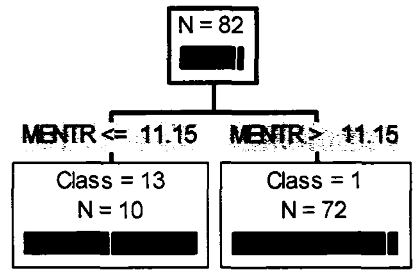


$R_c = 0.693$

MIS-CLASSIFICATION BY CLASS (Cross Validated)						
	Prior	Weight		Weight		
Class	Probability	Count	Count	Mis-classed	Mis-classed	Cost
1	0.50000	71.00	71	5.00	5	0.07042
		(71.00	71	4.00	4	0.05634)
13	0.50000	11.00	11	5.00	5	0.45455
		(11.00	11	7.00	7	0.63636)
Total	1.00000	82.00	82	10.00	10	
		(82.00	82	11.00	11)	

VARIABLE IMPORTANCE	
Metric	Relative Importance
MENTCC	100.00000

MentDR



$R_c = 0.812$

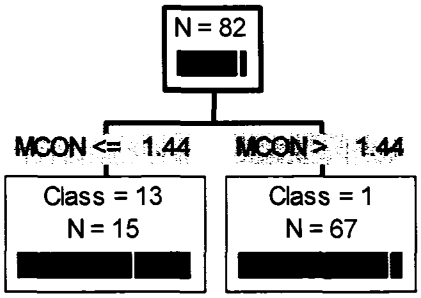
MIS-CLASSIFICATION BY CLASS
(Cross Validated)

Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.50000	71.00	71	5.00	5	0.07042
		(71.00	71	6.00	6	0.08451)
13	0.50000	11.00	11	6.00	6	0.54545
		(11.00	11	8.00	8	0.72727)
Total	1.00000	82.00	82	11.00	11	
		(82.00	82	14.00	14)	

VARIABLE IMPORTANCE

Metric	Relative Importance
MENTR	99.99999

Hillconn

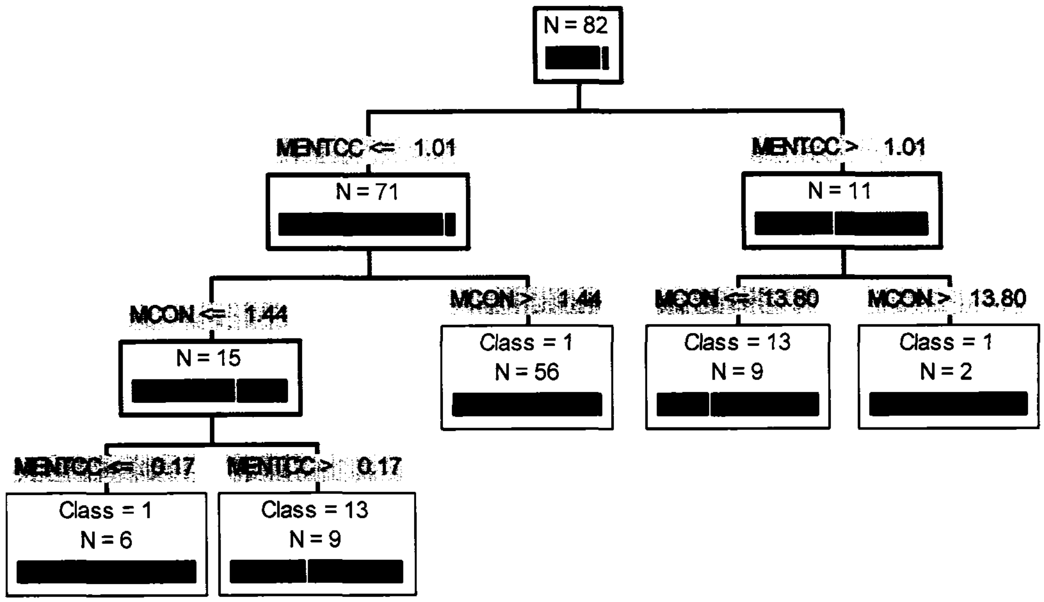


$R_c = 0.883$

MIS-CLASSIFICATION BY CLASS (Cross Validated)						
Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.50000	71.00	71	10.00	10	0.14085
		(71.00	71	11.00	11	0.15493)
13	0.50000	11.00	11	6.00	6	0.54545
		(11.00	11	8.00	8	0.72727)
Total	1.00000	82.00	82	16.00	16	
		(82.00	82	19.00	19)	

VARIABLE IMPORTANCE	
Metric	Relative Importance
MCON	100.00000

Limited Predictor 2-cluster



$R_c = 0.428$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	71	7	9.86	0.1	
13	11	0	0	0	
	82	7			91.5

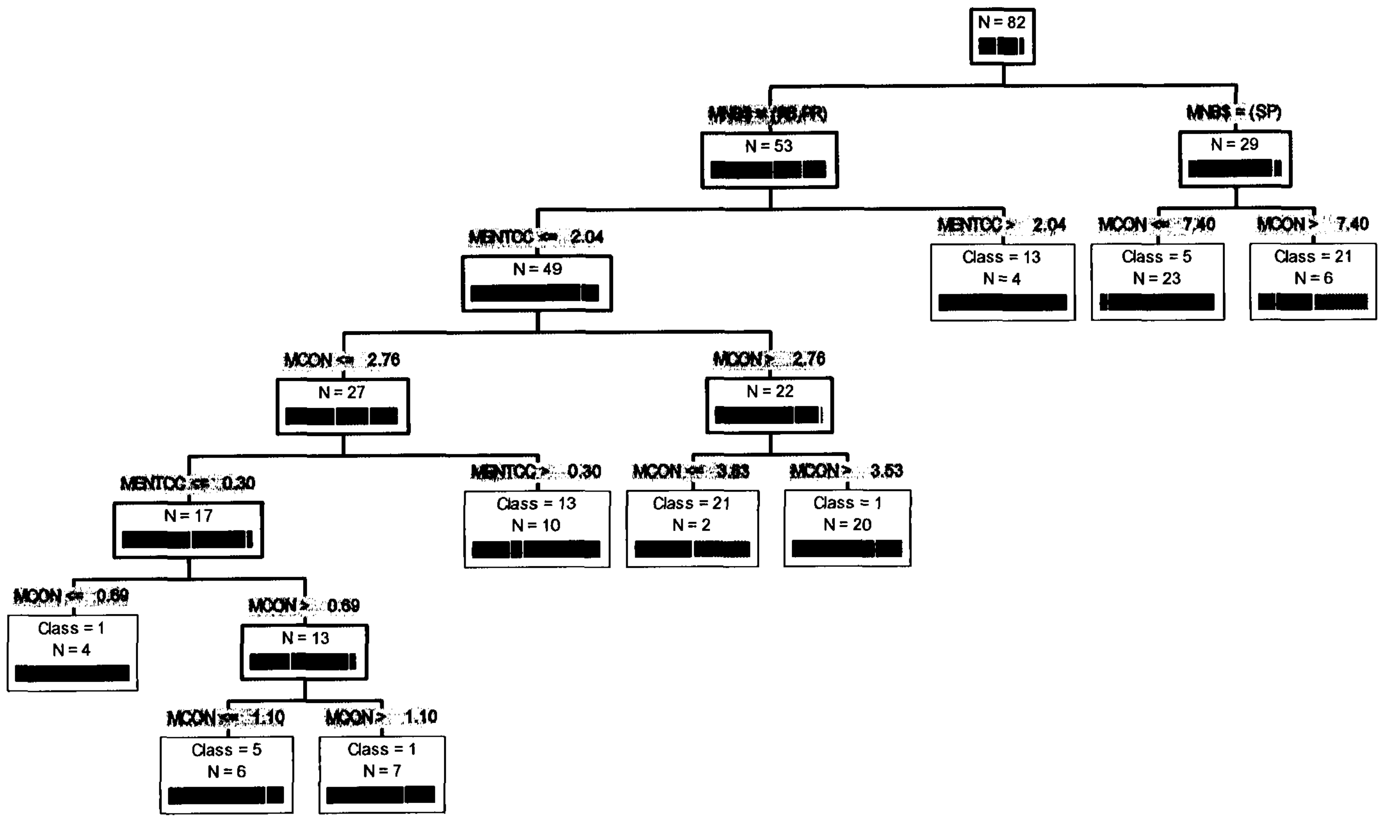
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	71	11	15.49	0.15	
13	11	3	27.27	0.27	
	82	14			82.9

VARIABLE IMPORTANCE

MCON	100
MENTCC	71.3
LO4PCA	39
ALL4PCA	34.83
HI4PCA	14.23

Limited Predictor 4-cluster

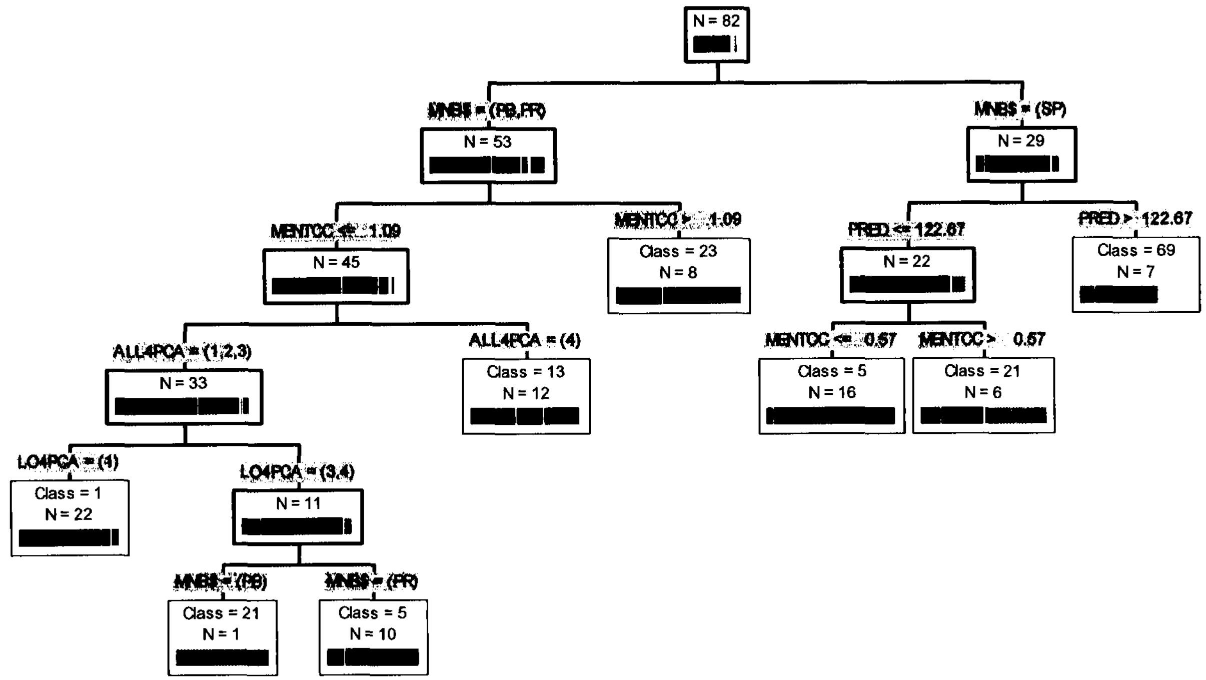


$R_c = 0.529$

MIS-CLASSIFICATION BY CLASS					
LEARNING SAMPLE					
Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	7	22.58	0.23	
13	11	1	9.09	0.09	
21	4	0	0	0	
5	36	10	27.78	0.28	
Total	82	18			78.0
TEST SAMPLE					
Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	16	51.61	0.52	
13	11	2	18.18	0.18	
21	4	2	50	0.5	
5	36	14	38.89	0.39	
Total	82	34			58.5

VARIABLE IMPORTANCE		
MCON	100	||||||||||||||||||||||||||||||||||||||||
MENTCC	82.82	|||||||||||||||||||||||||||||||||
MB	44.65	||||||||||||||||||

Limited Predictor 6-cluster



$R_c = 0.500$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	13	41.94	0.42	
13	4	0	0	0	
21	4	0	0	0	
23	7	2	28.57	0.29	
5	34	11	32.35	0.32	
69	2	0	0	0	
	82	26			68.3

TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	15	48.39	0.48	
13	4	0	0	0	
21	4	2	50	0.5	
23	7	3	42.86	0.43	
5	34	20	58.82	0.59	
69	2	1	50	0.5	
	82	41			50.0

VARIABLE IMPORTANCE

ALL4PCA	100	||||||||||||||||||||||||||||||||||||||||
PRED	94.8	||||||||||||||||||||||||||||||||||||||
MENTCC	86.85	||||||||||||||||||||||||||||||||||
LO4PCA	73.42	|||||||||||||||||||||||||||||
MNB$	52.27	|||||||||||||||||||||

APPENDIX C

W-EMAP LIMITED METRIC CLASSIFICATION TREES

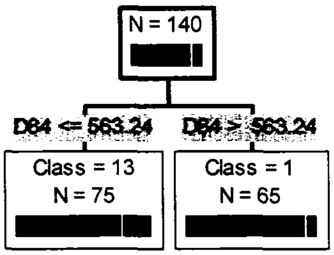
Predicted d_{50}

CART was not able to produce a classification tree.

USEPA Field-measured d_{50}

CART was not able to produce a classification tree.

USEPA Field-measured d_{84}



$R_c = 0.843$

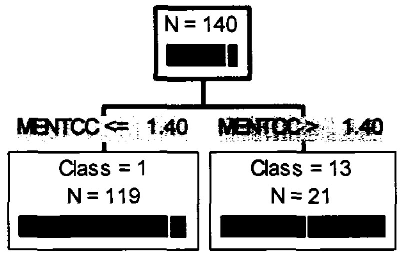
MIS-CLASSIFICATION BY CLASS (Cross Validated)						
Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.50000	117.00	117	58.00	58	0.49573
		(117.00	117	63.00	63	0.53846)
13	0.50000	23.00	23	6.00	6	0.26087
		(23.00	23	7.00	7	0.30435)
Total	1.00000	140.00	140	64.00	64	
		(140.00	140	70.00	70)	

VARIABLE IMPORTANCE	
Metric	Relative Importance
D84	100.00000

pSAFN

CART was not able to produce a classification tree.

MentCC

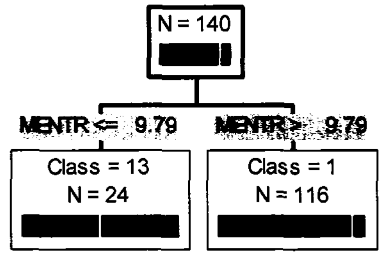


$R_c = 0.764$

MIS-CLASSIFICATION BY CLASS (Cross Validated)						
Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.50000	117.00	117	11.00	11	0.09402
		(117.00	117	8.00	8	0.06838)
13	0.50000	23.00	23	13.00	13	0.56522
		(23.00	23	16.00	16	0.69565)
Total	1.00000	140.00	140	24.00	24	
		(140.00	140	24.00	24)	

VARIABLE IMPORTANCE	
Metric	Relative Importance
MENTCC	100.00000

MentRR



$R_c = 0.633$

MIS-CLASSIFICATION BY CLASS
(Cross Validated)

Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.50000	117.00	117	12.00	12	0.10256
		(117.00	117	13.00	13	0.11111)
13	0.50000	23.00	23	11.00	11	0.47826
		(23.00	23	12.00	12	0.52174)
Total	1.00000	140.00	140	23.00	23	
		(140.00	140	25.00	25)	

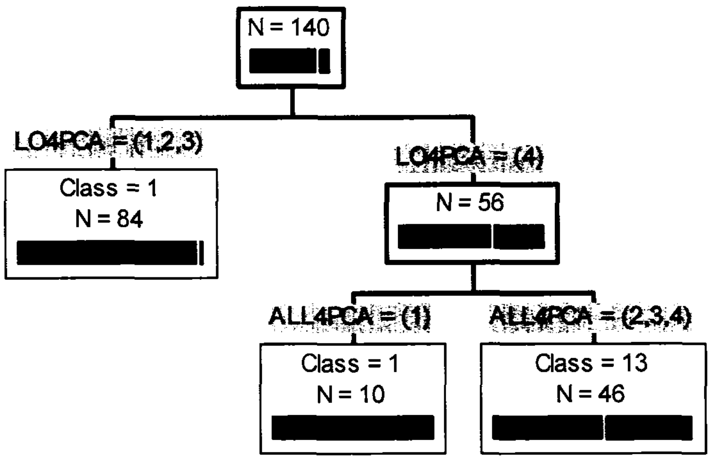
VARIABLE IMPORTANCE

Metric	Relative Importance
MENTR	100.00000

Hillconn

CART was not able to produce a classification tree.

Limited Predictor 2-cluster



$R_c = 0.353$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	117	26	22.22	0.22	
13	23	3	13.04	0.13	
	140	29			79.3

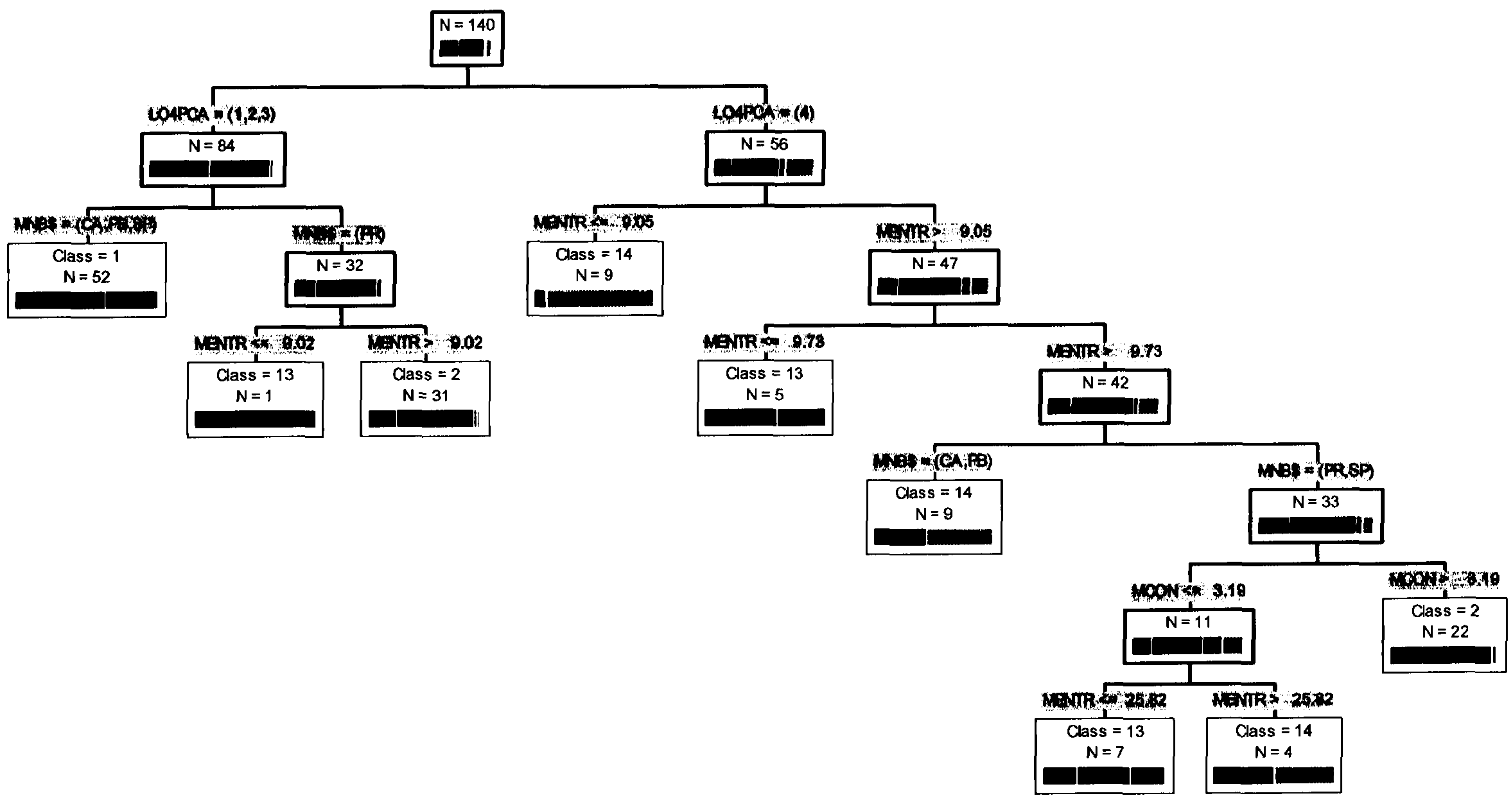
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	117	26	22.22	0.22	
13	23	3	13.04	0.13	
	82	14			79.3

VARIABLE IMPORTANCE

LO4PCA	100	||||||||||||||||||||||||||||||||||||||||
ALL4PCA	41.15	||||||||||||||||

Limited Predictor 4-cluster



$R_c = 0.646$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	51	18	35.29	0.35	
13	6	1	16.67	0.17	
14	17	2	11.76	0.12	
2	66	31	46.97	0.47	
	140	52			62.9

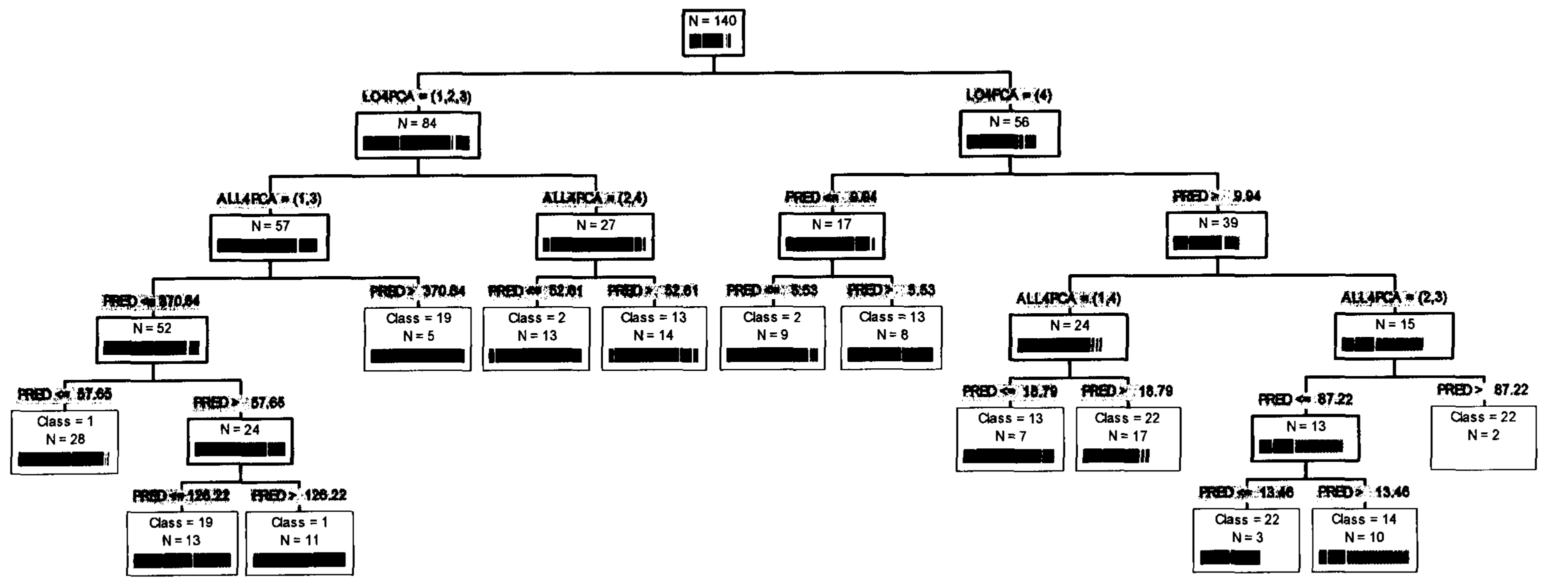
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	51	16	31.37	0.31	
13	6	3	50	0.5	
14	17	7	41.18	0.41	
2	66	47	71.21	0.71	
	140	73			47.9

VARIABLE IMPORTANCE

MENTR	100	||||||||||||||||||||||||||||||||||||||||
MCON	67.47	|||||||||||||||||||||||||||
MNB$	52.33	|||||||||||||||||||||
LO4PCA	46.94	|||||||||||||||||||

Limited Predictor 6-cluster



$R_c = 0.672$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	38	15	39.47	0.39	
13	6	0	0	0	
14	10	3	30	0.3	
19	13	3	23.08	0.23	
2	66	46	69.7	0.7	
22	7	0	0	0	
	140	67			52.1

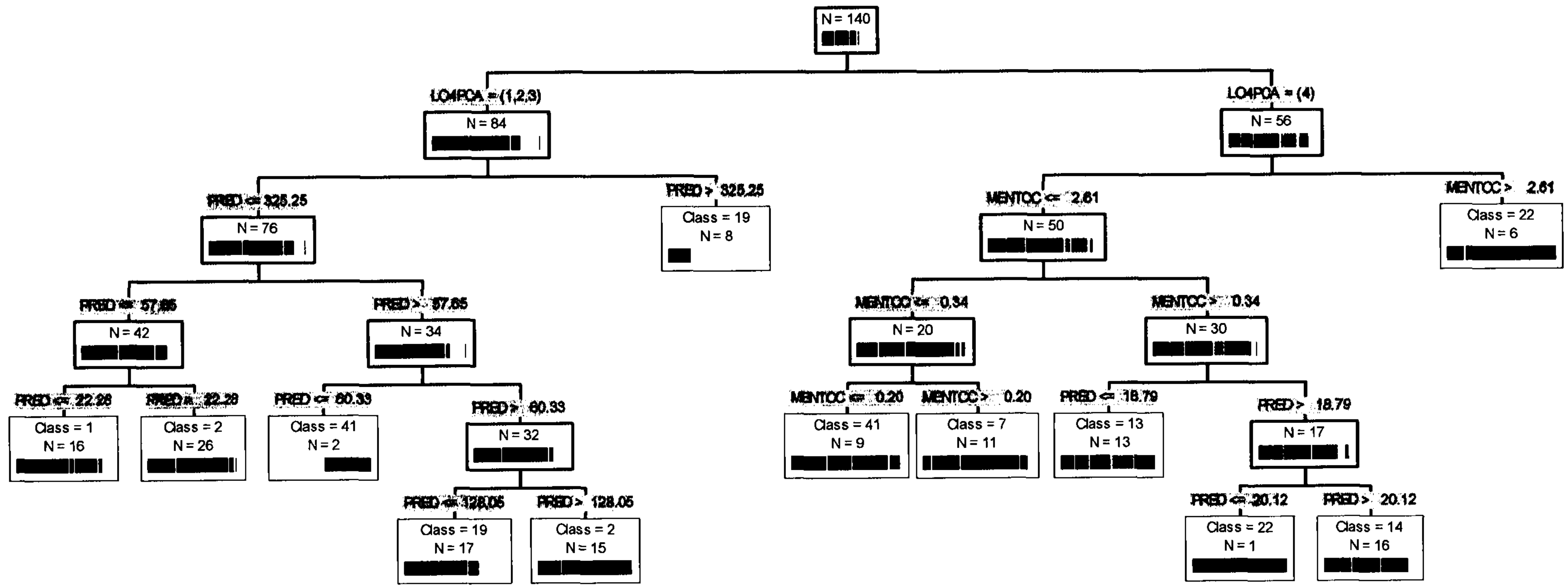
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	38	21	55.26	0.55	
13	6	4	66.67	0.67	
14	10	6	60	0.6	
19	13	5	38.46	0.38	
2	66	48	72.73	0.73	
22	7	3	42.86	0.43	
	140	87			37.9

VARIABLE IMPORTANCE

PRED	100	||||||||||||||||||||||||||||||||||||||||
ALL4PCA	31.5	||||||||||||
LO4PCA	24.12	|||||||||

Limited Predictor 8-cluster



$R_c = 0.756$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	38	29	76.32	0.76	
13	3	0	0	0	
14	10	5	50	0.5	
19	13	3	23.08	0.23	
2	41	15	36.59	0.37	
22	7	1	14.29	0.14	
41	3	1	33.33	0.33	
7	25	19	76	0.76	
	140	73			47.9

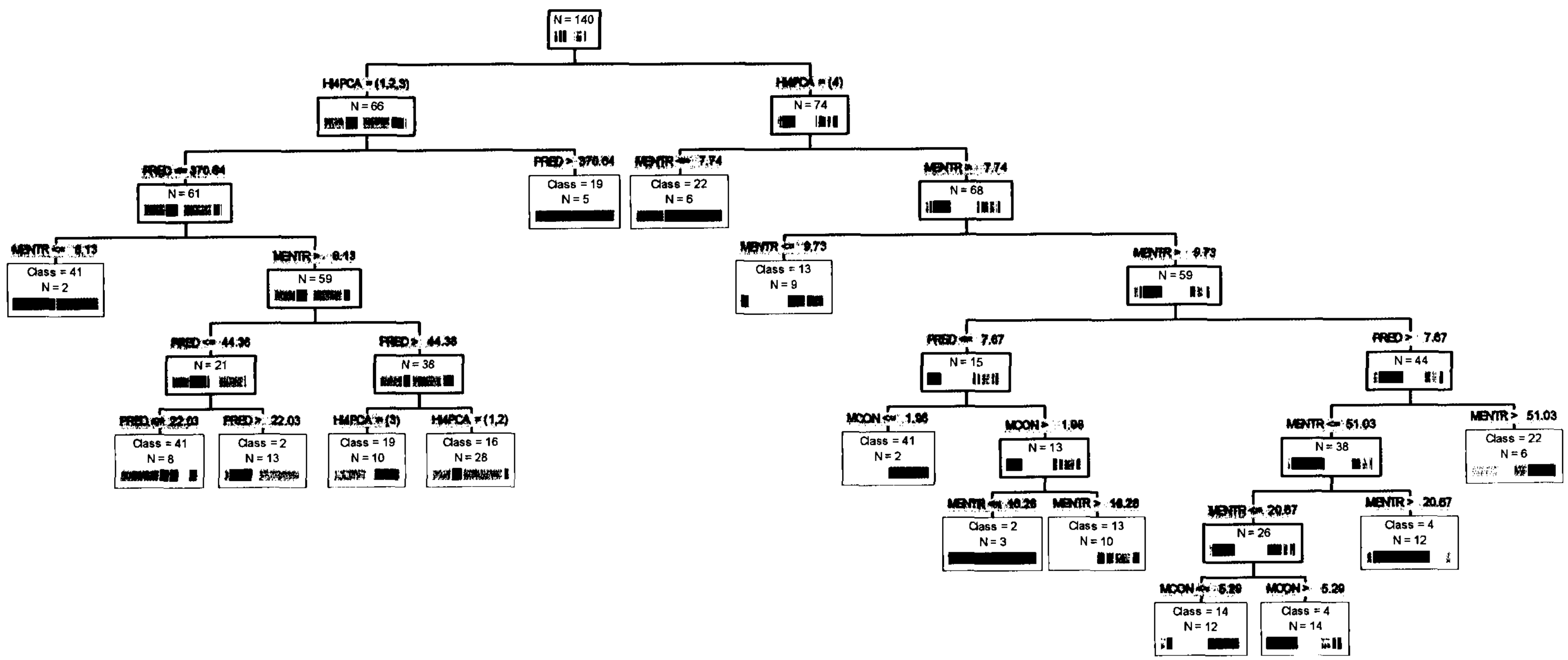
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	38	30	78.95	0.79	
13	3	2	66.67	0.67	
14	10	6	60	0.6	
19	13	9	69.23	0.69	
2	41	25	60.98	0.61	
22	7	3	42.86	0.43	
41	3	2	66.67	0.67	
7	25	21	84	0.84	
	140	98			30

VARIABLE IMPORTANCE

PRED	100
MENTCC	68.97
LO4PCA	29.13

Limited Predictor 10-cluster



$R_c = 0.788$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	21	21	100	1	
13	3	0	0	0	
14	10	5	50	0.5	
16	28	13	46.43	0.46	
19	13	4	30.77	0.31	
2	13	6	46.15	0.46	
22	7	1	14.29	0.14	
4	17	3	17.65	0.18	
41	3	0	0	0	
7	25	25	100	1	
	140	78			44.3

TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	21	14	66.67	0.67	
13	3	2	66.67	0.67	
14	10	6	60	0.6	
16	28	26	92.86	0.93	
19	13	6	46.15	0.46	
2	13	13	100	1	
22	7	4	57.14	0.57	
4	17	9	52.94	0.53	
41	3	2	66.67	0.67	
7	25	25	100	1	
	140	107			23.6

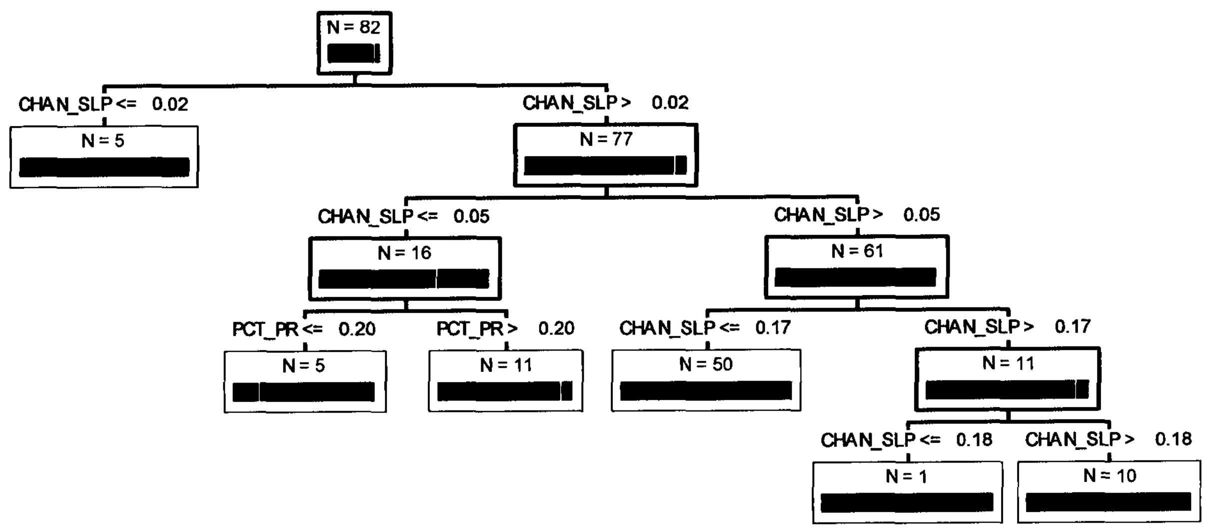
VARIABLE IMPORTANCE

PRED	100	||||||||||||||||||||||||||||||||||||||||
MENTR	89.09	|||||||||||||||||||||||||||||||||||
MCON	68.55	|||||||||||||||||||||||||||
HI4PCA	32.38	|||||||||||||
LO4PCA	24.38	||||||||||

APPENDIX D

OR-EMAP COMPREHENSIVE METRIC CLASSIFICATION TREES

Geomorphic 2-cluster



$R_c = 0.545$

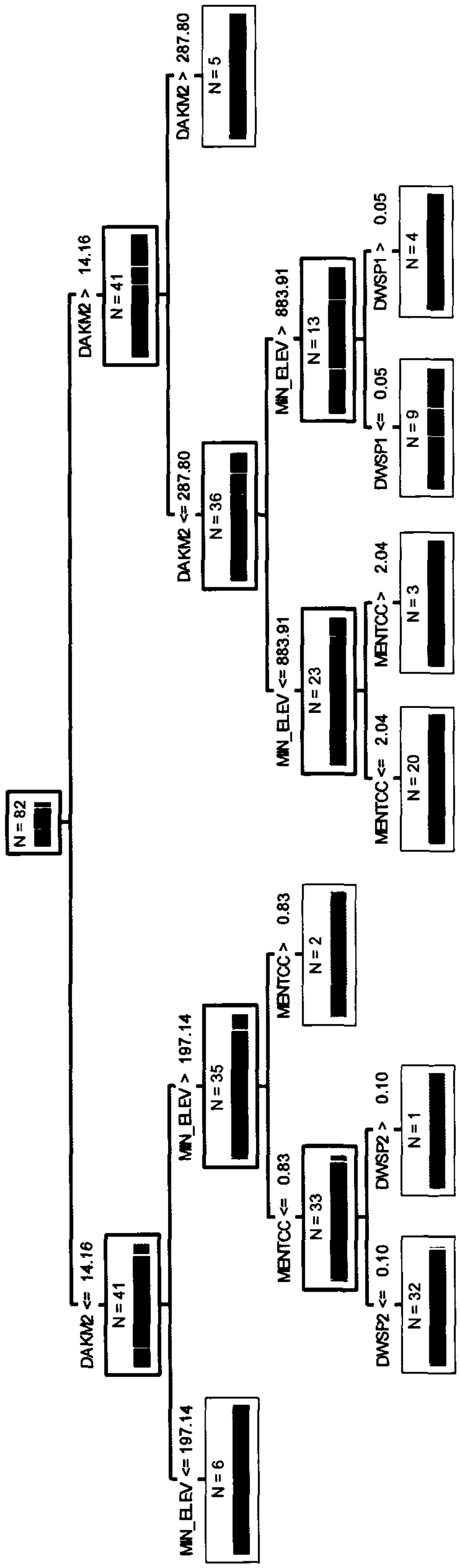
MIS-CLASSIFICATION BY CLASS					

LEARNING SAMPLE					
Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	71	1	1.41	0.01	
13	11	1	9.09	0.09	
Total	82	2	0.0243902		97.6

TEST SAMPLE					
Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	71	1	1.41	0.01	
13	11	5	45.45	0.45	
Total	82	6	0.0731707		92.7

VARIABLE IMPORTANCE		
CHAN_SLP	100	||||||||||||||||||||||||||||||||||||||||
PCT_PR	28.73	||||||||||||

Geomorphic 4-cluster



$R_c = 0.457$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	1	3.23	0.03	
13	11	3	27.27	0.27	
21	4	1	25	0.25	
5	36	2	5.56	0.06	
	82	7	0.0853659		91.5

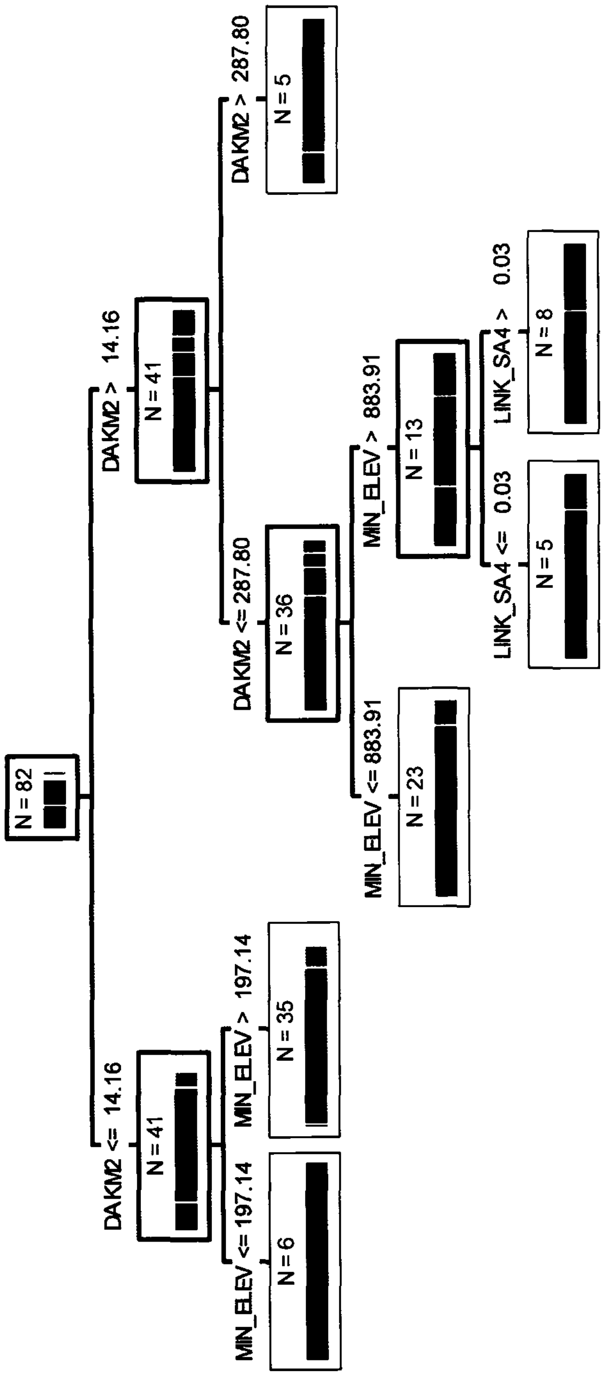
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	8	25.81	0.26	
13	11	6	54.55	0.55	
21	4	4	100	1	
5	36	3	8.33	0.08	
	82	21	0.2560976		74.4

VARIABLE IMPORTANCE

DAKM2	100
MENTCC	74.41
MIN_ELEV	68.81
SLP_ELON	43.22
MDW_SA0_4_25	27.02
DWSP1	23.86
PCT_PR	22.58
DWSP2	16.5

Geomorphic 6-cluster



$R_c = 0.458$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	1	3.23	0.03	
13	4	4	100	1	
21	4	4	100	1	
23	7	3	42.86	0.43	
5	34	1	2.94	0.03	
69	2	2	100	1	
	82	15	0.1829268		81.7

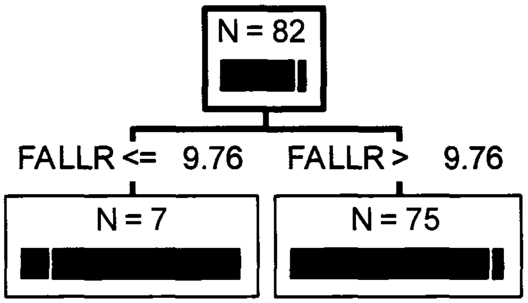
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	4	12.9	0.13	
13	4	4	100	1	
21	4	4	100	1	
23	7	4	57.14	0.57	
5	34	4	11.76	0.12	
69	2	2	100	1	
	82	22	0.2682927		73.2

VARIABLE IMPORTANCE

MIN_ELEV	100	||||||||||||||||||||||||||||||||||||||||||
DAKM2	89.95	|||||||||||||||||||||||||||||||||||||
LINK_SA4	34.01	||||||||||||||

Hydrologic 2-cluster



$R_c = 0.636$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	71	1	1.41	0.01	
13	11	5	45.45	0.45	
	82	6	0.0731707		92.7

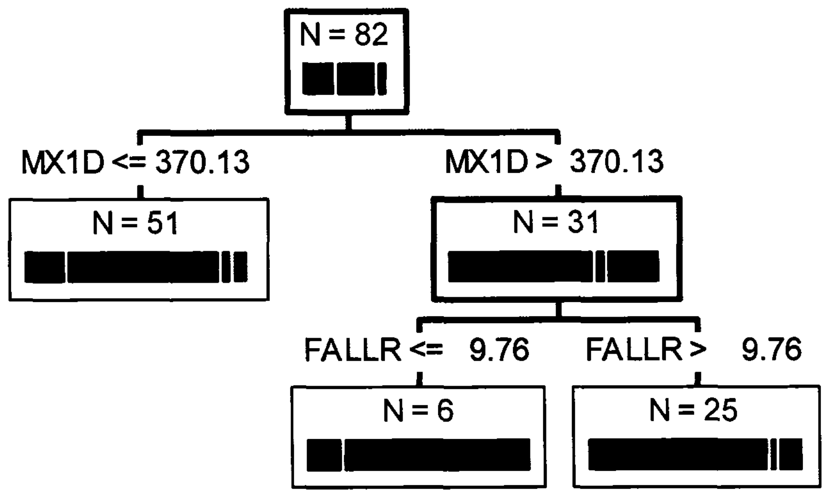
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	71	1	1.41	0.01	
13	11	6	54.55	0.55	
	82	7	0.0853659		91.5

VARIABLE IMPORTANCE

FALLR	100	||||||||||||||||||||||||||||||||||||||||
MX7D	58.35	|||||||||||||||||||||||
MN30D	53.39	|||||||||||||||||||||
MN7D	53.39	|||||||||||||||||||||
AVG_JUN	39.87	||||||||||||||||
MN3D	28.88	|||||||||||

Hydrologic 4-cluster



$R_c = 0.543$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	10	32.26	0.32	
13	11	6	54.55	0.55	
21	4	4	100	1	
5	36	2	5.56	0.06	
	82	22	0.2682927		73.2

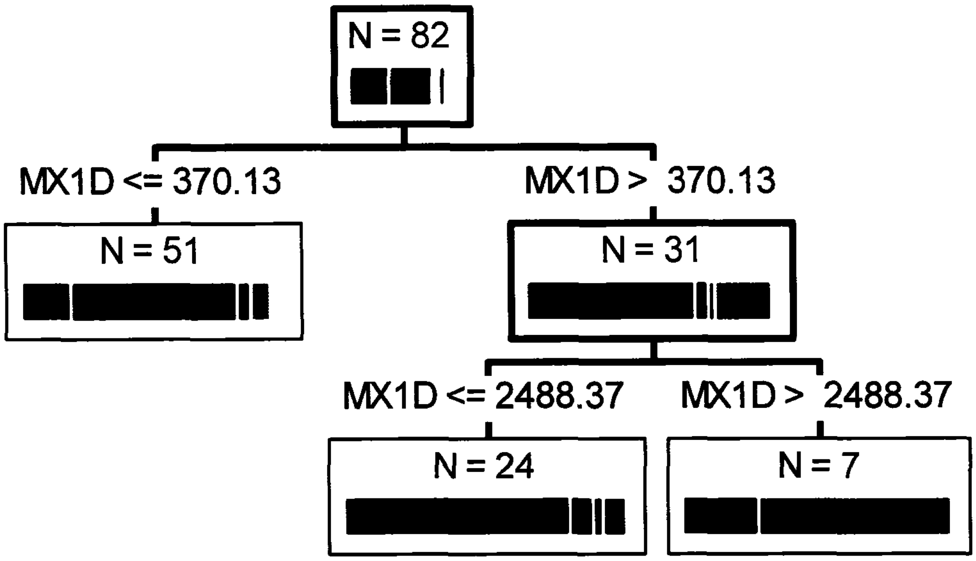
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	11	35.48	0.35	
13	11	6	54.55	0.55	
21	4	4	100	1	
5	36	4	11.11	0.11	
	82	25	0.304878		69.5

VARIABLE IMPORTANCE

MX1D	100
ML22	98.7
FALLR	71.76

Hydrologic 6-cluster



$R_c = 0.625$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	12	38.71	0.39	
13	4	4	100	1	
21	4	4	100	1	
23	7	2	28.57	0.29	
5	34	2	5.88	0.06	
69	2	2	100	1	
	82	26	0.3170732		68.3

