DISSERTATION

A MULTI-SCALE, HIERARCHICAL APPROACH TO MAP THE LOCATION AND CONDITION OF RIPARIAN ZONES IN THE SOUTHERN ROCKIES ECOREGION

Submitted by

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ABSTRACT

A MULTI-SCALE, HIERARCHICAL APPROACH TO MAP THE LOCATION AND CONDITION OF RIPARIAN ZONES IN THE SOUTHERN ROCKIES ECOREGION

Riparian zones are important for their contribution to biodiversity and ecosystem services, especially in the western United States where riparian zones occupy a small proportion of the landscape but support a majority of the biodiversity. Riparian zones are currently threatened by multiple stressors, and will likely face further stresses associated with climate change and additional water withdrawals due to population growth particularly in the western United States and other arid regions. Consequently, it is imperative to understand the current location and extent of riparian zones. Although many agencies and organizations are concerned with the location, condition, and benefits of these ecosystems, few accurate datasets of riparian zone are available over broad spatial extents, and cost-effective methods to map riparian zones at fine spatial resolutions do not currently exist.

My dissertation research develops a more comprehensive understanding of the location and condition riparian ecosystems in a semi-arid, mountainous region by developing methods that can be applied to other geographic regions. To do this, I took a three pronged approach to mapping riparian zone location and condition. First, I identify and evaluate existing GIS-based methods that have been previously used to map riparian zones in order to determine how accurately the methods are in a semi-arid, mountainous watershed. Second, I create a multi-scale, hierarchal method to map riparian zones by capturing the dominant physical processes to map the location of current and potential riparian zones using readily available, national datasets and demonstrate the approach for the Southern Rockies Ecoregion. Third, I estimate riparian

condition using a straightforward, cost-effective approach at management relevant scales (i.e. reach) and evaluate the dominant ecological and physical processes and anthropogenic stressors that impact riparian ecosystems.

Results from my dissertation indicate that existing methods to map potential riparian zones are not very accurate, having only a maximum accuracy of kappa coefficient of 0.38. The most appropriate existing method for mapping potential riparian zones in semi-arid mountainous regions incorporates upstream drainage area and valley topography. I develop a multi-scale, hierarchical, process guided model to map riparian zones and found that the Southern Rockies Ecoregion is composed of 3.2% (± 0.3%) potential and 2.5 (± 0.3%) current riparian zones, indicating that 20.3% (± 1.1%) of riparian zones have been removed by human activities. Based on field verification/validation, my new method has an overall accuracy of 92% for potential riparian zones and 91% in the current riparian zones. Finally, the method I developed to predict riparian condition indicated that riparian zones in the Southern Rockies Ecoregion are comprised of 7.2% low condition, 15.2% medium condition, and 77.7% high condition and that the most important variables in predicting riparian condition in the Southern Rockies Ecoregion are human modification in riparian zones, the number of upstream transportation crossings, human modification within the upstream watershed, and the proportion of the upstream watershed that is protected by GAP Status 1 management plans. The overall accuracy of my riparian condition model was 60.5%. The model could be improved though the use of higher resolution predictor variables. If fine grain (< 5 m) terrain data were available for the study area, additional geomorphic variables, such as valley width to channel width ratio, could be developed and should enhance model performance.

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TABLE OF CONTENTS

1. Introduction

Riparian ecosystems support critical ecological functions throughout western North America, yet they cover less than 5% of the land area (Swift, 1984; Dahl, 1990). Of the small portion of land that is covered by riparian areas, it is estimated that 20 – 50% (Dahl, 1990) have been altered by anthropogenic activity. The benefits associated with riparian ecosystems are vast: reducing erosion, protecting water quality by filtering sediment and nutrients, increasing biodiversity, and providing corridors for wildlife (Brauman et al., 2007). Although many agencies and organizations are concerned with the location, condition, and benefits of these ecosystems, an accurate estimate of location and condition is not available over broad geographic areas. In addition, the need for maps of riparian zones that include a rigorous estimate of uncertainty is well documented (Ward et al., 2002; NRC, 2002) and is critical to understand the extent and loss of these zones that host areas of high biodiversity and valued ecosystem services. Therefore, through this research, I develop a more comprehensive understanding of the location and condition riparian ecosystems in an arid, mountainous region by developing methods that can be applied to other geographic regions.

Riparian zones are currently threatened by multiple stressors, and will likely face further stresses associated with climate change and additional water withdrawals due to population growth (Theobald et al., 2010). Consequently, it is imperative to understand the current location and extent of riparian zones. It is also valuable to understand what processes are controlling potential riparian zones, as a means to understand both current conditions and vulnerabilities to land use and climate change, as well as to project how various management options might protect or restore these ecosystems.

I employ a common definition of riparian zones: the area that is adjacent to and influenced by streams, that typically contains vegetation that differs from the surrounding upland vegetation (Gregory et al., 1991; Verry et al., 2004; Naiman et al., 2005). I distinguish two types, potential and current, of riparian zones, consistent with other research (Clerici et al., 2013). A *potential riparian zone* is the area that would likely support natural riparian vegetation in the absence of human activity and corresponds to the geomorphic extent (i.e., the floodplains located between the active channel and the hillslope (Gregory et al., 1991)) of the "riparian zone." The *current riparian zone* is a subset of the potential riparian zone that is not strongly modified by human land uses and is assumed to support natural riparian vegetation.

Riparian zones of the Southern Rockies Ecoregion

The Southern Rockies Ecoregion (SRE) contains the headwaters for several major rivers in western and central North America that provide water for domestic, industrial, and agricultural uses (Figure 1.1). Population within the SRE is approximately 2 million people (US Census Bureau, 2010), and is projected to increase by another million by 2020 (SREP, 2004). It is estimated that by 2020 residential development will affect 25% of the total area of the SRE, negatively influencing river corridors and associated ecosystems. Expanding populations influence stream and riparian ecosystems by physically altering the ecosystem and through increasing demands for water and altering the physical environment through land use changes. Historically, humans settled along western rivers because of the ample water supply, waste disposal, and transportation opportunities, either for navigation or for locating road and rail systems along river corridors (Patten, 1998). Although much of this development is concentrated in the Front Range corridor, 95% of the SRE is within 2 miles of a road (from US Census Bureau's TIGER 2010). This leaves little land, including riparian ecosystems, free of human influence.

The SRE contains several riparian ecosystems; the most common are lower montane-foothills riparian woodlands and shrublands, subalpine-montane riparian shrublands and woodlands, and wet meadows (Kittel et al., 1999; NatureServe, 2009). The main physical factors that control the spatial and temporal characteristics of riparian vegetation are (1) ground water availability, (2) valley floor landforms, including shape and gradient; (3) river characteristics including flow and sediment regimes and location of the stream reach within the drainage network (Kovalchik and Chitwood, 1990; Naiman and Decamps, 1997); (4) local and regional fluvial processes; and (5) the parent material of the watershed (Kovalchik and Chitwood, 1990).

Because of their importance and vulnerability within the region, riparian zones within the SRE considered an ecosystem of special concern by many organizations, such as the Colorado Natural Heritage Program (Kittel et al., 1999), the Colorado Department of Parks and Wildlife (CDOW, 2006), and the Southern Rockies Landscape Conservation Cooperative (Rice, 2012). These organizations are interested in understanding riparian condition over large geographic extents, yet a detailed and comprehensive database does not currently exist.

Mapping riparian ecosystems

Riparian zones are difficult to map across large areas (Congalton et al., 2002; Goetz, 2006; Hollenhorst et al., 2006), despite their importance to biodiversity (Poff et al., 2011). Riparian zones associated with headwater streams are often obscured from view on orthogonal imagery by the forest canopy of adjacent terrestrial ecosystems or are too narrow to capture when using medium (>30 m) resolution data.

Existing riparian mapping efforts that cover large geographic extents in the United States generally capture either the potential (e.g. Jones et al., 2010; Wickham et al., 2011) or current riparian zones (e.g. LANDFIRE (2007) and Southwest Regional GAP (SWReGAP; Lowry et al., 2007)). To my knowledge none of the existing datasets were created primarily to map riparian zones. Rather, the primary objective of these datasets is to map land use or cover for large geographic extents and, therefore, the models do not explicitly include processes that create and maintain riparian zones, have vague or missing descriptions of the methods used to map riparian zones, and operate at a resolution that often misses narrow bands of riparian vegetation along small rivers (Goetz, 2006). Critically, accuracy information is usually not available for riparian land cover classes (i.e. for LANDFIRE, SWReGAP, NLCD).

Estimating riparian condition

Within the SRE the major drivers of anthropogenic change and largest threats to riparian ecosystems are alteration and regulation of stream flow, climate change, and land use change (Naiman et al., 2005; Poff et al., 2010). Previous work has assessed riparian condition in several different ways, by: measuring stream and riparian abiotic and biotic indicators and comparing them to pristine conditions (Peck et al., 2006 and Rocchio, 2007), examining hydrogeomorphic characteristics (Smith et al., 1995), or tracking the amount of disturbance that is potentially affecting the ecosystem (Reeves et al., 2004; Jones et al., 2010). Riparian condition research has been conducted at two broad scales, coarse grain remote (i.e. GIS based) or fine-grain field assessments, which include rapid and intensive evaluations (Faber-Langendoen et al., 2012). The expense associated with field assessments makes them unrealistic to conduct over large geographic extents. Nonetheless, regional condition assessments are important for managers and conservation scientists to understand ecosystems across broad geographic regions in order to manage land appropriately. Although previous GIS based condition assessments are useful, to my knowledge, none of the existing GIS approaches to estimate riparian condition address processes that occur at different scales to estimate riparian condition, conduct research at management relevant scales, or document the uncertainty associated with their methods.

My work is based on a general conceptual model of watersheds described by Reeves et al. (2004). This conceptual model separates the watershed into three physical subsystems, roughly represented as analytical scales that represent dominant ecological processes: upslope, riparian, and in channel. Within each subsystem, the main ecosystem processes that control the location and extent of riparian zones and can be interrupted by anthropogenic disturbance (Figure 1.2).

The lack of riparian zone maps over large areas with documented uncertainty and the ecological importance of riparian ecosystems motivated my interest in developing a more comprehensive understanding of the location and condition of these ecosystems. Initially, I was interested in quantifying the ecosystem services associated with riparian ecosystems, but quickly realized that the first step in the process was to locate maps of these ecosystems. When I was unable to locate maps that were created using a process guided approach and had documented accuracy, I realized the need for maps of the location, extent, and condition of riparian zones and my dissertation research commenced.

To develop a more comprehensive understanding of the location and condition of riparian ecosystems across broad geographic areas and address a critical need in the field of riparian landscape ecology, I took a three pronged approach to mapping riparian zone location and condition. In Chapter 2, I identify and evaluate eight existing methods that have been previously used to map riparian zones in order to determine how accurately the methods are in a semi-arid, mountainous watershed. In pursuit of this research, I answer the following questions: (1) what is the best way to map potential riparian zones over broad spatial extents; and (2) what resolution is appropriate to map headwater streams. In Chapter 3, I create a multi-scale, hierarchal method to map riparian zones by capturing the dominant physical processes to map the location of current and potential riparian zones using readily available, national datasets and demonstrate the approach for the Southern Rockies Ecoregion. To conduct this research: I (1) describe the dominant hydrological processes; (2) identify and map explanatory variables that capture the different scales/grains of the dominant processes; (3) produce sample-based estimates of detailed response variables (i.e. whether a location is current riparian, potential riparian, or upland); and (4) develop a statistical model to estimate locations of riparian zones and quantify change in riparian zones with documented uncertainty; In Chapter 4, I estimate riparian condition using a straightforward, cost-effective approach at management relevant scales (i.e. reach) and evaluate the dominant ecological and physical processes and anthropogenic stressors that impact riparian ecosystems. In pursuit of this research: I (1) describe the dominant influences on riparian condition; (2) identify and map explanatory variables that capture the different scales of variables that influence riparian condition; (3) produce sample-based estimates of riparian condition as the response variable; (4) develop a statistical model to estimate the condition of riparian zones with documented uncertainty; and (5) describe the most important variables in determining riparian condition.

This work contributes maps of riparian location, extent, and condition in the Southern Rockies Ecoregion, as well as general, cost effective and practical approaches to map riparian zones in other regions. Unlike many previous approaches that map riparian zones, my approach includes the processes that shape, control, and modify riparian zones and documents the uncertainty in the developed maps, providing critical information to aid in interpretation of the results by managers.

A note on format of this dissertation: chapters 2, 3, and 4 were written as stand-alone papers with Jessica Salo as the primary author. The co-authors of chapter 2 are David Theobald and Thomas Brown, David Theobald is the co-author of chapter 3, and David Theobald and David Merritt are the co-authors of chapter 4.

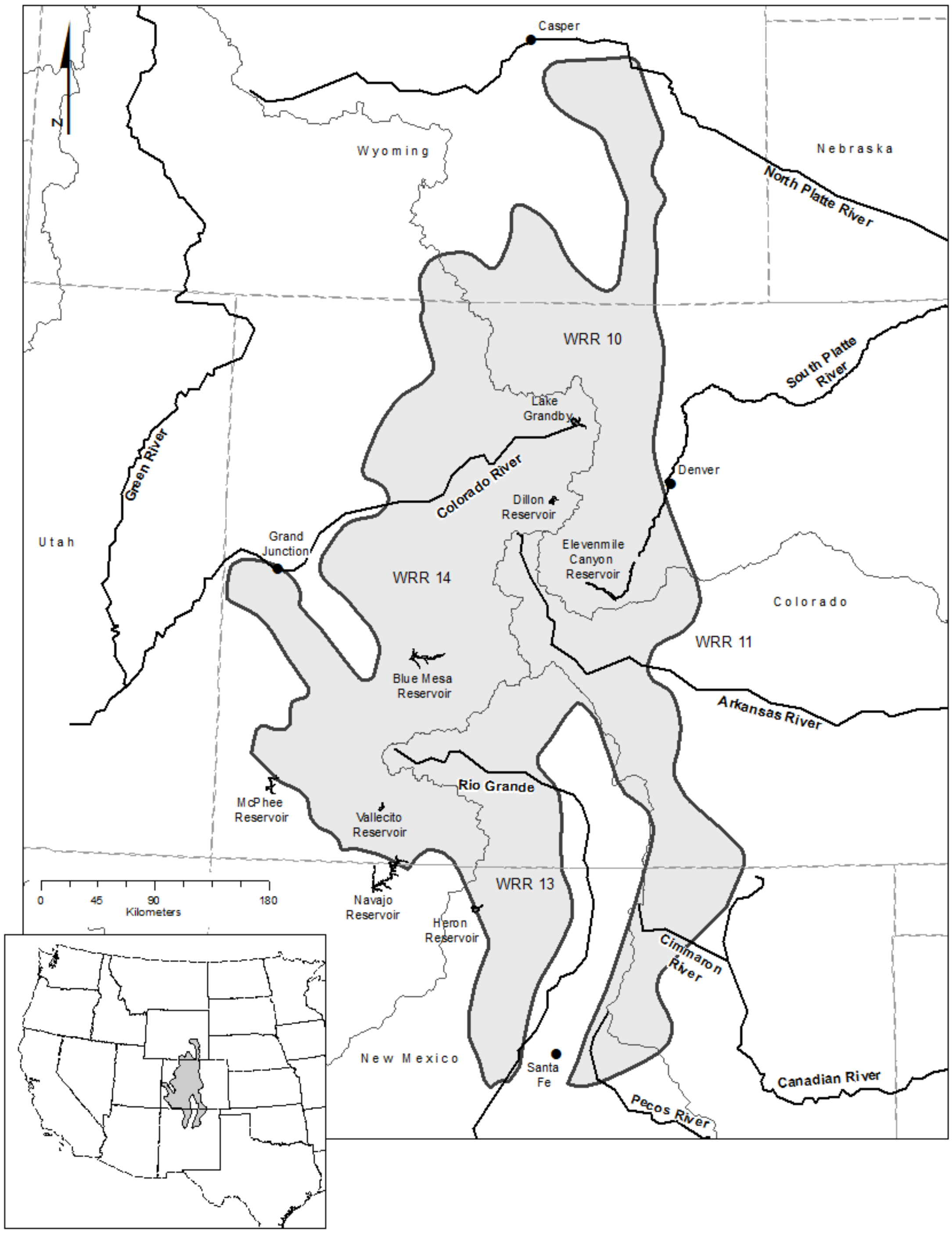

Figure 1.1. The Southern Rockies Ecoregion is comprised of mainly mountainous and forested areas of central Colorado, southern Wyoming, and northern New Mexico with an area of almost 144,000 km^2 (Bailey et al., 1994).

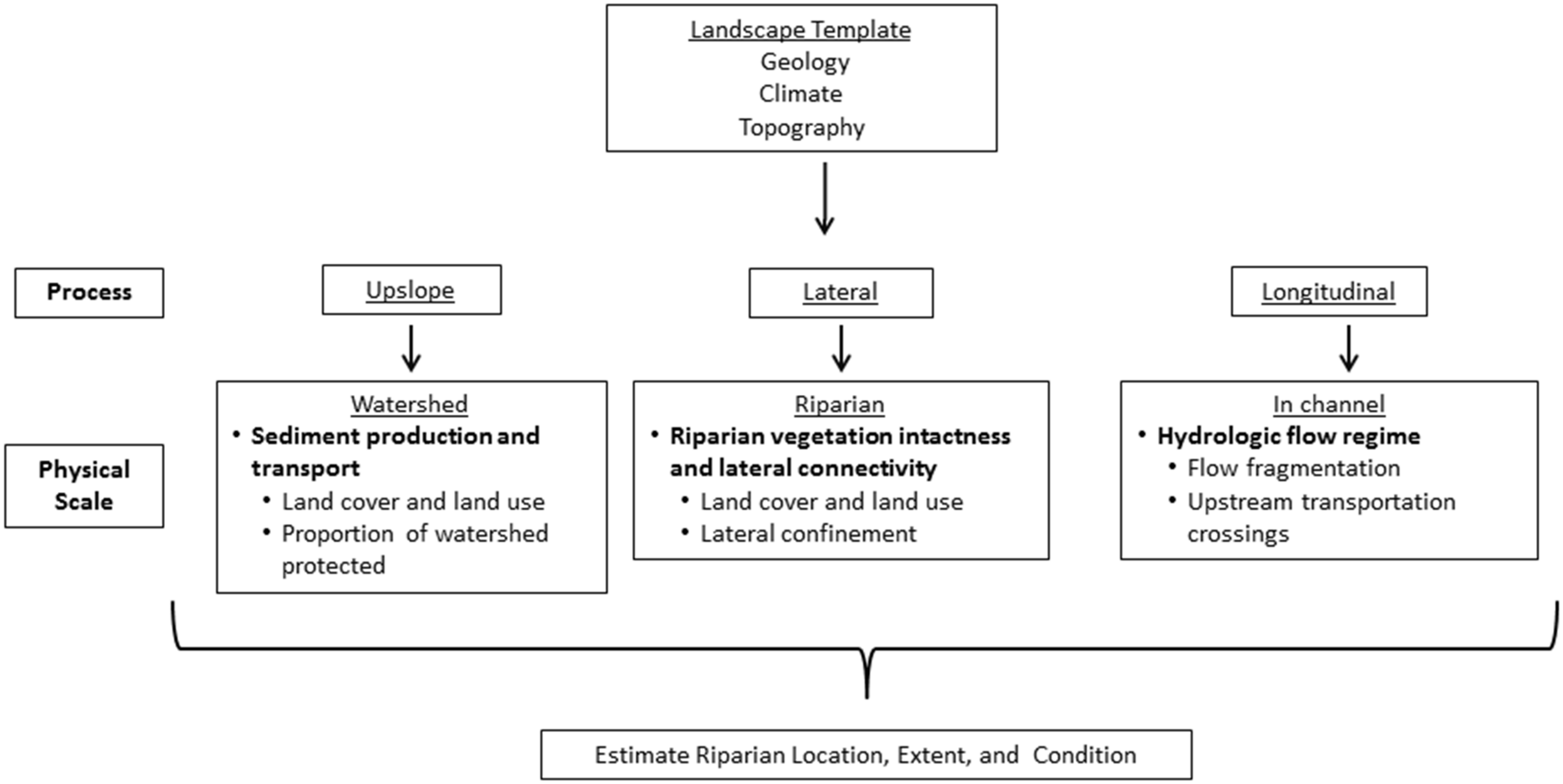

Figure 1.2. Conceptual framework used to estimate riparian location and condition as a function of processes that occur at three different scales (after Reeves et al. 2004).

2. Evaluation of methods for delineating potential riparian zones in semi-arid montane regions of the Western United States

Introduction

Riparian ecosystems are the most biologically diverse, productive, and threatened ecosystems in many semi-arid regions (Poff et al., 2011). These unique ecosystems are characterized by narrow bands of vegetation or extensive gallery forests that differ from the surrounding uplands. Intact riparian zones act as natural filters and storage areas for sediment, pollutants, and nutrients, regulate water and air temperature, dissipate energy during high flow events, and provide habitat and migration corridors for many species (Brauman et al., 2008).

Riparian zones form the interface between flowing aquatic and surrounding terrestrial ecosystems. They extend from the stream channel to the edge of geomorphic features and vegetation that are influenced by surface water and/or elevated ground water (Gregory et al., 1991; Naiman and Decamps, 1997). Because of water diversion, housing development, and other alterations, riparian zones are often less extensive than they naturally would be. We define a potential riparian zone as one that would likely be a vegetated, functional riparian system in the absence of human activity.

The location and condition of riparian zones are strongly influenced by geomorphic and hydrologic processes. The prevailing geomorphic processes include erosion, channel migration, development of fluvial features, and sediment transport and deposition (Naiman et al., 2005). Each of these processes varies in a systematic way as a function of catchment size and gradient, drainage density, and dominant sediment size (Schumm, 1977). The prevailing hydrologic processes include flow, infiltration, and evapotranspiration; and are characterized by precipitation magnitude and distribution, flow depth and velocity, the frequency, magnitude and duration of flooding, and the hydraulic conductivity and gradient and depth of ground water (Naiman et al., 2005).

Geomorphic and hydrologic processes are often separated into three systems: longitudinal, lateral, and upslope (Reeves et al., 2004). In delineating riparian zones, longitudinal processes are frequently represented by upstream drainage area. Lateral processes are represented by valley bottom topography, including the depth and width of the channel and the slope of the stream banks and valley floor. Upslope processes, such as sediment production and overland flow and delivery of sediment, are represented by overland flow processes, land cover, and human activity.

Despite their importance, mapping riparian zones across broad landscapes remains a challenge (Congalton et al., 2002; Goetz, 2006; Hollenhorst et al., 2006). In many mountainous regions, streams are narrow (often < 1 m in width) and have low flows or are ephemeral, making the associated riparian zones difficult to resolve in medium to coarse resolution remotely-sensed data (≥ 30 m) (Congalton et al., 2002). Moreover, riparian zones are frequently obscured from above by the forest canopy of adjacent terrestrial ecosystems and often lack a clear, delineated boundary between riparian and upland vegetation (Polvi, 2011). Potential riparian zones are often mapped using one of eight spatial modeling approaches (Tables 2.1 and 2.2). These methods vary from simple fixed-width buffers around stream lines, such as the 120 m buffer used by Wickham et al. (2011), to more advanced approaches which incorporate valley bottom topography and upstream drainage area. For example, among the latter is the method of Clarke et al. (2008), who modeled potential riparian zones in Oregon by using a 10 m digital elevation model (DEM) to estimate upstream drainage areas and bankfull depths that were then used to delineate valley bottoms.

To the best of our knowledge, there is no national or west-wide riparian map at high resolution (< 30 m). Many land management organizations have recognized the need to fill this data gap (e.g., United States Forest Service (USFS), Western Governors Association, United States Fish and Wildlife Service). Many of the methods used to map potential riparian zones (e.g., Strager et al. (2000), Hemstrom et al. (2002), and Theobald et al. (2010)) are from techniques published in grey literature and governmental reports, which have not been vetted by the peer review process. In addition, hydrologic and geomorphic processes are often ignored when mapping riparian zones (e.g., Jones et al. (2010) and Wickham et al. (2011)).

In our review of the literature (Table 2.1), we identified eleven papers (Strager et al., 2000; Williams et al., 2000; Goetz, 2001; Hemstrom et al., 2002; Gallant and Dowling, 2003; Dodov and Foufoula-Georgiou, 2005; Ruefenacht et al. 2005; Baker et al. 2006; Clarke et al. 2008 Grabs et al., 2011; Theobald et al., 2010) that presented maps of riparian zones using GIS-based methods with commonly-available raster data (e.g., digital elevation models). An important issue in these studies is the spatial resolution of the data. Eight (73%) of the raster based riparian maps used a 30 m resolution to delineate riparian zones in headwater streams (Strager et al. 2000; Williams et al., 2000; Goetz, 2001; Gallant and Dowling, 2003; Dodov and Foufoula-Georgiou, 2005; Ruefenacht et al. 2005; Baker et al. 2006; Theobald et al., 2010). Such a resolution may decrease the accuracy of the produced riparian maps, as, many headwater streams have narrow riparian zones that could be missed or over represented when using a 30 m resolution. For example, only 24% of riparian zones mapped using aerial photography for this study have a width greater than 60 m, suggesting that a 30 m resolution may be too coarse to delineate riparian zones in headwater streams of semi-arid, mountainous regions.

Despite the variety of landscape-level methods used to delineate riparian zones, to our knowledge a process to conduct a comparison of multiple methods has not been developed. Therefore, our objective is to create a process to evaluate the eight spatial modeling methods (Table 2.1) used to map potential riparian zones in order to determine how accurately the methods map potential riparian zones and to use that process in a case study located in a semi-arid, mountainous region. For such regions, we answer the following questions: (1) what is the best way to map potential riparian zones over broad spatial extents; and (2) what resolution is appropriate to map riparian zones. To meet these goals, we: (1) identified spatial modeling methods used to map potential riparian zones (Table 2.1); (2) characterized each method based on computational complexity; (3) implemented the algorithms on a standard platform (i.e., ArcGIS v10) to provide a consistent basis for comparison; (4) tested the performance of the candidate methods against an independent validation data set; and (5) summarized the quantitative accuracy and advantages/disadvantages of each approach.

Methods

We analyzed eight spatial modeling methods that were previously developed to map potential riparian zones or valley bottoms as a surrogate for potential riparian zones. The results of the spatial modeling methods were compared to potential riparian zone boundaries we generated for a validation data set.

In selecting the spatial modeling methods to evaluate, we focused on methods that are practical to apply to broad regions (e.g., an ecoregion or river basin) and use readily available data. We organized the spatial modeling methods based on the level of lateral and longitudinal processes each method incorporates (Table 2.2). Lateral processes can be undetermined (i.e., not incorporated into the method) or estimated by geomorphic processes as represented by valley bottom topography. Longitudinal processes were classified as undetermined or estimated by either stream order or upstream drainage area.

Study Area

We tested the eight spatial modeling methods in the Big Thompson watershed (Figure 2.1), which is located in the Northern Front Range of Colorado within the Southern Rockies Ecoregion. The Big Thompson watershed covers approximately 2,150 km^2, has roughly 3,000 m of topographic relief, and has an annual precipitation range of 1,194 mm in the headwaters to 375 mm at lower elevations (PRISM Climate Group, 2012). We focused our analysis on the mountainous portion of the watershed (~85%), which is west of 105° longitude and over 1,500 m in elevation, hereafter referred to as the study area. The study area is characterized by a variety of land use types, ranging from wilderness areas to agricultural lands and residential developments, and is typical of forested areas in the Intermountain West.

