ASSESSMENT OF THE THREE-DIMENSIONAL STRUCTURE OF RIPARIAN HABITAT ALONG FOOTHILLS AND PLAINS STREAMS

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Executive Summary

This project was motivated by the need to map and assess riparian habitat extent and quality in the foothills and plains of Boulder County, with an emphasis on habitat characteristics relevant to the threatened Preble's meadow jumping mouse (PMJM) and important to overall riparian ecosystem function. Because PMJM is considered by some to be an indicator of healthy riparian ecosystems, assessing and mapping riparian habitat characteristics relevant to PMJM provides valuable information for managers charged with managing and restoring these ecosystems throughout Boulder County. Functioning riparian ecosystems provide many important ecological functions and ecosystem services, including providing corridors for wildlife movement, contributing organic matter to streams, dissipating floods, improving water quality by storing nutrients and sediment, and reducing streambank erosion. The mapping and description of habitat areas suitable for PMJM may provide a means for identifying well-developed and structurally complex riparian areas. For BCPOS, such areas are considered to represent target conditions for restoration (i.e., support desired riparian conditions and functions).

The objectives of this project were to

1. Develop a classification of Boulder County riparian areas using remote sensing data (multispectral imagery and airborne LiDAR) applicable to watershed and restoration planning and for assessing PMJM habitat.
2. Conduct a landscape-scale assessment of the three-dimensional structure of Boulder County riparian areas using airborne LiDAR for use in habitat modeling, watershed and restoration planning, and future monitoring.
3. Generate and validate models and relevant data products.
4. Produce a written report synthesizing analyses, summarizing current riparian habitat conditions, and making recommendations for future monitoring and assessment using remote sensing.
5. Review current BCPOS riparian habitat monitoring, and recommend a framework for a future coordinated monitoring program to track trends in post-flood succession and riparian connectivity.
6. Develop an updatable framework for future monitoring that will enable managers to track post-flood succession and connectivity of riparian vegetation and is applicable to multiple resource objectives including PMJM management.

We developed a land cover classification for a study area with Boulder County that encompasses known PMJM habitat: riparian vegetation along foothills and plains streams at elevations less than 7,600 ft and the neighboring uplands. We used multispectral imagery, canopy height data estimated through the use of LiDAR, and ancillary data products of irrigated agricultural fields and lakes and reservoirs. The land cover classification maps the location of riparian vegetation and surrounding land cover types, some of which are known to negatively

impact riparian ecosystems and preferred PMJM habitat. Resource managers can use the land cover classification for a variety of purposes, including understanding the spatial configuration of land cover within the study area and identifying areas of intact riparian vegetation or potential locations for restoration. In this report, we demonstrate several management applications of the land cover classification by using it to develop a PMJM species distribution model, model connectivity between high quality habitat patches, and develop a framework for identifying restoration sites depending on management decisions.

To provide BCPOS information useful for planning future assessments and monitoring, we compared three complimentary remote sensing approaches for estimating riparian vegetation structure: terrestrial laser scanning (TLS), airborne LiDAR (ALS), and structure from motion (SfM). We processed ALS data and compared it point clouds created from TLS scans at selected BCPOS riparian sites and to point clouds produced from SfM analyses of imagery from UAS flights. Results were used to develop recommendations for the best use of each approach for assessing riparian structure as part of future monitoring. Each of the three techniques was found to have strengths and weakness for quantifying vegetation structure, so the utility of a given approach is conditioned by the objectives guiding sampling. TLS scans produce dense point clouds revealing fine details of structure, but equipment is expensive, data are difficult to store and analyze, and scans capture a relatively small area, making the approach unsuitable for landscape scale analyses. SfM point clouds are more efficient at generating 3D data at intermediate scales than TLS, but the quality of information is uneven compared with ALS or TLS data, especially for assessing understory vegetation. ALS data is best suited for landscape-scale analyses and provides sufficient detail to quantify riparian vegetation structure for most purposes. The main limitation is the relatively low frequency that new data are acquired, so for specific purposes, SfM and TLS approaches may be useful ways to supplement information.

Field observation and research have shown that PMJM prefer riparian vegetation with structural diversity, i.e., well developed riparian areas with a sub-shrub or shrub understory. We developed a species distribution model (SDM) to predict the distribution of habitat available to PMJM within the study area and to evaluate what variables contribute to PMJM habitat selection. In the full SDM, distance to stream dominated was the most important variable in predictive models, a fact that is known to managers and scientists. We created a reduced SDM by removing distance to stream as a variable, to better understand what other factors may drive PMJM habitat selection. We found that LiDAR-derived variation in height above ground, riparian vegetation cover type from the classification, elevation above mean sea level, and topographic position index had relatively high variable importance in the model. Of the LiDAR derived data products, the standard deviation of the canopy height was the most influential predictor.

To evaluate the connectivity of PMJM habitat, we used known population locations from trapping data (USFWS 2016), potential high quality habitat modeled by the SDM, and a resistance layer developed to reflect known and assumed PMJM movement behaviors. We created two connectivity models, one based on known populations and one based on habitat modeled by the SDM. The connectivity model of known populations depicted two, separate populations, one on St. Vrain Creek and one on South Boulder Creek. Within the individual populations, connectivity existed, but based on our models, it is unlikely that the two populations are connected. Additional known populations are present in other areas within the study area (e.g., Tom Davis Gulch in Walker Open Space). However, due to modeling limitations these were not captured. The second connectivity model, based on habitat modeled by the SDM, indicated that far more PMJM habitat exists than is currently being utilized and potential connectivity exists throughout much of the study area.

Our landscape level connectivity analysis provides insight into potential riparian habitat mapped by the SDM beyond the boundaries of BCPOS, movement corridors and barriers to movement for PMJM by identifying suitable habitat using the species distribution model, identifying habitat PMJM are currently using, and modeling the least cost paths between habitat patches. We found that, within the two known populations, connectivity exists but some corridors are vulnerable to modification of riparian habitat and should be the continued focus of field based monitoring. Additionally, the SDM identified areas along Left Hand Creek and Fourmile Canyon Creek that are well connected and have the potential to support PMJM populations. Further trapping and field-based research would need to be conducted to validate this result.

In addition to analyses specifically aimed at characterizing PMJM habitat and connectivity, we produced landscape analyses of riparian structure using multiple methods and ALS data aimed at more broadly informing riparian management, planning, and post-flood recovery. These included approaches representing structure as continuously-varying quantities across landscapes and an approach that discretized patterns of structure across the landscape using an updatable framework also compatible with field monitoring designs. ALS point cloud data was used to generate continuous raster layers representing different statistical point cloud derivatives including the maximum, average, standard deviation, and various percentiles of canopy height above ground (HAG). As a complimentary approach for visualizing landscape patterns in structure, we combined select variables into a multi-band raster viewable as a false-color image, assigning ALS-derived cover (a measure of horizontal pattern), 95th percentile height above ground (a measure of vertical structure), and HAG standard deviation (a measure of vertical heterogeneity) to the different image bands. As another way of evaluating structure, we analyzed ALS derivatives using Principle Components Analysis (PCA), a statistical data reduction technique used to produce synthetic variables capturing the main patterns of structural variability for visualization. Lastly, the study area was tessellated using a hexagonal grid to provide a discrete sampling frame for evaluating structure and to aid in future monitoring. ALS-derived structure and other variables were attributed to each hexagonal cell using zonal statistics. The resulting product provides a flexible and updatable framework for evaluating structure across Boulder County and identifying of management interest. The resulting data layer was used to create statistical summaries for various grouping variables including hydrologic unit basins (HUB10), Open Space properties, and elevation zones and to identify potential sites for restoration.

Currently, three BCPOS groups (Plant Ecology, Wildlife/PMJM, and Aquatic) are engaged in ground-based monitoring efforts that include a riparian vegetation component. In addition, there have been several recent ground-based riparian assessments completed by funded researchers. Chapter 6 reviews these efforts, focusing on goals/objectives, site selection criteria, site locations and field protocols. The three BCPOS riparian monitoring programs share some general similarities in terms of monitoring goals. However, there are important differences in focus which result in differences in site selection, spatial extent of data collection, and type of data collected. The plant ecology post-flood vegetation monitoring and the aquatic biomonitoring both focus on flood impacted sites. In contrast, PMJM riparian monitoring includes both sites impacted and not impacted by the 2013 flood. Examination of BCPOS monitoring locations indicates that some monitoring is taking place at shared flood-impacted sites on Saint Vrain Creek -- all three programs are collecting data in close proximity at Hall Ranch and Bullock, and relatively near to one another at Gage and Keyes. An important difference in riparian vegetation monitoring among the three programs relates to the spatial extent of the riparian zone being monitored at each site. For plant ecology post-flood vegetation monitoring, the focus is near-channel areas impacted by the 2013 flood. For aquatic biomonitoring, the collection of quantitative data is limited to the immediate channel area, although a rapid assessment is used to describe the entire riparian width. In contrast, the PMJM habitat monitoring protocol entails plot data collection in the entire riparian zone (up to ~150 m from the stream channel). There is some overlap in the plot data being collected for BCPOS PMJM habitat characterization and BCPOS post-flood vegetation monitoring, though they differ in level of detail.

Several BCPOS programs share an interest in mapping, assessing, and monitoring riparian vegetation in Boulder County. In particular, the BCPOS Plant Ecology, Wildlife/PMJM and Aquatic groups are all engaged in some form of riparian vegetation monitoring, and broader riparian assessment is critical for watershed scale planning and riparian restoration. Going forward, we recommend that BCPOS consider co-locating riparian monitoring sites, when/where possible, in order to enhance opportunities for data sharing, increase efficiency, and improve depth of ecological understanding at shared sites. We also recommend that BSPOS consider development of a shared ground-based data collection protocol to meet the needs of all three BCPOS monitoring programs, thereby enabling creation of a large and consistent data set across relevant sites. For ongoing monitoring using remote sensing approaches, we recommend that BCPOS conduct landscape level analyses (following the methods and suggestions reported here) every 5-8 years or after major disturbance events, at a 10 m resolution. Repeated remote sensing analyses can be used to provide landscape context and to guide ground based data collection, for example if new areas of potential habitat importance are identified. The sampling framework developed in this report can be used to support both aims. Remote sensing analysis will be especially useful for monitoring general trends or changes in riparian physical structure and connectivity over time at the watershed/landscape scale, and for conducting species-specific modeling. In addition, remote sensing can be used to identify potential areas for restoration, according to criteria important to BCPOS (e.g., areas lacking complex vegetation structure).

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CHAPTER 1. INTRODUCTION

This project was motivated by the need to map and assess riparian habitat extent and quality in the foothills and plains of Boulder County. Particular emphasis was placed on habitat characteristics relevant to the threatened Preble's meadow jumping mouse (PMJM), a Species of Special Concern (SSC) thought to be an indicator of riparian health. Analyses also more broadly evaluated structure to aid management and monitoring of multiple resources and facilitate planning and riparian restoration to improve watershed health and function. This assessment will facilitate planning for watershed scale riparian restoration and management vital to PMJM and to riparian ecosystem health and function more generally. Additionally, we developed a framework for monitoring that will enable managers to evaluate post-flood successional development and connectivity of riparian vegetation over time. The approach can be used to guide field assessments and can be easily updated with new remote sensing data sets (e.g. LiDAR, imagery).

PMJM is a riparian species that occurs in densely vegetated areas near open water in the foothills and plains of Boulder County (Bakeman 1997). Although PMJM has been documented in a variety of riparian vegetation types, the shrub component of the vegetation appears to be an important aspect of its preferred habitat (Bakeman 1997, Keinath 2001). For example, in Wyoming the shrub structural type comprised 44% of the vegetation at PMJM capture points, while herbaceous accounted for 32%, forest 22% and open 4% (Keinath 2001). In Boulder County, PMJM have been captured on transects characterized by coyote willow shrubs, forbs, irrigated pasture, and mesic grassland (Bakeman 1997). However, PMJM sites also supported other riparian vegetation types, including cottonwood/willow forest and snowberry shrubs which may contribute to PMJM habitat. In general, capture points tend to be characterized by high forb, grass, shrub and tree cover, as well as by high plant species richness (Clippinger 2004).

Elsewhere in the Colorado Front Range, radiotelemetry studies indicated that PMJM high-use areas were characterized by greater shrub cover, woody basal area, and woody debris cover compared to no-use areas (Trainor et al. 2007). Because high-use areas occurred near streams, both shrub and grass cover were dominated by wetland species. Thus, while proximity to streams largely determines potential PMJM habitat at the landscape scale, specific microhabitat conditions within the riparian zone appear to determine actual PMJM occurrence and habitat use. To assess the quality of PMJM habitat, it is crucial to know the extent and structure of riparian zone vegetation. To that end, the objectives of this project were to use remote sensing and GIS analysis to classify riparian vegetation in Boulder County, and to characterize riparian three-dimensional structure. Additional goals were to review ground-based riparian habitat monitoring being conducted by BCPOS, and to recommend a framework for a future coordinated monitoring program that would allow managers to track riparian succession and connectivity over time.

Because PMJM is considered to be an indicator species for riparian ecosystems (Clippinger 2002), assessing and mapping riparian habitat characteristics relevant to PMJM provides valuable information for managers charged with managing and restoring these ecosystems throughout Boulder County. Functioning riparian ecosystems provide a number of important ecological functions and ecosystem services, providing corridors for wildlife movement, contributing organic matter to streams, dissipating floods, and improving water quality by storing nutrients and sediment, and reducing streambank erosion (Jones et al. 2010). Description of habitat areas suitable for PMJM may provide a means for identifying well-developed and structurally complex riparian areas. For BCPOS, such areas may represent target conditions for riparian restoration in appropriate areas of the county.

Functioning riparian ecosystems are also naturally dynamic, experiencing dramatic changes in vegetation structure (e.g., via mortality, regeneration) in response to streamflow patterns (e.g., Friedman et al. 1996, Friedman and Lee 2002). Thus, from a landscape scale perspective, functioning riparian zones should consist of a mosaic of vegetation types, including forest patches of various ages/successional stages, and with varying physical structure and species composition. Therefore, we also conducted additional analyses of riparian structure not directly focused on PMJM.

Most studies of the spatial patterns of riparian forests (i.e., species and/or cohort distributions) have used detailed site-scale field mapping and/or visual analysis of aerial photographs to map riparian plant communities (e.g., Johnson 1994, Friedman et al. 1996, Friedman and Lee 2002). Such analyses are effective over relatively small study areas, but are time intensive and can be difficult to scale up to whole watersheds. To address the limitations of field based mapping, methods have been developed that combine the use of field based data collection and/or aerial photography interpretation with remotely sensed data, including terrain and multispectral imagery, to predict riparian vegetation extent, condition, and/or composition over large geographic extents (e.g., Goetz et al., 2003; Snyder et al., 2005, and Arroyo et al. 2010).

There are three prevailing remote sensing methods that incorporate field data and statistical modeling to map riparian zones. The first method uses medium to fine resolution imagery and relies on the spectral signature of different vegetation types to identify riparian vegetation (Snyder et al., 2005). The second method employs airborne LiDAR (light detecting and ranging) to determine the structure of forest canopies, including the canopy height and crown diameter of individual trees, which allow for the identification of riparian tree species (Farid et al. 2006 and Johansen et al. 2011). The third method combines the use of multispectral imagery and LiDAR data to map the extent, condition, structure and/or species composition of riparian zones (Arroyo et al. 2010 and Jeong et al. 2016). Of the three, the combination of LiDAR and multispectral imagery has best accuracy when mapping riparian extent and riparian tree species (Arroyo et al. 2010, Jeong et al. 2016).

Multiple approaches for quantifying three-dimensional forest structure have been developed (Lim et al. 2003), but few studies have compared methods for assessing riparian habitat structure. LiDAR has emerged as a dominant technology for three-dimensional analyses of terrain and vegetation (Lefsky et al. 2002) and can be collected from airborne platforms (ALS) or from terrestrial laser scanners (TLS) mounted on tripods. Both can produce detailed 3-dimensional point clouds useful for quantifying structural attributes like canopy height (Li et al. 2015, Greaves et al. 2015), but differ in information density, accuracy, and cost. Structure from motion (SfM) algorithms use information in overlapping sets of images, often collected using unmanned aerial vehicles (UAVs), to produce three-dimensional point clouds (Cruzan et al.

2016). Data can be analyzed in similar ways to data from laser scanning, but the accuracy of SfM for characterizing the vertical structure of vegetation is largely untested. While SfM has shown promise for measuring canopy height, validation against other data sets like TLS is needed to evaluate whether the technique can accurately assess structural characteristics important to habitat quality (Bakeman 2007).

In addition to identifying structural habitat components of riparian zones, habitat fragmentation and loss is a serious issue for many riparian obligates. As waterways are developed for agriculture, transportation, and resource extraction habitat area is reduced and the remaining habitat is fragmented. Natural hazards, such as major flooding, can put pressure on an already stressed ecosystem and further reduce the amount of habitat available (Li et al. 2010). Given the large amount of human modification and natural dynamics (e.g., floods) of riparian ecosystems in Boulder County, understanding the fragmentation of habitat and the remaining connectivity between known populations of PMJM and high quality habitats is important for the conservation of the species. Many GIS methods have been developed to map habitat fragmentation and the resulting connectivity (Beier et al. 2011). One such method, using least cost path analysis, can identify connections between populations or habitats and can be used to identify barriers to movement for a variety of species. These methods can assist in detecting important PMJM barriers and identify potential areas for restoration within Boulder County (McRea et al. 2012).

Monitoring is an important aspect of natural resources management, though the design and reliable implementation of effective long term monitoring programs has proven difficult in many settings (Lindenmayer and Likens 2010). Because riparian ecosystems are dynamic in space and time, effective monitoring frameworks must capture the effects of discrete natural and anthropogenic disturbances, track long term trends (e.g., due to environmental stressors), and document the trajectories of ecological succession. Traditionally, riparian monitoring protocols have focused on field based data collection (e.g., Winward 2000). However, natural resource monitoring programs are increasingly making use of remote sensing approaches or integrating remote sensing and field based protocols (e.g., Kennedy et al. 2009, Nagler et al. 2009, Lawley et al. 2016). Such monitoring programs have the potential to provide useful information to managers, in an efficient and reliable framework. Specifically, the incorporation of cost efficient methods (e.g., UAVs) and/or freely available data in riparian monitoring protocols will further the utility of this approach to managers.

The objectives of this project were to:

1. Develop and apply a classification of Boulder County riparian area using remote sensing data (multispectral imagery and airborne LiDAR) applicable to watershed and restoration planning and for assessing PMJM habitat.

2. Conduct a landscape-scale assessment of the three-dimensional structure of Boulder County riparian areas using airborne LiDAR for use in habitat modeling, watershed and restoration planning, and future monitoring.

3. Generate and validate models and relevant data products.

4. Produce a written report synthesizing analyses, summarizing current riparian habitat conditions and making recommendation for future monitoring and assessment using remote sensing.

5. Review current BCPOS riparian habitat monitoring, and recommend a framework for a future coordinated monitoring program to track trends in post-flood succession and riparian connectivity.

6. Develop an updatable framework for future monitoring that will enable managers to track post-flood succession and connectivity of riparian vegetation and is applicable to multiple resource objectives including PMJM management.

This report is organized around the project objectives as follows:

- Chapter 1: Introduction and overview of report
- Chapter 2: Multispectral analysis and riparian habitat classification (Objective 1)
- Chapter 3: Comparison of remote sensing methods for assessing riparian structure (Objective 2)
- Chapter 4: Assessment of Preble's Meadow Jumping Mouse Habitat (Objectives 3 and 4)
- Chapter 5: A Landscape-Scale Assessment of Riparian Vegetation Structure Using Remote Sensing Data (Objectives 2 and 6)
- Chapter 6: Review of BCPOS riparian habitat monitoring, and recent funded research (Objective 5, Task 1)
- Chapter 7: Synthesis and recommendations for a monitoring framework (Objective 5, Task 2)
- Appendix: List of maps and data files provided to BCPOS

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CHAPTER 2. MULTISPECTRAL ANALYSIS AND RIPARIAN CLASSIFICATION

Introduction

Riparian ecosystems support up to 80% of terrestrial animals in the western USA by providing essential habitat for numerous species (Gregory et al. 1991, Naiman and Decamps 1997) and corridors for movement (Johnson and Mackintosh, 1989). The Preble's meadow jumping mouse (PMJM), a federally threatened subspecies of the common meadow jumping mouse, is an example of a riparian obligate species (Armstrong 1972, Muchlinski 1988, Smith et al. 2004). PMJM occurrences have been associated with particular spatial, compositional and structural characteristics of riparian ecosystems and different field methods for assessment have been developed (Ruggles et al. 2001, Clippinger 2002, Meaney et al. 2003, Trainor et al. 2007). However, field methods are time intensive, often limited to accessible properties, and, unless data are collected as part of a rigorous statistical sampling design, results can be difficult to apply more broadly. Therefore, in addition to field-based data collection, resource managers have a need for comprehensive and detailed information at the landscape/watershed scale in order to implement conservation planning on a local, site-specific level. One solution is to use remote sensing methods and geospatial analysis to provide additional information at the landscape scale that can guide management efforts and decisions. Remote sensing and GIS products are models of the earth's surface and inherently have some level of error present. If the error is moderate, it likely does not detract from the usefulness of the products. Remote sensing products are still useful as a tool to guide field based conservation and management efforts a local scale.

Remote sensing data provide a broad synoptic view of the structure and composition of landscapes complimenting field data and providing critical landscape context (Turner et al. 2003, Gillespie et al. 2008). Advances in remote sensing data and processing tools allow for analyses at both fine spatial scales and broad extents and can contribute to the understanding of habitat distribution and quality (Rose et al. 2015). Airborne LiDAR and high-resolution multispectral imagery have been successfully used to classify and map riparian areas and characterize structural attributes like canopy cover, density or height (Goetz 2006, Johansen et al. 2010, Antonarakis 2011) applicable to managing a wide range of resources. Given the importance of riparian structure to PMJM habitat selection and use, structure information from remote sensing data can provide understanding of habitat distribution and support conservation planning such as analyses of habitat connectivity and identification of potential restoration sites.

Most studies of the spatial patterns of riparian ecosystems (i.e., species and/or cohort distributions) have used detailed site-scale field mapping and/or visual analysis of aerial photographs to map riparian plant communities (e.g., Johnson 1994, Friedman et al. 1996, Friedman and Lee 2002). Such analyses are effective over relatively small study areas, but are time intensive and can be difficult to scale up to whole watersheds or large jurisdictions, such as Boulder County. To address the limitations of field based mapping, methods have been developed that combine the use of field based data collection and/or aerial photography interpretation with remotely sensed data, including terrain and multispectral imagery, to predict riparian vegetation extent, condition, and/or composition over large geographic extents (e.g., Goetz et al., 2003; Snyder et al., 2005, and Arroyo et al. 2010).

There are three prevailing remote sensing methods that incorporate field data and statistical modeling to map riparian zones. The first method uses medium to fine resolution imagery and relies on the spectral signature of different vegetation types to identify riparian vegetation (Snyder et al. 2005). The second method employs airborne LiDAR (light detecting and ranging) to determine the structure of forest canopies, including the canopy height and crown diameter of individual trees, which allow for the identification of riparian tree species (Faird et al. 2006 and Johansen et al. 2011). The third method combines the use of multispectral imagery and LiDAR data to map the extent, condition, and/or structural or species composition of riparian zones (Arroyo et al. 2010 and Jeong et al. 2016). Of the three, the combination of LiDAR and multispectral imagery has best accuracy when mapping riparian extent and riparian tree species (Arroyo et al. 2010, Jeong et al. 2016).