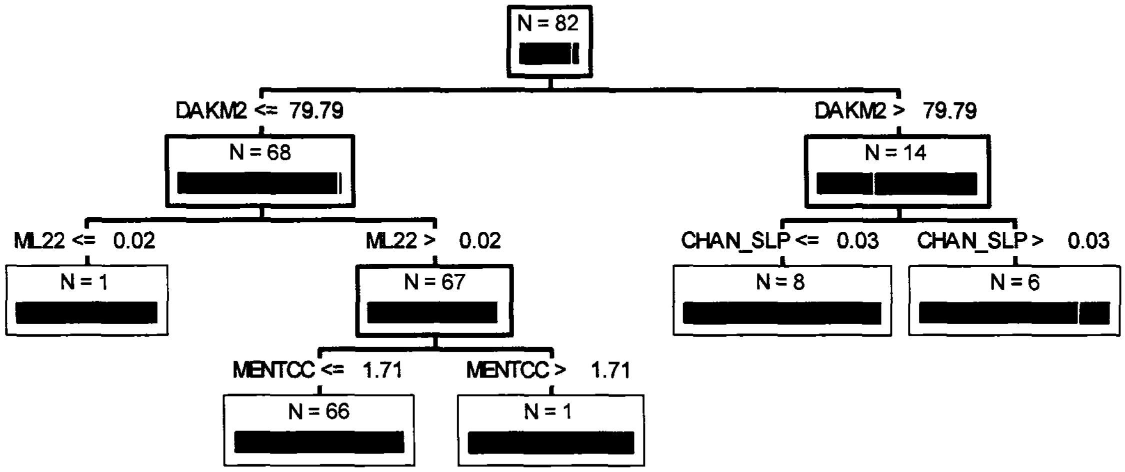
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	13	41.94	0.42	
13	4	4	100	1	
21	4	4	100	1	
23	7	3	42.86	0.43	
5	34	4	11.76	0.12	
69	2	2	100	1	
	82	30	0.3658537		63.4

VARIABLE IMPORTANCE

MX1D	100	||||||||||||||||||||||||||||||||||||||||
NHIPL	12.88	|||||

Hydrogeomorphic 2-cluster



$R_c = 0.545$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class		N Class	Mis-classed	Percent Error	Cost	% Correct
	1	71	0	0	0	
	13	11	1	9.09	0.09	
Total		82	1	0.0121951		98.8

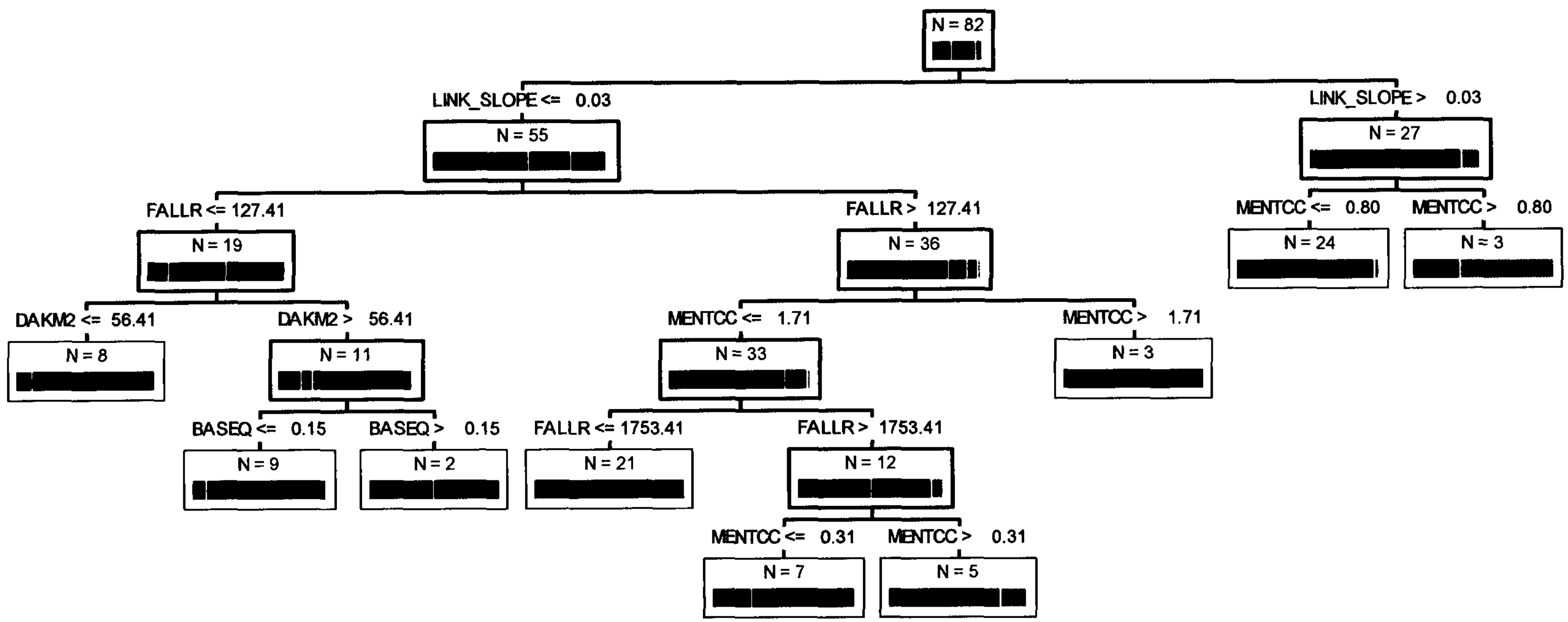
TEST SAMPLE

Class		N Class	Mis-classed	Percent Error	Cost	% Correct
	1	71	2	2.82	0.03	
	13	11	4	36.36	0.36	
Total		82	6	0.0731707		92.7

VARIABLE IMPORTANCE

CHAN_SLP	100
DAKM2	68.56
ML22	51.32
MX1D	40.42
MX7D	37.04
SLP_ELON	28.02
MDW_SA0_4_25	23.94
MN30D	23.92
MN3D	23.92
MENTR	15.78
MA3	15.57
MENTCC	15.46

Hydrogeomorphic 4-cluster



$R_c = 0.37$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	5	16.13	0.16	
13	11	0	0	0	
21	4	2	50	0.5	
5	36	1	2.78	0.03	
Total	82	8	0.097561		90.2

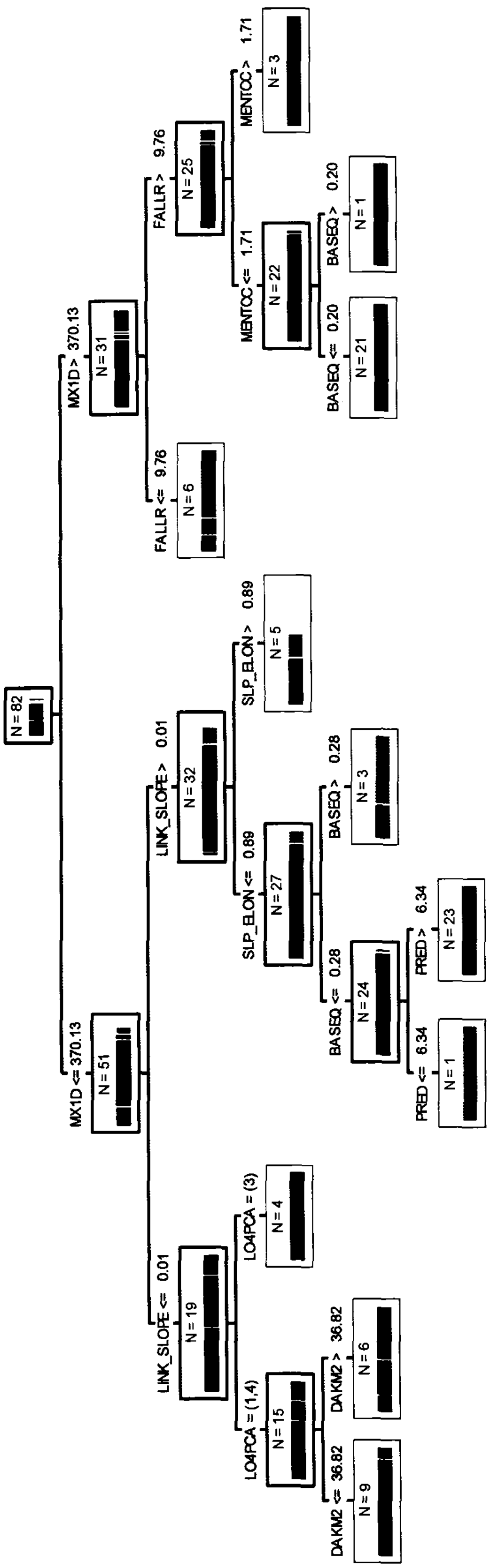
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	5	16.13	0.16	
13	11	3	27.27	0.27	
21	4	2	50	0.5	
5	36	7	19.44	0.19	
Total	82	17	0.2073171		79.3

VARIABLE IMPORTANCE

DAKM2	100	|||||||||||||||||||||||||||||||||||||||||
FALLR	78.17	||||||||||||||||||||||||||||||||
LINK_SLOPE	78.09	||||||||||||||||||||||||||||||||
MENTCC	66.92	|||||||||||||||||||||||||||
MX1D	57.46	||||||||||||||||||||||||
MENTR	42.35	|||||||||||||||||
ML22	39.04	||||||||||||||||
BASEQ	24.8	||||||||||

Hydrogeomorphic 6-cluster



$R_c = 0.521$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	2	6.45	0.06	
13	4	1	25	0.25	
21	4	1	25	0.25	
23	7	0	0	0	
5	34	6	17.65	0.18	
69	2	0	0	0	
Total	82	10	0.1219512		87.8

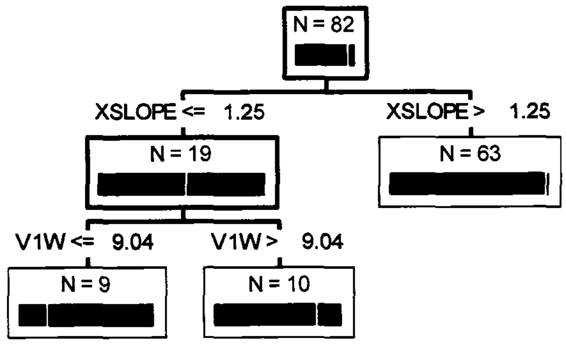
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	8	25.81	0.26	
13	4	2	50	0.5	
21	4	3	75	0.75	
23	7	1	14.29	0.14	
5	34	9	26.47	0.26	
69	2	2	100	1	
Total	82	25	0.304878		69.5

VARIABLE IMPORTANCE

DAKM2	100
MX1D	64.69
CHAN_SLP	64.43
LINK_SLOPE	48.59
FALLR	39.45
MENTCC	35.88
SLP_ELON	33.85
LO4PCA	30.5
BASEQ	26.17
PRED	20.62
NHIPL	17.97
DWSP1	11.35
DWSP2	6.28
PCT_PR	0.11

USEPA Physical Habitat Cluster 2-cluster



$R_c = 0.545$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	71	2	2.82	0.03	
13	11	4	36.36	0.36	
Total	82	6	0.0731707		92.7

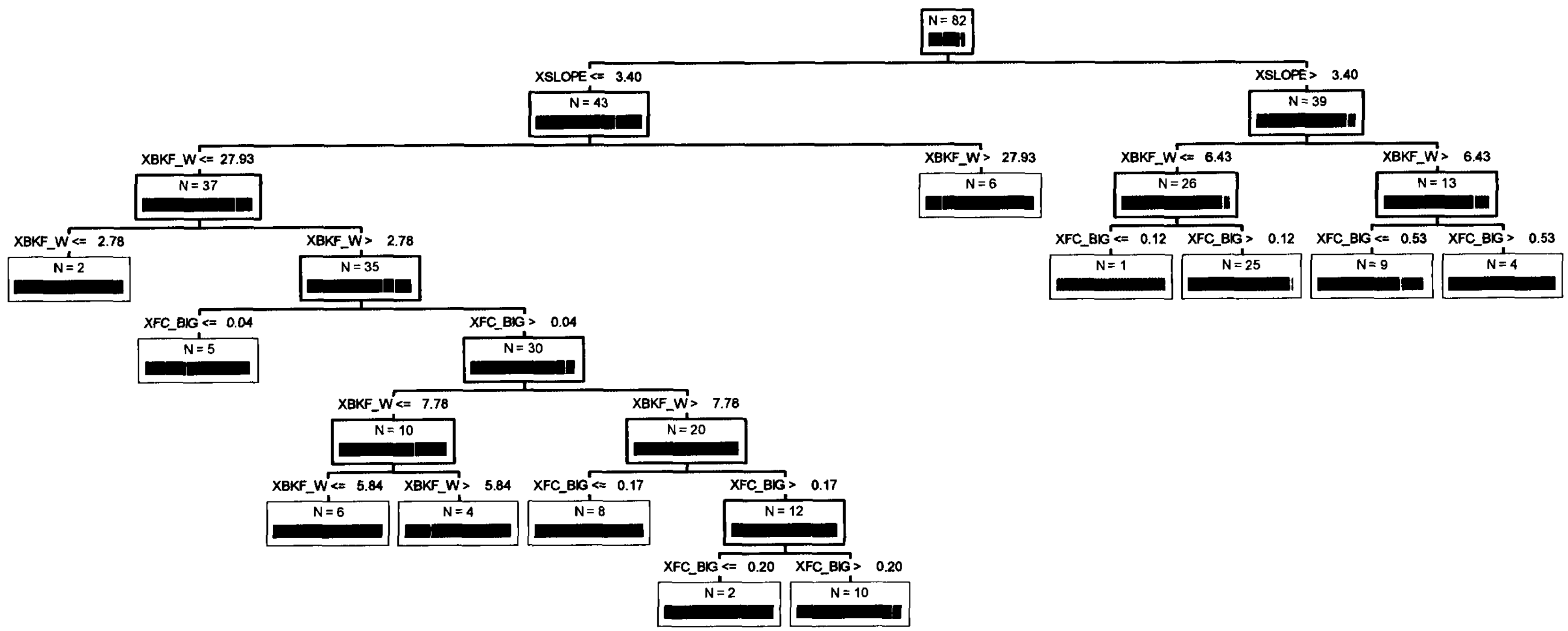
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	71	2	2.82	0.03	
13	11	4	36.36	0.36	
Total	82	6	0.0731707		92.7

VARIABLE IMPORTANCE

XSLOPE	100	||||||||||||||||||||||||||||||||||||||||
V1W	86.39	||||||||||||||||||||||||||||||||||

USEPA Physical Habitat Cluster 4-cluster



$R_c = 0.478$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	3	9.68	0.1	
13	11	1	9.09	0.09	
21	4	3	75	0.75	
5	36	3	8.33	0.08	
Total	82	10	0.1219512		87.8

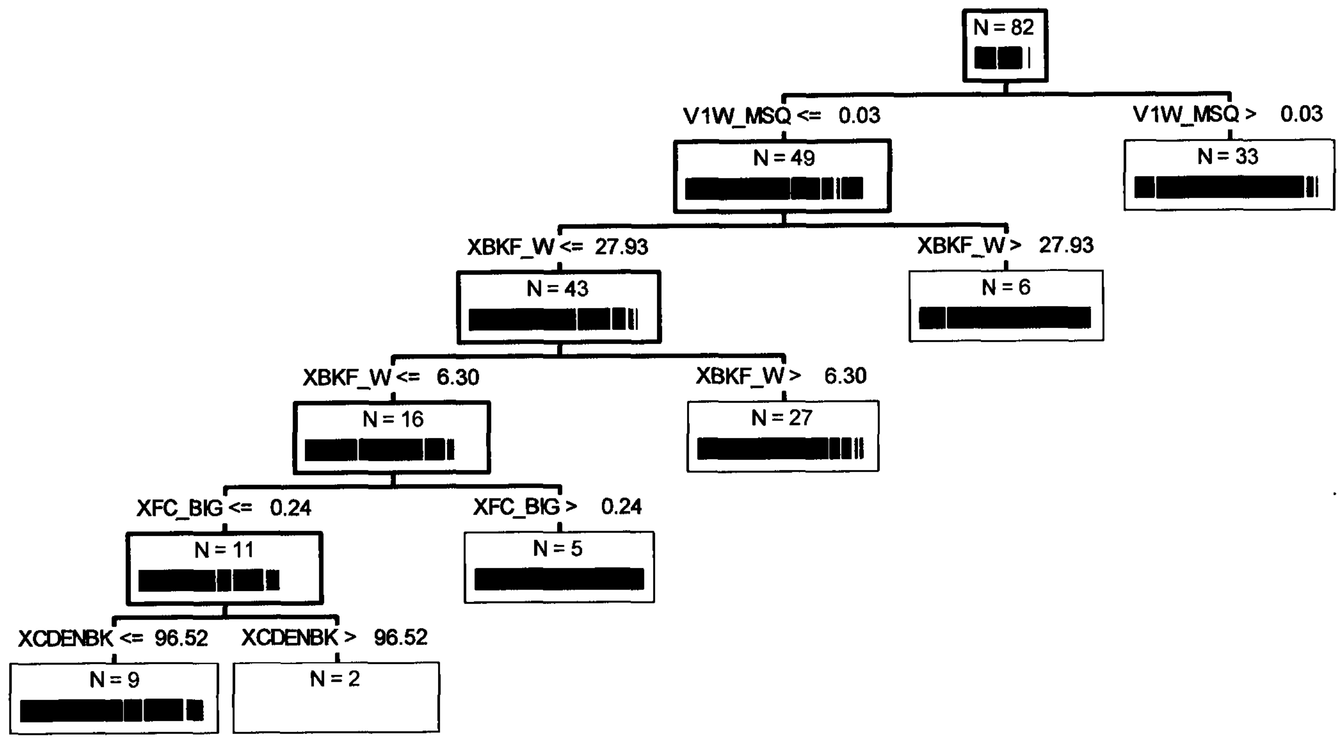
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	7	22.58	0.23	
13	11	2	18.18	0.18	
21	4	4	100	1	
5	36	9	25	0.25	
Total	82	22	0.2682927		73.2

VARIABLE IMPORTANCE

XBKF_W	100	||||||||||||||||||||||||||||||||||||||||
XSLOPE	88.9	|||||||||||||||||||||||||||||||||||
XFC_BIG	59.43	||||||||||||||||||||||||
XC	14.07	|||||

USEPA Physical Habitat Cluster 6-cluster



$R_c = 0.5$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	5	16.13	0.16	
13	4	4	100	1	
21	4	4	100	1	
23	7	2	28.57	0.29	
5	34	3	8.82	0.09	
69	2	0	0	0	
Total	82	18	0.2195122		78.0

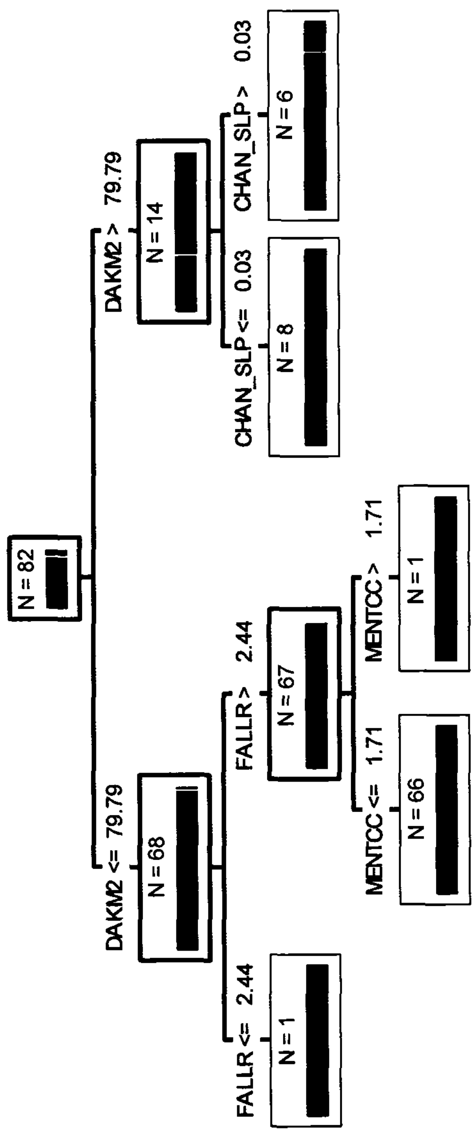
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	7	22.58	0.23	
13	4	3	75	0.75	
21	4	4	100	1	
23	7	2	28.57	0.29	
5	34	6	17.65	0.18	
69	2	2	100	1	
Total	82	24	0.2926829		70.7

VARIABLE IMPORTANCE

XBKF_W	100
V1W_MSQ	86.22
XCDENBK	75.91
XWD_RAT	46.12
XFC_BIG	37.92
XC	34.55
PCT_SLOW	28.33
XPCMG	22.82

All-metric 2-cluster



$R_c = 0.196$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	71	0	0	0	
13	11	1	9.09	0.09	
	82	1	0.0121951		98.8

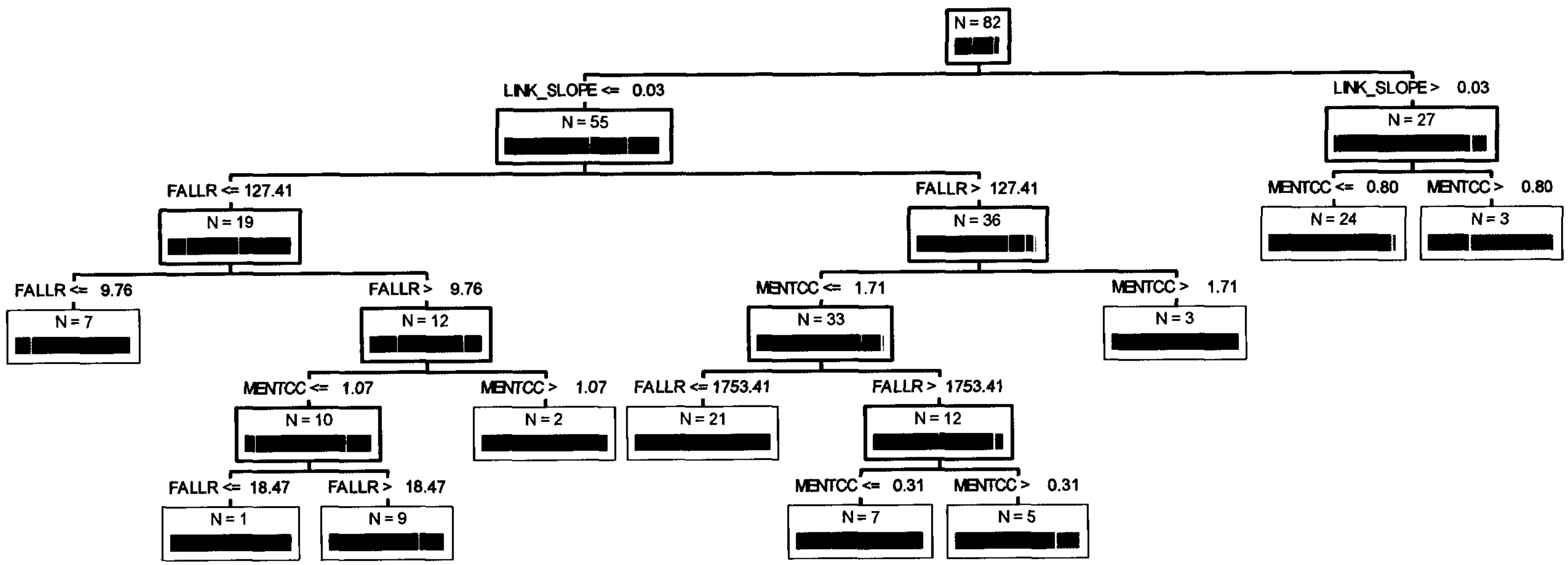
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	71	2	2.82	0.03	
13	11	4	36.36	0.36	
	82	6	0.0731707		92.7

VARIABLE IMPORTANCE

DAKM2	100
FALLR	98.84
ML22	74.86
XBKF_W	72.44
XWD_RAT	61.3
CHAN_SLP	54.5
SLP_ELON	40.87
MENTCC	37.26
MN3D	34.89
MN30D	34.89
MENTR	23.03
MA3	22.71
XC	21.88
PCT_SLOW	21.88
V1W	21.88

All-metric 4-cluster



$R_c = 0.37$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	3	9.68	0.1	
13	11	2	18.18	0.18	
21	4	2	50	0.5	
5	36	1	2.78	0.03	
	82	8	0.097561		90.2

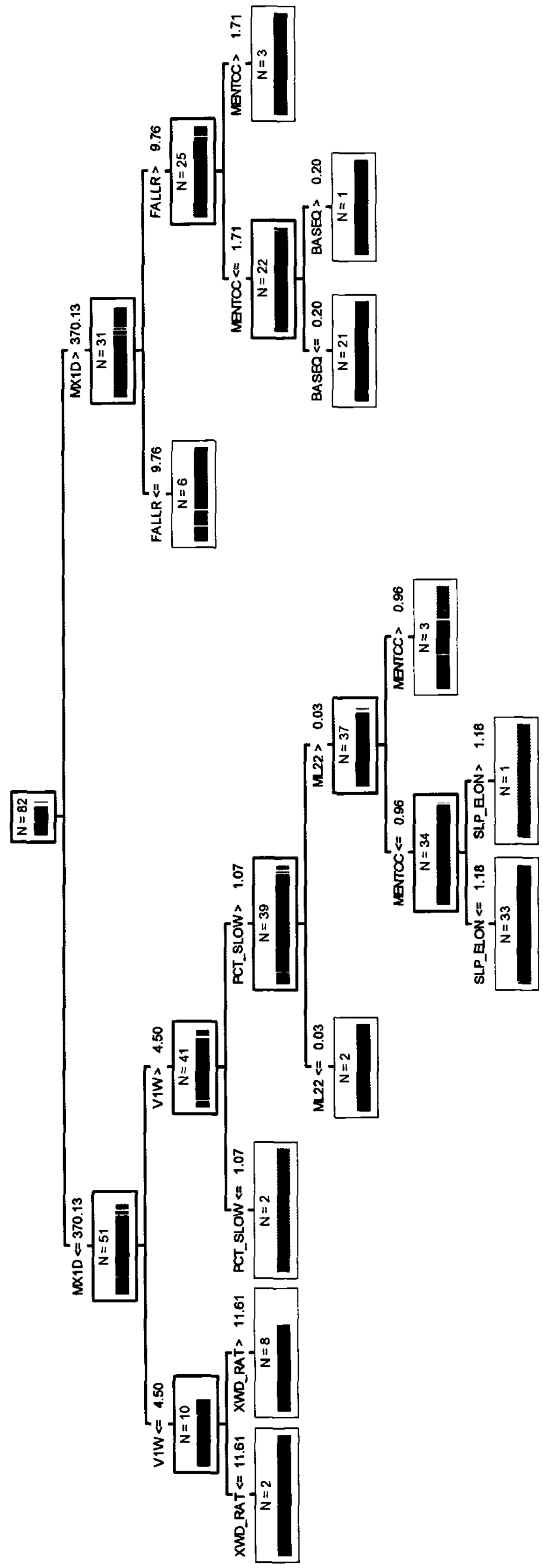
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	8	25.81	0.26	
13	11	2	18.18	0.18	
21	4	2	50	0.5	
5	36	5	13.89	0.14	
	82	17	0.2073171		79.3

VARIABLE IMPORTANCE

FALLR	100	||||||||||||||||||||||||||||||||||||||||
MENTCC	95.81	|||||||||||||||||||||||||||||||||||||||
LINK_SLOPE	79.66	||||||||||||||||||||||||||||||||

All-metric 6-cluster



$R_c = 0.479$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	1	3.23	0.03	
13	4	2	50	0.5	
21	4	1	25	0.25	
23	7	0	0	0	
5	34	1	2.94	0.03	
69	2	2	100	1	
	82	7	0.0853659		91.5

TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	31	6	19.35	0.19	
13	4	1	25	0.25	
21	4	4	100	1	
23	7	3	42.86	0.43	
5	34	8	23.53	0.24	
69	2	1	50	0.5	
	82	23	0.2804878		72.0

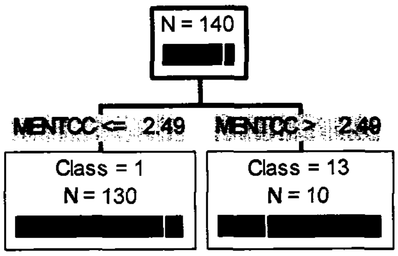
VARIABLE IMPORTANCE

DAKM2	100	
MX7D	85.4	
MX1D	75.59	
ML22	61.21	
XBKF_W	56.26	
CHAN_SLP	50.47	
MENTCC	44.88	
MN30D	42.61	
MN3D	41	
V1W	40.9	
PCT_SLOW	40.38	
V1W_MSQ	35.28	
FALLR	33.64	
MENTR	29.62	
XWD_RAT	23.48	
BASEQ	20.12	
SLP_ELON	18.51	
XC	12.02	
PRED	7.94	
XPCMG	6.92	

APPENDIX E

W-EMAP COMPREHENSIVE METRIC CLASSIFICATION TREES

Geomorphic 2-cluster



$R_c = 0.826$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	117	13	11.11	0.11	
13	23	0	0	0	
	140	13	0.092857		90.7

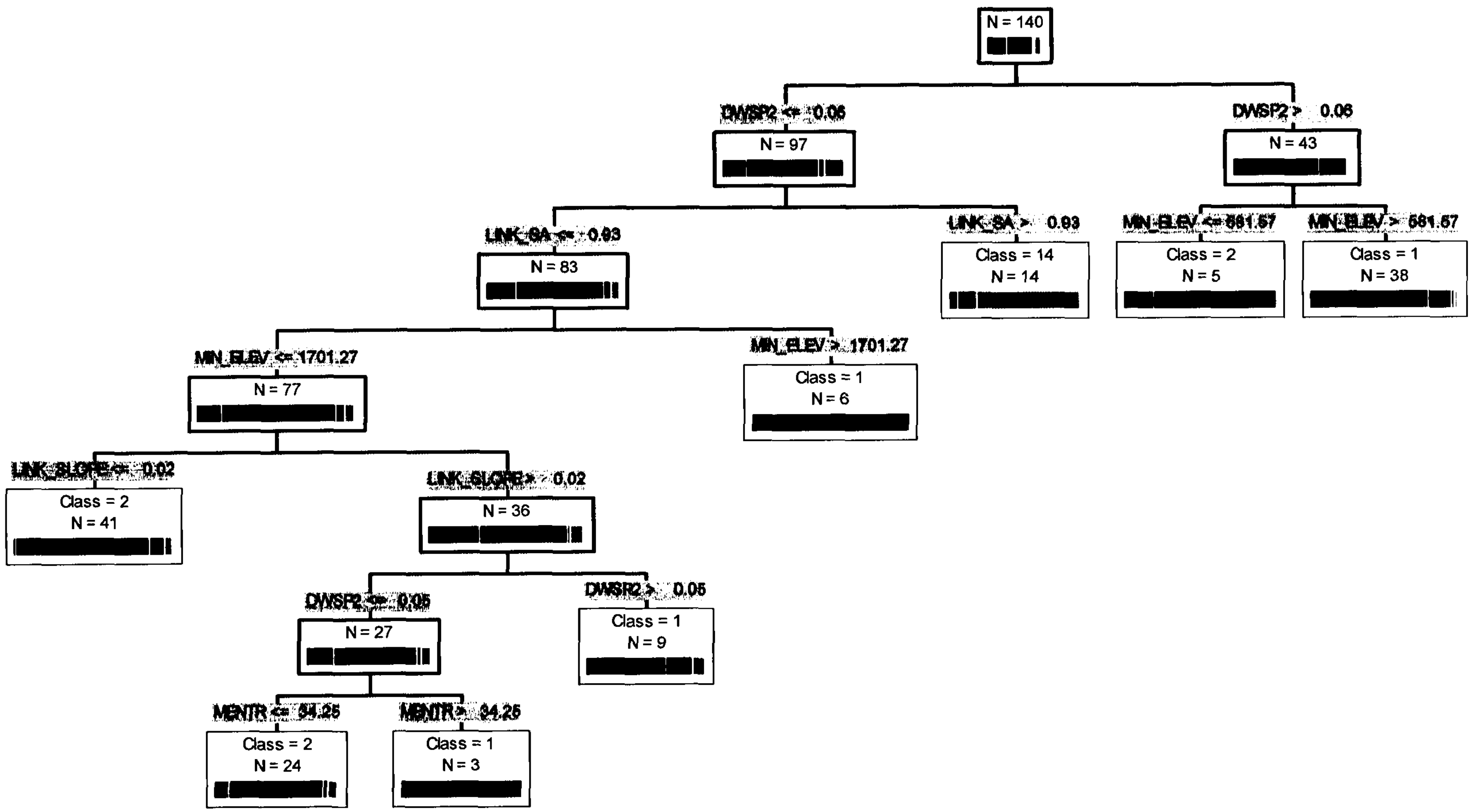
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	117	3	2.56	0.03	
13	23	16	69.57	0.7	
	140	19	0.135714		86.4

VARIABLE IMPORTANCE

MENTCC	100	||||||||||||||||||||||||||||||||||||||||

Geomorphic 4-cluster



$R_c = 0.527$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	51	6	11.76	0.12	
13	6	6	100	1	
14	17	6	35.29	0.35	
2	66	10	15.15	0.15	
	140	28	0.2		80.0

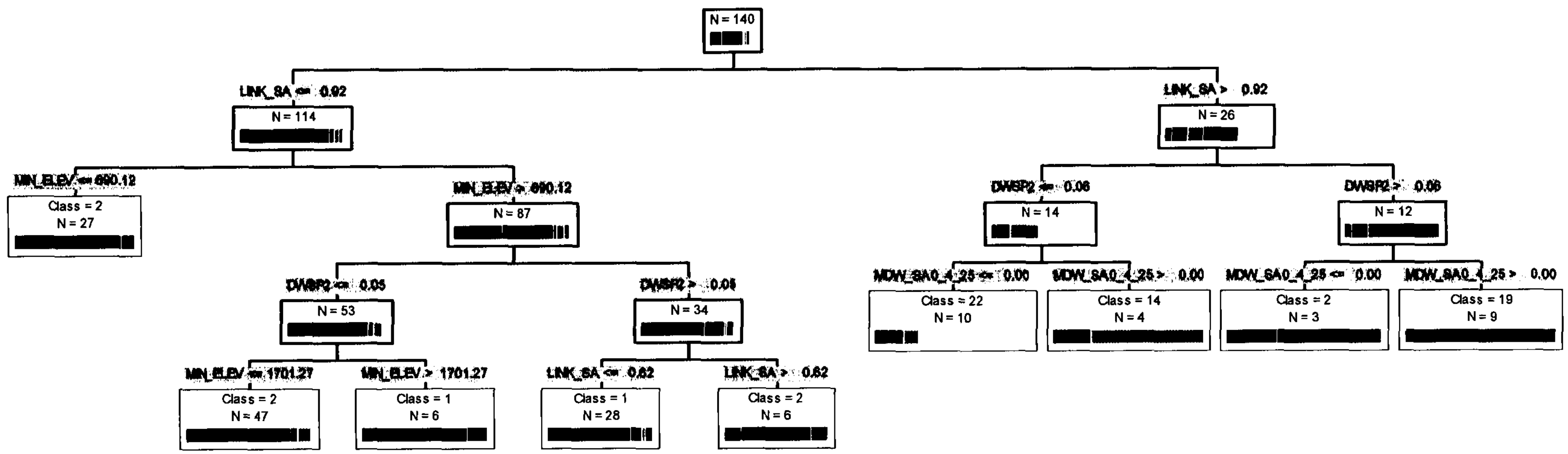
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	51	12	23.53	0.24	
13	6	6	100	1	
14	17	6	35.29	0.35	
2	66	15	22.73	0.23	
	140	39	0.278571		72.1

VARIABLE IMPORTANCE

DWSP2	100
LINK_SA	86.81
MIN_ELEV	83.02
LINK_SLOPE	64.61
MENTR	53.97
SLP_ELON	14.16
MDW_SA0_4_025	4.42

Geomorphic 6-cluster



Rc = 0.595

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	38	11	28.95	0.29	
13	6	6	100	1	
14	10	7	70	0.7	
19	13	4	30.77	0.31	
2	66	5	7.58	0.08	
22	7	0	0	0	
	140	33	0.235714		76.4

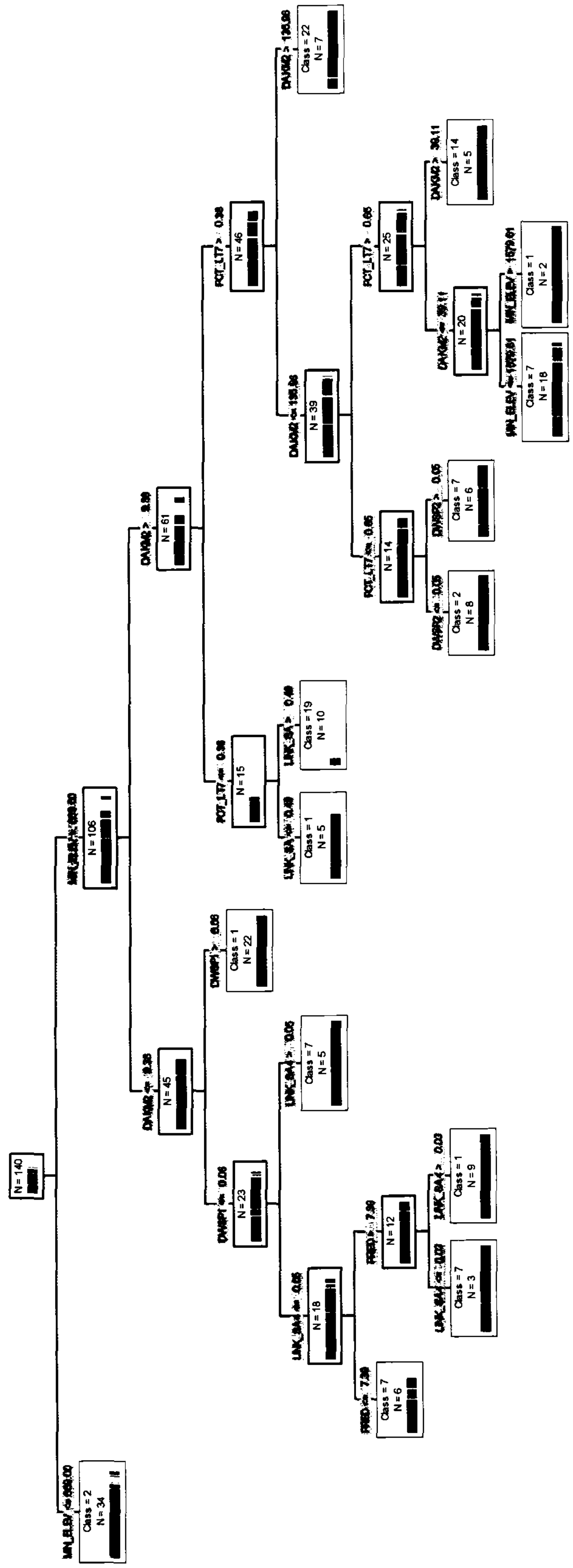
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	38	11	28.95	0.29	
13	6	6	100	1	
14	10	7	70	0.7	
19	13	7	53.85	0.54	
2	66	9	13.64	0.14	
22	7	4	57.14	0.57	
	140	44	0.314286		68.6

VARIABLE IMPORTANCE

LINK_SA	100
MIN_ELEV	94.21
DWSP2	85.15
MDW_SA0_4_25	73.36
MDW_A_25	32.53
PCT_PB	29.07

Geomorphic 8-cluster



$R_c = 0.556$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	38	4	10.53	0.11	
13	3	3	100	1	
14	10	6	60	0.6	
19	13	4	30.77	0.31	
2	41	8	19.51	0.2	
22	7	1	14.29	0.14	
41	3	3	100	1	
7	25	2	8	0.08	
	140	31	0.221429		77.9

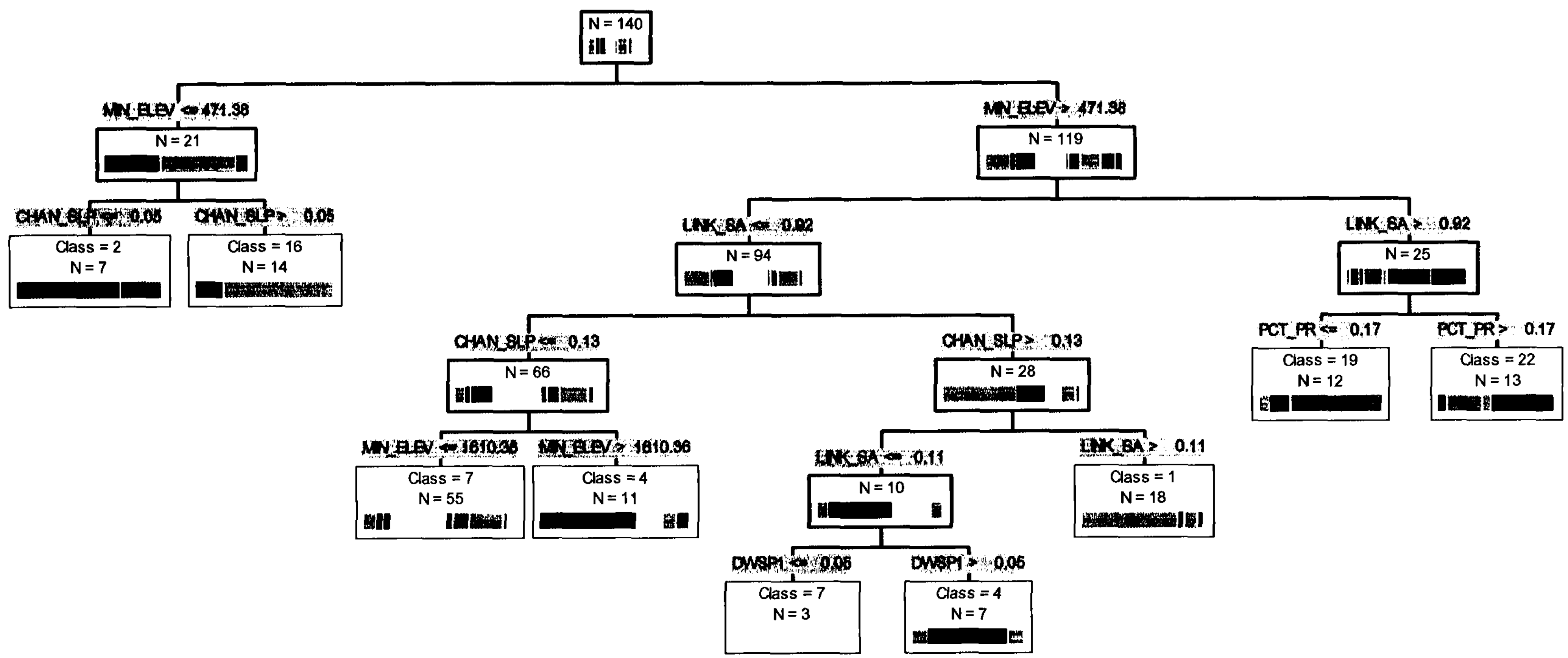
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	38	9	23.68	0.24	
13	3	3	100	1	
14	10	8	80	0.8	
19	13	6	46.15	0.46	
2	41	11	26.83	0.27	
22	7	1	14.29	0.14	
41	3	3	100	1	
7	25	14	56	0.56	
	140	55	0.392857		60.7

VARIABLE IMPORTANCE

MIN_ELEV	100
LINK_SA	97.35
DAKM2	96.81
PCT_LT7	92.68
LINK_SA4	88.18
DWSP1	83.86
DWSP2	80.09
PCT_PR	66.9
PRED	56.37
SLP_ELON	30.48

Geomorphic 10-cluster



$R_c = 0.661$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	21	7	33.33	0.33	
13	3	3	100	1	
14	10	10	100	1	
16	28	17	60.71	0.61	
19	13	4	30.77	0.31	
2	13	8	61.54	0.62	
22	7	0	0	0	
4	17	5	29.41	0.29	
41	3	3	100	1	
7	25	2	8	0.08	
	140	59	0.421429		57.9

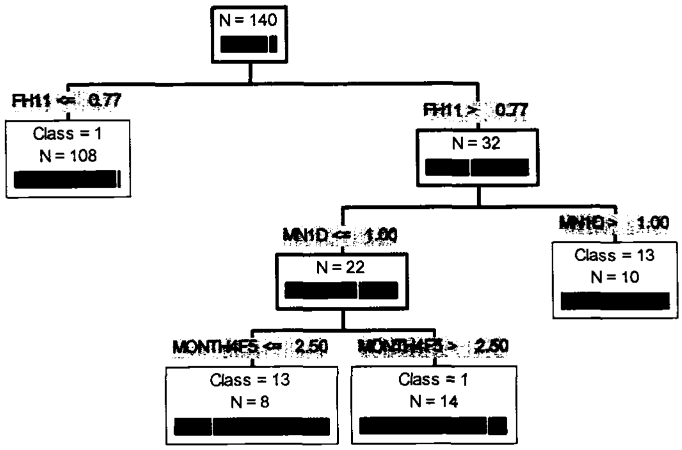
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost	% Correct
1	21	9	42.86	0.43	
13	3	3	100	1	
14	10	10	100	1	
16	28	17	60.71	0.61	
19	13	6	46.15	0.46	
2	13	7	53.85	0.54	
22	7	1	14.29	0.14	
4	17	6	35.29	0.35	
41	3	3	100	1	
7	25	12	48	0.48	
	140	74	0.528571		47.1

VARIABLE IMPORTANCE

<table>
<tr><td>CHAN_SLP</td><td>100</td><td>||||||||||||||||||||||||||||||||||||||||</td></tr>
<tr><td>LINK_SA</td><td>85.41</td><td>||||||||||||||||||||||||||||||||||</td></tr>
<tr><td>MIN_ELEV</td><td>80.86</td><td>||||||||||||||||||||||||||||||||</td></tr>
<tr><td>DWSP1</td><td>70.3</td><td>||||||||||||||||||||||||||||</td></tr>
<tr><td>PCT_C</td><td>67.06</td><td>|||||||||||||||||||||||||||</td></tr>
<tr><td>PCT_PR</td><td>62.57</td><td>|||||||||||||||||||||||||</td></tr>
<tr><td>PCT_SP</td><td>61.03</td><td>||||||||||||||||||||||||</td></tr>
<tr><td>PCT_PB</td><td>11.39</td><td>||||</td></tr>
<tr><td>MDW_SA_25</td><td>5.82</td><td>||</td></tr>
<tr><td>MDW_A_25</td><td>2.09</td><td></td></tr>
</table>

Hydrologic 2-cluster



$R_c = 0.478$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	117	2	1.71	0.02
13	23	7	30.43	0.3
	140	9	0.064286	93.6