Validation Data Set

We assessed the validity of the models by comparing the maps they produce with potential riparian zones interpreted from aerial photography at 100 plots (600 x 600 m) within the study area. The plots were selected to be large enough to capture the full width of potential riparian systems in our study area, but small enough to limit the incidence of multiple potential riparian systems (confluences) within a given plot. We located the plots using a stratified random design (Theobald et al., 2007) to assure an equal representation of headwaters (Strahler's stream order 1; S_1), mid-watershed (S_2), and larger streams (> S_2). Stream order was determined using the NHD High resolution scale data (i.e. 1:24,000, USGS, 2008). Following mapping guidelines developed by the US Fish and Wildlife Service (2009), we interpreted land cover from recent (> 2010), high-resolution (0.3 m) imagery (ESRI, 2010) that was taken during the summer months.

Riparian zones were identified by the presence of mesic vegetation surrounding streams, which appears greener and coarser in texture on the aerial photos than do upland areas. Potential riparian zones were delineated by using a combination of aerial photograph interpretation, topographic wetness index (Beven and Kirkby, 1979) created using a 10 m DEM, and slope (10 m) to locate relatively moist and flat areas near streams. To identify potential riparian zones, the interpreter identified locations along streams where human land cover modifications were present; next the interpreter looked for changes in slope moving away from the stream line, and then consulted the topographic wetness index to confirm the edge of the potential riparian zone. We verified our interpretation of potential riparian zones by field checking ten plots, in a variety of valley types and stream orders following methods developed by Polvi et al. (2011).

Methods to Predict Potential Riparian Zones

The eight methods used to delineate potential riparian zones (Tables 2.1 and 2.2) were each applied to three different stream representations, synthetic stream lines developed from DEMs (catchment area ≥ 40 ha) and two National Hydrography Datasets (NHD; 1:24,000 (USGS, 2008) and 1:100,000 (USEPA, 2008)). Each stream representation was implemented at two terrain scales, 10 and 30 m NED (USGS, 2006). In addition, a variety of model parameters were used with each of the models, as described below, resulting in a total of 138 model-based maps of potential riparian zones.

Buffers

We analyzed three commonly used fixed-width buffers (100, 120, and 180 m), and to broaden the range of buffer widths we also analyzed three smaller buffers (40, 60, and 80 m). To incorporate variable-width buffer approaches, we varied buffer width based on Strahler stream order (S), employing buffer widths of 15 m for S_1, 35 m for S_2 and S_3, and 70 m for > S_3 (following Li and Nigh, 2011).

Elevation Above Stream

We use "elevation above stream" to map potential riparian zones as the area of a valley bottom that would be inundated by a flood of a specific depth. Several researchers have applied this approach (Williams et al., 2000; Kost and Dillon, 2005; Grabs et al., 2010), using fixed water depths ranging from 2 to 15 m. We examined fixed depths of 2, 3, 5, 10, and 15 m. We also examined one version of variable depths, with depth dependent on stream order, as follows: 1 m for S_1, 3 m for S_2, 4 m S_3, 5 m for S_4, 6 m for S_5, and 8 m for > S_5 (following Goetz, 2001).

Bankfull Depth

Leopold and Maddock (1953) developed power functions to describe channel geometry based on drainage area, which have been adapted to predict bankfull depth based on drainage area and regional coefficients (Castro and Jackson, 2001) as follows:

$$\text{Bankfull depth} = a\text{D}^b$$

where D is the drainage area (km^2), a and b are region-specific parameters, and bankfull depth is the average (or hydraulic) depth at a cross section.

Several researchers (e.g., Castro and Jackson (2001); Dodov and Foufoula-Georgiou (2005); Clarke et al. (2008); Theobald et al. (2010)) have then mapped potential riparian zones by applying a threshold or multiplier to the estimate of bankfull depth, equating the potential riparian zone with bankfull depth area. For example, Dodov and Foufoula-Georgiou (2005) related upstream drainage area to the potential riparian zone extent by using two sets of values for parameters a and b, $0.6\text{D}^{0.34}$ for basins < 700 km^2 and $0.6\text{D}^{0.02}$ for basins > 700 km^2. Other researchers first estimated bankfull depth to incorporate the relative size and power of a stream and then multiply it by 2.5 (Theobald et al., 2010) or 5 (Clarke et al., 2008) to estimate the potential riparian zone. We used three sets of values for parameters *a* and *b* to calculate bankfull depth. Each set was developed by researchers for semi-arid, mountainous regions with hydrology and geomorphology similar to that of the study area. These three sets are as follows: $a = 0.61$, $b = 0.33$ (Castro and Jackson, 2001); $a = 0.38$, $b = 0.25$ (Clarke et al., 2008); and $a = 0.36$, $b = 0.20$ (Theobald et al., 2010). We then multiplied each estimate of bankfull depth by 2.5 and 5, producing six separate potential riparian zone maps.

Slope & Valley-bottom Topography

Slope and valley bottom topography methods incorporate hillslope processes and valley bottom topography to map potential riparian zones. We evaluated three such methods: topographic-weighted distance from streams (Strager et al., 2000; Hemstrom et al., 2002); topography, discharge, and slope (TDS); and multiple resolution valley bottom flatness (MRVBF) (Gallant and Dowling, 2003). Each of these methods uses subjective thresholds that are determined by visually comparing the modeled output to topography and aerial photographs in order to identify the boundary of potential riparian zones.

The first method, which we call topographic distance, calculates a topographically-weighted distance away from a stream, where weights reflect valley-bottom slope and distance from streams (Strager et al., 2000; Hemstrom et al., 2002). We used separate distance thresholds for each of the three groups of stream orders (i.e., 1-2, 3-4, and ≥ 5).

Building on the bankfull depth method (Castro and Jackson, 2001; Clarke et al., 2008; Theobald et al., 2010), the TDS method first calculates the bank full depth using Castro and Jackson (2001) coefficients, but, instead of multiplying the bankfull depth by 2.5 or 5, this method incorporates the distance away from the stream line by applying weights that are based on the valley bottom slope to the Euclidean distance. As steeper areas are encountered, the distance increases proportionately and a threshold, based on the size of a river (approximated by the upstream watershed area), determines the elevation above bankfull depth at which potential riparian zones are defined. The three multipliers of the depth (1, 2, and 5) were selected to represent typical values that will approximate 100 year flood magnitude (at value=1). The other values, 2 and 5, are similar to those recommended by Clarke et al. (2008).

The MRVBF method (Gallant and Dowling, 2003) identifies potential riparian zones as areas that are low and flat relative to the surrounding topography by producing a continuous index and using thresholds to determine which values represent potential riparian zones. This method describes potential riparian zones as occurring at a variety of scales, with large potential riparian zones tending to be flatter than smaller potential riparian zones, and uses slope thresholds at a variety of scales to define potential riparian zones. Following Gallant and Dowling's (2003) recommendations, we set the initial slope threshold at 8% for the 10 m DEM analysis and at 4% for the 30 m DEM analysis. We selected three different thresholds of the MRVBF index, < 1, < 0.75, and < 0.5, to identify potential riparian zones.

Evaluation

To evaluate each of the modeling methods, we: (1) compared the resulting potential riparian delineation to the validation data set, (2) evaluated the sensitivity of each spatial modeling method to stream source and DEM resolution, (3) estimated algorithm complexity, (4) tracked processing time, and (5) visually compared the resulting potential riparian maps.

Comparison to Validation Data

We compared our model-based delineations to those of the validation data set using three metrics, the kappa coefficient (Cohen, 1960), a precision measure, and the percent of the study area that is classified as potential riparian. Precision is the proportion of the positive test results that are true positives; that is, the proportion of model-based potential riparian cells in a plot that are also potential riparian in the validation data set. The kappa coefficient utilizes information about not only true positives (i.e., potential riparian matches) but also true negatives (non-riparian matches). The kappa coefficient and precision values were computed for each of the validation plots on a cell-by-cell basis, and then averaged across plots for the entire set of plots or for subsets of the plots containing streams of a particular size. We tested for statistical differences among kappa coefficients and among precision values using a non-parametric analysis of variation test, the Friedman test (Friedman 1940), with a post-hoc analysis to determine which methods differ from each other. For the subsets of the plots (headwaters (S_1), mid-watershed (S_2), and larger ($> S_2$) streams) we tested for statistical differences using Mann-Whitney U.

We calculated the percent of the entire study area that was predicted to be potential riparian for each method by dividing the number of cells delineated as potential riparian by the total number of cells in the study area. Our study constrained the plots to streams, limiting the sampling frame to 39% of the entire study area. To obtain an estimate of the percentage of the study area that was potential riparian based on the validation data, we multiplied the potential riparian percent found in the validation plots by the proportion of the study area we sampled (i.e., 0.39).

Effect of Stream Sources and DEM Resolutions

We sought to determine if the success of the methods was dependent on stream source (i.e. synthetic, 1:24,000 NHD, or 1:100,000 NHD) or DEM resolution. For each of the spatial modeling methods we delineated potential riparian zones using each of the six different combinations of stream source and DEM resolution, and compared each of the resulting delineations with that of the validation set by computing kappa coefficients and a precision values. We then evaluated the sets of kappa coefficients and precision values using the Friedman test with post-hoc analysis.

Algorithm Complexity

Algorithm complexity of each spatial modeling method was evaluated using three metrics: the number of estimated parameters, the number of measured parameters, and the number of lines of Python code needed to implement the method.

Processing Time

Processing time was measured as the number of hours required to delineate potential riparian zones for the entire study area. Processing time was calculated on a personal computer using Windows XP, an Intel Core II CPU with 3.5 GB RAM, and a 2.66 GHz processor.

Results

Recall that each of the eight methods for delineating potential riparian zones (buffers, variable width buffers, elevation above stream, variable elevation above stream, bankfull, topographic distance, TDS, and MRVBF) was implemented using various different parameterizations. For this summary of our evaluation of the eight methods, we utilize the parameterization that yielded the highest median kappa value for each method when implemented using the most detailed DEM resolution (10 m) and stream data (NHD 1:24,000).

We present the complete results, including comparison statistics (kappa and precision), percent of the watershed classified as riparian, and p-values for each of the 138 different potential riparian zone maps we created in Appendix I. The appendix is arranged by DEM resolution and then stream source (i.e. synthetic, 1:24,000 NHD, or 1:100,000 NHD) and presents results both by stream order and for the entire study area. In addition, complete statistical analysis using the Friedman test post-hoc analysis is presented; comparing different methods by DEM resolution and stream source is available in Appendix I.

Characteristics of the Validation Plots

Our detailed mapping of the potential riparian zones of the 100 validation plots revealed that an average of 7.9% of the plot area is potential riparian. When examined by stream order, we found the following average amounts of the plots are potential riparian: headwaters (S_1) 6.7%, mid-watershed (S_2) 4.8%, and larger (> S_2) streams 11.9 %. We estimated that 3.08% (i.e., 7.9 x 0.39) of the study area landscape is occupied by potential riparian zones.

Effect of Stream Sources and DEM Resolutions

For each of the spatial modeling methods, we computed the kappa coefficient and precision values to evaluate the effect of stream source and DEM resolution on the delineation of potential riparian zones with a given method and parameterization. Based on the kappa coefficients, only two methods, bankfull DT 2.5 and MRVBF <1, did not exhibit significant differences among the different stream sources and DEMs ($p > 0.05$). For all other methods evaluated using the kappa coefficient, and for all methods, except MRVBF <1 evaluated using the precision value, choice of stream source or DEM produced at least one significant difference. However, there was no consistent pattern across the different methods suggesting that a certain stream source or DEM was the superior choice. Details regarding specific p-values related to how stream source and/or DEM resolution impacts the performance of each of the 8 best methods are available in Appendix I (Tables A.10 and A.11).

Comparison to Validation Data

Study Area Comparison

Results for each of the eight spatial modeling methods are presented in Tables 2.3-2.5. When analyzing all plots, several significant differences ($p < 0.05$) occur between methods, specifically between methods that incorporate hydrologic processes and those that do not incorporate hydrologic processes. Based on kappa coefficients (Table 2.3), TDS 1X performs better than all other methods ($p < 0.05$) except for bankfull DT 2.5 and topographic distance; MRVBF < 1 performs more poorly than all other methods ($p < 0.05$); and the 40 m buffer is statistically similar to all methods except for TDS 1X and MRVBF < 1. Based on precision values (Table 2.4), TDS 1X performs better than all other methods ($p < .002$) except for bankfull DT 2.5; MRVBF <1 is not significantly different from 40 m buffers, elevation above stream 2 m, or variable elevation above stream; and the 40 m buffer is not statistically different from any other method except for bankfull depth DT 2.5 and TDS 1X (see Appendix I, Table A1.9). The percentage of the study area that each method estimates is potential riparian and the percentage estimated by the validation data are found in Table 2.5. When estimated using a 10 m DEM, the percent of the study area estimated to be potential riparian zones varies from 5.11% (TDS 1X) to 18.77% (MRVBF < 1).

Stream Order Comparison

We compared the performance of each method at the plots for three stream orders, S_1, S_2, $>S_2$, and compared the performance of 10 and 30 m terrain scales (DEMs) based on kappa coefficients and precision values. Based on the kappa coefficients (Table 2.3), we found that 40 m buffers performed better with larger streams ($>S_2$) than smaller streams (S_1 or S_2) when mapped using either a 10 or 30 m DEM ($p < 0.002$); that variable width buffers perform better in

$>S_2$ streams than in S_2 streams when mapped at 10 m ($p = 0.009$); that maps created using bankfull DT 2.5, elevation above stream, and topographic distance all performed better in $>S_2$ streams than in S_1 streams when mapped using at 10 m DEM ($p < 0.05$); and that the map created by TDS 1X using a 10 m DEM performed better than the map created using a 30 m DEM for S_2 and $>S_2$ streams ($p < 0.002$). All other methods were not significantly different ($p < 0.05$) when analyzed by stream order and DEM resolution. The precision values (Table 2.4) indicated that all methods, using either the 10 or 30 m DEM, perform better ($p < 0.05$) in $>S_2$ streams than in S_1 and S_2 streams and that DEM resolution (10 or 30 m) does not result in significant differences ($p < 0.05$) in the performance of the methods at any stream order (S_1, S_2, or $>S_2$).

Algorithm Complexity and Processing Time

Across the methods, the number of estimated parameters ranged from 1 to 9, the number of measured parameters ranged from 0 to 2, processing times ranged from 0.02 hours to 3 hours, and lines of code ranged from 19 to 149 (Table 2.6). For a given spatial modeling method, processing times varied little among the three stream sources. When using a 30 m DEM processing times were approximately 25% shorter than when using a 10 m DEM.

Method Comparison

For a stream segment near the center of the study area, we visually compared the modeled and validation estimates (Figure 2.2). Based on these eight comparisons, it is apparent that methods that incorporate valley bottom topography (elevation above stream 2 m, variable elevation above stream, bankfull, topographic distance, and TDS 1X methods) more accurately map the extent and spatial pattern of potential riparian zones.

Discussion

Our validation data set shows that 48% of the potential riparian zones that we mapped using aerial photo interpretation had widths less than 30 m and 88% had widths less than 90 m. If our data were used in a raster format with 30 m cells, the widths of 88% of the mapped potential riparian zones would be represented by only 1 – 3 cells, leading to omission errors when using automated mapping techniques. If potential riparian zones were represented using 10 m cells, 48% of the mapped potential riparian zones would be represented by only 1 – 3 cells, reducing omission errors. In the stream order analysis, the kappa coefficients were larger for three of the methods (40 m buffers, variable width buffers, and TDS 1X) when calculated using a 10 m DEM than when using a 30 m DEM in S_1 and S_2 streams. This is to be expected as riparian zones are narrow in headwater streams, which supports mapping potential riparian zones at a 10 m resolution for headwater streams. In addition, the best method for estimating potential riparian zones in our study area, TDS 1X, performed best when using a 10 m DEM. Based on these findings, we recommend mapping potential riparian zones at a 10 m resolution and, where appropriate, we limit our discussion to the results of the 10 m analysis.

In our comparison of how different stream sources and DEM resolutions impact the kappa coefficients and precision values for a specific method, we found varying results. The kappa coefficients for bankfull DT 2.5 method were not significantly different ($p < 0.05$) and the TDS 1X method performed the best with the 10 m, 1:24,000 stream lines. The other results are varied and do not suggest strong relationships between changing only DEM resolution or stream sources. Instead, there appears to be an interaction between stream source and DEM resolution. These results demonstrate the importance of testing how each method performs with different stream sources and DEM resolutions before choosing the best method to map potential riparian zones in a specific area.

The kappa coefficient and precision values provide slightly different measures, in that kappa considers true positives and true negatives and precision reports the proportion of positive results that are true positives. For the entire study area, precision and kappa values agree for the best performing spatial modeling methods (TDS 1X, topographic distance, bankfull DT 2.5, and elevation above stream 2 m). In addition, when examined by stream order (S_1, S_2, or $>S_2$), TDS 1X has the highest values for both kappa and precision.

The maps produced by all spatial modeling method identified potential riparian zones better than a randomly generated map would have (i.e., kappa > 0; Table 2.3), but some methods are better at estimating potential riparian zones. First, based on kappa and precision values (Table 2.3 and 2.4), we found methods that incorporate lateral and longitudinal processes (e.g., TDS and bankfull DT 2.5) are more accurate than methods that do not incorporate landscape-level drivers (e.g., fixed- and variable width buffers; Tables 2.3 and 2.4). Second, percent of the study area mapped as potential riparian most closely matches the validation dataset using only one method, TDS 1X (Table 2.5). Third, however, the improved accuracy comes at a price, in that the simplest methods to implement (e.g., buffers) typically take the shortest time to process and require the least input data and fewest lines of code (Table 2.6). Furthermore, based on both kappa and precision values (Tables 2.3 and 2.4), TDS 1X performs slightly better than bankfull depth DT 2.5 at the study area scale and for each stream order group (although not significant at $p \geq 0.05$). Visual analysis and a higher kappa coefficient and precision value in $>S_2$ streams reveals that in areas with low topographic relief, the potential riparian zones mapped using TDS 1X are less likely than those created using bankfull methods to extend far from the stream and create disjunction potential riparian zones, thus better estimating potential riparian zones in flat regions. Based on the results of our evaluation metrics (comparison to validation data, algorithm complexity, and processing time), we find that TDS 1X method estimated using a 10 m DEM and 1:24,000 stream lines is best suited to estimate potential riparian zones in our study area.

Using an appropriate method and resolution to map potential riparian zones will improve the understanding of their location and provide better estimates of how much land area they occupy. Following our procedure to identify and test the variety of methods available to map potential riparian zones, will produce improved maps of potential riparian zones that are necessary for the conservation of riparian zones and the quantification of the loss of riparian zones and associated ecosystem functions.

A commonly-cited statistic is that riparian zones occupy less than 2% of land in the West (McKinstry et al., 2004; Theobald et al., 2010; Poff et al., 2011); however, how this was estimated is unclear. And for Colorado, Dahl (1990) estimated that historical (potential) riparian zones accounted for 3% of the total land area and that 50% of these areas have been removed by humans. Our validation data indicate that potential riparian zones occupy 3.08% of the study area and the TDS 1X method estimates that 5.11% of the study area is potential riparian zone (Table 2.5).

Conclusion

We found that methods that incorporated surrogates of lateral and longitudinal processes were significantly better at estimating potential riparian zones than simpler methods based on buffers alone, and that the TDS 1X method performed best in mapping potential riparian zones. We recommend using the TDS 1X method estimated using a 10 m DEM and NHD 1:24,000 streams to map potential riparian zones in semi-arid mountainous regions. TDS 1X was best at matching the validation data, is scalable to stream size, and incorporates lateral and longitudinal processes. TDS 1X utilized field regressions from arid, mountainous ecosystems which are available for other regions (Castro and Jackson, 2001; Faustini et al, 2009) or can be developed through field work. We expect the recommended method to work well in semi-arid regions with watersheds that have perennial streams, a variety of valley types, dendritic drainage patterns, and relatively shallow soils. In other regions and for ephemeral and intermittent streams, it would be necessary to replicate our procedure to test the variety of potential riparian zone mapping techniques using available terrain and stream data.

Riparian zones are currently threatened by multiple stressors, and will likely face further stresses associated with climate change and additional water withdrawals due to population growth (Theobald et al., 2010). Consequently, it is imperative to understand the current location and extent of riparian zones. It is also valuable to understand what processes are controlling potential riparian zones, as a means to understand both current conditions and vulnerabilities to land use and climate change, as well as to project how various management options might protect or restore these ecosystems. Until detailed, consistent riparian maps from updated imagery can be created for large ecoregional extents, using our procedure to identify the best method to map potential riparian zones will help produce reasonable, credible, and consistent estimates. We recommend caution using some commonly employed methods, including uniform buffering and elevation above stream, because these methods require subjective estimations that are scale dependent and might not work well for an entire watershed or for watersheds with different sized rivers. Methods that incorporate detailed geomorphological patterns and dominant hydrological processes can improve estimates of potential riparian zones and can be used to inform scientists and managers of riparian location and of potential threats to riparian zones.

Table 2.1. A Brief Description, Study Area, and Citation(s) for the Eight Spatial Modeling Methods for Mapping Potential Riparian Zones.

Method	**Description**	**Study Area**	**Citation(s)**
Fixed-width Buffers	Uses a fixed distance from the stream line to define potential riparian zones	Eastern US, Conterminous US	Baker et al. (2006); Jones et al. (2010); Wickham et al. (2011)
Variable-width Buffers	Uses a variable distance from the stream line to define potential riparian zones	Central US	Li and Nigh (2011)
Elevation Above Stream	Simulates the inundation area surrounding a streamline with a flood of a specific depth to define potential riparian as any flooded area	Semi-arid mountainous US, Conterminous US	Williams et al. (2000); Kost and Dillon (2005); Grabs et al. (2010)
Variable Elevation Above Stream	Simulates the inundation area surrounding a streamline with a flood of a varying depths to define potential riparian zones as any flooded area	Semi-arid mountainous US	Goetz (2001); Ruefenacht et al. (2005)
Bankfull Depth	Uses empirical power functions to relate upstream drainage area to bankfull depth and then uses multipliers (2.5 or 5) to create a flood depth. All flood zones are defined as potential riparian zones	Semi-arid mountainous US, Central US, Mesic western US, Western US	Castro and Jackson (2001); Dodov and Foufoula-Georgiou (2005); Clarke et al. (2008); Theobald et al. (2010)
Strager	Uses a combination of slope, elevation increase, and distance from the streamline to identify potential riparian zones	Eastern US,Semi-arid mountainous US	Strager et al. (2000); Hemstrom et al.(2002)
Topography, Discharge, & Slope (TDS)	Uses a modified Euclidean distance (e.g., a buffer) computed using cost inputs that incorporate bankfull depth and slope to define potential riparian zones	Western US	Theobald unpublished
Multiple Resolution Valley Bottom Flatness (MRVBF)	Identities potential riparian zones by assuming that they are low and flat relative to the surrounding topography, occur at a variety of scales, and that large potential riparian zones tend to be flatter than smaller potential riparian zones	Australia	Gallant and Dowling (2003)

Table 2.2. Conceptual Organization of the Eight Spatial Modeling Methods for Mapping Potential Riparian Zones.

	Longitudinal Processes			
Lateral Processes		**Undetermined**	**Stream Order**	**Upstream Drainage Area**
	Undetermined	Fixed-width Buffers	Variable-width Buffers	
	Geomorphic	Elevation Above Stream Multiple Resolution Valley Bottom Flatness (MRVBF)	Variable Elevation Above Stream Topographic Distance	Bankfull Depth Topography, Discharge, & Slope (TDS)

Table 2.3. Comparison of the Eight Methods to the Validation Data Using Median Kappa Coefficients for the 100 Plots for 10 and 30 m DEMs.[a]

	Median Kappa Coefficient							
	***S_1* Plots**		***S_2* Plots**		**> *S_2* Plots**		**All Plots**	
	10 m	30 m	10 m	30 m	10 m	30 m	10 m	30 m
Buffer 40 m	0.21	0.20	0.14	0.13	0.43	0.43	0.23	0.24
Variable Width Buffer	0.25	0.25	0.14	0.15	0.37	0.36	0.25	0.24
Elevation Above Stream 2m	0.20	0.19	0.14	0.10	0.35	0.32	0.25	0.19
Variable Elevation Above Stream	0.21	0.21	0.17	0.12	0.31	0.32	0.24	0.19
Bankfull DT 2.5	0.24	0.23	0.17	0.11	0.39	0.38	0.27	0.23
Topographic Distance	0.19	0.28	0.24	0.17	0.40	0.38	0.29	0.28
TDS 1X	0.30	0.25	0.38	0.27	0.46	0.39	0.38	0.30
MRVBF < 1	0.10	0.14	0.10	0.11	0.16	0.17	0.13	0.15

[a] Values of kappa and percent of landscape are reported for selected spatial modeling methods calculated using NHD 1:24,000 streams.

[b]S1, and S2 refer to Strahler stream order 1 and 2, respectively.

Table 2.4. Comparison of the Eight Methods to the Validation Data Using Median Precision for the 100 Plots for 10 and 30 m DEMs.[a]

	Median Precision Values							
	S_1 Plots		**S_2 Plots**		**> S_2 Plots**		**All Plots**	
	10 m	30 m	10 m	30 m	10 m	30 m	10 m	30 m
Buffer 40 m	0.13	0.13	0.10	0.10	0.38	0.36	0.20	0.20
Variable Width Buffer	0.16	0.16	0.11	0.13	0.31	0.30	0.19	0.19
Elevation Above Stream 2m	0.14	0.13	0.14	0.10	0.35	0.31	0.21	0.18
Variable Elevation Above Stream	0.14	0.14	0.14	0.10	0.31	0.30	0.20	0.17
Bankfull DT 2.5	0.14	0.15	0.15	0.11	0.39	0.34	0.24	0.19
Topographic Distance	0.18	0.19	0.17	0.14	0.34	0.35	0.24	0.22
TDS 1X	0.25	0.20	0.27	0.23	0.43	0.34	0.33	0.26
MRVBF < 1	0.09	0.11	0.11	0.11	0.24	0.24	0.14	0.16

[a] Values of precision and percent of landscape are reported for selected spatial modeling methods calculated using NHD 1:24,000 streams.
[b]S1, and S2 refer to Strahler stream order 1 and 2, respectively.

Table 2.5. Percent of the Study Area Estimated to be a Potential Riparian Zone for each of the Eight Methods. [a]

	Percent of Study Area	
	10 m	30 m
Buffer 40 m	15.7	15.7
Variable Width Buffer	11.8	11.8
Elevation Above Stream 2m	17.9	22.2
Variable Elevation Above Stream	17.9	20.8
Bankfull DT 2.5	14.3	18.9
Topographic Distance	11.1	11.7
TDS 1X	5.1	7.2
MRVBF < 1	18.8	17.4
Validation Data	3.1	

[a] Values of percent of landscape are reported for selected spatial modeling methods calculated using NHD 1:24,000 streams.

Table 2.6. Algorithm Complexity and Processing Time of the Eight Methods. [a]

Method	Parameters		Processing Time (hrs)	Lines of Code
	Estimated	Measured		
Fixed-width Buffers	1	0	0.02	19
Variable-width Buffers	6	0	3.5	33
Elevation Above Stream	1	0	0.15	42
Variable Elevation Above Stream	9	0	3.75	49
Bankfull Depth	1	2	1.5	71
Topographic Distance	3	0	3.5	76
Topography, Discharge, & Slope (TDS)	6	2	3	149
Multiple Resolution Valley Bottom Flatness (MRVBF)	2	0	1.25	84

[a] Processing time was computed using a 10 m DEM and NHD 1:24,000 streams.