Although remote sensing methods tend to produce maps with moderate accuracy (60 – 80%) over broad spatial extents, these methods are important and informative tools in providing a landscape scale perspective on riparian ecosystems and PMJM habitat that can inform more detailed research and guide management decisions. Remote sensing is not a replacement for field based methods used to make management decisions. It compliments field based research and management by providing a landscape scale analysis of a specific geographic region and can guide where more detailed field investigation is required.

Objectives

In this chapter, we provide a landscape scale classification of vegetation within the study area using multispectral imagery and LiDAR derived products. Specifically, we:

- Classify land cover within an area surrounding riparian ecosystems that has the potential to support PMJM habitat and movement corridors.
- Within the land cover classification, we map riparian vegetation as trees, shrubs, or herbaceous.

The datasets produced using the methods outlined in this chapter can be used to improve the understanding of land cover within an expanded area surrounding riparian areas in Boulder County and predict locations for PMJM habitat using a species distribution model (Chapter 5). Further, the land cover classification will be used to develop a habitat connectivity model to identify corridors and potential impediments to PMJM movement (Chapter 5).

Methods

Study Area

The study area for this research project is located in Boulder County, Colorado. Boulder County is located along the Rocky Mountain Front Range, roughly 30 miles northeast of Denver, Colorado. Boulder County has a population of 322,226 (US Census Bureau 2017) and includes the major cities of Boulder, Longmont, Lafayette, and Louisville. Boulder County has several important waterways, including St. Vrain Creek, Left Hand Creek, and Boulder Creek, all tributaries to the South Platte River. The associated riparian ecosystems of many of these waterways support local populations of PMJM.

We restricted the area of analysis to areas that could potentially support PMJM habitat, i.e., riparian zones found at elevations of less than 7,600 feet. The study area was defined using several parameters. (1) We limited the area to all locations in Boulder County that have an elevation of less than 7,600 feet. (2) We included all potential and known PMJM habitat areas as mapped in the PMJM Habitat Conservation Areas (Boulder County Land Use Department 2017). (3) We included all areas within the FEMA 100 year floodplain (FEMA and Boulder County Transportation 2012). (4) We modeled geomorphic valley bottoms using LiDAR data and the topography, slope, and discharge (TDS) method (Salo et al. 2016) to map valley bottoms outside of the FEMA floodplain and known PMJM habitat. The TDS method uses bankfull depth (Castro and Jackson 2001) in combination with valley slope to estimate the extent of the geomorphic valley bottom and performs better than many other valley bottom mapping techniques (Salo et al. 2016). The geomorphic valley bottoms were restricted to the foothills and were buffered by 50 m to include adjacent uplands, areas known to support PMJM foraging and hibernation. We used a buffer distance of 50 m because these valley bottoms are constrained by steep valley walls and we made an assumption based on the literature (Schorr 2001, Clippinger 2002, Trainor et al., 2007) that PMJM would avoid climbing extremely steep slopes to hibernate. We assume the study area to be larger than the actual habitat that supports PMJM. We did this intentionally to be inclusive of all potential PMJM habitat; as local studies on PMJM behavioral ecology and knowledge about their habitat area requirements across individual watersheds are lacking. The final study area (Figure 2-1) is 343 square kilometers, covering roughly 17% of Boulder County and including 1,890 kilometers of waterways (Boulder County 2017c) in a variety of stream types. Twenty nine percent of the study area (99.6 square kilometers) is protected by one of several mechanisms, including Boulder County Parks and Open Space properties and conservation easements (Table 2-1). There are a total of 547 unique protected properties within the study area. Within the study area, 613 km of streams are found within Boulder County Parks and Open Space properties and conservation easements (Table 2-2)

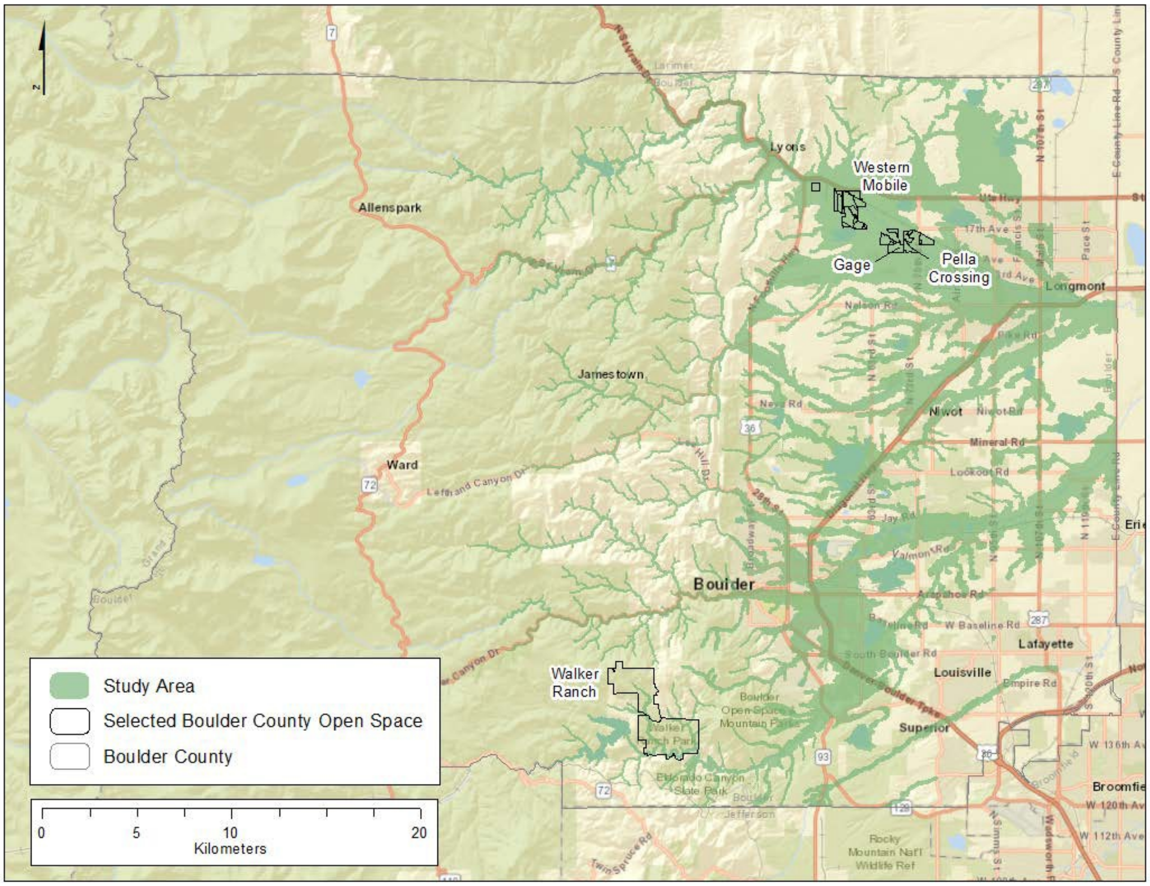

Figure 2-1. *Study area within Boulder County, including the four open space properties we focus on throughout the report.*

Table 2-1*. A summary of Boulder County Open Space and protected lands within the study area.*

Protection Mechanism	Land Area (square km)	Percent of Study Area
County Owned Open Space	49.91	14.55
County Conservation Easement	42.20	12.30
Open Space Option	3.05	0.89
Joint County and Municipal Open Space	2.90	0.84
County Managed	1.41	0.41
Miscellaneous Easement	0.17	0.05
Conservation Easement Option	0.01	0.00

Table 2-2. *A summary of stream type (Boulder County 2017c) that are protected by Boulder County Open Space within the study area.*

Stream Type	**Length (km)**
Aqueducts	5.22
Drain Tile	10.31
Ephemeral Stream	20.33
Field Lateral	71.20
Intermittent Stream	153.95
Lateral Ditch	68.35
Main Ditch	146.08
Other	3.00
Perennial Stream	115.49
Slough	7.62
Tailwater Ditch	11.94

We selected four Boulder County Open Space Properties Gage, Pella Crossing, Western Mobile, and Walker Ranch, to use as examples of the output of our analysis. These properties represent the variety of elevational habitats, land uses, and riparian ecosystems that PMJM are known to inhabit.

Gage Open Space

Gage Open Space was acquired by Boulder County in 1998. This open space is located in the St. Vrain watershed, west of Crane Hollow Road and the Pella Crossing property, and protects both banks of the St. Vrain Creek. The property is completely within the study area and is known to support PMJM. There is approximately 0.56 km of St. Vrain Creek and 1.2 km of the South Branch of the St. Vrain within the open space (Boulder County Parks & Open Space 2004). Currently, several irrigation ditches divert flow laterally through the property to serve irrigated agricultural needs. This open space is 79.36 hectares and contains a variety of key PMJM habitat including riparian shrubs, trees, and herbaceous cover, as well as agricultural land. Historically, this property was grazed year round and is currently managed by the county for grazing. The property is both a county managed open space and a conservation easement. Currently, there is no public access permitted at the Gage Open Space.

Pella Crossing Open Space

Pella Crossing Open Space was acquired by Boulder County between 1992 and 1995 and is the site of a reclaimed gravel mine. This open space is located in the St Vrain watershed, and consists of two parcels located south of Hygiene Road. The property is completely within the study area and is known to support PMJM. There is approximately 1.2 km of St. Vrain Creek within Pella Crossing. This open space protects 79.02 hectares, and contains a variety of important PMJM habitat features, including riparian shrubs, trees, and herbaceous cover, as well as multiple ponds. The northern parcel is open to the public for fishing and trail use, while the southern parcel is not open to public access and is used as a conservation area (Boulder County Parks & Open Space 2004).

Walker Ranch Open Space

Walker Ranch was acquired by the county in 1977. The open space is located in the South Boulder Creek watershed and consists of two parcels of land located along Flagstaff Road, west of the City of Boulder, directly downstream of Gross Reservoir, and north of Eldorado Canyon State Park. The property contains approximately 4.5 km of South Boulder Creek and approximately 25 km of unnamed, ephemeral tributaries in Meyer's and Hawkin Gulches. This open space protects 1033.45 hectares, of which 196.51 hectares are within the study area. This open space supports a variety of foothills ecosystems including forest and woodlands dominated by Ponderosa Pine and Douglas-fir. The riparian ecosystems present in this open space include riparian trees, shrubs, and herbaceous cover (Boulder County Parks and Open Space 2013).

Western Mobile Complex

The properties that form the Western Mobile Complex were acquired by the county between 1998 and 2001. This open space is located in the St Vrain watershed, and consists of 16 parcels, located between Hygiene Road and the St. Vrain Creek. The property is 227.2 hectares and falls completely within the study area and serves as a stronghold for PMJM in the county. There is approximately 1.5 km of St. Vrain Creek and 1.8 km of the South Branch of the St. Vrain within the open space (Boulder County Parks & Open Space 2004). The 16 parcels of land that compose Western Mobile Complex are owned/managed through a combination of county owned open space, open space options, and county conservation easements. Boulder County leases part of the property to Martin Marrietta Materials for mining and reclamation. In addition to the active mining operation and restoration efforts, the complex contains multiple ponds, riparian forests, and agricultural lands. Currently, the property is used for an active gravel mine is not open to the public.

Land Cover Classification

Predictor Variables

We used two sources of data to classify land cover within the study area, WorldView 2 images from May – July 2016 and maximum canopy height data derived from LiDAR data (2013). Due to the large study area, WorldView 2 imagery with minimal cloud cover was acquired from Digital Globe for four dates (22 May 2016, 31 May 2016, 27 June 2016, and 10 July 2016), resulting in 5 different images (Figure 2-2). The imagery has a spatial resolution of 2 m, and contains 8 bands: panchromatic (450 - 800 nm), coastal (400 - 500 nm), blue (450 - 495), green (495 - 470 nm), yellow (585 - 625 nm), red (620 - 750 nm), red edge (705-745 nm), near infrared 1 (725 - 860), and near infrared 2 (860 -1040 nm). Of particular use to this project are the coastal and near infrared bands, which support vegetation identification and analysis, and the red edge band, useful for assessing vegetation condition. The WorldView 2 images were atmospherically corrected and orthorectified using Envi 5.4 Remote Sensing software.

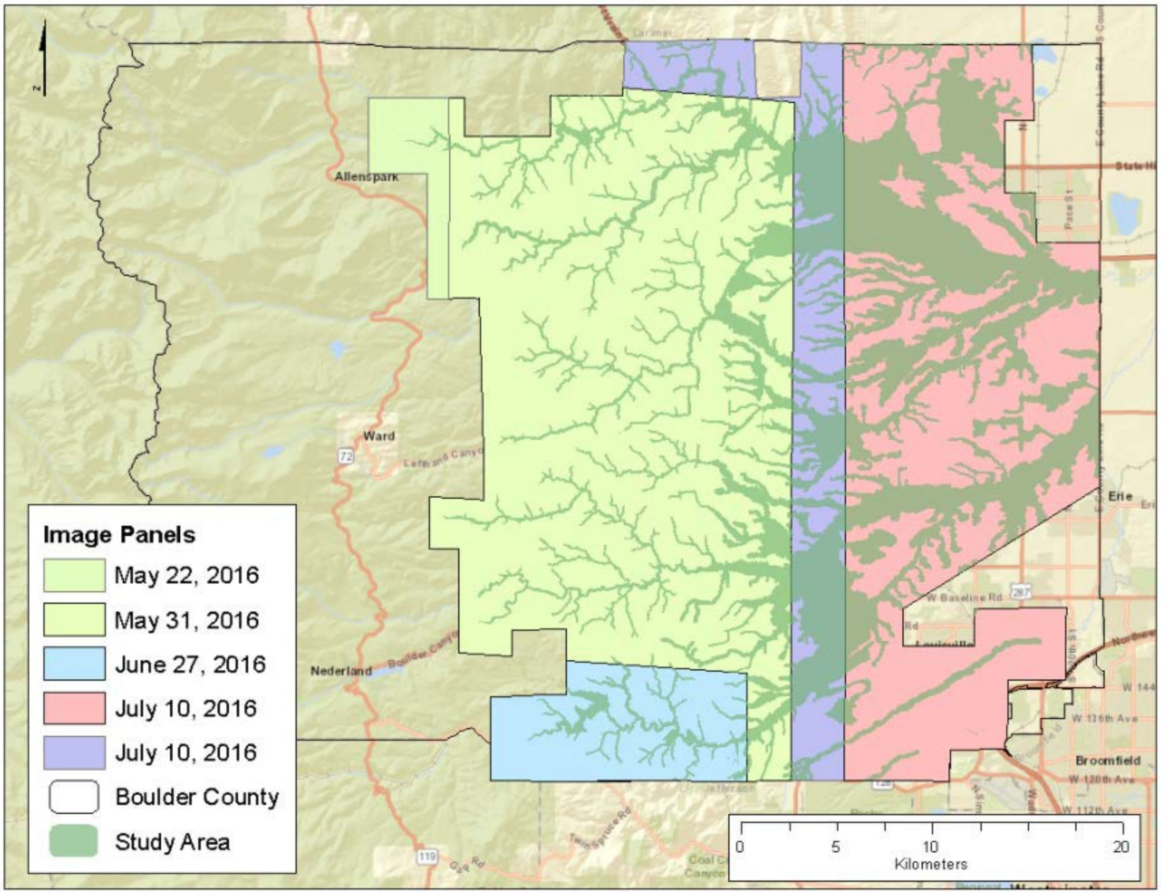

Figure 2-2. *WorldView 2 image panel locations and dates.*

The WorldView 2 images were processed using Envi 5.4 remote sensing software to develop a normalized vegetation difference index (NDVI) to differentiate between riparian and upland vegetation (Jeong et al., 2016). Using the LiDAR data we created a digital terrain model to derive the maximum canopy height, develop a distance from stream layer, and create a topographic wetness index (Beven and Kirkby 1979).

Response Variable

We used a spatially balanced, random method (Theobald et al. 2007) to create 350 points within the study area. Using established aerial photo interpretation techniques (USFWS 2009), we interpreted the land cover at each point and classified it as one of nine categories (riparian forest, riparian shrub, riparian herbaceous, irrigated agriculture, bare ground, open water, developed land (not agriculture), upland herbaceous (both natural lands and dryland agriculture including pastures), and upland forests). At each point, a polygon with the same classification was digitized in the contiguous region surrounding the point. For each of the five images, we ensured that each land cover type present in an image was represented in a minimum of two locations, resulting in the addition of roughly 40 sample locations. We attempted to keep the sampling equal (Table 2-3) across each of the five images, however we had to oversample in the images with smaller areas (May 22 and June 27) to ensure equal representation of land cover classes. We used 80% of the data collected for training the classifications and 20% to test the accuracy of the classification.

Table 2-3. The area of each image panel within the study area, number of response variable points, and points per square kilometer for each image panel.

Image Panel	Area (square km)	Number of Response Points	Points Per Square Kilometer
May 22, 2016	0.47	10	21.39
May 31, 2016	95.91	87	0.91
June 27, 2016	14.92	23	1.54
July 10, 2016	174.03	139	0.80
July 10, 2016	89.46	82	0.92

Classification Methods

To adjust for the different spectral signatures from different data collection dates, each of the individual WorldView2 images were processed and classified independently, then merged together to create the final riparian vegetation classification. All data were rescaled to 10 m resolution to proceed with the classification. Based on conversations with BCPOS personnel (personal communication, Tim Shafer) and USGS (personal communication, Wesley Newton and Jason Stoker), it was determined that a resolution of 10 m was appropriate to capture the variability in the PMJM habitat using remote sensing products, i.e., multipsectral imagery and LiDAR. A resolution of 10 m makes processing of large study areas feasible on personal computers, an important consideration if this process is to be repeated by BCPOS staff in the future.

The vegetation classification was conducted using two machine learning algorithms. Random forest modeling, a non-parametric classification and regression tree method that uses ensemble trees to make predictions (Breiman, 2001) was first used to classify riparian vegetation using the statistical program R. The response variable was the training data interpreted from the WorldView 2 images. The predictor variables were derived from the airborne LiDAR and WorldView 2 images. First, using the LiDAR data, we created the maximum height above ground, a distance from stream layer, and a topographic wetness index (Beven and Kirkby 1979). Second, we developed a normalized vegetation difference index (NDVI) to differentiate between riparian and upland vegetation (Jeong et al, 2016) using the WorldView 2 images. Third, we included each of the 8 bands from the WorldView 2 images as a predictive layer. We used the predict function of the randomForest package to create the classification. In addition to the randomForest package (Liaw and Wiener 2002), we used the rgdal (Bivand et al. 2017) and raster (Hijmans 2017) packages in program R to create our spatially explicit model and to predict our results. After creating a random forest model for each of the five WorldView images, ArcGIS 10.5 was used to merge the classified images into one layer.

Neural Net Classification (NNC) was also used to classify vegetation within the study area. Neural Net Classification is a layered feed-forward neural network classification technique that uses back propagation to improve classification accuracy (Campbell and Wynne, 2011). NNC was implemented for each of the five images in Envi 5.4, using eight bands of the WorldView Imagery with the following specifications: logistic activation method, a training threshold contribution of 0.9, a training rate of 0.2, a training momentum of 0.9, and a RMS exit criteria of 0.1. A total of 1000 training iterations were completed.

After the creating the NNC of the five images, ArcGIS 10.5 was used to merge the classified images into one layer and was combined with the height above ground data. We adjusted both the randomForest and NNC products post-classification to improve accuracy. First for both classifications, the height above ground data was organized into four categories to represent different vegetation types. The height above ground data was then used to refine the multispectral imagery into the following categories: herbaceous ground cover (0-1 m), sub-shrub (1-3 m), shrub (3-5 m), and canopy (>5 m). Next, we used the lakes and reservoirs (Boulder County, 2017b) to adjust pixels that are known to be water but, may have erroneously been classified as another cover type.

The land cover classification algorithms had difficultly discriminating irrigated agriculture and residential lawns from riparian vegetation using multispectral data because the spectral signatures are very similar. Although the Lidar height above ground data distinguishes different height classes, confusion can be present because the planted vegetation often falls within the same height classes as riparian vegetation. To address this issue within the NNC data product, we enhanced the land cover classification with additional data. First, to address the confusion between riparian vegetation and irrigated agricultural lands, we extracted the irrigated and subirrigated fields from the Boulder County Parks and Open Spaces agricultural fields shapefile (Boulder County Parks and Open Space 2017). We visually inspected all polygons within 200 m of NHD High Resolution water lines (USGS 2017) and manually edited the polygons to adjust errors, such as irrigated agricultural polygons overlapping riparian vegetation or areas that are under active restoration and currently irrigated, that would influence the identification of riparian vegetation. We then hand digitized large (> 0.5 ha), obviously irrigated fields from the WorldView-2 imagery for the entire study area. We adjusted the land cover classification to reflect the irrigated agricultural land cover from BCPOS layer and the hand digitized data.

To address the confusion between riparian vegetation and developed areas, we hand digitized large urban areas (i.e., the Cities of Boulder and Longmont) within the study area and classified these as developed lands in the NNC raster, which we refer to as a “modified NNC”. Digitizing irrigated agriculture and developed areas was a time consuming task (~30 hours) and required the collection of 6,349 hectares of land organized in 340 unique polygons. This was done to reduce obvious errors and moves this product from a true remotely sensed, supervised classification to a hybrid product that incorporates digital imagery interpretation and remote sensing. When examining the land cover classification, one may observe riparian vegetation being misclassified in agricultural and developed land cover classes that were not addressed; we did not digitize each individual ranch, house, or neighborhood due to the time it would take to collect these features manually.

Accuracy Assessment

Accuracy assessments of both the random forest and modified NNC classification layers were conducted in ArcGIS 10.5 using 20% of predictor variable that was withheld for testing. We used a confusion matrix to calculate overall accuracy, producer accuracy, user accuracy and kappa coefficients.

Results

Characteristics of the Response Variable

We interpreted a total of 392 points within the study area. We used 313 points for training and 79 points for testing (Table 2-4).

Table 2-4. *Characteristics of the response variable.*

Land Cover	Number of Points	Percent of Response Variable Points
Riparian Herbaceous	32	10.22
Riparian Forest	34	10.86
Riparian Shrub	27	8.63
Bare	28	8.95
Water	26	8.31
Upland Herbaceous	121	38.66
Upland Forest	22	7.03
Irrigated Agriculture	24	7.67
Developed	78	24.92

Classification & Accuracy Assessment

The accuracy of the two classifications varied considerably (Table 2-5). The modified NNC outperformed the random forest classification. Therefore, in this research, we present only the full results of the modified NNC classification and use the modified NNC land cover classification for further analysis.

Table 2-5. *Accuracy assessment for random forest and modified NNC land cover classification outputs.*

Classification	Accuracy	kappa coefficient
Random Forest	0.54	0.44
Modified Neural Net Classification	0.65	0.56

Modified Neural Net Classification

The modified NNC method, from here forward referred to as land cover classification, produced a dataset with an accuracy of 0.65 and a kappa coefficient of 0.56 (Table 2-5). A confusion matrix (Table 2-6), complete with producer (i.e., omission) and user (i.e., commission) accuracy provides further information about the accuracy of this classification method. Producer accuracy provides a measure of how much area was underestimated, while user accuracy indicates the amount that was over estimated. The land cover classes with the highest producer accuracy were water, upland herbaceous, and developed areas. The land cover classes with the highest user accuracy were water, and bare land. The three land cover classes of interest: riparian shrub, riparian trees, and riparian herbaceous had relatively low accuracy. This is to be expected because of the relatively low percentage of the study area that classified as riparian vegetation.

The land cover classification predicted that the most common land cover types (Table 2-7) in the study area are upland herbaceous (36.92%) and developed lands (20.96%). Roughly 10.5 % of the study area is composed of riparian ecosystems in a combination of forest, shrubs, and herbaceous vegetation.