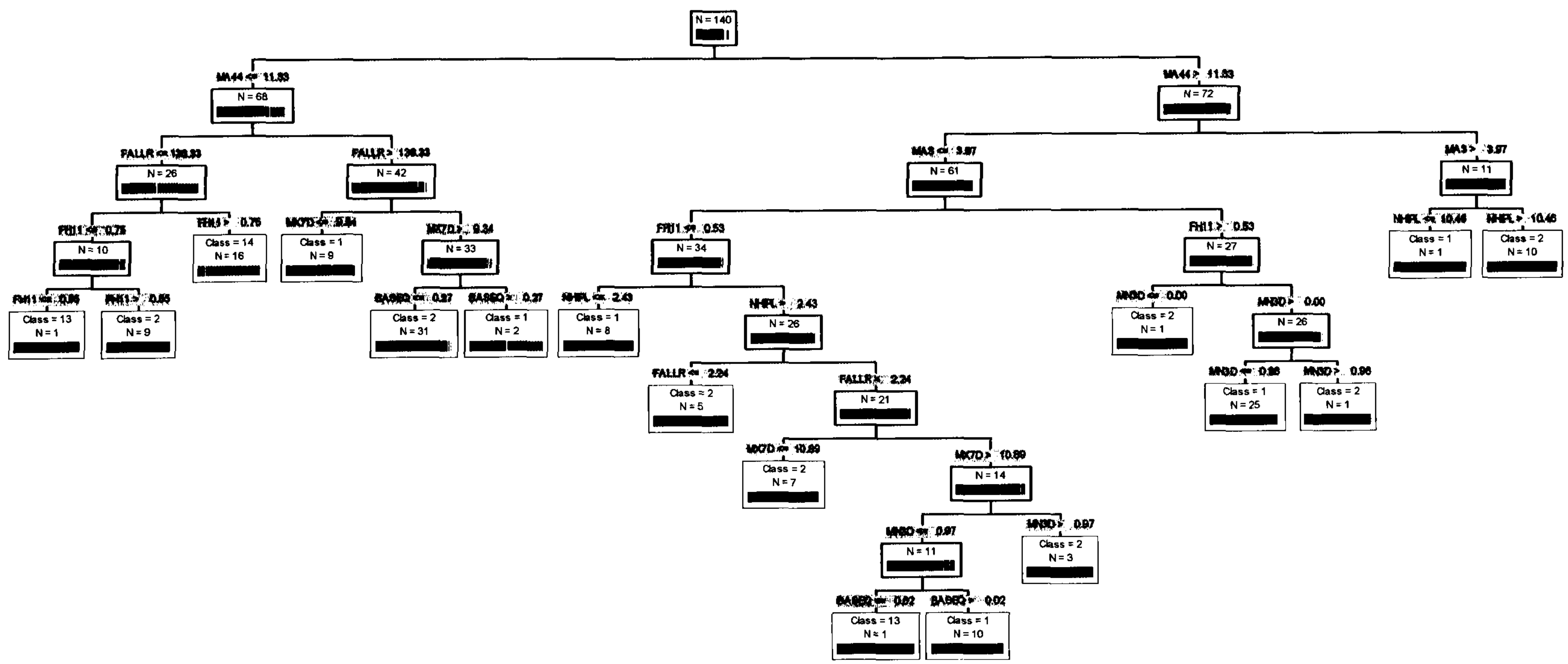
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	117	4	3.42	0.03
13	23	7	30.43	0.3
	140	11	0.078571	92.1

VARIABLE IMPORTANCE

FH11	100	||||||||||||||||||||||||||||||||||||||||
MA3	53.4	|||||||||||||||||||||
MENTR	45.35	|||||||||||||||||||
MX3D	28.25	|||||||||||
MX7D	28.25	|||||||||||
PCT_LT7	26.65	||||||||||
BASEQ	25.19	||||||||||
MENTCC	22.67	|||||||||
PCT_SP	22.49	|||||||||
PCT_PR	22.49	|||||||||
MN3D	17.24	|||||||
MH1	3.14	

Hydrologic 4-cluster



$R_c = 0.554$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	51	4	7.84	0.08
13	6	4	66.67	0.67
14	17	3	17.65	0.18
2	66	4	6.06	0.06
	140	15	0.107143	89.3

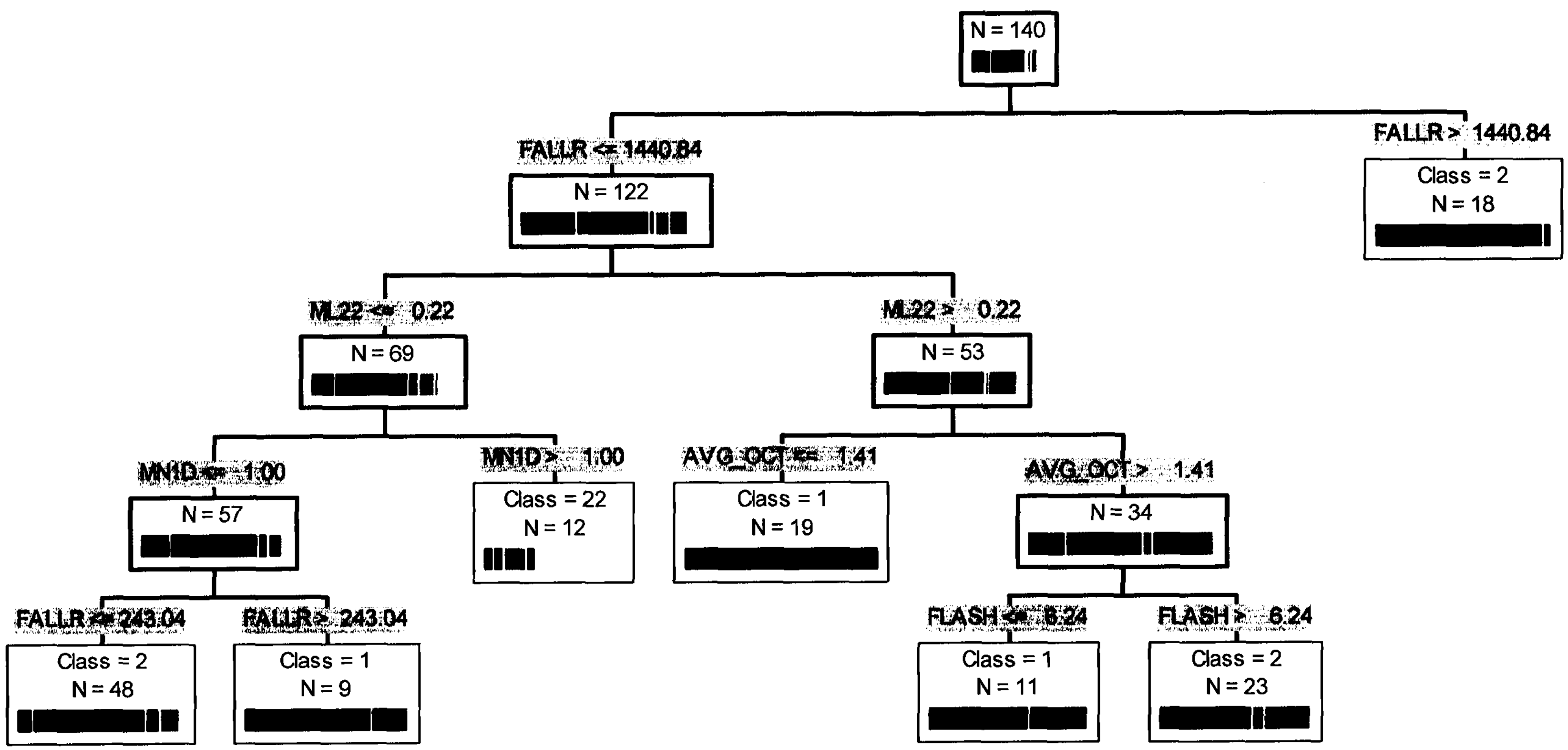
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	51	15	29.41	0.29
13	6	5	83.33	0.83
14	17	6	35.29	0.35
2	66	15	22.73	0.23
	140	41	0.292857	70.7

VARIABLE IMPORTANCE

MA44	100
FH11	98.1
MN3D	97.77
NHIPL	86.45
FALLR	71.94
MA3	71.14
MX7D	71.09
RISER	50.92
BASEQ	43.84

Hydrologic 6-cluster



$R_c = 0.581$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	5	13.16	0.13
13	6	6	100	1
14	10	10	100	1
19	13	13	100	1
2	66	3	4.55	0.05
22	7	0	0	0
	140	37	0.264286	73.6

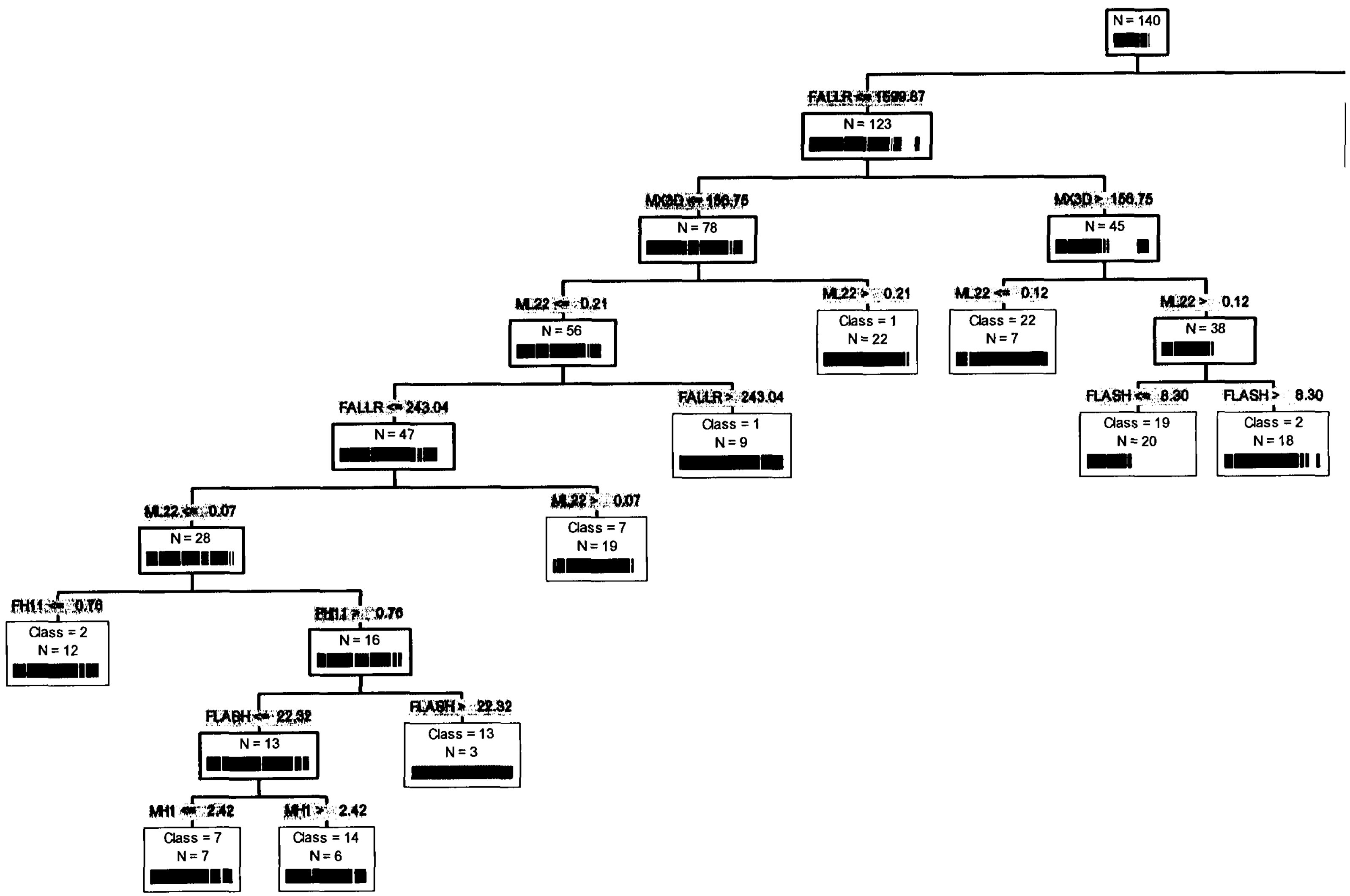
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	9	23.68	0.24
13	6	6	100	1
14	10	10	100	1
19	13	12	92.31	0.92
2	66	6	9.09	0.09
22	7	0	0	0
	140	43	0.307143	69.3

VARIABLE IMPORTANCE

AVG_OCT	100
FALLR	84.23
ML22	68.33
MN1D	63.03
FLASH	61.77

Hydrologic 8-cluster



$R_c = 0.475$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	11	28.95	0.29
13	3	0	0	0
14	10	7	70	0.7
19	13	2	15.38	0.15
2	41	6	14.63	0.15
22	7	1	14.29	0.14
41	3	3	100	1
7	25	6	24	0.24
	140	36	0.257143	74.3

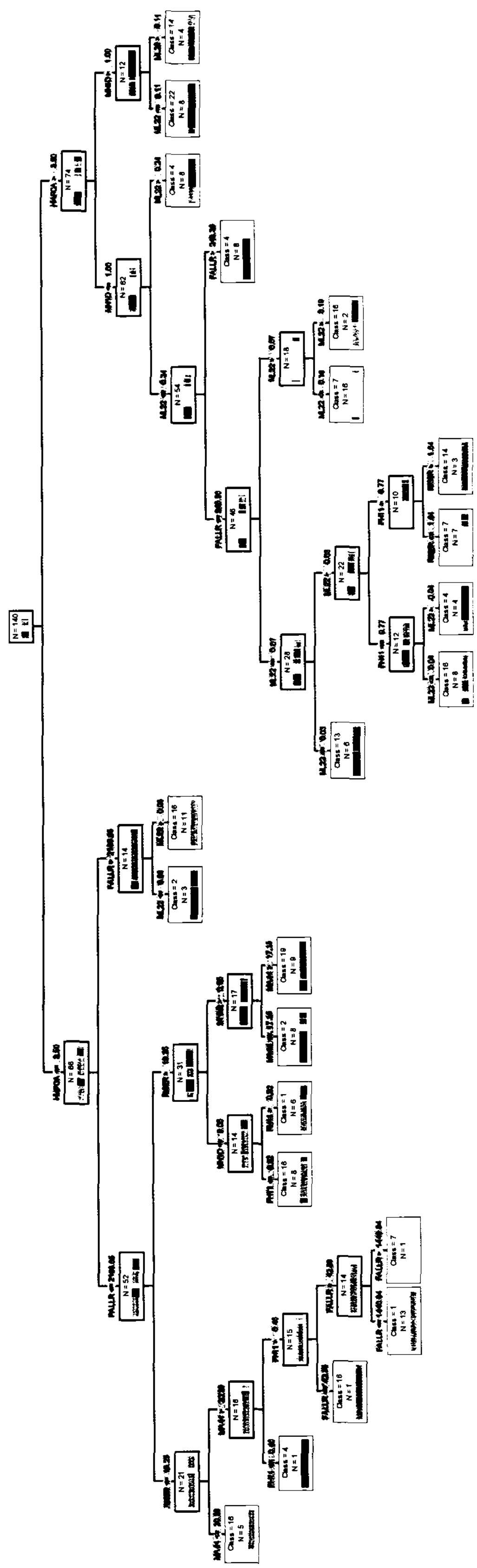
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	14	36.84	0.37
13	3	1	33.33	0.33
14	10	10	100	1
19	13	3	23.08	0.23
2	41	9	21.95	0.22
22	7	1	14.29	0.14
41	3	3	100	1
7	25	6	24	0.24
	140	47	0.335714	66.4

VARIABLE IMPORTANCE

ML22	100
FALLR	78.09
MX3D	74.27
FH11	63.14
FLASH	53.58
MH1	48.83
MN1D	37.51

Hydrologic 10-cluster



$R_c = 0.581$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	21	4	19.05	0.19
13	3	0	0	0
14	10	4	40	0.4
16	28	1	3.57	0.04
19	13	6	46.15	0.46
2	13	6	46.15	0.46
22	7	0	0	0
4	17	2	11.76	0.12
41	3	3	100	1
7	25	5	20	0.2
	140	31	0.221429	77.9

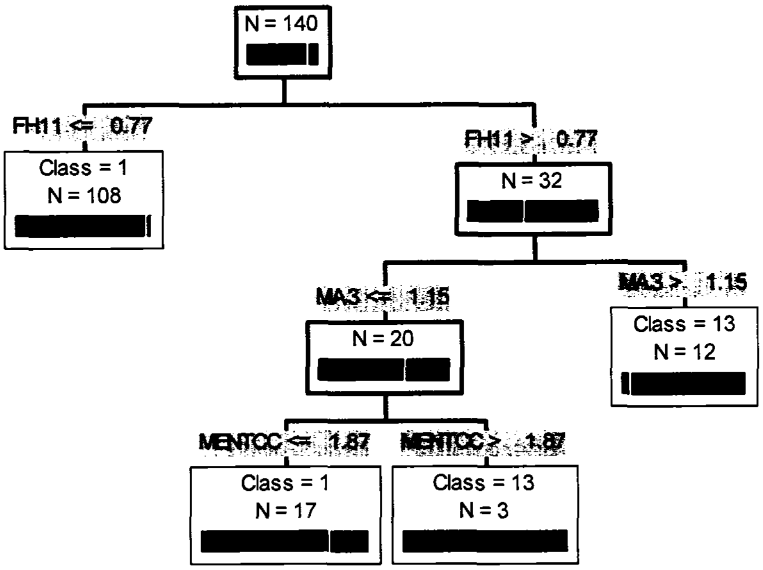
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	21	8	38.1	0.38
13	3	1	33.33	0.33
14	10	8	80	0.8
16	28	7	25	0.25
19	13	8	61.54	0.62
2	13	8	61.54	0.62
22	7	0	0	0
4	17	6	35.29	0.35
41	3	3	100	1
7	25	9	36	0.36
	140	58	0.414286	58.6

VARIABLE IMPORTANCE

ML22	100	||||||||||||||||||||||||||||||||||||||||||
FALLR	79.1	|||||||||||||||||||||||||||||||||
RISER	77.89	||||||||||||||||||||||||||||||||
MN1D	72.21	||||||||||||||||||||||||||||||
MA44	65	|||||||||||||||||||||||||||
FH11	64.72	|||||||||||||||||||||||||||
HI4PCA	24.84	||||||||||

Hydrogeomorphic 2-cluster



$R_c = 0.696$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	117	1	0.85	0.01
13	23	9	39.13	0.39
	140	10	0.071429	92.9

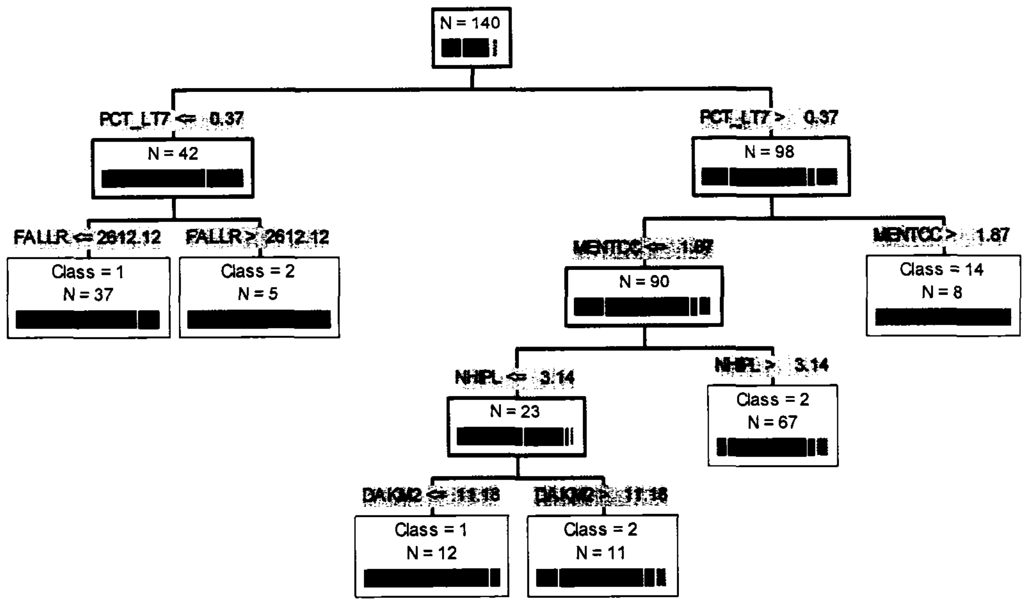
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	117	3	2.56	0.03
13	23	13	56.52	0.57
	140	16	0.114286	88.6

VARIABLE IMPORTANCE

FH11	100	||||||||||||||||||||||||||||||||||||||||
MA3	53.4	|||||||||||||||||||||
MENTR	45.35	||||||||||||||||||
MX3D	28.25	|||||||||||
MX7D	28.25	|||||||||||
PCT_LT7	26.65	||||||||||
BASEQ	25.19	||||||||||
MENTCC	22.67	|||||||||
PCT_SP	22.49	|||||||||
PCT_PR	22.49	|||||||||
MN3D	17.24	||||||
MH1	3.14	

Hydrogeomorphic 4-cluster



$R_c = 0.541$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	51	9	17.65	0.18
13	6	6	100	1
14	17	9	52.94	0.53
2	66	7	10.61	0.11
	140	31	0.221429	77.9

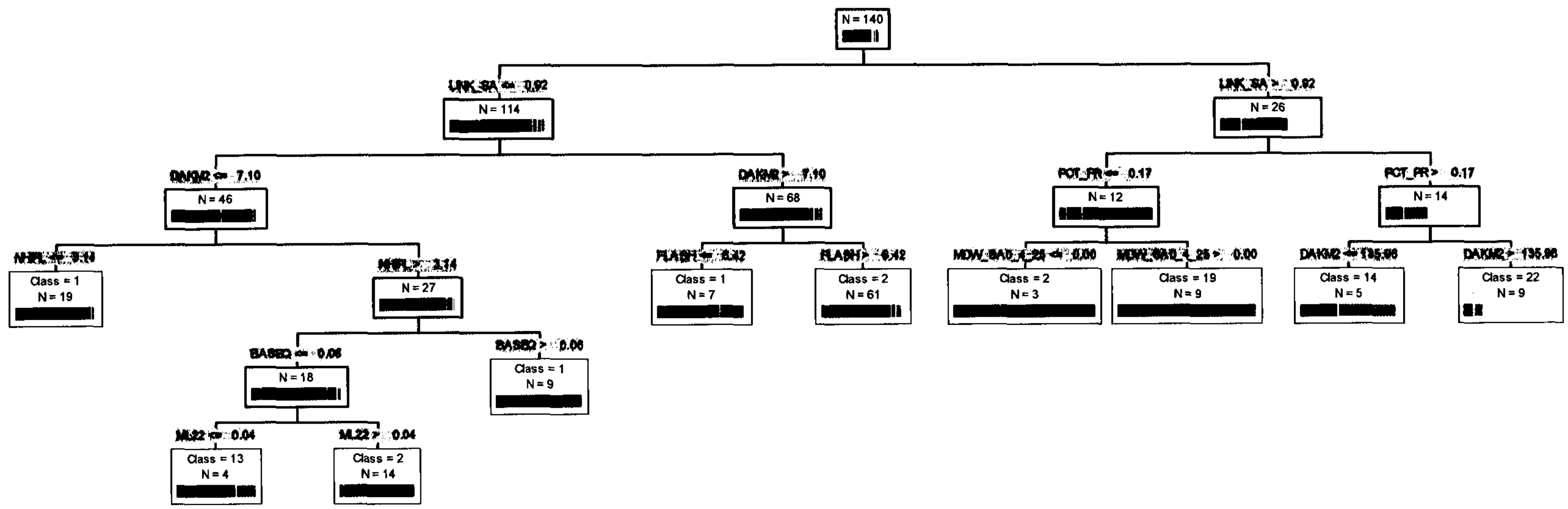
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	51	11	21.57	0.22
13	6	6	100	1
14	17	10	58.82	0.59
2	66	13	19.7	0.2
	140	40	0.285714	71.4

VARIABLE IMPORTANCE

PCT_LT7	100
DAKM2	84.44
MENTCC	80.94
LINK_SA4	65.14
NHIPL	61.54
FALLR	57.37
RISER	23.25
MX3D	18.79
PRED	11.26

Hydrogeomorphic 6-cluster



$R_c = 0.581$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	10	26.32	0.26
13	6	4	66.67	0.67
14	10	7	70	0.7
19	13	4	30.77	0.31
2	66	6	9.09	0.09
22	7	0	0	0
	140	31	0.221429	77.9

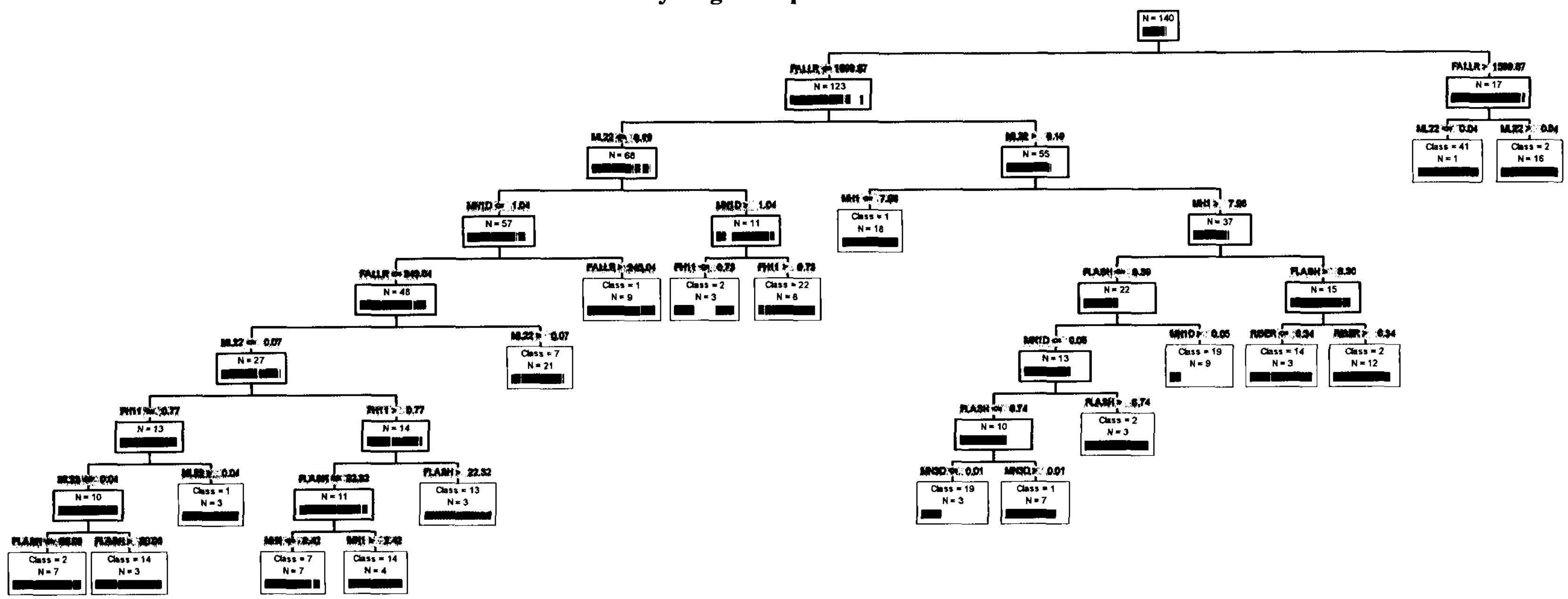
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	10	26.32	0.26
13	6	6	100	1
14	10	8	80	0.8
19	13	6	46.15	0.46
2	66	11	16.67	0.17
22	7	2	28.57	0.29
	140	43	0.307143	69.3

VARIABLE IMPORTANCE

DAKM2	100	||||||||||||||||||||||||||||||||||||||||||
ML22	77.62	||||||||||||||||||||||||||||||||
MN1D	77.47	||||||||||||||||||||||||||||||||
LINK_SA	75.28	|||||||||||||||||||||||||||||||
FLASH	74.3	|||||||||||||||||||||||||||||||
PCT_PR	74.17	|||||||||||||||||||||||||||||||
NHIPL	48.97	|||||||||||||||||||||
MA44	37.89	||||||||||||||||
BASEQ	36.48	||||||||||||||||
MDW_SA0_4_25	35.84	|||||||||||||||

Hydrogeomorphic 8-cluster



$R_c = 0.475$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	4	10.53	0.11
13	3	0	0	0
14	10	3	30	0.3
19	13	4	30.77	0.31
2	41	5	12.2	0.12
22	7	0	0	0
41	3	2	66.67	0.67
7	25	5	20	0.2
	140	23	0.164286	83.6

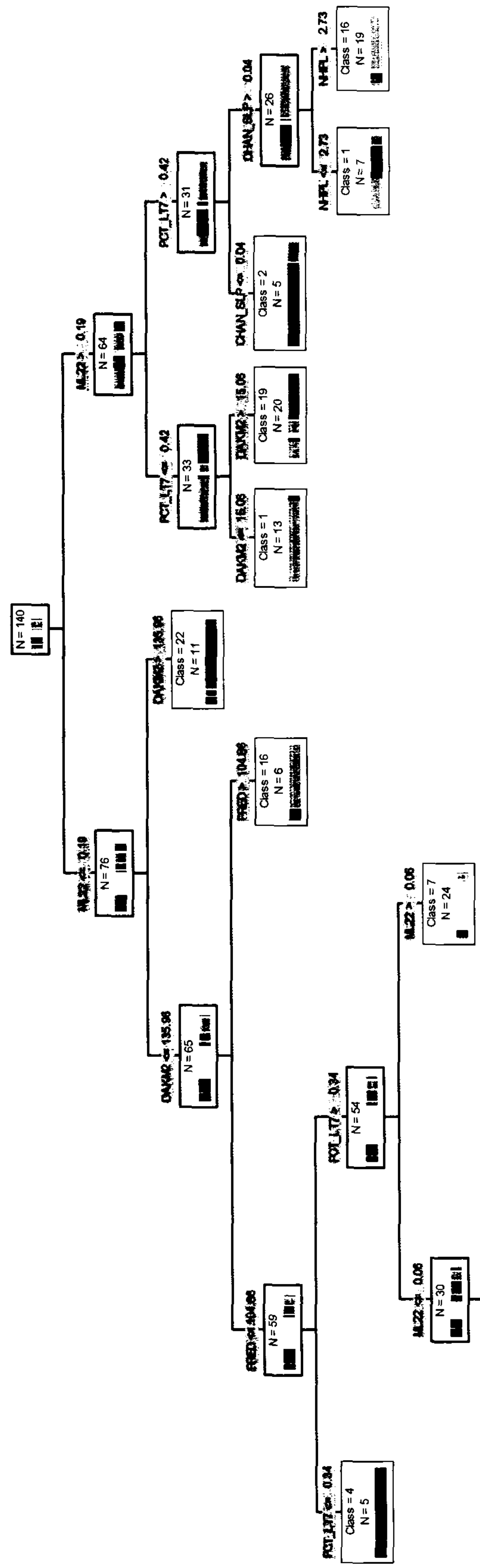
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	10	26.32	0.26
13	3	2	66.67	0.67
14	10	8	80	0.8
19	13	9	69.23	0.69
2	41	9	21.95	0.22
22	7	0	0	0
41	3	3	100	1
7	25	6	24	0.24
	140	47	0.335714	66.4

VARIABLE IMPORTANCE

RISER	100	
MH1	98.38	
ML22	90.4	
FLASH	89.45	
FALLR	85.13	
MN1D	69.12	
FH11	63.7	
MN3D	56.63	

Hydrogeomorphic 10-cluster



$R_c = 0.571$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	21	6	28.57	0.29
13	3	0	0	0
14	10	7	70	0.7
16	28	9	32.14	0.32
19	13	2	15.38	0.15
2	13	5	38.46	0.38
22	7	0	0	0
4	17	13	76.47	0.76
41	3	3	100	1
7	25	3	12	0.12
	140	48	0.342857	65.7

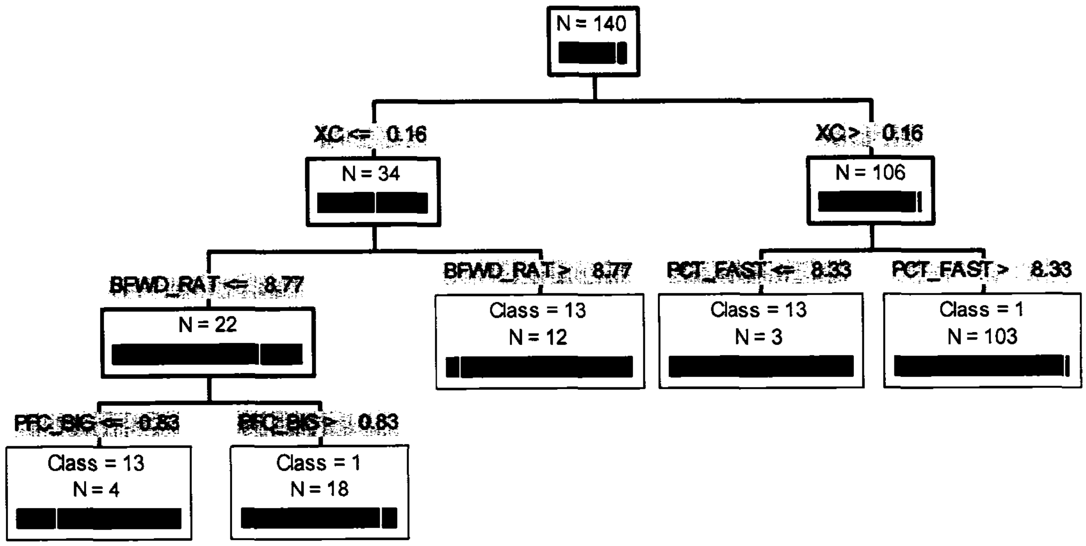
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	21	7	33.33	0.33
13	3	1	33.33	0.33
14	10	9	90	0.9
16	28	10	35.71	0.36
19	13	6	46.15	0.46
2	13	7	53.85	0.54
22	7	1	14.29	0.14
4	17	10	58.82	0.59
41	3	3	100	1
7	25	10	40	0.4
	140	64	0.457143	54.3

VARIABLE IMPORTANCE

MH1	100
DAKM2	89.77
CHAN_SLP	81.72
MX7D	66.75
ML22	64.07
MX3D	63.19
RISER	56.52
NHIPL	55.23
FALLR	49.24
PCT_LT7	44
PCT_C	42.76
FH11	41.77
PRED	29.79
PCT_SP	25.95
MENTCC	21.23

USEPA Physical Habitat Cluster 2-cluster



$R_c = 0.478$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	117	2	1.71	0.02
13	23	6	26.09	0.26
	140	8	0.057143	94.3

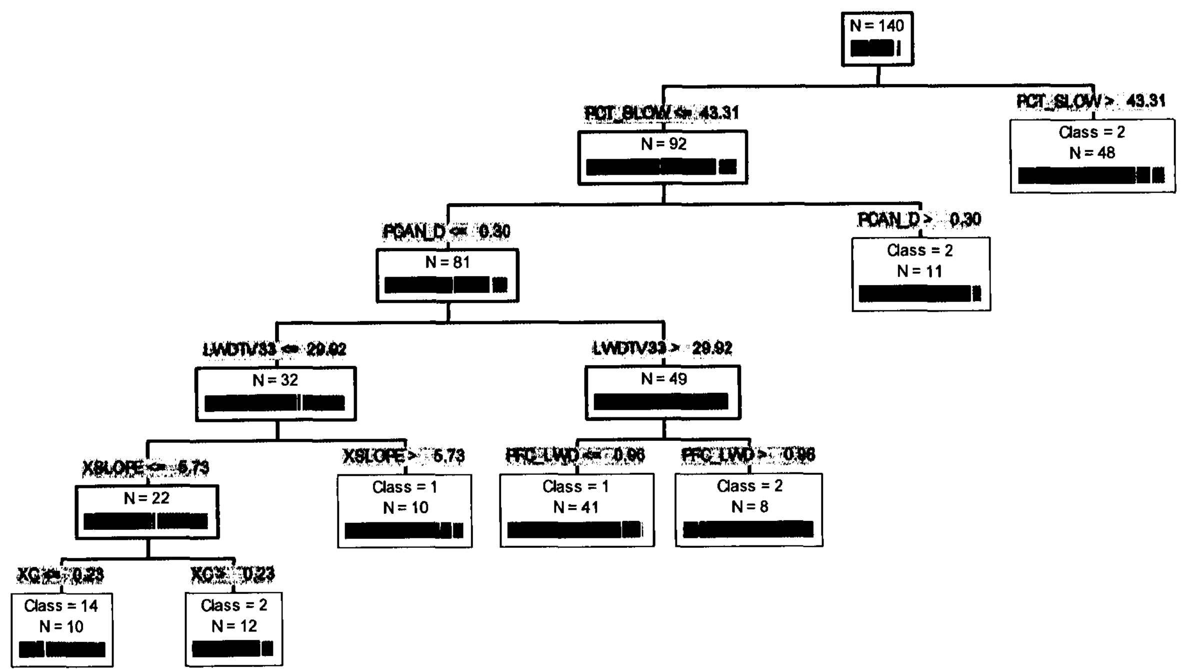
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	117	2	1.71	0.02
13	23	9	39.13	0.39
	140	11	0.078571	92.1

VARIABLE IMPORTANCE

XC	100
BFWD_RAT	84.82
PCT_RI	81.84
PCT_FAST	60.34
PFC_BIG	56.8
PFC_LWD	37.73
XSLOPE	36.27
XCDENBK	18.6

USEPA Physical Habitat Cluster 4-cluster



$R_c = 0.676$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	51	9	17.65	0.18
13	6	6	100	1
14	17	10	58.82	0.59
2	66	7	10.61	0.11
	140	32	0.228571	77.1

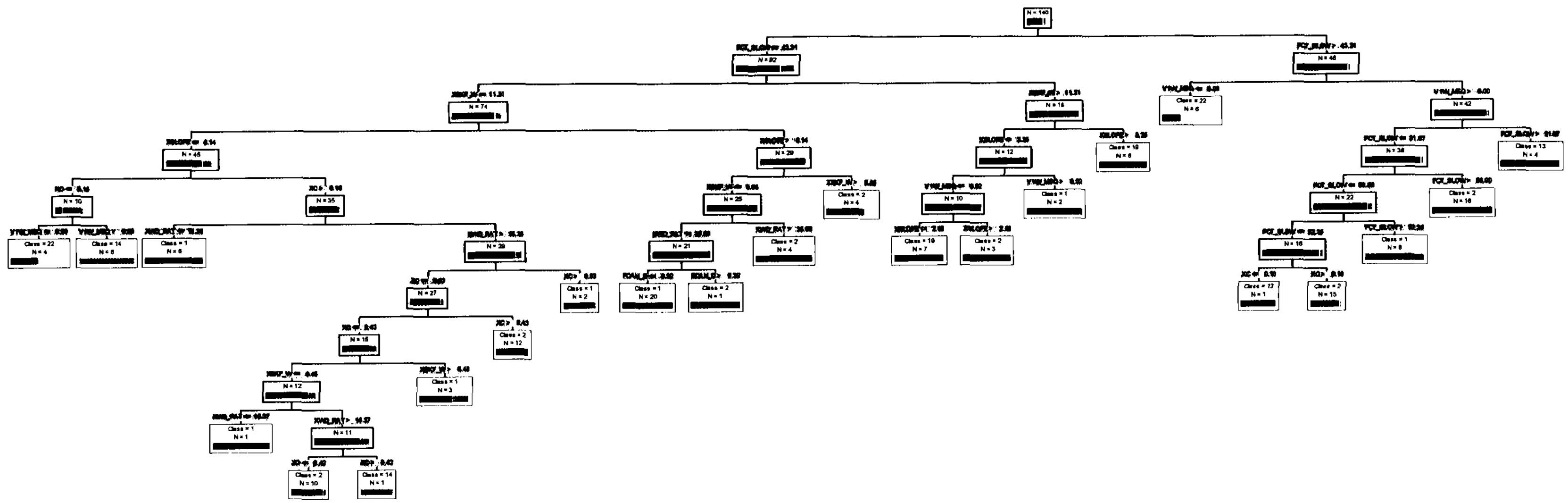
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	51	16	31.37	0.31
13	6	6	100	1
14	17	11	64.71	0.65
2	66	17	25.76	0.26
	140	50	0.357143	64.3

VARIABLE IMPORTANCE

PCAN_D	100
PFC_LWD	77.38
XSLOPE	74.04
LWDTV33	71.58
PCT_SLOW	68.32
XCDENBK	62.14
V1W	57.21
XC	54.76
XWD_RAT	50.94
V1W_MSQ	46.19
PCAN_C	38.95
XBKF_W	36.12
XFC_BIG	24.06
V4W	24.01
PFC_BIG	23.57
XDEPTH	21.57
XWIDTH	19.45
XBKF_H	6.94

USEPA Physical Habitat Cluster 6-cluster



$R_c = 0.73$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	3	7.89	0.08
13	6	2	33.33	0.33
14	10	3	30	0.3
19	13	2	15.38	0.15
2	66	7	10.61	0.11
22	7	1	14.29	0.14
	140	18	0.128571	87.1

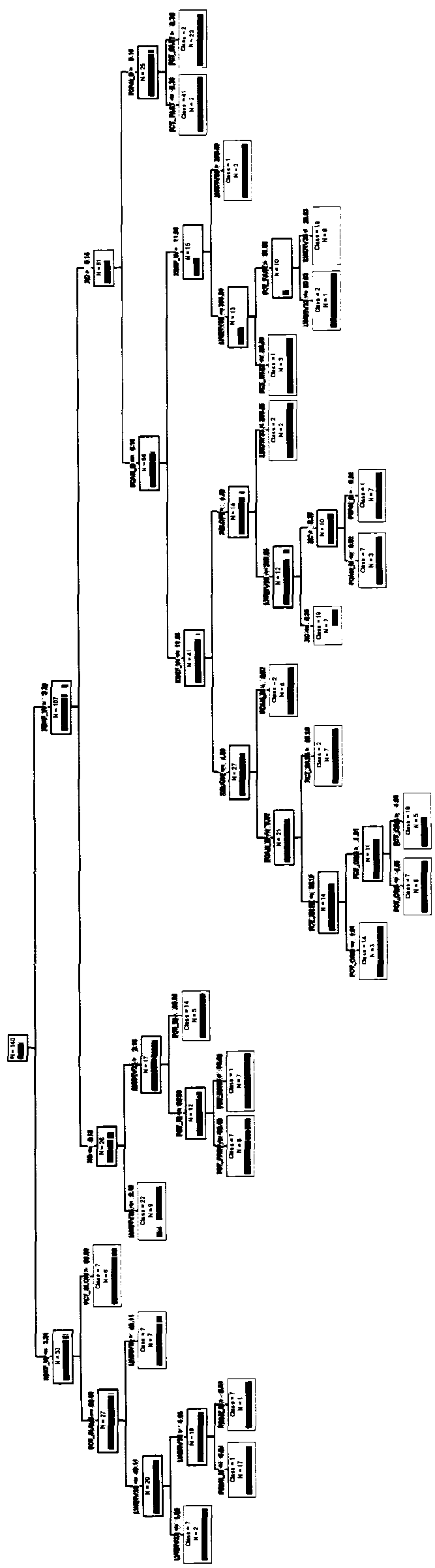
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	13	34.21	0.34
13	6	5	83.33	0.83
14	10	8	80	0.8
19	13	6	46.15	0.46
2	66	17	25.76	0.26
22	7	5	71.43	0.71
	140	54	0.385714	61.4

VARIABLE IMPORTANCE

XSLOPE	100
XBKF_W	97.16
XC	95.43
PCT_SLOW	94.6
V1W_MSQ	93.77
XWD_RAT	77.02
PCAN_D	37.14
PFC_BIG	25.12

USEPA Physical Habitat Cluster 8-cluster



$R_c = 0.687$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	5	13.16	0.13
13	3	3	100	1
14	10	3	30	0.3
19	13	1	7.69	0.08
2	41	5	12.2	0.12
22	7	1	14.29	0.14
41	3	1	33.33	0.33
7	25	4	16	0.16
	140	23	0.164286	83.6

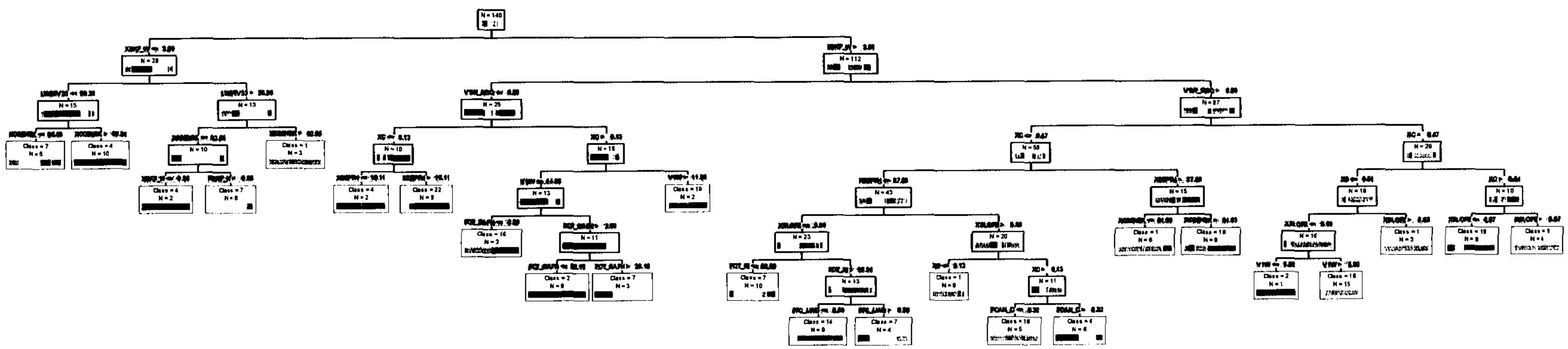
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	13	34.21	0.34
13	3	2	66.67	0.67
14	10	8	80	0.8
19	13	6	46.15	0.46
2	41	20	48.78	0.49
22	7	4	57.14	0.57
41	3	2	66.67	0.67
7	25	13	52	0.52
	140	68	0.485714	51.4

VARIABLE IMPORTANCE

PCT_FAST	100
LWDTV33	95.05
V1W	92.09
XBKF_W	89.83
PCT_SLOW	85.19
XSLOPE	65.63
V4W	56.62
PCT_ORG	48.55
XC	47.32
PCT_RI	41.04
PCAN_D	38.01
XDEPTH	32.68
PCT_SAFN	29.73
PCAN_M	28.84
XPCMG	25.44

USEPA Physical Habitat Cluster 10-cluster



$R_c = 0.679$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Misclassed	Percent Error	Cost
1	21	2	9.52	0.1
13	3	3	100	1
14	10	2	20	0.2
16	28	8	28.57	0.29
19	13	3	23.08	0.23
2	13	4	30.77	0.31
22	7	1	14.29	0.14
4	17	1	5.88	0.06
41	3	3	100	1
7	25	6	24	0.24
	140	33	0.235714	76.4

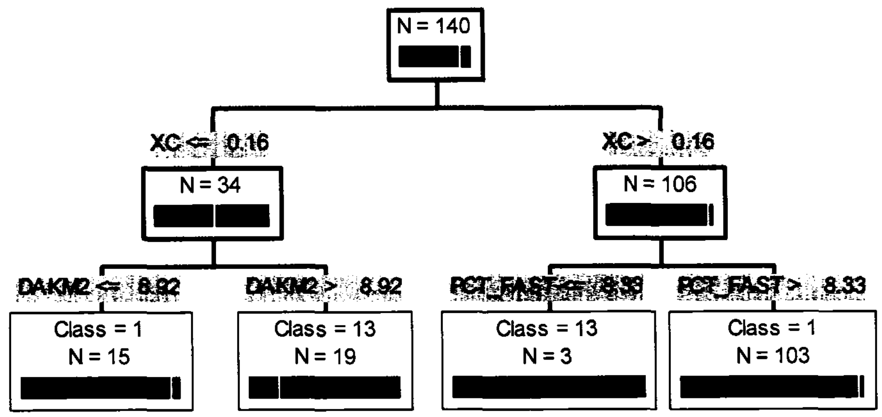
TEST SAMPLE

Class	N Class	Misclassed	Percent Error	Cost
1	21	14	66.67	0.67
13	3	1	33.33	0.33
14	10	6	60	0.6
16	28	14	50	0.5
19	13	5	38.46	0.38
2	13	9	69.23	0.69
22	7	3	42.86	0.43
4	17	11	64.71	0.65
41	3	2	66.67	0.67
7	25	11	44	0.44
	140	76	0.542857	45.7