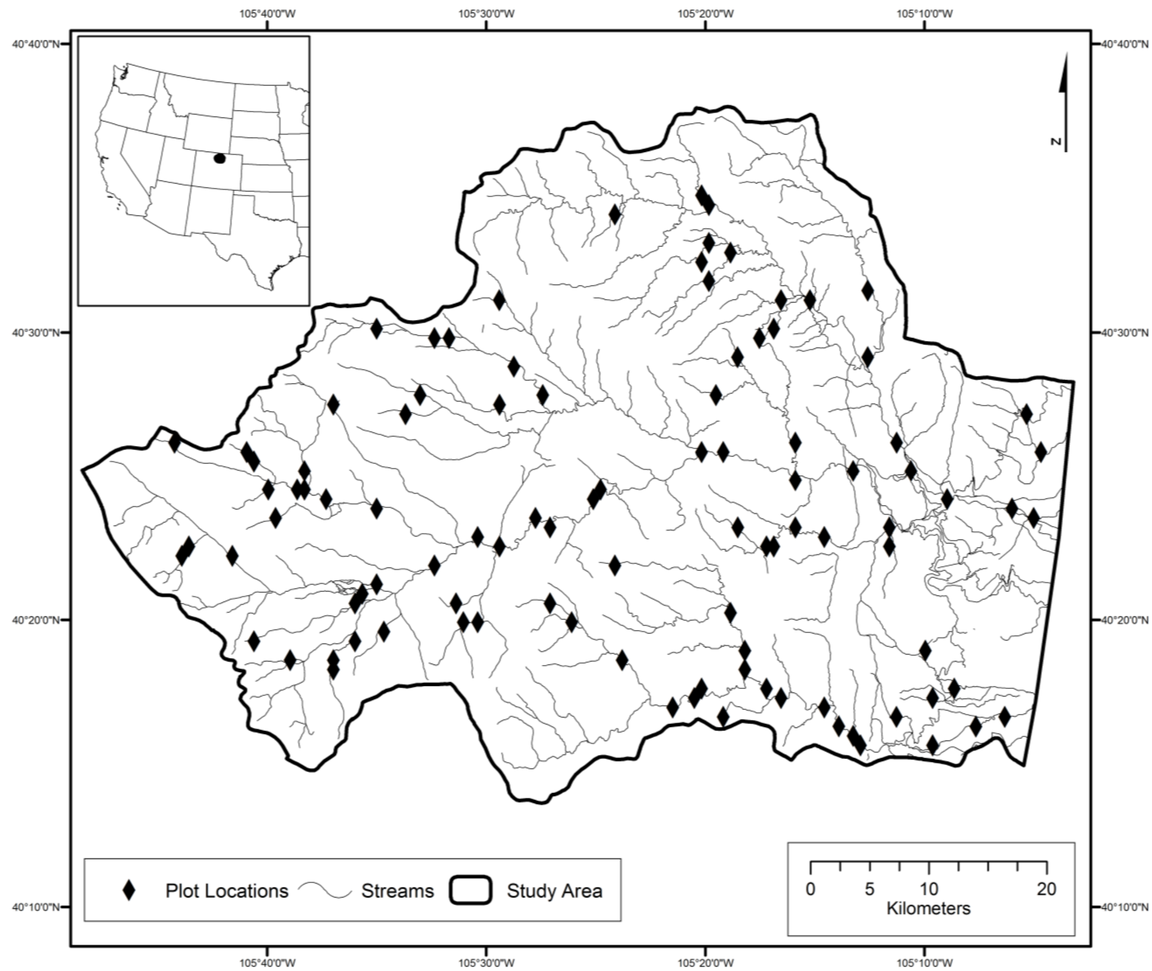

Figure 2.1. Our study area is limited to the mountainous portion of the Big Thompson Watershed in the Northern Front Range of Colorado. Plot locations indicate locations where validation data were collected and comparisons between spatial modeling methods were conducted.

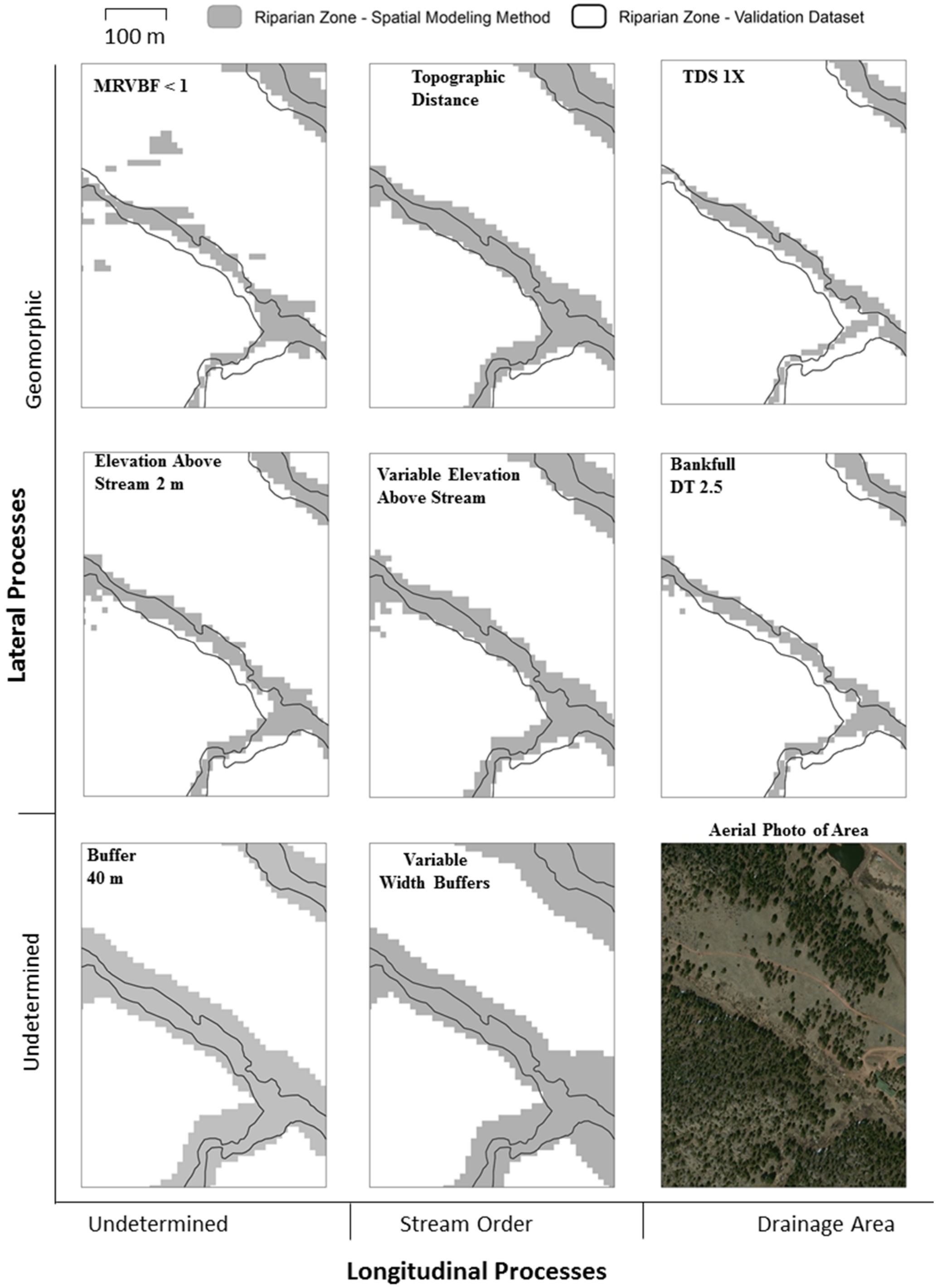

Figure 2.2. Illustration of each spatial modeling method with the best kappa values at a stream (Strahler stream order 2) in the middle reaches of the Big Thompson Watershed. Methods that align most closely with the validation data are the best estimates of potential riparian zones. By comparing the potential riparian (gray), areas to the validation data (black line), we see that many of the methods (40 m buffer, variable elevation above stream, and variable width buffers) over estimate the potential riparian zone. Examples of spatial modeling methods calculated using 10 m DEM and 1:24,000 NHD streams.

3. A multi-scale, hierarchical model to estimate riparian zones

Introduction

Riparian ecosystems support up to 80% of terrestrial animals in the western US by providing wildlife corridors and crucial wildlife habitat (Johnson, 1989), but they cover less than 5% of the land area (Swift, 1984; Dahl, 1990). In addition, these areas deliver numerous benefits to humans, including maintaining water quality and quantity and providing areas for recreation and agriculture. These characteristics make riparian zones one of the most important, but threatened ecosystems in the western United States (Nelson, 2007; Poff et al., 2011). Yet, a national panel concluded a decade ago that we lack a detailed map of the location and condition of these important ecosystems (NRC, 2002). To our knowledge, no such map exists today.

Since the national report (NRC, 2002), various entities have acknowledged the need for a comprehensive, detailed representation of riparian zones. The Western Governors Association, the U. S. Forest Service, the U.S. Fish and Wildlife Service's Landscape Conservation Cooperatives, and numerous state wildlife action plans and natural heritage programs have identified this as a data gap. For example, one of the six fundamental data layers in the Western Governors' Wildlife (WGA) Critical Habitat Assessment Tool (CHAT) is riparian zones, but currently it is not mapped adequately for 15 of 17 states. The Great Northern Landscape Conservation Cooperative (Chambers et al., 2013) has identified riparian zones as a conservation target that is not sufficiently mapped and the Southern Rockies Landscape Conservation Cooperative has identified that datasets depicting the location of riparian zones are needed to inform management decisions related to riparian obligate species (Rice 2012).

We define a riparian zone as the area that is adjacent to and influenced by streams, that typically contains vegetation that differs from the surrounding upland vegetation (Gregory et al., 1991; Verry et al., 2004; Naiman et al., 2005). We distinguish two types of riparian zones, consistent with other research (Clerici et al., 2013). A *potential riparian zone* is the area that would likely support natural riparian vegetation in the absence of human activity and corresponds to the geomorphic extent (i.e., the floodplains located between the active channel and the hillslope; Gregory et al., 1991) of the "riparian zone". The *current riparian zone* is a subset of the potential riparian zone that is currently not strongly modified by human land uses and is assumed to support natural riparian vegetation. The potential riparian zone can have a narrower extent than the current riparian zone in locations that have direct human modification or upstream flow modifications and larger than the current riparian zone in streams and rivers that receive water from inter-basin transfers (e.g., the South Platte River).

Riparian zones are shaped by physical processes that occur at multiple spatial and temporal scales. Following Reeves et al. (2004), we organize these physical factors into three process-based subsystems: upslope, riparian, and in-channel. Upslope processes and factors form the physical template for riparian zones, including the geologic characteristics of the watershed (Kovalchik and Chitwood, 1990), hillslope sediment production and transport, watershed climate and hydrologic factors including the amount and distribution of precipitation, and land use and cover (Reeves et al., 2004). Riparian processes occur within the valley bottom and are influenced by local and regional watershed processes. Riparian processes and factors are comprised of valley floor landforms, valley shape and gradient, riparian vegetation composition and condition, soil type, water storage and yield, and chemical, nutrient, and energy exchange between the upslope and in-channel systems (Reeves et al., 2004). In-channel processes are directly linked to the stream flow regime, and include local fluvial processes and watershed-scale geomorphology that influence the riparian zone by providing water and sediment delivery and storage and governing channel structure (Kovalchik and Chitwood, 1990; Naiman and Decamps, 1997; Reeves et al., 2004).

Despite their importance to biodiversity (Poff et al., 2011), riparian zones are difficult to map across large areas (Congalton et al., 2002; Goetz, 2006; Hollenhorst et al., 2006). Many headwater streams are narrow, have low flows or are ephemeral, and the associated riparian zones are often obscured from view on orthogonal imagery by the forest canopy of adjacent terrestrial ecosystems. In larger streams, it can be difficult to distinguish the associated riparian zone from the adjacent forest canopy resulting in difficulty identifying the riparian edge.

Existing riparian mapping efforts that cover large geographic extents in the United States generally capture either the potential (e.g. Jones et al., 2010; Wickham et al., 2011) or current riparian zones (e.g. LANDFIRE (2007) and Southwest Regional GAP (SWReGAP; Lowry et al., 2007). Typically, two approaches are used to map current riparian zones. The first is to map riparian zones from aerial photography interpretation (e.g. National Wetland Inventory, US FWS, 2009), which is time-consuming, expensive, and can have significant observer bias. The second approach is to model the location of riparian zones using relatively coarse resolution ($\geq$ 30 m cell size) landscape-based data including satellite imagery and elevation data (e.g. LANDFIRE (2007) and SWReGAP (Lowry et al., 2007)). To our knowledge none of the existing datasets were created primarily to map riparian zones. Rather, the primary objective of these datasets is to map land use or cover for large geographic extents. The models do not explicitly include processes that create and maintain riparian zones, have vague or missing descriptions of the methods used to map riparian zones, and operate at a resolution that often misses narrow bands of riparian vegetation along small rivers (Goetz, 2006). In addition, accuracy information is usually not available for riparian land cover classes (i.e. for LANDFIRE, SWReGAP, NLCD).

More recent and precise approaches have employed fine-grain (5-10 m) satellite imagery or IKONOS multispectral imagery (4 m) and various statistical methods to estimate the distribution, extent, and condition of riparian zones (Goetz et al., 2003; Johansen and Phinn, 2004; Snyder et al., 2005). These methods are typically cost-prohibitive to apply across broad regions, rely on a spectral signature that does not incorporate ecological, geomorphic, and hydrologic processes, and map only current (observable) riparian zones.

Our goal in this paper is to use a multi-scale, hierarchical approach that uses surrogate variables of dominant physical processes to map the location of current and potential riparian zones using readily available, national datasets. Our objectives in pursuit of this goal are to: (1) describe the dominant hydrological processes as our conceptual framework; (2) identify and map explanatory variables that capture the different scales/grains of the dominant processes; (3) produce sample-based estimates of a detailed response variables (i.e. whether a location is current riparian, potential riparian, or upland); (4) develop a statistical model to estimate locations of riparian zones and quantify change in riparian zones with documented uncertainty; and (5) demonstrate the approach for a large geographic extent, Southern Rockies Ecoregion (SRE).

Methods

Response Variable

The response variable was a simple attribute indicating whether a location was in one of three states: potential riparian, current riparian, or not riparian (i.e. upland or water) following the protocol developed by the US Fish and Wildlife Service (2009). We collected the response variable at 500 plots that were located using a stratified random design (Theobald et al., 2007) to assure an equal representation of headwaters (Strahler's stream order 1; S_1), mid-watershed (S_2), and larger streams (> S_2) based on NHDPlus streamlines (1:100,000K; USGS 2008). The plots, roughly 600 m by 600 m, are large enough to capture the full width of riparian systems in our study area, but small enough to limit the incidence of multiple riparian systems (confluences) within a given plot, and are consistent with other detailed mapping efforts (Leinwand et al., 2010). Within each plot, 300 spatially balanced and random points were generated (Theobald et al., 2007). The 300 points (total of 150,000) were used to create the process guided model estimates of riparian location. In addition to recording whether a point was potential riparian, current riparian, or not riparian; for each point, we collected the type of land use based on a classification developed by Leinwand et al. (2010), including agricultural, residential, transportation, or commercial and industrial. We interpreted this information from recent (>2010), high-resolution (0.3 m) imagery provided by ESRI ArcGIS Online (ESRI, 2012) that was taken during the leaf-on period (April – November). Current riparian zones were identified by the presence of mesic vegetation surrounding streams, which appears greener and coarser in texture on the aerial photos than do upland areas. In areas with human-dominated land cover, interpreters used 10 m DEMs to generate ancillary data on slope, topography, and a multiple-resolution expression of topographic wetness index plus (based on Theobald et al. (2009) see Riparian Processes and Factors below for full explanation) to map the edges of the potential riparian zones. We collected both the location (potential or current riparian zone or not riparian) and land use data to determine the type of land use modifying potential riparian zones (Table 3.1). We conducted a field verification exercise at twenty-five randomly selected plots to ensure accurate identification of potential and current riparian zones, following an existing protocol (Polvi et al., 2011). To identify the riparian edge, we used three variables: riparian vegetation, the first break in slope away from the stream channel, and evidence of fluvial activity by locating small sediment or debris deposits. We walked transects away from the stream channel and measured the distance at which we found all three corresponding variables. We field verified our aerial photo data collection at each of the common valley types (Carlson, 2009), but were limited by funding to conduct field surveys at 25 plots.

Predictor Variables

We estimated explanatory or predictor variables for the three process subsystems that influence riparian zones: upslope, riparian, and in-channel (Table 3.2) at each sample location, which represents a 10 m cell on the ground (See Appendix II for additional information regarding predictor variables).

Upslope Processes and Factors

Erosion rate, or sediment production and delivery to stream channels, was modeled using the revised universal soil loss equation at 30 m (RUSLE; Litschert et al., 2014). RUSLE estimates average annual soil loss based on five major factors: rainfall erosivity, soil type, topography composed length and slope, cover type, and management practices (Renard et al., 1997). RUSLE values were accumulated downstream using the flow accumulation tool in ArcGIS. The flow accumulation tool calculates the number of upstream cells that contribute to any given point in a watershed, and can accumulate weighted values (e.g. RUSLE values). The tool allows for weighted inputs (e.g. RUSLE values) that can be accumulated. After applying the flow accumulation tool, we used the Euclidean Allocation tool in ArcGIS to extend the values from the stream to the valley bottom to capture the influence of the accumulated RUSLE values in the riparian. We used a geologic database to include the distribution of parent material throughout the study area (USGS, 2006). We developed predictor variables to represent the hydroclimatology and the availability of water for riparian vegetation. Modeled average snow water equivalent (SWE) for 1 April (NOHRSC 2012) was included as a measure of the amount of water available to riparian vegetation for the warm season (Karl et al., 2009). We developed an accumulated SWE using the flow accumulation tool in ArcGIS. Latitude and longitude were incorporated as an index of the locational variability in the timing, source and type of precipitation influenced by monsoonal rains versus extra-tropical cyclones. We used elevation as a predictor variable because snow persistence influences stream flow (Painter et al., 2010) and research has found that elevation is the dominant control of snow persistence patterns in the Cache la Poudre basin (Richer et al., 2013). Finally, annual average temperature and accumulated average annual precipitation (PRISM, 2012; 800 m) were incorporated to characterize the variability in hydroclimatology, a factor known to impact lateral riparian extent (Naiman et al., 2005).

Riparian Processes and Factors

We used soil order from STATSGO (Soil Survey Staff, 2006) to represent upland and riparian soils in the model. Finer resolution data, such as SSURGO, were available for only 72% of the study area and many of the unmapped areas were located in the headwater regions -- areas known to be of ecological importance. We expanded on the topographic wetness index, a metric developed originally in TOPMODEL, a physically based distributed watershed model that simulates hydrologic flow of water and identifies where saturated land-surfaces develop (Kirby and Bevens, 1979). We calculated Topographic Wetness Index + (TWI+), which modifies the original model by using weights for aspects so that high insolation portions of a watershed accumulate less moisture (Theobald, 2007). We further expanded upon TWI+ by calculating a multiple resolution expression of TWI+, which was calculated at seven different resolutions (10-640 m) and then combined into a single data layer using a weighted average (Table 3.3). Using a multiple resolution approach to TWI+ produced gradients from wet to drier areas, resulting in more realistic transitions from riparian to upland vegetation. To incorporate lateral processes, we calculated the distance to the nearest stream line (ephemeral/intermittent or perennial) from the high resolution National Hydrography Dataset (USGS, 2012a).

The degree of human modification (Theobald 2013) was included as a predictor in the current riparian zone models to capture the impacts of human land use and the degree that human land use modifies an ecological system. This dataset was developed using expert knowledge and empirical relationships between human land use and ecological response and incorporates commercial, and industrial development, agriculture, energy production and mining, transportation and service corridors, biological resource use (e.g., hunting), recreation activities, invasive species, and pollution. The dataset is a continuous, fine-grained (90 m) raster with values ranging from 0 (complete naturalness) to 1 (high degree of human modification).

In-channel Processes and Factors

We estimated the mean annual flow using a continuous expression of Vogel's equation (Verdin and Worstell, 2008). Vogel's equation (Vogel et al. 1999) is a regression-based method that incorporates catchment area, mean annual precipitation and temperature and regional parameters to estimate flow. The regression equations developed by Vogel et al. (1999) are based on stream gage data from the hydro-climatic data network (HCDN), a series of 1,553 sites, determined by measured discharge values that have over 20 years of recorded data, high accuracy ratings per the USGS, and no obvious modifications to streamflow from dams and diversions (Vogel et al., 1999). We used the continuous expression of Vogel's equation because mean annual flow values from the NHDPlus (USGS, 2012b) were not available for headwater streams and NHDPlus data are available at the stream segment scale, not as a spatially continuous variable. We used average annual precipitation and temperature from PRISM (2012) for 1981 – 2010 (800 m) and a 10 m DEM to estimate mean annual flow. We included average annual stream flow in place of other flow regime variables because calculating flow characteristics at finer temporal scales (e.g., monthly peak and low flows) is complicated and time consuming for large areas where stream gages are not available. Finally, we included a categorical variable for stream type (ephemeral/intermittent or perennial) from the high resolution National Hydrography Dataset (USGS, 2012a).

Statistical Modeling

We used random forest modeling, a non-parametric classification and regression tree method that uses ensemble trees to make predictions. Random forest models grow multiple classification or regression trees based on bootstrapping data and, for an individual tree, divides the variation in the response variable based on the predictor variables. A random forest model creates a single prediction value by combining the predictions of all trees and provides measures of variable importance (Breiman, 2001).

The random forest method is commonly used to predict ecological phenomena and frequently outperforms other statistical techniques such as classification and regression trees, generalized linear models, and maximum entropy when used in vegetation mapping (Buechling and Tobalske, 2011; Zhang and Zhang, 2012; Timm and McGarigal, 2012). Random forest models are robust to correlated input variables, make no distributional assumptions, and can accept both categorical and continuous variables (Breiman, 2001). We implemented random forest in program R using the randomForest package (Liaw and Wiener, 2002) to create two separate models and predictions, one to map potential riparian zones and one to map current riparian zones. We adjusted the model using a class balanced expression of random forest (Evans and Cushman, 2009) because the potential riparian zone response data had far more upland locations (94.3%) than riparian locations (3.9%). We trained the model with 400 plots and validated the model with 100 plots that were randomly selected (500 total). We created the random forest model with 1500 trees and tried three variables at each node. Variable importance was determined using the permutated variable mean increase in error, which is a ratio across all nodes of the forest based on the error at each node for each randomly selected variable.

Model Validation

We validated our models using statistics of kappa coefficient (i.e. the agreement between the validation data and the potential and current riparian zone maps), accuracy (the proportion of all locations (riparian and upland) mapped correctly), sensitivity (the proportion of riparian zones mapped correctly), and the percent of the study area classified as current and potential riparian zones. We compared the potential and current riparian zones maps to the classified points within the 100 digitized plots that were withheld for validation. We tested the performance of the potential and current riparian zone maps by stream order (S_1, S_2, $> S_2$) using kappa coefficient, accuracy, and sensitivity. In addition, we performed an *ad hoc* visual comparison of the potential and current riparian zones to recent aerial photography in various valley types found throughout the SRE: headwaters, canyon, moderate energy confined and unconfined, low energy floodplain, glacial trough, and high energy open (Carlson, 2009).

We calculated the percent of the plots that were predicted to be current or potential riparian by dividing the number of points delineated as riparian by the total number of points in the plots. We constrained the study plots to streams, limiting the sampling frame to 42% of the entire study area. To estimate the percentage of the study area that was riparian using the response variable, we adjusted the percent of the current and potential riparian zones found in the validation plots by multiplying the area of riparian in the plots by the proportion of the study area we sampled (i.e. 0.42).

An important assumption that underlies our estimate of the amount of human modification of riparian zones is that the extent of potential riparian zones was mapped correctly. We tested this assumption in several ways. First, part of the field verification exercise was conducted in a national park in a variety of different valley types to ensure proper identification of the edge of the potential riparian zone in areas that are not highly impacted by human activity. The field exercise was also conducted in areas with varying land use to identify the limits of the potential riparian zones in locations that have been modified by humans. Finally, we identified plots that had minimal human impact (Stoddard et al., 2006), i.e. riparian zones that have no visual modifications and no major dams (U.S. Army Corps of Engineers, 2007) upstream. We repeated the model validation process with only these minimally disturbed plots.

Study Area

The SRE is a mountainous ecoregion region covering 143,901 km^2 in western North America. The SRE contains several riparian system types; the most common are lower montane-foothills riparian woodlands and shrublands, subalpine-montane riparian shrublands and woodlands, and wet meadows (Kittel et al., 1999; NatureServe, 2009). It is commonly reported that riparian zones occupy less than 2% of land in the SRE (McKinstry et al., 2004; Theobald et al., 2010; Poff et al., 2011); however, on what basis this was estimated remains unclear.

The SRE has roughly 3,041 m of topographic relief and an average annual precipitation ranging from 1,872 mm along the continental divide to 190 mm in the southwestern region (PRISM Climate Group, 2012). The SRE contains the headwaters for the Colorado, Platte, Rio Grande, and Arkansas Rivers (Figure 1.1) and portions of the Missouri (Water Resource Region 10), Arkansas-White-Red (11), Rio Grande (13), and Upper Colorado (14) water resource regions. The SRE provides water for domestic, industrial, and agricultural uses for much of the central and western North America and has several large reservoirs (>10 km^2), including Blue Mesa, Dillion, Elevenmile Canyon, Heron, Navajo, McPhee, Lake Grandby, and Vallecito Reservoirs, to meet water needs of communities within the SRE. The majority of land within the SRE is owned by the United States Forest Service (45%), privately (36%), and the Bureau of Land Management (10%).

The main hydroclimatologic drivers in the SRE that impact the availability of water for riparian vegetation are the source, timing, and type of precipitation. The southern SRE is influenced by the North American monsoon, with large influxes of precipitation typically occurring between July and September that can account for 50 – 70% of the annual precipitation (Grantz et al., 2007). Precipitation in the northern and central SRE generally results from extra-tropical cyclones that move through the area in the winter months and convective thunderstorms during the summer months.

Because of their importance to wildlife and their vulnerability within the region, riparian zones within in the SRE are considered an ecosystem of special concern by many organizations, such as the Colorado Natural Heritage Program (Kittel et al., 1999) and the Colorado State Wildlife Action Plan (CDOW, 2006). Riparian zones within the SRE have been mapped in a variety of ways. We identified four products that mapped riparian zones for the entire SRE:

LANDFIRE's existing vegetation layer (LANDFIRE, 2007), ReGAP (SWReGAP, Lowry et al., 2007 and NWReGAP (Davidson et al., 2009)), USGS terrestrial ecosystems map (Sayre et al., 2009), and National Land Cover Dataset (NLCD; Fry et al., 2011). We calculated the percent of the SRE that is considered riparian in each of these datasets and tested the accuracy of each dataset using the current riparian classification from the 100 plots reserved for validation using the methods outlined above. Note that two ReGAP products, the Southwest (Lowry et al., 2007) and Northwest (Davidson et al., 2009), needed to be combined to cover the SRE.

Results

Characteristics of the Response Data

Our detailed mapping of the 500 response variable plots revealed that an average of 3.9% of the SRE is composed of potential riparian zones and 2.4% is composed of current riparian zones, indicating that 38.0% of the extent of riparian zones has been modified by human activity (Table 3.4).