***Table 2-6**. Confusion matrix for the modified NCC land cover classification.*

		Aerial Photograph Interpretation ("Ground Truth")										
		Water	**Upland Herbaceous**	**Riparian Shrub**	**Riparian Herbaceous**	**Irrigated Agriculture**	**Riparian Forest**	**Developed**	**Bare**	**Upland Forest**	**Total**	**User Accuracy**
Modified NNC Classification	**Water**	**7**	0	0	0	0	0	0	1	0	8	0.88
	Upland Herbaceous	0	**21**	1	0	0	3	1	0	2	28	0.75
	Riparian Shrub	0	0	**1**	0	0	0	0	0	0	1	1.00
	Riparian Herbaceous	0	1	1	**2**	0	0	0	0	0	4	0.50
	Irrigated Agriculture	0	3	1	1	**1**	1	0	0	0	7	0.14
	Riparian Forest	0	0	1	1	0	**3**	0	0	0	5	0.60
	Developed	0	1	2	0	3	0	**13**	1	0	20	0.65
	Bare	0	0	0	0	0	0	0	**3**	0	3	1.00
	Upland Forest	0	2	0	0	0	1	0	0	**0**	3	0.00
	Total	7	28	7	4	4	8	14	5	2	**79**	0.00
	Producer Accuracy	1.00	0.75	0.14	0.50	0.25	0.38	0.93	0.60	0.00	0.00	0.65

Table 2-7. *Land cover classification of the study area.*

Land Cover	Percent of Study Area	Area (square km)
Riparian Herbaceous	5.31	18.22
Riparian Forest	3.78	12.98
Riparian Shrub	1.36	4.65
Bare	2.12	7.26
Water	7.89	27.08
Upland Herbaceous	36.92	126.70
Upland Forest	5.72	19.61
Irrigated Agriculture	15.95	54.72
Developed	20.96	71.93

We have selected four Boulder County Open Space Properties: Gage, Pella Crossing, Western Mobile, and Walker Ranch, to use as examples of the output of our analysis. These properties represent the variety of elevation and riparian habitats that PMJM are known to inhabit.

Gage Open Space

The land cover classification indicates that irrigated agriculture and upland herbaceous cover types are the most common within Gage Open Space (Table 2-8). The classification (Figure 2-3) detects the variability within the open space but, when compared to the imagery (Figure 2-4), misclassifies some of the riparian herbaceous vegetation as irrigated agriculture due to the similarity in the spectral signatures. For example, in the northeast corner of the property, one can see several pixels classified as irrigated agriculture interspersed with the riparian vegetation.

Table 2-8. *Land cover classification of Gage Open Space.*

Land Cover	Percent of Open Space	Area (hectare)
Riparian Herbaceous	3.42	3.74
Riparian Forest	3.63	3.97
Riparian Shrub	0.53	0.58
Bare	0.24	0.26
Water	0.90	0.99
Upland Herbaceous	22.91	25.07
Irrigated Agriculture	67.46	73.83
Developed	0.91	1

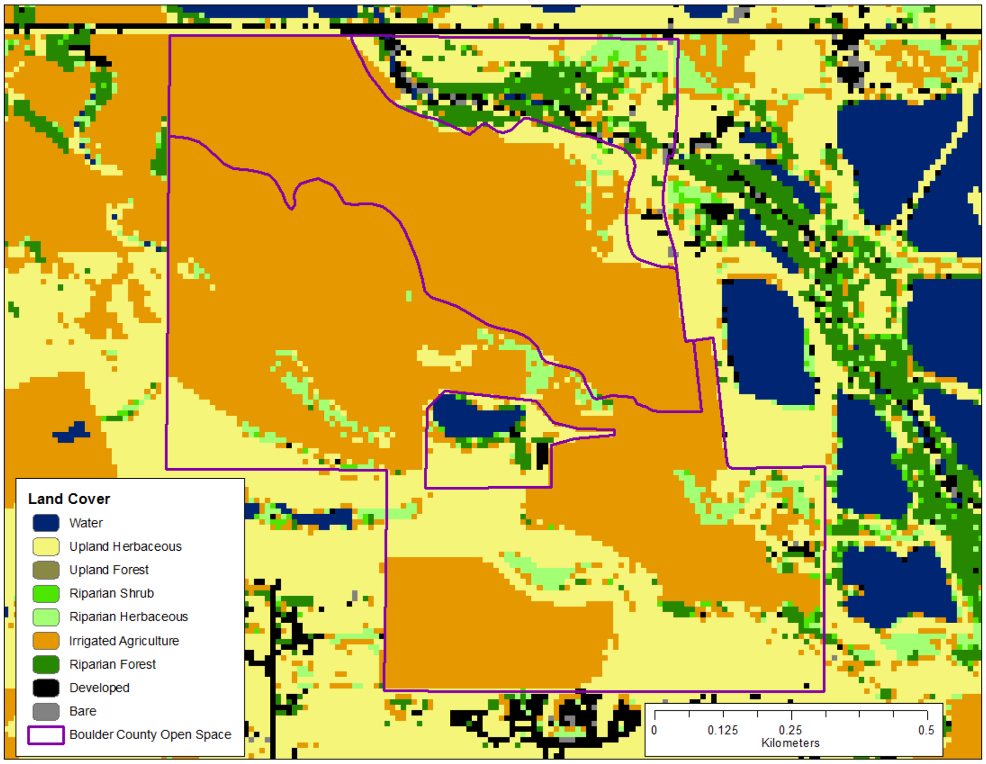

Figure 2-3. *Land cover classification of Gage Open Space (Boulder County, 2017a)*

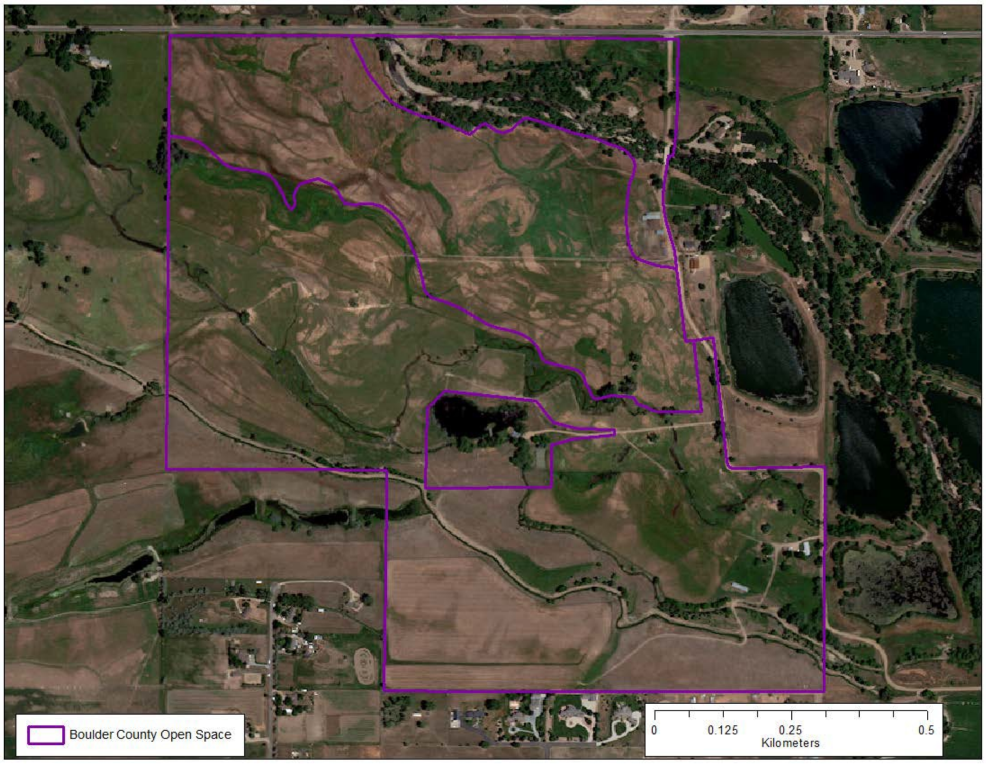

Figure 2-4. *WorldView 2 satellite imagery of Gage Space (Boulder County, 2017a)*

Pella Crossing Open Space

The land cover classification indicates that water, upland herbaceous, and riparian forest cover types are the most common within Pella Crossing Open Space (Table 2-9). The classification (Figure 2-5) detects the variability and land cover types within the open space to a high degree of accuracy when compared to the imagery (Figure 2-6), correctly identifying riparian vegetation, upland vegetation, and developed areas.

Table 2-9. *Land cover classification of Pella Crossing Open Space.*

Land Cover	Percent of Open Space	Area (hectare)
Riparian Herbaceous	4.37	3.43
Riparian Forest	13.07	10.25
Riparian Shrub	1.52	1.19
Bare	0.29	0.23
Water	54.40	42.66
Upland Herbaceous	17.85	14
Irrigated Agriculture	4.03	3.16
Developed	4.46	3.5

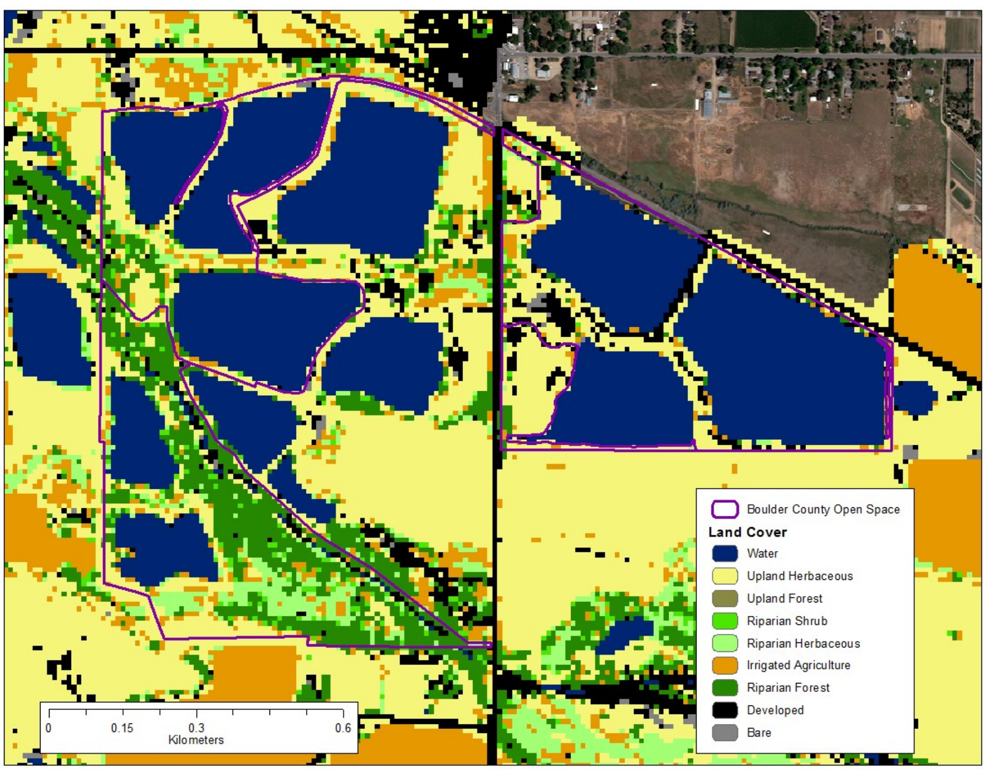

Figure 2-5. *Land cover classification of Pella Crossing Open Space (Boulder County, 2017a).*

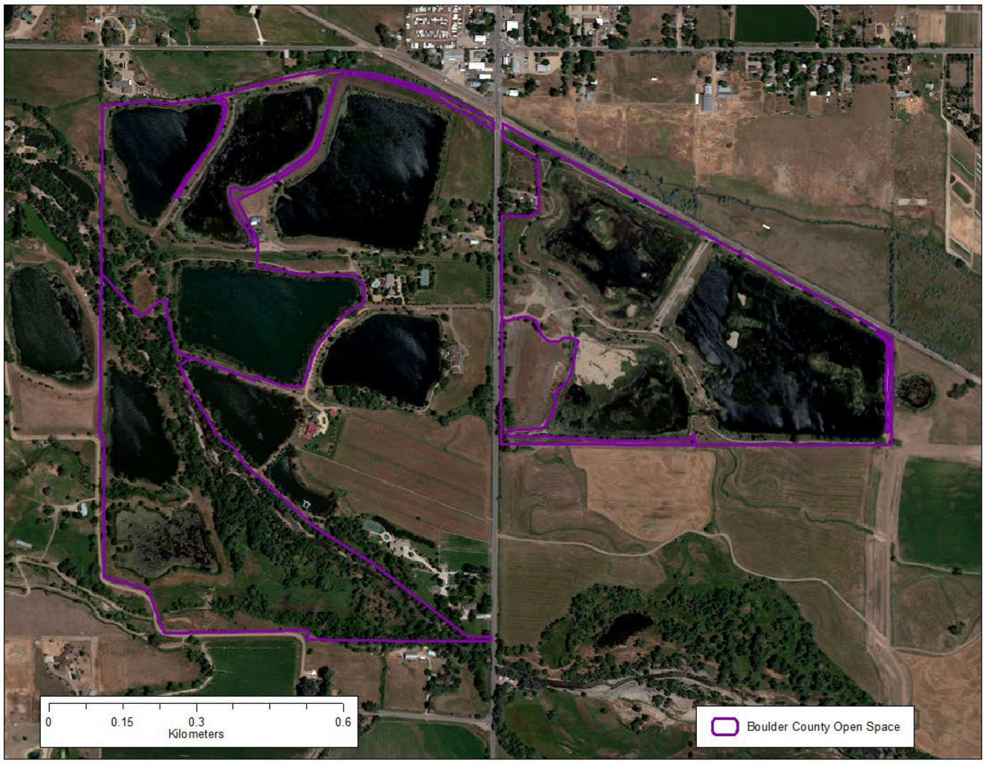

Figure 2-6. *WorldView 2 satellite imagery of Pella Crossing Open Space (Boulder County, 2017a).*

Western Mobile Complex

The land cover classification indicates that irrigated agriculture, upland herbaceous, and water cover types are the most common within the Western Mobile Complex (Table 2-10). Of the four sample open spaces, the Western Mobile Complex had the highest amount of developed land, as it is actively used for mining operations. The classification (Figure 2-7) detects the variability and land cover types within the open space but, as with the Gage Open Space, has difficulties separating irrigated agriculture from riparian herbaceous vegetation and naturally bare surfaces with developed areas (Figure 2-8). The confusion between developed and bare land cover classes can be seen in the northwest corner of the map and the confusion between irrigated agriculture from riparian herbaceous vegetation is evident through the center of the map, where irrigated agriculture pixels and present within the riparian pixels.

Table 2-10. *Land cover classification of Western Mobile Complex.*

Land Cover	Percent of Open Space	Area (hectare)
Riparian Herbaceous	6.01	14.55
Riparian Forest	5.68	13.75
Riparian Shrub	1.53	3.7
Bare	3.40	8.23
Water	13.50	32.68
Upland Herbaceous	13.93	33.74
Irrigated Agriculture	50.82	123.04
Developed	5.14	12.44

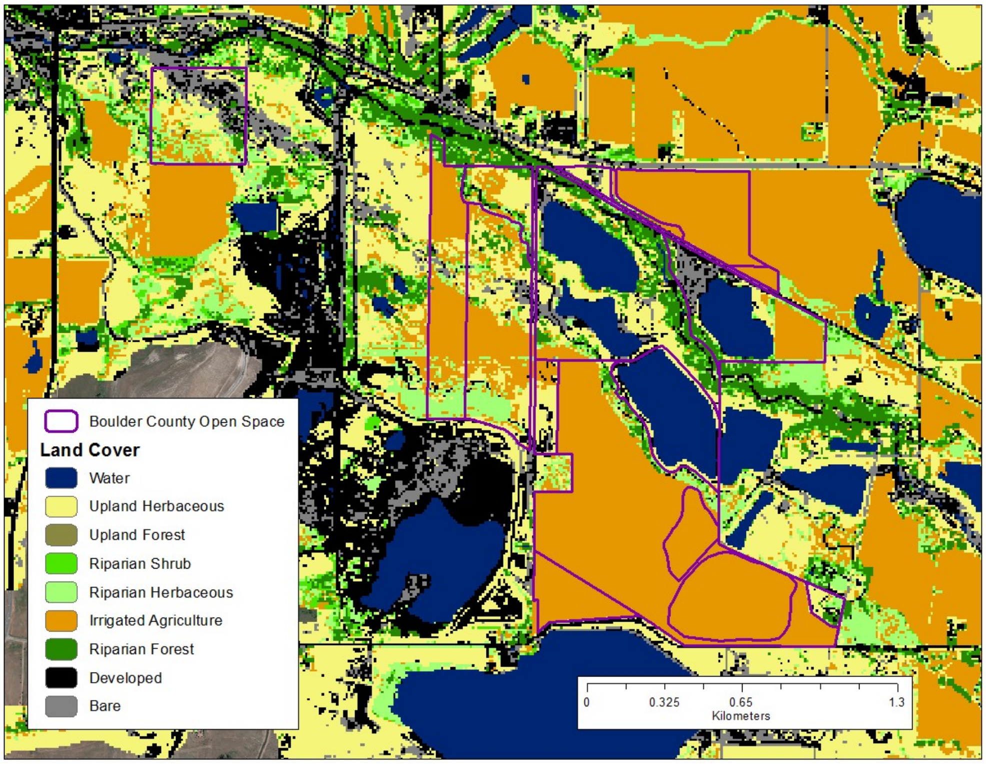

Figure 2-7. *Land cover classification of Western Mobile Complex (Boulder County, 2017a).*

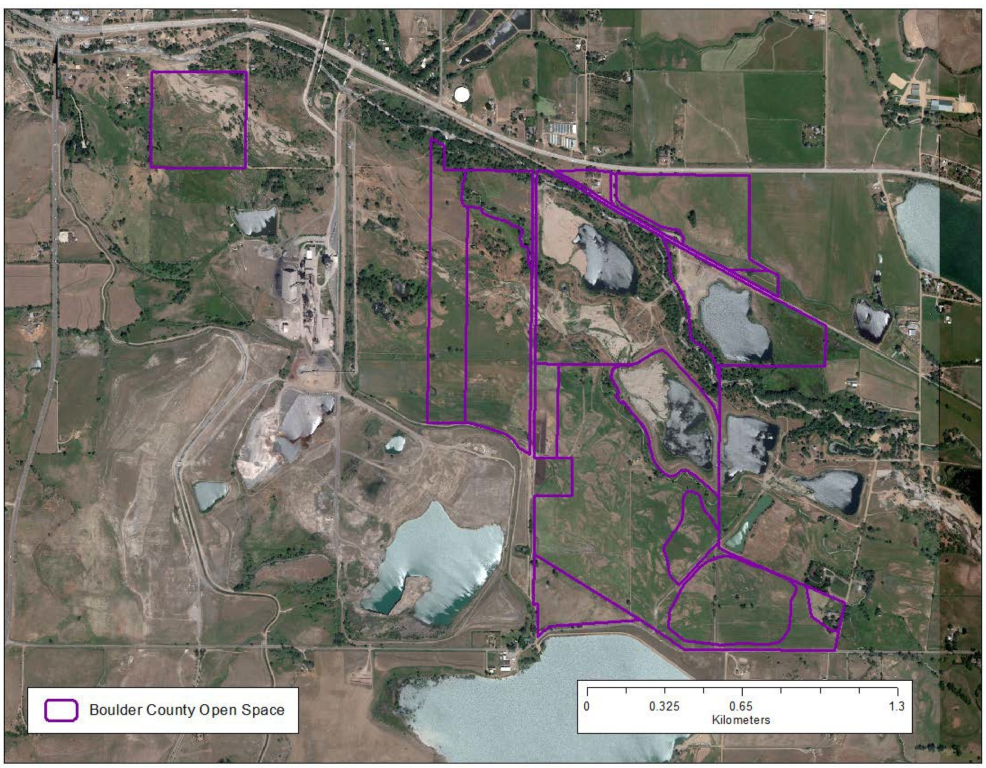

Figure 2-8. *WorldView 2 satellite imagery of Western Mobile Complex (Boulder County, 2017a).*

Walker Ranch Open Space

The riparian ecosystems in the foothills differ from the plains in that they are constricted to narrow valley bottoms due to the steep terrain. The land cover classification indicates that within the Walker Ranch Open Space upland herbaceous and upland forest cover types dominate the study area (Table 2-11). The classification (Figure 2-9) detects the variability and land cover types within the open space well but, confuses some locations of bare land with developed land (Figure 2-10).