VARIABLE IMPORTANCE

V1W	100
XC	93.15
XCDENBK	78.19
LWDTV33	71.05
V1W_MSQ	70.21
V4W	65.52
XBKF_W	63.81
XBKF_H	62.98
XSLOPE	59.22
PCT_RI	53.29
XDEPTH	53.23
PFC_LWD	38.13
PCT_SAFN	34.79
XPCMG	28.7
PCAN_C	27.72
PFC_OHV	25.86
LSUB_D50	21.4

All-metric 2-cluster



$R_c = 0.487$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	117	4	3.42	0.03
13	23	5	21.74	0.22
	140	9	0.064286	93.6

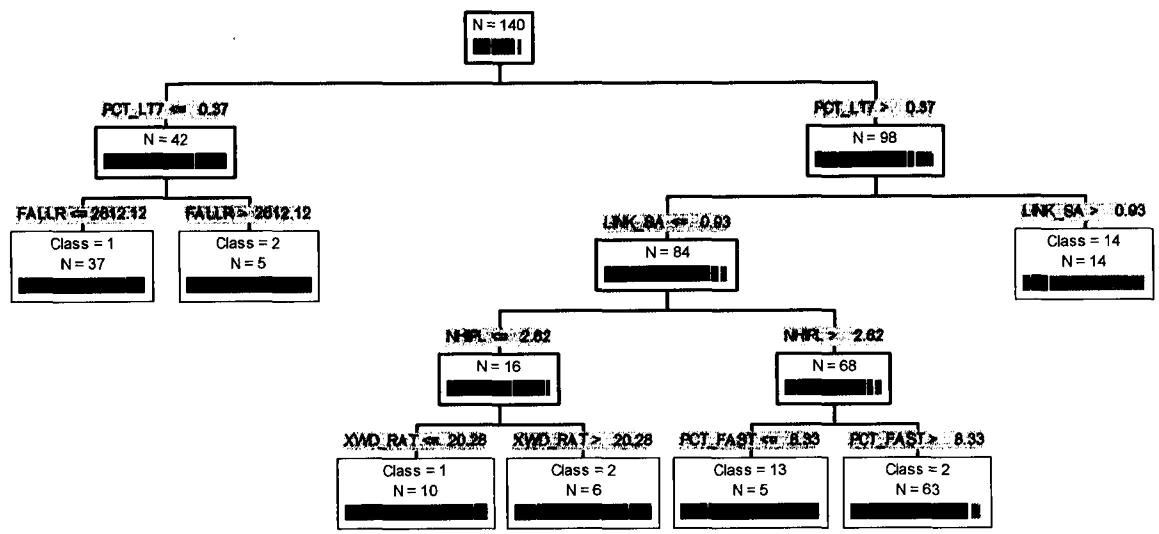
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	117	5	4.27	0.04
13	23	6	26.09	0.26
	140	11	0.078571	92.1

VARIABLE IMPORTANCE

DAKM2	100	||||||||||||||||||||||||||||||||||||||||
PCT_FAST	84.77	||||||||||||||||||||||||||||||||||
XC	82.89	||||||||||||||||||||||||||||||||||
XBKF_W	46.5	|||||||||||||||||||
XBKF_H	39.77	||||||||||||||||
XSLOPE	38.21	||||||||||||||||
XWD_RAT	30.87	|||||||||||||

All-metric 4-cluster



$R_c = 0.50$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	51	11	21.57	0.22
13	6	2	33.33	0.33
14	17	6	35.29	0.35
2	66	10	15.15	0.15
	140	29	0.207143	79.3

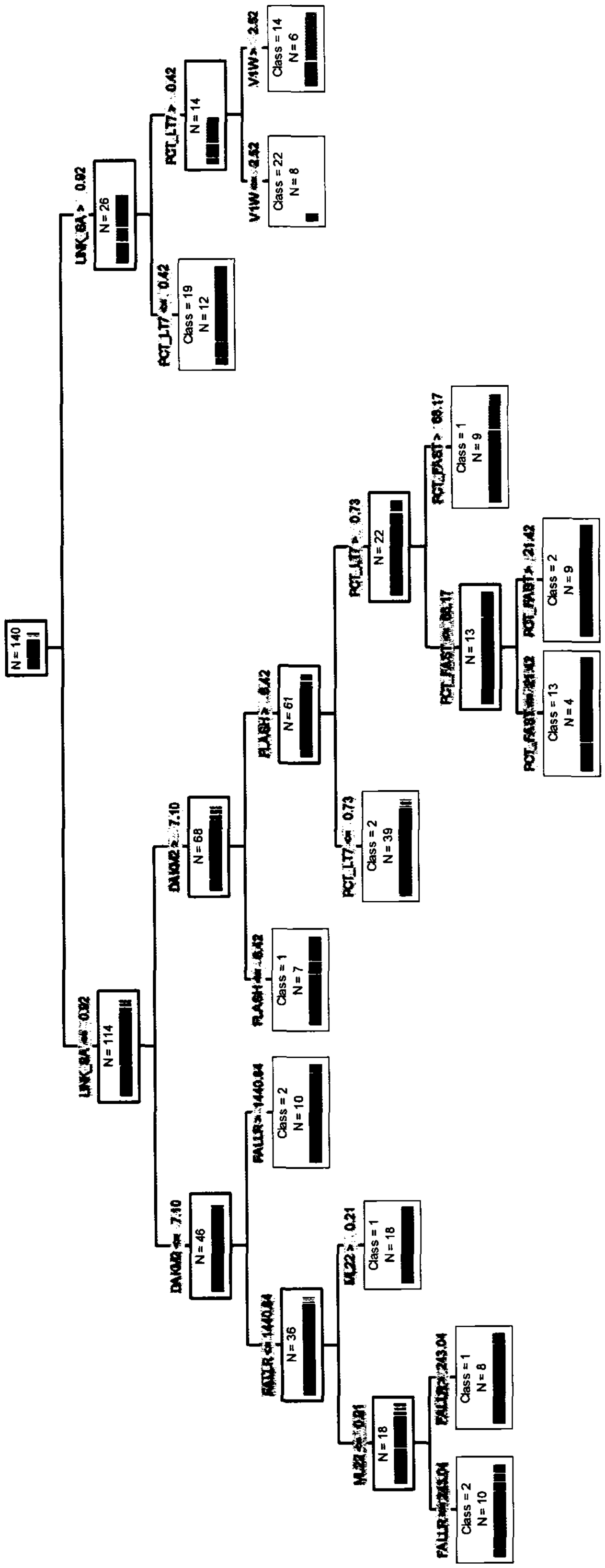
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	51	10	19.61	0.2
13	6	3	50	0.5
14	17	6	35.29	0.35
2	66	18	27.27	0.27
	140	37	0.264286	73.6

VARIABLE IMPORTANCE

PCT_LT7	100
LINK_SA	74.22
PCT_PR	65.09
MENTR	45.76
FALLR	43.35
MN1D	37.04
NHIPL	36.81
PCT_FAST	30.43
XBKF_W	25.54
XWD_RAT	25.35
XBKF_H	19.51
V1W	19.51
FH11	15.26
LWDTV33	14.05
XSLOPE	11.23
RISER	9.21
MH1	6.77
MX7D	6.66

All-metric 6-cluster



$R_c = 0.568$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	4	10.53	0.11
13	6	3	50	0.5
14	10	6	60	0.6
19	13	4	30.77	0.31
2	66	8	12.12	0.12
22	7	0	0	0
	140	25	0.178571	82.1

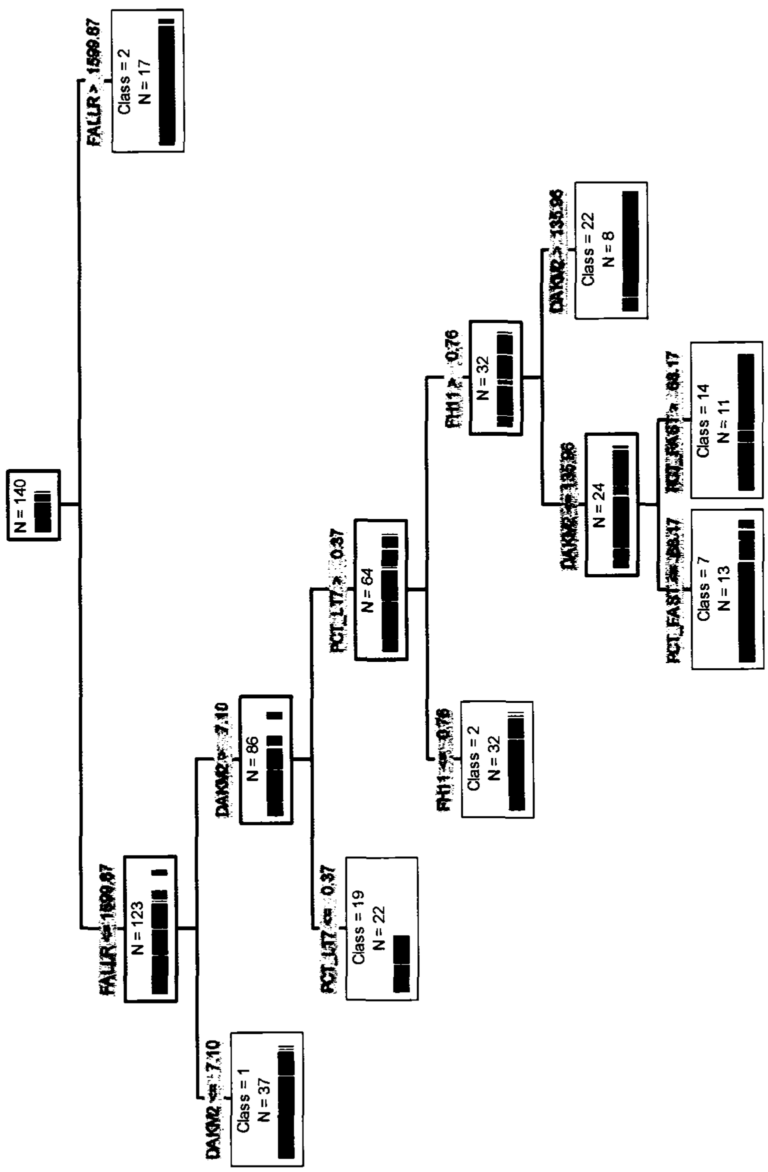
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	10	26.32	0.26
13	6	4	66.67	0.67
14	10	6	60	0.6
19	13	9	69.23	0.69
2	66	13	19.7	0.2
22	7	0	0	0
	140	42	0.3	70.0

VARIABLE IMPORTANCE

FALLR	100
PCT_PR	97.44
DAKM2	84.83
ML22	78.41
LINK_SA	76.24
PCT_LT7	75.51
RISER	67.97
FLASH	66.21
NHIPL	59.68
PCT_FAST	48.52
V1W	47.47
XBKF_H	47.47
MENTR	34.79
XBKF_W	34.46
LINK_SA4	28.25
BFWD_RAT	4.21

All-metric 8-cluster



$R_c = 0.556$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	12	31.58	0.32
13	3	3	100	1
14	10	4	40	0.4
19	13	1	7.69	0.08
2	41	7	17.07	0.17
22	7	0	0	0
41	3	3	100	1
7	25	16	64	0.64
	140	46	0.328571	67.1

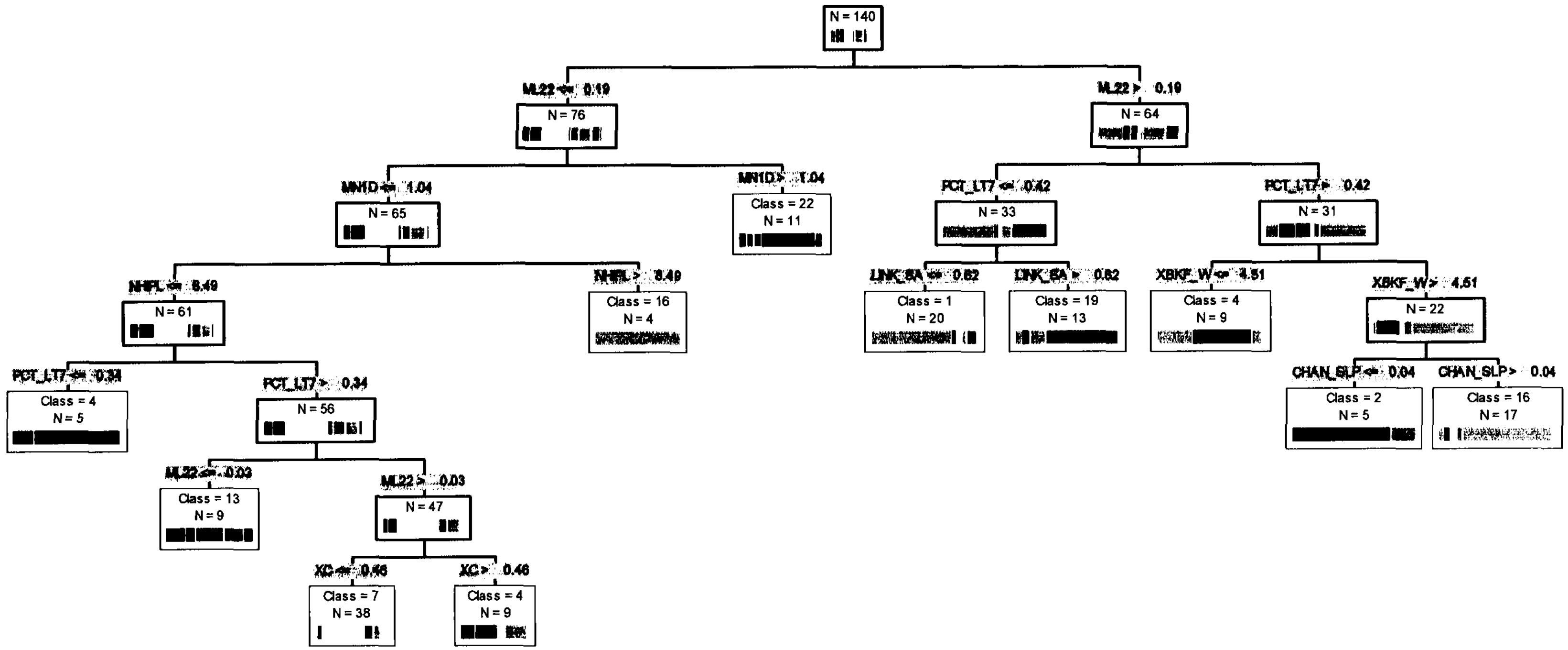
TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	38	13	34.21	0.34
13	3	3	100	1
14	10	5	50	0.5
19	13	2	15.38	0.15
2	41	12	29.27	0.29
22	7	0	0	0
41	3	3	100	1
7	25	17	68	0.68
	140	55	0.392857	60.7

VARIABLE IMPORTANCE

DAKM2	100
FALLR	75.46
LINK_SA	75.26
MX7D	69.3
RISER	68.63
PCT_LT7	61.62
MX3D	60.01
PCT_PR	58.76
ML22	38.39
FH11	38.23
MN1D	36.89
MA3	32.57
MH1	24.14
PCT_FAST	23.72
BFWD_RAT	22.79
XC	20.61
MN3D	17.64

All-metric 10-cluster



$R_c = 0.643$

MIS-CLASSIFICATION BY CLASS

LEARNING SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	21	6	28.57	0.29
13	3	0	0	0
14	10	10	100	1
16	28	11	39.29	0.39
19	13	4	30.77	0.31
2	13	9	69.23	0.69
22	7	0	0	0
4	17	5	29.41	0.29
41	3	3	100	1
7	25	3	12	0.12
	140	51	0.364286	63.6

TEST SAMPLE

Class	N Class	Mis-classed	Percent Error	Cost
1	21	9	42.86	0.43
13	3	1	33.33	0.33
14	10	7	70	0.7
16	28	14	50	0.5
19	13	6	46.15	0.46
2	13	9	69.23	0.69
22	7	1	14.29	0.14
4	17	10	58.82	0.59
41	3	3	100	1
7	25	12	48	0.48
	140	72	0.514286	48.6

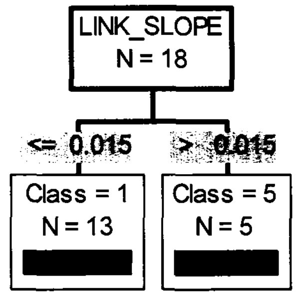
VARIABLE IMPORTANCE

MX7D	100
CHAN_SLP	88.94
LINK_SA	76.17
XBKF_W	75.21
FH11	61.53
PCT_LT7	54.51
NHIPL	54.2
ML22	53.05
MN1D	46.37
XC	42.36
XSLOPE	38.25
PCT_PR	30.77
MA3	14.26
PCT_FAST	3.14

APPENDIX F

OR-EMAP *A POSTERIORI* WITHIN ECOREGION CLASSIFICATION TREES

OR-EMAP, Blue Mountains



$R_c = 0.000$

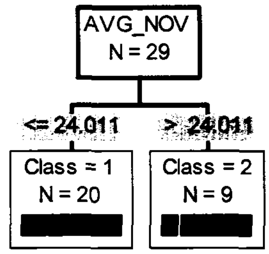
MIS-CLASSIFICATION BY CLASS
(Cross Validated)

Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.500	13.00	13	0.00	0	0.000
		(13.00	13	0.00	0	0.000)
5	0.500	5.00	5	0.00	0	0.000
		(5.00	5	0.00	0	0.000)
Total	1.000	18.00	18	0.00	0	
		(18.00	18	0.00	0)	

VARIABLE IMPORTANCE

Metric	Relative Importance
DAKM2	100.000
LINK_SLOPE	100.000
STRAH_AREA	100.000
PCT_LT7	73.333
MCON	73.333
CHAN_SLP	73.333

OR-EMAP, Cascades



$R_c = 0.234$

MIS-CLASSIFICATION BY CLASS (Cross Validated)						
	Prior	Weight		Weight		
Class	Probability	Count	Count	Mis-classed	Mis-classed	Cost
1	0.50000	22.00	22	2.00	2	0.09091
		(22.00	22	2.00	2	0.09091)
2	0.50000	7.00	7	0.00	0	0.00000
		(7.00	7	1.00	1	0.14286)
Total	1.00000	29.00	29	2.00	2	
		(29.00	29	3.00	3)	

VARIABLE IMPORTANCE	
Metric	Relative Importance
AVG_NOV	100.00000

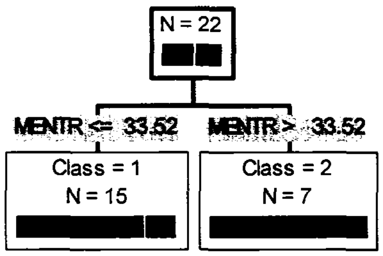
OR-EMAP, Klamath

CART was not able to produce a classification tree.

OR-EMAP, East Cascades Slopes and Foothills

CART was not able to produce a classification tree.

OR-EMAP, Coast Range



$R_c = 0.55$

MIS-CLASSIFICATION BY CLASS
(Cross Validated)

Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.50000	12.00	12	0.00	0	0.00000
		(12.00	12	3.00	3	0.25000)
2	0.50000	10.00	10	3.00	3	0.30000
		(10.00	10	3.00	3	0.30000)
Total	1.00000	22.00	22	3.00	3	
		(22.00	22	6.00	6)	

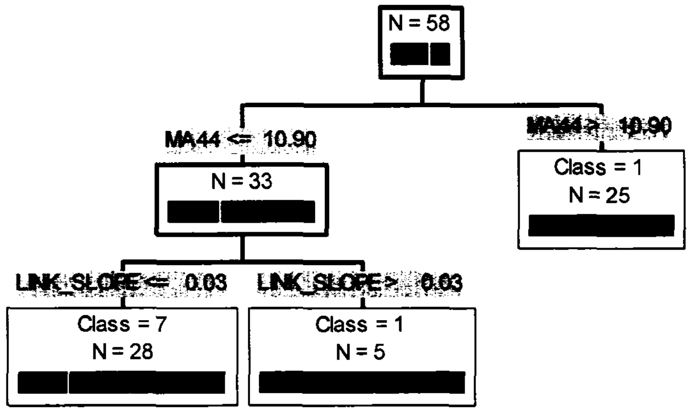
VARIABLE IMPORTANCE

Metric	Relative Importance
MENTR	100.00000

APPENDIX G

W-EMAP *A POSTERIORI* WITHIN ECOREGION CLASSIFICATION TREES

W-EMAP, Blue Mountains



$R_c = 0.264$

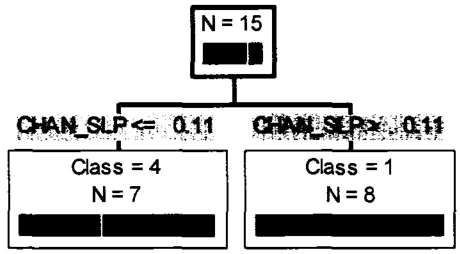
MIS-CLASSIFICATION BY CLASS
(Cross Validated)

Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.50000	37.00	37	7.00	7	0.18919
		(37.00	37	8.00	8	0.21622)
7	0.50000	21.00	21	0.00	0	0.00000
		(21.00	21	1.00	1	0.04762)
Total	1.00000	58.00	58	7.00	7	
		(58.00	58	9.00	9)	

VARIABLE IMPORTANCE

Metric	Relative Importance
MA44	100.00000
LINK_SLOPE	58.69149
FH11	55.38373

W-EMAP, Cascades



$R_c = 0.523$

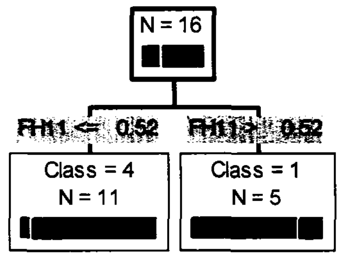
MIS-CLASSIFICATION BY CLASS
(Cross Validated)

Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.50000	11.00	11	5.00	5	0.45455
		(11.00	11	5.00	5	0.45455)
4	0.50000	4.00	4	0.00	0	0.00000
		(4.00	4	1.00	1	0.25000)
Total	1.00000	15.00	15	5.00	5	
		(15.00	15	6.00	6)	

VARIABLE IMPORTANCE

Metric	Relative Importance
LINK_SLOPE	100.00000

W-EMAP, Coast Range



$R_c = 0.291$

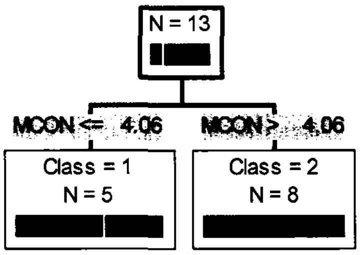
MIS-CLASSIFICATION BY CLASS
(Cross Validated)

Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.50000	5.00	5	1.00	1	0.20000
		(5.00	5	1.00	1	0.20000)
4	0.50000	11.00	11	1.00	1	0.09091
		(11.00	11	1.00	1	0.09091)
Total	1.00000	16.00	16	2.00	2	
		(16.00	16	2.00	2)	

VARIABLE IMPORTANCE

Metric	Relative Importance
FH11	100.00000

W-EMAP, Eastern Cascades Slopes and Foothills



$R_c = 0.533$

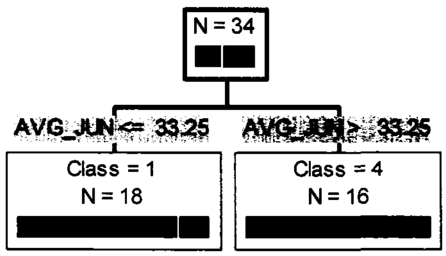
MIS-CLASSIFICATION BY CLASS (Cross Validated)						
Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.50000	3.00	3	0.00	0	0.00000
		(3.00	3	1.00	1	0.33333)
2	0.50000	10.00	10	2.00	2	0.20000
		(10.00	10	2.00	2	0.20000)
Total	1.00000	13.00	13	2.00	2	
		(13.00	13	3.00	3)	

VARIABLE IMPORTANCE	
Metric	Relative Importance
MCON	100.00001

OR-EMAP, Klamath

CART was not able to produce a classification tree.

W-EMAP, Northern Cascades



$R_c = 0.158$

MIS-CLASSIFICATION BY CLASS
(Cross Validated)

Class	Prior Probability	Weight Count	Count	Weight Mis-classed	Mis-classed	Cost
1	0.50000	15.00	15	0.00	0	0.00000
		(15.00	15	0.00	0	0.00000)
4	0.50000	19.00	19	3.00	3	0.15789
		(19.00	19	3.00	3	0.15789)
Total	1.00000	34.00	34	3.00	3	
		(34.00	34	3.00	3)	

VARIABLE IMPORTANCE

Metric	Relative Importance
AVG_JUN	100.00000

APPENDIX H

OR-EMAP CORRELATION MATRIX

Table P.1a: OR-EMAP correlation matrix (Columns 1 through 12).

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8	Column 9	Column 10	Column 11	Column 12
Type	Name	chan_slp	DA	DWSP1	DWSP2	link_sa	link_sa4	link_slope	MCON	MDW_A_025	MDW_A_1
MEAN		0.099	87.981	0.050	0.050	0.534	0.054	0.025	4.739	0.013	0.102
STD		0.074	343.080	0.039	0.020	1.216	0.041	0.028	3.578	0.037	0.709
CORR	chan_slp	**1.00**	-0.24	0.33	**0.54**	-0.27	0.26	**0.62**	0.29	0.21	-0.02
CORR	DA	-0.24	**1.00**	-0.17	-0.04	**0.89**	0.05	-0.17	-0.08	-0.07	-0.03
CORR	DWSP1	0.33	-0.17	**1.00**	**0.54**	0.08	**0.86**	**0.61**	0.30	0.00	-0.14
CORR	DWSP2	**0.54**	-0.04	**0.54**	**1.00**	0.06	0.46	0.36	0.37	0.05	-0.08
CORR	link_sa	-0.27	**0.89**	0.08	0.06	**1.00**	0.31	-0.14	-0.05	-0.11	-0.06
CORR	link_sa4	0.26	0.05	**0.86**	0.46	0.31	**1.00**	**0.66**	0.26	-0.03	-0.15
CORR	link_slope	**0.62**	-0.17	**0.61**	0.36	-0.14	**0.66**	**1.00**	0.27	0.15	-0.09
CORR	MCON	0.29	-0.08	0.30	0.37	-0.05	0.26	0.27	**1.00**	-0.11	-0.08
CORR	MDW_A_025	0.21	-0.07	0.00	0.05	-0.11	-0.03	0.15	-0.11	**1.00**	0.30
CORR	MDW_A_1	-0.02	-0.03	-0.14	-0.08	-0.06	-0.15	-0.09	-0.08	0.30	**1.00**
CORR	MDW_A_25	0.01	-0.04	-0.13	-0.08	-0.07	-0.14	-0.07	-0.06	0.28	**0.99**
CORR	MDW_SA_025	0.16	-0.04	0.07	0.03	-0.07	0.04	0.22	-0.08	**0.78**	0.08
CORR	MDW_SA_1	-0.01	-0.03	-0.14	-0.08	-0.06	-0.15	-0.08	-0.08	0.34	**1.00**
CORR	MDW_SA_25	0.01	-0.04	-0.13	-0.08	-0.07	-0.14	-0.07	-0.06	0.28	**0.99**
CORR	MDW_SA0_4_025	0.12	-0.03	0.08	-0.01	-0.05	0.05	0.21	-0.06	**0.62**	0.03
CORR	MDW_SA0_4_1	0.11	-0.03	0.09	0.00	-0.05	0.05	0.22	-0.07	**0.62**	0.06
CORR	MDW_SA0_4_25	0.30	-0.11	-0.05	-0.04	-0.16	-0.06	0.22	0.03	0.45	**0.69**
CORR	MENTCC	-0.27	**0.73**	0.05	0.09	**0.73**	0.19	-0.15	0.40	-0.16	-0.07
CORR	MENTR	-0.06	-0.04	-0.07	0.03	-0.05	-0.12	0.00	-0.43	0.00	-0.01
CORR	min_elev	0.28	-0.07	0.08	-0.06	-0.09	0.10	0.16	-0.02	0.16	0.18
CORR	pct_C	0.09	0.03	0.18	**0.52**	0.14	0.20	-0.07	-0.09	-0.03	-0.06
CORR	pct_lt4	***-0.65***	0.14	-0.43	***-0.83***	0.09	-0.34	-0.49	-0.40	-0.16	0.05
CORR	pct_lt7	***-0.64***	0.11	-0.45	***-0.89***	0.03	-0.37	-0.46	-0.44	-0.10	0.09
CORR	pct_PB	-0.49	0.40	-0.06	-0.04	0.46	-0.07	-0.44	-0.25	-0.23	-0.09
CORR	pct_PR	***-0.64***	0.15	-0.43	***-0.79***	0.10	-0.33	-0.47	-0.34	-0.16	0.04
CORR	pct_SP	**0.66**	-0.17	0.42	**0.75**	-0.14	0.31	0.50	0.36	0.18	-0.03
CORR	Pred	-0.10	-0.10	-0.05	-0.14	-0.10	-0.04	0.08	0.03	-0.01	0.00
CORR	slp_elon	**0.51**	-0.19	0.11	0.21	-0.25	0.07	0.42	0.19	0.26	0.00

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8	Column 9	Column 10	Column 11	Column 12
Type	Name	chan_slp	DA	DWSP1	DWSP2	link_sa	link_sa4	link_slope	MCON	MDW_A_025	MDW_A_1
CORR	Avg_Jun	-0.30	**0.80**	-0.12	0.03	**0.81**	0.08	-0.24	-0.20	-0.11	-0.05
CORR	Avg_Nov	-0.32	0.35	0.02	0.09	0.48	0.12	-0.20	-0.16	-0.10	-0.04
CORR	Avg_Oct	-0.32	0.49	-0.02	0.07	**0.58**	0.12	-0.22	-0.22	-0.12	-0.05
CORR	BaseQ	-0.07	0.00	0.05	-0.08	0.02	0.09	-0.07	-0.10	0.07	0.03
CORR	Dh12	0.23	-0.07	0.39	0.33	-0.06	0.37	0.41	0.11	0.15	-0.03
CORR	DHiPl	0.09	0.18	-0.13	-0.09	0.11	-0.10	-0.11	-0.05	-0.08	0.11
CORR	FallR	0.34	-0.20	0.04	-0.02	-0.25	0.05	0.49	0.05	0.12	-0.08
CORR	Fh11	0.07	0.20	0.03	0.05	0.19	0.00	-0.19	0.00	-0.05	0.16
CORR	Flash	-0.05	-0.13	0.13	0.15	-0.09	0.04	-0.02	0.40	-0.22	-0.05
CORR	Ma3	0.15	-0.08	0.29	0.27	-0.08	0.27	0.31	0.08	0.14	-0.06
CORR	Ma41	0.03	-0.17	0.15	0.11	-0.11	0.14	0.18	0.04	0.07	-0.11
CORR	Ma44	0.27	-0.06	0.35	0.36	-0.06	0.32	0.37	0.07	0.20	-0.02
CORR	MAR	-0.34	**0.63**	-0.05	0.07	**0.71**	0.11	-0.24	-0.17	-0.10	-0.05
CORR	Mh1	-0.30	0.41	0.02	0.11	**0.54**	0.14	-0.20	-0.17	-0.10	-0.05
CORR	Ml13	0.03	-0.12	-0.08	-0.01	-0.16	-0.16	0.04	0.32	-0.15	-0.03
CORR	Ml22	0.04	-0.07	-0.02	-0.07	-0.05	0.06	0.00	-0.15	0.08	-0.05
CORR	Mn1d	-0.18	0.32	-0.12	-0.10	0.34	0.01	-0.16	-0.21	-0.07	-0.03
CORR	Mn30d	-0.22	**0.55**	-0.14	-0.07	**0.55**	0.02	-0.18	-0.20	-0.08	-0.03
CORR	Mn3d	-0.20	0.49	-0.14	-0.08	0.49	0.01	-0.17	-0.20	-0.07	-0.03
CORR	Mn7d	-0.20	**0.50**	-0.14	-0.08	**0.50**	0.02	-0.18	-0.20	-0.08	-0.03
CORR	Mx1d	-0.32	0.33	-0.04	0.06	0.40	0.04	-0.22	-0.11	-0.09	-0.04
CORR	Mx3d	-0.33	0.45	-0.06	0.06	**0.51**	0.05	-0.22	-0.11	-0.09	-0.04
CORR	Mx7d	-0.33	0.49	-0.07	0.06	**0.55**	0.05	-0.23	-0.12	-0.09	-0.04
CORR	NHiPl	0.01	-0.20	0.23	0.12	-0.12	0.19	0.19	-0.01	0.15	-0.05
CORR	RiseR	-0.32	0.25	-0.02	0.07	0.34	0.04	-0.22	-0.09	-0.10	-0.04
CORR	BFWD_RAT	-0.45	0.42	0.00	0.01	0.49	0.05	-0.33	-0.08	-0.15	-0.02
CORR	LSUB_D50	0.00	0.08	0.14	0.27	0.08	0.15	0.07	0.23	0.12	-0.10
CORR	LSUB_D84	0.07	-0.07	0.23	0.26	-0.08	0.17	0.22	0.29	0.16	-0.11
CORR	LWDTV33	-0.06	-0.05	0.02	-0.02	-0.05	0.03	0.08	-0.01	-0.07	-0.05
CORR	PCAN_C	0.25	0.12	0.03	-0.06	0.05	0.01	0.17	0.02	0.04	-0.06
CORR	PCAN_D	-0.34	-0.01	-0.18	-0.06	0.03	-0.18	-0.28	-0.10	-0.12	-0.11

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8	Column 9	Column 10	Column 11	Column 12
Type	Name	chan_slp	DA	DWSP1	DWSP2	link_sa	link_sa4	link_slope	MCON	MDW_A_025	MDW_A_1
CORR	PCAN_M	0.16	-0.13	0.29	0.24	-0.13	0.28	0.25	0.24	0.07	-0.10
CORR	PCT_FAST	0.41	-0.15	0.23	0.22	-0.18	0.23	0.28	0.27	0.10	-0.04
CORR	PCT_ORG	0.07	-0.11	0.02	-0.09	-0.15	0.12	0.19	-0.17	-0.13	-0.04
CORR	pct_pool	-0.22	-0.07	-0.19	-0.23	-0.11	-0.22	-0.03	-0.09	-0.08	-0.04
CORR	PCT_RI	0.22	-0.05	-0.01	-0.03	-0.10	-0.02	0.02	0.07	0.05	0.02
CORR	PCT_SAFN	-0.24	0.01	-0.36	-0.34	-0.06	-0.35	-0.25	-0.23	-0.16	0.01
CORR	PCT_SLOW	-0.38	0.12	-0.23	-0.29	0.11	-0.22	-0.25	-0.24	-0.08	0.05
CORR	pfc_big	0.17	0.05	0.20	0.31	0.06	0.20	0.21	0.30	-0.02	-0.41
CORR	pfc_lwd	0.16	-0.21	0.10	-0.09	-0.23	0.11	0.29	0.03	0.04	-0.16
CORR	pfc_ohv	0.08	-0.24	0.04	-0.14	-0.21	0.03	0.08	-0.10	-0.10	-0.21
CORR	V1W	-0.09	-0.04	-0.03	-0.04	-0.05	-0.02	0.02	-0.02	-0.07	-0.05
CORR	v1w_msq	0.41	-0.16	0.22	0.03	-0.19	0.25	0.50	0.09	0.03	-0.08
CORR	V4W	-0.10	-0.04	-0.03	-0.05	-0.04	-0.02	0.01	-0.03	-0.07	-0.04
CORR	XBKF_H	-0.18	0.49	0.01	0.16	0.50	0.10	-0.07	0.00	-0.08	-0.10
CORR	XBKF_W	-0.44	**0.72**	-0.06	0.10	**0.79**	0.08	-0.32	-0.14	-0.14	-0.06
CORR	XC	0.14	-0.15	0.16	0.16	-0.14	0.14	0.17	0.18	-0.04	-0.16
CORR	XCDENBK	0.21	***-0.54***	0.26	0.10	***-0.52***	0.17	0.36	0.32	-0.03	-0.40
CORR	XDEPTH	-0.40	0.29	-0.12	-0.01	0.30	-0.06	-0.38	-0.21	-0.10	-0.03
CORR	xfc_big	0.09	-0.01	0.32	0.25	0.05	0.34	0.28	0.06	-0.03	-0.13
CORR	XPCMG	0.16	-0.21	0.27	0.17	-0.21	0.17	0.27	0.21	-0.01	-0.41
CORR	XSLOPE	**0.61**	-0.17	0.37	0.35	-0.20	0.37	**0.76**	0.32	0.23	-0.06
CORR	xwd_rat	-0.36	**0.54**	-0.07	-0.04	**0.61**	0.04	-0.19	-0.05	-0.12	-0.10
CORR	xwidth	-0.43	**0.71**	-0.05	0.04	**0.79**	0.10	-0.30	-0.13	-0.12	-0.06

bold text = values that are greater than 0.5

bold and italic text = values that are less than -0.5

Table P.1b: OR-EMAP correlation matrix (Columns 1, 2, and 13 through 19).

Column 1	Column 2	Column 13	Column 14	Column 15	Column 16	Column 17	Column 18	Column 19
Type	Name	MDW_A_25	MDW_SA_025	MDW_SA_1	MDW_SA_25	MDW_SA0_4_025	MDW_SA0_4_1	MDW_SA0_4_25
MEAN		0.714	0.001	0.027	0.711	0.000	0.000	0.134
STD		3.685	0.004	0.192	3.686	0.000	0.000	0.305
CORR	chan_slp	0.01	0.16	-0.01	0.01	0.12	0.11	0.30
CORR	DA	-0.04	-0.04	-0.03	-0.04	-0.03	-0.03	-0.11
CORR	DWSP1	-0.13	0.07	-0.14	-0.13	0.08	0.09	-0.05
CORR	DWSP2	-0.08	0.03	-0.08	-0.08	-0.01	0.00	-0.04
CORR	link_sa	-0.07	-0.07	-0.06	-0.07	-0.05	-0.05	-0.16
CORR	link_sa4	-0.14	0.04	-0.15	-0.14	0.05	0.05	-0.06
CORR	link_slope	-0.07	0.22	-0.08	-0.07	0.21	0.22	0.22
CORR	MCON	-0.06	-0.08	-0.08	-0.06	-0.06	-0.07	0.03
CORR	MDW_A_025	0.28	**0.78**	0.34	0.28	**0.62**	**0.62**	0.45
CORR	MDW_A_1	**0.99**	0.08	**1.00**	**0.99**	0.03	0.06	**0.69**
CORR	MDW_A_25	**1.00**	0.05	**0.99**	**1.00**	0.01	0.04	**0.72**
CORR	MDW_SA_025	0.05	**1.00**	0.13	0.05	**0.97**	**0.97**	0.30
CORR	MDW_SA_1	**0.99**	0.13	**1.00**	**0.99**	0.08	0.11	**0.70**
CORR	MDW_SA_25	**1.00**	0.05	**0.99**	**1.00**	0.01	0.04	**0.72**
CORR	MDW_SA0_4_025	0.01	**0.97**	0.08	0.01	**1.00**	**1.00**	0.26
CORR	MDW_SA0_4_1	0.04	**0.97**	0.11	0.04	**1.00**	**1.00**	0.28
CORR	MDW_SA0_4_25	**0.72**	0.30	**0.70**	**0.72**	0.26	0.28	**1.00**
CORR	MENTCC	-0.08	-0.10	-0.08	-0.08	-0.08	-0.09	-0.19
CORR	MENTR	-0.01	0.02	-0.01	-0.01	0.03	0.07	0.03
CORR	min_elev	0.18	0.12	0.18	0.18	0.10	0.11	0.21
CORR	pct_C	-0.06	-0.05	-0.06	-0.06	-0.07	-0.05	-0.18
CORR	pct_lt4	0.03	-0.17	0.03	0.03	-0.14	-0.15	-0.18
CORR	pct_lt7	0.08	-0.10	0.08	0.07	-0.07	-0.08	-0.09
CORR	pct_PB	-0.11	-0.13	-0.10	-0.12	-0.09	-0.08	-0.34
CORR	pct_PR	0.02	-0.16	0.03	0.02	-0.13	-0.14	-0.19
CORR	pct_SP	-0.01	0.18	-0.02	-0.01	0.14	0.15	0.23
CORR	Pred	-0.01	-0.01	0.01	-0.01	-0.03	-0.04	-0.12
CORR	slp_elon	0.02	0.18	0.00	0.02	0.13	0.12	0.43

Column 1	Column 2	Column 13	Column 14	Column 15	Column 16	Column 17	Column 18	Column 19
Type	Name	MDW_A_25	MDW_SA_025	MDW_SA_1	MDW_SA_25	MDW_SA0_4_025	MDW_SA0_4_1	MDW_SA0_4_25
CORR	Avg_Jun	-0.06	-0.07	-0.05	-0.06	-0.05	-0.05	-0.17
CORR	Avg_Nov	-0.07	-0.06	-0.05	-0.07	-0.05	-0.05	-0.16
CORR	Avg_Oct	-0.07	-0.07	-0.06	-0.07	-0.05	-0.05	-0.18
CORR	BaseQ	0.04	-0.03	0.03	0.04	-0.03	-0.03	-0.05
CORR	Dh12	-0.02	0.21	-0.02	-0.02	0.18	0.20	0.11
CORR	DHiPl	0.12	-0.12	0.09	0.12	-0.10	-0.10	0.07
CORR	FallR	-0.07	0.07	-0.08	-0.07	0.06	0.05	0.21
CORR	Fh11	0.16	-0.07	0.15	0.16	-0.05	-0.04	-0.02
CORR	Flash	-0.04	-0.16	-0.06	-0.04	-0.11	-0.12	-0.13
CORR	Ma3	-0.05	0.26	-0.04	-0.05	0.24	0.25	0.09
CORR	Ma41	-0.10	0.14	-0.10	-0.10	0.13	0.13	0.01
CORR	Ma44	-0.02	0.24	0.00	-0.02	0.18	0.20	0.12
CORR	MAR	-0.07	-0.07	-0.05	-0.07	-0.05	-0.05	-0.17
CORR	Mh1	-0.06	-0.06	-0.05	-0.06	-0.05	-0.04	-0.16
CORR	Ml13	-0.01	-0.12	-0.03	0.00	-0.09	-0.10	0.07
CORR	Ml22	-0.04	0.12	-0.04	-0.04	0.12	0.12	0.05
CORR	Mn1d	-0.05	-0.04	-0.03	-0.05	-0.03	-0.04	-0.11
CORR	Mn30d	-0.05	-0.05	-0.04	-0.05	-0.04	-0.04	-0.12
CORR	Mn3d	-0.05	-0.05	-0.04	-0.05	-0.03	-0.04	-0.12
CORR	Mn7d	-0.05	-0.05	-0.04	-0.05	-0.04	-0.04	-0.12
CORR	Mx1d	-0.06	-0.07	-0.05	-0.06	-0.05	-0.05	-0.16
CORR	Mx3d	-0.06	-0.07	-0.05	-0.07	-0.05	-0.05	-0.16
CORR	Mx7d	-0.06	-0.07	-0.05	-0.06	-0.05	-0.05	-0.16
CORR	NHiPl	-0.05	0.25	-0.03	-0.05	0.23	0.24	0.03
CORR	RiseR	-0.07	-0.07	-0.05	-0.07	-0.05	-0.05	-0.16
CORR	BFWD_RAT	-0.05	-0.11	-0.03	-0.05	-0.08	-0.07	-0.24
CORR	LSUB_D50	-0.13	0.09	-0.10	-0.13	0.06	0.05	-0.19
CORR	LSUB_D84	-0.13	0.18	-0.10	-0.13	0.15	0.14	-0.09
CORR	LWDTV33	-0.01	-0.02	-0.05	-0.01	-0.01	0.00	-0.05
CORR	PCAN_C	-0.07	0.13	-0.05	-0.07	0.17	0.16	0.00
CORR	PCAN_D	-0.11	-0.11	-0.11	-0.11	-0.10	-0.10	-0.16

Column 1	Column 2	Column 13	Column 14	Column 15	Column 16	Column 17	Column 18	Column 19
Type	Name	MDW_A_25	MDW_SA_025	MDW_SA_1	MDW_SA_25	MDW_SA0_4_025	MDW_SA0_4_1	MDW_SA0_4_25
CORR	PCAN_M	-0.08	0.00	-0.10	-0.08	-0.03	-0.03	0.05
CORR	PCT_FAST	-0.02	0.06	-0.04	-0.02	0.03	0.04	0.10
CORR	PCT_ORG	-0.01	-0.12	-0.05	-0.01	-0.09	-0.09	0.05
CORR	pct_pool	-0.04	-0.05	-0.05	-0.04	-0.04	-0.05	0.01
CORR	PCT_RI	0.04	0.01	0.02	0.04	0.01	0.02	0.13
CORR	PCT_SAFN	0.02	-0.14	0.00	0.02	-0.10	-0.09	0.06
CORR	PCT_SLOW	0.03	-0.05	0.05	0.03	-0.03	-0.03	-0.08
CORR	pfc_big	-0.40	0.01	-0.41	-0.40	0.00	-0.01	-0.26
CORR	pfc_lwd	-0.14	0.05	-0.16	-0.14	0.04	0.04	-0.02
CORR	pfc_ohv	-0.20	0.04	-0.20	-0.20	0.09	0.09	-0.02
CORR	V1W	-0.01	-0.03	-0.05	-0.01	-0.01	-0.01	-0.04
CORR	v1w_msq	-0.05	0.10	-0.07	-0.05	0.13	0.13	0.23
CORR	V4W	0.00	-0.03	-0.05	0.00	-0.01	-0.01	-0.03
CORR	XBKF_H	-0.10	-0.10	-0.10	-0.10	-0.12	-0.11	-0.12
CORR	XBKF_W	-0.09	-0.10	-0.07	-0.09	-0.09	-0.08	-0.25
CORR	XC	-0.17	0.02	-0.16	-0.17	0.04	0.04	-0.02
CORR	XCDENBK	-0.38	0.04	-0.40	-0.38	0.05	0.04	-0.15
CORR	XDEPTH	-0.07	-0.11	-0.04	-0.07	-0.11	-0.10	-0.27
CORR	xfc_big	-0.13	-0.01	-0.13	-0.13	-0.01	0.01	-0.09
CORR	XPCMG	-0.40	0.07	-0.41	-0.40	0.09	0.08	-0.17
CORR	XSLOPE	-0.05	0.30	-0.04	-0.05	0.28	0.28	0.18
CORR	xwd_rat	-0.11	-0.03	-0.10	-0.11	-0.01	-0.01	-0.19
CORR	xwidth	-0.08	-0.10	-0.06	-0.08	-0.08	-0.08	-0.24

bold text = values that are greater than 0.5
bold and italic text = values that are less than -0.5

Table P.1c: OR-EMAP correlation matrix (Columns 1, 2, and 20 through 29).