Based on the data that were collected from aerial photos (Table 3.1), changes in the potential riparian zone are caused primarily by agriculture (66.0%) and the direct presence of water management structures, including dams, diversions, and reservoirs (13.4%). Human development, including residential, transportation, commercial, and industrial land use accounts for a total of 10.9% of the modifications to riparian zones. The amount and cause of the modification varies geographically, and in areas with large water management projects, such as Rio Grande water resource region (WRR) and Upper Colorado WRR, agriculture accounts for 54.7% (Upper Colorado) and 58.9% (Rio Grande) of the modifications and water management accounts for 15.1% (Upper Colorado) and 29.3% (Rio Grande) of the modifications. The Missouri WRR has fewer water management projects than the other water resource regions in the study area: agriculture accounts for 75.6% and water management structures only account for 6.5% of the modifications to riparian zones.

Random Forest Model Results

Our random forest model estimates that 3.2% of the land area in the SRE is occupied by potential riparian zones and 2.5% is occupied by current riparian zones (Table 3.4), indicating that 20.3% of riparian zones have been modified by human actions. Potential riparian zones covered 4,663.2 km^2 and current riparian zones covered 3,675.6 km2 of the SRE landscape. Riparian zones accounted for the largest percentage of the landscape in the Missouri (WRR) and the smallest amount of the landscape in the Arkansas-White-Red WRR. The percent of the potential riparian zone that has been modified ranges from 14.5 – 30.5%, with the largest amount of modifications to potential riparian zones occur in the Rio Grande WRR and the smallest amount of modifications occurred in the Missouri WRR (Table 3.4).

We compared the percentage of the landscape classified as potential and current riparian in our models with the same values in our validation data (Table 3.4). We found models roughly over-estimate potential riparian zones by 18.6% and under-estimate current riparian zones by 5.4% for the entire SRE.

Overall, the potential riparian zone maps had an accuracy of 92% and the current riparian zones map had an accuracy of 91% (Table 3.5). Accuracy varied by water resource regions, the Arkansas-White-Red and Rio Grande WRRs had the highest potential and current riparian zone accuracy. The kappa coefficient for the potential riparian zones in the SRE was higher than the kappa coefficient for the current riparian zones. Kappa coefficients also varied by WRR, the Arkansas-White-Red WRR had the highest current riparian zone kappa coefficient, and the Missouri WRR had the highest potential riparian zone kappa coefficient (Table 3.5). Overall, sensitivity was higher for potential riparian zones than current riparian zones. Sensitivity ranged across water resource regions for both potential and current riparian zones. However, the Missouri WRR had the highest sensitivity for the both potential and current riparian zones (Table 3.5).

We found that the validation statistics varied when examined by stream order (Table 3.6). The current and potential riparian zones of larger streams (>S_2) performed the best according to the kappa coefficients (potential kappa = 0.65 and current kappa = 0.43) and sensitivity (potential sensitivity = 0.83 and current sensitivity = 0.66) but had the lowest overall accuracy (potential accuracy = 0.90 and current accuracy = 0.92).

We identified 137 plots that had minimally disturbed riparian zones (Stoddard et al. 2006). The minimally disturbed riparian zones were found in a variety of valley types, but were most commonly found in confined valleys. The majority (97%) of the minimally disturbed riparian zones was found in first or second order streams and those found in higher order streams (>S_2) were in confined valleys. In addition, many of these plots (85%) were located on protected land (Conservation Biology Institute, 2012). According to the data we collected, we found that 2.3% of these plots were classified as potential riparian zones. The potential riparian zone maps classified 4.0 % of these plots as riparian. For the SRE, the kappa coefficient was 0.40, accuracy was 0.92, and sensitivity was 0.60.

We created maps of representative riparian zones from seven different valley types found throughout the SRE to visualize estimated riparian zones for headwaters, canyon, moderate energy confined and unconfined, low energy floodplain, glacial trough, and high energy opened (Figure 3.1). We see a slight over-estimation of potential riparian zones in more arid regions and valleys with gentle valley slopes (~ < 4 %), such as the moderate energy confined valleys (Figure

3.1.d). In wider valleys, such as moderate energy unconfined (Figure 3.1.e) and glacial valleys (Figure 3.1.f), and low energy floodplains (Figure 3.1.g), we see a slight under estimation of both the potential and current riparian zones.

Our model indicated that TWI+, distance from streamline, and average annual precipitation were the three most important predictors (Table 3.2). We found that mean annual flow, stream type, geology, and soils explained little variance in both the potential and current riparian models.

Existing Riparian Map Results

We found that the existing map products had low accuracy when tested by our validation data. Overall, the USGS terrestrial ecosystem maps had the worst performance, with a kappa coefficient of 0.09 and a sensitivity of 0.11. The NLCD data performed the best out of the four existing datasets with a kappa coefficient of 0.33 and a sensitivity of 0.36 for the entire SRE. The performance of the existing datasets varied by WRR and there was little consistency between the different methods (Table 3.8).

Discussion

We created a hierarchical, processed guided framework by using known processes and physical factors that shape riparian zones at multiple scales: upslope, riparian, and in-channel. We reviewed the literature to identify explanatory variables for each of the processes and gathered or developed explanatory data from readily-available national datasets to capture the different scales of the dominant processes. We developed a sample-based estimate of whether points were located in the potential or current riparian zone or in the upland from field mapping data that we collected from aerial photos and tested these methods at a variety of field sites. Using random forest modeling, we developed a statistical model to estimate, with documented and quantified uncertainty, the location of both the potential and current riparian zones and quantified the amount of change riparian zones have experienced.

We used the SRE to demonstrate our hierarchical, processed guided model and found that the overall accuracy and kappa coefficient values from the output of the random forest models were reasonable but varied by water resource region. Our accuracy assessment (Table 3.5) shows that overall kappa coefficient values, accuracy, and sensitivity are consistent across the entire study area for both potential and current riparian zones. We found that accuracy was very high, with an average of 92% and a range from 90 – 92%, but that our more specific measure of sensitivity was lower, with an average of 71% and a range of 65 – 79%. Recall that sensitivity is the percentage of the riparian zone that we classified correctly, while the accuracy considers both the riparian zone and upland areas. For the entire SRE, potential riparian zones had a kappa coefficient of 0.58 and current riparian zones had a kappa coefficient of 0.39, indicating that our methods mapped potential riparian zones more accurately than current riparian zones. We found that the potential riparian zone maps had higher accuracy than the current riparian maps for the SRE and for each individual water resource region (Table 3.5).

In comparison to previous methods used to map potential riparian areas, our maps offer a much improved method. The best method to map potential riparian zones, the Topography, Discharge, and Slope (TDS) method has a kappa coefficient of 0.33 and our potential riparian zone maps have a kappa coefficient of 0.57. The best method to map current riparian zones is the NLCD dataset, which has a kappa coefficient of 0.33. Our maps of current riparian zones have a kappa coefficient of 0.38. The improved accuracy provides more precise measures of riparian location and the total area covered by riparian zones within the SRE.

Our response variable indicates that potential riparian zones cover 3.9% of the SRE and current riparian zones cover 2.4%. Our model found that 3.2% of the SRE was composed of potential riparian zones and 2.6 % of current riparian zones. The resulting difference is due to error in our models (Table 3.5). The sensitivity, or the proportion of the riparian area that is modelled correctly, for potential riparian zones is .71, indicating that we are misclassifying 29% of the potential riparian zones. The difference between 3.9 and 3.2 is 17%, well within the margin of error of the model. The same holds true for the current riparian zones, where the specificity is 0.57, indicating an error of 43% for current riparian zones. The difference between 2.4% and 2.6% is 8%, is again, within the quantified error of the model.

Our model was better at identifying potential riparian zones than current riparian zones because physical processes and valley and channel form govern the location of the potential riparian zones. However, human factors determine where riparian zones are altered by human activities. In addition, the visual analysis (Figure 3.1) shows that the models perform best in confined valleys such as high energy uncoupled valleys and canyons, areas that have limited human development. The topography of confined valleys and canyons is captured in the TWI+ predictor. The visual analysis shows an over-estimation in some valley types (e.g. moderate energy confined valleys, Figure 3.1.d) and underestimation in other locations (e.g. low energy floodplains, Figure 3.1.g). The edge that defines the boundary of a riparian zone is in reality a gradient rather than a well-defined boundary. In wider valleys the transition from riparian to upland vegetation may occur more gradually and over longer geographic distances than in confined and moderately confined valleys, leading to difficulty in identifying a single location for the riparian boundary in low energy and glacial valleys. Average annual precipitation was found to be an important predictor variable in both the potential and current riparian zone models.

We found that the potential and current riparian zone maps perform differently when analyzed by stream order (Table 3.6). The sensitivity (potential = 0.83 and current = 0.66) and kappa coefficients (potential = 0.63 and current = 0.39) indicate that, not surprisingly, the model worked best in rivers ($> S_2$). Rivers ($> S_2$) had lower, but still very good, overall accuracy (potential = 0.89 and current = 0.86). We attribute the higher overall accuracy in S_1 and S_2 streams to the higher proportion of the landscape occupied by upland land cover types in these streams. The sensitivity values indicate that the maps are best at predicting riparian zones in rivers ($> S_2$). The omission and commission errors (Table 3.6) show that our model is more likely to overestimate riparian zones in all stream orders that to under estimate riparian zones. In rivers ($> S_2$), our model has considerably more commission than omission errors, while in other stream sizes, suggested that in broad valley bottoms riparian zones may be overestimated more frequently than under estimated. We expected the maps to work best in rivers because of wider valley bottoms and riparian zones. Using a 10 m resolution limits the width of riparian zones the model can capture to greater than roughly 10 m wide. However, until finer resolution terrain data is developed, 10 m DEMs are the best available at broad extents. Most importantly, the resulting maps of riparian zones from our model outperform existing mapping products (Table 3.8). Future higher resolution DEMs and computing capabilities will likely allow more precise mapping of riparian zones using our modeling method.

We estimated a 21.3% decrease in riparian zones due to human activities in the SRE, which is not uniform across water resource regions. Rio Grande WWR has the highest (30.5%) percent of decrease in riparian zones, while Missouri WRR has seen the smallest decrease

(14.5%; Table 3.4). The modification data collected at each plot provides a snap shot of what type of land use is altering riparian zones and to what extent specific riparian zones have been altered. These values assist in understanding general patterns and drivers of landscape change in riparian zones, but additional research is needed to further quantify how these modifications are altering the ecological condition of riparian and aquatic ecosystems.

The top two predictor variables in the random forest model were TWI+ and distance to stream. We expected these two predictors to be important because in some cases TWI correlates with locations of overland flow, saturated soils, and long-term average wetness, which should be higher near streams and riparian zones (Grabs et al., 2009; Shoutis, et al., 2010). In addition, other researchers (e.g. Grabs et al., 2009; Shoutis, et al., 2010) found that TWI is an important predictor of the location of riparian vegetation. Generally, a threshold is applied to TWI values in order to map riparian zones; however using a random forest based approach removes the need to create thresholds of predictor variables and creates a statistical basis for the inclusion of this variable, thus making the method more robust, accurate, and straightforward to apply to different ecoregions. Although riparian vegetation relies primarily on stream flow as a main water source, accumulated average annual precipitation was the third most important predictor in our model, however, an empirical model of stream flow is not an accurate representation of what these channels actually experience and other researchers (Naiman et al., 2005) have found that precipitation influences the extent of riparian zones.

We sought to create a method that maps riparian zones across broad geographic areas, rather than smaller geographic areas with homogenous characteristics. By using variables such as average annual precipitation and temperature, we are able to capture processes that vary over larger geographic areas, which influence stream flow and in turn riparian zones. Several predictor variables categorized in the upland subsystem: erosion rate, SWE, average annual temperature, elevation, latitude, and longitude, had similar importance, but explained less variability in the random forest model. We think these predictors were less important because they have indirect impacts on riparian ecosystems through a series of intermediate geomorphic and ecological processes (e.g., average annual temperature controls primary productivity). These factors are still important to riparian zones because they form the watershed template, but are of secondary importance because they are physically removed from the riparian zone. Soils and geology had very low importance in the model and were included at scales too coarse to capture changes in soil or rock type along small streams with narrow valley bottoms. It has been demonstrated that the magnitude, timing, duration, and frequency of high and low flows are important to riparian zones (reviewed in Nilsson and Svedmark, 2002) but, we found that mean annual flow was not an important predictor variable. It may be that the mean annual flow is important to riparian zones; but other stream flow characteristics, such as average, peak, and low monthly flow values, may be better predictors of riparian location or that due to the large amount of error that is inherent in calculating stream flow based on Vogel's equation, this variable is not capturing processes that shape riparian zones. The adjusted R^2 values for Vogel's equation (Vogel et al., 1999) in the SRE range from 27.3% (Rio Grande) to 84.9% (Colorado River Basin) resulting in large variations in the prediction accuracy. Unfortunately, calculating flow characteristics at finer temporal scales is complicated and time consuming for large areas where stream gages are not available and was not included as a predictor variable. Creating flow characteristics for the SRE at a monthly time scale would take several months to develop the data and run the models. The main objective of this research is to develop a new method to map riparian zones with quantifiable error, given the high overall accuracy of our model (Table 3.5), we have not further investigated using additional flow characteristics.

We found moderate accuracy when we compared the data from minimally disturbed plots to potential riparian zone maps. In the minimally disturbed plots, we found that our models estimated a higher proportion of the each plot to be riparian than our data collected from aerial photos (Table 3.7). These findings indicate that, in these plots, our method overestimates potential riparian zones, resulting in less actual modification of riparian zones than we show in our results. However, these plots are located along first and second order streams, in confined valley types, and on protected lands -- all areas that are not likely to experience human land use alterations. We were not able to find minimally disturbed sites on higher order streams with larger valley and these results are not representative of the stream and valley types found throughout the region.

The poor accuracy of the existing land cover datasets (Table 3.8) underscores the need for more precise riparian maps in the SRE and generally throughout the US. Our maps provide more accurate and precise measurements about the location of riparian zones, which can inform and prioritize management and conservation decisions. Our maps can be easily incorporated into region-wide tools, such as the WGA CHAT and conservation initiatives by the Great Northern and Southern Rockies Landscape Conservation Cooperatives, to answer questions about riparian habitat availability and connectivity. By comparing the potential and current riparian zones, managers and biologists can make coarse estimates of the historic and current riparian extent and the potential restorable riparian zone. Although these maps provide a good first step to understand riparian location and a coarse measure of riparian condition, on the ground mapping would be needed for any site-scale project.

Conclusion

The need for maps of riparian zones that include a rigorous estimate of uncertainty is well documented (Ward et al., 2002; NRC, 2002) and is critical to understand the extent and loss of these zones that host areas of high biodiversity and valued ecosystem services. This is especially important in arid regions where riparian zones support the majority of terrestrial species but occupy only a small percentage of the landscape. This research provides a novel method for a cost-effective way to map riparian zones across broad spatial extents at a fine resolution (10 m), using freely available, national datasets. In addition, this research quantifies the amount of potential and current riparian zones found in the SRE, providing managers and scientists with accurate, up-to-date riparian zone maps. By comparing the extent of potential and current riparian zones, we were able to quantify the amount of riparian zones impacted as well as the type of human activity impacting riparian zones.

This research provides a much needed method to map riparian zones that can be applied at a variety of scales. It provides conservation scientists and managers in the SRE with a consistent regional map, with documented and quantified uncertainties, that can be used to manage riparian zones. This research provides a framework and methodology that could be used to conduct a national scale riparian inventory and analysis, which would allow scientists to complement sample-based programs to assess the condition of riparian zones in the United States in a spatially-explicit manner. Finally, these products can be used as the basis for analyzing riparian ecosystem function, ecosystem services and for conservation and restoration efforts.

Table 3.1. The percent of modification of potential riparian zones. Values are from the raw data gathered to create the random forest model and are reported as the percent of the potential riparian zone that was converted by each activity. Agriculture includes grazing, pastures, and crop land. Barren land is any land devoid of vegetation that was caused by human activities. Water management includes dams, diversions, and reservoirs that were visible on the aerial photography. Unknown modifications are areas that appear to be modified by humans but based on aerial photography the land use associated with the modification is unclear.

	Agriculture	Barren (Man)	Residential	Transportation	Commercial & Industrial	Incision	Water Management	Unknown
SRE (WRR 10, 11, 13 & 14)	66.1	2.5	6.6	2.5	1.8	1.9	13.4	5.3
Missouri (WRR 10)	75.6	0.1	3.6	2.0	3.8	0.0	6.5	8.4
Arkansas-White-Red (WRR 11)	83.1	0.2	8.8	0.6	0.3	0.0	4.1	2.8
Rio Grande (WRR 13)	54.7	6.4	6.3	2.0	0.0	0.0	29.3	1.4
Upper Colorado (WRR 14)	58.9	3.4	8.0	3.5	1.6	4.2	15.1	5.3

Table 3.2. Variables used to predict current riparian zones and the relative and absolute rank of the predictor in the random forest model, including the scale, date, and source of each predictor.

Process	Predictor Variable	Scale / Resolution (m)	Date	Source	Relative Importance		Importance Rank	
					Potential	Current	Potential	Current
Upslope	Erosion Rate (RUSLE)	30	1971 - 2000	Litschert et al. (2014)	0.18	0.24	5	6
	Geology	1:500,000	-	USGS (2006)	0.08	0.10	12	14
	Snow Water Equivalent (SWE)	1000	2003 - 2012	NOHRSC (2012)	0.33	0.32	2	4
	Average Annual Precipitation	800	1981 - 2010	PRISM (2012)	0.26	0.36	4	3
	Average Annual Temperature	800	1981 - 2010	PRISM (2012)	0.16	0.21	9	9
	Elevation	10	-	NED (2006)	0.18	0.22	6	8
	Latitude	10	-	-	0.17	0.26	8	5
	Longitude	10	-	-	0.17	0.22	7	7
Riparian	Soils	1:100,000	-	Soil Survey Staff (2006)	0.10	0.15	10	11
	Topographic Wetness Index + (TWI+)	10	-	Theobald (2007)	1.00	1.00	1	1
	Distance from streamline	10	-	USEPA (2012)	0.29	0.99	3	2
	Human modification	90	-	Theobald (2013)	-	0.21	-	10
In-channel	Mean annual discharge	1:24,000	1981 - 2010	Verdin and Worstell (2008)	0.07	0.12	13	12
	Stream type	1:24,000	-	USEPA (2012)	0.09	0.11	11	13

Table 3.3. Resolutions and weights used to create 10 m, multiple resolution TWI+.

Resolution (m)	Weight
10	0.50
20	0.25
40	0.13
80	0.06
160	0.03
320	0.02
640	0.01

Table 3.4. Area and percent of the landscape occupied by potential and current riparian zones for the entire SRE and by WRR. Note that the validation data predict that 3.9% of the SRE is composed of potential riparian zones and 2.4% is composed of current riparian zones.

	Area of Landscape Riparian (km^2)		**Percent of Landscape Riparian**		**% Change**	**Area Lost (km^2)**
	Potential	**Current**	**Potential**	**Current**		
SRE (WRR 10, 11, 13 & 14)	4663.2	3675.6	3.2	2.6	-21.2	987.6
Missouri (WRR 10)	1830.8	1565.0	5.1	4.4	-14.5	265.8
Arkansas-White-Red (WRR 11)	436.3	320.3	1.8	1.3	-26.6	116.0
Rio Grande (WRR 13)	655.5	455.8	2.7	1.9	-30.5	199.7
Upper Colorado (WRR 14)	1740.3	1334.3	2.9	2.3	-23.3	406.0

Table 3.5. Measurements of kappa coefficient (the agreement between the validation data and the potential and current riparian zone maps), accuracy (proportion of all values predicted correctly), and sensitivity (proportion of riparian zones predicted correctly) for potential and current models for the entire SRE and by WRR.

	Kappa Coefficient		**Direct Accuracy**		**Sensitivity**	
	Potential	**Current**	**Potential**	**Current**	**Potential**	**Current**
SRE (WRR 10, 11, 13 & 14)	0.57	0.38	0.92	0.91	0.71	0.57
Missouri (WRR 10)	0.66	0.37	0.91	0.88	0.79	0.67
Arkansas-White-Red (WRR 11)	0.57	0.47	0.94	0.94	0.69	0.63
Rio Grande (WRR 13)	0.54	0.42	0.95	0.95	0.67	0.54
Upper Colorado (WRR 14)	0.49	0.33	0.90	0.91	0.65	0.49

Table 3.6. Measurements of kappa coefficient (the agreement between the validation data and the potential and current riparian zone maps), accuracy (proportion of all values predicted correctly), and sensitivity (proportion of riparian zones predicted correctly) for potential and current models for the entire SRE by stream order.

	Kappa Coefficient		**Direct Accuracy**		**Sensitivity**		**Omission**		**Commission**	
	Potential	**Current**	**Potential**	**Current**	**Potential**	**Current**	**Potential**	**Current**	**Potential**	**Current**
S_1	0.40	0.27	0.96	0.96	0.41	0.32	0.02	0.02	0.02	0.02
S_2	0.23	0.23	0.90	0.92	0.34	0.35	0.04	0.03	0.06	0.05
$> S_2$	0.63	0.39	0.89	0.86	0.83	0.66	0.02	0.03	0.08	0.11

Table 3.7. Measurements of kappa coefficient (the agreement between the validation data and the potential and current riparian zone maps), accuracy (proportion of all values predicted correctly), sensitivity (proportion of riparian zones predicted correctly), and percent of the landscape classified as riparian during data collection efforts (measured) and from the potential riparian zone maps (mapped) for minimally disturbed potential riparian zones for the entire SRE and by WRR.

	Kappa Coefficient	Direct Accuracy	Sensitivity	Percent Riparian	
				Measured	**Mapped**
SRE (WRR 10, 11, 13 & 14)	0.40	0.92	0.60	2.3	4.0
Missouri (WRR 10)	0.43	0.91	0.59	2.8	4.9
Arkansas-White-Red (WRR 11)	0.36	0.92	0.64	2.2	5.0
Rio Grande (WRR 13)	0.41	0.90	0.67	3.2	4.2
Upper Colorado (WRR 14)	0.38	0.94	0.56	1.6	3.3

Table 3.8. Measurements of kappa coefficient (the agreement between the validation data and the potential and current riparian zone maps), accuracy (proportion of all values predicted correctly), and sensitivity (proportion of riparian zones predicted correctly) for the existing data sets for the entire SRE and by WRR.

	Percent of Landscape				**Kappa Coefficient**			
	ReGAP	**Landfire**	**NLCD**	**USGS**	**ReGAP**	**Landfire**	**NLCD**	**USGS**
SRE (WRR 10, 11, 13 & 14)	2.7	2.7	2.2	1.2	0.24	0.21	0.33	0.09
Missouri (WRR 10)	2.6	3.3	3.2	1.8	0.22	0.26	0.41	0.06
Arkansas-White-Red (WRR 11)	2.2	2.2	1.7	1.0	0.44	0.42	0.45	0.14
Rio Grande (WRR 13)	2.9	1.7	2.9	1.3	0.22	0.05	0.32	0.00
Upper Colorado (WRR 14)	3.0	3.0	1.7	0.8	0.17	0.14	0.20	0.14

	Direct Accuracy				**Sensitivity**			
	ReGAP	**Landfire**	**NLCD**	**USGS**	**ReGAP**	**Landfire**	**NLCD**	**USGS**
SRE (WRR 10, 11, 13 & 14)	0.93	0.92	0.92	0.92	0.22	0.25	0.36	0.11
Missouri (WRR 10)	0.93	0.91	0.91	0.91	0.17	0.29	0.48	0.07
Arkansas-White-Red (WRR 11)	0.95	0.95	0.95	0.94	0.53	0.47	0.61	0.13
Rio Grande (WRR 13)	0.95	0.94	0.94	0.91	0.19	0.06	0.31	0.06
Upper Colorado (WRR 14)	0.93	0.90	0.90	0.92	0.16	0.20	0.21	0.14

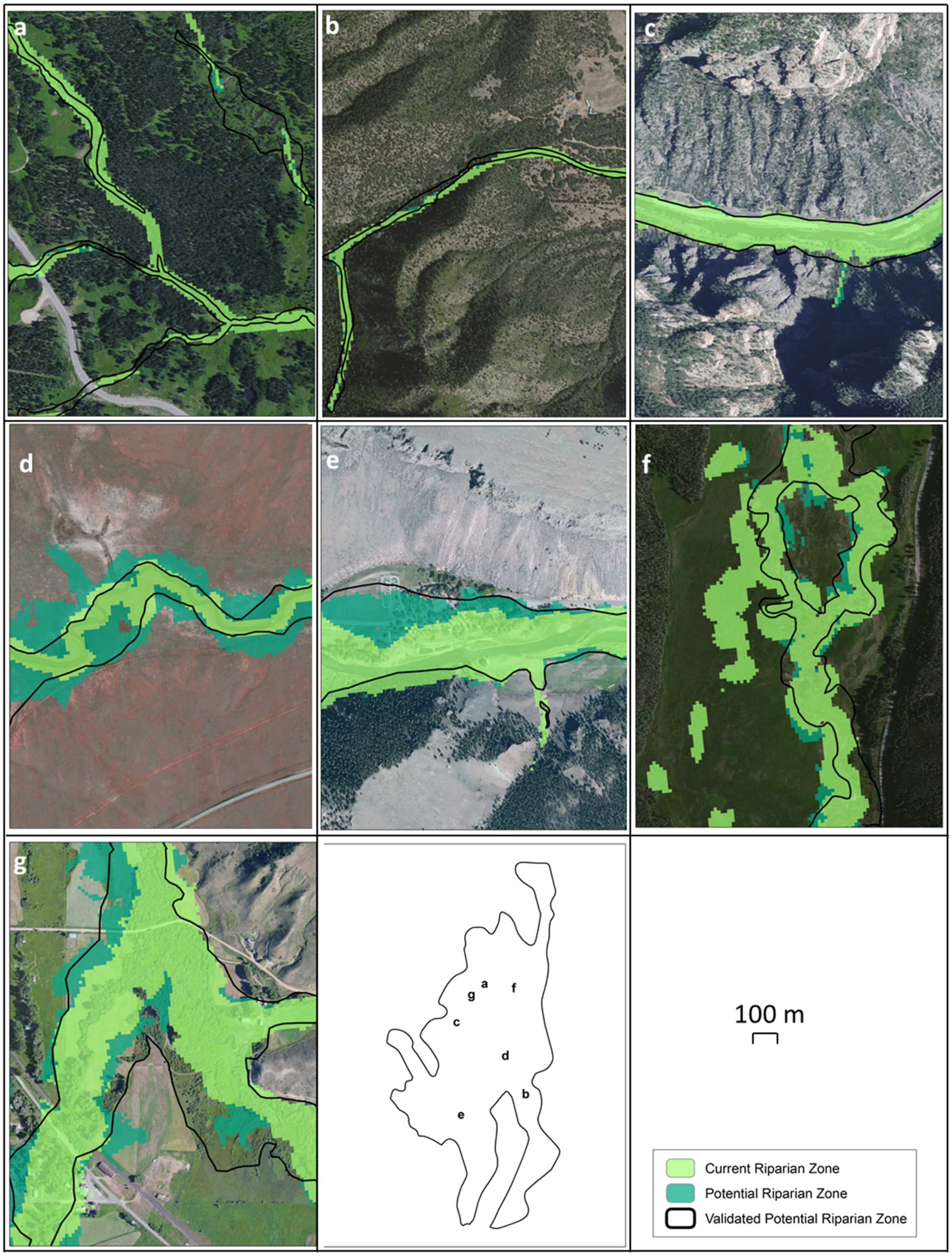

Figure 3.1. Example riparian zones mapped by our models from representative valley types throughout the SRE. (a) Headwater streams in the North Platte Watershed. (b) High energy uncoupled valley in the Arkansas River watershed. (c) Canyon valley type, Colorado River in Glenwood Canyon. (d) Moderate energy confined valley on the South Platte River. (e) Moderate energy unconfined valley on the Rio Grande. (f) Glacial valley, the Colorado River in the Kawuneechee Valley in Rocky Mountain National Park. (g) Low energy floodplain along the Yampa River.