Table 2-11. *Land cover classification of the study area within Walker Ranch Open Space.*

Land Cover	Percent of Open Space	Area (hectare)
Riparian Herbaceous	3.09	6.08
Riparian Forest	5.50	10.82
Riparian Shrub	3.09	6.08
Water	1.72	3.38
Upland Herbaceous	70.79	139.15
Upland Forest	13.00	25.55
Developed	2.81	5.52

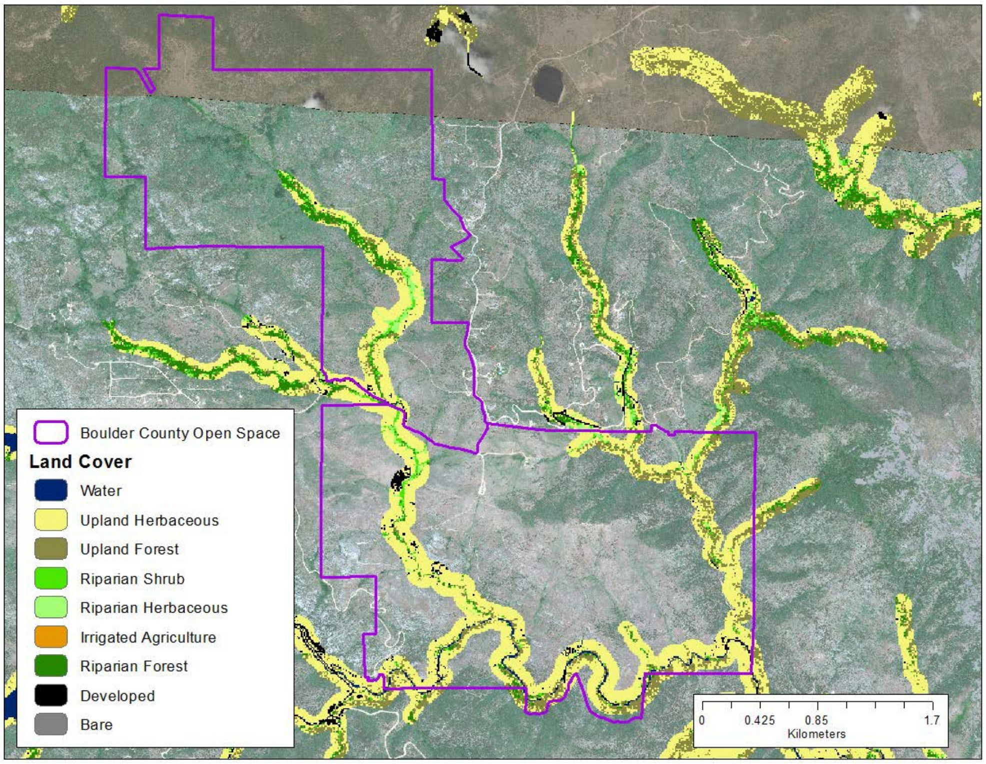

Figure 2-9. *Land cover classification of Walker Ranch Open Space (Boulder County, 2017a).*

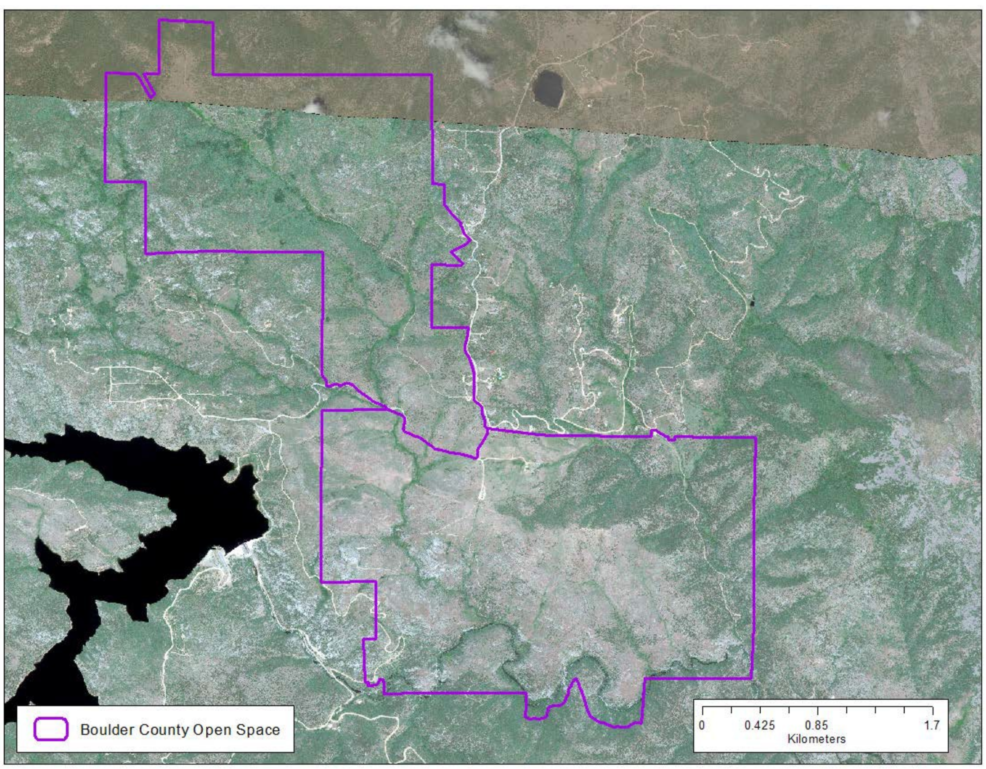

Figure 2-10. *WorldView 2 satellite imagery of Walker Ranch Open Space (Boulder County, 2017a).*

Discussion

Within the study area, we found that the modified NNC method produced better results (Table 2-5) than the proposed random forest classification technique. Although the accuracy was lower than expected, the classification captured the land cover and the variation in land cover within the study area moderately well and had higher accuracy than existing land cover classifications which have been used for PMJM research. Previous research conducted to classify PMJM habitat relationships (Clippinger 2002) used the National Land Cover Dataset (NLCD). We determined that within the study area, the most recent NLCD (Fry et al., 2011) has an overall accuracy of 0.46 and a kappa coefficient of 0.37.

The accuracy of many riparian mapping techniques tends to be relatively low (Salo et al. 2016) as these ecosystems cover small portions (1-10%) of the landscape, making it difficult to distinguish them from upland vegetation. For example, research conducted in the Big Thompson Watershed (Salo et al. 2016) compared a variety of different riparian mapping algorithms and found that the average kappa coefficient for each method ranged from 0.13 – 0.38 and the ability to identify riparian vegetation had an accuracy that ranged from 0.14 – 0.33. Another project that mapped riparian zones in the Southern Rockies Ecoregion (Salo and Theobald 2006) reported a kappa coefficient of 0.37 and accuracy of identifying riparian ecosystems of 0.53.

The land cover classification that we produced is an improvement upon previous attempts to map riparian vegetation in or near the study area. The kappa coefficient of the modified NNC classification was 0.56, a measure indicating moderate agreement with the testing data (Ndehedehe et al. 2013) and signifying that our model performs better than a random model would, and the accuracy was 0.65, a large improvement over previous land cover classifications. Although efforts were made to address the following limitations, issues remain. Three specific limitations of this dataset are: (1) the difficultly to map riparian shrubs. Riparian shrubs compose a very small portion of the study area (1.3%), making it difficult to map this land cover type with high accuracy. (2) The confusion between riparian vegetation and areas that are irrigated, either for agriculture or for residential and commercial lawns within developed areas. (3) As with any geospatial data product, errors exist when representing the real world. Managers must be aware that at any given pixel, this data set has a 35% chance of classifying the land cover type incorrectly. Likewise, at any specific location within the study area, errors may be noted, and site specific research would be necessary before making management decisions. As managers use this data set, they will need to rely on their own knowledge of site specific conditions and location of riparian vegetation.

Conclusion

We have produced a landscape level classification of land cover within the study area at a scale (10 m) that can be used to inform management decisions related to PMJM, riparian vegetation, and BCPOS properties. We have mapped the location of riparian vegetation and other land cover types known to be negatively associated PMJM occurrence or to have negative impacts on riparian ecosystems and preferred PMJM habitat. Resource managers can use the land cover classification for a variety of purposes, including understanding the spatial configuration of land cover within the study area and identifying areas of intact riparian vegetation or potential locations for restoration. In the following chapters, we demonstrate several management applications of the land cover classification by using it to develop a PMJM species distribution model, model connectivity between high quality habitat patches and, develop a framework for identifying restoration sites depending on management decisions.

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CHAPTER 3. A COMPARISON OF REMOTE SENSING METHODS FOR ASSESSING RIPARIAN VEGETATION STRUCTURE

Introduction

Many metrics have been developed for assessing structure, in part due to the varied goals of researchers and the diversity of vegetation types. A study assessing fuel loading for wildfire risk assessment will often focus on different aspects of structure than a model developed to assess avian wildlife habitat. Some of the most common metrics include vegetation height, stem diameter distribution, foliage density, and stand volume, but other approaches emphasizing structural complexity and diversity have also been developed (Munks et al. 1996, McElhinny et al. 2005, Lunney and Ashby 1987).

Canopy structure describes the three-dimensional distribution of leaves, branches, tree trunks and other vegetation elements (Pan et al. 2013). Vegetation canopy structure is a critical factor affecting many important ecological processes and functions such as wildlife habitat (Lunney and Ashby 1987, Spies et al. 1990, Ishii et al. 2004, Bergen et al. 2009). Structure is an especially important characteristic of riparian areas, helping to buffer stream temperatures important to aquatic organisms and providing habitat features essential for many riparian-dependent species (Knopf and Samson 1994, Shaw and Bible 1996, Lyons et al. 2000).

The accuracy, precision, spatial extent, and cost of methods for measuring structure vary widely (Chason et al. 1991, Battles et al. 1996, Frazer et al. 2001, Korhonen et al. 2006). Historically, canopy structure has been assessed manually in the field, but such sampling is time-intensive and captures a relatively small sampling area, reducing the utility of data in heterogeneous environments (Hyyppä et al. 2000, McElhinny et al. 2005, Korhonen et al. 2006, Haara and Leskinen 2009). Alternative approaches based on remote sensing are increasingly used in structure analyses often offering greater data quality and allowing for analyses at scales not possible using traditional field methods (Hyyppa et al. 1997, Næsset 2002).

Of particular value are methods based on light detection and ranging (LiDAR) technology, an active remote sensing technology that uses laser pulses to measure distance and create 3-dimensional point clouds (Lefsky et al. 1999, Means et al. 1999, Lefsky et al. 2002a, Lefsky et al. 2002b, Straatsma and Middelkoop 2006, Dassot et al. 2011). LiDAR data have been used to retrieve canopy structure variables such as canopy height, fractional cover, and leaf area index (LAI)(Morsdorf et al. 2004, Morsdorf et al. 2006, Solberg et al. 2006, Solberg et al. 2009, Abegg et al. 2017). LiDAR data can be from aircraft (airborne laser scanning, ALS) or on the ground (terrestrial laser scanning, TLS)(Lim and Treitz 2004, Watt and Donoghue 2005).

Structure from motion (SfM) algorithms use geometric relationships between features in overlapping sets of images, commonly acquired using small unmanned aerial systems (UAS) to produce three-dimensional point clouds that, for some applications, can match the accuracy of LiDAR sensors at a lower cost (Turner et al. 2012, Westoby et al. 2012, Mathews and Jensen 2013, Morgenroth and Gomez 2014, Pajares 2015, Cruzan et al. 2016). Point clouds from SfM analyses can be analyzed in similar ways to data from laser scanning, for example, to create digital surface models (DSM) for characterizing the vertical structure of forests. The low cost and flexibility of UAV data acquisition make it an attractive option for future riparian monitoring (Fonstad et al. 2013). However, unlike active remote sensing technologies (e.g., LiDAR) that can penetrate dense canopies, SfM relies exclusively on information visible in standard photographs, so it may less accurately characterize understory habitat structure (Chasmer et al. 2006, Ruggles et al. 2016). More research is needed to understand the limitations of this technology in relation to field methods or other remote sensing techniques.

Objectives

Our goal in this study was to compare three complimentary remote sensing approaches for estimating riparian vegetation structure, terrestrial laser scanning (TLS), airborne LiDAR (ALS), and structure from motion (SfM), and to develop recommendations for the best use of each approach for PMJM habitat management and monitoring. The aim is not to provide a landscape scale assessment of structure–this is presented in Chapters 4 and 5–but to provide information that can be used by managers in selecting methods for future monitoring. Our specific objectives included the following:

- Compare the accuracy and precision of ALS, TLS and SfM methods
- Evaluate the strengths and limitations of these methods for assessing riparian structure and develop recommendations for their use in monitoring

Methods

Overview

Select BCPOS properties on St. Vrain, Coal Creek, and South Boulder Creek were chosen for UAV image acquisition and TLS scanning. Using airborne LiDAR data sets and PMJM occurrence data for reference, areas representing a range of riparian structural characteristics were selected for sampling. The specific workflow differed between the ALS, TLS, and SfM datasets, but the product of each was the same: a three-dimensional point cloud layer represented as a *.las file (Figure 3-1).

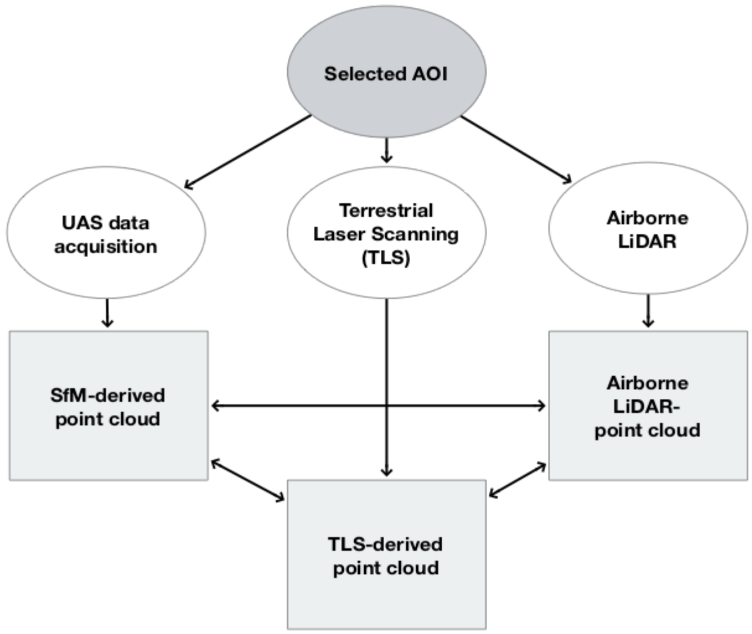

Figure 3-1. Flow chart illustrating primary steps in analysis. Although differing in preprocessing steps, the output of each is a three-dimensional point cloud.

TLS data acquisition and processing

At each scanning site, a Faro Focus 3D 120 terrestrial laser scanner was mounted on a tripod and used to collect a 43.7 Mpts scan (4x quality, ¼ resolution, horizon weighted metering, clear sky and clear contour settings). The density of scan points decreases exponentially with distance from the scanner, degrading the quality of the three-dimensional model, so only points within 100 m^2 of the scanner were utilized in comparisons. Basic composition was sampled using plots centered on the TLS scan locations and a survey-grade GPS was used to capture the coordinates of TLS scan locations to enable comparisons with ALS and SfM data. Raw scans were processed using CloudCompare (http://www.cloudcompare.org) software before export to LASTools (https://rapidlasso.com/lastools/) for further processing of point cloud derivatives (Figure 3-2).

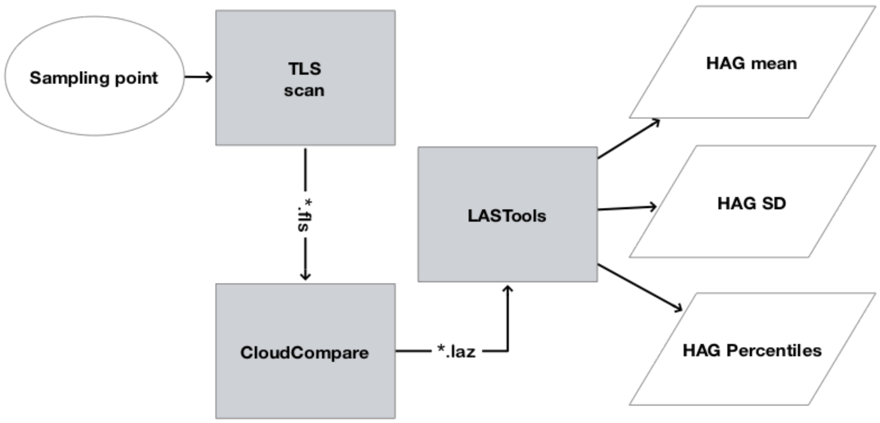

Figure 3-2. Flow chart illustrating software workflow used to convert TLS scans into raster derivatives.

ALS data processing

We used discrete airborne LiDAR collected in October and November of 2013 and distributed by the USGS 3DEP program (https://nationalmap.gov/3DEP/) in this analysis. Raw point cloud data were extracted from 100m^2 circular plots centered on the locations where TLS had been acquired (Figure 3-3). After height normalizing point clouds, functions in the lidR package in R (R Core Team 2017) were used to calculate metrics for comparison including the height above ground (HAG) mean, max, standard deviation, total return count, and different HAG percentiles.

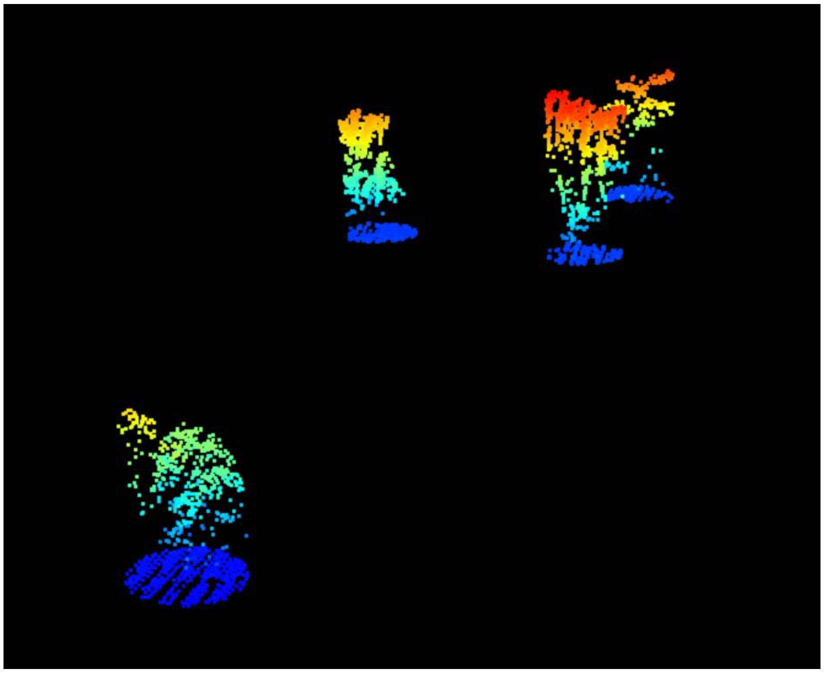

Figure 3-3. Extracted ALS height above ground point clouds extracted for 100 m^2 polygons coincident with TLS scans.

SfM data acquisition and processing

We used an Inspire 2 small UAV (DJI, Inc.) to acquire imagery used in SfM analyses. Three separate BCPOS properties were selected to represent a range of stream and riparian habitat characteristics: Walker Ranch, North Pointe, and Pella Crossing. Prior to flight, ground control points were placed into the scene and surveyed using an Emlid Reach RTK GPS unit. To ensure sufficient overlap in images to allow for SfM modeling, the UAS was flown in a double grid pattern (Figure 3-4). Flights occurred at an elevation of approximately 45 m, yielding imagery with a nominal resolution of ~1.3 cm. Images collected during flights were processed in Pix4D to produce DSM models and orthoimagery.

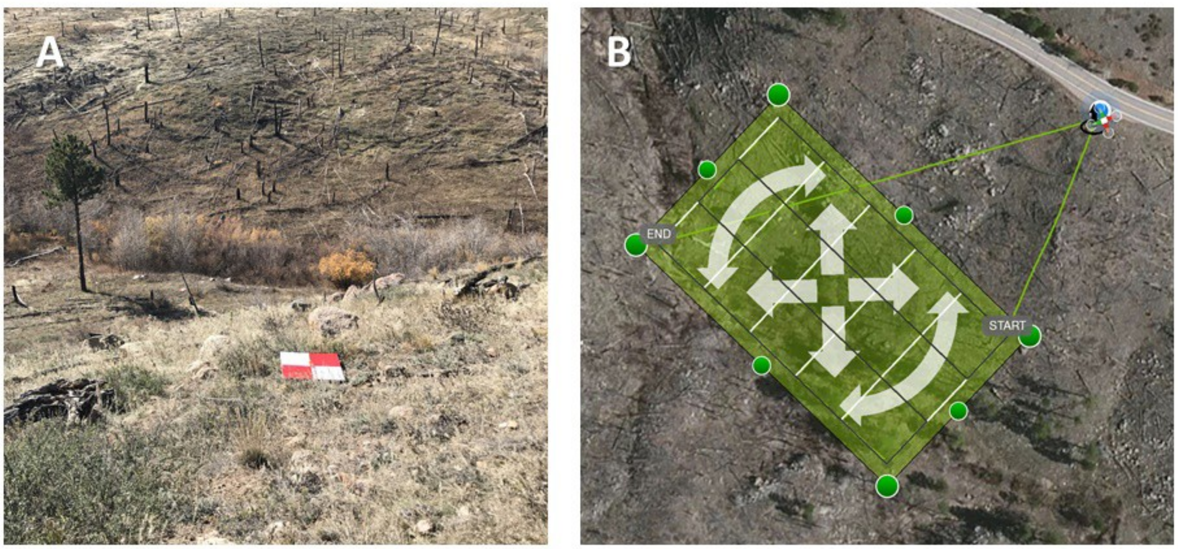

Figure 3-4. Example of ground control point (panel A) and UAV flight plan (panel B) used for data acquisition at Walker Ranch OS. To facilitate structure from motion analyses, the flight plan used two sets of intersecting flight lines to create a large image set with high overlap.

Data from the three methods were then run through functions in R to calculate metrics such as the height above ground (HAG) mean, max, standard deviation, and different HAG percentiles. Differences in these variables were the basis for comparison among the three different methods evaluated in the study. For example, the maximum HAG and 99^{th} HAG percentile provided a means of comparing estimates of canopy height, while metrics, such as the HAG standard deviation were helpful for comparing variation in the vertical distribution of points between different methods.

Results

A total of 52 locations were scanned and processed using the TLS unit. Scans included a wide range of riparian structural characteristics from simple single-layer canopies dominated by grasses and herbaceous dicots to complex multi-tiered canopies (Figure 3-5).

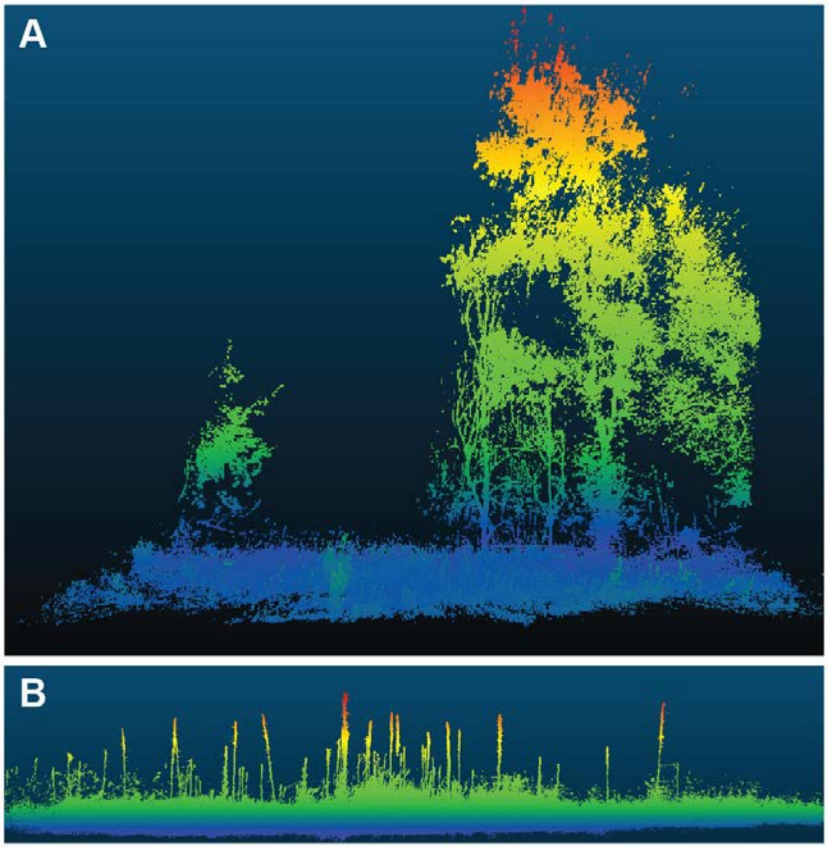

Figure 3-5. Examples of two ALS point clouds. In panel A, the vegetation supports mature cottonwoods (Populus deltoides), while in panel B, grasses and herbaceous dicots dominate (note the tall Verbascum thapsus flowering stalks). Color gradients are for display only and not comparable between panels.

Height above ground characteristics varied widely among TLS scans. For example, the 99th HAG percentile ranged from less than 5 m to over 20 m (Figure 3-6). Lower HAG percentiles had a more compressed range, with the max of all scans less than 5 m for all percentiles below the 75th.