Column 1	Column 2	Column 20	Column 21	Column 22	Column 23	Column 24	Column 25	Column 26	Column 27	Column 28	Column 29
Type	Name	MENTCC	MENTR	min_elev	pct_C	pct_lt4	pct_lt7	pct_PB	pct_PR	pct_SP	Pred
MEAN		0.608	30.859	731.062	0.007	0.333	0.532	0.007	0.207	0.778	77.615
STD		0.838	26.636	567.575	0.012	0.200	0.230	0.009	0.148	0.149	67.338
CORR	chan_slp	-0.27	-0.06	0.28	0.09	***-0.65***	***-0.64***	-0.49	***-0.64***	**0.66**	-0.10
CORR	DA	**0.73**	-0.04	-0.07	0.03	0.14	0.11	0.40	0.15	-0.17	-0.10
CORR	DWSP1	0.05	-0.07	0.08	0.18	-0.43	-0.45	-0.06	-0.43	0.42	-0.05
CORR	DWSP2	0.09	0.03	-0.06	**0.52**	***-0.83***	***-0.89***	-0.04	***-0.79***	**0.75**	-0.14
CORR	link_sa	**0.73**	-0.05	-0.09	0.14	0.09	0.03	0.46	0.10	-0.14	-0.10
CORR	link_sa4	0.19	-0.12	0.10	0.20	-0.34	-0.37	-0.07	-0.33	0.31	-0.04
CORR	link_slope	-0.15	0.00	0.16	-0.07	-0.49	-0.46	-0.44	-0.47	0.50	0.08
CORR	MCON	0.40	-0.43	-0.02	-0.09	-0.40	-0.44	-0.25	-0.34	0.36	0.03
CORR	MDW_A_025	-0.16	0.00	0.16	-0.03	-0.16	-0.10	-0.23	-0.16	0.18	-0.01
CORR	MDW_A_1	-0.07	-0.01	0.18	-0.06	0.05	0.09	-0.09	0.04	-0.03	0.00
CORR	MDW_A_25	-0.08	-0.01	0.18	-0.06	0.03	0.08	-0.11	0.02	-0.01	-0.01
CORR	MDW_SA_025	-0.10	0.02	0.12	-0.05	-0.17	-0.10	-0.13	-0.16	0.18	-0.01
CORR	MDW_SA_1	-0.08	-0.01	0.18	-0.06	0.03	0.08	-0.10	0.03	-0.02	0.01
CORR	MDW_SA_25	-0.08	-0.01	0.18	-0.06	0.03	0.07	-0.12	0.02	-0.01	-0.01
CORR	MDW_SA0_4_025	-0.08	0.03	0.10	-0.07	-0.14	-0.07	-0.09	-0.13	0.14	-0.03
CORR	MDW_SA0_4_1	-0.09	0.07	0.11	-0.05	-0.15	-0.08	-0.08	-0.14	0.15	-0.04
CORR	MDW_SA0_4_25	-0.19	0.03	0.21	-0.18	-0.18	-0.09	-0.34	-0.19	0.23	-0.12
CORR	MENTCC	**1.00**	-0.30	-0.10	-0.01	0.04	-0.02	0.38	0.06	-0.09	0.03
CORR	MENTR	-0.30	**1.00**	-0.01	0.27	0.03	0.00	0.16	0.03	-0.06	-0.20
CORR	min_elev	-0.10	-0.01	**1.00**	-0.06	0.11	0.08	-0.06	0.11	-0.10	-0.21
CORR	pct_C	-0.01	0.27	-0.06	**1.00**	-0.26	-0.34	0.07	-0.22	0.13	-0.09
CORR	pct_lt4	0.04	0.03	0.11	-0.26	**1.00**	**0.95**	0.28	**0.97**	***-0.97***	0.10
CORR	pct_lt7	-0.02	0.00	0.08	-0.34	**0.95**	**1.00**	0.21	**0.88**	***-0.87***	0.06
CORR	pct_PB	0.38	0.16	-0.06	0.07	0.28	0.21	**1.00**	0.26	-0.33	-0.07
CORR	pct_PR	0.06	0.03	0.11	-0.22	**0.97**	**0.88**	0.26	**1.00**	***-0.99***	0.14
CORR	pct_SP	-0.09	-0.06	-0.10	0.13	***-0.97***	***-0.87***	-0.33	***-0.99***	**1.00**	-0.13
CORR	Pred	0.03	-0.20	-0.21	-0.09	0.10	0.06	-0.07	0.14	-0.13	**1.00**
CORR	slp_elon	-0.21	0.04	0.07	-0.14	-0.43	-0.38	-0.44	-0.44	0.47	0.04

Column 1	Column 2	Column 20	Column 21	Column 22	Column 23	Column 24	Column 25	Column 26	Column 27	Column 28	Column 29
Type	Name	MENTCC	MENTR	min_elev	pct_C	pct_lt4	pct_lt7	pct_PB	pct_PR	pct_SP	Pred
CORR	Avg_Jun	**0.53**	0.19	-0.12	0.30	0.14	0.07	0.41	0.17	-0.22	-0.15
CORR	Avg_Nov	0.19	0.04	-0.34	0.22	-0.01	-0.06	0.25	0.02	-0.05	0.00
CORR	Avg_Oct	0.29	0.15	-0.30	0.31	0.07	0.00	0.30	0.09	-0.14	-0.07
CORR	BaseQ	-0.03	0.17	0.42	0.19	0.29	0.22	0.04	0.29	-0.31	-0.15
CORR	Dh12	-0.01	0.13	-0.05	0.05	-0.24	-0.27	-0.18	-0.21	0.22	-0.05
CORR	DHiPl	0.03	0.11	**0.55**	-0.07	0.09	0.09	0.28	0.06	-0.07	-0.24
CORR	FallR	-0.25	0.08	-0.13	-0.13	-0.22	-0.17	-0.49	-0.23	0.27	0.20
CORR	Fh11	0.22	-0.12	0.39	-0.09	0.12	0.11	0.41	0.09	-0.11	-0.10
CORR	Flash	0.15	-0.41	-0.30	-0.16	-0.23	-0.21	0.01	-0.20	0.21	0.12
CORR	Ma3	-0.02	0.09	-0.21	0.07	-0.23	-0.25	-0.19	-0.21	0.21	-0.02
CORR	Ma41	-0.18	0.14	-0.46	0.19	-0.15	-0.17	-0.37	-0.14	0.15	0.08
CORR	Ma44	-0.02	0.14	-0.02	0.11	-0.23	-0.27	-0.16	-0.20	0.20	-0.04
CORR	MAR	0.40	0.06	-0.28	0.21	0.04	-0.01	0.35	0.07	-0.11	-0.06
CORR	Mh1	0.24	0.08	-0.31	0.25	-0.01	-0.06	0.28	0.01	-0.05	-0.02
CORR	Ml13	0.03	-0.25	-0.33	-0.19	-0.25	-0.20	-0.21	-0.21	0.23	0.08
CORR	Ml22	-0.16	0.28	0.23	0.26	0.14	0.09	-0.16	0.16	-0.17	-0.14
CORR	Mn1d	0.13	0.23	0.02	0.20	0.22	0.17	0.16	0.26	-0.28	-0.12
CORR	Mn30d	0.31	0.21	-0.01	0.18	0.21	0.15	0.26	0.24	-0.27	-0.14
CORR	Mn3d	0.27	0.22	0.00	0.18	0.21	0.16	0.22	0.25	-0.27	-0.13
CORR	Mn7d	0.28	0.22	0.00	0.18	0.21	0.16	0.23	0.24	-0.27	-0.14
CORR	Mx1d	0.22	-0.01	-0.34	0.15	0.00	-0.05	0.24	0.03	-0.05	0.04
CORR	Mx3d	0.30	0.00	-0.32	0.15	0.01	-0.03	0.28	0.04	-0.07	0.00
CORR	Mx7d	0.33	0.00	-0.32	0.15	0.02	-0.03	0.30	0.04	-0.08	0.00
CORR	NHiPl	-0.12	-0.01	-0.43	0.16	-0.17	-0.16	-0.33	-0.15	0.16	0.09
CORR	RiseR	0.18	-0.02	-0.38	0.16	-0.02	-0.06	0.20	0.01	-0.04	0.05
CORR	BFWD_RAT	0.40	-0.01	-0.32	0.10	0.15	0.09	0.42	0.17	-0.21	-0.02
CORR	LSUB_D50	0.16	-0.05	-0.16	0.13	-0.23	-0.25	-0.07	-0.22	0.21	0.03
CORR	LSUB_D84	0.10	-0.12	-0.17	-0.01	-0.27	-0.28	-0.20	-0.23	0.24	0.19
CORR	LWDTV33	-0.07	0.01	-0.20	0.00	-0.02	-0.04	-0.07	0.01	-0.01	0.20
CORR	PCAN_C	0.04	-0.02	**0.62**	-0.05	0.08	0.05	-0.03	0.08	-0.07	-0.05
CORR	PCAN_D	-0.01	0.09	***-0.50***	0.02	0.05	0.01	0.16	0.08	-0.09	0.16

Column 1	Column 2	Column 20	Column 21	Column 22	Column 23	Column 24	Column 25	Column 26	Column 27	Column 28	Column 29
Type	Name	MENTCC	MENTR	min_elev	pct_C	pct_lt4	pct_lt7	pct_PB	pct_PR	pct_SP	Pred
CORR	PCAN_M	0.00	-0.12	-0.31	0.10	-0.28	-0.21	-0.32	-0.31	0.32	-0.11
CORR	PCT_FAST	-0.09	-0.10	0.32	0.18	-0.19	-0.17	-0.29	-0.20	0.20	-0.02
CORR	PCT_ORG	-0.22	0.11	0.21	0.14	0.09	0.10	-0.16	0.08	-0.08	-0.02
CORR	pct_pool	-0.14	0.00	-0.36	-0.23	0.03	0.07	-0.13	0.06	-0.03	0.10
CORR	PCT_RI	-0.07	-0.05	0.15	-0.13	0.06	0.07	-0.12	0.03	-0.01	-0.03
CORR	PCT_SAFN	-0.09	0.05	-0.07	-0.06	0.25	0.28	0.09	0.26	-0.26	0.03
CORR	PCT_SLOW	0.07	-0.04	-0.31	-0.21	0.22	0.21	0.16	0.25	-0.24	0.06
CORR	pfc_big	0.16	0.01	-0.09	0.09	-0.30	-0.33	-0.16	-0.31	0.31	0.05
CORR	pfc_lwd	-0.26	0.12	-0.12	0.07	-0.07	-0.05	-0.43	-0.05	0.07	0.09
CORR	pfc_ohv	-0.19	0.17	0.04	0.09	0.06	0.10	-0.14	0.05	-0.05	-0.05
CORR	V1W	-0.06	0.02	-0.20	-0.03	-0.01	-0.01	-0.06	0.03	-0.02	0.15
CORR	v1w_msq	-0.17	0.12	0.08	-0.06	-0.17	-0.14	-0.39	-0.18	0.21	-0.02
CORR	V4W	-0.06	0.02	-0.21	-0.04	0.00	-0.01	-0.06	0.03	-0.02	0.15
CORR	XBKF_H	0.37	0.10	-0.32	0.14	-0.10	-0.14	0.17	-0.06	0.04	-0.02
CORR	XBKF_W	**0.54**	0.15	-0.34	0.23	0.06	-0.01	0.49	0.10	-0.15	-0.09
CORR	XC	-0.03	0.12	-0.32	0.09	-0.20	-0.20	-0.27	-0.23	0.24	-0.05
CORR	XCDENBK	-0.30	-0.11	-0.28	-0.05	-0.23	-0.19	***-0.50***	-0.25	0.28	0.11
CORR	XDEPTH	0.19	0.15	-0.24	0.29	0.18	0.11	0.29	0.22	-0.26	-0.08
CORR	xfc_big	-0.02	0.26	0.00	0.25	-0.20	-0.24	-0.19	-0.17	0.16	-0.09
CORR	XPCMG	-0.07	-0.03	-0.28	0.10	-0.27	-0.25	-0.41	-0.28	0.30	0.05
CORR	XSLOPE	-0.17	-0.07	0.34	-0.03	-0.45	-0.45	-0.42	-0.40	0.43	0.13
CORR	xwd_rat	0.45	-0.04	-0.40	0.06	0.07	0.05	0.28	0.10	-0.12	0.07
CORR	xwidth	**0.52**	0.06	-0.33	0.22	0.10	0.03	0.41	0.14	-0.18	-0.09

bold text = **values that are greater than 0.5**
bold and italic text = **values that are less than -0.5**

Table P.1d: OR-EMAP correlation matrix (Columns 1, 2, and 30 through 39).

Column 1	Column 2	Column 30	Column 31	Column 32	Column 33	Column 34	Column 35	Column 36	Column 37	Column 38	Column 39
Type	Name	slp_elon	Avg_Jun	Avg_Nov	Avg_Oct	BaseQ	Dh12	DHiPl	FallR	Fh11	Flash
MEAN		0.640	41.345	63.268	20.025	0.090	508.301	7.762	1727.173	0.572	12.214
STD		0.175	95.313	158.299	42.462	0.144	1248.274	4.974	2064.916	0.144	4.436
CORR	chan_slp	**0.51**	-0.30	-0.32	-0.32	-0.07	0.23	0.09	0.34	0.07	-0.05
CORR	DA	-0.19	**0.80**	0.35	0.49	0.00	-0.07	0.18	-0.20	0.20	-0.13
CORR	DWSP1	0.11	-0.12	0.02	-0.02	0.05	0.39	-0.13	0.04	0.03	0.13
CORR	DWSP2	0.21	0.03	0.09	0.07	-0.08	0.33	-0.09	-0.02	0.05	0.15
CORR	link_sa	-0.25	**0.81**	0.48	**0.58**	0.02	-0.06	0.11	-0.25	0.19	-0.09
CORR	link_sa4	0.07	0.08	0.12	0.12	0.09	0.37	-0.10	0.05	0.00	0.04
CORR	link_slope	0.42	-0.24	-0.20	-0.22	-0.07	0.41	-0.11	0.49	-0.19	-0.02
CORR	MCON	0.19	-0.20	-0.16	-0.22	-0.10	0.11	-0.05	0.05	0.00	0.40
CORR	MDW_A_025	0.26	-0.11	-0.10	-0.12	0.07	0.15	-0.08	0.12	-0.05	-0.22
CORR	MDW_A_1	0.00	-0.05	-0.04	-0.05	0.03	-0.03	0.11	-0.08	0.16	-0.05
CORR	MDW_A_25	0.02	-0.06	-0.07	-0.07	0.04	-0.02	0.12	-0.07	0.16	-0.04
CORR	MDW_SA_025	0.18	-0.07	-0.06	-0.07	-0.03	0.21	-0.12	0.07	-0.07	-0.16
CORR	MDW_SA_1	0.00	-0.05	-0.05	-0.06	0.03	-0.02	0.09	-0.08	0.15	-0.06
CORR	MDW_SA_25	0.02	-0.06	-0.07	-0.07	0.04	-0.02	0.12	-0.07	0.16	-0.04
CORR	MDW_SA0_4_025	0.13	-0.05	-0.05	-0.05	-0.03	0.18	-0.10	0.06	-0.05	-0.11
CORR	MDW_SA0_4_1	0.12	-0.05	-0.05	-0.05	-0.03	0.20	-0.10	0.05	-0.04	-0.12
CORR	MDW_SA0_4_25	0.43	-0.17	-0.16	-0.18	-0.05	0.11	0.07	0.21	-0.02	-0.13
CORR	MENTCC	-0.21	**0.53**	0.19	0.29	-0.03	-0.01	0.03	-0.25	0.22	0.15
CORR	MENTR	0.04	0.19	0.04	0.15	0.17	0.13	0.11	0.08	-0.12	-0.41
CORR	min_elev	0.07	-0.12	-0.34	-0.30	0.42	-0.05	**0.55**	-0.13	0.39	-0.30
CORR	pct_C	-0.14	0.30	0.22	0.31	0.19	0.05	-0.07	-0.13	-0.09	-0.16
CORR	pct_lt4	-0.43	0.14	-0.01	0.07	0.29	-0.24	0.09	-0.22	0.12	-0.23
CORR	pct_lt7	-0.38	0.07	-0.06	0.00	0.22	-0.27	0.09	-0.17	0.11	-0.21
CORR	pct_PB	-0.44	0.41	0.25	0.30	0.04	-0.18	0.28	-0.49	0.41	0.01
CORR	pct_PR	-0.44	0.17	0.02	0.09	0.29	-0.21	0.06	-0.23	0.09	-0.20
CORR	pct_SP	0.47	-0.22	-0.05	-0.14	-0.31	0.22	-0.07	0.27	-0.11	0.21
CORR	Pred	0.04	-0.15	0.00	-0.07	-0.15	-0.05	-0.24	0.20	-0.10	0.12
CORR	slp_elon	**1.00**	-0.21	-0.30	-0.24	-0.05	0.23	-0.13	**0.54**	-0.12	-0.11

Column 1	Column 2	Column 30	Column 31	Column 32	Column 33	Column 34	Column 35	Column 36	Column 37	Column 38	Column 39
Type	Name	slp_elon	Avg_Jun	Avg_Nov	Avg_Oct	BaseQ	Dh12	DHiPl	FallR	Fh11	Flash
CORR	Avg_Jun	-0.21	**1.00**	**0.55**	**0.77**	0.26	-0.03	0.08	-0.30	0.07	-0.29
CORR	Avg_Nov	-0.30	**0.55**	**1.00**	**0.85**	-0.08	0.05	-0.15	-0.26	-0.10	0.04
CORR	Avg_Oct	-0.24	**0.77**	**0.85**	**1.00**	0.09	0.16	-0.13	-0.30	-0.07	-0.17
CORR	BaseQ	-0.05	0.26	-0.08	0.09	**1.00**	-0.07	0.09	-0.19	0.24	-0.37
CORR	Dh12	0.23	-0.03	0.05	0.16	-0.07	**1.00**	-0.22	-0.06	-0.12	-0.13
CORR	DHiPl	-0.13	0.08	-0.15	-0.13	0.09	-0.22	**1.00**	-0.33	0.36	-0.11
CORR	FallR	**0.54**	-0.30	-0.26	-0.30	-0.19	-0.06	-0.33	**1.00**	-0.45	-0.09
CORR	Fh11	-0.12	0.07	-0.10	-0.07	0.24	-0.12	0.36	-0.45	**1.00**	0.16
CORR	Flash	-0.11	-0.29	0.04	-0.17	-0.37	-0.13	-0.11	-0.09	0.16	**1.00**
CORR	Ma3	0.18	-0.04	0.11	0.23	-0.18	**0.94**	-0.33	-0.07	-0.21	-0.05
CORR	Ma41	0.12	0.01	0.25	0.36	-0.15	0.49	***-0.53***	0.22	***-0.55***	-0.17
CORR	Ma44	0.27	-0.02	0.03	0.13	-0.03	**0.97**	-0.26	-0.03	-0.09	-0.21
CORR	MAR	-0.32	**0.75**	**0.94**	**0.85**	-0.03	-0.01	-0.04	-0.30	-0.01	-0.03
CORR	Mh1	-0.28	**0.62**	**0.98**	**0.90**	-0.04	0.09	-0.13	-0.28	-0.07	-0.02
CORR	Ml13	0.16	-0.27	-0.13	-0.27	-0.49	-0.17	-0.09	0.26	-0.23	**0.70**
CORR	Ml22	0.04	0.34	0.05	0.31	**0.68**	0.12	-0.02	-0.11	-0.21	***-0.56***
CORR	Mn1d	-0.08	**0.72**	0.29	0.45	**0.54**	-0.10	0.06	-0.18	-0.05	-0.32
CORR	Mn30d	-0.11	**0.87**	0.34	**0.53**	0.46	-0.10	0.07	-0.20	0.01	-0.32
CORR	Mn3d	-0.09	**0.83**	0.30	**0.50**	0.48	-0.10	0.06	-0.19	0.00	-0.33
CORR	Mn7d	-0.10	**0.84**	0.31	**0.51**	0.48	-0.10	0.06	-0.19	0.00	-0.33
CORR	Mx1d	-0.32	0.45	**0.95**	**0.71**	-0.13	-0.01	-0.12	-0.26	-0.09	0.14
CORR	Mx3d	-0.33	**0.55**	**0.96**	**0.74**	-0.11	-0.02	-0.08	-0.27	-0.06	0.09
CORR	Mx7d	-0.33	**0.58**	**0.95**	**0.75**	-0.10	-0.02	-0.08	-0.27	-0.04	0.08
CORR	NHiPl	0.10	-0.11	0.13	0.18	-0.17	0.42	***-0.73***	0.18	-0.40	-0.04
CORR	RiseR	-0.32	0.40	**0.96**	**0.71**	-0.15	0.02	-0.17	-0.25	-0.13	0.17
CORR	BFWD_RAT	-0.33	0.47	**0.62**	**0.66**	-0.06	-0.01	-0.12	-0.33	0.03	0.02
CORR	LSUB_D50	-0.08	0.09	0.07	0.07	0.03	-0.01	-0.22	0.06	-0.20	-0.08
CORR	LSUB_D84	0.01	-0.14	-0.07	-0.14	-0.11	0.16	-0.25	0.11	-0.21	0.07
CORR	LWDTV33	-0.11	-0.06	0.08	0.02	-0.08	0.13	-0.14	0.03	-0.18	0.16
CORR	PCAN_C	0.05	-0.02	-0.22	-0.18	0.21	-0.14	0.26	0.08	0.20	-0.27
CORR	PCAN_D	-0.07	0.16	0.34	0.32	-0.14	-0.02	-0.20	0.01	-0.21	0.18

Column 1	Column 2	Column 30	Column 31	Column 32	Column 33	Column 34	Column 35	Column 36	Column 37	Column 38	Column 39
Type	Name	slp_elon	Avg_Jun	Avg_Nov	Avg_Oct	BaseQ	Dh12	DHiPl	FallR	Fh11	Flash
CORR	PCAN_M	0.03	-0.18	-0.08	-0.12	-0.13	0.22	-0.29	0.03	-0.24	0.12
CORR	PCT_FAST	0.17	-0.25	-0.27	-0.22	0.07	0.15	0.04	0.09	-0.02	-0.19
CORR	PCT_ORG	-0.05	-0.09	-0.15	-0.10	0.06	-0.02	0.18	0.10	-0.11	-0.11
CORR	pct_pool	0.07	-0.12	0.15	0.04	-0.24	-0.04	-0.15	0.18	-0.30	0.26
CORR	PCT_RI	0.04	-0.18	-0.19	-0.14	-0.07	0.10	0.06	-0.05	0.11	-0.06
CORR	PCT_SAFN	-0.08	0.02	0.06	0.00	-0.13	-0.18	0.17	-0.05	-0.05	0.05
CORR	PCT_SLOW	-0.13	0.16	0.26	0.18	-0.09	-0.14	-0.07	-0.06	-0.03	0.25
CORR	pfc_big	0.01	-0.09	0.09	0.01	-0.15	0.11	-0.08	0.14	-0.16	0.04
CORR	pfc_lwd	-0.03	-0.23	0.02	-0.07	-0.13	0.10	-0.12	0.29	-0.39	-0.05
CORR	pfc_ohv	0.01	-0.17	-0.14	-0.20	-0.17	-0.18	-0.05	0.15	-0.13	-0.01
CORR	V1W	-0.12	-0.05	0.09	0.02	-0.08	0.10	-0.13	0.01	-0.17	0.15
CORR	v1w_msq	0.27	-0.23	-0.22	-0.22	-0.05	0.23	0.02	0.30	-0.22	-0.12
CORR	V4W	-0.11	-0.04	0.09	0.02	-0.07	0.10	-0.13	0.01	-0.17	0.15
CORR	XBKF_H	-0.07	0.49	0.36	0.37	-0.03	0.16	-0.17	-0.01	-0.08	0.02
CORR	XBKF_W	-0.33	**0.80**	**0.72**	**0.75**	-0.02	-0.02	-0.04	-0.32	0.03	-0.07
CORR	XC	0.07	-0.16	0.03	-0.03	-0.27	0.10	-0.22	0.20	-0.36	0.06
CORR	XCDENBK	0.23	-0.49	-0.22	-0.28	-0.08	0.12	-0.45	0.40	-0.49	0.17
CORR	XDEPTH	-0.29	**0.60**	**0.53**	**0.58**	0.24	-0.05	-0.06	-0.35	-0.17	-0.12
CORR	xfc_big	0.01	-0.01	0.11	0.01	-0.15	0.14	-0.07	0.08	-0.25	0.01
CORR	XPCMG	0.05	-0.17	0.03	-0.04	-0.07	0.08	-0.44	0.27	-0.43	0.09
CORR	XSLOPE	0.41	-0.26	-0.24	-0.27	-0.04	0.25	0.06	0.39	-0.14	-0.08
CORR	xwd_rat	-0.28	0.49	**0.51**	0.49	-0.21	-0.05	-0.13	-0.13	-0.04	0.05
CORR	xwidth	-0.36	**0.79**	**0.78**	**0.77**	-0.04	-0.04	-0.05	-0.32	-0.01	-0.03

bold text **= values that are greater than 0.5**
bold and italic text **= values that are less than -0.5**

Table P.1e: OR-EMAP correlation matrix (Columns 1, 2, and 40 through 49).

Column 1	Column 2	Column 40	Column 41	Column 42	Column 43	Column 44	Column 45	Column 46	Column 47	Column 48	Column 49
Type	Name	Ma3	Ma41	Ma44	MAR	Mh1	Ml13	Ml22	Mn1d	Mn30d	Mn3d
MEAN		2.354	42.726	196.580	60.763	82.642	1.416	0.640	3.432	4.619	3.859
STD		2.263	29.550	641.216	140.391	205.627	0.892	1.052	12.842	15.814	13.942
CORR	chan_slp	0.15	0.03	0.27	-0.34	-0.30	0.03	0.04	-0.18	-0.22	-0.20
CORR	DA	-0.08	-0.17	-0.06	**0.63**	0.41	-0.12	-0.07	0.32	**0.55**	0.49
CORR	DWSP1	0.29	0.15	0.35	-0.05	0.02	-0.08	-0.02	-0.12	-0.14	-0.14
CORR	DWSP2	0.27	0.11	0.36	0.07	0.11	-0.01	-0.07	-0.10	-0.07	-0.08
CORR	link_sa	-0.08	-0.11	-0.06	**0.71**	**0.54**	-0.16	-0.05	0.34	**0.55**	0.49
CORR	link_sa4	0.27	0.14	0.32	0.11	0.14	-0.16	0.06	0.01	0.02	0.01
CORR	link_slope	0.31	0.18	0.37	-0.24	-0.20	0.04	0.00	-0.16	-0.18	-0.17
CORR	MCON	0.08	0.04	0.07	-0.17	-0.17	0.32	-0.15	-0.21	-0.20	-0.20
CORR	MDW_A_025	0.14	0.07	0.20	-0.10	-0.10	-0.15	0.08	-0.07	-0.08	-0.07
CORR	MDW_A_1	-0.06	-0.11	-0.02	-0.05	-0.05	-0.03	-0.05	-0.03	-0.03	-0.03
CORR	MDW_A_25	-0.05	-0.10	-0.02	-0.07	-0.06	-0.01	-0.04	-0.05	-0.05	-0.05
CORR	MDW_SA_025	0.26	0.14	0.24	-0.07	-0.06	-0.12	0.12	-0.04	-0.05	-0.05
CORR	MDW_SA_1	-0.04	-0.10	0.00	-0.05	-0.05	-0.03	-0.04	-0.03	-0.04	-0.04
CORR	MDW_SA_25	-0.05	-0.10	-0.02	-0.07	-0.06	0.00	-0.04	-0.05	-0.05	-0.05
CORR	MDW_SA0_4_025	0.24	0.13	0.18	-0.05	-0.05	-0.09	0.12	-0.03	-0.04	-0.03
CORR	MDW_SA0_4_1	0.25	0.13	0.20	-0.05	-0.04	-0.10	0.12	-0.04	-0.04	-0.04
CORR	MDW_SA0_4_25	0.09	0.01	0.12	-0.17	-0.16	0.07	0.05	-0.11	-0.12	-0.12
CORR	MENTCC	-0.02	-0.18	-0.02	0.40	0.24	0.03	-0.16	0.13	0.31	0.27
CORR	MENTR	0.09	0.14	0.14	0.06	0.08	-0.25	0.28	0.23	0.21	0.22
CORR	min_elev	-0.21	-0.46	-0.02	-0.28	-0.31	-0.33	0.23	0.02	-0.01	0.00
CORR	pct_C	0.07	0.19	0.11	0.21	0.25	-0.19	0.26	0.20	0.18	0.18
CORR	pct_lt4	-0.23	-0.15	-0.23	0.04	-0.01	-0.25	0.14	0.22	0.21	0.21
CORR	pct_lt7	-0.25	-0.17	-0.27	-0.01	-0.06	-0.20	0.09	0.17	0.15	0.16
CORR	pct_PB	-0.19	-0.37	-0.16	0.35	0.28	-0.21	-0.16	0.16	0.26	0.22
CORR	pct_PR	-0.21	-0.14	-0.20	0.07	0.01	-0.21	0.16	0.26	0.24	0.25
CORR	pct_SP	0.21	0.15	0.20	-0.11	-0.05	0.23	-0.17	-0.28	-0.27	-0.27
CORR	Pred	-0.02	0.08	-0.04	-0.06	-0.02	0.08	-0.14	-0.12	-0.14	-0.13
CORR	slp_elon	0.18	0.12	0.27	-0.32	-0.28	0.16	0.04	-0.08	-0.11	-0.09

Column 1	Column 2	Column 40	Column 41	Column 42	Column 43	Column 44	Column 45	Column 46	Column 47	Column 48	Column 49
Type	Name	Ma3	Ma41	Ma44	MAR	Mh1	Ml13	Ml22	Mn1d	Mn30d	Mn3d
CORR	Avg_Jun	-0.04	0.01	-0.02	**0.75**	**0.62**	-0.27	0.34	**0.72**	**0.87**	**0.83**
CORR	Avg_Nov	0.11	0.25	0.03	**0.94**	**0.98**	-0.13	0.05	0.29	0.34	0.30
CORR	Avg_Oct	0.23	0.36	0.13	**0.85**	**0.90**	-0.27	0.31	0.45	**0.53**	**0.50**
CORR	BaseQ	-0.18	-0.15	-0.03	-0.03	-0.04	-0.49	**0.68**	**0.54**	0.46	0.48
CORR	Dh12	**0.94**	0.49	**0.97**	-0.01	0.09	-0.17	0.12	-0.10	-0.10	-0.10
CORR	DHiPl	-0.33	***-0.53***	-0.26	-0.04	-0.13	-0.09	-0.02	0.06	0.07	0.06
CORR	FallR	-0.07	0.22	-0.03	-0.30	-0.28	0.26	-0.11	-0.18	-0.20	-0.19
CORR	Fh11	-0.21	***-0.55***	-0.09	-0.01	-0.07	-0.23	-0.21	-0.05	0.01	0.00
CORR	Flash	-0.05	-0.17	-0.21	-0.03	-0.02	**0.70**	***-0.56***	-0.32	-0.32	-0.33
CORR	Ma3	**1.00**	**0.65**	**0.90**	0.02	0.14	-0.07	0.12	-0.16	-0.17	-0.17
CORR	Ma41	**0.65**	**1.00**	0.46	0.12	0.27	-0.09	0.32	-0.03	-0.07	-0.06
CORR	Ma44	**0.90**	0.46	**1.00**	-0.02	0.06	-0.22	0.12	-0.08	-0.09	-0.08
CORR	MAR	0.02	0.12	-0.02	**1.00**	**0.95**	-0.16	0.04	0.39	**0.51**	0.47
CORR	Mh1	0.14	0.27	0.06	**0.95**	**1.00**	-0.18	0.10	0.31	0.38	0.35
CORR	Ml13	-0.07	-0.09	-0.22	-0.16	-0.18	**1.00**	-0.48	-0.25	-0.25	-0.24
CORR	Ml22	0.12	0.32	0.12	0.04	0.10	-0.48	**1.00**	**0.66**	**0.55**	**0.59**
CORR	Mn1d	-0.16	-0.03	-0.08	0.39	0.31	-0.25	**0.66**	**1.00**	**0.95**	**0.97**
CORR	Mn30d	-0.17	-0.07	-0.09	**0.51**	0.38	-0.25	**0.55**	**0.95**	**1.00**	**1.00**
CORR	Mn3d	-0.17	-0.06	-0.08	0.47	0.35	-0.24	**0.59**	**0.97**	**1.00**	**1.00**
CORR	Mn7d	-0.17	-0.06	-0.09	0.47	0.35	-0.24	**0.58**	**0.97**	**1.00**	**1.00**
CORR	Mx1d	0.04	0.14	-0.03	**0.91**	**0.91**	-0.06	-0.05	0.23	0.27	0.24
CORR	Mx3d	0.02	0.11	-0.03	**0.95**	**0.93**	-0.07	-0.05	0.27	0.34	0.30
CORR	Mx7d	0.02	0.10	-0.03	**0.96**	**0.93**	-0.09	-0.06	0.28	0.37	0.33
CORR	NHiPl	**0.62**	**0.80**	0.43	0.01	0.13	-0.02	0.16	-0.14	-0.18	-0.17
CORR	RiseR	0.08	0.21	0.00	**0.88**	**0.91**	-0.03	-0.05	0.20	0.22	0.19
CORR	BFWD_RAT	0.04	0.15	-0.03	**0.63**	**0.62**	-0.17	0.00	0.19	0.25	0.22
CORR	LSUB_D50	0.00	0.16	0.00	0.09	0.06	-0.09	0.02	0.02	0.05	0.04
CORR	LSUB_D84	0.17	0.21	0.15	-0.09	-0.11	-0.01	-0.09	-0.16	-0.15	-0.16
CORR	LWDTV33	0.18	0.16	0.11	0.04	0.06	0.25	-0.02	-0.04	-0.05	-0.05
CORR	PCAN_C	-0.24	-0.27	-0.10	-0.13	-0.19	-0.23	0.12	-0.04	0.00	0.00
CORR	PCAN_D	0.06	0.19	-0.03	0.26	0.33	0.24	-0.04	0.17	0.13	0.13

Column 1	Column 2	Column 40	Column 41	Column 42	Column 43	Column 44	Column 45	Column 46	Column 47	Column 48	Column 49
Type	Name	Ma3	Ma41	Ma44	MAR	Mh1	Ml13	Ml22	Mn1d	Mn30d	Mn3d
CORR	PCAN_M	0.27	0.31	0.17	-0.12	-0.11	0.06	-0.01	-0.17	-0.19	-0.18
CORR	PCT_FAST	0.09	0.11	0.16	-0.29	-0.24	-0.13	0.11	-0.24	-0.26	-0.25
CORR	PCT_ORG	-0.05	-0.05	-0.06	-0.16	-0.14	0.00	0.16	-0.03	-0.05	-0.04
CORR	pct_pool	0.07	0.13	-0.05	0.08	0.10	0.39	-0.22	-0.12	-0.14	-0.14
CORR	PCT_RI	0.08	0.03	0.10	-0.19	-0.16	-0.02	0.00	-0.17	-0.17	-0.16
CORR	PCT_SAFN	-0.16	-0.20	-0.19	0.06	0.04	0.11	-0.08	0.07	0.05	0.05
CORR	PCT_SLOW	-0.05	-0.07	-0.14	0.25	0.21	0.16	-0.09	0.25	0.20	0.20
CORR	pfc_big	0.11	0.21	0.10	0.09	0.08	0.08	-0.12	-0.29	-0.24	-0.26
CORR	pfc_lwd	0.17	0.35	0.06	-0.07	-0.01	0.17	0.07	-0.18	-0.22	-0.21
CORR	pfc_ohv	-0.16	0.01	-0.19	-0.18	-0.17	0.06	0.10	0.01	-0.05	-0.03
CORR	V1W	0.15	0.14	0.08	0.06	0.06	0.26	-0.02	-0.03	-0.04	-0.04
CORR	v1w_msq	0.22	0.17	0.20	-0.24	-0.22	0.15	0.12	-0.15	-0.18	-0.17
CORR	V4W	0.15	0.14	0.08	0.06	0.07	0.26	-0.01	-0.02	-0.03	-0.03
CORR	XBKF_H	0.16	0.16	0.18	0.48	0.37	-0.02	-0.07	0.24	0.35	0.31
CORR	XBKF_W	0.00	0.07	-0.02	**0.86**	**0.73**	-0.17	-0.01	0.37	**0.54**	0.49
CORR	XC	0.15	0.31	0.06	-0.04	-0.01	0.08	-0.01	-0.17	-0.19	-0.19
CORR	XCDENBK	0.19	0.40	0.09	-0.39	-0.26	0.22	0.08	-0.22	-0.36	-0.32
CORR	XDEPTH	-0.04	0.10	-0.06	**0.56**	**0.52**	-0.25	0.37	**0.64**	**0.61**	**0.61**
CORR	xfc_big	0.13	0.24	0.11	0.10	0.06	-0.01	-0.03	-0.08	-0.07	-0.08
CORR	XPCMG	0.14	0.36	0.04	-0.06	-0.01	0.15	0.15	-0.07	-0.12	-0.11
CORR	XSLOPE	0.16	0.09	0.26	-0.26	-0.24	0.01	0.03	-0.16	-0.19	-0.18
CORR	xwd_rat	0.04	0.16	-0.05	**0.60**	**0.50**	0.05	-0.17	0.12	0.25	0.21
CORR	xwidth	-0.01	0.11	-0.05	**0.89**	**0.77**	-0.15	0.01	0.39	**0.53**	0.48

bold text = values that are greater than 0.5

bold and italic text = values that are less than -0.5

Table P.1f: OR-EMAP correlation matrix (Columns 1, 2, and 50 through 59).

Column 1	Column 2	Column 50	Column 51	Column 52	Column 53	Column 54	Column 55	Column 56	Column 57	Column 58	Column 59
Type	Name	Mn7d	Mx1d	Mx3d	Mx7d	NHiPl	RiseR	BFWD_RAT	LSUB_D50	LSUB_D84	LWDTV33
MEAN		4.020	797.897	604.752	421.543	6.874	37.809	11.231	1.639	2.601	111.898
STD		14.339	1927.307	1469.849	1049.760	2.774	89.006	6.152	0.881	0.947	252.973
CORR	chan_slp	-0.20	-0.32	-0.33	-0.33	0.01	-0.32	-0.45	0.00	0.07	-0.06
CORR	DA	**0.50**	0.33	0.45	0.49	-0.20	0.25	0.42	0.08	-0.07	-0.05
CORR	DWSP1	-0.14	-0.04	-0.06	-0.07	0.23	-0.02	0.00	0.14	0.23	0.02
CORR	DWSP2	-0.08	0.06	0.06	0.06	0.12	0.07	0.01	0.27	0.26	-0.02
CORR	link_sa	**0.50**	0.40	**0.51**	**0.55**	-0.12	0.34	0.49	0.08	-0.08	-0.05
CORR	link_sa4	0.02	0.04	0.05	0.05	0.19	0.04	0.05	0.15	0.17	0.03
CORR	link_slope	-0.18	-0.22	-0.22	-0.23	0.19	-0.22	-0.33	0.07	0.22	0.08
CORR	MCON	-0.20	-0.11	-0.11	-0.12	-0.01	-0.09	-0.08	0.23	0.29	-0.01
CORR	MDW_A_025	-0.08	-0.09	-0.09	-0.09	0.15	-0.10	-0.15	0.12	0.16	-0.07
CORR	MDW_A_1	-0.03	-0.04	-0.04	-0.04	-0.05	-0.04	-0.02	-0.10	-0.11	-0.05
CORR	MDW_A_25	-0.05	-0.06	-0.06	-0.06	-0.05	-0.07	-0.05	-0.13	-0.13	-0.01
CORR	MDW_SA_025	-0.05	-0.07	-0.07	-0.07	0.25	-0.07	-0.11	0.09	0.18	-0.02
CORR	MDW_SA_1	-0.04	-0.05	-0.05	-0.05	-0.03	-0.05	-0.03	-0.10	-0.10	-0.05
CORR	MDW_SA_25	-0.05	-0.06	-0.07	-0.06	-0.05	-0.07	-0.05	-0.13	-0.13	-0.01
CORR	MDW_SA0_4_025	-0.04	-0.05	-0.05	-0.05	0.23	-0.05	-0.08	0.06	0.15	-0.01
CORR	MDW_SA0_4_1	-0.04	-0.05	-0.05	-0.05	0.24	-0.05	-0.07	0.05	0.14	0.00
CORR	MDW_SA0_4_25	-0.12	-0.16	-0.16	-0.16	0.03	-0.16	-0.24	-0.19	-0.09	-0.05
CORR	MENTCC	0.28	0.22	0.30	0.33	-0.12	0.18	0.40	0.16	0.10	-0.07
CORR	MENTR	0.22	-0.01	0.00	0.00	-0.01	-0.02	-0.01	-0.05	-0.12	0.01
CORR	min_elev	0.00	-0.34	-0.32	-0.32	-0.43	-0.38	-0.32	-0.16	-0.17	-0.20
CORR	pct_C	0.18	0.15	0.15	0.15	0.16	0.16	0.10	0.13	-0.01	0.00
CORR	pct_lt4	0.21	0.00	0.01	0.02	-0.17	-0.02	0.15	-0.23	-0.27	-0.02
CORR	pct_lt7	0.16	-0.05	-0.03	-0.03	-0.16	-0.06	0.09	-0.25	-0.28	-0.04
CORR	pct_PB	0.23	0.24	0.28	0.30	-0.33	0.20	0.42	-0.07	-0.20	-0.07
CORR	pct_PR	0.24	0.03	0.04	0.04	-0.15	0.01	0.17	-0.22	-0.23	0.01
CORR	pct_SP	-0.27	-0.05	-0.07	-0.08	0.16	-0.04	-0.21	0.21	0.24	-0.01
CORR	Pred	-0.14	0.04	0.00	0.00	0.09	0.05	-0.02	0.03	0.19	0.20
CORR	slp_elon	-0.10	-0.32	-0.33	-0.33	0.10	-0.32	-0.33	-0.08	0.01	-0.11
CORR	Avg_Jun	**0.84**	0.45	**0.55**	**0.58**	-0.11	0.40	0.47	0.09	-0.14	-0.06

Column 1	Column 2	Column 50	Column 51	Column 52	Column 53	Column 54	Column 55	Column 56	Column 57	Column 58	Column 59
Type	Name	Mn7d	Mx1d	Mx3d	Mx7d	NHiPl	RiseR	BFWD_RAT	LSUB_D50	LSUB_D84	LWDTV33
CORR	Avg_Nov	0.31	**0.95**	**0.96**	**0.95**	0.13	**0.96**	**0.62**	0.07	-0.07	0.08
CORR	Avg_Oct	**0.51**	**0.71**	**0.74**	**0.75**	0.18	**0.71**	**0.66**	0.07	-0.14	0.02
CORR	BaseQ	0.48	-0.13	-0.11	-0.10	-0.17	-0.15	-0.06	0.03	-0.11	-0.08
CORR	Dh12	-0.10	-0.01	-0.02	-0.02	0.42	0.02	-0.01	-0.01	0.16	0.13
CORR	DHiPl	0.06	-0.12	-0.08	-0.08	***-0.73***	-0.17	-0.12	-0.22	-0.25	-0.14
CORR	FallR	-0.19	-0.26	-0.27	-0.27	0.18	-0.25	-0.33	0.06	0.11	0.03
CORR	Fh11	0.00	-0.09	-0.06	-0.04	-0.40	-0.13	0.03	-0.20	-0.21	-0.18
CORR	Flash	-0.33	0.14	0.09	0.08	-0.04	0.17	0.02	-0.08	0.07	0.16
CORR	Ma3	-0.17	0.04	0.02	0.02	**0.62**	0.08	0.04	0.00	0.17	0.18
CORR	Ma41	-0.06	0.14	0.11	0.10	**0.80**	0.21	0.15	0.16	0.21	0.16
CORR	Ma44	-0.09	-0.03	-0.03	-0.03	0.43	0.00	-0.03	0.00	0.15	0.11
CORR	MAR	0.47	**0.91**	**0.95**	**0.96**	0.01	**0.88**	**0.63**	0.09	-0.09	0.04
CORR	Mh1	0.35	**0.91**	**0.93**	**0.93**	0.13	**0.91**	**0.62**	0.06	-0.11	0.06
CORR	Ml13	-0.24	-0.06	-0.07	-0.09	-0.02	-0.03	-0.17	-0.09	-0.01	0.25
CORR	Ml22	**0.58**	-0.05	-0.05	-0.06	0.16	-0.05	0.00	0.02	-0.09	-0.02
CORR	Mn1d	**0.97**	0.23	0.27	0.28	-0.14	0.20	0.19	0.02	-0.16	-0.04
CORR	Mn30d	**1.00**	0.27	0.34	0.37	-0.18	0.22	0.25	0.05	-0.15	-0.05
CORR	Mn3d	**1.00**	0.24	0.30	0.33	-0.17	0.19	0.22	0.04	-0.16	-0.05
CORR	Mn7d	**1.00**	0.25	0.31	0.33	-0.17	0.20	0.22	0.04	-0.16	-0.05
CORR	Mx1d	0.25	**1.00**	**0.99**	**0.98**	0.07	**0.99**	**0.57**	0.08	-0.02	0.10
CORR	Mx3d	0.31	**0.99**	**1.00**	**1.00**	0.04	**0.97**	**0.57**	0.08	-0.05	0.09
CORR	Mx7d	0.33	**0.98**	**1.00**	**1.00**	0.03	**0.96**	**0.58**	0.09	-0.05	0.08
CORR	NHiPl	-0.17	0.07	0.04	0.03	**1.00**	0.13	0.06	0.18	0.25	0.19
CORR	RiseR	0.20	**0.99**	**0.97**	**0.96**	0.13	**1.00**	**0.57**	0.07	-0.01	0.13
CORR	BFWD_RAT	0.22	**0.57**	**0.57**	**0.58**	0.06	**0.57**	**1.00**	0.17	0.04	-0.06
CORR	LSUB_D50	0.04	0.08	0.08	0.09	0.18	0.07	0.17	**1.00**	**0.70**	-0.22
CORR	LSUB_D84	-0.16	-0.02	-0.05	-0.05	0.25	-0.01	0.04	**0.70**	**1.00**	-0.16
CORR	LWDTV33	-0.05	0.10	0.09	0.08	0.19	0.13	-0.06	-0.22	-0.16	**1.00**
CORR	PCAN_C	0.00	-0.22	-0.18	-0.18	-0.27	-0.26	-0.09	0.00	-0.12	-0.05
CORR	PCAN_D	0.13	0.33	0.29	0.28	0.09	0.36	0.27	-0.01	-0.01	0.12
CORR	PCAN_M	-0.18	-0.06	-0.07	-0.07	0.38	-0.04	-0.11	0.32	0.39	-0.03
CORR	PCT_FAST	-0.25	-0.28	-0.30	-0.30	0.01	-0.29	-0.17	0.13	0.06	-0.04

Column 1	Column 2	Column 50	Column 51	Column 52	Column 53	Column 54	Column 55	Column 56	Column 57	Column 58	Column 59
Type	Name	Mn7d	Mx1d	Mx3d	Mx7d	NHiPl	RiseR	BFWD_RAT	LSUB_D50	LSUB_D84	LWDTV33
CORR	PCT_ORG	-0.04	-0.14	-0.16	-0.17	-0.12	-0.14	-0.18	-0.38	-0.30	0.38
CORR	pct_pool	-0.14	0.17	0.16	0.15	0.13	0.21	-0.01	-0.14	-0.03	0.25
CORR	PCT_RI	-0.17	-0.20	-0.21	-0.21	-0.01	-0.20	0.03	0.01	-0.10	0.02
CORR	PCT_SAFN	0.05	0.13	0.11	0.11	-0.24	0.12	-0.03	***-0.62***	***-0.55***	0.24
CORR	PCT_SLOW	0.20	0.29	0.28	0.28	0.05	0.30	0.27	-0.16	-0.03	0.06
CORR	pfc_big	-0.25	0.11	0.11	0.11	0.14	0.11	0.00	0.40	0.32	0.08
CORR	pfc_lwd	-0.22	0.02	-0.01	-0.02	0.33	0.05	-0.15	0.11	0.16	0.39
CORR	pfc_ohv	-0.03	-0.09	-0.14	-0.15	0.04	-0.09	-0.14	-0.09	0.00	-0.01
CORR	V1W	-0.04	0.12	0.10	0.10	0.16	0.14	-0.04	-0.23	-0.17	**0.99**
CORR	v1w_msq	-0.17	-0.21	-0.22	-0.22	0.16	-0.21	-0.31	-0.02	0.03	0.18
CORR	V4W	-0.03	0.12	0.11	0.10	0.17	0.14	-0.03	-0.23	-0.17	**0.99**
CORR	XBKF_H	0.32	0.33	0.38	0.40	0.15	0.31	0.22	0.18	0.24	0.14
CORR	XBKF_W	**0.50**	**0.67**	**0.73**	**0.76**	-0.01	**0.63**	**0.68**	0.17	0.04	0.00
CORR	XC	-0.19	0.04	0.01	0.00	0.27	0.07	0.10	0.34	0.26	-0.03
CORR	XCDENBK	-0.33	-0.19	-0.27	-0.30	0.38	-0.13	-0.15	0.26	0.35	0.12
CORR	XDEPTH	**0.61**	**0.55**	**0.53**	**0.53**	0.00	**0.53**	0.47	0.07	0.03	-0.07
CORR	xfc_big	-0.08	0.11	0.11	0.10	0.26	0.12	0.03	0.23	0.28	0.20
CORR	XPCMG	-0.11	0.05	0.01	0.00	0.37	0.08	0.01	0.37	0.36	0.09
CORR	XSLOPE	-0.18	-0.24	-0.24	-0.24	0.00	-0.24	-0.30	0.19	0.34	0.01
CORR	xwd_rat	0.22	0.46	**0.50**	**0.52**	0.15	0.45	**0.67**	0.22	0.16	0.18
CORR	xwidth	0.49	**0.74**	**0.78**	**0.80**	0.03	**0.70**	**0.76**	0.16	0.05	-0.01

bold text = **values that are greater than 0.5**

bold and italic text = **values that are less than -0.5**

Table P.1g: OR-EMAP correlation matrix (Columns 1, 2, and 60 through 68).