4. A practical method to estimate riparian condition at a reach scale in semi-arid mountainous regions

Introduction

Riparian ecosystems support critical ecological functions throughout western North America, yet they cover less than 5% of the land area (Swift, 1984; Dahl, 1990). The benefits associated with riparian ecosystems are vast: reducing erosion, protecting water quality by filtering sediment and nutrients, increasing biodiversity, and providing corridors for widlife and alterations to riparian ecosystems can result in a reduction of these benefits (Brauman et al., 2007). Of the small portion of land that is covered by riparian ecosystems, it is estimated that 20 – 50% (Dahl, 1990) has been altered by anthropogenic activity. And although many agencies and organizations are concerned with the condition of these ecosystems and the benefits provided, it remains challenging to understand the ecological condition of riparian zones over broad geographic areas.

The challenge to map the ecological condition of riparian zones emerges because the condition of an individual riparian zone is a function of modifications to ecological processes that occur at a variety of spatial and temporal scales (i.e. watershed, landscape, regional, or larger scales) and the relationship of riparian zones to other ecosystems and land use types, including the delivery of water to geographic distant locations. Integrated, quantitative assessments of human impacts over broad geographic areas are important tools in conservation research and land management (Danz et al., 2006; Esselman et al., 2011). From both a scientific and policy perspective, it is important to map and measure ecosystem condition within large contexts at broad spatial scales (Bedford and Preston, 1988). Therefore, in this paper we develop a practical methodology to quantify ecological condition of riparian zones over a broad geographic area at a reach (defined as confluence to confluence) scale.

We employ a common definition of a riparian zone: the area that is adjacent to and influenced by streams, which typically contains vegetation that differs from the surrounding upland vegetation (Gregory et al., 1991; Verry et al., 2004; Naiman et al., 2005). We distinguish two types of riparian zones, potential and current, consistent with other research (Clerici et al., 2013). A *potential riparian zone* is the area that would likely support natural riparian vegetation in the absence of human activity and corresponds to the geomorphic extent of the "riparian zone". The *current riparian zone* is a subset of the potential riparian zone that is not strongly modified by human land uses and is assumed to support natural riparian vegetation.

We define riparian condition as the degree to which natural riparian vegetation, canopy, and structure, and the eco-hydrologic processes that govern these factors are modified (Innis et al., 2000; Allan, 2004; Naiman et al., 2005). We quantify riparian condition by estimating the degree of modification to the riparian zone by human land use activity and dams and diversions that occur both within the riparian zone and throughout the upstream catchment. In this research, we examine riparian condition at the reach scale, defined by the riparian zone between two stream confluences.

The major drivers of anthropogenic change and largest threats to riparian ecosystems are alteration and regulation of stream flow, climate change, and land use change (Naiman et al., 2005; Poff et al., 2010). These modifications operate in three physical subsystems, roughly represented as analytical scales and hereafter referred to as "scales". These scales -- watershed, riparian, and in-channel -- represent dominant processes and the principal effects that each of these elements has varies based on watershed geomorphology and climate (Strayer et al., 2003;

Reeves et al., 2004). In this paper, we developed a method to estimate riparian condition as a function of processes that occur at watershed, riparian, and in-channel scales.

Watershed Scale

The overall characteristics of the watershed, including geology, climate, and land use, create the context for any given riparian zone. Land use impacts riparian ecosystems in two ways: (1) by directly altering the riparian zone and (2) by altering watershed land cover and in turn, resulting impacts are experienced in the riparian zone (Allan, 2004). The influence that watershed land use has on riparian zones has been well established in the literature (e.g., Richards et al., 1996; Allan et al., 1997; Strayer et al., 2003). At the watershed scale, the impact of human modifications ranges from altered nutrient and sediment loads to alterations in hydrologic processes. The principle mechanisms by which watershed land use influence riparian ecosystems includes sedimentation, nutrient enrichment, containment pollution, hydrologic alteration, and loss of large woody debris (Allan, 2004).

Riparian Scale

At the riparian scale, the presence of direct human modifications removes riparian vegetation and can result in a disruption of connectivity between streams and the associated valley bottoms because these alterations have the potential to interrupt water movement during high flows. Common human modifications of riparian zones include transportation infrastructure, deforestation, mining, grazing, water removal for human uses, and development within the floodplain. In addition, future development is likely to occur along stream corridors, exacerbating the negative consequences of existing stressors (Naiman et al., 2005). The lateral connectivity between streams and riparian zones contributes to the spatial heterogeneity of river systems and strongly influences the biodiversity of the river and associated riparian zones

(Stanford and Ward, 1993). If lateral connectivity is disrupted by human modifications, such as roads or railways built in the riparian zone, the stream channel may be constrained (Hall et al., 2007) and interactions between ground and surface water may be eliminated (Stanford and Ward, 1993). Reduction of channel movement alters vital habitat for aquatic and terrestrial organisms by removing point bars and cut banks from streams and rivers (Naiman and Décamps, 1997). Disruption in lateral connectivity can result in a disconnection between backwater, oxbows, and secondary channels and the main channel, leading to the loss of functioning riparian ecosystems.

In-channel Scale

Stream flow alteration and regulation is primarily the result of dams and diversions constructed along rivers, which are essential to supporting agriculture, urban growth, and industry in arid and semi-arid regions (Goodwin et al., 1997). Diversions occur at all scales (e.g., flood irrigation diversions and inter-basin transfers) and move water from one location to another (Poff et al., 2011). The principle impact of flow modifications and regulation is alteration of flow, nutrient, sediment, and temperature regimes downstream of dams and diversions, which introduce equilibrium to naturally dynamic ecosystems (Naiman et al., 2005). Altering flow regimes can result in modifications of riparian zones through the loss of species (Stromberg, 2001) and life history clues, reductions in the area of riparian vegetation (Dominick and O'Neil, 1998), and changes in the composition of riparian vegetation communities, including increases in the number of invasive species found in riparian zones (Elderd, 2003; Caruso et al., 2013). In addition to flow alterations, road and rail crossings can impact stream flow and riparian ecosystems in a variety of ways. These features can influence riparian ecosystems up- and downstream from crossings, resulting in changes in flow rates, sediment regimes, stream geomorphology, and interactions between streams and riparian ecosystems (Forman and

Alexander, 1998; Blanton and Marcus, 2009). Climate change has the potential to alter the balance of watershed processes (Kundzewicz et al., 2007) through changes in stream flow and researchers have found that climate change, through warming temperatures and changes in precipitation patterns, is already impacting riparian ecosystems in western North America (Perry et al., 2012).

Previous work has assessed riparian condition in several different ways, by: measuring stream and riparian abiotic and biotic indicators and comparing them to pristine conditions (Peck et al., 2006; Rocchio, 2007), examining hydrogeomorphic characteristics (Smith et al., 1995), or tracking the amount of disturbance that is potentially affecting the ecosystem (Reeves et al., 2004; Jones et al., 2010). Riparian condition has been assessed using mapped and imagery based data (typically using a GIS) or from data collected in the fields, including rapid and intensive evaluations (Faber-Langendoen et al., 2012). Field based analysis generally occurs over relatively small geographic areas (e.g., HUC 8 watersheds), focuses on direct measures that are used to characterize riparian condition, and are often published in governmental or organizational documents, but typically not in peer-reviewed literature. In the western United States, these projects have focused on minimally disturbed riparian zones (Vance et al., 2012) or on target watershed of ecological or conservation concern (Lemly, 2012). These intensive assessments of riparian zones (e.g., Lemly, 2012 and Vance et al., 2012) require rigorous, field based measurements that provide detailed site integrity information and are based on detailed field measurements with sites determined by a statistical sampling design. The goal of intensive, fine-grain assessments is to identify status and trends of ecosystem condition (Faber-Langendoen et al., 2012). However, the expense associated with these riparian condition assessments makes them prohibitive to conduct over large geographic extents. Nonetheless, regional condition assessments are important for managers and conservation scientists to understand ecosystems across broad geographic regions in order to manage land appropriately. Regional assessments are also helpful in screening candidate sites for restoration, conservation, or other management actions (Faber-Langendoen et al., 2012).

Assessments using GIS allow both on and off-site conditions surrounding riparian zones to be assessed easily. Current GIS approaches combine various existing datasets using weights based on “expert knowledge” to calculate a condition score or level of threat that riparian zones are exposed to (Jones et al., 2010; Theobald et al., 2010; Brown and Froemke, 2012). These methods generally operate at one of two analytical units, watersheds or coarsely estimated riparian zones. To do this, researchers typically calculate a single value for an entire watershed by developing loose relationships between watershed and riparian condition (Brown and Froemke, 2012) or limit this watershed approach to the riparian zones (Theobald et al., 2010). They lack quantifiable measures of uncertainty, or rely on rough estimates of the riparian zone using uniform distance buffers (Jones et al., 2010; U. S. Environmental Protection Agency, 2013) or the geomorphic valley bottom (Theobald et al., 2010). Although useful, to our knowledge, these existing approaches to estimate riparian condition do not: (a) address processes that occur at different scales to estimate riparian condition; (b) conduct research at management relevant scales that capture controlling eco-hydrological processes; and (c) document the uncertainty associated with their results.

A second type of riparian assessment rely on spectral signature information from fine-grain satellite imagery (<10 m) and various statistical methods to estimate riparian condition (Goetz et al., 2003; Snyder et al., 2005; Johansen et al., 2010, Johansen et al., 2013). These methods are often cost-prohibitive to apply across large geographic regions and fail to incorporate natural processes that form and alter riparian ecosystems and the intensity of human impacts to riparian ecosystems. Many methods (e.g., Hanowski, et al., 2002, Ivits et al., 2009) use freely available, coarse resolution (> 30 m) satellite imagery to map riparian condition, however, this resolution is known to exclude narrow riparian zones along headwater streams (Congalton et al., 2002), streams known for their ecological and physical importance (Wohl, 2006).

Our goal in this paper is to create a spatially-explicit, practical method to estimate riparian condition at management relevant scales over broad geographic extents using relatively fine grain (10 m) data. We develop estimates of riparian zone condition using a process guided approach to provide an assessment of riparian condition at the reach scale. Our objectives in pursuit of this goal are to: (1) describe the dominant influences on riparian condition; (2) identify and map explanatory variables that capture the different scales of variables that influence riparian condition; (3) produce sample-based estimates of riparian condition as our response variable; (4) develop a statistical model to estimate the condition of riparian zones with documented uncertainty; (5) describe the most important variables in determining riparian condition, and (6) demonstrate our approach for the Southern Rockies Ecoregion (SRE). Because of their importance and vulnerability within the region, riparian zones within the SRE are considered an ecosystem of special concern by many organizations, such as the Colorado Natural Heritage Program (Kittel et al., 1999), the Colorado Department of Parks and Wildlife (CDOW, 2006), and the Southern Rockies Landscape Conservation Cooperative (Rice, 2012). These organizations are interested in understanding riparian condition over large geographic extents, yet a detailed and comprehensive database does not currently exist.

Methods

We estimated riparian condition as a function of the processes that influence riparian zone and occur in three different scales within a watershed: watershed, riparian, and in channel (Figure 1.2). To do this, we created a reach specific response variable from aerial photo interpretation and used predictor variables, created from existing datasets to capture information within each scale.

The extent of each scale was defined by existing data: the watershed was defined by the HUC-8 watershed boundary dataset (USGS, 2012a), the riparian zone was defined using a multiple-scale, hierarchical model developed in chapter 3, and the in-channel scale was defined by 1:24,000 NHD (USGS, 2012a) streams and dams from the NID (U.S. Army Corps of Engineers, 2007) (Figure 4.1). Potential riparian zones were mapped using the major processes that form and maintain riparian ecosystems, including climate, stream flow, and geomorphic variables and both potential and current riparian zones were identified using random forest modeling.

To estimate riparian condition for potential riparian zones, we included three criteria: (1) the spatial distribution of riparian ecosystems, (2) the connectedness of riparian ecosystems and (3) the processes and interactions that occur within riparian ecosystems and between the adjacent uplands. Our riparian condition measure recognizes that many factors, at different scales, contribute to riparian condition, including the hydrologic and geomorphic context, physical and ecological processes, and anthropogenic disturbances (Reeves et al., 2004). We estimate riparian condition using a straightforward, cost-effective approach that statistically evaluates the dominant ecological and physical processes and anthropogenic stressors that impact riparian ecosystems.

We identified threats to riparian zone condition (Graf, 2001; Theobald, et al. 2010; Poff et al., 2011) and then developed predictor variables to capture these threats at a multiple scales. We used a sample-based estimate of riparian condition to develop a statistical model to map riparian ecosystem condition across the Southern Rockies Ecoregion (SRE).

Response Variable

The response variable designates the condition of a specific riparian zone as one of three classes: low, medium or high. To estimate the condition, we calculated the ratio of current to potential riparian zones from data collected through aerial photography interpretation. These data were collected for riparian zones within 500 plots, limited to stream lines mapped by the NHDPlus (USGS, 2012b) dataset. These plots were located using a stratified random design stratified random design (Theobald et al., 2007) to assure an equal representation of headwaters (Strahler's stream order 1; S_1), mid-watershed (S_2), and larger streams ($> S_2$). The plots, roughly 600 m by 600 m, are large enough to capture the full width of riparian systems in our study area, but small enough to limit the incidence of multiple riparian systems (confluences) within a given plot, and are consistent with other detailed mapping efforts (Leinwand et al., 2010). Within each plot, 300 spatially balanced and random points were generated (Theobald et al., 2007). Each of the 300 points (total of 150,000) were classified as potential riparian, current riparian, or not riparian (see Chapter 3 for full methodology).

For each of the 500 plots, we determined the proportion of the potential riparian zone that was modified by human land use by dividing number of points classified as current riparian zones by the number of points classified as potential riparian zones. This resulted in a total of 394 sample locations because some plots did not contain riparian vegetation. Each value was then classified into one of three categories (low, medium or high) using natural breaks to classify the proportion of the riparian zone that has been modified (Table 4.1). Thus, our response variables is a measure of the relative condition within a given study area.

Predictor Variables

We selected a set of measurements based on a review of the literature and professional experience that include flow alteration and regulation and human modification that occur at different scales to predict riparian condition (Table 4.2). See Appendix III for additional discussion about our selection and development of predictor variables.

Watershed Scale

We used the degree of human modification (Theobald, 2013) to capture both the physical footprint of human modification and the magnitude that an activity modifies an ecological system. This dataset was developed using expert knowledge and empirical relationships and incorporates commercial, and industrial development, agriculture, energy production and mining, transportation and service corridors, biological resource use (e.g., hunting), recreation activities, invasive species, and pollution. The dataset is a continuous, fine-grained (90 m) raster with values ranging from 0 (complete naturalness) to 1 (high degree of human modification). The human modification index allows us to characterize the degree of modification that upstream land uses have on riparian ecosystems. We used the human modification index at the watershed scale by calculating the proportion of the upstream watershed that has been modified by humans at any given location within a potential riparian zone.

We used the Protected Areas Database Version 2 (Conservation Biology Institute, 2012) to calculate the percent of the upstream watershed that is protected, assuming higher proportion of protected lands will result in better riparian zone conditions. We divided protected lands into four categories (GAP Status 1-4) based on protection and management status. GAP Status ranks range from lands with high levels of protection (GAP Status 1) to land with protection but no known management plans (GAP Status 4). Intermediate land protection includes GAP Status 2 lands where conversion of natural land cover is restricted but non-extractive management practices (e.g., wildfire suppression or grazing) are allowed and GAP Status 3 land that has permanent protection from conversion of natural land cover but are subject to extractive uses (e.g., logging and mining).

Riparian Scale

Transportation corridors built adjacent to riparian zones destroy riparian vegetation and likely constrict fluvial processes and lateral connectivity within riparian zones. To estimate lateral confinement caused by transportation infrastructure, we divided the total length of streamlines (from NHD 1:24,000; USGS, 2012a) by the total length of roads and railways (from US Census Bureau's TIGER, 2010) within each potential riparian zone reach.

We measured human modification in potential riparian zones and estimated the relative level that natural processes have been modified within potential riparian zones. To do this, we used the human modification index (Theobald 2013) to estimate the proportion of a single potential riparian zone reach that has been modified by human activity.

In-channel

We used two measures of longitudinal connectivity to access the connectedness of riparian ecosystems to upstream and downstream reaches. We estimated modifications to the natural stream flow regime by calculating a measure of flow fragmentation, which is the ratio of the normal storage volume of all upstream dams (acre feet) to the mean annual flow following the work of previous researchers (Dynesius and Nilsson, 1994; Graf, 1999; Nilsson et al., 2005; Theobald et al., 2010). Normal storage volume (acre feet) was provided by the National

Inventory of Dams dataset (NID; U.S. Army Corps of Engineers, 2007). The NID contains dams that at least 25 feet high and have a minimum of 15 acre feet of storage capacity or at least 6 feet high and have a minimum of 50 acre feet of storage capacity or are classified as a high or significant hazard (*n*=276).

We estimated the mean annual flow using a continuous expression of Vogel's equation calculated on a 10 m raster (Verdin and Worstell, 2008). Vogel's equation (Vogel et al., 1999) is a regression-based method that incorporates catchment area, mean annual precipitation, and temperature and regional parameters to estimate flow.

Our flow modification metric values range from 0 to 1. Values of 0 indicate no flow modification and values of 1 indicating that upstream reservoirs are able to store roughly the mean annual discharge flowing through a given stream. Occasionally, values of greater than 1 were calculated, indicating that more than the mean annual flow was stored in specific streams. High values (>1) occurred along channels directly downstream of large dams (e.g., Gunnison River downstream of Blue Mesa Dam). We truncated any ratio greater than 10 to a value of 10 to minimize scale artifacts, following methods developed by Theobald et al. (2010).

We calculated the number of upstream road and railroad crossings for each stream. To do this, we intersected mapped roads and rails (TIGER, 2010) with NHD 1:24,000 (USGS, 2012a) stream lines, and converted these intersections to a raster with a 10 m resolution. We then used the Flow Accumulation tool in ArcGIS to count the number of rail and road crossings that are upstream of any point along a streamline. The flow accumulation tool typically is used to calculate the number of upstream cells that contribute to any given point in a watershed. The tool allows for weighted inputs (e.g., road crossing, each assigned a value of 1 and all other cells assigned a value of 0) to be counted.

Statistical Model

We used random forest modeling, which is a non-parametric classification and regression tree method that uses ensemble trees to make predictions. The random forest models grow multiple classification or regression trees based on bootstrapping data and, for an individual tree, divides the variation in the response variable based on the predictor variables. A random forest model creates a single prediction value by combining the predictions of all trees and provides measures of variable importance (Breiman, 2001).

The random forest method is commonly used to predict ecological phenomena and frequently outperforms other statistical techniques such as classification and regression trees, generalized linear models, and maximum entropy when used in ecological research (Buechling and Tobalske, 2011; Zhang and Zhang, 2012; Timm and McGarigal, 2012). Random forest models are robust to correlated input variables, make no distributional assumptions, and can accept both categorical and continuous variables (Breiman, 2001). We implemented random forest in program R using the randomForest package (Liaw and Wiener, 2002). We included 80% of our sample locations (315) in our random forest model and reserved 20% (79) for validation.

Random forests models do not include a term to penalize for a high number of predictor variables or predictor variables that have low importance, but from a practical perspective, we wanted to create the most parsimonious model possible. To select predictor variables, we systematically removed any predictor variable so that it was removed from the model if the classification error did not increase by more than 1%. See Appendix III for additional information regarding model accuracy with the removal of predictor variables.

Model validation

We validated our models by comparing the modeled riparian condition to the riparian condition within the 79 riparian zones that were withheld for validation using kappa coefficient (i.e. the agreement between the validation data and modeled condition scores) and accuracy (the proportion of condition scores that were mapped correctly). We also compared our estimates of riparian condition to the habitat condition class in 47 locations from the EPA's wadeable stream assessment (WSA) database (U.S. Environmental Protection Agency, 2006) as a way to verify our results against a national standard. However, this is not a true validation but rather a verification our condition score against the relative nature of the WSA database.

Study Area

The SRE is a mountainous ecoregion region covering 143,901 km^2 in western North America. The SRE contains several riparian system types; the most common are lower montane-foothills riparian woodlands and shrublands, subalpine-montane riparian shrublands and woodlands, and wet meadows (Kittel et al., 1999; NatureServe, 2009).

Riparian condition within the SRE is compromised by stream flow alterations, climate change, and human land use. The main threats to riparian ecosystem condition within the SRE are: dams and diversions that alter the stream flow regime; climate change that alters the wildfire and flow regimes; and changes in land use, including grazing by livestock and wild animals (e.g., elk), road construction, and use of the riparian zones for recreation, residential, commercial and industrial development; and resource extraction including mining and timber harvesting (Poff et al., 2011).

The SRE has roughly 3,041 m of topographic relief and an average annual precipitation ranging from 1,872 mm along the continental divide to 190 mm in the southwestern region

(PRISM Climate Group, 2012). The SRE contains the headwaters for the Colorado, Platte, Rio Grande, and Arkansas Rivers (Figure 1.1) and portions of the Missouri (Water Resource Region 10), Arkansas-White-Red (11), Rio Grande (13), and Upper Colorado (14) water resource regions. The SRE provides water for domestic, industrial, and agricultural uses for much of the central and western North America and has several large reservoirs (>10 km^2) to meet water needs of communities within the SRE, including Blue Mesa, Dillion, Elevenmile Canyon, Heron, Navajo, McPhee, Lake Grandby, and Vallecito Reservoirs. The majority of land within the SRE is owned by the United States Forest Service (45%), privately (36%), and the Bureau of Land Management (10%).

Results

Characteristics of the Response Data

Our detailed categorization of the 394 riparian zones revealed that 18.0% of the study area was classified as low condition, 17.0% was classified as medium condition, and 65.1% of the riparian zones in the study area were in high condition (Table 4.1). The stream distance of the riparian zones we sampled had an average length of 376 m and a standard deviation of 272 m, and ranged in length from 3 – 3,000 m. This is at a finer scale than a NHD 1:24,000 (USGS, 2012a) reach, which in our study area average 418 m and had a range of 1 – 54,974 m but, slightly coarser than regional field based assessments (e.g., Vance et al., 2012 and Lemly, 2012), which are limited to 1,000 m^2 plots and survey both wetland and riparian ecosystems.

Random Forest Model Results

Our random forest model had an overall accuracy of 60.5% and a kappa coefficient of 0.13 (Table 4.3), though the accuracy of each condition category varies greatly (Table 4.4). Our model is best at predicting the riparian zones in high condition with an accuracy of 91.3%. The model predicts riparian zones in low riparian condition with and accuracy of 6.6% and average riparian condition with an accuracy of 20.0%. There was more producer's (omission) error (93.3%) than user's (commission) error (66.7%) for riparian zones with low riparian condition; more producer's error (51%) than user's error (49%) for the riparian zones in medium condition; and more user's error (35.4%) than producers error (8.7%) for riparian zones in high condition.

We compared our model output with the WSA data (U.S. Environmental Protection Agency, 2006) and found an agreement of 47.8% and a kappa coefficient of 0.17 (Table 4.5), indicating the relationship between our model and the WSA data is better than by random chance, but that roughly half of the data do not agree.

Overall, the human modification index at the riparian scale was the most important predictor variable, followed by the number of upstream transportation crossings, and human modification index at the watershed scale (Table 4.6). The proportion of the watershed that is protected by GAP Status 1, 2, or 3 lands was not included as a predictor variable in the final model because removing these variables did not influence the accuracy of the model.

The importance of predictor variables varies by condition class (Table 4.6). For the low condition class, the most important predictors were the number of upstream transportation crossings, the flow fragmentation index, and the proportion of upstream area protected by GAP Status 4. For the medium condition class, the most important predictors were human modification at the riparian scale, human modification at the watershed scale, and the proportion of upstream area protected by GAP Status 4. For the high condition class, the most important predictors were human modification at the riparian scale, followed by human modification at the watershed scale, and the number of upstream transportation crossings.

The spatial distribution (Figure 4.2) and percent of the SRE in each class of riparian condition varies predictably (Table 4.7). The riparian zones of the SRE are composed of 7.2% low condition, 15.2% medium condition, and 77.7% high condition. In general, high riparian conditions are found in headwater streams, average riparian conditions are found in the middle reaches of watersheds, and low riparian conditions are found mainly along larger rivers. The majority (69%) of riparian zones in low condition occur along large rivers, which are known to have large reservoirs and wide valley bottoms that are used for agriculture and other human land uses, including residential, commercial, and industrial purposes. These rivers include the Big Thompson River, Colorado River, Gunnison River, North and South Platte Rivers, Rio Grande, White River, and Yampa River. Smaller streams that have low riparian condition are located directly downstream of large reservoirs, in areas of extensive agriculture activity, or in urbanized locations.

We calculated the percent of each riparian condition class found within each GAP status and on unprotected lands in order to understand land protection mechanisms (i.e. GAP status) for each of the three riparian condition classes. We found that 75.2% of riparian zones in low condition and 77.2% of riparian zones in medium condition occur on lands with unknown or no protection, while only 57.5% of riparian zones in high condition occur on lands with unknown or no protection (Table 4.8).

Discussion

We developed a practical, statistically based model to estimate the relative condition of riparian zones with a given study area using explanatory variables that capture the different scales of variables that influence riparian condition. Our model relies on data that is sampled and predicted at a management relevant reach scale, improving upon previous research that uses watersheds or crudely estimated riparian zones as an analytic unit to estimate condition. In addition, we developed explicit measures of uncertainty, which is lacking in previous efforts and provides critical information to aid in interpretation of the results by managers.

We used the SRE to demonstrate our riparian condition model and found that overall accuracy and kappa coefficient values from the output of the random forest model were low but within reasonable ranges. We identified that the most important variables in predicting overall riparian condition were the amount of human modification that occurs in a riparian zone and the number of upstream transportation crossings, followed by the amount of human modification that occurs in the watershed, the flow fragmentation index, and lateral confinement.

Our model predicts low and medium riparian condition (Table 4.4) with low accuracy. Low accuracy in riparian zones with low ecological condition can be explained by the relatively small amount of low riparian conditions in the SRE. Our sample size of riparian zones in low condition (n = 72) and the percent of the all riparian zones in low condition (7.2%) within the SRE reflects this reality. The areas found to be in low riparian condition are located on lands that are not protected and associated with large rivers (e.g., Colorado River and Platte River), many of these rivers have large reservoirs and extensive riparian zones that have been modified by human land use. The majority (57.9%) of the streams and rivers within the SRE are headwaters (based on NHD 1:100,000; USGS 2012b), which generally are found on publicly owned, protected lands in narrow valleys with limited riparian zones. Narrow valleys and the associated riparian zones are typically more difficult for access, resulting in medium and high riparian condition. The producer's error (93.3%) is greater than the user's error (66.6%), indicating that our models are more likely to misclassify areas of low condition as either medium or high condition than to overestimate riparian zones with low condition.

Riparian zones in medium condition occur throughout the SRE, in all stream orders and comprise 15.1% of all riparian zones. Riparian zones in medium condition tend to be slightly modified by human land use, primarily for agriculture or low density residential purposes and occur primarily (77.2%) on lands lacking protection. The low accuracy for the medium condition class may be a function of the natural variation in these riparian zones. The producer's error (80%) is greater than the user's error (62.5%), indicating that our models are more likely to misclassify areas of medium condition as low or high condition than to overestimate riparian zones with medium condition.