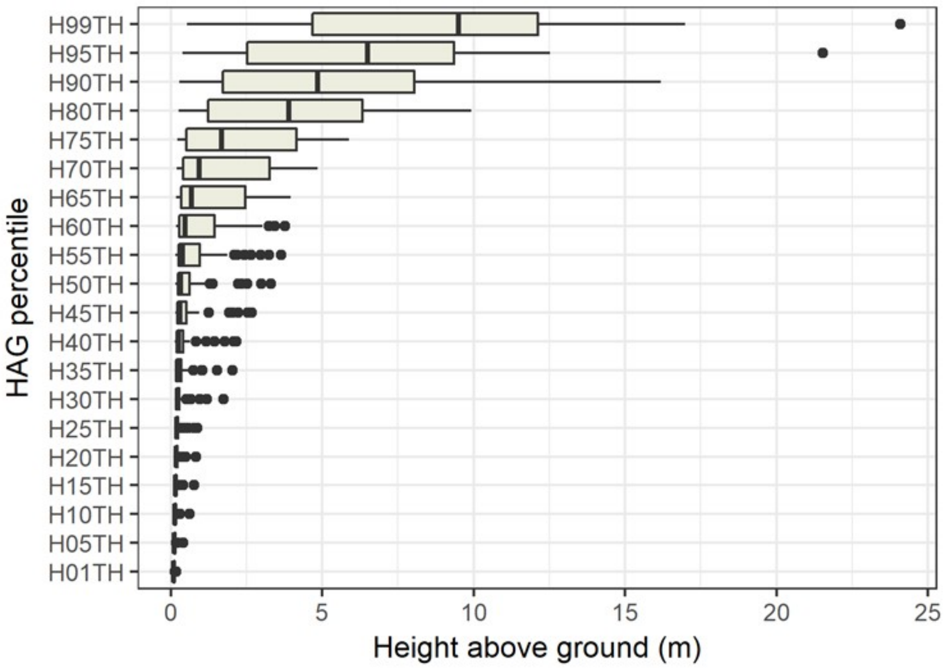

Figure 3-6. Boxplots of different height above ground percentiles for TLS scans.

Point clouds from different scanning methods exhibited different point distributions. For example, the mean HAG of TLS points was lower than that of the ALS point clouds. A greater percentage of returns occurred below the mean HAG for a given scan for the TLS data, reflecting the position of the sensor under the canopy versus above for the ALS data (Figure 3-7).

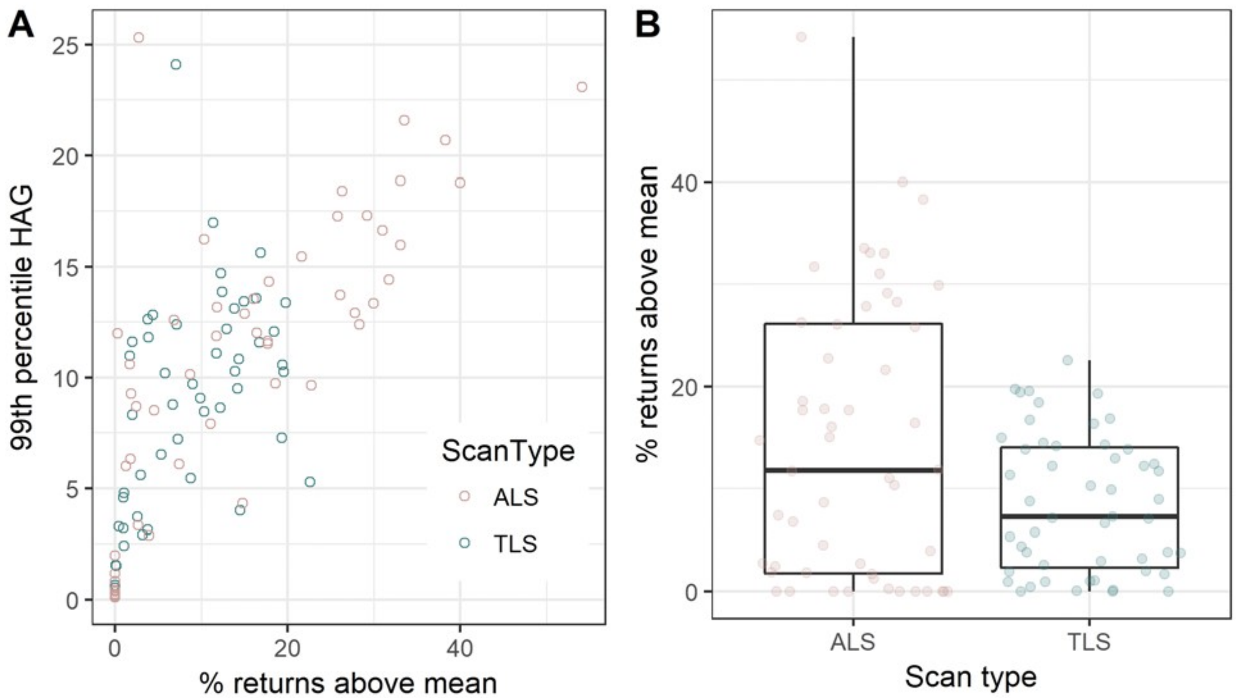

Figure 3-7. Scatterplot comparing the 99th percentile HAG and the percent of returns above the mean scan height (panel A); boxplots of the percent of returns above the mean for ALS and TLS datasets (panel B).

Imagery from UAS collections were of high quality due to the low ground surface distance (~1.3 cm). However, the quality of SfM point clouds were variable. Under leaf on conditions, algorithms fairly effectively captured the uppermost canopy (Figure 3-8), but occlusion limited information for the understory. Under leaf-off conditions (Figure 3-9), algorithms were unable to consistently find sufficient tie points between images to create usable canopy models.

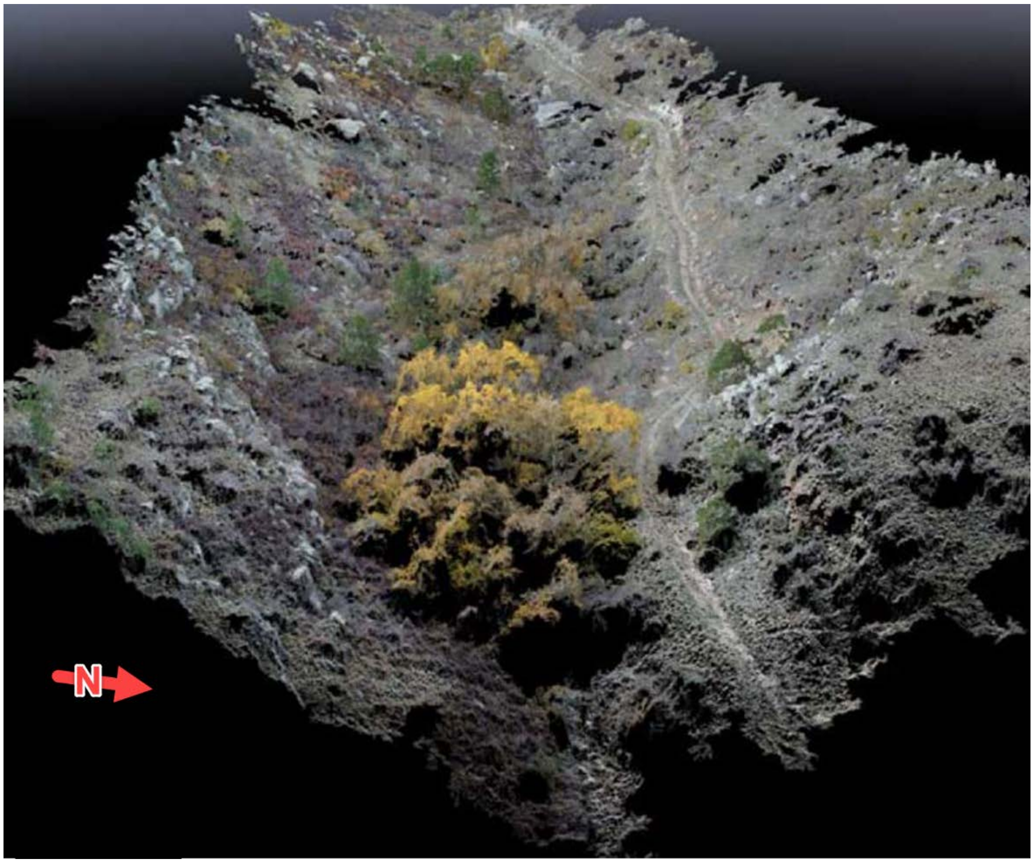

Figure 3-8. Three-dimensional model of the Northpointe Open Space study area.

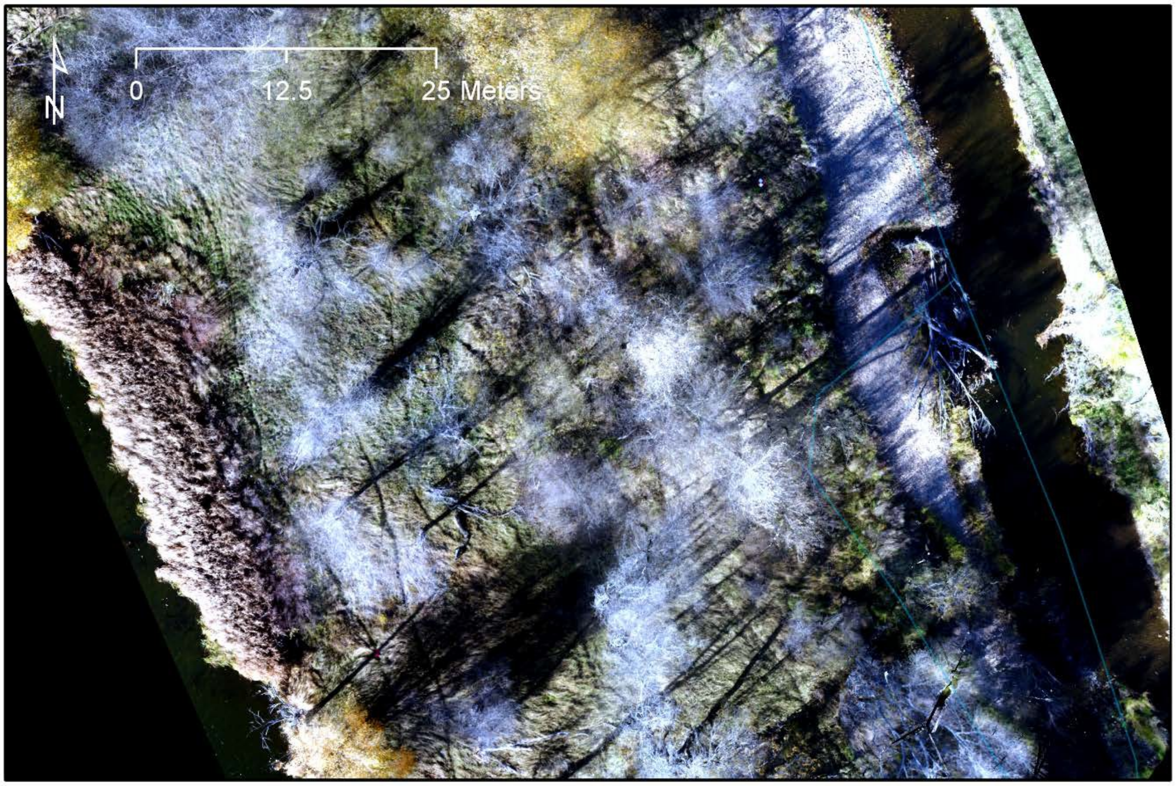

Figure 3-9. Orthophoto generated using imagery collected by UAS, Pella Crossing Open Space.

Discussion

Each of the techniques compared in this study have strengths and weakness for quantifying three-dimensional vegetation structure. As with all measurement approaches, the most important factor to consider when comparing options is the end goal. There are unavoidable trade-offs between accuracy, precision, cost, and efficiency that must be evaluated in light of the objectives. There is no single best method for assessing structure, rather a set of approaches that alone or in combination can best address the question under consideration.

TLS scans have the highest overall accuracy and can be considered the "gold standard" as far as accuracy and overall information density. TLS scanning produces a dense point cloud, but this high point density can also be a liability. Data must be processed and stored, a non-trivial issue considering the size of scans (>45,000,000 points per scan, on average, in this study). TLS scans also have a relatively small footprint, so a large number of scans must be acquired to image larger areas.

Other downsides of this technology are the high cost of equipment. Laser scanners like the one used in this study cost tens of thousands of dollars, too steep a price tag for a typical land manager's equipment budget. The primary market for TLS scanners is engineers and professional land surveyors, not ecologists. While Boulder County Parks and Open Space is unlikely to have either the need or resources to justify such an expensive purchase, there may be a larger constituency at the county level (e.g., road engineers involved in infrastructure) that could partner in purchase and use of a device. As with many expensive pieces of technology (e.g., survey equipment), rental options may be available.

Airborne LiDAR is generally less accurate than TLS for the simple reason that the sensor is located at much greater distances from the target than with a terrestrial system. Discrete return LiDAR systems like that used to acquire the data for this study produce point densities on the order of 10 points per square meter. While more than sufficient to produce high-resolution digital terrain models, it may be below what is needed to effectively characterize patterns below the forest canopy and far lower than point densities produced using a TLS unit. Lidar technology is rapidly evolving, and newer technologies such as waveform LiDAR systems with better resolution than that used in this study are already in the marketplace, so any limitations due to lower point densities will be less of an issue over time (Hyde et al. 2005, Heinzel and Koch 2011, Hancock et al. 2017).

An additional consideration is whether the technical expertise necessary to process and utilize data is available in-house. For example, LiDAR processing requires specialized software. While ArcGIS supports LiDAR, its capabilities for many specialized tasks is limited. Open source software used in this study (CloudCompare, R) offer many powerful functions found in more expensive commercial software, but these have steep learning curves. Commercial software products are commonly more user-friendly, offering pushbutton solutions for common tasks, but software licensing can be expensive. As with expensive equipment, one potential solution for a large organization like Boulder County is to connect the different end users interested in LiDAR analysis across traditional departments. A model for this already exists with GIS departments, which often support different internal constituencies with varied core missions.

Structure from motion analyses in this study produced three-dimensional models of uneven quality due to several factors. Unlike active remote sensing technologies like LiDAR that can penetrate dense canopies, SfM exclusively relies on information in standard photographs. In dense canopies, the only information usable by the algorithms comes from the uppermost canopy layers, so while the algorithms may do a satisfactory job of characterizing canopy cover and height, they may have little to say about structure beneath the canopy.

Because UAS flights occurred in the Fall, images were collected under varying degrees of leaf cover. The issue of canopy occlusion limiting information on understory structure was evident in sites where trees retained their leaves. However, a different issue impedes the accuracy of SfM algorithms under leaf-off conditions. To construct three dimensional models, features must be identifiable by the algorithms in multiple overlapping images (Chasmer et al. 2006, Ruggles et al. 2016). This is relatively straightforward for simple geometric objects like stockpiles of dirt or rock faces, and SfM techniques are already widely used in fields like construction, mining, geology, and land surveying where the emphasis is often on the topography of bare ground (Hugenholtz et al. 2014, Johnson et al. 2014, Chirico and DeWitt 2017, Rauhala et al. 2017). However, plant canopies are much more complex geometrically, which can prevent algorithms from co-locating tie points in overlapping sets of images. In this study, this resulted in poor performance under leaf-off conditions. As a consequence, current SfM algorithms appear to be a poor substitute for active remote sensing technologies like LiDAR for assessing the attributes of vegetation structure important for PMJM.

Occlusion is an issue with all of the methods used in this study. With ALS measurements, this is usually caused by dense vegetation in the highest canopy layers, preventing laser pulses from reaching lower canopy layers. The issue is most pronounced when pulse densities are low. Other factors such as poor flight strip overlap can result in occlusion. In contrast to ALS, where occlusion occurs in lower canopy layers, TLS measurements are vulnerable to occlusion in the top and middle of the tree canopies (Béland et al. 2011), but with suitable scan positions and settings, the effects of occlusion can be minimized (Hilker et al. 2010).

Management implications

Monitoring is an important component of natural resources management, although the design and reliable implementation of effective long-term monitoring programs is difficult in many settings (Lindenmayer and Likens 2010). Riparian ecosystems are spatially and temporally dynamic, so monitoring frameworks must simultaneously capture the effects of discrete natural and human-caused disturbances, track long term responses to environmental stressors, and track the trajectories of ecological succession. Traditional riparian monitoring protocols have emphasized field based data collection, but monitoring programs increasingly rely on remote sensing approaches.

Comparisons of different methods in this analysis reveal both the strengths and limitations of different approaches for habitat assessment. Of the approaches discussed, ALS provides the best overall balance of scale, cost and accuracy. Per acre costs are low, but the expense of mounting a data acquisition campaign limits the temporal frequency of data updates. The other methods evaluated here can help fill gaps in time, by allowing managers to capture data in between ALS acquisitions (e.g., after a large flood disturbance). While structure from motion analysis can produce detailed 3D models, the method proved unreliable for characterizing structure of vegetation in this study. More research is needed to identify ways to improve SfM output in complex riparian areas. While the output of SfM analyses were disappointing, the flexibility and low cost of UAV data acquisition still make it an attractive option for future riparian monitoring. Because UAVs capture images closer to the target, they can achieve much higher image resolution than possible using satellites and at lower cost (Turner et al. 2012), data useful or a variety of applications.

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CHAPTER 4. ASSESSMENT OF PREBLE'S MEADOW JUMPING MOUSE HABITAT

Introduction

Riparian areas are centers of biodiversity, providing essential habitat for numerous species (Gregory et al. 1991, Naiman and Decamps 1997) and supporting up to 80% of terrestrial animals in the western US (Johnson and Mackintosh 1989). The Preble's meadow jumping mouse (PMJM), a federally threatened subspecies of the common meadow jumping mouse, is a riparian obligate considered by some as an indicator of properly functioning riparian ecosystems (Armstrong 1972, Muchlinski 1988, Smith et al. 2004). PMJM occurrences have been associated with particular compositional and structural characteristics, motivating the development of various field methods for characterizing habitat attributes (Ruggles et al. 2001, Clippinger 2002, Meaney et al. 2003, Trainor et al. 2007). However, field methods can be time-intensive and expensive, and unless data are collected as part of a rigorous statistical sampling design, results can be difficult to apply more broadly. For example, it would not be appropriate to extrapolate field data collected at BCPOS properties to the entire county based on a sampling design used for site-specific monitoring. An understanding of the broader landscape context and habitat attributes of PMJM occurrences outside of BCPOS properties is important to the overall management of the species.

Remote sensing data provide a broad synoptic view of the structure and composition of landscapes complimenting field data and providing critical landscape context (Turner et al. 2003, Gillespie et al. 2008). Advances in remote sensing data and processing tools allow for analyses at both fine spatial scales and broad extents. Airborne LiDAR and high-resolution multispectral imagery have been successfully used to classify and map riparian areas and characterize structural attributes such as canopy cover, density or height (Goetz 2006, Johansen et al. 2010, Antonarakis 2011) applicable to managing a wide range of resources. Given the importance of riparian structure in PMJM habitat descriptions, structure information from remote sensing data can provide understanding of habitat distribution and support analyses of habitat connectivity.

Species distribution models can be developed using data from LiDAR, imagery and other explanatory variables to predict habitat across landscapes (Bradley and Fleishman 2008, Jones et al. 2010, Farrell et al. 2013). Various algorithms have been developed (Breiman 2001, Anderson et al. 2006, Phillips et al. 2006, Elith et al. 2008, Wiens et al. 2009, Zimmermann et al. 2010) and current software tools enable the fitting and comparison of multiple models and selection of the best for prediction (Naimi and Araujo 2016). Applied to PMJM, SDMs can facilitate management by identifying variation in habitat quality and as input to analyses of habitat connectivity analysis.

Habitat fragmentation and loss is a serious issue for many riparian obligates. Waterways are developed for agriculture, transportation, and resource extraction, reducing and fragmenting the remaining habitat. The major threats to PMJM habitat are habitat loss and degradation from cattle grazing and other agriculture activities, residential, industrial and commercial development, and alteration of natural hydrologic regimes (USFWS 2003). Natural hazards, such as major flooding, can put pressure on an already stressed ecosystem and further reduce the amount of habitat available (Li et al. 2010). Given the large amount of human modification and dynamic nature of riparian ecosystems in Boulder County, understanding the fragmentation of habitat and the remaining connectivity between known populations of PMJM and high quality habitat is important for the conservation of the species.

Many GIS tools exist to analyze landscape connectivity and identify locations that may be barriers to movement along corridors. Three common methods include: least cost path analysis, a method that assumes organisms are likely to take the path of least resistance when moving between two locations (Pinto and Keitt 2009); graph theory which represents the landscape as a series of nodes that represent patches and edges that connect each cell center to its nearest neighbors (Pinto and Keitt 2009); and models based on electrical circuit theory that allow for the analysis of multiple dispersal pathways (McRae et al. 2008). Of these, least cost corridor analysis is the most commonly applied connectivity planning tool (McRea et al. 2012).

Least cost analysis uses GIS to identify the route with the lowest cumulative travel cost for a species based on core habitat locations and a preset combination of relevant environmental variables referred to as a resistance layer. Resistance layers often include land cover type, roads, hydrologic features, and landscape features such as slope (Li et al. 2010) that impact movement of the target species. Multiple methods have been used to identify core habitat for target species: identifying suitable, continuous habitat of a specific mapping unit (Barrows et al. 2011); defining the habitat based on the density of observed species (Kenward et al. 2001); and relying on expert opinion of suitable/known habitat patches (LaRue and Nielson 2008). To calculate the least costly travel corridors, least cost analysis calculates the cost-weighted distance (CWD) of all pixels to a source location (core habitat) based on the resistance layer. The analysis adds together the CWD for two adjacent locations and develops the least path corridors based on the lowest values from the addition.

The output of least cost path analysis is a geospatial file in a line format that displays the least costly path between adjacent habitat patches. It can inform management decisions and provide information that has the potential to preserve effective population size, maintain gene flow, and facilitate migration, dispersal, and recolonization of flood impacted areas or restored riparian zones. Additionally, results from connectivity analyses can guide managers in investing conservation practices that maintain or increase the connectivity between habitat patches. To identify barriers, or areas that could be a hindrance to connectivity, McRae et al. (2012) developed a moving window method that can be used to identify restrictions and potential barriers to connectivity between patches. Using the CWD surface developed from the habitat patches and resistance layer during the least cost path analysis, this method calculates the minimum CWD within a specified distance of each habitat patch to estimate the least cost distance if areas with higher resistance were restored, resulting in new least cost path after barrier removal. The least cost distance with barriers removed is then compared to the original least cost distance, if the barrier removal least cost distance is less than the original least cost distance value, restoring the area within the specified distance would increase connectivity between the two patches.

A second tool, Pinch Point Mapper, developed by McRea et al. (2012) assists in detecting pinch points, or areas that have the potential to constrain movement in wildlife habitat corridors. Pinchpoint Mapper uses Circuitscape, a software that relies on electric circuit theory, to identify areas of constricted "flow" within the corridors identified using Linkage Mapper. This tool helps identify least cost paths that are constricted due to unfavorable habitat such as reservoirs, development, or roads or where alternative pathways are not available, such as narrow riparian habitat constrained by agricultural activity (Dutta et al. 2016). The results of the Pinchpoint Mapper can identify where further loss of habitat could threaten connectivity. Although our focus species, PMJM, may only need narrow corridors for movement, impingement upon these corridors by other land use can reduce habitat availability and connectivity.

Objectives

In this chapter, we used species distribution models and least cost paths analysis to model PMJM habitat quality and connectivity across Boulder County riparian areas. Our specific objectives included:

- Use structure and composition data and other explanatory variables to develop predictive habitat models for PMJM distribution
- Evaluate PMJM habitat connectivity

These analyses contribute to an improved understanding of Boulder County riparian areas, with direct applications to BCPOS. Workflows and derived data sets provide a template for future analyses using updated remote sensing data. Predictive models provide insights into landscape-scale habitat variability useful for PMJM management and monitoring. The geospatial produced from analyses can be used to bridge field and remote sensing approaches by providing a scalable sampling frame.

Methods

Study area

In this study, we used the study area developed for the multispectral image classification (Figure 4-1; see Chapter 2 for details).