Column 1	Column 2	Column 60	Column 61	Column 62	Column 63	Column 64	Column 65	Column 66	Column 67	Column 68
Type	Name	PCAN_C	PCAN_D	PCAN_M	PCT_FAST	PCT_ORG	pct_pool	PCT_RI	PCT_SAFN	PCT_SLOW
MEAN		0.282	0.278	0.312	53.708	3.067	24.316	40.784	19.265	44.975
STD		0.351	0.328	0.326	24.501	4.042	20.620	19.102	15.537	24.270
CORR	chan_slp	0.25	-0.34	0.16	0.41	0.07	-0.22	0.22	-0.24	-0.38
CORR	DA	0.12	-0.01	-0.13	-0.15	-0.11	-0.07	-0.05	0.01	0.12
CORR	DWSP1	0.03	-0.18	0.29	0.23	0.02	-0.19	-0.01	-0.36	-0.23
CORR	DWSP2	-0.06	-0.06	0.24	0.22	-0.09	-0.23	-0.03	-0.34	-0.29
CORR	link_sa	0.05	0.03	-0.13	-0.18	-0.15	-0.11	-0.10	-0.06	0.11
CORR	link_sa4	0.01	-0.18	0.28	0.23	0.12	-0.22	-0.02	-0.35	-0.22
CORR	link_slope	0.17	-0.28	0.25	0.28	0.19	-0.03	0.02	-0.25	-0.25
CORR	MCON	0.02	-0.10	0.24	0.27	-0.17	-0.09	0.07	-0.23	-0.24
CORR	MDW_A_025	0.04	-0.12	0.07	0.10	-0.13	-0.08	0.05	-0.16	-0.08
CORR	MDW_A_1	-0.06	-0.11	-0.10	-0.04	-0.04	-0.04	0.02	0.01	0.05
CORR	MDW_A_25	-0.07	-0.11	-0.08	-0.02	-0.01	-0.04	0.04	0.02	0.03
CORR	MDW_SA_025	0.13	-0.11	0.00	0.06	-0.12	-0.05	0.01	-0.14	-0.05
CORR	MDW_SA_1	-0.05	-0.11	-0.10	-0.04	-0.05	-0.05	0.02	0.00	0.05
CORR	MDW_SA_25	-0.07	-0.11	-0.08	-0.02	-0.01	-0.04	0.04	0.02	0.03
CORR	MDW_SA0_4_025	0.17	-0.10	-0.03	0.03	-0.09	-0.04	0.01	-0.10	-0.03
CORR	MDW_SA0_4_1	0.16	-0.10	-0.03	0.04	-0.09	-0.05	0.02	-0.09	-0.03
CORR	MDW_SA0_4_25	0.00	-0.16	0.05	0.10	0.05	0.01	0.13	0.06	-0.08
CORR	MENTCC	0.04	-0.01	0.00	-0.09	-0.22	-0.14	-0.07	-0.09	0.07
CORR	MENTR	-0.02	0.09	-0.12	-0.10	0.11	0.00	-0.05	0.05	-0.04
CORR	min_elev	**0.62**	***-0.50***	-0.31	0.32	0.21	-0.36	0.15	-0.07	-0.31
CORR	pct_C	-0.05	0.02	0.10	0.18	0.14	-0.23	-0.13	-0.06	-0.21
CORR	pct_lt4	0.08	0.05	-0.28	-0.19	0.09	0.03	0.06	0.25	0.22
CORR	pct_lt7	0.05	0.01	-0.21	-0.17	0.10	0.07	0.07	0.28	0.21
CORR	pct_PB	-0.03	0.16	-0.32	-0.29	-0.16	-0.13	-0.12	0.09	0.16
CORR	pct_PR	0.08	0.08	-0.31	-0.20	0.08	0.06	0.03	0.26	0.25
CORR	pct_SP	-0.07	-0.09	0.32	0.20	-0.08	-0.03	-0.01	-0.26	-0.24
CORR	Pred	-0.05	0.16	-0.11	-0.02	-0.02	0.10	-0.03	0.03	0.06
CORR	slp_elon	0.05	-0.07	0.03	0.17	-0.05	0.07	0.04	-0.08	-0.13

Column 1	Column 2	Column 60	Column 61	Column 62	Column 63	Column 64	Column 65	Column 66	Column 67	Column 68
Type	Name	PCAN_C	PCAN_D	PCAN_M	PCT_FAST	PCT_ORG	pct_pool	PCT_RI	PCT_SAFN	PCT_SLOW
CORR	Avg_Jun	-0.02	0.16	-0.18	-0.25	-0.09	-0.12	-0.18	0.02	0.16
CORR	Avg_Nov	-0.22	0.34	-0.08	-0.27	-0.15	0.15	-0.19	0.06	0.26
CORR	Avg_Oct	-0.18	0.32	-0.12	-0.22	-0.10	0.04	-0.14	0.00	0.18
CORR	BaseQ	0.21	-0.14	-0.13	0.07	0.06	-0.24	-0.07	-0.13	-0.09
CORR	Dh12	-0.14	-0.02	0.22	0.15	-0.02	-0.04	0.10	-0.18	-0.14
CORR	DHiPl	0.26	-0.20	-0.29	0.04	0.18	-0.15	0.06	0.17	-0.07
CORR	FallR	0.08	0.01	0.03	0.09	0.10	0.18	-0.05	-0.05	-0.06
CORR	Fh11	0.20	-0.21	-0.24	-0.02	-0.11	-0.30	0.11	-0.05	-0.03
CORR	Flash	-0.27	0.18	0.12	-0.19	-0.11	0.26	-0.06	0.05	0.25
CORR	Ma3	-0.24	0.06	0.27	0.09	-0.05	0.07	0.08	-0.16	-0.05
CORR	Ma41	-0.27	0.19	0.31	0.11	-0.05	0.13	0.03	-0.20	-0.07
CORR	Ma44	-0.10	-0.03	0.17	0.16	-0.06	-0.05	0.10	-0.19	-0.14
CORR	MAR	-0.13	0.26	-0.12	-0.29	-0.16	0.08	-0.19	0.06	0.25
CORR	Mh1	-0.19	0.33	-0.11	-0.24	-0.14	0.10	-0.16	0.04	0.21
CORR	Ml13	-0.23	0.24	0.06	-0.13	0.00	0.39	-0.02	0.11	0.16
CORR	Ml22	0.12	-0.04	-0.01	0.11	0.16	-0.22	0.00	-0.08	-0.09
CORR	Mn1d	-0.04	0.17	-0.17	-0.24	-0.03	-0.12	-0.17	0.07	0.25
CORR	Mn30d	0.00	0.13	-0.19	-0.26	-0.05	-0.14	-0.17	0.05	0.20
CORR	Mn3d	0.00	0.13	-0.18	-0.25	-0.04	-0.14	-0.16	0.05	0.20
CORR	Mn7d	0.00	0.13	-0.18	-0.25	-0.04	-0.14	-0.17	0.05	0.20
CORR	Mx1d	-0.22	0.33	-0.06	-0.28	-0.14	0.17	-0.20	0.13	0.29
CORR	Mx3d	-0.18	0.29	-0.07	-0.30	-0.16	0.16	-0.21	0.11	0.28
CORR	Mx7d	-0.18	0.28	-0.07	-0.30	-0.17	0.15	-0.21	0.11	0.28
CORR	NHiPl	-0.27	0.09	0.38	0.01	-0.12	0.13	-0.01	-0.24	0.05
CORR	RiseR	-0.26	0.36	-0.04	-0.29	-0.14	0.21	-0.20	0.12	0.30
CORR	BFWD_RAT	-0.09	0.27	-0.11	-0.17	-0.18	-0.01	0.03	-0.03	0.27
CORR	LSUB_D50	0.00	-0.01	0.32	0.13	-0.38	-0.14	0.01	***-0.62***	-0.16
CORR	LSUB_D84	-0.12	-0.01	0.39	0.06	-0.30	-0.03	-0.10	***-0.55***	-0.03
CORR	LWDTV33	-0.05	0.12	-0.03	-0.04	0.38	0.25	0.02	0.24	0.06
CORR	PCAN_C	**1.00**	***-0.59***	-0.41	0.24	0.12	-0.19	0.18	-0.09	-0.23
CORR	PCAN_D	***-0.59***	**1.00**	-0.32	-0.21	-0.09	0.23	-0.07	0.15	0.24

Column 1	Column 2	Column 60	Column 61	Column 62	Column 63	Column 64	Column 65	Column 66	Column 67	Column 68
Type	Name	PCAN_C	PCAN_D	PCAN_M	PCT_FAST	PCT_ORG	pct_pool	PCT_RI	PCT_SAFN	PCT_SLOW
CORR	PCAN_M	-0.41	-0.32	**1.00**	0.13	-0.01	-0.04	0.00	-0.21	-0.11
CORR	PCT_FAST	0.24	-0.21	0.13	**1.00**	0.15	***-0.60***	**0.60**	-0.26	***-0.90***
CORR	PCT_ORG	0.12	-0.09	-0.01	0.15	**1.00**	-0.05	0.12	0.39	-0.12
CORR	pct_pool	-0.19	0.23	-0.04	***-0.60***	-0.05	**1.00**	-0.42	0.28	**0.60**
CORR	PCT_RI	0.18	-0.07	0.00	**0.60**	0.12	-0.42	**1.00**	-0.13	***-0.50***
CORR	PCT_SAFN	-0.09	0.15	-0.21	-0.26	0.39	0.28	-0.13	**1.00**	0.31
CORR	PCT_SLOW	-0.23	0.24	-0.11	***-0.90***	-0.12	**0.60**	***-0.50***	0.31	**1.00**
CORR	pfc_big	0.12	-0.01	0.23	0.35	-0.01	-0.12	0.22	-0.30	-0.38
CORR	pfc_lwd	0.03	0.02	0.20	0.11	0.31	0.13	0.12	-0.04	-0.06
CORR	pfc_ohv	0.08	-0.06	0.08	0.16	0.26	-0.13	0.19	0.18	-0.11
CORR	V1W	-0.08	0.14	-0.04	-0.06	0.39	0.24	0.02	0.26	0.08
CORR	v1w_msq	0.25	-0.21	0.12	0.22	0.32	-0.01	0.27	-0.14	-0.19
CORR	V4W	-0.08	0.14	-0.04	-0.07	0.39	0.24	0.03	0.26	0.09
CORR	XBKF_H	-0.20	0.19	0.06	-0.33	-0.25	0.18	-0.26	-0.13	0.29
CORR	XBKF_W	-0.13	0.22	-0.10	-0.38	-0.21	0.06	-0.24	-0.02	0.26
CORR	XC	-0.16	0.02	0.48	0.02	0.08	0.00	0.08	-0.12	0.01
CORR	XCDENBK	-0.12	0.16	0.37	0.26	0.14	0.17	0.11	-0.13	-0.12
CORR	XDEPTH	-0.22	0.32	-0.09	-0.29	-0.12	0.02	-0.24	0.13	0.38
CORR	xfc_big	0.11	-0.21	0.25	0.05	0.19	-0.03	0.01	-0.20	-0.05
CORR	XPCMG	0.03	0.06	0.45	0.19	0.07	0.07	0.11	-0.18	-0.10
CORR	XSLOPE	0.35	-0.29	0.06	0.37	0.09	-0.06	0.04	-0.34	-0.33
CORR	xwd_rat	-0.08	0.18	0.00	-0.33	-0.18	0.19	-0.16	-0.06	0.34
CORR	xwidth	-0.12	0.26	-0.09	-0.31	-0.18	0.04	-0.20	0.00	0.32

bold text **= values that are greater than 0.5**
bold and italic text **= values that are less than -0.5**

Table P.1h: OR-EMAP correlation matrix (Columns 1, 2, and 69 through 78).

Column 1	Column 2	Column 69	Column 70	Column 71	Column 72	Column 73	Column 74	Column 75	Column 76	Column 77	Column 78
Type	Name	pfc_big	pfc_lwd	pfc_ohv	V1W	v1w_msq	V4W	XBKF_H	XBKF_W	XC	XCDENBK
MEAN		0.909	0.474	0.767	72.139	0.050	54.923	0.574	10.809	0.441	84.198
STD		0.192	0.314	0.275	181.775	0.072	144.451	0.366	11.460	0.263	19.387
CORR	chan_slp	0.17	0.16	0.08	-0.09	0.41	-0.10	-0.18	-0.44	0.14	0.21
CORR	DA	0.05	-0.21	-0.24	-0.04	-0.16	-0.04	0.49	**0.72**	-0.15	***-0.54***
CORR	DWSP1	0.20	0.10	0.04	-0.03	0.22	-0.03	0.01	-0.06	0.16	0.26
CORR	DWSP2	0.31	-0.09	-0.14	-0.04	0.03	-0.05	0.16	0.10	0.16	0.10
CORR	link_sa	0.06	-0.23	-0.21	-0.05	-0.19	-0.04	0.50	**0.79**	-0.14	***-0.52***
CORR	link_sa4	0.20	0.11	0.03	-0.02	0.25	-0.02	0.10	0.08	0.14	0.17
CORR	link_slope	0.21	0.29	0.08	0.02	0.50	0.01	-0.07	-0.32	0.17	0.36
CORR	MCON	0.30	0.03	-0.10	-0.02	0.09	-0.03	0.00	-0.14	0.18	0.32
CORR	MDW_A_025	-0.02	0.04	-0.10	-0.07	0.03	-0.07	-0.08	-0.14	-0.04	-0.03
CORR	MDW_A_1	-0.41	-0.16	-0.21	-0.05	-0.08	-0.04	-0.10	-0.06	-0.16	-0.40
CORR	MDW_A_25	-0.40	-0.14	-0.20	-0.01	-0.05	0.00	-0.10	-0.09	-0.17	-0.38
CORR	MDW_SA_025	0.01	0.05	0.04	-0.03	0.10	-0.03	-0.10	-0.10	0.02	0.04
CORR	MDW_SA_1	-0.41	-0.16	-0.20	-0.05	-0.07	-0.05	-0.10	-0.07	-0.16	-0.40
CORR	MDW_SA_25	-0.40	-0.14	-0.20	-0.01	-0.05	0.00	-0.10	-0.09	-0.17	-0.38
CORR	MDW_SA0_4_025	0.00	0.04	0.09	-0.01	0.13	-0.01	-0.12	-0.09	0.04	0.05
CORR	MDW_SA0_4_1	-0.01	0.04	0.09	-0.01	0.13	-0.01	-0.11	-0.08	0.04	0.04
CORR	MDW_SA0_4_25	-0.26	-0.02	-0.02	-0.04	0.23	-0.03	-0.12	-0.25	-0.02	-0.15
CORR	MENTCC	0.16	-0.26	-0.19	-0.06	-0.17	-0.06	0.37	**0.54**	-0.03	-0.30
CORR	MENTR	0.01	0.12	0.17	0.02	0.12	0.02	0.10	0.15	0.12	-0.11
CORR	min_elev	-0.09	-0.12	0.04	-0.20	0.08	-0.21	-0.32	-0.34	-0.32	-0.28
CORR	pct_C	0.09	0.07	0.09	-0.03	-0.06	-0.04	0.14	0.23	0.09	-0.05
CORR	pct_lt4	-0.30	-0.07	0.06	-0.01	-0.17	0.00	-0.10	0.06	-0.20	-0.23
CORR	pct_lt7	-0.33	-0.05	0.10	-0.01	-0.14	-0.01	-0.14	-0.01	-0.20	-0.19
CORR	pct_PB	-0.16	-0.43	-0.14	-0.06	-0.39	-0.06	0.17	0.49	-0.27	***-0.50***
CORR	pct_PR	-0.31	-0.05	0.05	0.03	-0.18	0.03	-0.06	0.10	-0.23	-0.25
CORR	pct_SP	0.31	0.07	-0.05	-0.02	0.21	-0.02	0.04	-0.15	0.24	0.28
CORR	Pred	0.05	0.09	-0.05	0.15	-0.02	0.15	-0.02	-0.09	-0.05	0.11
CORR	slp_elon	0.01	-0.03	0.01	-0.12	0.27	-0.11	-0.07	-0.33	0.07	0.23

Column 1	Column 2	Column 69	Column 70	Column 71	Column 72	Column 73	Column 74	Column 75	Column 76	Column 77	Column 78
Type	Name	pfc_big	pfc_lwd	pfc_ohv	V1W	v1w_msq	V4W	XBKF_H	XBKF_W	XC	XCDENBK
CORR	Avg_Jun	-0.09	-0.23	-0.17	-0.05	-0.23	-0.04	0.49	**0.80**	-0.16	-0.49
CORR	Avg_Nov	0.09	0.02	-0.14	0.09	-0.22	0.09	0.36	**0.72**	0.03	-0.22
CORR	Avg_Oct	0.01	-0.07	-0.20	0.02	-0.22	0.02	0.37	**0.75**	-0.03	-0.28
CORR	BaseQ	-0.15	-0.13	-0.17	-0.08	-0.05	-0.07	-0.03	-0.02	-0.27	-0.08
CORR	Dh12	0.11	0.10	-0.18	0.10	0.23	0.10	0.16	-0.02	0.10	0.12
CORR	DHiPl	-0.08	-0.12	-0.05	-0.13	0.02	-0.13	-0.17	-0.04	-0.22	-0.45
CORR	FallR	0.14	0.29	0.15	0.01	0.30	0.01	-0.01	-0.32	0.20	0.40
CORR	Fh11	-0.16	-0.39	-0.13	-0.17	-0.22	-0.17	-0.08	0.03	-0.36	-0.49
CORR	Flash	0.04	-0.05	-0.01	0.15	-0.12	0.15	0.02	-0.07	0.06	0.17
CORR	Ma3	0.11	0.17	-0.16	0.15	0.22	0.15	0.16	0.00	0.15	0.19
CORR	Ma41	0.21	0.35	0.01	0.14	0.17	0.14	0.16	0.07	0.31	0.40
CORR	Ma44	0.10	0.06	-0.19	0.08	0.20	0.08	0.18	-0.02	0.06	0.09
CORR	MAR	0.09	-0.07	-0.18	0.06	-0.24	0.06	0.48	**0.86**	-0.04	-0.39
CORR	Mh1	0.08	-0.01	-0.17	0.06	-0.22	0.07	0.37	**0.73**	-0.01	-0.26
CORR	Ml13	0.08	0.17	0.06	0.26	0.15	0.26	-0.02	-0.17	0.08	0.22
CORR	Ml22	-0.12	0.07	0.10	-0.02	0.12	-0.01	-0.07	-0.01	-0.01	0.08
CORR	Mn1d	-0.29	-0.18	0.01	-0.03	-0.15	-0.02	0.24	0.37	-0.17	-0.22
CORR	Mn30d	-0.24	-0.22	-0.05	-0.04	-0.18	-0.03	0.35	**0.54**	-0.19	-0.36
CORR	Mn3d	-0.26	-0.21	-0.03	-0.04	-0.17	-0.03	0.31	0.49	-0.19	-0.32
CORR	Mn7d	-0.25	-0.22	-0.03	-0.04	-0.17	-0.03	0.32	**0.50**	-0.19	-0.33
CORR	Mx1d	0.11	0.02	-0.09	0.12	-0.21	0.12	0.33	**0.67**	0.04	-0.19
CORR	Mx3d	0.11	-0.01	-0.14	0.10	-0.22	0.11	0.38	**0.73**	0.01	-0.27
CORR	Mx7d	0.11	-0.02	-0.15	0.10	-0.22	0.10	0.40	**0.76**	0.00	-0.30
CORR	NHiPl	0.14	0.33	0.04	0.16	0.16	0.17	0.15	-0.01	0.27	0.38
CORR	RiseR	0.11	0.05	-0.09	0.14	-0.21	0.14	0.31	**0.63**	0.07	-0.13
CORR	BFWD_RAT	0.00	-0.15	-0.14	-0.04	-0.31	-0.03	0.22	**0.68**	0.10	-0.15
CORR	LSUB_D50	0.40	0.11	-0.09	-0.23	-0.02	-0.23	0.18	0.17	0.34	0.26
CORR	LSUB_D84	0.32	0.16	0.00	-0.17	0.03	-0.17	0.24	0.04	0.26	0.35
CORR	LWDTV33	0.08	0.39	-0.01	**0.99**	0.18	**0.99**	0.14	0.00	-0.03	0.12
CORR	PCAN_C	0.12	0.03	0.08	-0.08	0.25	-0.08	-0.20	-0.13	-0.16	-0.12
CORR	PCAN_D	-0.01	0.02	-0.06	0.14	-0.21	0.14	0.19	0.22	0.02	0.16

Column 1	Column 2	Column 69	Column 70	Column 71	Column 72	Column 73	Column 74	Column 75	Column 76	Column 77	Column 78
Type	Name	pfc_big	pfc_lwd	pfc_ohv	V1W	v1w_msq	V4W	XBKF_H	XBKF_W	XC	XCDENBK
CORR	PCAN_M	0.23	0.20	0.08	-0.04	0.12	-0.04	0.06	-0.10	0.48	0.37
CORR	PCT_FAST	0.35	0.11	0.16	-0.06	0.22	-0.07	-0.33	-0.38	0.02	0.26
CORR	PCT_ORG	-0.01	0.31	0.26	0.39	0.32	0.39	-0.25	-0.21	0.08	0.14
CORR	pct_pool	-0.12	0.13	-0.13	0.24	-0.01	0.24	0.18	0.06	0.00	0.17
CORR	PCT_RI	0.22	0.12	0.19	0.02	0.27	0.03	-0.26	-0.24	0.08	0.11
CORR	PCT_SAFN	-0.30	-0.04	0.18	0.26	-0.14	0.26	-0.13	-0.02	-0.12	-0.13
CORR	PCT_SLOW	-0.38	-0.06	-0.11	0.08	-0.19	0.09	0.29	0.26	0.01	-0.12
CORR	pfc_big	**1.00**	0.36	0.04	0.07	0.19	0.07	0.08	0.06	0.32	0.33
CORR	pfc_lwd	0.36	**1.00**	0.26	0.37	**0.53**	0.36	0.12	-0.12	0.43	0.40
CORR	pfc_ohv	0.04	0.26	**1.00**	0.00	0.25	0.00	-0.19	-0.23	0.28	0.24
CORR	V1W	0.07	0.37	0.00	**1.00**	0.16	**1.00**	0.15	0.02	-0.04	0.10
CORR	v1w_msq	0.19	**0.53**	0.25	0.16	**1.00**	0.17	-0.21	-0.32	0.29	0.24
CORR	V4W	0.07	0.36	0.00	**1.00**	0.17	**1.00**	0.14	0.03	-0.04	0.10
CORR	XBKF_H	0.08	0.12	-0.19	0.15	-0.21	0.14	**1.00**	**0.67**	0.03	-0.20
CORR	XBKF_W	0.06	-0.12	-0.23	0.02	-0.32	0.03	**0.67**	**1.00**	0.01	-0.45
CORR	XC	0.32	0.43	0.28	-0.04	0.29	-0.04	0.03	0.01	**1.00**	0.46
CORR	XCDENBK	0.33	0.40	0.24	0.10	0.24	0.10	-0.20	-0.45	0.46	**1.00**
CORR	XDEPTH	-0.20	-0.18	-0.04	-0.06	-0.33	-0.06	0.40	**0.57**	-0.02	-0.15
CORR	xfc_big	0.42	0.42	0.28	0.20	0.26	0.19	0.24	0.17	0.50	0.19
CORR	XPCMG	0.46	0.42	0.34	0.07	0.32	0.07	-0.01	-0.12	**0.54**	**0.70**
CORR	XSLOPE	0.24	0.20	-0.05	-0.04	0.32	-0.05	-0.13	-0.32	0.09	0.31
CORR	xwd_rat	0.11	0.07	-0.12	0.21	-0.17	0.21	**0.53**	**0.75**	0.13	-0.19
CORR	xwidth	0.07	-0.09	-0.16	0.01	-0.30	0.01	**0.61**	**0.98**	0.03	-0.38

bold text = values that are greater than 0.5

bold and italic text = values that are less than -0.5

Table P.1i: OR-EMAP correlation matrix (Columns 1, 2, and 79 through 84).

Column 1	Column 2	Column 79	Column 80	Column 81	Column 82	Column 83	Column 84
Type	Name	XDEPTH	xfc_big	XPCMG	XSLOPE	xwd_rat	xwidth
MEAN		31.177	0.346	0.837	5.567	23.499	6.254
STD		20.365	0.274	0.224	6.465	13.140	7.074
CORR	chan_slp	-0.40	0.09	0.16	**0.61**	-0.36	-0.43
CORR	DA	0.29	-0.01	-0.21	-0.17	**0.54**	**0.71**
CORR	DWSP1	-0.12	0.32	0.27	0.37	-0.07	-0.05
CORR	DWSP2	-0.01	0.25	0.17	0.35	-0.04	0.04
CORR	link_sa	0.30	0.05	-0.21	-0.20	**0.61**	**0.79**
CORR	link_sa4	-0.06	0.34	0.17	0.37	0.04	0.10
CORR	link_slope	-0.38	0.28	0.27	**0.76**	-0.19	-0.30
CORR	MCON	-0.21	0.06	0.21	0.32	-0.05	-0.13
CORR	MDW_A_025	-0.10	-0.03	-0.01	0.23	-0.12	-0.12
CORR	MDW_A_1	-0.03	-0.13	-0.41	-0.06	-0.10	-0.06
CORR	MDW_A_25	-0.07	-0.13	-0.40	-0.05	-0.11	-0.08
CORR	MDW_SA_025	-0.11	-0.01	0.07	0.30	-0.03	-0.10
CORR	MDW_SA_1	-0.04	-0.13	-0.41	-0.04	-0.10	-0.06
CORR	MDW_SA_25	-0.07	-0.13	-0.40	-0.05	-0.11	-0.08
CORR	MDW_SA0_4_025	-0.11	-0.01	0.09	0.28	-0.01	-0.08
CORR	MDW_SA0_4_1	-0.10	0.01	0.08	0.28	-0.01	-0.08
CORR	MDW_SA0_4_25	-0.27	-0.09	-0.17	0.18	-0.19	-0.24
CORR	MENTCC	0.19	-0.02	-0.07	-0.17	0.45	**0.52**
CORR	MENTR	0.15	0.26	-0.03	-0.07	-0.04	0.06
CORR	min_elev	-0.24	0.00	-0.28	0.34	-0.40	-0.33
CORR	pct_C	0.29	0.25	0.10	-0.03	0.06	0.22
CORR	pct_lt4	0.18	-0.20	-0.27	-0.45	0.07	0.10
CORR	pct_lt7	0.11	-0.24	-0.25	-0.45	0.05	0.03
CORR	pct_PB	0.29	-0.19	-0.41	-0.42	0.28	0.41
CORR	pct_PR	0.22	-0.17	-0.28	-0.40	0.10	0.14
CORR	pct_SP	-0.26	0.16	0.30	0.43	-0.12	-0.18
CORR	Pred	-0.08	-0.09	0.05	0.13	0.07	-0.09
CORR	slp_elon	-0.29	0.01	0.05	0.41	-0.28	-0.36

Column 1	Column 2	Column 79	Column 80	Column 81	Column 82	Column 83	Column 84
Type	Name	XDEPTH	xfc_big	XPCMG	XSLOPE	xwd_rat	xwidth
CORR	Avg_Jun	**0.60**	-0.01	-0.17	-0.26	0.49	**0.79**
CORR	Avg_Nov	**0.53**	0.11	0.03	-0.24	**0.51**	**0.78**
CORR	Avg_Oct	**0.58**	0.01	-0.04	-0.27	0.49	**0.77**
CORR	BaseQ	0.24	-0.15	-0.07	-0.04	-0.21	-0.04
CORR	Dh12	-0.05	0.14	0.08	0.25	-0.05	-0.04
CORR	DHiPl	-0.06	-0.07	-0.44	0.06	-0.13	-0.05
CORR	FallR	-0.35	0.08	0.27	0.39	-0.13	-0.32
CORR	Fh11	-0.17	-0.25	-0.43	-0.14	-0.04	-0.01
CORR	Flash	-0.12	0.01	0.09	-0.08	0.05	-0.03
CORR	Ma3	-0.04	0.13	0.14	0.16	0.04	-0.01
CORR	Ma41	0.10	0.24	0.36	0.09	0.16	0.11
CORR	Ma44	-0.06	0.11	0.04	0.26	-0.05	-0.05
CORR	MAR	**0.56**	0.10	-0.06	-0.26	**0.60**	**0.89**
CORR	Mh1	**0.52**	0.06	-0.01	-0.24	**0.50**	**0.77**
CORR	Ml13	-0.25	-0.01	0.15	0.01	0.05	-0.15
CORR	Ml22	0.37	-0.03	0.15	0.03	-0.17	0.01
CORR	Mn1d	**0.64**	-0.08	-0.07	-0.16	0.12	0.39
CORR	Mn30d	**0.61**	-0.07	-0.12	-0.19	0.25	**0.53**
CORR	Mn3d	**0.61**	-0.08	-0.11	-0.18	0.21	0.48
CORR	Mn7d	**0.61**	-0.08	-0.11	-0.18	0.22	0.49
CORR	Mx1d	**0.55**	0.11	0.05	-0.24	0.46	**0.74**
CORR	Mx3d	**0.53**	0.11	0.01	-0.24	**0.50**	**0.78**
CORR	Mx7d	**0.53**	0.10	0.00	-0.24	**0.52**	**0.80**
CORR	NHiPl	0.00	0.26	0.37	0.00	0.15	0.03
CORR	RiseR	**0.53**	0.12	0.08	-0.24	0.45	**0.70**
CORR	BFWD_RAT	0.47	0.03	0.01	-0.30	**0.67**	**0.76**
CORR	LSUB_D50	0.07	0.23	0.37	0.19	0.22	0.16
CORR	LSUB_D84	0.03	0.28	0.36	0.34	0.16	0.05
CORR	LWDTV33	-0.07	0.20	0.09	0.01	0.18	-0.01
CORR	PCAN_C	-0.22	0.11	0.03	0.35	-0.08	-0.12
CORR	PCAN_D	0.32	-0.21	0.06	-0.29	0.18	0.26

Column 1	Column 2	Column 79	Column 80	Column 81	Column 82	Column 83	Column 84
Type	Name	XDEPTH	xfc_big	XPCMG	XSLOPE	xwd_rat	xwidth
CORR	PCAN_M	-0.09	0.25	0.45	0.06	0.00	-0.09
CORR	PCT_FAST	-0.29	0.05	0.19	0.37	-0.33	-0.31
CORR	PCT_ORG	-0.12	0.19	0.07	0.09	-0.18	-0.18
CORR	pct_pool	0.02	-0.03	0.07	-0.06	0.19	0.04
CORR	PCT_RI	-0.24	0.01	0.11	0.04	-0.16	-0.20
CORR	PCT_SAFN	0.13	-0.20	-0.18	-0.34	-0.06	0.00
CORR	PCT_SLOW	0.38	-0.05	-0.10	-0.33	0.34	0.32
CORR	pfc_big	-0.20	0.42	0.46	0.24	0.11	0.07
CORR	pfc_lwd	-0.18	0.42	0.42	0.20	0.07	-0.09
CORR	pfc_ohv	-0.04	0.28	0.34	-0.05	-0.12	-0.16
CORR	V1W	-0.06	0.20	0.07	-0.04	0.21	0.01
CORR	v1w_msq	-0.33	0.26	0.32	0.32	-0.17	-0.30
CORR	V4W	-0.06	0.19	0.07	-0.05	0.21	0.01
CORR	XBKF_H	0.40	0.24	-0.01	-0.13	**0.53**	**0.61**
CORR	XBKF_W	**0.57**	0.17	-0.12	-0.32	**0.75**	**0.98**
CORR	XC	-0.02	0.50	**0.54**	0.09	0.13	0.03
CORR	XCDENBK	-0.15	0.19	**0.70**	0.31	-0.19	-0.38
CORR	XDEPTH	**1.00**	0.07	-0.02	-0.37	0.17	**0.63**
CORR	xfc_big	0.07	**1.00**	0.21	0.21	0.16	0.18
CORR	XPCMG	-0.02	0.21	**1.00**	0.15	0.07	-0.04
CORR	XSLOPE	-0.37	0.21	0.15	**1.00**	-0.19	-0.31
CORR	xwd_rat	0.17	0.16	0.07	-0.19	**1.00**	**0.77**
CORR	xwidth	**0.63**	0.18	-0.04	-0.31	**0.77**	**1.00**

bold text = **values that are greater than 0.5**

bold and italic text = **values that are less than -0.5**

APPENDIX I

W-EMAP CORRELATION MATRIX

Table Q.1a: W-EMAP correlation matrix (Columns 1 through 12).

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8	Column 9	Column 10	Column 11	Column 12
Type	Name	chan_slp	DA	DWSP1	DWSP2	link_sa	link_sa4	link_slope	MCON	MDW_A_025	MDW_A_1
MEAN		0.107	56.316	0.067	0.051	0.735	0.077	0.031	5.606	0.013	0.001
STD		0.083	122.737	0.048	0.025	1.317	0.062	0.035	3.639	0.040	0.010
CORR	chan_slp	**1.00**	-0.29	0.32	**0.69**	-0.24	0.25	**0.70**	0.18	0.21	0.30
CORR	DA	-0.29	**1.00**	0.07	-0.09	**0.77**	0.14	-0.24	0.01	-0.05	-0.06
CORR	DWSP1	0.32	0.07	**1.00**	**0.55**	0.37	**0.86**	**0.55**	0.29	0.08	0.05
CORR	DWSP2	**0.69**	-0.09	**0.55**	**1.00**	0.02	0.42	0.48	0.26	0.10	0.13
CORR	link_sa	-0.24	**0.77**	0.37	0.02	**1.00**	**0.54**	-0.09	0.16	-0.01	-0.06
CORR	link_sa4	0.25	0.14	**0.86**	0.42	**0.54**	**1.00**	**0.64**	0.36	-0.02	-0.04
CORR	link_slope	**0.70**	-0.24	**0.55**	0.48	-0.09	**0.64**	**1.00**	0.27	0.03	0.04
CORR	MCON	0.18	0.01	0.29	0.26	0.16	0.36	0.27	**1.00**	-0.14	-0.11
CORR	MDW_A_025	0.21	-0.05	0.08	0.10	-0.01	-0.02	0.03	-0.14	**1.00**	**0.64**
CORR	MDW_A_1	0.30	-0.06	0.05	0.13	-0.06	-0.04	0.04	-0.11	**0.64**	**1.00**
CORR	MDW_A_25	0.29	-0.04	0.07	0.16	-0.04	-0.02	0.03	-0.08	**0.51**	**0.97**
CORR	MDW_SA_025	0.23	-0.06	0.07	0.11	-0.03	-0.03	0.02	-0.09	**0.89**	**0.62**
CORR	MDW_SA_1	0.31	-0.07	0.06	0.11	-0.06	-0.04	0.05	-0.12	**0.76**	**0.92**
CORR	MDW_SA_25	0.29	-0.04	0.07	0.16	-0.04	-0.02	0.03	-0.08	0.50	**0.96**
CORR	MDW_SA0_4_025	0.16	-0.22	-0.06	-0.06	-0.21	-0.15	0.02	-0.01	0.28	0.17
CORR	MDW_SA0_4_1	0.16	-0.22	-0.07	-0.07	-0.22	-0.15	0.03	0.00	0.27	0.17
CORR	MDW_SA0_4_25	0.25	-0.15	-0.06	-0.03	-0.17	-0.11	0.14	0.01	0.26	0.20
CORR	MENTCC	-0.20	**0.63**	0.18	0.02	**0.67**	0.32	-0.13	**0.57**	-0.11	-0.08
CORR	MENTR	0.03	-0.03	-0.02	0.00	-0.03	-0.12	-0.10	-0.36	0.15	0.12
CORR	min_elev	0.10	-0.20	0.05	-0.09	-0.13	0.06	0.20	-0.03	-0.04	0.05
CORR	pct_C	0.41	0.06	0.42	**0.66**	0.15	0.41	0.29	0.05	0.24	0.44
CORR	pct_lt4	***-0.70***	0.23	-0.35	***-0.81***	0.16	-0.21	-0.45	-0.22	-0.08	-0.07
CORR	pct_lt7	***-0.75***	0.16	-0.40	***-0.90***	0.08	-0.26	-0.44	-0.22	-0.13	-0.12
CORR	pct_PB	-0.43	0.39	0.12	0.00	0.42	0.13	-0.35	0.10	-0.14	-0.12
CORR	pct_PR	***-0.60***	0.24	-0.32	***-0.74***	0.16	-0.19	-0.39	-0.22	-0.05	-0.03
CORR	pct_SP	**0.58**	-0.27	0.27	**0.67**	-0.21	0.13	0.38	0.21	0.02	-0.02
CORR	Pred	0.04	0.05	0.47	0.21	0.32	**0.50**	0.14	0.42	-0.05	-0.03
CORR	slp_elon	0.38	0.01	0.02	0.20	-0.02	-0.09	-0.01	0.03	0.15	0.13

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8	Column 9	Column 10	Column 11	Column 12
Type	Name	chan_slp	DA	DWSP1	DWSP2	link_sa	link_sa4	link_slope	MCON	MDW_A_025	MDW_A_1
CORR	Avg_Jun	-0.10	0.35	0.10	0.28	0.28	0.05	-0.17	-0.05	-0.05	-0.05
CORR	Avg_Nov	-0.13	0.32	0.02	0.18	0.22	-0.02	-0.20	-0.10	-0.06	-0.05
CORR	Avg_Oct	-0.11	0.29	0.04	0.20	0.21	0.00	-0.18	-0.09	-0.06	-0.05
CORR	BaseQ	-0.19	0.02	0.05	-0.08	0.03	0.01	-0.12	-0.01	-0.11	-0.07
CORR	Dh12	0.11	-0.14	-0.11	0.00	-0.17	-0.11	0.07	-0.01	-0.03	-0.02
CORR	DHiPl	0.10	0.05	0.22	0.09	0.16	0.26	0.22	-0.05	0.13	0.08
CORR	FallR	0.16	-0.15	-0.07	0.03	-0.17	-0.10	0.09	0.02	0.01	-0.01
CORR	Fh11	-0.24	0.18	-0.03	-0.25	0.19	0.03	-0.09	0.05	-0.07	-0.05
CORR	Flash	0.09	-0.24	-0.12	-0.16	-0.22	-0.07	0.26	0.07	-0.01	-0.03
CORR	Ma3	0.06	-0.06	-0.12	0.06	-0.10	-0.12	-0.06	-0.04	-0.01	-0.03
CORR	Ma41	0.11	-0.06	-0.08	0.19	-0.11	-0.14	-0.09	0.00	-0.02	-0.02
CORR	Ma44	0.01	-0.02	-0.05	0.13	-0.05	-0.08	-0.09	-0.01	-0.06	-0.05
CORR	MAR	-0.07	0.47	0.16	0.24	0.39	0.10	-0.17	-0.08	0.01	-0.04
CORR	Mh1	-0.12	0.32	0.05	0.20	0.24	0.00	-0.19	-0.10	-0.06	-0.05
CORR	Ml13	0.14	-0.16	0.00	0.04	-0.13	0.04	0.23	0.04	0.21	0.04
CORR	Ml22	0.17	0.01	0.16	0.40	0.05	0.08	-0.03	0.11	-0.04	0.01
CORR	Mn1d	0.00	0.38	0.15	0.14	0.33	0.11	-0.09	-0.03	0.03	-0.02
CORR	Mn30d	-0.01	0.45	0.15	0.13	0.36	0.10	-0.10	-0.03	0.03	-0.03
CORR	Mn3d	0.00	0.43	0.15	0.14	0.35	0.10	-0.09	-0.03	0.03	-0.02
CORR	Mn7d	0.00	0.44	0.15	0.14	0.35	0.10	-0.09	-0.03	0.03	-0.02
CORR	Mx1d	-0.11	0.46	0.11	0.16	0.35	0.07	-0.19	-0.11	0.02	-0.05
CORR	Mx3d	-0.08	0.47	0.14	0.17	0.36	0.09	-0.17	-0.10	0.03	-0.04
CORR	Mx7d	-0.14	**0.51**	0.07	0.12	0.35	0.04	-0.21	-0.13	0.01	-0.05
CORR	NHiPl	0.01	-0.09	-0.13	0.06	-0.16	-0.19	-0.16	0.03	-0.06	-0.07
CORR	RiseR	-0.13	0.39	0.04	0.11	0.26	0.01	-0.20	-0.14	0.00	-0.05
CORR	BFWD_RAT	-0.21	0.38	0.01	0.12	0.28	0.00	-0.28	-0.05	-0.15	-0.10
CORR	LSUB_D50	0.15	0.16	0.41	0.33	0.26	0.42	0.21	0.29	-0.25	-0.06
CORR	LSUB_D84	0.16	0.15	0.29	0.29	0.23	0.33	0.13	0.28	-0.19	-0.01
CORR	LWDTV33	0.19	-0.13	0.12	0.29	-0.08	0.07	0.11	0.05	0.04	-0.06
CORR	PCAN_C	0.05	-0.18	0.01	-0.08	-0.14	0.01	0.13	0.11	-0.12	-0.12
CORR	PCAN_D	-0.13	0.05	-0.16	-0.04	-0.01	-0.16	-0.19	-0.21	0.02	-0.02

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8	Column 9	Column 10	Column 11	Column 12
Type	Name	chan_slp	DA	DWSP1	DWSP2	link_sa	link_sa4	link_slope	MCON	MDW_A_025	MDW_A_1
CORR	PCAN_M	0.09	-0.05	0.07	0.18	-0.03	0.04	0.02	0.10	0.00	-0.05
CORR	PCT_FAST	0.35	-0.13	0.28	0.37	0.00	0.27	0.32	0.17	-0.10	0.00
CORR	PCT_ORG	0.26	-0.27	-0.14	-0.07	-0.30	-0.18	0.19	-0.13	0.18	0.14
CORR	PCT_POOL	-0.08	-0.03	-0.10	-0.17	-0.08	-0.12	-0.10	-0.06	0.17	0.08
CORR	PCT_RI	-0.10	-0.08	-0.12	-0.11	-0.07	-0.16	-0.11	-0.03	-0.19	-0.10
CORR	PCT_SAFN	-0.20	-0.11	-0.38	-0.33	-0.23	-0.40	-0.26	-0.31	0.23	0.07
CORR	PCT_SLOW	-0.36	0.15	-0.29	-0.37	0.02	-0.27	-0.34	-0.18	0.07	-0.01
CORR	PFC_BIG	-0.04	0.05	0.07	-0.03	0.07	0.09	-0.05	0.06	-0.09	-0.02
CORR	PFC_LWD	0.10	-0.29	-0.04	-0.02	-0.28	-0.07	0.12	-0.04	-0.02	-0.08
CORR	PFC_OHV	0.01	-0.15	-0.20	-0.22	-0.27	-0.21	0.06	-0.17	0.09	0.08
CORR	V1W	0.14	-0.10	0.08	0.26	-0.05	0.04	0.07	0.06	0.10	-0.05
CORR	V1W_MSQ	0.22	-0.23	0.03	0.03	-0.22	0.00	0.27	0.07	0.09	-0.02
CORR	V4W	0.10	-0.09	0.06	0.23	-0.04	0.02	0.03	0.05	0.12	-0.04
CORR	XBKF_H	0.14	-0.10	0.08	0.26	-0.05	0.04	0.07	0.06	0.10	-0.05
CORR	XBKF_W	-0.18	0.46	0.10	0.24	0.42	0.09	-0.28	-0.06	0.01	-0.06
CORR	XC	0.04	-0.19	-0.02	0.00	-0.17	-0.06	0.00	0.04	-0.09	-0.12
CORR	XCDENBK	0.23	-0.22	0.11	0.09	-0.19	0.07	0.21	0.17	0.03	0.01
CORR	XDEPTH	-0.13	0.39	0.11	0.29	0.37	0.09	-0.27	-0.03	0.02	0.00
CORR	XFC_BIG	-0.07	-0.01	0.08	-0.05	0.07	0.16	0.05	0.10	-0.16	-0.08
CORR	XPCMG	0.05	-0.31	-0.05	0.02	-0.30	-0.11	0.04	0.07	-0.18	-0.26
CORR	XSLOPE	**0.67**	-0.24	0.35	0.38	-0.17	0.44	**0.86**	0.27	0.06	0.04
CORR	XWD_RAT	-0.07	0.08	-0.06	-0.06	0.03	-0.05	-0.04	0.12	-0.09	-0.07
CORR	XWIDTH	-0.16	0.47	0.08	0.24	0.39	0.06	-0.29	-0.09	0.01	-0.05

bold text = values that are greater than 0.5

bold and italic text = values that are less than -0.5

Table Q.1b: W-EMAP correlation matrix (Columns 1, 2, and 13 through 19).