Riparian zones in high condition occur primarily in headwater streams and comprise 77.7% of all riparian zones in the SRE. Our model predicts riparian zones in this class with the highest accuracy (91.3%). Riparian zones in high condition tend to be found on lands that are protected (GAP Status 1-3; 42.6%). Within the SRE, many headwater streams are found on public lands, in steep terrain with narrow valley bottoms, resulting in protection both as a result of the physical setting of the riparian zone and land ownership. The producer's error (8.7%) is less than the user's error (35.4%), indicating that our models are more likely to overestimate riparian zones with high condition than to misclassify them as low or medium condition.

Our model had low agreement with the WSA (U.S. Environmental Protection Agency, 2006) database (Table 4.5), which occurred for several reasons. First, there was a small sample (n = 47) of wadeable streams within our study area that may not reflect the entire distribution of riparian zones. Second, we found that the most disagreement occurred between our medium and high conditions and the intermediate and most disturbed classes in the WSA data. This is likely related to how we defined medium and high conditions compared to the divisions in the WSA data. Finally, the WSA data were collected in the field between 2000 and 2004 and some of the most important predictors (human modification at the riparian and watershed scale) in our model were estimated in 2013 with data collected between 2005 - 2012, resulting in different sampling years which may have different levels of disturbance present. If more development has occurred since 2004, it would have been captured by the human modification datasets and not the WSA, resulting in different riparian condition scores.

Conclusion

The physical and ecological importance of mountain streams is disproportionately greater than the area they cover (Wohl, 2006). Creating a method to estimate the condition of the associated riparian zone of these streams fills a much needed information gap for regional land and water managers. In our efforts to develop a practical, management relevant method to estimate the condition of riparian zones with documented uncertainty we produced a data product with low, but acceptable, accuracy. It is likely that the variation in our predictor variables is too great to develop a direct deterministic relationship between plot level riparian condition and predictors, reducing the accuracy of our models.

Regional condition assessments provide information about the overall range of riparian conditions across a region and are useful in prioritizing site visits for field-based assessments. However, characterizing riparian condition using remotely-sensed data over broad geographic areas is relatively difficult and prone to errors due to natural variation in the selected predictor variables and indirect relationships between variables captured at different scales and local, plot level riparian condition. We have created a method to model riparian condition in a detailed and consistent manner, with documented uncertainty that provides an important tool for scientists, land management agencies, and conservation groups.

Table 4.1. Response variable classification based on the ratio of points classified as current riparian zones to those classified as potential riparian zones.

Ratio of current to potential riparian zones	Condition Rank	Sample Size (n)	Percent of Locations Sampled
0.00 - 0.34	Low	72	18.0
0.34 - 0.79	Medium	68	17.0
0.80 - 1.00	High	261	65.1

Table 4.2. Variables used to predict riparian condition, including the scale, date, and source of each predictor.

Scale	Predictor Variable	Scale / Resolution (m)	Date	Source
Watershed	Human Modification Index Watershed	90	2013	Theobald (2013)
	Proportion Upstream Protected Area	Unknown	2012	Conservation Biology Institute (2012)
	GAP Status 1			
	GAP Status 2			
	GAP Status 3			
	GAP Status 4			
Riparian	Human Modification Index Riparian	90	2013	Theobald (2013)
	Lateral Confinement	10		U.S. Census Bureau (2010); USGS (2012b)
In-channel	Flow Fragmentation Index	10	1981 - 2010	U.S. Army Corps of Engineers (2007); Verdin and Worstell (2008)
	Upstream Transportation Crossings	1:100,000*	2010 & 2012	U.S. Census Bureau (2010); USGS (2012b)

* Due to realignment procedures in 2010, the TIGER 2010 data have an estimated accuracy of 7.6 m, which is far more precise than previous datasets.

Table 4.3. Measurements of kappa coefficient (the agreement between the validation data and the modeled condition) and accuracy (proportion of all values predicted correctly) for the riparian condition model.

	Model
Kappa Coefficient	0.13
Direct Accuracy	0.61

Table 4.4. Confusion matrix, including accuracies for each condition class for the riparian condition model.

		Actual Condition Class			Proportion	Users Error
		Low	**Medium**	**High**	**Correct**	**(Commission)**
Predicted Condition Class	**Low**	1	1	1	0.33	0.67
	Medium	2	3	3	0.38	0.63
	High	12	11	42	0.65	0.35
Proportion Correct		0.07	0.20	0.91		
Producers Error (Omission)		0.93	0.80	0.09		

Table 4.5. Measurements of kappa coefficient (the agreement between the wadeable stream assessment data and the modeled condition) and accuracy (proportion of all values predicted correctly) for the riparian condition model.

Kappa Coefficient	0.17
Direct Accuracy	0.47

Table 4.6. Importance rank of each predictor variable in the riparian condition models.

Scale	Predictor Variable	Relative Importance			
		Overall	**Low**	**Medium**	**High**
Watershed	Human Modification Index Watershed	3	5	2	2
	Proportion Upstream Protected Area GAP Status 4	6	2	3	8
Riparian	Human Modification Index Riparian	1	6	1	1
	Lateral Confinement	5	4	5	6
In-channel	Flow Fragmentation Index	4	3	6	5
	Upstream Transportation Crossings	2	1	4	3

Table 4.7. The percent of riparian zones within the SRE by condition class and total area of each condition.

	Percent of Riparian Zones in SRE	Land Area (km^2)
Low	7.17	340.61
Medium	15.15	719.78
High	77.69	3,691.71

Table 4.8. The percent of each riparian condition class that occurs on lands protected by GAP Status or unknown protection/not protected lands. In addition, we provided the percent of the total land area in the SRE that is protected by each GAP status.

GAP Status	Riparian Condition			Percent of SRE
	Low	Medium	High	
1	9.26	9.19	12.69	11.91
2	8.08	7.29	25.08	21.17
3	7.47	6.31	4.78	5.20
Unknown or Not Protected	75.19	77.21	57.45	57.06

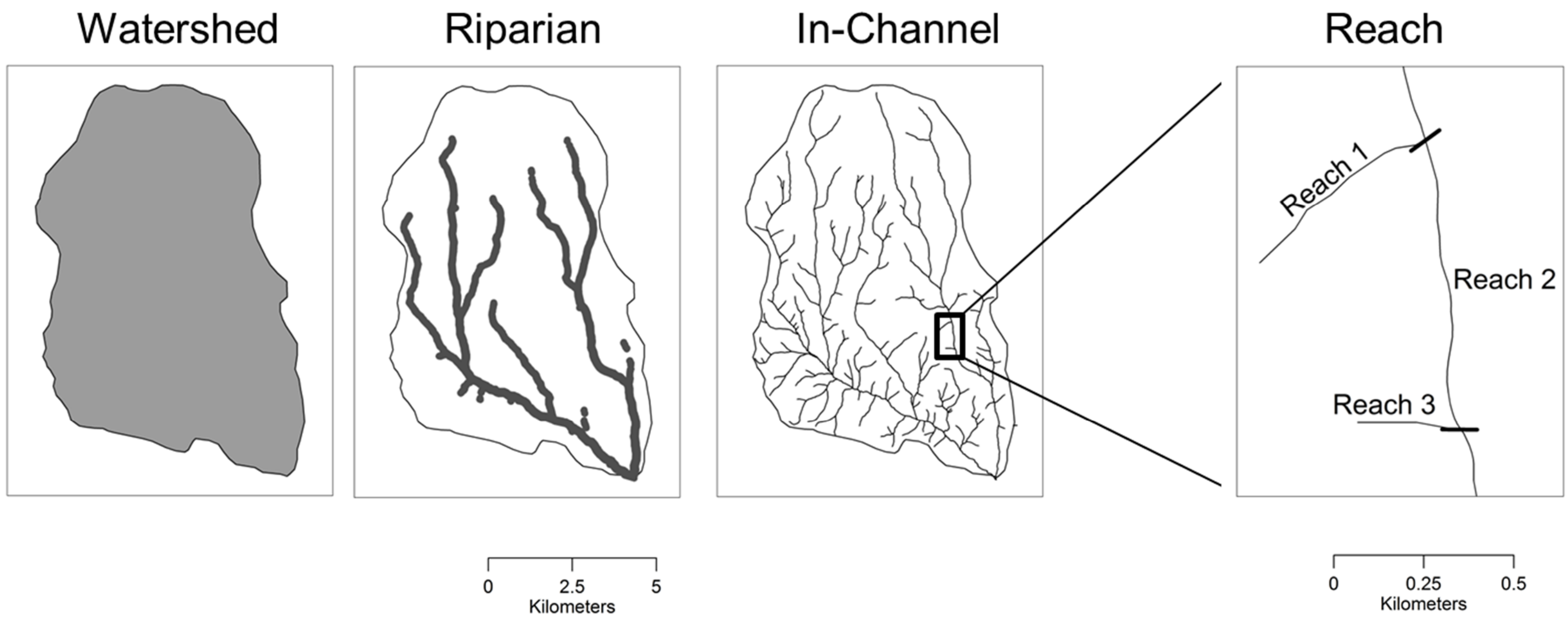

Figure 4.1. Three scales (watershed, riparian, and stream) used to estimate riparian condition and the scale (reach) at which riparian condition is reported at.

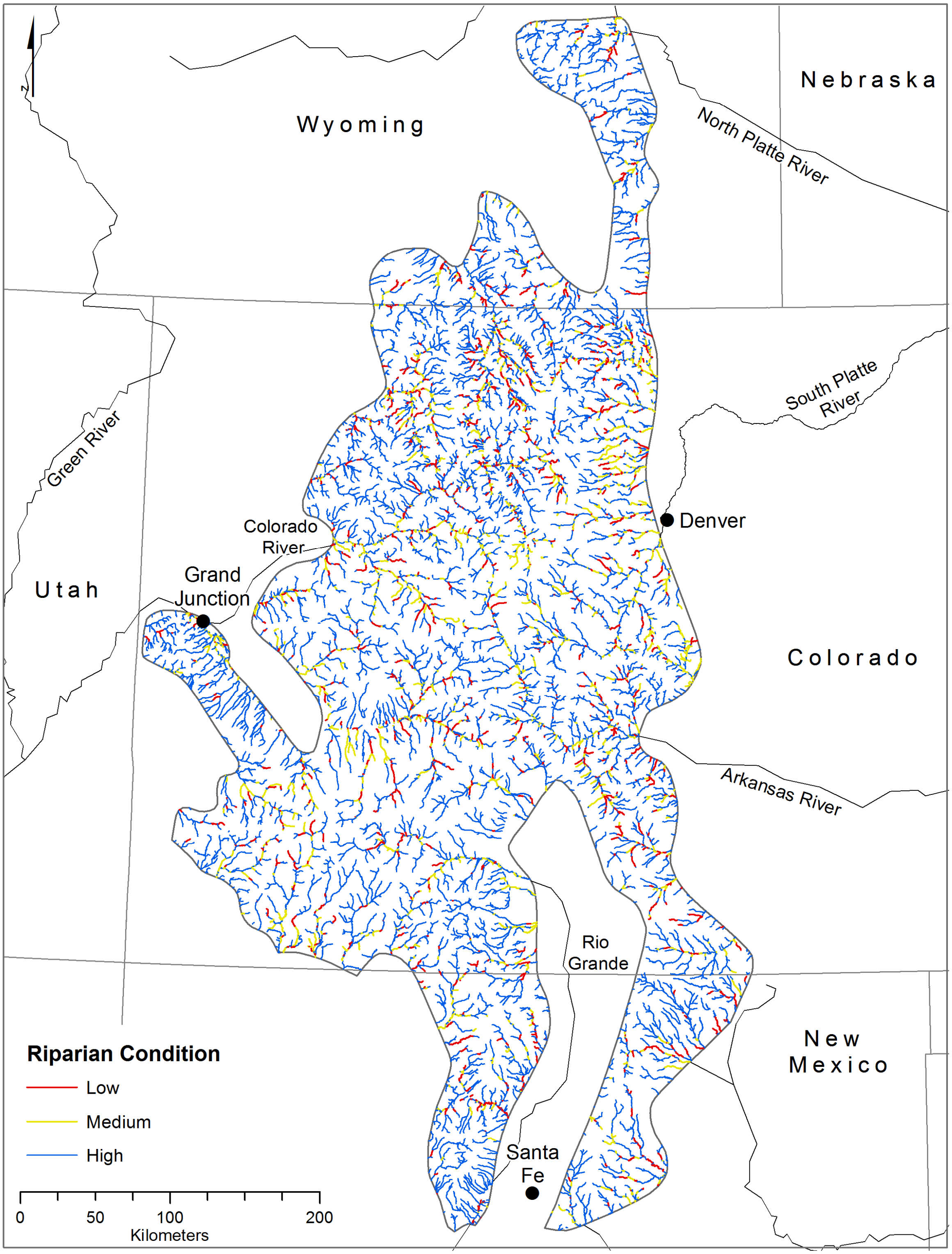

Figure 4.2. Riparian condition in the SRE

5. Synthesis

Through my dissertation research, I developed a more comprehensive understanding of the location and condition of riparian ecosystems in the Southern Rockies Ecoregion and created general methods that can be used to map riparian ecosystems in other regions. I used geospatial and statistical techniques to identify and evaluate existing methods to map riparian zones (Chapter 2); created a statistical model to map riparian zone locations at broad spatial scales (Chapter 3); and developed a practical, management relevant method to estimate and map riparian condition at broad spatial scales (Chapter 4).

In examining existing methods to map riparian zones, I found that methods that incorporated lateral and longitudinal processes were significantly better at estimating potential riparian zones than simpler methods based on buffers alone, and that the topographic, discharge, and slope (TDS) 1X method performed best in mapping potential riparian zones. For research in in semi-arid mountainous regions when process guided estimates of riparian zones are not practical, I recommend using the TDS 1X method estimated using a 10 m DEM and NHD 1:24,000 streams to map potential riparian zones. I expect the recommended method to work well in semi-arid regions with watersheds that have perennial streams, a variety of valley types, dendritic drainage patterns, and relatively shallow soils.

The need for maps of riparian zones that include a rigorous estimate of uncertainty is well documented (Ward et al., 2002; NRC 2002) and is critical to understand the extent and loss of these zones that host areas of high biodiversity and valued ecosystem services. This is especially important in arid regions where riparian zones support the majority of terrestrial species but occupy only a small percentage of the landscape. This research provides a novel method and a cost-effective way to map riparian zones across broad spatial extents at a fine resolution (10 m), using freely available, national datasets. In addition, this research quantifies the amount of potential and current riparian zones found in the SRE, providing managers and scientists with accurate, up-to-date riparian zone maps. By comparing the extent of potential and current riparian zones, I was able to quantify the amount of riparian zones modified by human activity.

Riparian zone boundaries were digitized as polygons from aerial photographs within 100 plots to estimate the percent riparian and compare existing spatial modeling methods to field based estimates of riparian zones. Using this validation dataset within the Big Thompson Watershed, I found that 3.1% of the watershed was occupied by potential riparian zones. Riparian zone validation data for Chapter 3 were developed by classifying 300 points per plot in 500 plots for the entire SRE. Using the validation data for Chapter 3, I found that 3.9% of the SRE was occupied by potential riparian zones. The difference is likely due to different sampling methods (classifying points verses digitizing riparian boundaries). In addition, the geographic variation and extent of the SRE is larger than that of the Big Thompson Watershed, capturing watersheds that may have slightly more or less potential riparian zones. This does not mean that the various methods tested in Chapter 2 were compromised by limiting the extent of the study to a single watershed. The TDS method incorporates lateral and longitudinal processes to capture riparian zones more accurately than any of the other methods tested. TDS is empirically based, adjusted for upstream drainage area, and includes a cost measure to incorporate the valley floor slope, thus making it adaptable to many regions. Specifically, it will work well in semi-arid regions with watersheds that have perennial streams, a variety of valley types, dendritic drainage patterns, and relatively shallow soils.

The new potential riparian zone map (Table 3.5) created in this research is a vast improvement over the best existing method to map potential riparian zones (Table 2.3). The best existing method, TDS 1X has a kappa coefficient of 0.38, while the new potential riparian zone mapping method has a kappa coefficient of 0.57 (Table 3.5). The new current riparian zone map (Table 3.5) also offer a marked improvement over the best existing methods to map current riparian zones (Table 3.8). The best existing data product to map current riparian zones, the NLCD, has a kappa coefficient of 0.33 and the new current riparian zone maps have a kappa coefficient of 0.38. This research has provided a much needed, improved map of riparian zones throughout the Southern Rockies Ecoregion.

Creating a method to estimate the conditions of riparian zones fills a much needed information gap within the SRE. Regional condition assessments provide information about the overall range of riparian conditions across a region and are useful in prioritizing site visits for field-based assessments. However, characterizing riparian condition using GIS based methods over broad geographic areas is relatively difficult and prone to errors due to natural variation in the selected predictor variables and indirect relationships between variables captured at different scales and local, plot level riparian condition. I created a method to map riparian condition, with documented uncertainty, which provides an important tool for scientists, land management agencies, and conservation groups.

Overall, my dissertation research provides a much needed method to map riparian zones that can be applied to a variety of scales. It provides conservation scientists and managers in the SRE with a consistent regional map of riparian location, extent, and condition, with documented and quantified uncertainties, that can be used to manage riparian zones. This research provides a framework and methodology that could be used to conduct a national scale riparian inventory and analysis, which would allow scientists to complement sample-based programs to assess the condition of riparian zones in the United States in a spatially-explicit manner. Finally, the products of my dissertation can be used as the basis for analyzing riparian ecosystem function, ecosystem services and for conservation and restoration efforts.

In the future, I will use the products and methods produced in this research to expand riparian ecosystem research in western North America. First, I will quantify the historic and current ecosystem services that riparian zones provide in the SRE. Second, I will quantify the general patterns, trends, and values/benefits of land protection in Colorado by examining conservation of riparian and aquatic ecosystems compared to conservation of terrestrial ecosystems. Third, I will expand my method of mapping riparian location and extent to the entire United States to quantify potential and current riparian zones, providing an important tool to managers and scientists.

This dissertation research is part of a larger multi-disciplinary project funded by the United States Forest Service Rocky Mountain Research Station to investigate the impacts of climate change and wildfire on water and sediment yields in the SRE and included committee members with various backgrounds in water economics, fluvial geomorphology, ecology, and physical hydrology. Being involved in such a multi-disciplinary project and earning my doctorate in a multi-disciplined program expanded my horizons, taught me new research tools and approaches, and required excellent written and verbal communication skills. In addition, I had many other opportunities while at Colorado State University to develop teaching and research skills. Being a fellow in the Colorado State University School of Global Environmental Sustainably Leadership Fellows, program encouraged interaction with my peers, prompted many interesting conversations about how to approach research, improved my written and verbal communication skills, and developed professional relationships between peers and professionals within the community.

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Appendix I

The following appendix contains the full results of the analysis done for the second chapter, evaluation of methods for delineating potential riparian zones in semi-arid montane regions of the Western United States.

Table A1.1. Comparison of Validation Data Using Median Kappa Values for NHD 1:24,000 streams and 10 m and 30 m DEMs

	Median Kappa Coefficient							
	S₁		***S₂***		**> *S₂***		**Study Area**	
	10 m	30 m	10 m	30 m	10 m	30 m	10 m	30 m
Buffer 40 m	0.21	0.20	0.14	0.13	0.43	0.43	0.23	0.24
Buffer 60 m	0.13	0.14	0.08	0.08	0.33	0.31	0.16	0.16
Buffer 80 m	0.09	0.09	0.05	0.05	0.23	0.22	0.11	0.10
Buffer 100 m	0.07	0.07	0.03	0.03	0.16	0.16	0.08	0.08
Buffer 120 m	0.05	0.05	0.02	0.02	0.12	0.11	0.05	0.05
Buffer 180 m	0.01	0.01	0.00	0.00	0.04	0.04	0.01	0.01
Variable Width Buffer	0.25	0.25	0.14	0.15	0.37	0.36	0.25	0.24
Elevation Above Stream 2 m	0.20	0.19	0.14	0.10	0.35	0.32	0.25	0.19
Elevation Above Stream 3 m	0.17	0.17	0.13	0.09	0.30	0.31	0.21	0.18
Elevation Above Stream 5 m	0.14	0.12	0.11	0.08	0.27	0.25	0.16	0.13
Elevation Above Stream 10 m	0.06	0.07	0.06	0.05	0.18	0.15	0.08	0.07
Elevation Above Stream 15 m	0.03	0.03	0.03	0.03	0.09	0.09	0.04	0.04
Variable Elevation Above Stream	0.21	0.21	0.17	0.12	0.31	0.32	0.24	0.19
Dodov	0.25	0.23	0.18	0.11	0.39	0.37	0.26	0.22
Bankfull C 5	0.18	0.21	0.17	0.11	0.34	0.36	0.22	0.21
Bankfull C 2.5	0.22	0.23	0.17	0.11	0.40	0.38	0.27	0.23
Bankfull CJ 5	0.22	0.22	0.15	0.12	0.38	0.39	0.22	0.26
Bankfull CJ 2.5	0.21	0.21	0.13	0.13	0.29	0.39	0.21	0.26
Bankfull DT 5	0.22	0.21	0.17	0.10	0.35	0.35	0.24	0.21
Bankfull DT 2.5	0.24	0.23	0.17	0.11	0.39	0.38	0.27	0.23
Topographic Distance	0.19	0.28	0.24	0.17	0.40	0.38	0.29	0.28
TDS 1X	0.30	0.25	0.38	0.27	0.46	0.39	0.38	0.30
TDS 2X	0.17	0.11	0.18	0.12	0.32	0.17	0.23	0.13
TDS 5X	0.13	0.07	0.11	0.07	0.26	0.09	0.16	0.08

Table A1.2. Comparison of Validation Data Using Median Kappa Values for NHD 1:100,000 streams and 10 m and 30 m DEMs

	Median Kappa Coefficient							
	S_1		S_2		$> S_2$		**Study Area**	
	10 m	30 m	10 m	30 m	10 m	30 m	10 m	30 m
Buffer 40 m	0.23	0.21	0.22	0.25	0.43	0.46	0.29	0.31
Buffer 60 m	0.17	0.17	0.16	0.17	0.37	0.39	0.25	0.23
Buffer 80 m	0.12	0.12	0.11	0.12	0.34	0.33	0.18	0.18
Buffer 100 m	0.09	0.09	0.09	0.09	0.28	0.27	0.13	0.13
Buffer 120 m	0.07	0.07	0.06	0.07	0.22	0.21	0.10	0.10
Buffer 180 m	0.03	0.03	0.03	0.03	0.11	0.12	0.05	0.05
Variable Width Buffer	0.23	0.24	0.26	0.24	0.38	0.39	0.30	0.31
Elevation Above Stream 2 m	0.25	0.24	0.28	0.23	0.46	0.47	0.32	0.29
Elevation Above Stream 3 m	0.24	0.19	0.24	0.21	0.42	0.41	0.30	0.26
Elevation Above Stream 5 m	0.15	0.14	0.22	0.19	0.33	0.32	0.25	0.24
Elevation Above Stream 10 m	0.07	0.09	0.13	0.10	0.21	0.20	0.15	0.13
Elevation Above Stream 15 m	0.04	0.05	0.09	0.07	0.15	0.15	0.09	0.08
Variable Elevation Above Stream	0.26	0.25	0.26	0.21	0.35	0.33	0.29	0.28
Dodov	0.27	0.25	0.30	0.26	0.43	0.46	0.32	0.32
Bankfull C 5	0.25	0.24	0.26	0.20	0.37	0.45	0.28	0.26
Bankfull C 2.5	0.27	0.26	0.29	0.25	0.44	0.45	0.32	0.32
Bankfull CJ 5	0.26	0.31	0.26	0.27	0.51	0.53	0.37	0.34
Bankfull CJ 2.5	0.22	0.26	0.26	0.26	0.49	0.52	0.35	0.35
Bankfull DT 5	0.25	0.24	0.26	0.20	0.36	0.43	0.28	0.26
Bankfull DT 2.5	0.28	0.26	0.29	0.25	0.45	0.47	0.32	0.32
Topographic Distance	0.13	0.07	0.22	0.17	0.35	0.26	0.28	0.18
TDS 1X	0.21	0.27	0.27	0.24	0.39	0.39	0.28	0.27
TDS 2X	0.09	0.15	0.11	0.11	0.21	0.19	0.14	0.14
TDS 5X	0.11	0.07	0.16	0.08	0.23	0.10	0.20	0.09

Table A1.3. Comparison of Validation Data Using Median Kappa Values for synthetic streams and 10 m and 30 m DEMs

	Median Kappa Coefficient							
	S₁		***S₂***		**> *S₂***		**Study Area**	
	10 m	30 m	10 m	30 m	10 m	30 m	10 m	30 m
Buffer 40 m	0.20	0.19	0.20	0.20	0.39	0.43	0.25	0.29
Buffer 60 m	0.13	0.14	0.13	0.14	0.30	0.35	0.19	0.20
Buffer 80 m	0.09	0.11	0.09	0.09	0.23	0.26	0.13	0.15
Buffer 100 m	0.07	0.07	0.06	0.06	0.17	0.20	0.08	0.10
Buffer 120 m	0.05	0.05	0.04	0.04	0.14	0.15	0.06	0.08
Buffer 180 m	0.03	0.03	0.02	0.02	0.05	0.06	0.03	0.03
Variable Width Buffer	0.25	0.26	0.24	0.24	0.38	0.41	0.27	0.31
Elevation Above Stream 2 m	0.23	0.24	0.30	0.20	0.40	0.43	0.30	0.26
Elevation Above Stream 3 m	0.22	0.18	0.26	0.20	0.41	0.39	0.26	0.23
Elevation Above Stream 5 m	0.17	0.13	0.22	0.17	0.32	0.34	0.22	0.19
Elevation Above Stream 10 m	0.09	0.05	0.12	0.12	0.19	0.21	0.12	0.13
Elevation Above Stream 15 m	0.05	0.04	0.07	0.06	0.12	0.13	0.07	0.07
Variable Elevation Above Stream	0.21	0.23	0.27	0.23	0.38	0.49	0.30	0.35
Dodov	0.22	0.00	0.37	0.23	0.39	0.33	0.33	0.16
Bankfull C 5	0.18	0.20	0.31	0.23	0.38	0.38	0.29	0.27
Bankfull C 2.5	0.23	0.23	0.37	0.23	0.44	0.44	0.34	0.30
Bankfull CJ 5	0.23	0.22	0.26	0.25	0.42	0.47	0.33	0.37
Bankfull CJ 2.5	0.21	0.23	0.24	0.24	0.35	0.49	0.30	0.34
Bankfull DT 5	0.18	0.21	0.30	0.23	0.37	0.40	0.28	0.27
Bankfull DT 2.5	0.23	0.23	0.36	0.23	0.42	0.43	0.33	0.32
Topographic Distance	0.19	0.23	0.29	0.23	0.39	0.38	0.30	0.27
TDS 1X	0.20	0.19	0.35	0.22	0.40	0.34	0.33	0.24
TDS 2X	0.08	0.10	0.18	0.11	0.21	0.19	0.18	0.13
TDS 5X	0.07	0.06	0.11	0.08	0.17	0.15	0.12	0.09
MRVBF < 1.0	0.10	0.14	0.10	0.11	0.16	0.17	0.13	0.15
MRVBF < 0.50	0.06	0.09	0.06	0.09	0.11	0.13	0.07	0.10
MRVBF < 0.75	0.08	0.11	0.09	0.11	0.13	0.15	0.10	0.13

Table A1.4. Comparison of Validation Data Using Median Precision Values for 1:24,000 streams and 10 m and 30 m DEMs