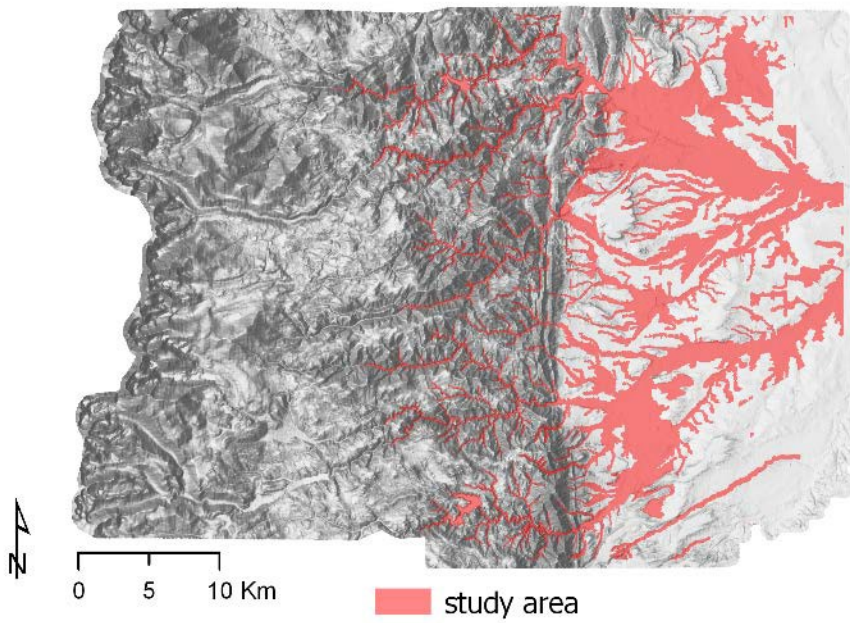

Figure 4-1. Study area used in SDM and connectivity analyses.

Species distribution modeling

To better understand patterns of PMJM habitat across the study area, we developed and compared several species distribution models (SDMs). SDMs have been widely used to analyze rare species, model invasive plants, and predict responses to climate change and a variety of algorithms have been developed (Phillips et al. 2004, Elith and Leathwick 2009, Wiens et al. 2009, Gibson et al. 2014, Sousa-Silva et al. 2014).

PMJM occurrence data collected between 1989 and 2016 (USFW 2016) and a range of explanatory rasters were processed in R for SDM modeling. Explanatory layers included variables derived from airborne LiDAR (elevation above sea level, height above ground percentiles, etc.) and the land cover classification produced from the multispectral image analysis. To isolate the influence of specific cover types in variable importance analyses, we created separate predictor rasters for shrubs, trees, and riparian herbaceous classes from the classification.

Using ALS-derived bare earth elevations, we calculated the Topographic Wetness Index (TWI) and Topographic Position Index (TPI) (Table 4-1). TWI is a topographically-defined index intended to indicate relative saturation across a basin and it has been used in a variety of ecological analyses (Beven and Kirkby 1979, Moeslund et al. 2013), with higher TWI values representing drainages and lower values topographic crests and ridges. TPI provides an indication of landform position by comparing the elevation of raster cells to the local mean elevation of a moving window, with high positive TPI values represent higher areas of the landscape, negative values represent locations in valleys, and values near zero represent flat areas or areas of constant slope (De Reu et al. 2013; Jenness et al. 2013; Weiss 2001). TPI and TWI may be useful to predicting habitat because these indices provide simple synthetic proxies of landscape physiography and landform, factors known to influence vegetation important to PMJM. Lastly, we created a distance to stream layer (EucDist) in ArcGIS using the Euclidean

Distance function and the Boulder County streams dataset. Because PMJM is a riparian obligate species, distance to streams is likely a useful variable in modeling occurrences, since areas with similar vegetation structure to riparian areas not associated with streams (e.g., some irrigated urban landscaping) are not likely to support PMJM.

Table 4-1. Explanatory variables used in species distribution modeling. All the variables listed were included in the full model specification; the reduced model specification dropped the Euclidean distance to streams layer. Variables were selected based on professional judgement to represent a variety of structural attributes including measures of canopy height (e.g., HAG percentiles), variability (e.g., HAG standard deviation), and horizontal structure (e.g., land cover classes). While other variables have been defined in the PMJM literature, if they couldn't be represented as a continuous raster surface throughout the modeling domain, they couldn't be included.

Variable	**Description**	**Source**
HAG_STD	HAG standard deviation	ALS
HAG_max	HAG max	ALS
HAG_mean	HAG mean	ALS
HAG_p90	HAG 90th percentile	ALS
HAG_p50	HAG 50th percentile	ALS
HAG_p10	HAG 10th percentile	ALS
Elev10m	Elevation ASL (m)	ALS
TPI	Topographic position index	ALS
TWI	Topographic wetness index	ALS
Classification	Multispectral/ALS classification	Multispectral imagery and ALS
mask.forest	Forest mask	Derived from classification
mask.shrub	Shrub mask	Derived from classification
mask.ripHerb	Riparian herb mask	Derived from classification
EucDistStr	Euclidean distance to stream (m)	ALS bare earth elevation and streams

We used the SDM package (Naimi and Araújo 2016) in R to produce three types of SDMs. Support vector machines (SVM), boosted regression trees (BRT) and random forests (RF) models were fit using confirmed occurrence data and 2000 randomly-generated background points generated across the study area (Breiman 2001, Elith et al. 2008). SVM is a pattern recognition algorithm used to analyze a variety of complex data sets and in remote sensing analysis and modeling (Noble 2006, Fukuda et al. 2013). BRT is a machine learning algorithm used in classification and regression tasks that fits numerous classification and regression trees and using a statistical technique called boosting to combine models (Elith et al. 2008, Elith and Leathwick 2009). With boosting, decision trees models are fitted iteratively to training data, gradually emphasizing observations modeled poorly by the current collection of trees, thereby achieving higher prediction accuracy. RF is another machine learning algorithm that uses classification and regression trees, but differs from BRT in how ensembles are created (Breiman 2001). Among its diverse applications, the RF algorithm has been widely used in SDM models (Fukuda et al. 2013, Gibson et al. 2014, Gage et al. 2015).

We used a five-fold cross-validation with a 70% testing/training split to evaluate model performance. K-fold cross-validation works by splitting data into K approximately equal-sized parts (5 in this study), and then fits the models K times (Naimi and Araujo 2016). To assess the predictive performance of models, we compared threshold -dependent and independent performance measures including true positive (TP), false positive (FP), false negative (FN) and true negative (TN), true skill statistic (TSS), kappa and correctly classified instances (CCI) (Allouche et al. 2006, Fukuda et al. 2013). TSS accounts for both omission and commission errors and ranges from -1 to +1, with +1 indicating perfect agreement and values <=0 no better than expected at random (Allouche et al. 2006). The area under the receiver operating characteristic curve (AUC) was used to examine the relationship between model sensitivity and specificity and to identify thresholds used to convert continuous predictions of PMJM occurrence into presence/absence rasters for conductivity analysis (Swets 1988).

Modeling was done on two sets of predictor variables. The first—the full model—included all the variables described in Table 4-1. Because of the dominating influence of the Euclidean distance from stream predictor—unsurprising considering all occurrence data are near streamlines—a separate set of predictor variables (the reduced model) was created omitting the distance to stream layer. Although performing slightly more poorly in overall model prediction, the reduced model provided greater discrimination in variable importance for data layers derived from remote sensing data (ALS, multispectral imagery).

Models were used to generate separate prediction rasters for the study area, one for each cross-validation run, which were then averaged for each model type (RF, BRT, SVM) and parameterization (full or reduced set of predictors). The RF model showed superior overall performance and was selected for use in subsequent connectivity analyses.

Characterizing the role of predictor variables in achieving modeling outcomes can be useful for assessing model performance (Gage and Cooper 2015, Naimi and Araujo 2016). The SDM package implements several model-independent techniques to evaluate variable importance. The aucTest calculates improvement in model performance with inclusion of each variable compared to when a variable is excluded through a cross-validation procedure. The corTest metric is an alternative variable importance approach that measures the correlation between the predicted values when variables are randomly varied through a randomization procedure. Variables with high contributions to model prediction are expected to be more affected by permutation and therefore show a lower correlation (Thuiller et al. 2004, Naimi and Araujo 2016).

Connectivity

To predict connectivity, we used Linkage Mapper (McRae and Kavanagh 2011) to create least cost paths and identified pinch point and barriers in movement corridors. The inputs to Linkage Mapper include a resistance layer and a core habitat layer. The resistance layer represents the per-pixel energetic cost, difficulty, or mortality risk moving across a landscape (McRae and Kavanagh 2011) and can be summarized as the predicted cost of movement. The core habitat layer represents known or modeled habitat for a given species or group of species. We created a resistance layer to estimate the difficulty of movement of PMJM and two core area layers, representing known PMJM locations and high quality habitat.

Resistance Layer

Scientists (Zeller et al. 2010, Spencer et al. 2010, WHCWG 2010) acknowledge that developing a resistance layer can be difficulty and may rely on arbitrary and biased decisions. Therefore, best practices dictate using scientific literature and information from subject matter experts (Zeller et al. 2010). We created a resistance layer for PMJM movement based of information found in the literature that examined PMJM habitat (Schorr 2001, Clippinger 2002, Trainor et al. 2007) and conversations with BCPOS staff. We developed the resistance layer using three factors following recommendations in the literature (Zeller et al. 2012): the land cover classification developed in Chapter 2, Boulder County roads data (Boulder County 2013), and lakes and reservoir data (Boulder County 2017. The resistance layer was scaled from 1 to 100, with higher values having a higher cost or resistance to PMJM movement. The lowest possible resistance value was set to 1 to avoid computational issues with the algorithms used to calculate the least cost distances because using a value of 0 has the potential to create mathematical problems (Spencer et al. 2010).

Land cover resistance

The land cover classification (Table 4-2) was reclassified into resistance values ranging from 1 (low resistance) to 100 (highest resistance) based on known habitat preferences, relationships, and assumptions of PMJM habitat use and movement identified in the scientific literature (Schorr 2001, Clippinger 2002, USFWS 2003, Trainor et al. 2007) and conversations with BCPOS staff (personal communication, Tim Shafer). Table 4-2 describes the land cover class, the resistance value, and the justification for assigning value.

Table 4-2. Land cover classification, resistance values, and justification for resistance values.

Land Cover	Resistance	Justification
Riparian Herbaceous	5	Preferred habitat (Trainor et al. 2007)
Riparian Forest	5	Preferred habitat (Trainor et al. 2007)
Riparian Shrub	1	Preferred habitat (Trainor et al. 2007)
Bare	25	Dangerous, no cover for predator avoidance
Open Stream Water	50	PMJM are terrestrial (Schorr 2001)
Upland Herbaceous	10	PMJM forage and hibernate in upland areas (USFWS 2003)
Upland Forest (Coniferous forests in the lower montane region)	50	Dangerous, no cover, likely predators
Irrigated Agriculture	50	Conversion to agriculture is a major threat to PMJM (USGS 2003) and personal communication with Tim Shafer
Developed	100	Likely to avoid developed areas (Clippinger 2002)

Roads resistance

Roads are known to be sources of mortality and barriers to animal movement (Coffin 2007) and specifically to rodent dispersal and mortality (e.g., Wilkins 1982, Swihart and Slade 1984, Merriam et al. 1989). While, we do not know exactly how PMJM responds to the presence of roads, we relied on literature about road ecology and animal movement (Coffin 2007) which suggests that wider roads with higher traffic volumes are likely to form barriers to movement and connectivity and increase the chance of mortality for an animal that crosses the roadway.

Resistance was assigned to roads based on several variables based on the attributes of the GIS data (Boulder County 2013). First, the surface type of the road was used to separate primitive, unimproved, and unpaved roads and resistance values were assigned (Table 4-3). Unpaved roads tend to be narrower and less traveled than paved roads, resulting is less resistance to PMJM movement. Next, within the GIS data, several roads included a function class as an attribute in the geospatial data. Function class is assigned by the type of service the road provides, whether the route is urban or rural, and dictates the allowable width of the road (CDOT 2017). In the case of PMJM, we use function class as a surrogate for road width and use, assuming that wider roads provide greater resistance to movement and assigned resistance based on the function class (Table 4-4). The third variable used to assign resistance values to paved roads without an assigned function class, such as smaller city and neighborhood streets, was average annual daily traffic (AADT) estimates (Table 4-5).

Table 4-3. Resistance values for unpaved roads by surface.

Surface	Resistance	Justification
Primitive & unimproved	25	Lightly traveled, likely narrow
Graded & Drained	25	Lightly traveled, likely narrow
Soil, Gravel, Stone	35	More maintained, more use

Table 4-4. Resistance values for paved roads, assigned by function class.

Function Class	Resistance	Justification
Principal Arterial - Fwys and Expwys	100	Large roads, high speed limits, high traffic volume
Principal Arterial - Other	100	Large roads, high speed limits, high traffic volume
Minor Arterial	85	More rural routes (canyons), high speed limits
Major Collector	85	More rural routes (canyons), high speed limits
Minor Collector	-	None in study area

Table 4-5. Resistance values assigned to roads based on AADT.

AADT	Resistance	Justification
>= 10,000	100	Wider roads with high speed limits and large traffic volume
< 10,000	85	Less traveled roads with lower speed limits

Lake and Reservoir Resistance

Using a lakes and reservoir shapefile (Boulder County 2017), all standing waterbodies were assigned a resistance of 100. The justification for this is that while PMJM are strong swimmers, research (Schorr 2001) has indicated that a terrestrial route would be preferred. Additionally, while PMJM may swim across a narrow stream, they are not likely to cross large expanses of open water. The three inputs (land classification, roads, and lakes and reservoirs) were combined into a single resistance layer scaled from 1 to 100.

Core Area Identification

We created two core area layers to predict connectivity. First, we mapped the distribution of known PMJM locations using kernel density analysis. Kernel density analysis is a non-parametric method to estimate probability densities from point data (Rodgers and Kie 2011). Kernel density analysis is frequently used to map home ranges for a variety of species based on trapping and telemetry data (Worton 1989, Kie et al. 2010, Gosdall et al. 2014). To identify core habitat areas, we created a kernel density layer in ArcGIS 10.5 using the USFWS (2016) PMJM database and a search radius of 1 km. We identified core habitat as the locations estimated using kernel density that had a 95% probability of detecting a mouse, referred to as "core population areas". Second, we used the SDM produced by randomForests to identify core habitat, referred to as "core habitat areas". To do this, we selected locations from the SDM that had a 95% probability of detecting a mouse using the USFWS (2016) PMJM trapping locations. Due to a large amount of small areas produced in the core habitat layer, we set a minimum mapping unit of 1 hectare. This value was because individual home range sizes can be up to ~6,000 m^2 and generally multiple mice have overlapping home ranges (Trainor et al. 2012), resulting in a functionally larger area of high quality habitat and high usage by PMJM. There was only one patch in the core population areas that was smaller than 1 hectare, therefore, we opted to include this smaller area.

Creating Connectivity Maps

To create the connectivity maps, we used the Linkage Mapper Module in Linkage Mapper in ArcGIS 10.5, a connectivity analysis software which automates the mapping of wildlife habitat corridors using least path corridor analysis (McRea et al. 2012). Linkage Mapper uses a habitat core area layer and a resistance layer to estimate the least costly way to travel between adjacent habitat patches. We created two connectivity models, one using the core population areas and the other using the core habitat areas, to recognize that PMJM may occur in riparian habitats that have not been sampled, or in areas where trapping did occur, but no PMJM were detected. We think of these two models as a population model of how the detected PMJM population is connected and a habitat model of the potential of connections between viable habitat patches.

Identifying Bottlenecks and Barriers

To identify bottlenecks in the least cost paths developed using Linkage Mapper, we used the Pinchpoint Mapper Module within Linkage Mapper. We set the maximum corridor width to 25 km based on moderate recommendations in other connectivity studies (Spencer et al. 2010; WHCWG 2010)

We used the Barrier Mapper module in Linkage Mapper to identify potential barriers to movement at a variety of distances. This tool allows the user to define a search radius, based on known movements of the target species and the size of potential barriers (e.g., roads or agricultural fields), to identify barriers. Little is known about PMJM movement. Research (Schorr 2001; Clippinger 2001) has found that most PMJM movement occurs within 160 m of streams but, PMJM have been observed traveling up to 500 m per night and to a maximum known extent of approximately 1 km (Schorr 2001). To capture this variability, we use a minimum radius of 50 m and a maximum radius of 1 km, and evaluated barriers at 50 m intervals. In addition to relating the barriers to mouse movement, barriers of different sizes are able to highlight features with different widths. Smaller intervals, for example 50 to 100 m, are able identify roads and highways, while larger barriers highlight the impediment to travel caused by agricultural fields.

Results

Species distribution modeling

Model performance and selection

Model performance on testing data varied among SDMs, with the RF showing the best overall performance across threshold-independent performance measures, followed by the BRT and SVM models (Table 4-6). RF showed the highest mean AUC values. Mean AUC for the BRT model was close to that of the RF model, but values were more variable among cross-validation runs (Figure 4-2). The RF model had the highest mean Kappa and a mean TSS just below that of the BRT model.

Table 4-6. Model performance metrics for the boosted regression trees (BRT), random forests (RF), and support vector machines SDMs. Values represent the mean of performance metrics across five model runs.

Model	AUC	TSS	Kappa	threshold	sensitivity	specificity
BRT	0.79	0.41	0.17	0.07	0.54	0.87
RF	0.84	0.39	0.27	0.15	0.45	0.94
SVM	0.67	0.26	0.16	0.02	0.33	0.93

Scatter diagrams between model performance metrics and the area under the receiver operating characteristic curve (AUC) evaluated for the boosted regression trees and random forests species distribution models showed differences between boosted regression trees and random forest models (Figure 4-2). Although the values for performance metrics differed between individual model runs, the RF model showed better overall performance for all metrics.

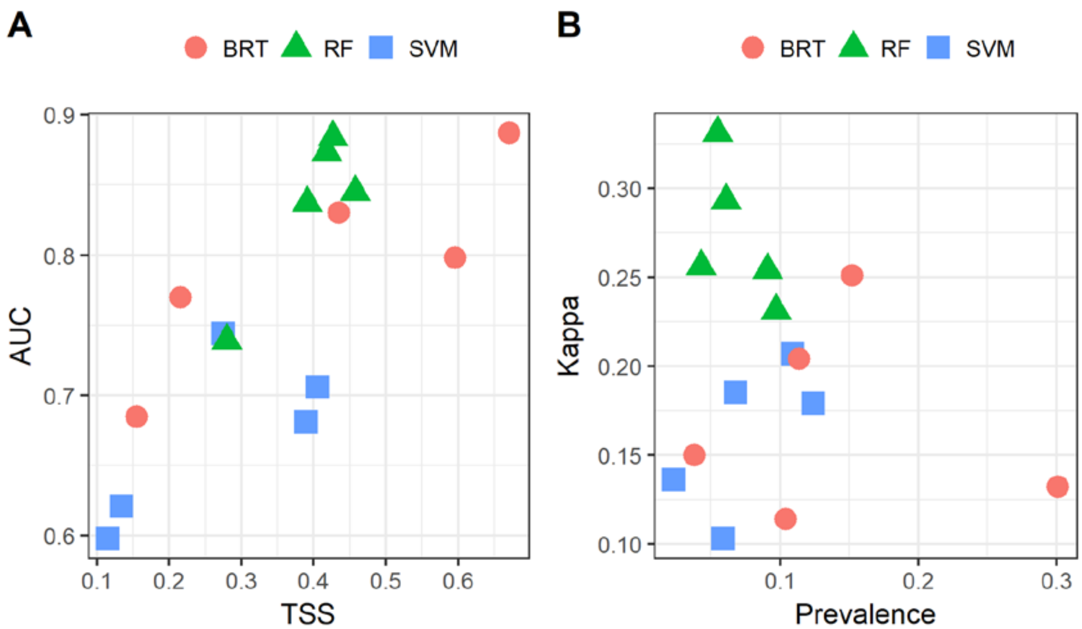

Figure 4-2. Scatterplots comparing AUC and TSS for the BRT, RF, and SVM models fit to the full set of predictor variables (panel A); plot comparing Kappa and prevalence score for the three SDMs (panel B). Points represent performance metrics for individual cross validation runs (n = 5).

ROC curves, which plot the true positive rate against the false positive rate, show the tradeoff between sensitivity and specificity; the closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test, while curves approaching the 1:1 diagonal line are less accurate. Comparisons of the ROC curves for both the full and reduced models showed relatively similar performance by the RF and BRT models on the testing data (heavy blue lines and Figures 4-3 and 4-4), but the RF model performed slightly better for both the full and reduced model parameterizations.

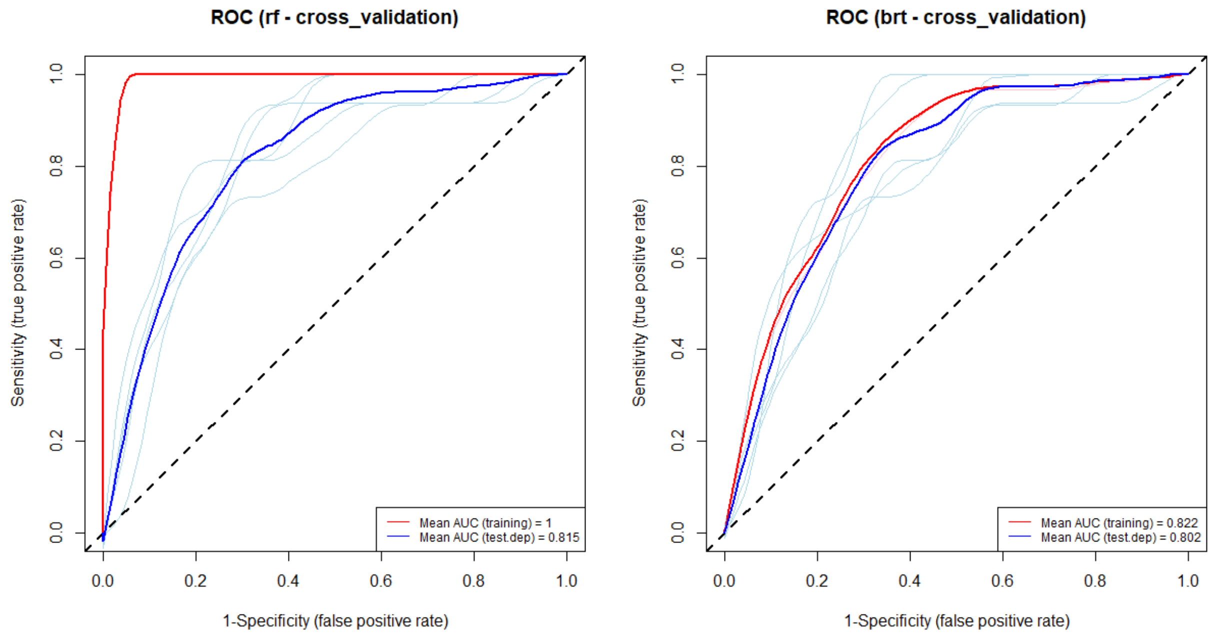

Figure 4-3. Receiver operating curves (ROC) for random forests and boosted regression trees models run with the full set of predictor variables. The red line shows the ROC curve for the training data, while the blue line shows the curve for the testing data.