Column 1	Column 2	Column 13	Column 14	Column 15	Column 16	Column 17	Column 18	Column 19
Type	Name	MDW_A_25	MDW_SA_025	MDW_SA_1	MDW_SA_25	MDW_SA0_4_025	MDW_SA0_4_1	MDW_SA0_4_25
MEAN		0.000	0.019	0.006	0.000	0.263	0.260	0.094
STD		0.002	0.058	0.029	0.003	0.427	0.429	0.264
CORR	chan_slp	0.29	0.23	0.31	0.29	0.16	0.16	0.25
CORR	DA	-0.04	-0.06	-0.07	-0.04	-0.22	-0.22	-0.15
CORR	DWSP1	0.07	0.07	0.06	0.07	-0.06	-0.07	-0.06
CORR	DWSP2	0.16	0.11	0.11	0.16	-0.06	-0.07	-0.03
CORR	link_sa	-0.04	-0.03	-0.06	-0.04	-0.21	-0.22	-0.17
CORR	link_sa4	-0.02	-0.03	-0.04	-0.02	-0.15	-0.15	-0.11
CORR	link_slope	0.03	0.02	0.05	0.03	0.02	0.03	0.14
CORR	MCON	-0.08	-0.09	-0.12	-0.08	-0.01	0.00	0.01
CORR	MDW_A_025	**0.51**	**0.89**	**0.76**	0.50	0.28	0.27	0.26
CORR	MDW_A_1	**0.97**	**0.62**	**0.92**	**0.96**	0.17	0.17	0.20
CORR	MDW_A_25	**1.00**	**0.55**	**0.87**	**1.00**	0.14	0.14	0.17
CORR	MDW_SA_025	**0.55**	**1.00**	**0.81**	**0.54**	0.43	0.42	0.34
CORR	MDW_SA_1	**0.87**	**0.81**	**1.00**	**0.87**	0.29	0.29	0.30
CORR	MDW_SA_25	**1.00**	**0.54**	**0.87**	**1.00**	0.14	0.14	0.17
CORR	MDW_SA0_4_025	0.14	0.43	0.29	0.14	**1.00**	**1.00**	**0.78**
CORR	MDW_SA0_4_1	0.14	0.42	0.29	0.14	**1.00**	**1.00**	**0.79**
CORR	MDW_SA0_4_25	0.17	0.34	0.30	0.17	**0.78**	**0.79**	**1.00**
CORR	MENTCC	-0.05	-0.10	-0.10	-0.05	-0.16	-0.15	-0.14
CORR	MENTR	0.09	0.13	0.14	0.09	0.09	0.08	0.06
CORR	min_elev	0.07	0.01	0.08	0.07	-0.01	-0.01	-0.01
CORR	pct_C	0.48	0.24	0.37	0.48	-0.06	-0.06	-0.01
CORR	pct_lt4	-0.08	-0.11	-0.08	-0.08	-0.06	-0.05	-0.07
CORR	pct_lt7	-0.12	-0.12	-0.11	-0.12	0.01	0.01	-0.02
CORR	pct_PB	-0.08	-0.15	-0.14	-0.08	-0.35	-0.35	-0.32
CORR	pct_PR	-0.05	-0.09	-0.05	-0.06	-0.07	-0.07	-0.08
CORR	pct_SP	0.00	0.07	0.01	0.00	0.10	0.10	0.10
CORR	Pred	-0.02	-0.05	-0.04	-0.02	-0.02	-0.02	-0.06
CORR	slp_elon	0.10	0.13	0.12	0.10	0.20	0.20	0.22

Column 1	Column 2	Column 13	Column 14	Column 15	Column 16	Column 17	Column 18	Column 19
Type	Name	MDW_A_25	MDW_SA_025	MDW_SA_1	MDW_SA_25	MDW_SA0_4_025	MDW_SA0_4_1	MDW_SA0_4_25
CORR	Avg_Jun	-0.03	-0.06	-0.07	-0.03	-0.16	-0.17	-0.12
CORR	Avg_Nov	-0.03	-0.07	-0.07	-0.03	-0.14	-0.14	-0.12
CORR	Avg_Oct	-0.03	-0.06	-0.07	-0.03	-0.12	-0.12	-0.11
CORR	BaseQ	-0.06	-0.10	-0.08	-0.06	-0.12	-0.12	-0.13
CORR	Dh12	0.00	0.03	0.01	0.00	0.17	0.18	0.21
CORR	DHiPl	0.08	0.19	0.18	0.08	0.03	0.02	0.09
CORR	FallR	-0.02	-0.02	-0.03	-0.03	0.07	0.07	0.12
CORR	Fh11	-0.04	-0.05	-0.02	-0.04	-0.14	-0.13	-0.13
CORR	Flash	-0.03	0.00	0.02	-0.03	-0.04	-0.04	0.01
CORR	Ma3	-0.01	0.04	-0.02	-0.01	0.21	0.22	0.23
CORR	Ma41	-0.03	-0.02	-0.06	-0.04	0.17	0.17	0.15
CORR	Ma44	-0.03	-0.01	-0.06	-0.02	0.14	0.14	0.18
CORR	MAR	-0.03	-0.02	-0.06	-0.03	-0.15	-0.16	-0.12
CORR	Mh1	-0.03	-0.06	-0.07	-0.03	-0.14	-0.14	-0.12
CORR	Ml13	0.01	0.11	0.09	0.00	-0.01	-0.02	0.01
CORR	Ml22	0.04	-0.01	-0.01	0.04	0.05	0.06	0.01
CORR	Mn1d	-0.02	0.00	-0.03	-0.01	-0.10	-0.10	-0.07
CORR	Mn30d	-0.02	0.00	-0.04	-0.02	-0.10	-0.11	-0.07
CORR	Mn3d	-0.02	0.00	-0.03	-0.01	-0.09	-0.10	-0.07
CORR	Mn7d	-0.02	0.00	-0.03	-0.02	-0.10	-0.10	-0.07
CORR	Mx1d	-0.03	-0.01	-0.06	-0.03	-0.15	-0.16	-0.13
CORR	Mx3d	-0.03	-0.01	-0.06	-0.03	-0.14	-0.15	-0.13
CORR	Mx7d	-0.03	-0.02	-0.07	-0.03	-0.16	-0.17	-0.14
CORR	NHiPl	-0.08	-0.06	-0.11	-0.08	0.16	0.16	0.11
CORR	RiseR	-0.03	-0.02	-0.06	-0.03	-0.14	-0.14	-0.13
CORR	BFWD_RAT	-0.05	-0.10	-0.14	-0.04	-0.15	-0.15	-0.12
CORR	LSUB_D50	0.03	-0.11	-0.09	0.04	-0.08	-0.08	-0.12
CORR	LSUB_D84	0.05	-0.09	-0.04	0.05	-0.10	-0.09	-0.05
CORR	LWDTV33	-0.05	0.04	-0.04	-0.05	-0.03	-0.04	-0.04
CORR	PCAN_C	-0.11	-0.08	-0.08	-0.11	0.06	0.07	-0.01
CORR	PCAN_D	-0.03	-0.04	-0.04	-0.03	-0.06	-0.06	-0.01

Column 1	Column 2	Column 13	Column 14	Column 15	Column 16	Column 17	Column 18	Column 19
Type	Name	MDW_A_25	MDW_SA_025	MDW_SA_1	MDW_SA_25	MDW_SA0_4_025	MDW_SA0_4_1	MDW_SA0_4_25
CORR	PCAN_M	-0.06	-0.01	-0.09	-0.07	0.07	0.07	0.05
CORR	PCT_FAST	0.06	0.00	0.00	0.07	0.06	0.05	0.07
CORR	PCT_ORG	0.05	0.12	0.15	0.04	0.18	0.18	0.26
CORR	PCT_POOL	0.00	0.04	0.05	-0.01	0.07	0.07	0.08
CORR	PCT_RI	-0.05	-0.10	-0.12	-0.04	0.12	0.12	0.06
CORR	PCT_SAFN	0.00	0.12	0.11	-0.01	0.09	0.08	0.10
CORR	PCT_SLOW	-0.06	0.00	-0.01	-0.06	-0.06	-0.05	-0.08
CORR	PFC_BIG	0.00	-0.08	-0.08	0.00	0.13	0.13	0.07
CORR	PFC_LWD	-0.08	0.00	-0.07	-0.08	0.16	0.16	0.14
CORR	PFC_OHV	0.05	0.05	0.09	0.05	0.00	-0.01	0.12
CORR	V1W	-0.04	0.08	-0.01	-0.04	-0.03	-0.04	-0.03
CORR	V1W_MSQ	-0.04	0.18	0.12	-0.03	0.19	0.20	0.17
CORR	V4W	-0.03	0.10	-0.01	-0.03	-0.05	-0.06	-0.06
CORR	XBKF_H	-0.04	0.08	-0.01	-0.04	-0.03	-0.04	-0.03
CORR	XBKF_W	-0.03	-0.03	-0.10	-0.03	-0.20	-0.21	-0.20
CORR	XC	-0.13	-0.05	-0.11	-0.13	0.08	0.08	0.02
CORR	XCDENBK	-0.02	0.03	0.01	-0.02	0.19	0.20	0.16
CORR	XDEPTH	0.02	0.01	-0.05	0.01	-0.17	-0.18	-0.20
CORR	XFC_BIG	-0.05	-0.13	-0.09	-0.05	-0.13	-0.12	-0.10
CORR	XPCMG	-0.28	-0.16	-0.27	-0.28	0.17	0.17	0.07
CORR	XSLOPE	0.01	0.04	0.07	0.01	0.04	0.05	0.15
CORR	XWD_RAT	-0.06	-0.11	-0.09	-0.06	-0.08	-0.08	-0.03
CORR	XWIDTH	-0.02	-0.02	-0.09	-0.02	-0.19	-0.20	-0.20

bold text = values that are greater than 0.5

bold and italic text = values that are less than -0.5

Table Q.1c: W-EMAP correlation matrix (Columns 1, 2, and 20 through 28).

Column 1	Column 2	Column 20	Column 21	Column 22	Column 23	Column 24	Column 25	Column 26	Column 27	Column 28
Type	Name	MENTCC	MENTR	min_elev	pct_C	pct_lt4	pct_lt7	pct_PB	pct_PR	pct_SP
MEAN		0.855	28.637	1003.851	0.012	0.345	0.536	0.010	0.212	0.766
STD		1.123	30.722	464.576	0.024	0.225	0.258	0.011	0.188	0.184
CORR	chan_slp	-0.20	0.03	0.10	0.41	***-0.70***	***-0.75***	-0.43	***-0.60***	**0.58**
CORR	DA	**0.63**	-0.03	-0.20	0.06	0.23	0.16	0.39	0.24	-0.27
CORR	DWSP1	0.18	-0.02	0.05	0.42	-0.35	-0.40	0.12	-0.32	0.27
CORR	DWSP2	0.02	0.00	-0.09	**0.66**	***-0.81***	***-0.90***	0.00	***-0.74***	**0.67**
CORR	link_sa	**0.67**	-0.03	-0.13	0.15	0.16	0.08	0.42	0.16	-0.21
CORR	link_sa4	0.32	-0.12	0.06	0.41	-0.21	-0.26	0.13	-0.19	0.13
CORR	link_slope	-0.13	-0.10	0.20	0.29	-0.45	-0.44	-0.35	-0.39	0.38
CORR	MCON	**0.57**	-0.36	-0.03	0.05	-0.22	-0.22	0.10	-0.22	0.21
CORR	MDW_A_025	-0.11	0.15	-0.04	0.24	-0.08	-0.13	-0.14	-0.05	0.02
CORR	MDW_A_1	-0.08	0.12	0.05	0.44	-0.07	-0.12	-0.12	-0.03	-0.02
CORR	MDW_A_25	-0.05	0.09	0.07	0.48	-0.08	-0.12	-0.08	-0.05	0.00
CORR	MDW_SA_025	-0.10	0.13	0.01	0.24	-0.11	-0.12	-0.15	-0.09	0.07
CORR	MDW_SA_1	-0.10	0.14	0.08	0.37	-0.08	-0.11	-0.14	-0.05	0.01
CORR	MDW_SA_25	-0.05	0.09	0.07	0.48	-0.08	-0.12	-0.08	-0.06	0.00
CORR	MDW_SA0_4_025	-0.16	0.09	-0.01	-0.06	-0.06	0.01	-0.35	-0.07	0.10
CORR	MDW_SA0_4_1	-0.15	0.08	-0.01	-0.06	-0.05	0.01	-0.35	-0.07	0.10
CORR	MDW_SA0_4_25	-0.14	0.06	-0.01	-0.01	-0.07	-0.02	-0.32	-0.08	0.10
CORR	MENTCC	**1.00**	-0.24	-0.12	0.05	0.14	0.07	0.43	0.13	-0.16
CORR	MENTR	-0.24	**1.00**	-0.09	0.15	0.02	-0.02	-0.17	0.05	-0.06
CORR	min_elev	-0.12	-0.09	**1.00**	-0.09	0.01	0.11	-0.14	-0.03	0.05
CORR	pct_C	0.05	0.15	-0.09	**1.00**	-0.38	***-0.50***	0.04	-0.30	0.17
CORR	pct_lt4	0.14	0.02	0.01	-0.38	**1.00**	**0.92**	0.22	**0.96**	***-0.94***
CORR	pct_lt7	0.07	-0.02	0.11	***-0.50***	**0.92**	**1.00**	0.14	**0.82**	***-0.78***
CORR	pct_PB	0.43	-0.17	-0.14	0.04	0.22	0.14	**1.00**	0.17	-0.23
CORR	pct_PR	0.13	0.05	-0.03	-0.30	**0.96**	**0.82**	0.17	**1.00**	***-0.99***
CORR	pct_SP	-0.16	-0.06	0.05	0.17	***-0.94***	***-0.78***	-0.23	***-0.99***	**1.00**
CORR	Pred	0.41	-0.09	-0.11	0.23	-0.13	-0.18	0.13	-0.10	0.07
CORR	slp_elon	-0.06	0.14	-0.09	0.13	-0.31	-0.32	-0.20	-0.24	0.24

Column 1	Column 2	Column 20	Column 21	Column 22	Column 23	Column 24	Column 25	Column 26	Column 27	Column 28
Type	Name	MENTCC	MENTR	min_elev	pct_C	pct_lt4	pct_lt7	pct_PB	pct_PR	pct_SP
CORR	Avg_Jun	0.14	0.12	-0.21	0.43	-0.14	-0.23	0.25	-0.10	0.03
CORR	Avg_Nov	0.07	0.16	-0.38	0.33	-0.06	-0.16	0.18	-0.01	-0.04
CORR	Avg_Oct	0.06	0.16	-0.36	0.33	-0.08	-0.18	0.18	-0.03	-0.02
CORR	BaseQ	0.04	-0.04	0.06	0.00	0.17	0.15	0.23	0.12	-0.14
CORR	Dh12	-0.15	0.16	-0.05	0.02	-0.16	-0.06	-0.22	-0.17	0.18
CORR	DHiPl	0.09	-0.01	**0.54**	0.05	-0.06	0.02	0.05	-0.11	0.10
CORR	FallR	-0.16	0.02	-0.29	-0.07	-0.08	-0.16	-0.24	0.02	0.00
CORR	Fh11	0.20	-0.21	0.19	-0.24	0.35	0.36	0.26	0.29	-0.28
CORR	Flash	-0.22	-0.16	0.33	-0.34	0.02	0.16	-0.24	-0.03	0.09
CORR	Ma3	-0.10	0.23	-0.39	0.09	-0.12	-0.12	-0.14	-0.12	0.11
CORR	Ma41	-0.09	0.25	***-0.60***	0.20	-0.15	-0.27	-0.11	-0.06	0.05
CORR	Ma44	-0.02	0.20	-0.38	0.17	-0.11	-0.15	-0.01	-0.10	0.08
CORR	MAR	0.17	0.27	-0.29	0.41	-0.10	-0.20	0.23	-0.05	-0.01
CORR	Mh1	0.08	0.17	-0.35	0.35	-0.08	-0.18	0.20	-0.03	-0.03
CORR	Ml13	-0.13	-0.04	0.17	-0.04	-0.12	-0.06	-0.23	-0.10	0.12
CORR	Ml22	0.05	0.15	-0.25	0.49	-0.28	-0.38	0.03	-0.21	0.15
CORR	Mn1d	0.16	0.24	-0.12	0.26	-0.05	-0.10	0.16	-0.03	-0.01
CORR	Mn30d	0.19	0.24	-0.13	0.25	-0.04	-0.09	0.17	-0.02	-0.03
CORR	Mn3d	0.18	0.24	-0.13	0.25	-0.05	-0.10	0.16	-0.02	-0.02
CORR	Mn7d	0.18	0.24	-0.13	0.25	-0.05	-0.10	0.16	-0.02	-0.02
CORR	Mx1d	0.15	0.22	-0.37	0.31	-0.04	-0.14	0.21	0.01	-0.06
CORR	Mx3d	0.16	0.24	-0.33	0.33	-0.05	-0.15	0.20	-0.01	-0.05
CORR	Mx7d	0.17	0.17	-0.41	0.28	-0.01	-0.11	0.23	0.04	-0.09
CORR	NHiPl	-0.11	0.10	***-0.55***	0.05	-0.06	-0.15	-0.10	-0.01	0.01
CORR	RiseR	0.10	0.18	-0.44	0.24	-0.01	-0.11	0.18	0.04	-0.08
CORR	BFWD_RAT	0.25	0.02	-0.39	0.19	0.01	-0.09	0.43	0.04	-0.09
CORR	LSUB_D50	0.28	-0.02	-0.14	0.28	-0.14	-0.23	0.20	-0.10	0.06
CORR	LSUB_D84	0.34	-0.02	-0.23	0.26	-0.13	-0.25	0.16	-0.07	0.02
CORR	LWDTV33	-0.09	0.09	-0.03	0.25	-0.19	-0.26	-0.04	-0.14	0.11
CORR	PCAN_C	0.02	-0.12	**0.64**	-0.12	0.00	0.03	-0.14	0.00	0.02
CORR	PCAN_D	-0.13	0.14	***-0.54***	-0.08	0.04	0.02	0.10	0.03	-0.03

Column 1	Column 2	Column 20	Column 21	Column 22	Column 23	Column 24	Column 25	Column 26	Column 27	Column 28
Type	Name	MENTCC	MENTR	min_elev	pct_C	pct_lt4	pct_lt7	pct_PB	pct_PR	pct_SP
CORR	PCAN_M	-0.04	0.13	-0.49	0.11	-0.19	-0.21	-0.06	-0.17	0.16
CORR	PCT_FAST	0.02	-0.07	0.23	0.21	-0.36	-0.35	0.11	-0.38	0.35
CORR	PCT_ORG	-0.30	0.08	0.12	-0.12	-0.08	-0.03	-0.38	-0.07	0.11
CORR	PCT_POOL	-0.03	0.04	-0.37	-0.09	0.20	0.13	-0.20	0.25	-0.23
CORR	PCT_RI	-0.04	-0.05	0.34	-0.25	-0.03	0.07	0.16	-0.09	0.12
CORR	PCT_SAFN	-0.26	0.01	0.00	-0.20	0.17	0.24	-0.13	0.14	-0.11
CORR	PCT_SLOW	-0.01	0.08	-0.26	-0.19	0.37	0.35	-0.11	0.39	-0.36
CORR	PFC_BIG	0.16	-0.06	0.06	0.12	0.10	0.06	-0.03	0.12	-0.14
CORR	PFC_LWD	-0.23	0.06	0.16	-0.04	-0.04	-0.03	-0.28	-0.03	0.05
CORR	PFC_OHV	-0.27	0.01	0.24	-0.12	0.06	0.16	-0.23	0.03	0.00
CORR	V1W	-0.08	0.07	-0.04	0.25	-0.16	-0.24	0.03	-0.13	0.10
CORR	V1W_MSQ	-0.20	0.00	0.24	-0.09	-0.06	-0.02	-0.29	-0.06	0.09
CORR	V4W	-0.05	0.06	-0.05	0.21	-0.14	-0.21	0.05	-0.11	0.08
CORR	XBKF_H	-0.08	0.07	-0.04	0.25	-0.16	-0.24	0.03	-0.13	0.10
CORR	XBKF_W	0.25	0.13	-0.50	0.40	-0.04	-0.19	0.39	0.00	-0.08
CORR	XC	-0.14	0.01	-0.21	-0.11	-0.13	-0.12	-0.15	-0.14	0.17
CORR	XCDENBK	-0.09	0.03	-0.17	0.01	-0.11	-0.14	-0.20	-0.10	0.11
CORR	XDEPTH	0.26	0.17	-0.45	0.47	-0.11	-0.24	0.30	-0.06	-0.02
CORR	XFC_BIG	0.12	-0.03	0.19	0.07	0.14	0.05	0.02	0.18	-0.20
CORR	XPCMG	-0.20	0.06	-0.03	-0.17	-0.14	-0.12	-0.21	-0.13	0.17
CORR	XSLOPE	-0.14	-0.08	0.17	0.19	-0.37	-0.40	-0.36	-0.29	0.29
CORR	XWD_RAT	0.08	0.01	-0.09	-0.03	0.11	0.07	0.16	0.14	-0.14
CORR	XWIDTH	0.23	0.18	-0.47	0.44	-0.07	-0.21	0.35	-0.02	-0.06

bold text = values that are greater than 0.5

bold and italic text = values that are less than -0.5

Table Q.1d: W-EMAP correlation matrix (Columns 1, 2, and 29 through 37).

Column 1	Column 2	Column 29	Column 30	Column 31	Column 32	Column 33	Column 34	Column 35	Column 36	Column 37
Type	Name	Pred	slp_elon	Avg_Jun	Avg_Nov	Avg_Oct	BaseQ	Dh12	DHiPI	FallR
MEAN		113.697	0.706	57.718	48.742	30.476	0.077	424.406	12.758	811.210
STD		416.005	0.279	166.456	137.703	85.954	0.071	576.259	7.762	1953.166
CORR	chan_slp	0.04	0.38	-0.10	-0.13	-0.11	-0.19	0.11	0.10	0.16
CORR	DA	0.05	0.01	0.35	0.32	0.29	0.02	-0.14	0.05	-0.15
CORR	DWSP1	0.47	0.02	0.10	0.02	0.04	0.05	-0.11	0.22	-0.07
CORR	DWSP2	0.21	0.20	0.28	0.18	0.20	-0.08	0.00	0.09	0.03
CORR	link_sa	0.32	-0.02	0.28	0.22	0.21	0.03	-0.17	0.16	-0.17
CORR	link_sa4	**0.50**	-0.09	0.05	-0.02	0.00	0.01	-0.11	0.26	-0.10
CORR	link_slope	0.14	-0.01	-0.17	-0.20	-0.18	-0.12	0.07	0.22	0.09
CORR	MCON	0.42	0.03	-0.05	-0.10	-0.09	-0.01	-0.01	-0.05	0.02
CORR	MDW_A_025	-0.05	0.15	-0.05	-0.06	-0.06	-0.11	-0.03	0.13	0.01
CORR	MDW_A_1	-0.03	0.13	-0.05	-0.05	-0.05	-0.07	-0.02	0.08	-0.01
CORR	MDW_A_25	-0.02	0.10	-0.03	-0.03	-0.03	-0.06	0.00	0.08	-0.02
CORR	MDW_SA_025	-0.05	0.13	-0.06	-0.07	-0.06	-0.10	0.03	0.19	-0.02
CORR	MDW_SA_1	-0.04	0.12	-0.07	-0.07	-0.07	-0.08	0.01	0.18	-0.03
CORR	MDW_SA_25	-0.02	0.10	-0.03	-0.03	-0.03	-0.06	0.00	0.08	-0.03
CORR	MDW_SA0_4_025	-0.02	0.20	-0.16	-0.14	-0.12	-0.12	0.17	0.03	0.07
CORR	MDW_SA0_4_1	-0.02	0.20	-0.17	-0.14	-0.12	-0.12	0.18	0.02	0.07
CORR	MDW_SA0_4_25	-0.06	0.22	-0.12	-0.12	-0.11	-0.13	0.21	0.09	0.12
CORR	MENTCC	0.41	-0.06	0.14	0.07	0.06	0.04	-0.15	0.09	-0.16
CORR	MENTR	-0.09	0.14	0.12	0.16	0.16	-0.04	0.16	-0.01	0.02
CORR	min_elev	-0.11	-0.09	-0.21	-0.38	-0.36	0.06	-0.05	**0.54**	-0.29
CORR	pct_C	0.23	0.13	0.43	0.33	0.33	0.00	0.02	0.05	-0.07
CORR	pct_lt4	-0.13	-0.31	-0.14	-0.06	-0.08	0.17	-0.16	-0.06	-0.08
CORR	pct_lt7	-0.18	-0.32	-0.23	-0.16	-0.18	0.15	-0.06	0.02	-0.16
CORR	pct_PB	0.13	-0.20	0.25	0.18	0.18	0.23	-0.22	0.05	-0.24
CORR	pct_PR	-0.10	-0.24	-0.10	-0.01	-0.03	0.12	-0.17	-0.11	0.02
CORR	pct_SP	0.07	0.24	0.03	-0.04	-0.02	-0.14	0.18	0.10	0.00
CORR	Pred	**1.00**	0.02	0.09	0.08	0.07	-0.02	-0.05	0.09	-0.01
CORR	slp_elon	0.02	**1.00**	0.09	0.12	0.15	-0.13	0.08	-0.10	0.07

Column 1	Column 2	Column 29	Column 30	Column 31	Column 32	Column 33	Column 34	Column 35	Column 36	Column 37
Type	Name	Pred	slp_elon	Avg_Jun	Avg_Nov	Avg_Oct	BaseQ	Dh12	DHiPI	FallR
CORR	Avg_Jun	0.09	0.09	**1.00**	**0.85**	**0.83**	0.22	0.06	-0.25	-0.09
CORR	Avg_Nov	0.08	0.12	**0.85**	**1.00**	**0.98**	0.19	0.11	-0.33	-0.07
CORR	Avg_Oct	0.07	0.15	**0.83**	**0.98**	**1.00**	0.21	0.14	-0.35	-0.09
CORR	BaseQ	-0.02	-0.13	0.22	0.19	0.21	**1.00**	-0.21	-0.04	-0.12
CORR	Dh12	-0.05	0.08	0.06	0.11	0.14	-0.21	**1.00**	-0.11	-0.09
CORR	DHiPI	0.09	-0.10	-0.25	-0.33	-0.35	-0.04	-0.11	**1.00**	-0.38
CORR	FallR	-0.01	0.07	-0.09	-0.07	-0.09	-0.12	-0.09	-0.38	**1.00**
CORR	Fh11	-0.15	-0.25	-0.15	-0.22	-0.22	0.31	-0.48	0.17	-0.29
CORR	Flash	-0.19	-0.16	-0.38	-0.36	-0.36	-0.14	0.00	0.22	-0.15
CORR	Ma3	-0.02	0.15	0.23	0.34	0.39	-0.12	**0.80**	-0.41	-0.02
CORR	Ma41	0.07	0.21	0.37	0.50	**0.54**	0.08	0.33	***-0.64***	0.41
CORR	Ma44	0.01	0.09	0.39	0.42	0.46	0.10	**0.63**	-0.47	0.00
CORR	MAR	0.16	0.30	**0.69**	**0.75**	**0.73**	0.08	0.02	-0.09	-0.11
CORR	Mh1	0.08	0.15	**0.87**	**0.99**	**0.99**	0.20	0.13	-0.32	-0.09
CORR	Ml13	0.01	-0.09	-0.26	-0.29	-0.31	-0.50	0.21	0.21	0.17
CORR	Ml22	0.16	0.24	**0.58**	**0.59**	**0.64**	0.24	0.19	-0.39	-0.01
CORR	Mn1d	0.12	0.34	0.21	0.21	0.16	0.01	-0.11	0.15	-0.06
CORR	Mn30d	0.12	0.34	0.21	0.21	0.16	-0.03	-0.11	0.14	-0.06
CORR	Mn3d	0.12	0.34	0.21	0.21	0.17	-0.03	-0.10	0.14	-0.06
CORR	Mn7d	0.12	0.34	0.21	0.21	0.16	-0.03	-0.11	0.14	-0.06
CORR	Mx1d	0.15	0.26	**0.55**	**0.72**	**0.70**	0.03	0.04	-0.10	-0.11
CORR	Mx3d	0.17	0.29	**0.52**	**0.66**	**0.64**	0.02	0.03	-0.06	-0.11
CORR	Mx7d	0.12	0.20	**0.61**	**0.80**	**0.78**	0.07	0.06	-0.18	-0.10
CORR	NHiPI	-0.03	0.17	0.30	0.38	0.43	0.14	0.21	***-0.83***	0.34
CORR	RiseR	0.11	0.20	**0.56**	**0.80**	**0.80**	0.05	0.10	-0.22	-0.08
CORR	BFWD_RAT	0.04	0.06	0.41	0.46	0.47	0.21	0.02	-0.26	0.04
CORR	LSUB_D50	0.24	-0.03	0.17	0.15	0.15	0.09	-0.05	-0.06	0.15
CORR	LSUB_D84	0.27	0.02	0.19	0.21	0.20	0.09	-0.03	-0.15	0.22
CORR	LWDTV33	0.00	0.06	0.16	0.12	0.15	0.04	0.09	-0.17	0.32
CORR	PCAN_C	0.03	0.00	-0.06	-0.19	-0.17	0.09	-0.06	0.21	-0.14
CORR	PCAN_D	-0.05	-0.10	-0.01	0.13	0.11	-0.12	0.13	-0.16	0.07

Column 1	Column 2	Column 29	Column 30	Column 31	Column 32	Column 33	Column 34	Column 35	Column 36	Column 37
Type	Name	Pred	slp_elon	Avg_Jun	Avg_Nov	Avg_Oct	BaseQ	Dh12	DHiPI	FallR
CORR	PCAN_M	0.06	0.21	0.14	0.22	0.22	0.00	0.08	-0.36	0.22
CORR	PCT_FAST	0.06	0.10	0.03	-0.11	-0.09	0.08	0.02	0.30	-0.06
CORR	PCT_ORG	-0.15	0.05	-0.16	-0.14	-0.13	-0.05	0.24	0.14	0.03
CORR	PCT_POOL	0.05	0.05	-0.02	0.03	0.02	-0.09	0.06	-0.36	0.31
CORR	PCT_RI	-0.14	-0.06	-0.08	-0.19	-0.18	0.09	-0.07	0.24	-0.11
CORR	PCT_SAFN	-0.17	0.01	-0.08	-0.05	-0.06	-0.15	0.00	0.04	-0.12
CORR	PCT_SLOW	-0.05	-0.11	-0.01	0.13	0.11	-0.11	0.01	-0.30	0.08
CORR	PFC_BIG	0.10	0.05	0.09	0.05	0.05	0.05	0.16	0.02	0.09
CORR	PFC_LWD	-0.12	0.04	-0.09	-0.05	-0.03	-0.03	0.31	-0.03	0.07
CORR	PFC_OHV	-0.24	-0.17	-0.23	-0.24	-0.25	-0.09	0.10	0.11	-0.03
CORR	V1W	0.00	0.03	0.20	0.16	0.20	0.04	0.06	-0.08	0.20
CORR	V1W_MSQ	-0.08	-0.09	-0.16	-0.18	-0.17	-0.06	0.00	0.24	0.23
CORR	V4W	-0.01	0.02	0.16	0.11	0.14	0.03	0.03	-0.07	0.21
CORR	XBKF_H	0.00	0.03	0.20	0.16	0.20	0.04	0.06	-0.08	0.20
CORR	XBKF_W	0.16	0.16	**0.71**	**0.77**	**0.77**	0.14	0.05	-0.29	-0.05
CORR	XC	0.07	0.11	0.10	0.16	0.15	0.07	0.04	-0.30	0.19
CORR	XCDENBK	0.10	0.12	-0.04	-0.01	-0.02	-0.02	0.02	-0.20	0.21
CORR	XDEPTH	0.27	0.17	**0.71**	**0.75**	**0.75**	0.13	0.08	-0.26	-0.05
CORR	XFC_BIG	0.10	-0.15	0.16	0.02	0.02	0.14	0.06	-0.06	0.33
CORR	XPCMG	0.04	0.14	0.05	0.07	0.07	0.05	0.10	-0.26	0.13
CORR	XSLOPE	0.08	0.01	-0.16	-0.19	-0.19	-0.10	0.05	0.15	0.21
CORR	XWD_RAT	-0.09	-0.07	0.06	0.09	0.09	0.12	-0.02	-0.16	0.05
CORR	XWIDTH	0.16	0.16	**0.74**	**0.78**	**0.77**	0.13	0.07	-0.28	-0.05

bold text = values that are greater than 0.5

bold and italic text = values that are less than -0.5

Table Q.1e: W-EMAP correlation matrix (Columns 1, 2, and 38 through 46).

Column 1	Column 2	Column 38	Column 39	Column 40	Column 41	Column 42	Column 43	Column 44	Column 45	Column 46
Type	Name	Fh11	Flash	Ma3	Ma41	Ma44	MAR	Mh1	Ml13	Ml22
MEAN		0.619	13.427	2.065	30.574	89.118	61.414	75.577	1.260	0.836
STD		0.125	6.094	1.301	34.651	180.520	162.550	208.301	0.582	1.413
CORR	chan_slp	-0.24	0.09	0.06	0.11	0.01	-0.07	-0.12	0.14	0.17
CORR	DA	0.18	-0.24	-0.06	-0.06	-0.02	0.47	0.32	-0.16	0.01
CORR	DWSP1	-0.03	-0.12	-0.12	-0.08	-0.05	0.16	0.05	0.00	0.16
CORR	DWSP2	-0.25	-0.16	0.06	0.19	0.13	0.24	0.20	0.04	0.40
CORR	link_sa	0.19	-0.22	-0.10	-0.11	-0.05	0.39	0.24	-0.13	0.05
CORR	link_sa4	0.03	-0.07	-0.12	-0.14	-0.08	0.10	0.00	0.04	0.08
CORR	link_slope	-0.09	0.26	-0.06	-0.09	-0.09	-0.17	-0.19	0.23	-0.03
CORR	MCON	0.05	0.07	-0.04	0.00	-0.01	-0.08	-0.10	0.04	0.11
CORR	MDW_A_025	-0.07	-0.01	-0.01	-0.02	-0.06	0.01	-0.06	0.21	-0.04
CORR	MDW_A_1	-0.05	-0.03	-0.03	-0.02	-0.05	-0.04	-0.05	0.04	0.01
CORR	MDW_A_25	-0.04	-0.03	-0.01	-0.03	-0.03	-0.03	-0.03	0.01	0.04
CORR	MDW_SA_025	-0.05	0.00	0.04	-0.02	-0.01	-0.02	-0.06	0.11	-0.01
CORR	MDW_SA_1	-0.02	0.02	-0.02	-0.06	-0.06	-0.06	-0.07	0.09	-0.01
CORR	MDW_SA_25	-0.04	-0.03	-0.01	-0.04	-0.02	-0.03	-0.03	0.00	0.04
CORR	MDW_SA0_4_025	-0.14	-0.04	0.21	0.17	0.14	-0.15	-0.14	-0.01	0.05
CORR	MDW_SA0_4_1	-0.13	-0.04	0.22	0.17	0.14	-0.16	-0.14	-0.02	0.06
CORR	MDW_SA0_4_25	-0.13	0.01	0.23	0.15	0.18	-0.12	-0.12	0.01	0.01
CORR	MENTCC	0.20	-0.22	-0.10	-0.09	-0.02	0.17	0.08	-0.13	0.05
CORR	MENTR	-0.21	-0.16	0.23	0.25	0.20	0.27	0.17	-0.04	0.15
CORR	min_elev	0.19	0.33	-0.39	***-0.60***	-0.38	-0.29	-0.35	0.17	-0.25
CORR	pct_C	-0.24	-0.34	0.09	0.20	0.17	0.41	0.35	-0.04	0.49
CORR	pct_lt4	0.35	0.02	-0.12	-0.15	-0.11	-0.10	-0.08	-0.12	-0.28
CORR	pct_lt7	0.36	0.16	-0.12	-0.27	-0.15	-0.20	-0.18	-0.06	-0.38
CORR	pct_PB	0.26	-0.24	-0.14	-0.11	-0.01	0.23	0.20	-0.23	0.03
CORR	pct_PR	0.29	-0.03	-0.12	-0.06	-0.10	-0.05	-0.03	-0.10	-0.21
CORR	pct_SP	-0.28	0.09	0.11	0.05	0.08	-0.01	-0.03	0.12	0.15
CORR	Pred	-0.15	-0.19	-0.02	0.07	0.01	0.16	0.08	0.01	0.16
CORR	slp_elon	-0.25	-0.16	0.15	0.21	0.09	0.30	0.15	-0.09	0.24

Column 1	Column 2	Column 38	Column 39	Column 40	Column 41	Column 42	Column 43	Column 44	Column 45	Column 46
Type	Name	Fh11	Flash	Ma3	Ma41	Ma44	MAR	Mh1	Ml13	Ml22
CORR	Avg_Jun	-0.15	-0.38	0.23	0.37	0.39	**0.69**	**0.87**	-0.26	**0.58**
CORR	Avg_Nov	-0.22	-0.36	0.34	0.50	0.42	**0.75**	**0.99**	-0.29	**0.59**
CORR	Avg_Oct	-0.22	-0.36	0.39	**0.54**	0.46	**0.73**	**0.99**	-0.31	**0.64**
CORR	BaseQ	0.31	-0.14	-0.12	0.08	0.10	0.08	0.20	-0.50	0.24
CORR	Dh12	-0.48	0.00	**0.80**	0.33	**0.63**	0.02	0.13	0.21	0.19
CORR	DHiPl	0.17	0.22	-0.41	***-0.64***	-0.47	-0.09	-0.32	0.21	-0.39
CORR	FallR	-0.29	-0.15	-0.02	0.41	0.00	-0.11	-0.09	0.17	-0.01
CORR	Fh11	**1.00**	0.36	-0.48	-0.47	-0.31	-0.24	-0.21	-0.27	-0.33
CORR	Flash	0.36	**1.00**	-0.25	***-0.54***	-0.34	-0.35	-0.37	0.34	***-0.54***
CORR	Ma3	-0.48	-0.25	**1.00**	**0.69**	**0.90**	0.16	0.36	-0.08	0.45
CORR	Ma41	-0.47	***-0.54***	**0.69**	**1.00**	**0.74**	0.26	**0.50**	-0.28	**0.71**
CORR	Ma44	-0.31	-0.34	**0.90**	**0.74**	**1.00**	0.22	0.45	-0.32	**0.56**
CORR	MAR	-0.24	-0.35	0.16	0.26	0.22	**1.00**	**0.77**	-0.18	0.38
CORR	Mh1	-0.21	-0.37	0.36	**0.50**	0.45	**0.77**	**1.00**	-0.30	**0.61**
CORR	Ml13	-0.27	0.34	-0.08	-0.28	-0.32	-0.18	-0.30	**1.00**	-0.38
CORR	Ml22	-0.33	***-0.54***	0.45	**0.71**	**0.56**	0.38	**0.61**	-0.38	**1.00**
CORR	Mn1d	-0.12	-0.18	-0.12	-0.06	-0.09	**0.77**	0.22	-0.06	0.03
CORR	Mn30d	-0.11	-0.19	-0.12	-0.06	-0.09	**0.77**	0.22	-0.05	0.02
CORR	Mn3d	-0.11	-0.19	-0.11	-0.06	-0.09	**0.78**	0.23	-0.05	0.03
CORR	Mn7d	-0.11	-0.19	-0.12	-0.06	-0.09	**0.78**	0.23	-0.05	0.02
CORR	Mx1d	-0.27	-0.34	0.20	0.27	0.22	**0.94**	**0.72**	-0.17	0.27
CORR	Mx3d	-0.27	-0.32	0.16	0.23	0.18	**0.96**	**0.67**	-0.15	0.25
CORR	Mx7d	-0.25	-0.35	0.25	0.33	0.28	**0.91**	**0.80**	-0.22	0.31
CORR	NHiPl	-0.25	-0.38	**0.62**	**0.86**	**0.70**	0.13	0.39	-0.36	**0.62**
CORR	RiseR	-0.29	-0.33	0.32	0.39	0.32	**0.85**	**0.80**	-0.21	0.32
CORR	BFWD_RAT	-0.13	-0.39	0.22	0.38	0.36	0.49	0.47	-0.28	0.31
CORR	LSUB_D50	-0.08	-0.31	0.03	0.21	0.09	0.22	0.16	-0.15	0.25
CORR	LSUB_D84	-0.14	-0.37	0.06	0.29	0.15	0.20	0.22	-0.24	0.28
CORR	LWDTV33	-0.20	-0.18	0.18	0.34	0.22	0.09	0.14	0.04	0.25
CORR	PCAN_C	0.07	0.20	-0.22	-0.28	-0.15	-0.13	-0.17	0.04	-0.02
CORR	PCAN_D	-0.08	-0.10	0.27	0.21	0.22	0.05	0.10	0.03	-0.06

Column 1	Column 2	Column 38	Column 39	Column 40	Column 41	Column 42	Column 43	Column 44	Column 45	Column 46
Type	Name	Fh11	Flash	Ma3	Ma41	Ma44	MAR	Mh1	Ml13	Ml22
CORR	PCAN_M	-0.28	-0.22	0.22	0.41	0.17	0.20	0.22	-0.11	0.21
CORR	PCT_FAST	-0.07	-0.04	-0.11	-0.14	-0.08	-0.01	-0.07	-0.04	0.05
CORR	PCT_ORG	-0.08	0.23	0.06	-0.02	-0.01	-0.18	-0.15	0.14	-0.10
CORR	PCT_POOL	-0.18	-0.12	0.21	0.32	0.16	-0.04	0.00	0.16	0.06
CORR	PCT_RI	0.14	0.14	-0.20	-0.28	-0.16	-0.16	-0.16	-0.07	-0.20
CORR	PCT_SAFN	0.01	0.20	-0.01	-0.15	-0.09	-0.11	-0.07	0.16	-0.17
CORR	PCT_SLOW	0.02	-0.01	0.15	0.18	0.11	0.03	0.10	0.06	-0.03
CORR	PFC_BIG	-0.23	-0.43	0.11	0.16	0.12	0.10	0.06	0.04	0.13
CORR	PFC_LWD	-0.22	-0.01	0.21	0.18	0.19	-0.11	-0.06	0.10	0.07
CORR	PFC_OHV	-0.01	0.29	-0.06	-0.24	-0.13	-0.22	-0.25	0.25	-0.28
CORR	V1W	-0.17	-0.17	0.15	0.30	0.18	0.14	0.18	0.03	0.27
CORR	V1W_MSQ	0.09	0.25	-0.11	-0.07	-0.11	-0.18	-0.18	0.22	-0.16
CORR	V4W	-0.14	-0.16	0.13	0.27	0.17	0.11	0.13	0.03	0.22
CORR	XBKF_H	-0.17	-0.17	0.15	0.30	0.18	0.14	0.18	0.03	0.27
CORR	XBKF_W	-0.27	***-0.53***	0.32	**0.50**	0.41	**0.79**	**0.79**	-0.31	**0.54**
CORR	XC	-0.32	-0.08	0.17	0.33	0.16	0.08	0.14	-0.05	0.17
CORR	XCDENBK	-0.24	-0.09	0.07	0.20	0.07	-0.05	-0.03	0.03	0.06
CORR	XDEPTH	-0.35	***-0.60***	0.36	**0.55**	0.45	**0.69**	**0.76**	-0.30	**0.64**
CORR	XFC_BIG	-0.11	-0.29	0.02	0.16	0.13	0.00	0.04	0.00	0.12
CORR	XPCMG	-0.27	-0.01	0.13	0.24	0.17	0.06	0.06	-0.04	0.14
CORR	XSLOPE	-0.05	0.29	-0.08	-0.05	-0.11	-0.19	-0.19	0.19	-0.05
CORR	XWD_RAT	0.15	0.14	-0.06	0.04	0.03	0.10	0.09	-0.09	-0.03
CORR	XWIDTH	-0.31	***-0.55***	0.34	**0.51**	0.45	**0.80**	**0.79**	-0.29	**0.55**

bold text = values that are greater than 0.5

bold and italic text = values that are less than -0.5

Table Q.1f: W-EMAP correlation matrix (Columns 1, 2, and 47 through 55).