	Median Precision							
	S $_1$		***S*** $_2$		> ***S*** $_2$		**Study Area**	
	10 m	30 m	10 m	30 m	10 m	30 m	10 m	30 m
Buffer 40 m	0.13	0.13	0.10	0.10	0.38	0.36	0.20	0.20
Buffer 60 m	0.10	0.10	0.07	0.07	0.29	0.30	0.14	0.15
Buffer 80 m	0.07	0.07	0.05	0.05	0.23	0.24	0.12	0.12
Buffer 100 m	0.06	0.06	0.05	0.04	0.19	0.20	0.10	0.10
Buffer 120 m	0.05	0.05	0.04	0.04	0.17	0.18	0.08	0.09
Buffer 180 m	0.04	0.04	0.03	0.03	0.14	0.13	0.06	0.06
Variable Width Buffer	0.16	0.16	0.11	0.13	0.31	0.30	0.19	0.19
Elevation Above Stream 2 m	0.14	0.13	0.14	0.10	0.35	0.31	0.21	0.18
Elevation Above Stream 3 m	0.11	0.11	0.13	0.09	0.31	0.27	0.19	0.16
Elevation Above Stream 5 m	0.09	0.09	0.10	0.08	0.27	0.25	0.16	0.14
Elevation Above Stream 10 m	0.07	0.07	0.07	0.06	0.21	0.19	0.11	0.10
Elevation Above Stream 15 m	0.05	0.05	0.06	0.05	0.17	0.16	0.08	0.08
Variable Elevation Above Stream	0.14	0.14	0.14	0.10	0.31	0.30	0.20	0.17
Dodov	0.16	0.15	0.16	0.12	0.41	0.35	0.22	0.19
Bankfull C 5	0.15	0.15	0.15	0.12	0.33	0.31	0.20	0.17
Bankfull C 2.5	0.15	0.15	0.16	0.12	0.38	0.34	0.23	0.19
Bankfull CJ 5	0.19	0.17	0.14	0.12	0.49	0.42	0.22	0.21
Bankfull CJ 2.5	0.18	0.17	0.12	0.12	0.50	0.41	0.22	0.21
Bankfull DT 5	0.14	0.14	0.15	0.12	0.33	0.31	0.20	0.17
Bankfull DT 2.5	0.14	0.15	0.15	0.11	0.39	0.34	0.24	0.19
Topographic Distance	0.18	0.19	0.17	0.14	0.34	0.35	0.24	0.22
TDS 1X	0.25	0.20	0.27	0.23	0.43	0.34	0.33	0.26
TDS 2X	0.11	0.12	0.14	0.11	0.33	0.19	0.19	0.15
TDS 5X	0.09	0.07	0.10	0.08	0.26	0.15	0.16	0.12

Table A1.5. Comparison of Validation Data Using Median Precision Values for 1:100,000 streams and 10 m and 30 m DEMs

	Median Precision							
	S_1		***S_2***		**> *S_2***		**Study Area**	
	10 m	30 m	10 m	30 m	10 m	30 m	10 m	30 m
Buffer 40 m	0.14	0.14	0.18	0.17	0.44	0.42	0.25	0.25
Buffer 60 m	0.10	0.11	0.13	0.13	0.35	0.37	0.19	0.18
Buffer 80 m	0.08	0.09	0.10	0.10	0.29	0.29	0.15	0.16
Buffer 100 m	0.06	0.07	0.08	0.08	0.24	0.25	0.13	0.13
Buffer 120 m	0.05	0.06	0.06	0.07	0.20	0.21	0.11	0.11
Buffer 180 m	0.04	0.04	0.04	0.05	0.15	0.15	0.07	0.07
Variable Width Buffer	0.20	0.20	0.19	0.18	0.35	0.36	0.27	0.28
Elevation Above Stream 2 m	0.12	0.15	0.20	0.18	0.44	0.41	0.27	0.25
Elevation Above Stream 3 m	0.10	0.11	0.19	0.17	0.38	0.38	0.23	0.22
Elevation Above Stream 5 m	0.07	0.08	0.17	0.16	0.32	0.33	0.19	0.20
Elevation Above Stream 10 m	0.08	0.06	0.12	0.10	0.25	0.25	0.14	0.14
Elevation Above Stream 15 m	0.05	0.06	0.10	0.08	0.20	0.21	0.11	0.11
Variable Elevation Above Stream	0.18	0.12	0.19	0.17	0.32	0.33	0.22	0.21
Dodov	0.18	0.18	0.22	0.18	0.38	0.43	0.23	0.26
Bankfull C 5	0.12	0.15	0.19	0.17	0.32	0.38	0.20	0.22
Bankfull C 2.5	0.15	0.17	0.21	0.18	0.39	0.43	0.24	0.25
Bankfull CJ 5	0.21	0.19	0.23	0.22	0.57	0.53	0.35	0.27
Bankfull CJ 2.5	0.22	0.17	0.23	0.22	0.61	0.53	0.35	0.28
Bankfull DT 5	0.12	0.15	0.19	0.17	0.35	0.41	0.21	0.23
Bankfull DT 2.5	0.15	0.17	0.21	0.18	0.39	0.43	0.25	0.25
Topographic Distance	0.10	0.07	0.27	0.13	0.36	0.30	0.27	0.16
TDS 1X	0.19	0.21	0.21	0.20	0.37	0.34	0.26	0.25
TDS 2X	0.11	0.12	0.14	0.10	0.25	0.21	0.17	0.15
TDS 5X	0.07	0.09	0.10	0.08	0.21	0.18	0.13	0.12

Table A1.6. Comparison of Validation Data Using Median Precision Values for synthetic streams and 10 m and 30 m DEMs

	Median Precision							
	S₁		***S₂***		**> *S₂***		**Study Area**	
	10 m	30 m	10 m	30 m	10 m	30 m	10 m	30 m
Buffer 40 m	0.14	0.13	0.15	0.16	0.43	0.43	0.23	0.23
Buffer 60 m	0.09	0.10	0.10	0.11	0.33	0.33	0.17	0.18
Buffer 80 m	0.07	0.07	0.07	0.09	0.26	0.27	0.13	0.13
Buffer 100 m	0.06	0.06	0.06	0.07	0.21	0.22	0.10	0.11
Buffer 120 m	0.05	0.05	0.05	0.06	0.18	0.19	0.09	0.09
Buffer 180 m	0.04	0.04	0.04	0.04	0.13	0.13	0.06	0.06
Variable Width Buffer	0.18	0.18	0.18	0.20	0.34	0.35	0.24	0.24
Elevation Above Stream 2 m	0.17	0.17	0.29	0.16	0.39	0.41	0.29	0.27
Elevation Above Stream 3 m	0.15	0.12	0.24	0.16	0.35	0.37	0.24	0.22
Elevation Above Stream 5 m	0.12	0.09	0.19	0.14	0.29	0.33	0.19	0.18
Elevation Above Stream 10 m	0.06	0.06	0.10	0.10	0.30	0.26	0.14	0.14
Elevation Above Stream 15 m	0.05	0.05	0.08	0.07	0.23	0.21	0.11	0.11
Variable Elevation Above Stream	0.22	0.26	0.42	0.27	0.55	0.51	0.41	0.37
Dodov	0.19	0.00	0.35	0.21	0.38	0.40	0.34	0.25
Bankfull C 5	0.15	0.15	0.25	0.19	0.34	0.35	0.24	0.23
Bankfull C 2.5	0.19	0.21	0.35	0.22	0.40	0.43	0.33	0.30
Bankfull CJ 5	0.22	0.24	0.42	0.27	0.47	0.47	0.41	0.37
Bankfull CJ 2.5	0.23	0.24	0.39	0.27	0.55	0.51	0.39	0.38
Bankfull DT 5	0.15	0.15	0.24	0.19	0.34	0.38	0.24	0.24
Bankfull DT 2.5	0.18	0.20	0.33	0.22	0.39	0.42	0.33	0.30
Topographic Distance	0.14	0.15	0.24	0.18	0.35	0.37	0.26	0.24
TDS 1X	0.22	0.15	0.27	0.21	0.40	0.34	0.29	0.24
TDS 2X	0.12	0.10	0.15	0.11	0.22	0.23	0.18	0.16
TDS 5X	0.08	0.07	0.11	0.08	0.19	0.20	0.13	0.12
MRVBF < 1.0	0.09	0.11	0.11	0.11	0.24	0.24	0.14	0.16
MRVBF < 0.50	0.06	0.07	0.07	0.08	0.16	0.19	0.08	0.12
MRVBF < 0.75	0.07	0.08	0.09	0.09	0.19	0.21	0.10	0.14

Table A1.7. Percent of Study Area for each method based on stream source and DEM resolution

	Percent of Study Area Predicted to be Riparian					
	NHD 1:24,000		NHD 1:100,000		SYNTHETIC	
	10 m	30 m	10 m	30 m	10 m	30 m
Buffer 40 m	15.69	15.68	5.37	5.37	8.88	8.50
Buffer 60 m	23.03	23.08	7.99	7.99	13.05	12.84
Buffer 80 m	30.01	30.01	10.57	10.57	17.11	16.37
Buffer 100 m	36.40	36.39	13.10	13.10	21.40	20.50
Buffer 120 m	42.22	42.21	15.58	15.59	25.27	24.30
Buffer 180 m	56.32	56.31	22.76	22.76	36.39	35.26
Variable Width Buffer	11.76	11.76	3.66	3.66	6.36	6.07
Elevation Above Stream 2 m	17.91	22.24	11.85	12.62	11.86	12.00
Elevation Above Stream 3 m	21.02	24.91	13.24	13.98	13.93	14.03
Elevation Above Stream 5 m	26.54	29.97	15.64	16.32	17.47	17.59
Elevation Above Stream 10 m	37.19	40.70	20.26	20.99	23.88	24.32
Elevation Above Stream 15 m	45.70	48.98	23.89	24.66	28.98	29.56
Variable Elevation Above Stream	17.85	20.79	11.39	12.23	6.72	7.39
Dodov	13.19	17.84	10.44	10.57	9.05	5.49
Bankfull C 5	16.74	20.30	12.79	12.26	12.41	12.66
Bankfull C 2.5	14.20	18.76	10.93	11.05	9.82	10.26
Bankfull CJ 5	10.94	17.03	8.22	9.43	7.16	7.88
Bankfull CJ 2.5	10.48	17.23	8.00	9.26	6.58	7.36
Bankfull DT 5	17.07	20.66	12.73	12.37	12.51	12.73
Bankfull DT 2.5	14.32	18.91	10.87	11.08	9.87	10.27
Topographic Distance	11.07	11.65	11.07	14.77	10.15	9.62
TDS 1X	5.11	7.19	6.02	7.49	6.73	8.31
TDS 2X	9.41	13.21	10.66	13.45	11.88	13.73
TDS 5X	13.17	17.96	14.27	18.13	15.68	17.62
MRVBF < 1.0	-	-	-	-	18.77	17.41
MRVBF < 0.50	-	-	-	-	32.70	26.06
MRVBF < 0.75	-	-	-	-	25.25	21.54

Table A1.8. Friedman test post-hoc analysis p value results based on kappa coefficients for 8 best methods using the 10 m DEM and 1:24,000 streams

	Buffer 40 m	**Variable Width Buffer**	**Elevation Above Stream 2m**	**Variable Elevation Above Stream**	**Bankfull DT 2.5**	**Topographic Distance**	**TDS 1X**	**MRVBF < 1**
Buffer 40 m								
Variable Width Buffer	1.000							
Elevation Above Stream 2m	0.999	0.963						
Variable Elevation Above Stream	1.000	0.990	1.000					
Bankfull DT 2.5	0.353	0.686	0.102	0.173				
Topographic Distance	0.249	0.559	0.062	0.111	1.000			
TDS 1X	0.000	0.000	0.000	0.000	0.090	0.145		
MRVBF < 1	0.003	0.000	0.024	0.012	0.000	0.000	0.000	

Table A1.9. Friedman test with post-hoc analysis p value results based on precision values for 8 best methods using the 10 m DEM and 1:24,000 streams

	Buffer 40 m	**Variable Width Buffer**	**Elevation Above Stream 2m**	**Variable Elevation Above Stream**	**Bankfull DT 2.5**	**Topographic Distance**	**TDS 1X**	**MRVBF < 1**
Buffer 40 m								
Variable Width Buffer	1.000							
Elevation Above Stream 2m	0.853	0.611						
Variable Elevation Above Stream	1.000	0.999	0.910					
Bankfull DT 2.5	0.034	0.105	0.000	0.022				
Topographic Distance	0.886	0.983	0.110	0.822	0.600			
TDS 1X	0.000	0.000	0.000	0.000	0.389	0.002		
MRVBF < 1	0.090	0.028	0.853	0.128	0.000	0.001	0.000	

Table A1.10. Friedman test with post-hoc analysis p value results for kappa coefficients each of the 8 best methods as estimated by each stream source and DEM combination. Bankfull DT 2.5 and MRVBF < 1 had no significant differences between different expressions of the method and were not included in the table.

Buffer 40 m

		10 m DEM NHD 1:24,000	10 m DEM NHD 1:100,000	10 m DEM Synthetic	30 m DEM NHD 1:24,000	30 m DEM NHD 1:100,000	30 m DEM Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.018					
	Synthetic	0.998	0.063				
30 m DEM	NHD 1:24,000	1.000	0.047	1.000			
	NHD 1:100,000	0.033	1.000	0.102	0.078		
	Synthetic	0.646	0.564	0.875	0.828	0.686	

Variable Width Buffer

		10 m DEM NHD 1:24,000	10 m DEM NHD 1:100,000	10 m DEM Synthetic	30 m DEM NHD 1:24,000	30 m DEM NHD 1:100,000	30 m DEM Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.913					
	Synthetic	0.436	0.962				
30 m DEM	NHD 1:24,000	0.969	0.462	0.089			
	NHD 1:100,000	0.543	0.985	1.000	0.132		
	Synthetic	0.076	0.543	0.958	0.006	0.913	

Elevation Above Stream 2m

		10 m DEM			30 m DEM		
		NHD 1:24,000	NHD 1:100,000	Synthetic	NHD 1:24,000	NHD 1:100,000	Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.068					
	Synthetic	0.475	0.932				
30 m DEM	NHD 1:24,000	0.261	0.000	0.001			
	NHD 1:100,000	0.488	0.926	1.000	0.001		
	Synthetic	0.689	0.797	1.000	0.004	1.000	

Variable Elevation Above Stream

		10 m DEM			30 m DEM		
		NHD 1:24,000	NHD 1:100,000	Synthetic	NHD 1:24,000	NHD 1:100,000	Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.065					
	Synthetic	0.899	0.530				
30 m DEM	NHD 1:24,000	0.262	0.000	0.017			
	NHD 1:100,000	0.304	0.983	0.914	0.000		
	Synthetic	0.072	1.000	0.557	0.000	0.987	

Topographic Distance

		10 m DEM			30 m DEM		
		NHD 1:24,000	NHD 1:100,000	Synthetic	NHD 1:24,000	NHD 1:100,000	Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.997					
	Synthetic	0.811	0.508				
30 m DEM	NHD 1:24,000	0.277	0.576	0.010			
	NHD 1:100,000	0.000	0.000	0.000	0.001		
	Synthetic	1.000	1.000	0.629	0.455	0.000	

TDS 1X

		10 m DEM			30 m DEM		
		NHD 1:24,000	NHD 1:100,000	Synthetic	NHD 1:24,000	NHD 1:100,000	Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.000					
	Synthetic	0.931	0.009				
30 m DEM	NHD 1:24,000	0.000	1.000	0.004			
	NHD 1:100,000	0.000	1.000	0.005	1.000		
	Synthetic	0.000	0.091	0.000	0.148	0.135	

Table A1.11. Friedman test post-hoc analysis p value results for precision values each of the 8 best methods as estimated by each stream source and DEM combination. MRVBF < 1 had no significant differences between different expressions of the method and was not included in this table.

Buffer 40 m

		10 m DEM			30 m DEM		
		NHD 1:24,000	NHD 1:100,000	Synthetic	NHD 1:24,000	NHD 1:100,000	Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.018					
	Synthetic	0.998	0.063				
30 m DEM	NHD 1:24,000	1.000	0.078	1.000			
	NHD 1:100,000	0.033	1.000	0.102	0.078		
	Synthetic	0.646	0.564	0.875	0.828	0.686	

Variable Width Buffer

		10 m DEM			30 m DEM		
		NHD 1:24,000	NHD 1:100,000	Synthetic	NHD 1:24,000	NHD 1:100,000	Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.000					
	Synthetic	0.117	0.479				
30 m DEM	NHD 1:24,000	0.999	0.000	0.044			
	NHD 1:100,000	0.000	1.000	0.338	0.000		
	Synthetic	0.001	0.999	0.735	0.000	0.990	

Elevation Above Stream 2m

		10 m DEM NHD 1:24,000	10 m DEM NHD 1:100,000	10 m DEM Synthetic	30 m DEM NHD 1:24,000	30 m DEM NHD 1:100,000	30 m DEM Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.258					
	Synthetic	0.162	1.000				
30 m DEM	NHD 1:24,000	0.011	0.000	0.000			
	NHD 1:100,000	0.971	0.741	0.967	0.001		
	Synthetic	0.610	0.993	0.967	0.000	0.967	

Variable Elevation Above Stream

		10 m DEM NHD 1:24,000	10 m DEM NHD 1:100,000	10 m DEM Synthetic	30 m DEM NHD 1:24,000	30 m DEM NHD 1:100,000	30 m DEM Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.050					
	Synthetic	0.000	0.011				
30 m DEM	NHD 1:24,000	0.107	0.000	0.000			
	NHD 1:100,000	1.000	0.097	0.000	0.056		
	Synthetic	0.000	0.454	0.646	0.000	0.000	

Bankfull DT 2.5

		10 m DEM NHD 1:24,000	10 m DEM NHD 1:100,000	10 m DEM Synthetic	30 m DEM NHD 1:24,000	30 m DEM NHD 1:100,000	30 m DEM Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.722					
	Synthetic	0.017	0.464				
30 m DEM	NHD 1:24,000	0.794	0.077	0.000			
	NHD 1:100,000	0.547	1.000	0.643	0.036		
	Synthetic	0.616	1.000	0.574	0.049	1.000	

Topographic Distance

		10 m DEM			30 m DEM		
		NHD 1:24,000	NHD 1:100,000	Synthetic	NHD 1:24,000	NHD 1:100,000	Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.299					
	Synthetic	0.623	0.996				
30 m DEM	NHD 1:24,000	0.499	0.002	0.012			
	NHD 1:100,000	0.000	0.000	0.000	0.016		
	Synthetic	0.820	0.959	0.999	0.034	0.000	

TDS 1X

		10 m DEM			30 m DEM		
		NHD 1:24,000	NHD 1:100,000	Synthetic	NHD 1:24,000	NHD 1:100,000	Synthetic
10 m DEM	NHD 1:24,000						
	NHD 1:100,000	0.000					
	Synthetic	0.224	0.253				
30 m DEM	NHD 1:24,000	0.000	0.582	0.002			
	NHD 1:100,000	0.000	0.582	0.002	1.000		
	Synthetic	0.000	0.540	0.002	1.000	1.000	

Appendix II

The following appendix contains supplementary information regarding the predictors chosen to map potential and current riparian zone in Chapter 3.

Justification of why predictor variables were included in the model

Upslope Processes and Factors

Erosion rate was estimated using the RUSLE modeled by Litschert et al. (2014). This variable was included in the model to capture the process of erosion and routed through the stream network using the Flow Accumulation tool in ArcGIS 10.1 to roughly estimate transportation of sediment from upstream to downstream locations. The Flow Accumulation tool creates a single value for each raster cell by accumulating, as the total, the weight of all cells flowing into each downslope cell. The downslope cell is determined by the Flow Direction tool, which uses elevation to determine what direction a cell in a raster will flow into based on eight neighboring cells. The Flow Accumulation uses the flow direction raster and any weighted raster to determine the accumulated total of all upstream cells (ESRI, 2014).

Bedrock geology was included as a predictor variable to set the physical template for each riparian zone. Geology influences drainage density, material shear strength, and mean grain size of stream sediments, all factors influences geomorphic processes that occur within riparian zones (Naiman et al., 2005)

We included several measures of hydroclimatology as predictors in the random forest model. April 1 SWE, was modeled by NOHRSC (2012) using an energy and mass balanced snow model. SWE was included in the model as a measure of the amount of moisture that is available to riparian vegetation during the dry season. The SWE layer provided by NORHSC (2012) is a modeled product that incorporates measured variables from ground stations, fixed winged aircraft, and satellite imagery with numerical weather prediction forcing models (Carroll et al., 2006). We accumulated the SWE values downstream using the Flow Accumulation tool in

ArcGIS to mimic the process of snowmelt and water available from snowmelt throughout the stream network.

Latitude and longitude were included as a continuous variable to capture climatic variability throughout the study area. The southern SRE is influenced by the North American monsoon, with large influxes of precipitation typically occurring between July and September that can account for 50 – 70% of the annual precipitation (Grantz et al., 2007). Precipitation in the northern and central SRE generally results from extra-tropical cyclones that move through the area in the winter and spring months and convective thunderstorms during the summer months. Using latitude and longitude allowed us to estimate these differences without creating boundaries between different precipitation regimes.

Elevation was included as a predictor variable because snow persistence influences stream flow (Painter et al., 2010) and in some areas of the SRE (i.e, the Front Range), research has indicated that elevation can influence whether stream flow is primarily caused by snow melt or conductive thunderstorms (Jarrett, 1990).

Average annual precipitation data from PRISM (2012) at a resolution of 800 m were used as a predictor variable. Long term precipitation impacts the location and extent of riparian zones through ecologic and hydrologic processes (Naiman, et al. 2005) and was included in favor of shorter term precipitation measures, such as monthly mean precipitation, or extremes, including minimum and maximum monthly precipitation which, may impact specific riparian plants, but would likely not impact the location and extent of riparian zones.

Temperature controls many physical processes important to riparian zones, including decomposition dynamics, the rate that organic matter decays, energy fluxes, primary productivity and the type of precipitation that influences stream flow (Naiman et al, 2005). Instead of including a temperature value with a finer temporal scale, we included average annual temperature (PRISM, 2012; 800 m) because long term temperature patterns are likely to be more important to long term riparian dynamics reflected in location and extent of riparian zones.

Riparian Processes and Factors

Soil order from STATSGO (Soil Survey Staff, 2006) was included in the model to capture both upland and riparian soil characteristics. Riparian soils tend to differ from upland soils in regards to moisture, mineral, and organic compounds and could prove to be an important factor in distinguishing between upland and riparian zones (Naiman et al., 2005).

TWI+ was included as a predictor because other researchers (e.g. Grabs et al., 2009; Shoutis, et al., 2010) found that TWI is an important predictor of the location of riparian vegetation. We created a multiple resolution TWI+ because in comparison to a fine grain, single resolution TWI (Figure A2.1), the multi-resolution TWI+ creates a more realistic and gradual gradient from moist to dry areas and is less sensitive to striping, an artifact of some DEMs. The algorithm used to calculate our multiple resolution TWI+ was based on a 10 m DEM and includes flow accumulation, slope, and aspect algorithms which were all derived in ArcGIS 10.0.

Riparian zones, by definitions are found near stream lines, leading to the logical decision to include distance from 1:24,000 NHD streamlines as a predictor variable in my model. While there is some concern that this may impact headwater reaches that have been excluded from 1:24,000 stream lines, I have observed that it is more likely that the 1:24,000 NHD streamlines include dry drainages in headwater streams than exclude headwater streams within the SRE.

In-channel Processes and Factors

Stream flow was included as a predictor variable as a hydrologic variable. Stream flow is an important conduit to deliver moisture, nutrients, and sediments to riparian zones. We included average annual stream flow because calculating flow characteristics at finer temporal scales is complicated and time consuming for large areas where stream gages are not available. Stream type was included as a predictor variable in the riparian location models based on the assumption that perennial streams would support larger riparian zones than ephemeral/intermittent streams.

The human modification index (Theobald 2013) was included as a predictor variable in the current riparian zone model to include a measure of human influence in this model.

Characteristics of Predictor Variables

To provide further information about the predictor variables, we developed a table (Table A2.1) that included the minimum, maximum, mean, and standard deviation for each predictor variable used.

Correlations Between Predictor Variables

Random forest modelling is robust to correlated predictor variables. To demonstrate this, we calculated the Spearman's rank correlation coefficient between each of the 13 predictor variables used in the potential riparian zone model (Table A2.2). We created models with only independent variables, based on a correlation coefficient of ± 0.35, and reported the out-of-the-bag error rates for the full model and each independent model (Tables A2.3 and A2.4)

Random Forest Model Parsimony

Many of the variables used to create the random forest model to estimate riparian location take time to develop and contribute little to the result (Table 3.2). Random forests models do not include a term to penalize for a high number of predictor variables or predictor variables that low importance; however, to provide guidance on how a reduced model will perform when estimating potential or current riparian location, we progressively removed less-effective variables and recorded the out-of-the-bag error rate in the potential (Table A2.5 and Figure A2.3) and current (Table A2.6 and Figure A2.4) riparian zone random forest models. The out of the bag error rate is an internal cross validation test employed by random forest models to provide an unbiased estimate of model error. Each classification tree used in a random forest model is constructed using a different bootstrap sample from the original data, where approximately a third of the data is withheld for each tree and used to create an error estimate. Following the growth of the entire forest, the out of the bag error rate is calculated using the individual tree error. The out of the bag error rate roughly corresponds to the overall accuracy of the predicted riparian maps. The full predicted riparian maps were not included in this analysis because creating each model takes 48 hours, resulting in over 1200 hours of processing time.

Table A2.1. Characteristics of predictor variables.

Process	Predictor Variable	Minimum	Maximum	Mean	Standard Deviation
Watershed	Erosion Rate (RUSLE)	0.00	1,385,292,416.00	735,257.90	14,568,510.07
	Geology	1.00	57.00	Categorical	Categorical
	Hydroclimatology				
	Snow Water Equivalent (SWE; kg/m^2)	500.00	703,069,888.00	3,281,582.46	30,342,163.05
	Average Annual Precipitation (mm)	0.00	254,150,176.00	166,401.19	3,161,164.85
	Average Annual Temperature (ºF)	21.92	55.36	40.30	5.15
	Elevation (m)	1,356.41	4,397.06	2,646.12	493.90
	Latitude	35.43	42.75	38.83	1.62
	Longitude	-109.01	-104.32	-106.37	0.97
Riparian	Soils	1.00	450.00	Categorical	Categorical
	Topographic Wetness Index + (TWI+)	-0.95	27.06	2.80	1.66
	Distance from streamline (m)	0.00	5,309.47	214.92	240.24
	Human modification	0.00	1.00	0.23	0.18
In-channel	Mean annual flow (cfs)	0.00	423,445,472.00	6,687.84	858,224.10
	Stream type	46,003.00	46,006.00	Categorical	Categorical

Table A2.2. Correlations between predictor variables. (n = 150,000)

	Erosion Rate (RUSLE)	Geology	Snow Water Equivalent (SWE)	Average Annual Precipitation	Average Annual Temperature	Elevation	Latitude	Longitude	Soils	Topographic Wetness Index + (TWI+)	Distance from streamline	Human modification	Average annual flow	Stream type
Erosion Rate (RUSLE)	-													
Geology	0.01	-												
Snow Water Equivalent (SWE)	0.28	0.03	-											
Average Annual Precipitation	0.49	0.01	0.42	-										
Average Annual Temperature	-0.01	-0.28	0.33	0.08	-									
Elevation	-0.06	0.33	-0.35	-0.12	-0.88	-								
Latitude	0.04	-0.06	-0.18	-0.04	-0.30	-0.04	-							
Longitude	-0.07	0.19	0.06	0.00	0.26	-0.21	0.04	-						
Soils	0.04	-0.09	-0.08	0.01	-0.17	0.01	0.40	0.07	-					
Topographic Wetness Index + (TWI+)	0.26	-0.03	0.28	0.24	0.09	-0.19	0.00	0.07	-0.02	-				
Distance from streamline	-0.27	-0.05	-0.18	-0.34	0.04	0.00	-0.02	-0.01	0.00	-0.39	-			
Human modification	0.08	0.00	0.28	0.11	0.32	-0.33	-0.18	0.16	-0.02	0.24	0.02	-		
Average annual flow	0.06	-0.05	-0.13	-0.02	-0.26	0.11	0.38	-0.28	0.15	0.05	-0.07	-0.12	-	
Stream type	0.27	0.10	0.26	0.29	0.04	0.13	0.08	-0.09	0.10	0.12	0.03	0.04	0.09	-

Table A2.3. Complete random forest model error rates compared to only independent random forest model results

	Potential Riparian Zone Error (%)	**Current Riparian Zone Error (%)**
Complete Model	5.1	6.8
Independent Model	5.8	7.8

Table A2.4. Predictor variables included in complete and independent model.