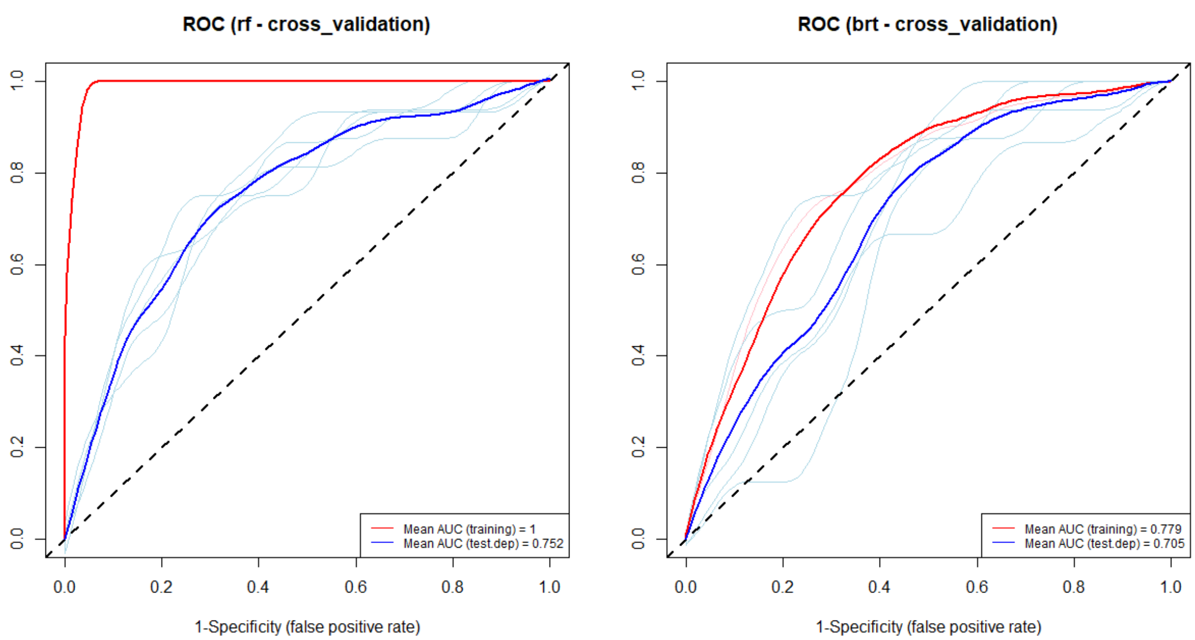

Figure 4-4. Receiver operating curves (ROC) for random forests and boosted regression trees models run with the reduced set of predictor variables (EucDist dropped). The red line shows the ROC curve for the training data, while the blue line shows the curve for the testing data.

Variable importance metrics varied among models and model specifications. In the full model, Euclidean distance to streams (EucDistStr) dominated both the RF and BRT models (Figure 4-5, panel A). The high variable importance for Euclidean distance to streams is unsurprising considering the way occurrence data are pinned near stream lines and the fact PMJM is known as a riparian obligate.

Variable importance in the reduced model differed between RF and BRT models and importance metric. For the BRT model, the riparian classification layer had the highest importance using both the AUC and correlation metrics. In contrast, elevation had the highest mean variable importance followed by the classification, TPI, and the individual riparian cover type layers (Figure 4-5, panel B). An important point for interpretation is that the variables used by models for prediction are not necessarily the same as one would measure as a wildlife biologist on the ground as part of an assessment. Instead, these were data derived from remote sensing or GIS data available as continuous raster layers across the modeling domain. The model simply seeks to achieve the best predictive performance using whatever patterns exist in the underlying data, regardless if they're easily perceived or interpreted by a user on the ground.

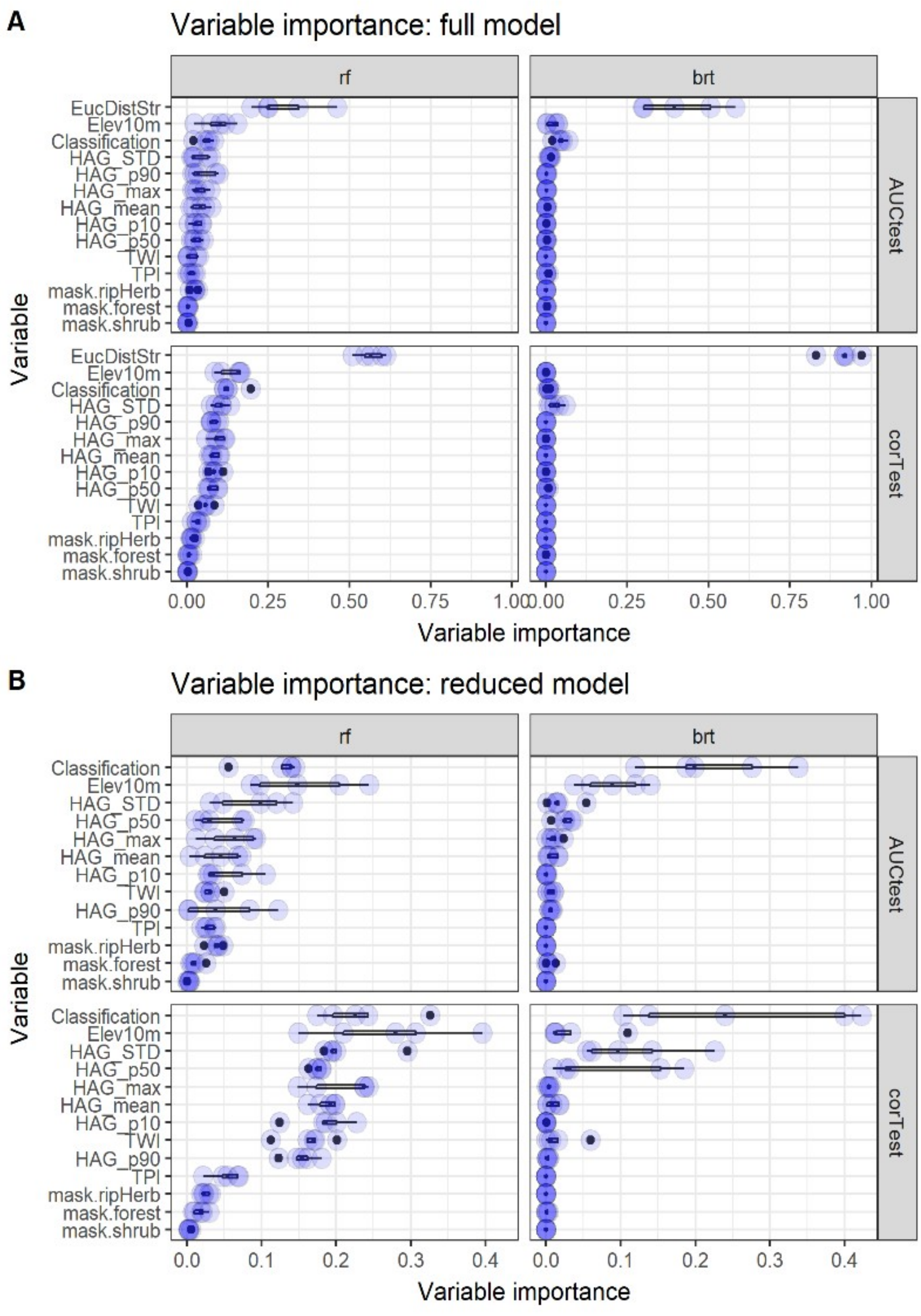

Figure 4-5. Variable importance plots assessed using the AUC test and CorTest metrics for the full (panel A) and reduced models (panel B).

Random Forest SDM map results

We mapped the output of the prediction surface created using RF SDM (Figure 4-6). High values (i.e., closer to one) predict higher quality habitat and low values (close to zero) predict lower quality habitat (Figure 4-7). Maps reveal that the majority of the higher quality habitat exists in vicinity and to the east of Lyons in the St. Vrain watershed, to the east and south of Boulder, in the South Boulder Creek watershed, and south of Louisville and Lafayette along Coal Creek, all areas identified by Boulder County as PMJM Management Areas (Figure 4-6).

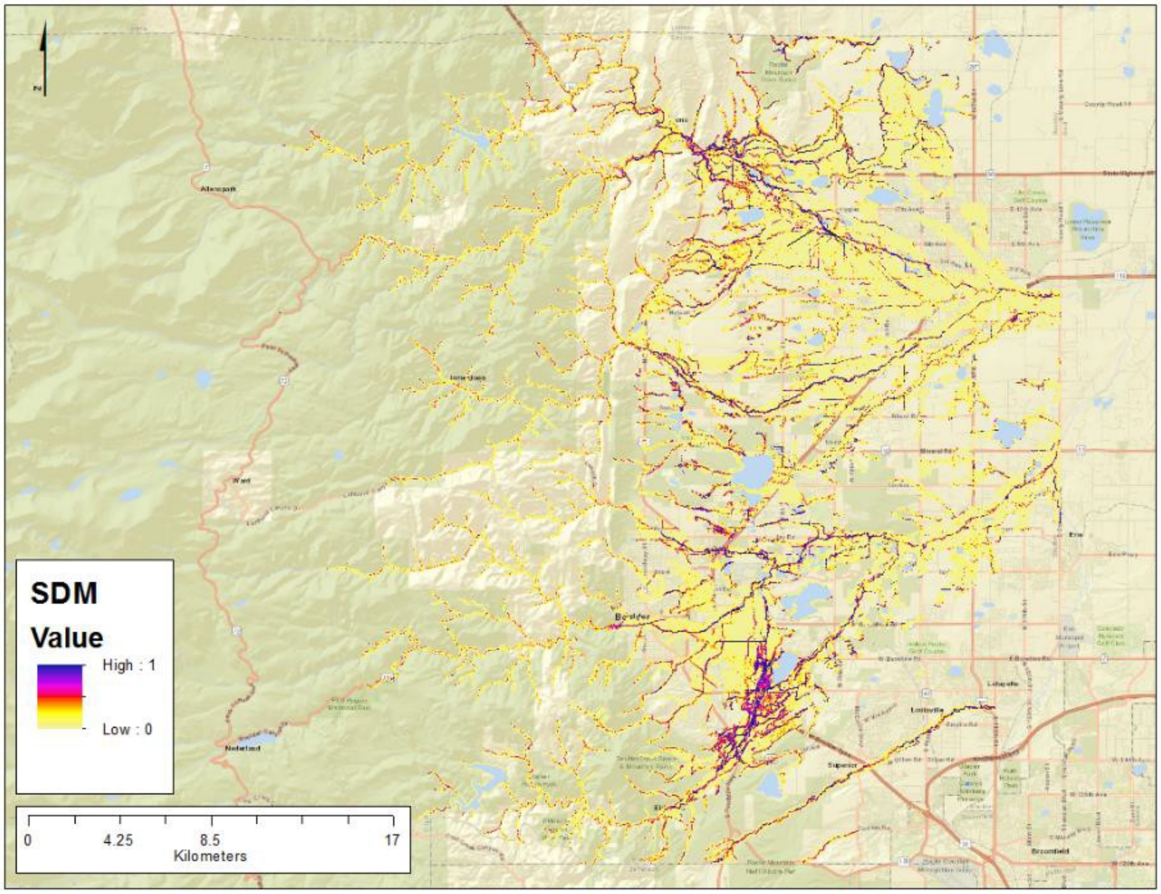

Figure 4-6. Map of the SDM created using random forest modeling.

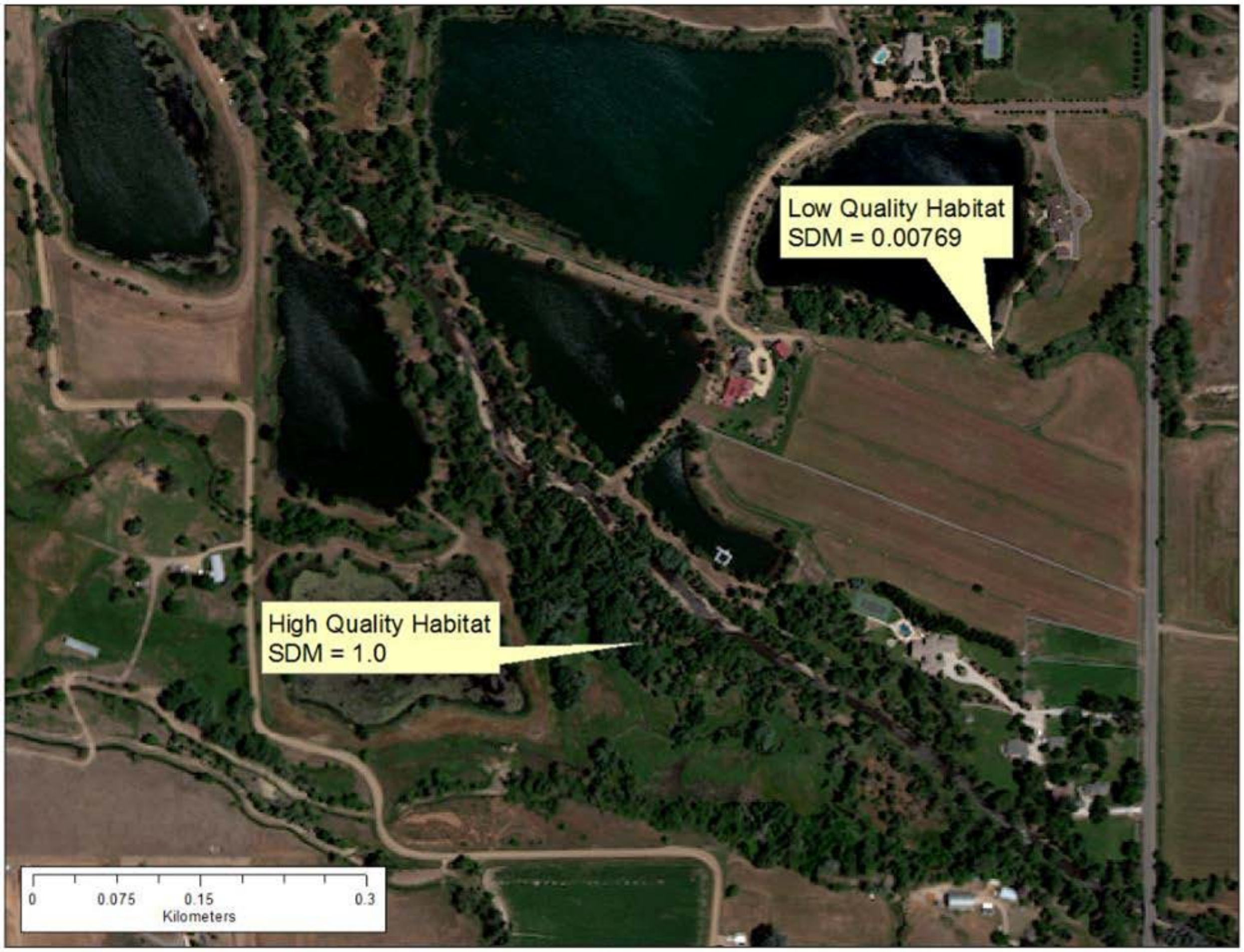

Figure 4-7. Examples of high and low quality habitat as predicted by the SDM.

Connectivity

Core Area Characteristics

The core population (Figure 4-8) and habitat core areas (Figure 4-9) developed for this project respectively represent known locations of PMJM and potential habitat modeled using the SDM (Table 4-7). Due to limited trapping locations that produce positive results, the core population area is roughly a quarter of the area of the core habitat area.

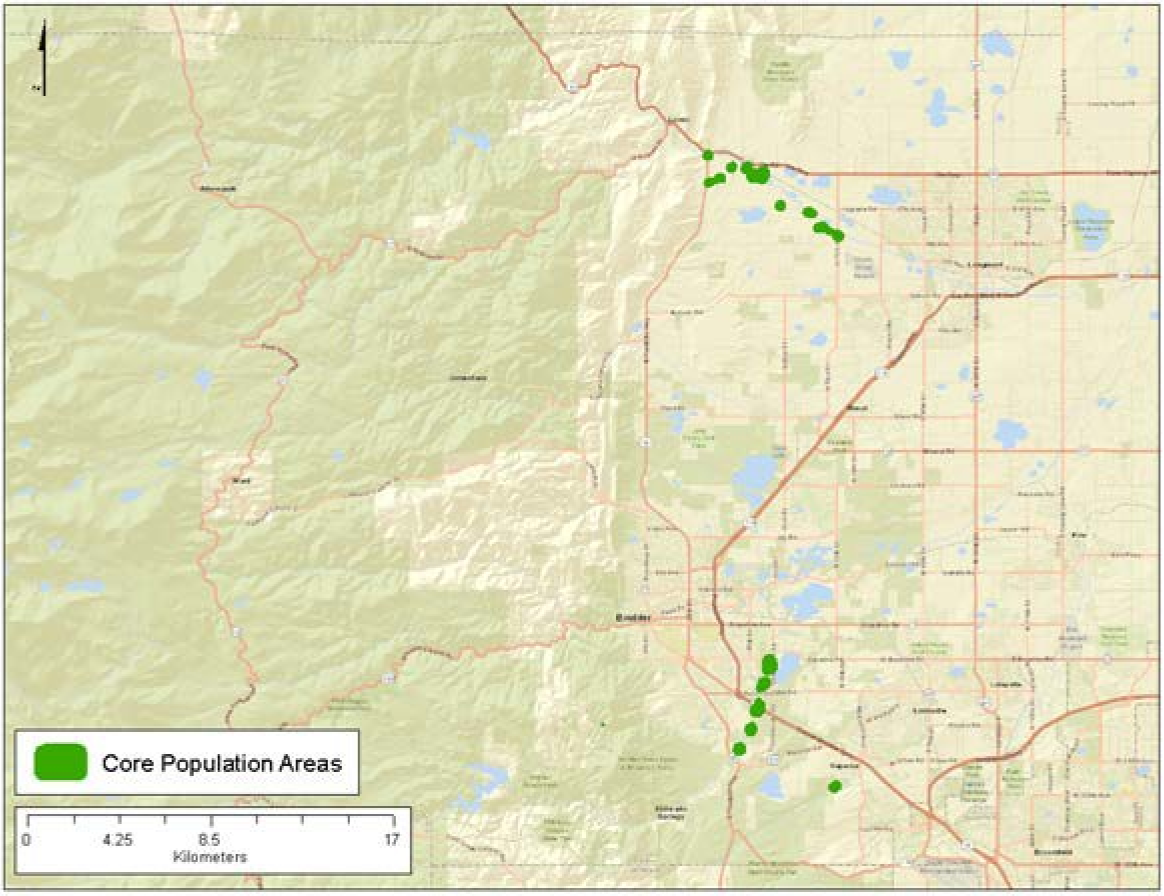

Figure 4-7. Core population areas, based on kernel density modeling for PMJM in Boulder County. Note: symbols exaggerated to be visible at this scale.

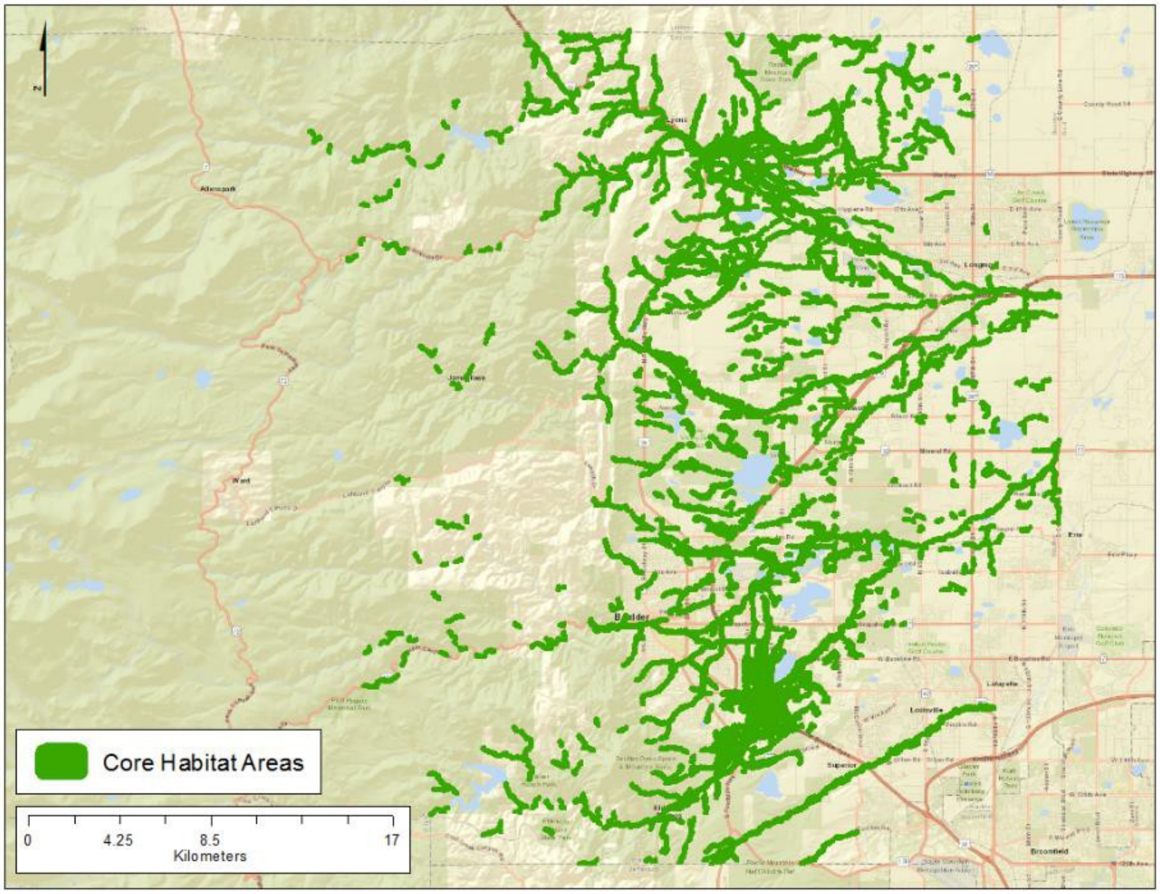

Figure 4-8. Core habitat areas, based on species distribution modeling for PMJM in Boulder County. Note: symbols exaggerated to be visible at this scale.

Table 4-7. Characteristics of the two core areas used in connectivity analysis.

Core Area	Defined By	Area (ha) Total	Average	Minimum	Maximum	Number of Patches	Standard Deviation	Percent of Study Area
Core Population	Kernel density estimation of positive PMJM trap locations	252	3.73	1.00	182.44	261	11.62	0.73
Core Habitat Area	SDM high quality habitat	972.8	18	5.78	53.42	31	12.94	2.83

Resistance Layer Characteristics

Developed areas, such as the cities of Boulder and Longmont, have the highest resistance while protected areas and lands used for recreation and agriculture have much lower resistance (Figure 4-10). The study area is composed of 10% low resistance (1-5), 39% moderate resistance (10-35) and 51% high resistance (50-100) (Table 4-8). PMJM would move most effectively in areas of low resistance and avoid areas of high resistance when possible. Overall, within the study area there is a small amount of area that with low travel costs, this is also reflected in the land cover classification that indicates only 15.8% of the study area is covered by riparian vegetation. The limited amount of low resistance land cover has the potential to limit PMJM movement and concentrate animals in small geographic areas.

Table 4-8. Characteristics of the resistance layer used in the connectivity analysis.