Column 1	Column 2	Column 47	Column 48	Column 49	Column 50	Column 51	Column 52	Column 53	Column 54	Column 55
Type	Name	Mn1d	Mn30d	Mn3d	Mn7d	Mx1d	Mx3d	Mx7d	NHiPl	RiseR
MEAN		1.808	2.276	1.876	1.974	584.896	450.841	265.043	5.963	23.875
STD		8.650	10.517	9.026	9.390	1356.598	1119.939	613.022	3.590	55.556
CORR	chan_slp	0.00	-0.01	0.00	0.00	-0.11	-0.08	-0.14	0.01	-0.13
CORR	DA	0.38	0.45	0.43	0.44	0.46	0.47	**0.51**	-0.09	0.39
CORR	DWSP1	0.15	0.15	0.15	0.15	0.11	0.14	0.07	-0.13	0.04
CORR	DWSP2	0.14	0.13	0.14	0.14	0.16	0.17	0.12	0.06	0.11
CORR	link_sa	0.33	0.36	0.35	0.35	0.35	0.36	0.35	-0.16	0.26
CORR	link_sa4	0.11	0.10	0.10	0.10	0.07	0.09	0.04	-0.19	0.01
CORR	link_slope	-0.09	-0.10	-0.09	-0.09	-0.19	-0.17	-0.21	-0.16	-0.20
CORR	MCON	-0.03	-0.03	-0.03	-0.03	-0.11	-0.10	-0.13	0.03	-0.14
CORR	MDW_A_025	0.03	0.03	0.03	0.03	0.02	0.03	0.01	-0.06	0.00
CORR	MDW_A_1	-0.02	-0.03	-0.02	-0.02	-0.05	-0.04	-0.05	-0.07	-0.05
CORR	MDW_A_25	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-0.03	-0.08	-0.03
CORR	MDW_SA_025	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.02	-0.06	-0.02
CORR	MDW_SA_1	-0.03	-0.04	-0.03	-0.03	-0.06	-0.06	-0.07	-0.11	-0.06
CORR	MDW_SA_25	-0.01	-0.02	-0.01	-0.02	-0.03	-0.03	-0.03	-0.08	-0.03
CORR	MDW_SA0_4_025	-0.10	-0.10	-0.09	-0.10	-0.15	-0.14	-0.16	0.16	-0.14
CORR	MDW_SA0_4_1	-0.10	-0.11	-0.10	-0.10	-0.16	-0.15	-0.17	0.16	-0.14
CORR	MDW_SA0_4_25	-0.07	-0.07	-0.07	-0.07	-0.13	-0.13	-0.14	0.11	-0.13
CORR	MENTCC	0.16	0.19	0.18	0.18	0.15	0.16	0.17	-0.11	0.10
CORR	MENTR	0.24	0.24	0.24	0.24	0.22	0.24	0.17	0.10	0.18
CORR	min_elev	-0.12	-0.13	-0.13	-0.13	-0.37	-0.33	-0.41	***-0.55***	-0.44
CORR	pct_C	0.26	0.25	0.25	0.25	0.31	0.33	0.28	0.05	0.24
CORR	pct_lt4	-0.05	-0.04	-0.05	-0.05	-0.04	-0.05	-0.01	-0.06	-0.01
CORR	pct_lt7	-0.10	-0.09	-0.10	-0.10	-0.14	-0.15	-0.11	-0.15	-0.11
CORR	pct_PB	0.16	0.17	0.16	0.16	0.21	0.20	0.23	-0.10	0.18
CORR	pct_PR	-0.03	-0.02	-0.02	-0.02	0.01	-0.01	0.04	-0.01	0.04
CORR	pct_SP	-0.01	-0.03	-0.02	-0.02	-0.06	-0.05	-0.09	0.01	-0.08
CORR	Pred	0.12	0.12	0.12	0.12	0.15	0.17	0.12	-0.03	0.11
CORR	slp_elon	0.34	0.34	0.34	0.34	0.26	0.29	0.20	0.17	0.20

Column 1	Column 2	Column 47	Column 48	Column 49	Column 50	Column 51	Column 52	Column 53	Column 54	Column 55
Type	Name	Mn1d	Mn30d	Mn3d	Mn7d	Mx1d	Mx3d	Mx7d	NHiPl	RiseR
CORR	Avg_Jun	0.21	0.21	0.21	0.21	**0.55**	**0.52**	**0.61**	0.30	**0.56**
CORR	Avg_Nov	0.21	0.21	0.21	0.21	**0.72**	**0.66**	**0.80**	0.38	**0.80**
CORR	Avg_Oct	0.16	0.16	0.17	0.16	**0.70**	**0.64**	**0.78**	0.43	**0.80**
CORR	BaseQ	0.01	-0.03	-0.03	-0.03	0.03	0.02	0.07	0.14	0.05
CORR	Dh12	-0.11	-0.11	-0.10	-0.11	0.04	0.03	0.06	0.21	0.10
CORR	DHiPl	0.15	0.14	0.14	0.14	-0.10	-0.06	-0.18	***-0.83***	-0.22
CORR	FallR	-0.06	-0.06	-0.06	-0.06	-0.11	-0.11	-0.10	0.34	-0.08
CORR	Fh11	-0.12	-0.11	-0.11	-0.11	-0.27	-0.27	-0.25	-0.25	-0.29
CORR	Flash	-0.18	-0.19	-0.19	-0.19	-0.34	-0.32	-0.35	-0.38	-0.33
CORR	Ma3	-0.12	-0.12	-0.11	-0.12	0.20	0.16	0.25	**0.62**	0.32
CORR	Ma41	-0.06	-0.06	-0.06	-0.06	0.27	0.23	0.33	**0.86**	0.39
CORR	Ma44	-0.09	-0.09	-0.09	-0.09	0.22	0.18	0.28	**0.70**	0.32
CORR	MAR	**0.77**	**0.77**	**0.78**	**0.78**	**0.94**	**0.96**	**0.91**	0.13	**0.85**
CORR	Mh1	0.22	0.22	0.23	0.23	**0.72**	**0.67**	**0.80**	0.39	**0.80**
CORR	Ml13	-0.06	-0.05	-0.05	-0.05	-0.17	-0.15	-0.22	-0.36	-0.21
CORR	Ml22	0.03	0.02	0.03	0.02	0.27	0.25	0.31	**0.62**	0.32
CORR	Mn1d	**1.00**	**0.99**	**0.99**	**0.99**	**0.71**	**0.78**	**0.58**	-0.15	0.49
CORR	Mn30d	**0.99**	**1.00**	**1.00**	**1.00**	**0.71**	**0.78**	**0.59**	-0.15	0.48
CORR	Mn3d	**0.99**	**1.00**	**1.00**	**1.00**	**0.71**	**0.78**	**0.59**	-0.15	0.49
CORR	Mn7d	**0.99**	**1.00**	**1.00**	**1.00**	**0.71**	**0.78**	**0.59**	-0.15	0.49
CORR	Mx1d	**0.71**	**0.71**	**0.71**	**0.71**	**1.00**	**0.99**	**0.98**	0.14	**0.96**
CORR	Mx3d	**0.78**	**0.78**	**0.78**	**0.78**	**0.99**	**1.00**	**0.95**	0.09	**0.92**
CORR	Mx7d	**0.58**	**0.59**	**0.59**	**0.59**	**0.98**	**0.95**	**1.00**	0.21	**0.98**
CORR	NHiPl	-0.15	-0.15	-0.15	-0.15	0.14	0.09	0.21	**1.00**	0.26
CORR	RiseR	0.49	0.48	0.49	0.49	**0.96**	**0.92**	**0.98**	0.26	**1.00**
CORR	BFWD_RAT	0.27	0.28	0.27	0.27	**0.53**	**0.51**	**0.57**	0.32	**0.55**
CORR	LSUB_D50	0.16	0.16	0.16	0.16	0.20	0.20	0.20	0.14	0.17
CORR	LSUB_D84	0.10	0.11	0.11	0.11	0.21	0.20	0.23	0.19	0.22
CORR	LWDTV33	-0.02	-0.03	-0.02	-0.02	0.06	0.06	0.06	0.28	0.07
CORR	PCAN_C	-0.05	-0.05	-0.05	-0.05	-0.19	-0.16	-0.23	-0.19	-0.23
CORR	PCAN_D	-0.02	-0.02	-0.02	-0.02	0.15	0.11	0.18	0.16	0.21

Column 1	Column 2	Column 47	Column 48	Column 49	Column 50	Column 51	Column 52	Column 53	Column 54	Column 55
Type	Name	Mn1d	Mn30d	Mn3d	Mn7d	Mx1d	Mx3d	Mx7d	NHiPl	RiseR
CORR	PCAN_M	0.11	0.10	0.11	0.10	0.20	0.19	0.21	0.37	0.23
CORR	PCT_FAST	0.05	0.03	0.04	0.04	-0.08	-0.06	-0.12	-0.21	-0.14
CORR	PCT_ORG	-0.15	-0.15	-0.15	-0.15	-0.19	-0.18	-0.19	-0.08	-0.17
CORR	PCT_POOL	-0.08	-0.08	-0.08	-0.08	0.00	-0.01	0.03	0.35	0.04
CORR	PCT_RI	-0.07	-0.09	-0.09	-0.08	-0.20	-0.18	-0.21	-0.27	-0.22
CORR	PCT_SAFN	-0.10	-0.10	-0.10	-0.10	-0.10	-0.11	-0.09	-0.11	-0.08
CORR	PCT_SLOW	-0.04	-0.02	-0.03	-0.03	0.11	0.08	0.15	0.23	0.17
CORR	PFC_BIG	0.07	0.07	0.07	0.07	0.09	0.09	0.08	0.06	0.07
CORR	PFC_LWD	-0.12	-0.13	-0.12	-0.13	-0.11	-0.10	-0.11	0.10	-0.08
CORR	PFC_OHV	-0.10	-0.10	-0.10	-0.10	-0.21	-0.19	-0.20	-0.19	-0.20
CORR	V1W	0.00	-0.01	0.00	-0.01	0.11	0.11	0.12	0.21	0.12
CORR	V1W_MSQ	-0.11	-0.11	-0.11	-0.11	-0.20	-0.19	-0.21	-0.12	-0.20
CORR	V4W	0.01	0.00	0.00	0.00	0.08	0.09	0.09	0.19	0.09
CORR	XBKF_H	0.00	-0.01	0.00	-0.01	0.11	0.11	0.12	0.21	0.12
CORR	XBKF_W	0.41	0.42	0.42	0.42	**0.80**	**0.77**	**0.83**	0.38	**0.81**
CORR	XC	-0.01	-0.02	-0.02	-0.02	0.10	0.09	0.11	0.38	0.15
CORR	XCDENBK	-0.06	-0.07	-0.06	-0.06	-0.04	-0.04	-0.04	0.19	-0.01
CORR	XDEPTH	0.31	0.32	0.32	0.32	**0.66**	**0.63**	**0.69**	0.40	**0.67**
CORR	XFC_BIG	-0.05	-0.05	-0.05	-0.05	-0.07	-0.06	-0.06	0.09	-0.08
CORR	XPCMG	0.02	0.01	0.02	0.02	0.05	0.06	0.04	0.30	0.07
CORR	XSLOPE	-0.10	-0.11	-0.10	-0.10	-0.23	-0.21	-0.24	-0.10	-0.24
CORR	XWD_RAT	0.06	0.06	0.06	0.06	0.12	0.12	0.14	0.07	0.14
CORR	XWIDTH	0.44	0.45	0.44	0.44	**0.80**	**0.78**	**0.84**	0.37	**0.80**

bold text = values that are greater than 0.5
bold and italic text = values that are less than -0.5

Table Q.1g: W-EMAP correlation matrix (Columns 1, 2, and 56 through 64).

Column 1	Column 2	Column 56	Column 57	Column 58	Column 59	Column 60	Column 61	Column 62	Column 63	Column 64
Type	Name	BFWD_RAT	LSUB_D50	LSUB_D84	LWDTV33	PCAN_C	PCAN_D	PCAN_M	PCT_FAST	PCT_ORG
MEAN		9.072	1.574	2.533	67.509	0.478	0.134	0.227	61.410	5.184
STD		4.140	0.974	0.740	93.102	0.385	0.229	0.271	23.375	5.676
CORR	chan_slp	-0.21	0.15	0.16	0.19	0.05	-0.13	0.09	0.35	0.26
CORR	DA	0.38	0.16	0.15	-0.13	-0.18	0.05	-0.05	-0.13	-0.27
CORR	DWSP1	0.01	0.41	0.29	0.12	0.01	-0.16	0.07	0.28	-0.14
CORR	DWSP2	0.12	0.33	0.29	0.29	-0.08	-0.04	0.18	0.37	-0.07
CORR	link_sa	0.28	0.26	0.23	-0.08	-0.14	-0.01	-0.03	0.00	-0.30
CORR	link_sa4	0.00	0.42	0.33	0.07	0.01	-0.16	0.04	0.27	-0.18
CORR	link_slope	-0.28	0.21	0.13	0.11	0.13	-0.19	0.02	0.32	0.19
CORR	MCON	-0.05	0.29	0.28	0.05	0.11	-0.21	0.10	0.17	-0.13
CORR	MDW_A_025	-0.15	-0.25	-0.19	0.04	-0.12	0.02	0.00	-0.10	0.18
CORR	MDW_A_1	-0.10	-0.06	-0.01	-0.06	-0.12	-0.02	-0.05	0.00	0.14
CORR	MDW_A_25	-0.05	0.03	0.05	-0.05	-0.11	-0.03	-0.06	0.06	0.05
CORR	MDW_SA_025	-0.10	-0.11	-0.09	0.04	-0.08	-0.04	-0.01	0.00	0.12
CORR	MDW_SA_1	-0.14	-0.09	-0.04	-0.04	-0.08	-0.04	-0.09	0.00	0.15
CORR	MDW_SA_25	-0.04	0.04	0.05	-0.05	-0.11	-0.03	-0.07	0.07	0.04
CORR	MDW_SA0_4_025	-0.15	-0.08	-0.10	-0.03	0.06	-0.06	0.07	0.06	0.18
CORR	MDW_SA0_4_1	-0.15	-0.08	-0.09	-0.04	0.07	-0.06	0.07	0.05	0.18
CORR	MDW_SA0_4_25	-0.12	-0.12	-0.05	-0.04	-0.01	-0.01	0.05	0.07	0.26
CORR	MENTCC	0.25	0.28	0.34	-0.09	0.02	-0.13	-0.04	0.02	-0.30
CORR	MENTR	0.02	-0.02	-0.02	0.09	-0.12	0.14	0.13	-0.07	0.08
CORR	min_elev	-0.39	-0.14	-0.23	-0.03	**0.64**	***-0.54***	-0.49	0.23	0.12
CORR	pct_C	0.19	0.28	0.26	0.25	-0.12	-0.08	0.11	0.21	-0.12
CORR	pct_lt4	0.01	-0.14	-0.13	-0.19	0.00	0.04	-0.19	-0.36	-0.08
CORR	pct_lt7	-0.09	-0.23	-0.25	-0.26	0.03	0.02	-0.21	-0.35	-0.03
CORR	pct_PB	0.43	0.20	0.16	-0.04	-0.14	0.10	-0.06	0.11	-0.38
CORR	pct_PR	0.04	-0.10	-0.07	-0.14	0.00	0.03	-0.17	-0.38	-0.07
CORR	pct_SP	-0.09	0.06	0.02	0.11	0.02	-0.03	0.16	0.35	0.11
CORR	Pred	0.04	0.24	0.27	0.00	0.03	-0.05	0.06	0.06	-0.15
CORR	slp_elon	0.06	-0.03	0.02	0.06	0.00	-0.10	0.21	0.10	0.05

Column 1	Column 2	Column 56	Column 57	Column 58	Column 59	Column 60	Column 61	Column 62	Column 63	Column 64
Type	Name	BFWD_RAT	LSUB_D50	LSUB_D84	LWDTV33	PCAN_C	PCAN_D	PCAN_M	PCT_FAST	PCT_ORG
CORR	Avg_Jun	0.41	0.17	0.19	0.16	-0.06	-0.01	0.14	0.03	-0.16
CORR	Avg_Nov	0.46	0.15	0.21	0.12	-0.19	0.13	0.22	-0.11	-0.14
CORR	Avg_Oct	0.47	0.15	0.20	0.15	-0.17	0.11	0.22	-0.09	-0.13
CORR	BaseQ	0.21	0.09	0.09	0.04	0.09	-0.12	0.00	0.08	-0.05
CORR	Dh12	0.02	-0.05	-0.03	0.09	-0.06	0.13	0.08	0.02	0.24
CORR	DHiPl	-0.26	-0.06	-0.15	-0.17	0.21	-0.16	-0.36	0.30	0.14
CORR	FallR	0.04	0.15	0.22	0.32	-0.14	0.07	0.22	-0.06	0.03
CORR	Fh11	-0.13	-0.08	-0.14	-0.20	0.07	-0.08	-0.28	-0.07	-0.08
CORR	Flash	-0.39	-0.31	-0.37	-0.18	0.20	-0.10	-0.22	-0.04	0.23
CORR	Ma3	0.22	0.03	0.06	0.18	-0.22	0.27	0.22	-0.11	0.06
CORR	Ma41	0.38	0.21	0.29	0.34	-0.28	0.21	0.41	-0.14	-0.02
CORR	Ma44	0.36	0.09	0.15	0.22	-0.15	0.22	0.17	-0.08	-0.01
CORR	MAR	0.49	0.22	0.20	0.09	-0.13	0.05	0.20	-0.01	-0.18
CORR	Mh1	0.47	0.16	0.22	0.14	-0.17	0.10	0.22	-0.07	-0.15
CORR	Ml13	-0.28	-0.15	-0.24	0.04	0.04	0.03	-0.11	-0.04	0.14
CORR	Ml22	0.31	0.25	0.28	0.25	-0.02	-0.06	0.21	0.05	-0.10
CORR	Mn1d	0.27	0.16	0.10	-0.02	-0.05	-0.02	0.11	0.05	-0.15
CORR	Mn30d	0.28	0.16	0.11	-0.03	-0.05	-0.02	0.10	0.03	-0.15
CORR	Mn3d	0.27	0.16	0.11	-0.02	-0.05	-0.02	0.11	0.04	-0.15
CORR	Mn7d	0.27	0.16	0.11	-0.02	-0.05	-0.02	0.10	0.04	-0.15
CORR	Mx1d	**0.53**	0.20	0.21	0.06	-0.19	0.15	0.20	-0.08	-0.19
CORR	Mx3d	**0.51**	0.20	0.20	0.06	-0.16	0.11	0.19	-0.06	-0.18
CORR	Mx7d	**0.57**	0.20	0.23	0.06	-0.23	0.18	0.21	-0.12	-0.19
CORR	NHiPl	0.32	0.14	0.19	0.28	-0.19	0.16	0.37	-0.21	-0.08
CORR	RiseR	**0.55**	0.17	0.22	0.07	-0.23	0.21	0.23	-0.14	-0.17
CORR	BFWD_RAT	**1.00**	0.37	0.36	0.17	-0.17	0.20	0.20	0.01	-0.28
CORR	LSUB_D50	0.37	**1.00**	**0.72**	0.15	-0.08	-0.06	0.19	0.32	-0.33
CORR	LSUB_D84	0.36	**0.72**	**1.00**	0.11	-0.10	-0.07	0.28	0.19	-0.16
CORR	LWDTV33	0.17	0.15	0.11	**1.00**	0.12	-0.12	0.14	0.08	0.09
CORR	PCAN_C	-0.17	-0.08	-0.10	0.12	**1.00**	***-0.62***	***-0.52***	0.15	0.12
CORR	PCAN_D	0.20	-0.06	-0.07	-0.12	***-0.62***	**1.00**	0.04	-0.18	-0.02

Column 1	Column 2	Column 56	Column 57	Column 58	Column 59	Column 60	Column 61	Column 62	Column 63	Column 64
Type	Name	BFWD_RAT	LSUB_D50	LSUB_D84	LWDTV33	PCAN_C	PCAN_D	PCAN_M	PCT_FAST	PCT_ORG
CORR	PCAN_M	0.20	0.19	0.28	0.14	***-0.52***	0.04	**1.00**	-0.03	0.02
CORR	PCT_FAST	0.01	0.32	0.19	0.08	0.15	-0.18	-0.03	**1.00**	-0.06
CORR	PCT_ORG	-0.28	-0.33	-0.16	0.09	0.12	-0.02	0.02	-0.06	**1.00**
CORR	PCT_POOL	-0.04	-0.17	-0.14	0.08	-0.19	0.24	0.16	***-0.59***	0.22
CORR	PCT_RI	-0.01	-0.02	-0.17	-0.12	0.26	-0.14	-0.19	**0.66**	-0.07
CORR	PCT_SAFN	-0.37	***-0.82***	***-0.60***	-0.13	-0.01	0.18	-0.16	-0.35	0.25
CORR	PCT_SLOW	0.02	-0.23	-0.16	-0.06	-0.19	0.21	0.06	***-0.96***	0.02
CORR	PFC_BIG	0.21	0.27	0.22	0.20	0.12	-0.12	0.08	0.11	0.10
CORR	PFC_LWD	-0.02	-0.08	-0.09	0.39	0.32	-0.05	0.00	0.11	0.46
CORR	PFC_OHV	-0.29	-0.28	-0.26	-0.08	0.07	0.11	-0.11	-0.07	0.28
CORR	V1W	0.19	0.12	0.09	**0.86**	0.14	-0.12	0.09	0.08	0.20
CORR	V1W_MSQ	-0.26	-0.06	-0.08	0.47	0.27	-0.20	-0.11	0.00	0.43
CORR	V4W	0.18	0.13	0.09	**0.85**	0.12	-0.14	0.12	0.05	0.14
CORR	XBKF_H	0.19	0.12	0.09	**0.86**	0.14	-0.12	0.09	0.08	0.20
CORR	XBKF_W	**0.74**	0.31	0.32	0.23	-0.27	0.21	0.26	-0.07	-0.27
CORR	XC	0.20	0.11	0.17	0.21	0.18	0.03	0.31	0.02	0.07
CORR	XCDENBK	-0.04	0.12	0.26	0.12	0.06	0.04	0.32	0.15	0.28
CORR	XDEPTH	**0.53**	0.27	0.32	0.23	-0.24	0.12	0.30	-0.09	-0.23
CORR	XFC_BIG	0.04	0.24	0.28	0.18	0.26	-0.20	-0.14	0.19	-0.02
CORR	XPCMG	0.12	0.05	0.10	0.27	0.39	0.00	0.31	0.04	0.20
CORR	XSLOPE	-0.33	0.17	0.18	0.10	0.13	-0.16	-0.02	0.34	0.24
CORR	XWD_RAT	0.34	0.14	0.11	0.07	0.00	0.03	0.01	-0.09	0.04
CORR	XWIDTH	**0.70**	0.29	0.31	0.25	-0.24	0.21	0.25	-0.06	-0.24

bold text = values that are greater than 0.5
bold and italic text = values that are less than -0.5

Table Q.1h: W-EMAP correlation matrix (Columns 1, 2, and 65 through 73).

Column 1	Column 2	Column 65	Column 66	Column 67	Column 68	Column 69	Column 70	Column 71	Column 72	Column 73
Type	Name	PCT_POOL	PCT_RI	PCT_SAFN	PCT_SLOW	PFC_BIG	PFC_LWD	PFC_OHV	V1W	V1W_MSQ
MEAN		18.106	49.118	18.436	37.395	0.909	0.516	0.756	38.335	0.040
STD		15.326	23.195	15.247	22.526	0.194	0.334	0.275	55.710	0.065
CORR	chan_slp	-0.08	-0.10	-0.20	-0.36	-0.04	0.10	0.01	0.14	0.22
CORR	DA	-0.03	-0.08	-0.11	0.15	0.05	-0.29	-0.15	-0.10	-0.23
CORR	DWSP1	-0.10	-0.12	-0.38	-0.29	0.07	-0.04	-0.20	0.08	0.03
CORR	DWSP2	-0.17	-0.11	-0.33	-0.37	-0.03	-0.02	-0.22	0.26	0.03
CORR	link_sa	-0.08	-0.07	-0.23	0.02	0.07	-0.28	-0.27	-0.05	-0.22
CORR	link_sa4	-0.12	-0.16	-0.40	-0.27	0.09	-0.07	-0.21	0.04	0.00
CORR	link_slope	-0.10	-0.11	-0.26	-0.34	-0.05	0.12	0.06	0.07	0.27
CORR	MCON	-0.06	-0.03	-0.31	-0.18	0.06	-0.04	-0.17	0.06	0.07
CORR	MDW_A_025	0.17	-0.19	0.23	0.07	-0.09	-0.02	0.09	0.10	0.09
CORR	MDW_A_1	0.08	-0.10	0.07	-0.01	-0.02	-0.08	0.08	-0.05	-0.02
CORR	MDW_A_25	0.00	-0.05	0.00	-0.06	0.00	-0.08	0.05	-0.04	-0.04
CORR	MDW_SA_025	0.04	-0.10	0.12	0.00	-0.08	0.00	0.05	0.08	0.18
CORR	MDW_SA_1	0.05	-0.12	0.11	-0.01	-0.08	-0.07	0.09	-0.01	0.12
CORR	MDW_SA_25	-0.01	-0.04	-0.01	-0.06	0.00	-0.08	0.05	-0.04	-0.03
CORR	MDW_SA0_4_025	0.07	0.12	0.09	-0.06	0.13	0.16	0.00	-0.03	0.19
CORR	MDW_SA0_4_1	0.07	0.12	0.08	-0.05	0.13	0.16	-0.01	-0.04	0.20
CORR	MDW_SA0_4_25	0.08	0.06	0.10	-0.08	0.07	0.14	0.12	-0.03	0.17
CORR	MENTCC	-0.03	-0.04	-0.26	-0.01	0.16	-0.23	-0.27	-0.08	-0.20
CORR	MENTR	0.04	-0.05	0.01	0.08	-0.06	0.06	0.01	0.07	0.00
CORR	min_elev	-0.37	0.34	0.00	-0.26	0.06	0.16	0.24	-0.04	0.24
CORR	pct_C	-0.09	-0.25	-0.20	-0.19	0.12	-0.04	-0.12	0.25	-0.09
CORR	pct_lt4	0.20	-0.03	0.17	0.37	0.10	-0.04	0.06	-0.16	-0.06
CORR	pct_lt7	0.13	0.07	0.24	0.35	0.06	-0.03	0.16	-0.24	-0.02
CORR	pct_PB	-0.20	0.16	-0.13	-0.11	-0.03	-0.28	-0.23	0.03	-0.29
CORR	pct_PR	0.25	-0.09	0.14	0.39	0.12	-0.03	0.03	-0.13	-0.06
CORR	pct_SP	-0.23	0.12	-0.11	-0.36	-0.14	0.05	0.00	0.10	0.09
CORR	Pred	0.05	-0.14	-0.17	-0.05	0.10	-0.12	-0.24	0.00	-0.08
CORR	slp_elon	0.05	-0.06	0.01	-0.11	0.05	0.04	-0.17	0.03	-0.09

Column 1	Column 2	Column 65	Column 66	Column 67	Column 68	Column 69	Column 70	Column 71	Column 72	Column 73
Type	Name	PCT_POOL	PCT_RI	PCT_SAFN	PCT_SLOW	PFC_BIG	PFC_LWD	PFC_OHV	V1W	V1W_MSQ
CORR	Avg_Jun	-0.02	-0.08	-0.08	-0.01	0.09	-0.09	-0.23	0.20	-0.16
CORR	Avg_Nov	0.03	-0.19	-0.05	0.13	0.05	-0.05	-0.24	0.16	-0.18
CORR	Avg_Oct	0.02	-0.18	-0.06	0.11	0.05	-0.03	-0.25	0.20	-0.17
CORR	BaseQ	-0.09	0.09	-0.15	-0.11	0.05	-0.03	-0.09	0.04	-0.06
CORR	Dh12	0.06	-0.07	0.00	0.01	0.16	0.31	0.10	0.06	0.00
CORR	DHiPl	-0.36	0.24	0.04	-0.30	0.02	-0.03	0.11	-0.08	0.24
CORR	FallR	0.31	-0.11	-0.12	0.08	0.09	0.07	-0.03	0.20	0.23
CORR	Fh11	-0.18	0.14	0.01	0.02	-0.23	-0.22	-0.01	-0.17	0.09
CORR	Flash	-0.12	0.14	0.20	-0.01	-0.43	-0.01	0.29	-0.17	0.25
CORR	Ma3	0.21	-0.20	-0.01	0.15	0.11	0.21	-0.06	0.15	-0.11
CORR	Ma41	0.32	-0.28	-0.15	0.18	0.16	0.18	-0.24	0.30	-0.07
CORR	Ma44	0.16	-0.16	-0.09	0.11	0.12	0.19	-0.13	0.18	-0.11
CORR	MAR	-0.04	-0.16	-0.11	0.03	0.10	-0.11	-0.22	0.14	-0.18
CORR	Mh1	0.00	-0.16	-0.07	0.10	0.06	-0.06	-0.25	0.18	-0.18
CORR	Ml13	0.16	-0.07	0.16	0.06	0.04	0.10	0.25	0.03	0.22
CORR	Ml22	0.06	-0.20	-0.17	-0.03	0.13	0.07	-0.28	0.27	-0.16
CORR	Mn1d	-0.08	-0.07	-0.10	-0.04	0.07	-0.12	-0.10	0.00	-0.11
CORR	Mn30d	-0.08	-0.09	-0.10	-0.02	0.07	-0.13	-0.10	-0.01	-0.11
CORR	Mn3d	-0.08	-0.09	-0.10	-0.03	0.07	-0.12	-0.10	0.00	-0.11
CORR	Mn7d	-0.08	-0.08	-0.10	-0.03	0.07	-0.13	-0.10	-0.01	-0.11
CORR	Mx1d	0.00	-0.20	-0.10	0.11	0.09	-0.11	-0.21	0.11	-0.20
CORR	Mx3d	-0.01	-0.18	-0.11	0.08	0.09	-0.10	-0.19	0.11	-0.19
CORR	Mx7d	0.03	-0.21	-0.09	0.15	0.08	-0.11	-0.20	0.12	-0.21
CORR	NHiPl	0.35	-0.27	-0.11	0.23	0.06	0.10	-0.19	0.21	-0.12
CORR	RiseR	0.04	-0.22	-0.08	0.17	0.07	-0.08	-0.20	0.12	-0.20
CORR	BFWD_RAT	-0.04	-0.01	-0.37	0.02	0.21	-0.02	-0.29	0.19	-0.26
CORR	LSUB_D50	-0.17	-0.02	***-0.82***	-0.23	0.27	-0.08	-0.28	0.12	-0.06
CORR	LSUB_D84	-0.14	-0.17	***-0.60***	-0.16	0.22	-0.09	-0.26	0.09	-0.08
CORR	LWDTV33	0.08	-0.12	-0.13	-0.06	0.20	0.39	-0.08	**0.86**	0.47
CORR	PCAN_C	-0.19	0.26	-0.01	-0.19	0.12	0.32	0.07	0.14	0.27
CORR	PCAN_D	0.24	-0.14	0.18	0.21	-0.12	-0.05	0.11	-0.12	-0.20

Column 1	Column 2	Column 65	Column 66	Column 67	Column 68	Column 69	Column 70	Column 71	Column 72	Column 73
Type	Name	PCT_POOL	PCT_RI	PCT_SAFN	PCT_SLOW	PFC_BIG	PFC_LWD	PFC_OHV	V1W	V1W_MSQ
CORR	PCAN_M	0.16	-0.19	-0.16	0.06	0.08	0.00	-0.11	0.09	-0.11
CORR	PCT_FAST	***-0.59***	**0.66**	-0.35	***-0.96***	0.11	0.11	-0.07	0.08	0.00
CORR	PCT_ORG	0.22	-0.07	0.25	0.02	0.10	0.46	0.28	0.20	0.43
CORR	PCT_POOL	**1.00**	***-0.53***	0.28	**0.58**	0.14	0.06	-0.02	0.04	0.00
CORR	PCT_RI	***-0.53***	**1.00**	-0.05	***-0.63***	-0.03	0.05	0.03	-0.11	-0.02
CORR	PCT_SAFN	0.28	-0.05	**1.00**	0.32	-0.23	0.04	0.28	-0.06	0.05
CORR	PCT_SLOW	**0.58**	***-0.63***	0.32	**1.00**	-0.07	-0.10	0.08	-0.07	-0.01
CORR	PFC_BIG	0.14	-0.03	-0.23	-0.07	**1.00**	0.38	-0.14	0.18	0.11
CORR	PFC_LWD	0.06	0.05	0.04	-0.10	0.38	**1.00**	0.31	0.44	0.41
CORR	PFC_OHV	-0.02	0.03	0.28	0.08	-0.14	0.31	**1.00**	0.01	0.16
CORR	V1W	0.04	-0.11	-0.06	-0.07	0.18	0.44	0.01	**1.00**	**0.54**
CORR	V1W_MSQ	0.00	-0.02	0.05	-0.01	0.11	0.41	0.16	**0.54**	**1.00**
CORR	V4W	0.03	-0.09	-0.07	-0.04	0.15	0.37	-0.01	**0.98**	**0.52**
CORR	XBKF_H	0.04	-0.11	-0.06	-0.07	0.18	0.44	0.01	**1.00**	**0.54**
CORR	XBKF_W	0.06	-0.22	-0.19	0.10	0.16	-0.07	-0.34	0.31	-0.29
CORR	XC	0.07	0.01	-0.08	-0.01	0.11	0.34	0.02	0.22	0.10
CORR	XCDENBK	0.14	0.02	-0.07	-0.15	0.19	0.32	0.17	0.12	0.14
CORR	XDEPTH	0.08	-0.28	-0.13	0.14	0.16	-0.05	-0.32	0.29	-0.28
CORR	XFC_BIG	0.04	0.06	-0.23	-0.16	0.44	0.32	0.04	0.17	0.16
CORR	XPCMG	0.09	0.06	-0.05	-0.04	0.22	0.49	0.09	0.24	0.17
CORR	XSLOPE	-0.12	-0.08	-0.24	-0.37	-0.09	0.12	0.10	0.06	0.31
CORR	XWD_RAT	0.03	-0.05	-0.17	-0.01	0.07	0.08	-0.02	0.10	0.01
CORR	XWIDTH	0.03	-0.21	-0.16	0.10	0.19	-0.03	-0.28	0.33	-0.26

bold text = values that are greater than 0.5
bold and italic text = values that are less than -0.5

Table Q.1i: W-EMAP correlation matrix (Columns 1, 2, and 74 through 82).

Column 1	Column 2	Column 74	Column 75	Column 76	Column 77	Column 78	Column 79	Column 80	Column 81	Column 82
Type	Name	V4W	XBKF_H	XBKF_W	XC	XCDENBK	XDEPTH	XFC_BIG	XPCMG	XSLOPE
MEAN		24.191	38.335	7.778	0.337	79.693	26.817	0.292	0.840	5.602
STD		42.959	55.710	6.855	0.207	19.509	22.975	0.213	0.241	5.884
CORR	chan_slp	0.10	0.14	-0.18	0.04	0.23	-0.13	-0.07	0.05	**0.67**
CORR	DA	-0.09	-0.10	0.46	-0.19	-0.22	0.39	-0.01	-0.31	-0.24
CORR	DWSP1	0.06	0.08	0.10	-0.02	0.11	0.11	0.08	-0.05	0.35
CORR	DWSP2	0.23	0.26	0.24	0.00	0.09	0.29	-0.05	0.02	0.38
CORR	link_sa	-0.04	-0.05	0.42	-0.17	-0.19	0.37	0.07	-0.30	-0.17
CORR	link_sa4	0.02	0.04	0.09	-0.06	0.07	0.09	0.16	-0.11	0.44
CORR	link_slope	0.03	0.07	-0.28	0.00	0.21	-0.27	0.05	0.04	**0.86**
CORR	MCON	0.05	0.06	-0.06	0.04	0.17	-0.03	0.10	0.07	0.27
CORR	MDW_A_025	0.12	0.10	0.01	-0.09	0.03	0.02	-0.16	-0.18	0.06
CORR	MDW_A_1	-0.04	-0.05	-0.06	-0.12	0.01	0.00	-0.08	-0.26	0.04
CORR	MDW_A_25	-0.03	-0.04	-0.03	-0.13	-0.02	0.02	-0.05	-0.28	0.01
CORR	MDW_SA_025	0.10	0.08	-0.03	-0.05	0.03	0.01	-0.13	-0.16	0.04
CORR	MDW_SA_1	-0.01	-0.01	-0.10	-0.11	0.01	-0.05	-0.09	-0.27	0.07
CORR	MDW_SA_25	-0.03	-0.04	-0.03	-0.13	-0.02	0.01	-0.05	-0.28	0.01
CORR	MDW_SA0_4_025	-0.05	-0.03	-0.20	0.08	0.19	-0.17	-0.13	0.17	0.04
CORR	MDW_SA0_4_1	-0.06	-0.04	-0.21	0.08	0.20	-0.18	-0.12	0.17	0.05
CORR	MDW_SA0_4_25	-0.06	-0.03	-0.20	0.02	0.16	-0.20	-0.10	0.07	0.15
CORR	MENTCC	-0.05	-0.08	0.25	-0.14	-0.09	0.26	0.12	-0.20	-0.14
CORR	MENTR	0.06	0.07	0.13	0.01	0.03	0.17	-0.03	0.06	-0.08
CORR	min_elev	-0.05	-0.04	-0.50	-0.21	-0.17	-0.45	0.19	-0.03	0.17
CORR	pct_C	0.21	0.25	0.40	-0.11	0.01	0.47	0.07	-0.17	0.19
CORR	pct_lt4	-0.14	-0.16	-0.04	-0.13	-0.11	-0.11	0.14	-0.14	-0.37
CORR	pct_lt7	-0.21	-0.24	-0.19	-0.12	-0.14	-0.24	0.05	-0.12	-0.40
CORR	pct_PB	0.05	0.03	0.39	-0.15	-0.20	0.30	0.02	-0.21	-0.36
CORR	pct_PR	-0.11	-0.13	0.00	-0.14	-0.10	-0.06	0.18	-0.13	-0.29
CORR	pct_SP	0.08	0.10	-0.08	0.17	0.11	-0.02	-0.20	0.17	0.29
CORR	Pred	-0.01	0.00	0.16	0.07	0.10	0.27	0.10	0.04	0.08
CORR	slp_elon	0.02	0.03	0.16	0.11	0.12	0.17	-0.15	0.14	0.01
CORR	Avg_Jun	0.16	0.20	**0.71**	0.10	-0.04	**0.71**	0.16	0.05	-0.16

Column 1	Column 2	Column 74	Column 75	Column 76	Column 77	Column 78	Column 79	Column 80	Column 81	Column 82
Type	Name	V4W	XBKF_H	XBKF_W	XC	XCDENBK	XDEPTH	XFC_BIG	XPCMG	XSLOPE
CORR	Avg_Nov	0.11	0.16	**0.77**	0.16	-0.01	**0.75**	0.02	0.07	-0.19
CORR	Avg_Oct	0.14	0.20	**0.77**	0.15	-0.02	**0.75**	0.02	0.07	-0.19
CORR	BaseQ	0.03	0.04	0.14	0.07	-0.02	0.13	0.14	0.05	-0.10
CORR	Dh12	0.03	0.06	0.05	0.04	0.02	0.08	0.06	0.10	0.05
CORR	DHiPl	-0.07	-0.08	-0.29	-0.30	-0.20	-0.26	-0.06	-0.26	0.15
CORR	FallR	0.21	0.20	-0.05	0.19	0.21	-0.05	0.33	0.13	0.21
CORR	Fh11	-0.14	-0.17	-0.27	-0.32	-0.24	-0.35	-0.11	-0.27	-0.05
CORR	Flash	-0.16	-0.17	***-0.53***	-0.08	-0.09	***-0.60***	-0.29	-0.01	0.29
CORR	Ma3	0.13	0.15	0.32	0.17	0.07	0.36	0.02	0.13	-0.08
CORR	Ma41	0.27	0.30	**0.50**	0.33	0.20	**0.55**	0.16	0.24	-0.05
CORR	Ma44	0.17	0.18	0.41	0.16	0.07	0.45	0.13	0.17	-0.11
CORR	MAR	0.11	0.14	**0.79**	0.08	-0.05	**0.69**	0.00	0.06	-0.19
CORR	Mh1	0.13	0.18	**0.79**	0.14	-0.03	**0.76**	0.04	0.06	-0.19
CORR	Ml13	0.03	0.03	-0.31	-0.05	0.03	-0.30	0.00	-0.04	0.19
CORR	Ml22	0.22	0.27	**0.54**	0.17	0.06	**0.64**	0.12	0.14	-0.05
CORR	Mn1d	0.01	0.00	0.41	-0.01	-0.06	0.31	-0.05	0.02	-0.10
CORR	Mn30d	0.00	-0.01	0.42	-0.02	-0.07	0.32	-0.05	0.01	-0.11
CORR	Mn3d	0.00	0.00	0.42	-0.02	-0.06	0.32	-0.05	0.02	-0.10
CORR	Mn7d	0.00	-0.01	0.42	-0.02	-0.06	0.32	-0.05	0.02	-0.10
CORR	Mx1d	0.08	0.11	**0.80**	0.10	-0.04	**0.66**	-0.07	0.05	-0.23
CORR	Mx3d	0.09	0.11	**0.77**	0.09	-0.04	**0.63**	-0.06	0.06	-0.21
CORR	Mx7d	0.09	0.12	**0.83**	0.11	-0.04	**0.69**	-0.06	0.04	-0.24
CORR	NHiPl	0.19	0.21	0.38	0.38	0.19	0.40	0.09	0.30	-0.10
CORR	RiseR	0.09	0.12	**0.81**	0.15	-0.01	**0.67**	-0.08	0.07	-0.24
CORR	BFWD_RAT	0.18	0.19	**0.74**	0.20	-0.04	**0.53**	0.04	0.12	-0.33
CORR	LSUB_D50	0.13	0.12	0.31	0.11	0.12	0.27	0.24	0.05	0.17
CORR	LSUB_D84	0.09	0.09	0.32	0.17	0.26	0.32	0.28	0.10	0.18
CORR	LWDTV33	**0.85**	**0.86**	0.23	0.21	0.12	0.23	0.18	0.27	0.10
CORR	PCAN_C	0.12	0.14	-0.27	0.18	0.06	-0.24	0.26	0.39	0.13
CORR	PCAN_D	-0.14	-0.12	0.21	0.03	0.04	0.12	-0.20	0.00	-0.16
CORR	PCAN_M	0.12	0.09	0.26	0.31	0.32	0.30	-0.14	0.31	-0.02
CORR	PCT_FAST	0.05	0.08	-0.07	0.02	0.15	-0.09	0.19	0.04	0.34

Column 1	Column 2	Column 74	Column 75	Column 76	Column 77	Column 78	Column 79	Column 80	Column 81	Column 82
Type	Name	V4W	XBKF_H	XBKF_W	XC	XCDENBK	XDEPTH	XFC_BIG	XPCMG	XSLOPE
CORR	PCT_ORG	0.14	0.20	-0.27	0.07	0.28	-0.23	-0.02	0.20	0.24
CORR	PCT_POOL	0.03	0.04	0.06	0.07	0.14	0.08	0.04	0.09	-0.12
CORR	PCT_RI	-0.09	-0.11	-0.22	0.01	0.02	-0.28	0.06	0.06	-0.08
CORR	PCT_SAFN	-0.07	-0.06	-0.19	-0.08	-0.07	-0.13	-0.23	-0.05	-0.24
CORR	PCT_SLOW	-0.04	-0.07	0.10	-0.01	-0.15	0.14	-0.16	-0.04	-0.37
CORR	PFC_BIG	0.15	0.18	0.16	0.11	0.19	0.16	0.44	0.22	-0.09
CORR	PFC_LWD	0.37	0.44	-0.07	0.34	0.32	-0.05	0.32	0.49	0.12
CORR	PFC_OHV	-0.01	0.01	-0.34	0.02	0.17	-0.32	0.04	0.09	0.10
CORR	V1W	**0.98**	**1.00**	0.31	0.22	0.12	0.29	0.17	0.24	0.06
CORR	V1W_MSQ	**0.52**	**0.54**	-0.29	0.10	0.14	-0.28	0.16	0.17	0.31
CORR	V4W	**1.00**	**0.98**	0.29	0.22	0.10	0.28	0.17	0.22	0.01
CORR	XBKF_H	**0.98**	**1.00**	0.31	0.22	0.12	0.29	0.17	0.24	0.06
CORR	XBKF_W	0.29	0.31	**1.00**	0.14	-0.09	**0.88**	0.04	0.05	-0.32
CORR	XC	0.22	0.22	0.14	**1.00**	0.45	0.15	0.13	**0.70**	-0.02
CORR	XCDENBK	0.10	0.12	-0.09	0.45	**1.00**	-0.06	0.17	**0.55**	0.24
CORR	XDEPTH	0.28	0.29	**0.88**	0.15	-0.06	**1.00**	0.06	0.03	-0.29
CORR	XFC_BIG	0.17	0.17	0.04	0.13	0.17	0.06	**1.00**	0.12	0.12
CORR	XPCMG	0.22	0.24	0.05	**0.70**	**0.55**	0.03	0.12	**1.00**	0.05
CORR	XSLOPE	0.01	0.06	-0.32	-0.02	0.24	-0.29	0.12	0.05	**1.00**
CORR	XWD_RAT	0.07	0.10	0.16	0.03	0.01	-0.05	0.03	0.06	0.03
CORR	XWIDTH	0.30	0.33	**0.97**	0.18	-0.03	**0.91**	0.06	0.08	-0.31

bold text = values that are greater than 0.5

bold and italic text = values that are less than -0.5

Table Q.1j: W-EMAP correlation matrix (Columns 1, 2, 83, and 84).

Column 1	Column 2	Column 83	Column 84
Type	Name	XWD_RAT	XWIDTH
MEAN		23.925	4.923
STD		11.223	4.921
CORR	chan_slp	-0.07	-0.16
CORR	DA	0.08	0.47
CORR	DWSP1	-0.06	0.08
CORR	DWSP2	-0.06	0.24
CORR	link_sa	0.03	0.39
CORR	link_sa4	-0.05	0.06
CORR	link_slope	-0.04	-0.29
CORR	MCON	0.12	-0.09
CORR	MDW_A_025	-0.09	0.01
CORR	MDW_A_1	-0.07	-0.05
CORR	MDW_A_25	-0.06	-0.02
CORR	MDW_SA_025	-0.11	-0.02
CORR	MDW_SA_1	-0.09	-0.09
CORR	MDW_SA_25	-0.06	-0.02
CORR	MDW_SA0_4_025	-0.08	-0.19
CORR	MDW_SA0_4_1	-0.08	-0.20
CORR	MDW_SA0_4_25	-0.03	-0.20
CORR	MENTCC	0.08	0.23
CORR	MENTR	0.01	0.18
CORR	min_elev	-0.09	-0.47
CORR	pct_C	-0.03	0.44
CORR	pct_lt4	0.11	-0.07
CORR	pct_lt7	0.07	-0.21
CORR	pct_PB	0.16	0.35
CORR	pct_PR	0.14	-0.02
CORR	pct_SP	-0.14	-0.06
CORR	Pred	-0.09	0.16
CORR	slp_elon	-0.07	0.16

Column 1	Column 2	Column 83	Column 84
Type	Name	XWD_RAT	XWIDTH
CORR	Avg_Jun	0.06	**0.74**
CORR	Avg_Nov	0.09	**0.78**
CORR	Avg_Oct	0.09	**0.77**
CORR	BaseQ	0.12	0.13
CORR	Dh12	-0.02	0.07
CORR	DHiPl	-0.16	-0.28
CORR	FallR	0.05	-0.05
CORR	Fh11	0.15	-0.31
CORR	Flash	0.14	***-0.55***
CORR	Ma3	-0.06	0.34
CORR	Ma41	0.04	**0.51**
CORR	Ma44	0.03	0.45
CORR	MAR	0.10	**0.80**
CORR	Mh1	0.09	**0.79**
CORR	Ml13	-0.09	-0.29
CORR	Ml22	-0.03	**0.55**
CORR	Mn1d	0.06	0.44
CORR	Mn30d	0.06	0.45
CORR	Mn3d	0.06	0.44
CORR	Mn7d	0.06	0.44
CORR	Mx1d	0.12	**0.80**
CORR	Mx3d	0.12	**0.78**
CORR	Mx7d	0.14	**0.84**
CORR	NHiPl	0.07	0.37
CORR	RiseR	0.14	**0.80**
CORR	BFWD_RAT	0.34	**0.70**
CORR	LSUB_D50	0.14	0.29
CORR	LSUB_D84	0.11	0.31
CORR	LWDTV33	0.07	0.25
CORR	PCAN_C	0.00	-0.24
CORR	PCAN_D	0.03	0.21

Column 1	Column 2	Column 83	Column 84
Type	Name	XWD_RAT	XWIDTH
CORR	PCAN_M	0.01	0.25
CORR	PCT_FAST	-0.09	-0.06
CORR	PCT_ORG	0.04	-0.24
CORR	PCT_POOL	0.03	0.03
CORR	PCT_RI	-0.05	-0.21
CORR	PCT_SAFN	-0.17	-0.16
CORR	PCT_SLOW	-0.01	0.10
CORR	PFC_BIG	0.07	0.19
CORR	PFC_LWD	0.08	-0.03
CORR	PFC_OHV	-0.02	-0.28
CORR	V1W	0.10	0.33
CORR	V1W_MSQ	0.01	-0.26
CORR	V4W	0.07	0.30
CORR	XBKF_H	0.10	0.33
CORR	XBKF_W	0.16	**0.97**
CORR	XC	0.03	0.18
CORR	XCDENBK	0.01	-0.03
CORR	XDEPTH	-0.05	**0.91**
CORR	XFC_BIG	0.03	0.06
CORR	XPCMG	0.06	0.08
CORR	XSLOPE	0.03	-0.31
CORR	XWD_RAT	**1.00**	0.14
CORR	XWIDTH	0.14	**1.00**

bold text = values that are greater than 0.5

bold and italic text = values that are less than -0.5