Variables Included in Independent Models
Average Annual Temperature
Erosion Rate
Geology
Longitude
Mean annual flow
Snow Water Equivalent (SWE)
Soils
Stream type
Topographic Wetness Index + (TWI+)

Table A2.5. Error in potential riparian zone model accuracy when progressively removing predictor variables from the model.

Number of Predictors	Predictors Included	Percent Error
13	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE), Distance from streamline, Average Annual Precipitation, Erosion Rate (RUSLE), Elevation, Longitude, Latitude, Average Annual Temperature, Soils, Stream type, Geology, Mean annual discharge	5.1
12	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE), Distance from streamline, Average Annual Precipitation, Erosion Rate (RUSLE), Elevation, Longitude, Latitude, Average Annual Temperature, Soils, Stream type, Geology	5.0
11	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE), Distance from streamline, Average Annual Precipitation, Erosion Rate (RUSLE), Elevation, Longitude, Latitude, Average Annual Temperature, Soils, Stream type,	5.1
10	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE), Distance from streamline, Average Annual Precipitation, Erosion Rate (RUSLE), Elevation, Longitude, Latitude, Average Annual Temperature, Soils	5.1
9	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE), Distance from streamline, Average Annual Precipitation, Erosion Rate (RUSLE), Elevation, Longitude, Latitude, Average Annual Temperature	5.2
8	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE), Distance from streamline, Average Annual Precipitation, Erosion Rate (RUSLE), Elevation, Longitude, Latitude	5.3
7	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE), Distance from streamline, Average Annual Precipitation, Erosion Rate (RUSLE), Elevation, Longitude	5.6
6	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE), Distance from streamline, Average Annual Precipitation, Erosion Rate (RUSLE), Elevation	6.1
5	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE), Distance from streamline, Average Annual Precipitation, Erosion Rate (RUSLE)	7.0
4	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE), Distance from streamline, Average Annual Precipitation	7.5
3	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE), Distance from streamline	10.4
2	Topographic Wetness Index + (TWI+), Snow Water Equivalent (SWE)	10.7

Table A2.6. Error in potential riparian zone model accuracy when progressively removing predictor variables from the model.

Number of Predictors	Predictors Included	Percent Error
14	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation, Snow Water Equivalent (SWE), Latitude, Erosion Rate (RUSLE), Elevation, Human modification, Longitude, Average Annual Temperature, Soils, Mean annual flow, Geology, Stream type	6.8
13	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation, Snow Water Equivalent (SWE), Latitude, Erosion Rate (RUSLE), Elevation, Human modification, Longitude, Average Annual Temperature, Soils, Mean annual discharge, Geology	6.8
12	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation, Snow Water Equivalent (SWE), Latitude, Erosion Rate (RUSLE), Elevation, Human modification, Longitude, Average Annual Temperature, Soils, Mean annual flow	7.0
11	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation, Snow Water Equivalent (SWE), Latitude, Erosion Rate (RUSLE), Elevation, Human modification, Longitude, Average Annual Temperature, Soils	6.8
10	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation, Snow Water Equivalent (SWE), Latitude, Erosion Rate (RUSLE), Elevation, Human modification, Longitude, Average Annual Temperature	6.8
9	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation, Snow Water Equivalent (SWE), Latitude, Erosion Rate (RUSLE), Elevation, Human modification, Longitude	7.1
8	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation, Snow Water Equivalent (SWE), Latitude, Erosion Rate (RUSLE), Elevation, Human modification	7.1
7	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation, Snow Water Equivalent (SWE), Latitude, Erosion Rate (RUSLE), Elevation	7.5
6	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation, Snow Water Equivalent (SWE), Latitude, Erosion Rate (RUSLE)	7.6
5	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation, Snow Water Equivalent (SWE), Latitude	8.2
4	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation, Snow Water Equivalent (SWE)	10.0
3	Topographic Wetness Index + (TWI+), Distance from streamline, Average Annual Precipitation	12.9
2	Topographic Wetness Index + (TWI+), Distance from streamline	17.3

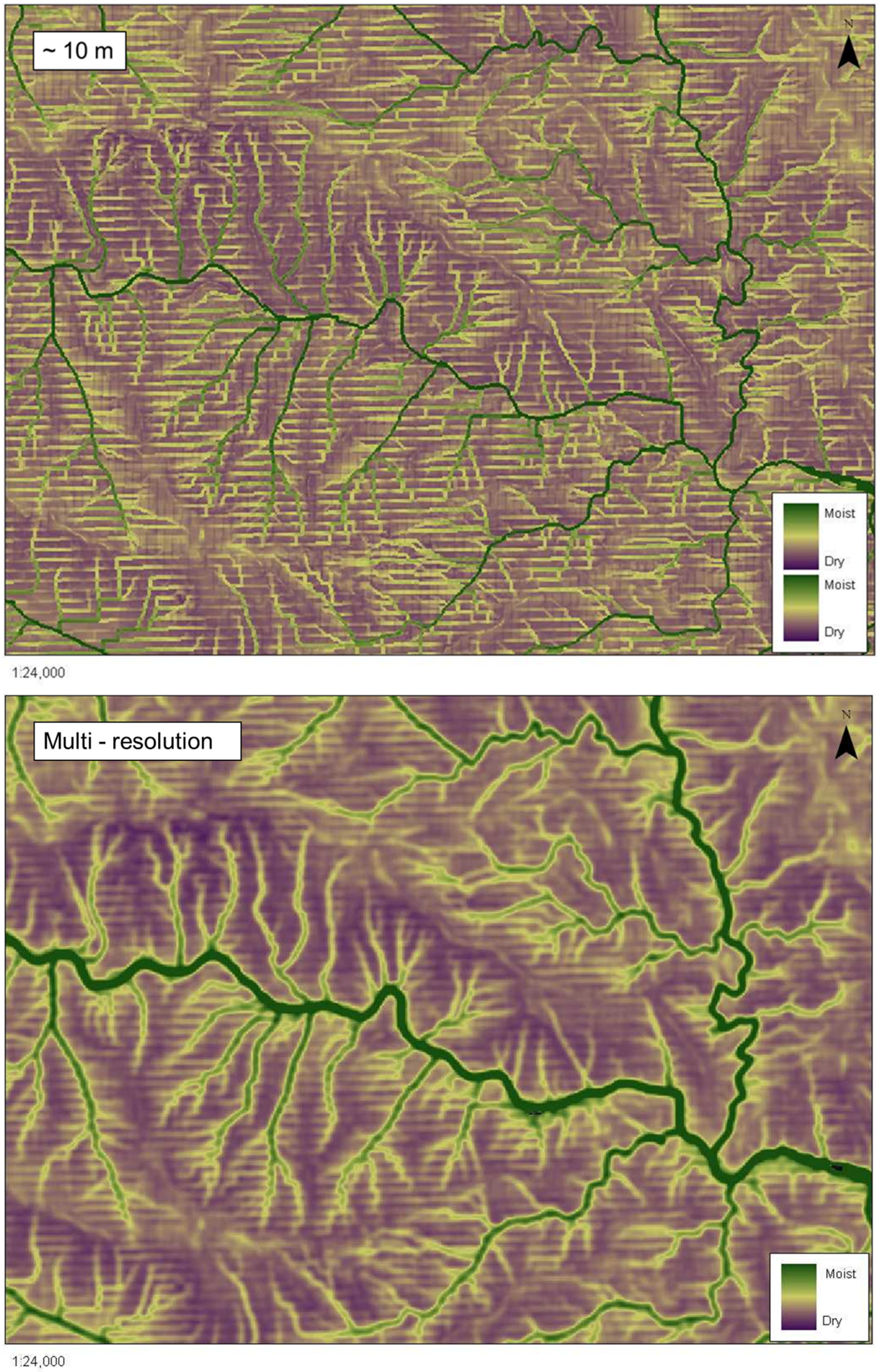

Figure A2.1. Standard TWI+ (top) calculated at 10 m resolution. Multiple resolution TWI+. Notice the smoother transitions form moist (green) to dry (purple) in the multiple resolution TWI+.

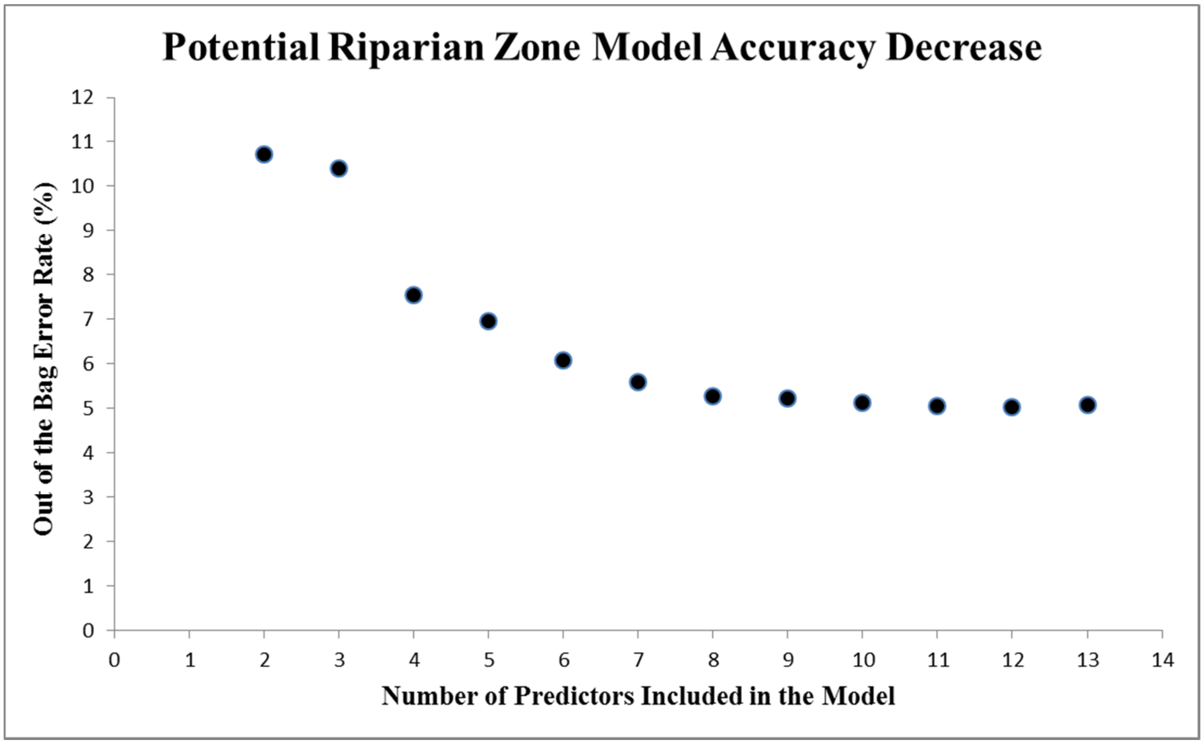

Figure A2.2. Error in reduced potential riparian zone models. See Table A2.5 for exact values.

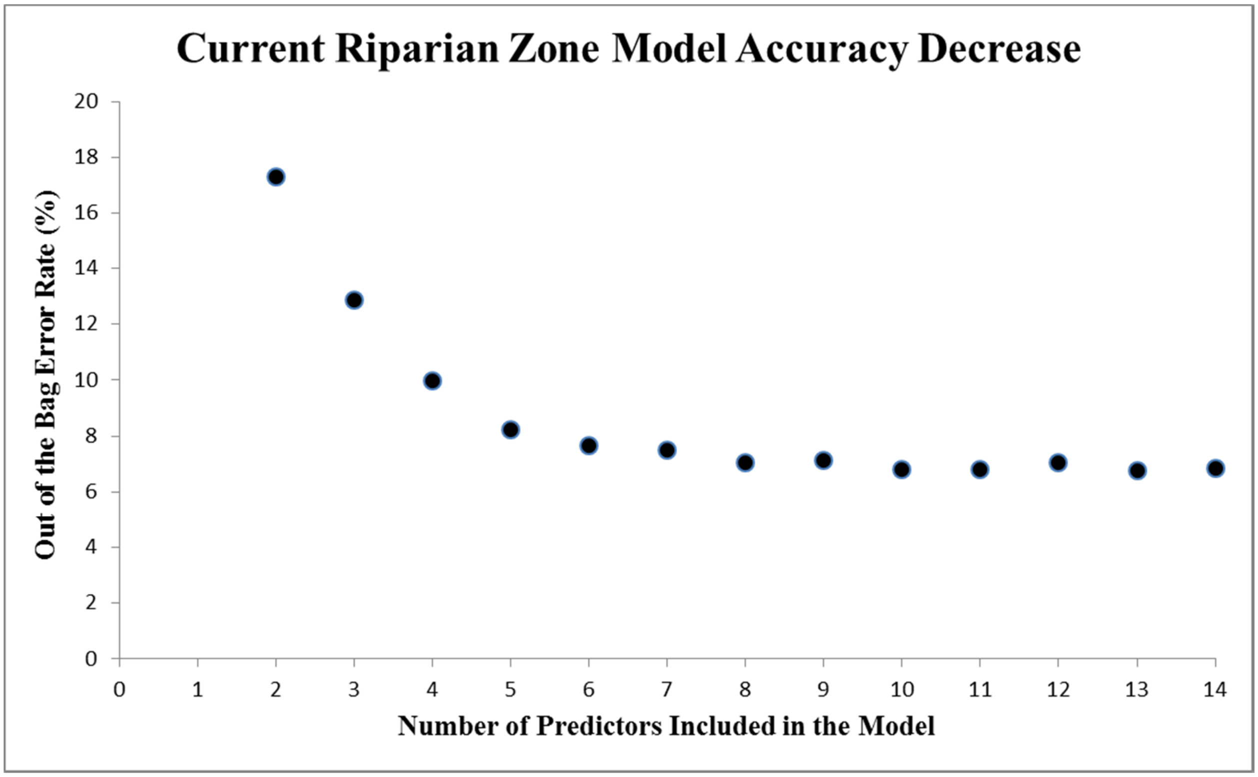

Figure A2.3. Error in reduced potential riparian zone models. See Table A2.6 for exact values.

Appendix III

The following appendix contains supplementary information regarding the predictors chosen to estimate riparian condition in Chapter 4.

Justification of why predictor variables were included in the model

Watershed Scale

To estimate impacts to riparian condition at the watershed scale, we included the proportion of the upstream catchment that was modified by humans. To do this, we used Theobald's (2013) human modification index and calculated the proportion of the upstream catchment that was modified. To create this predictor variable, we took the inverse of the human modification index and used the ArcGIS Flow Accumulation tool to accumulate all upstream values. Next, we created a raster of the SRE with values of 1 to indicate a completely natural state with no human modification and used the ArcGIS Flow Accumulation tool to accumulate all upstream values. We then divided the accumulated human modification values by the accumulated values that indicate no human modification to estimate the proportion of the upstream catchment that had been modified by human activity. Finally, we used the zonal statistic tool in ArcGIS to calculate the maximum amount of modification upstream of each riparian zone reach.

We included the proportion of the upstream catchment that was protected by varying degrees of land use, assuming that higher proportion of protected lands will result in better riparian zone conditions. We divided protected lands into four categories (GAP Status 1-4) based on protection and management status. Lands designated as GAP Status 1 have permanent protection from the conversion of natural land cover and management plans that require a natural state in which disturbances (e.g., fire) are allow to proceed or are mimicked through management. GAP Status 2 land has permanent protection to restrict the conversion of natural land cover but allow management practices (e.g., wildfire suppression or grazing) that may degrade the quality of natural ecosystems. GAP Status 3 land has permanent protection from conversion of natural land cover but are subject to extractive uses (e.g., logging and mining). GAP Status 4 land is protected but does not have any known institutional management plans in place. Our random forest model indicated that the inclusion of the proportion of the upstream watershed protected by GAP Status 1, 2, or 3 did not have an impact on the out of the bag error rate and these predictor variables were removed from the final riparian condition model.

In addition to using protected areas in our predictor model, we investigate the percent of streams that were protected by each GAP Status, 1, 2, 3 or unprotected lands (GAP Status 4, unknown gap status, or private, unprotected lands). Based on the length of streams in each stream order (NHD 1:100,000; USGS 2012b) and GAP Status, we found that (Table A3.1) 59.2% of headwater streams (S_1) are protected, 49.2% of mid-sized streams (S_2) are on protected lands, and 33.6% of rivers ($>S_2$) are on protected lands. We do not believe these values have an impact on our ability to predict riparian condition or cause any issues with our analysis.

Riparian Scale

We included a measure of lateral confinement in our riparian condition model because lateral confinement due to transportation corridors is known to be an important predictor of riparian condition (Stanford and Ward, 1993; Forman and Alexander, 1998). To develop a measure of lateral confinement caused by riparian corridors for each riparian reach within the SRE, we used the potential riparian zones mapped in the third chapter of this dissertation. Within each potential riparian zone reach, we calculated the total length of streams and transportation lines and divided the total stream length by the transportation length. For potential riparian zone reaches with no transportation features present, we assigned a value of 0. Finally, we created an index of values where 1 indicated complete confinement and 0 indicated that there were no transportation features present in a particular potential riparian zone reach.

In addition to including human modification at the watershed scale, we also included a measure of human modification at the riparian scale because our measure of riparian condition was based on human modifications to riparian vegetation and channel conditions (e.g., modifying the flow regime). To do this, we calculated the proportion of each potential riparian zone reach that was modified by human activity based on Theobald's (2013) human modification index.

<u>In-Channel</u>

We included the flow fragmentation index as a predictor variable in our riparian condition model because multiple researchers (e.g., Stromberg, 2001; Wohl, 2006; Theobald et al., 2010; Poff et al., 2011) have shown that modifications in the flow regime negatively impact rivers and riparian vegetation. We included upstream transportation crossings as a predictor variable because these features have the ability to disrupt natural stream and sediment flow, impacting riparian vegetation (Forman and Alexander, 1998).

Characteristics of Predictor Variables

To provide further information about the predictor variables, we developed a table (Table A3.2) that included the minimum, maximum, mean, and standard deviation for each predictor variable used.

Correlations Between Predictor Variables

Random forest modelling is robust to correlated predictor variables. However, we calculated the Spearman's rank correlation coefficient between each of the 13 predictor variables used in riparian condition model (Table A3.3).

Random Forest Model Parsimony

Many of the variables used to create the random forest model to estimate riparian condition take time to develop and contribute little to the result (Table 4.6). Random forests models do not include a term to penalize for a high number of predictor variables or predictor variables that low importance; however, to provide guidance on how a reduced model will perform when estimating potential or current riparian location, we progressively removed less-effective variables and recorded the out-of-the-bag error rate (Table A3.4 and Figure A3.1) in the riparian condition model. The out of the bag error rate is an internal cross validation test employed by random forest models to provide an unbiased estimate of model error. Each classification tree used in a random forest model is constructed using a different bootstrap sample from the original data, where approximately a third of the data is withheld for each tree and used to create an error estimate. Following the growth of the entire forest, the out of the bag error rate is calculated using the individual tree error. The out of the bag error rate roughly corresponds to the overall accuracy of the predicted riparian maps. The full predicted riparian maps were not included in this analysis because creating each model takes 48 hours, resulting in over 350 hours of processing time.

Table A3.1. Percent of streams in headwaters (S_1), mid-sized streams (S_2), and rivers ($>S_2$) by land protection status.

	Percent of Stream Length		
GAP STATUS	S_1	S_2	$>S_2$
1	10.08	8.23	4.18
2	33.58	27.18	17.31
3	15.55	13.75	12.07
Unknown/Unprotected	40.79	50.84	66.45

Table A3.2. Characteristics of predictor variables.

Scale	Predictor Variable	Minimum	Maximum	Mean	Standard Deviation
Watershed	Human Modification Index Watershed	0.00	1.00	0.44	0.26
	Proportion Upstream Protected Area				
	GAP Status 1	0.00	1.00	0.12	0.31
	GAP Status 2	0.00	1.00	0.36	0.46
	GAP Status 3	0.00	1.00	0.16	0.34
	GAP Status 4	0.00	1.00	0.00	0.04
Riparian	Human Modification Index Riparian	0.00	1.00	0.33	0.24
	Lateral Confinement	0.00	1.00	0.13	0.25
In-channel	Flow Fragmentation Index	0.00	10.00	0.06	0.79
	Upstream Transportation Crossings	0.00	84005.00	37.02	796.94

Table A3.3. Correlations between predictor variables. (n = 394)

	Human Modification Index Watershed	GAP Status 1	GAP Status 2	GAP Status 3	GAP Status 4	Human Modification Index Riparian	Lateral Confinement	Flow Fragmentation Index	Upstream Transportation Crossings
Human Modification Index Watershed									
GAP Status 1	0.04								
GAP Status 2	-0.03	0.01							
GAP Status 3	0.25	-0.08							
GAP Status 4	0.09	-0.04	-0.07						
Human Modification Index Riparian	0.93	0.06	-0.08	0.22	0.09				
Lateral Confinement	0.47	0.02	0.03	0.06	0.17	0.41			
Flow Fragmentation Index	0.31	0.27	0.14	0.24	0.00	0.30	0.15		
Upstream Transportation Crossings	0.49	0.21	0.14	0.38	0.13	0.43	0.31	0.47	

Table A3.4. Error in riparian condition model accuracy when progressively removing predictor variables from the model.

Number of Predictors	Predictors Included	Percent Error
9	Human Modification Index Riparian, Upstream Transportation Crossings, Human Modification Index Watershed, Flow Fragmentation Index, Lateral Confinement, GAP Status 4, GAP Status 3, GAP Status 2, GAP Status 1	34.9
8	Human Modification Index Riparian, Upstream Transportation Crossings, Human Modification Index Watershed, Flow Fragmentation Index, Lateral Confinement, GAP Status 4, GAP Status 3, GAP Status 2	34.6
7	Human Modification Index Riparian, Upstream Transportation Crossings, Human Modification Index Watershed, Flow Fragmentation Index, Lateral Confinement, GAP Status 4, GAP Status 3	34.6
6	Human Modification Index Riparian, Upstream Transportation Crossings, Human Modification Index Watershed, Flow Fragmentation Index, Lateral Confinement, GAP Status 4	33.7
5	Human Modification Index Riparian, Upstream Transportation Crossings, Human Modification Index Watershed, Flow Fragmentation Index, Lateral Confinement	34.3
4	Human Modification Index Riparian, Upstream Transportation Crossings, Human Modification Index Watershed, Flow Fragmentation Index	34.6
3	Human Modification Index Riparian, Upstream Transportation Crossings, Human Modification Index Watershed	34.0
2	Human Modification Index Riparian, Upstream Transportation Crossings	34.0

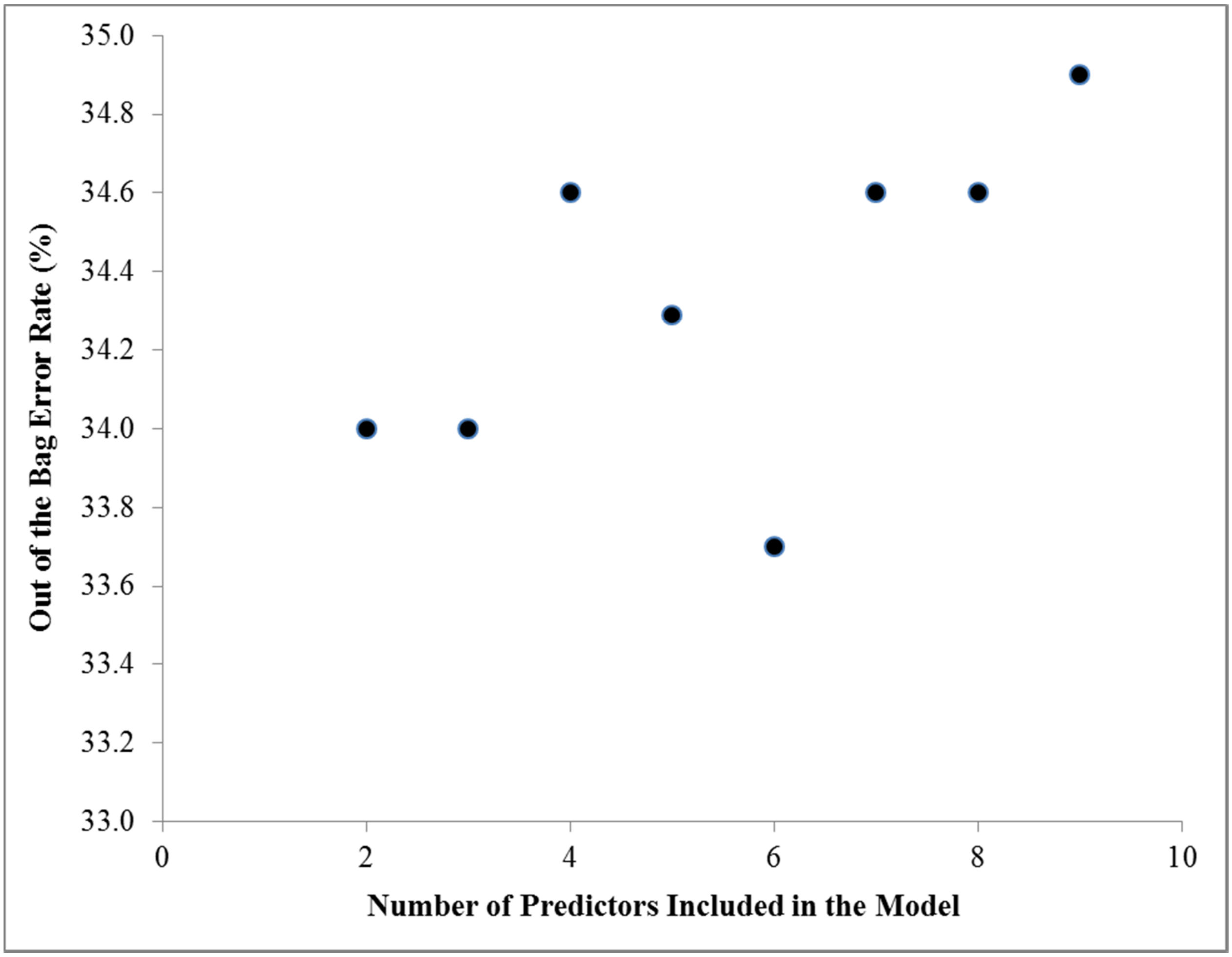

Figure A3.1. Error in reduced riparian condition models. See Table A3.4 for exact values.