Resistance	Percent of Study Area	Area (hectare)
1	1.35	462.67
5	9.06	3,104.43
10	36.62	12,545.29
25	2.01	689.52
35	0.18	62.02
50	22.08	7,564.41
85	0.24	81.97
100	28.44	9,743.14

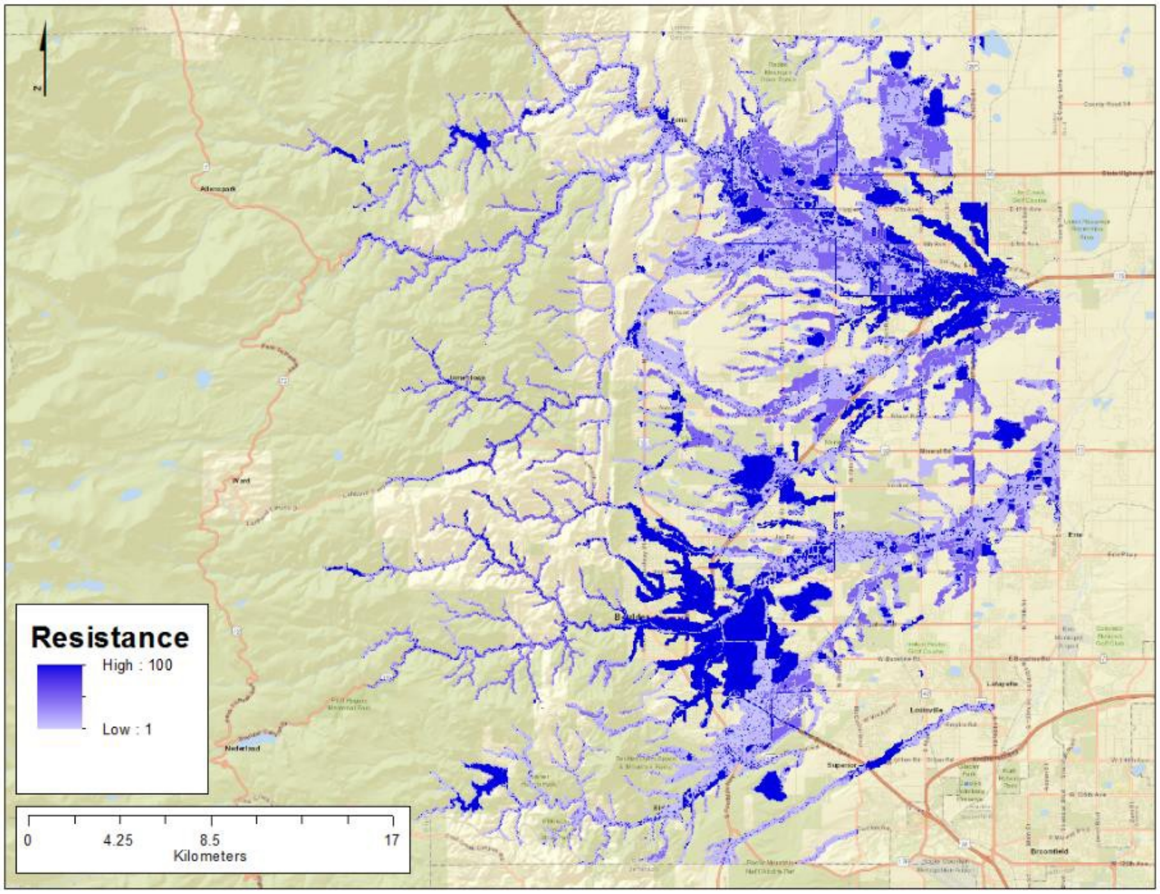

Figure 4-9. Resistance layer, taking land cover types, roads, and lakes and reservoirs into account.

Connectivity Analysis

Using Linkage Mapper and a single resistance layer, we developed core population and core habitat connectivity models. The connectivity models provide least cost corridors connecting habitat patches to neighboring patches following the path of least resistance. The resulting paths reflect the easiest modeled movement routes between adjacent habitat patches and are sensitive to our modeling assumptions and errors in our input data layers.

First, we developed raster layers that indicate the cost of travel throughout the study area (Figures 4-11 and 4-12). From the raster layer, we developed vectors, or lines, of the least cost path between core areas and neighboring patches (Figure 4-13 and Figure 4-14). Here, we have displayed the ratio of the cost weighted distance to actual path distance between two patches for two main areas within Boulder County. Lower ratio values indicate less resistance is present between the two patches and higher values indicate more resistance. For example (Figure 4-13), there is less resistance to movement between patches 4 and 7 than between patches 7 and 8, even though the distance between 4 and 7 is greater. The least path corridor connecting patches 7 and 8 crosses a road which has high resistance, while the least cost path between 4 and 7 follows vegetation along an irrigation ditch that supports a small amount of riparian vegetation.

Likewise, there is less resistance between patches 18 and 22 than between patches 15 and 16. The higher resistance of movement between patches 208 and 210 in the core habitat least cost paths analysis (Figure 4-14) illustrates the additional cost of crossing multiple major roads. It is noted that due to the large amount of suitable habitat produced by the SDM (Figure 4-9), least cost paths are shorter and more difficult to see at these scales (Figure 4-14). We provide these maps as an example and recommend that the data be examined in a GIS for further use.

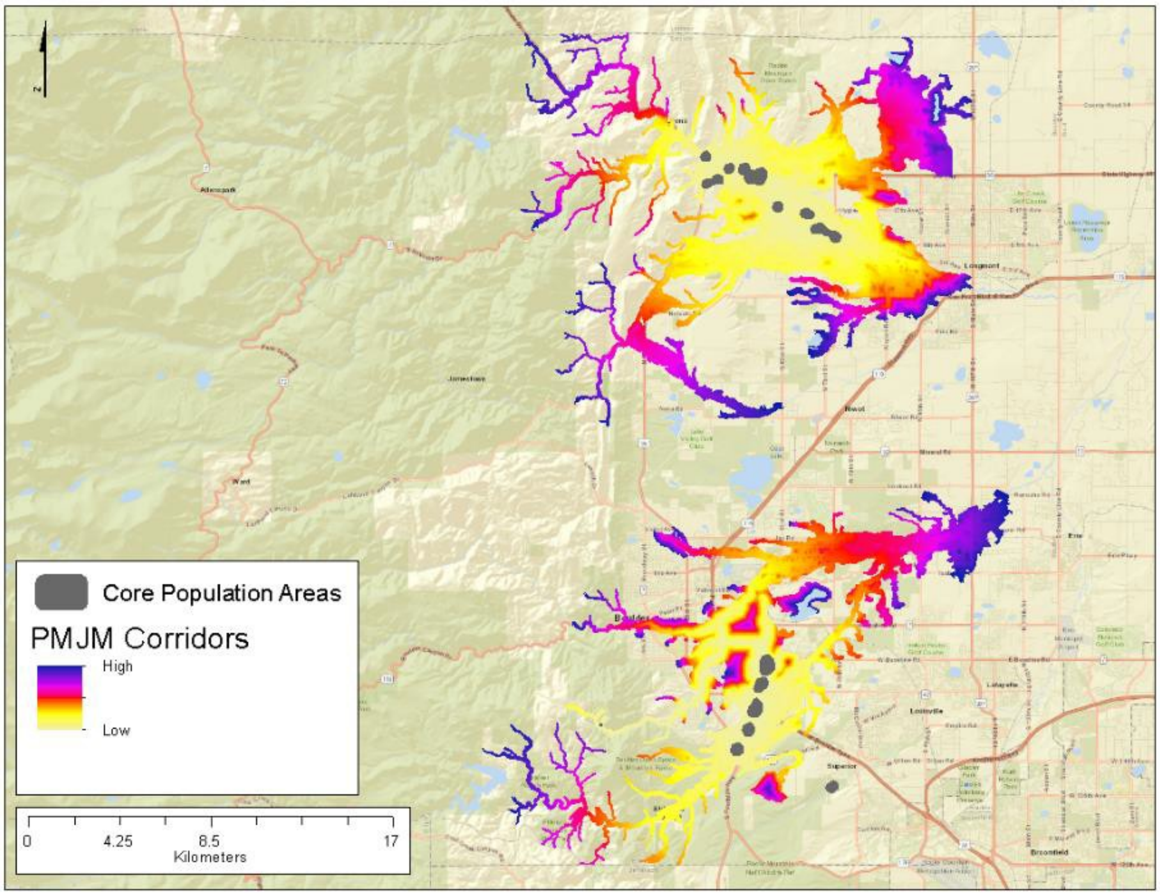

Figure 4-10. Core population corridor cost weighted distance analysis.

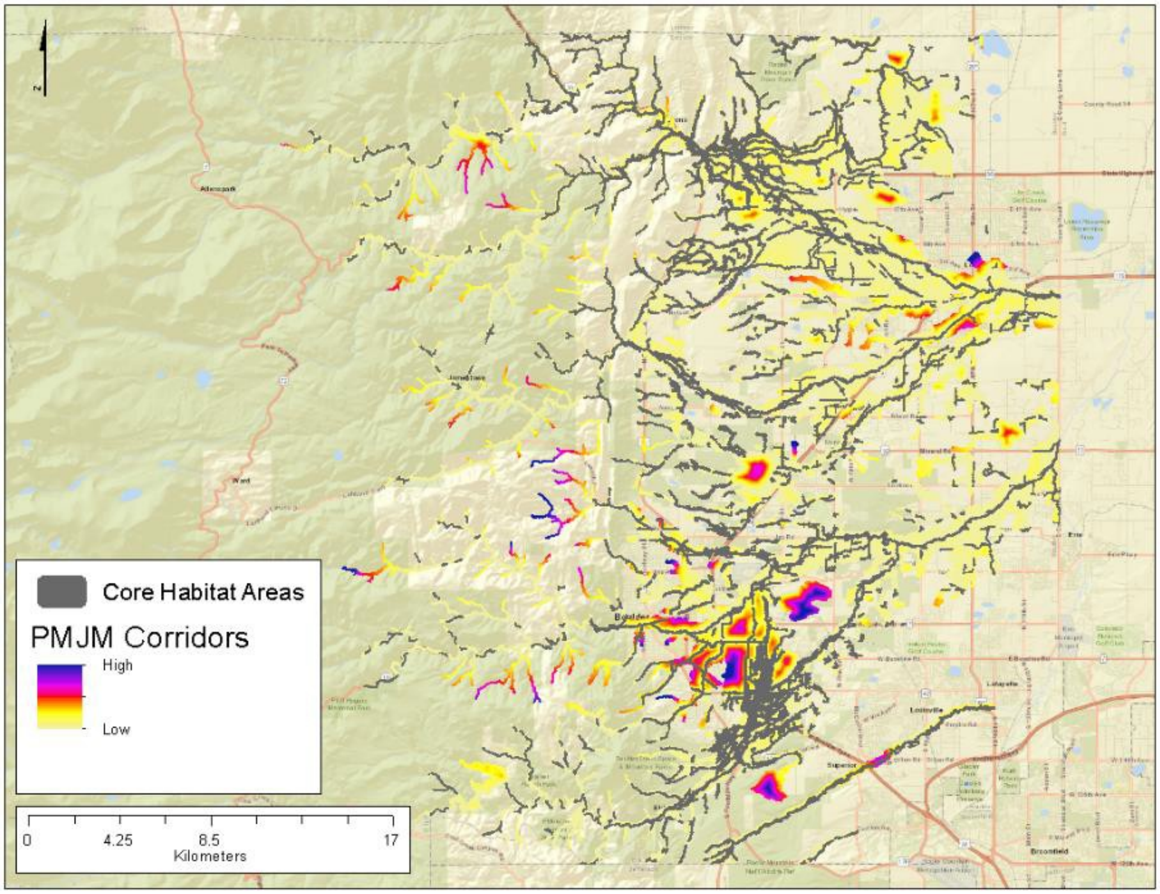

Figure 4-11. Core habitat corridor cost weighted distance analysis.

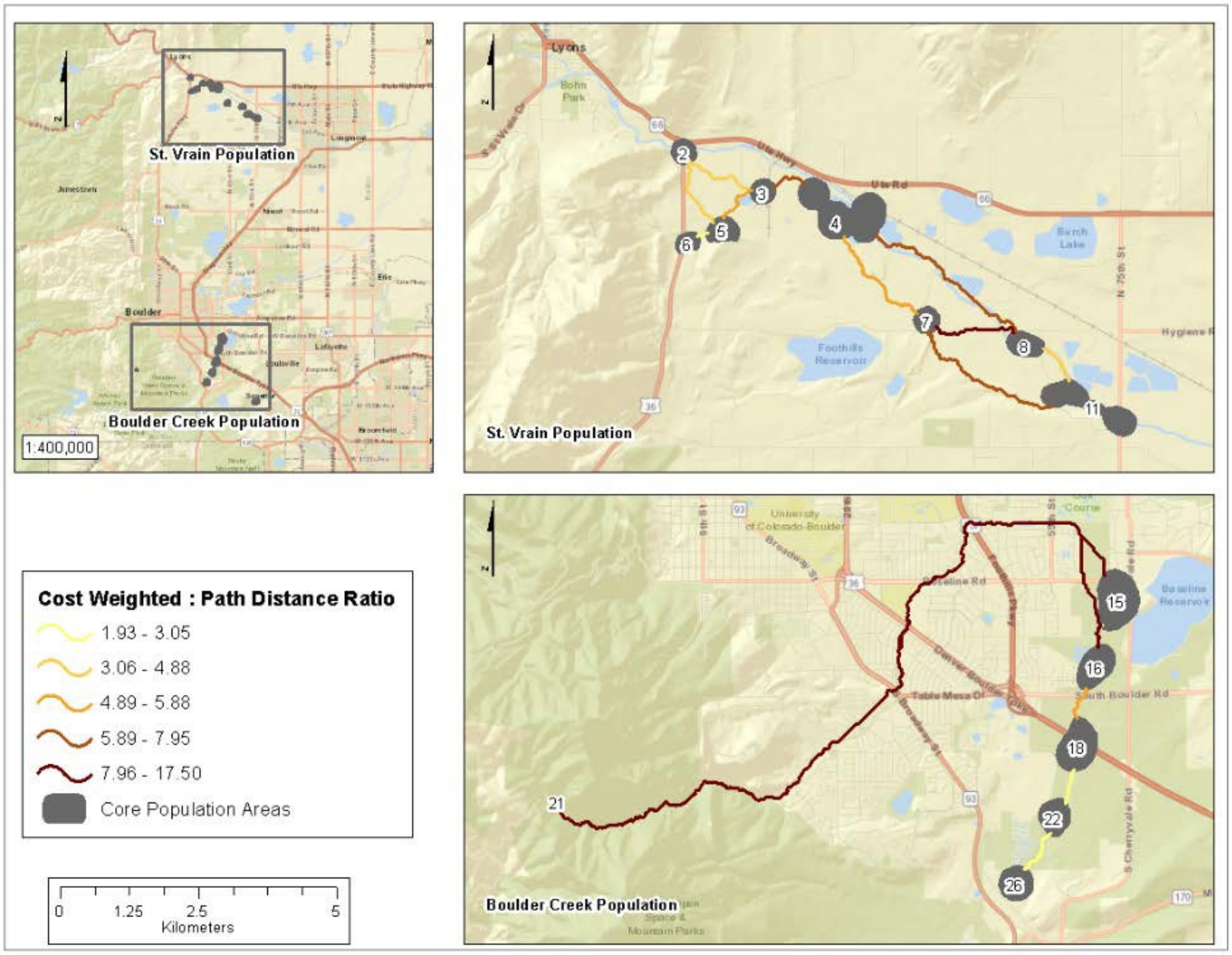

Figure 4-12. Least cost paths for core population areas indicating the average resistance encountered along the least cost path between two areas, lower values indicate less resistance and a value of 1 would connect two habitat patches through ideal habitat.

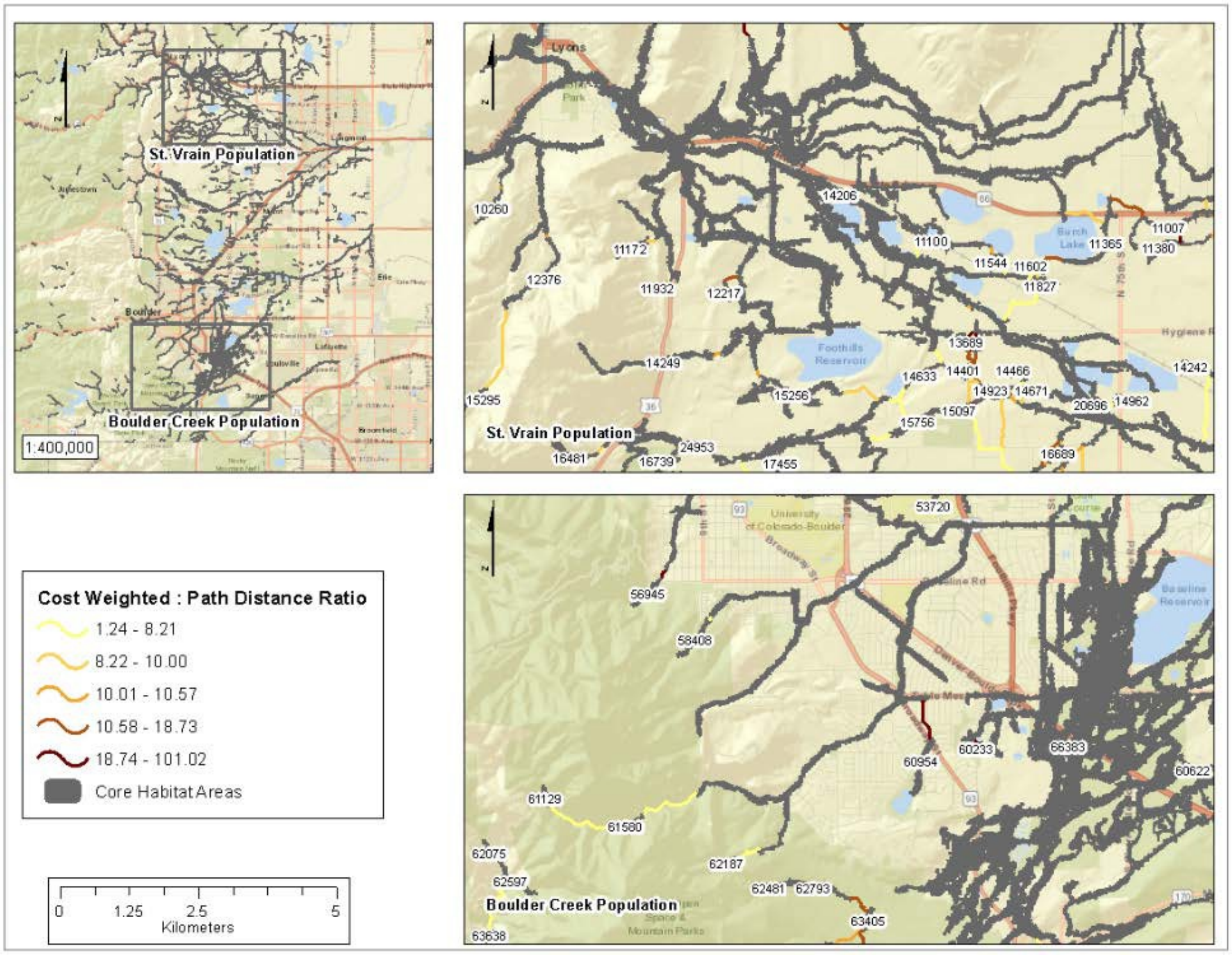

Figure 4-13. Least cost paths for core habitat areas indicating the average resistance encountered along the least cost path between two areas, lower values indicate less resistance and a value of 1 would connect two habitat patches through ideal habitat.

Pinch points

Using Pinchpoint Mapper within Linkage Mapper, we identified areas that have the potential to restrict movement between patches. As with the corridor analysis, the pinch point analysis maps raster layers that indicate resistance along the least cost paths (Figures 4-15 and 4-16) and then applies the effective resistance to each least cost path between adjacent patches (Figures 4-17 and 4-18). In the raster analysis, higher values identify areas where changes to habitat could have a higher potential to decrease connectivity between patches. The ratio of cost weighted distance to effective distance symbolized in the vector data can be thought of as a measure of vulnerability, the higher the value the more vulnerable the least cost path is to removal or degradation of suitable habitat. For example (Figure 4-17), the corridor between patches 7 and 8 is more vulnerable to modifications of suitable habitat because it is currently constrained by irrigated agriculture and reservoirs, while the path between patches 5 and 6 have more riparian vegetation present surrounding the identified least cost path, resulting in a more resilient connection

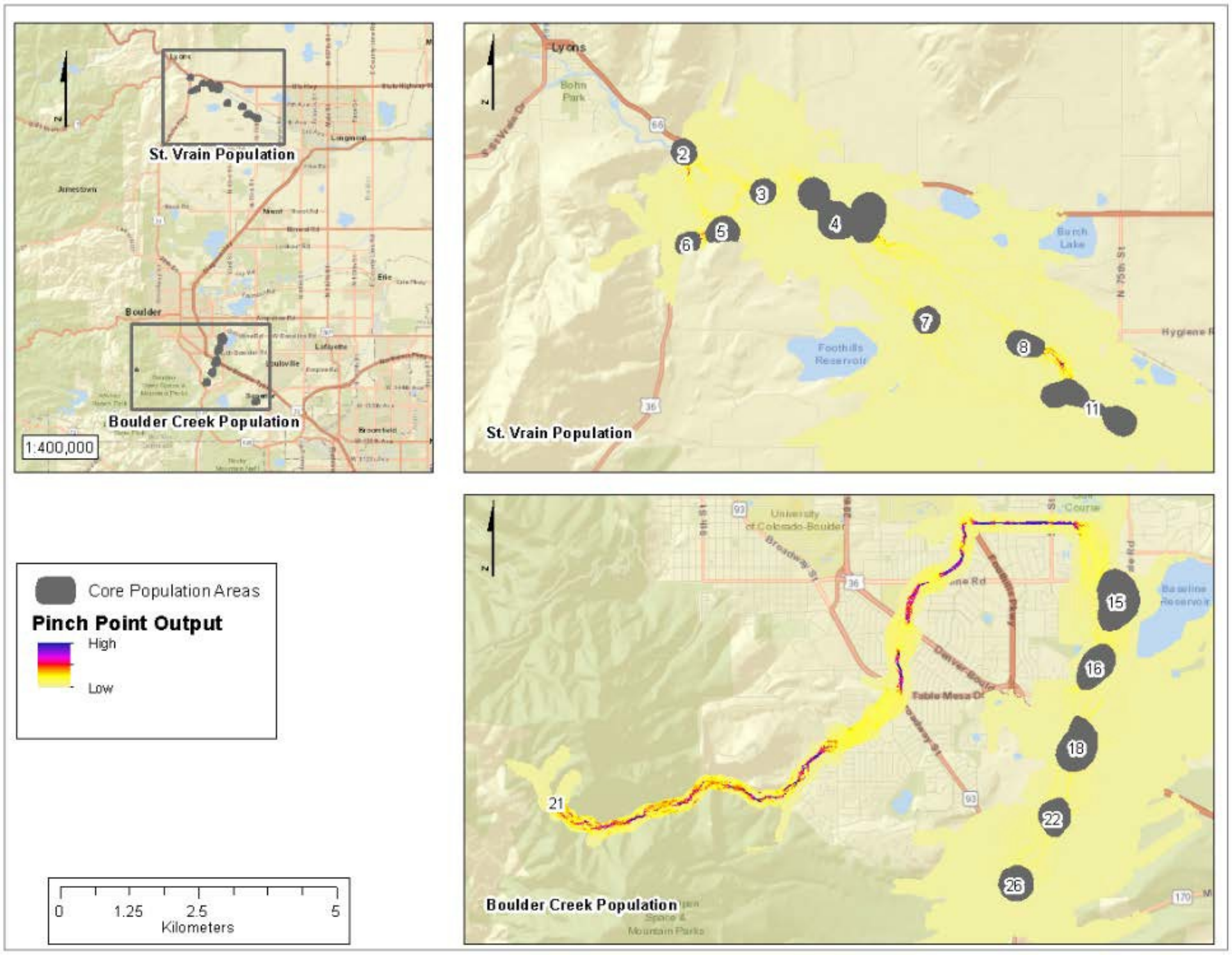

Figure 4-14. Pinch point analysis for core population corridors.

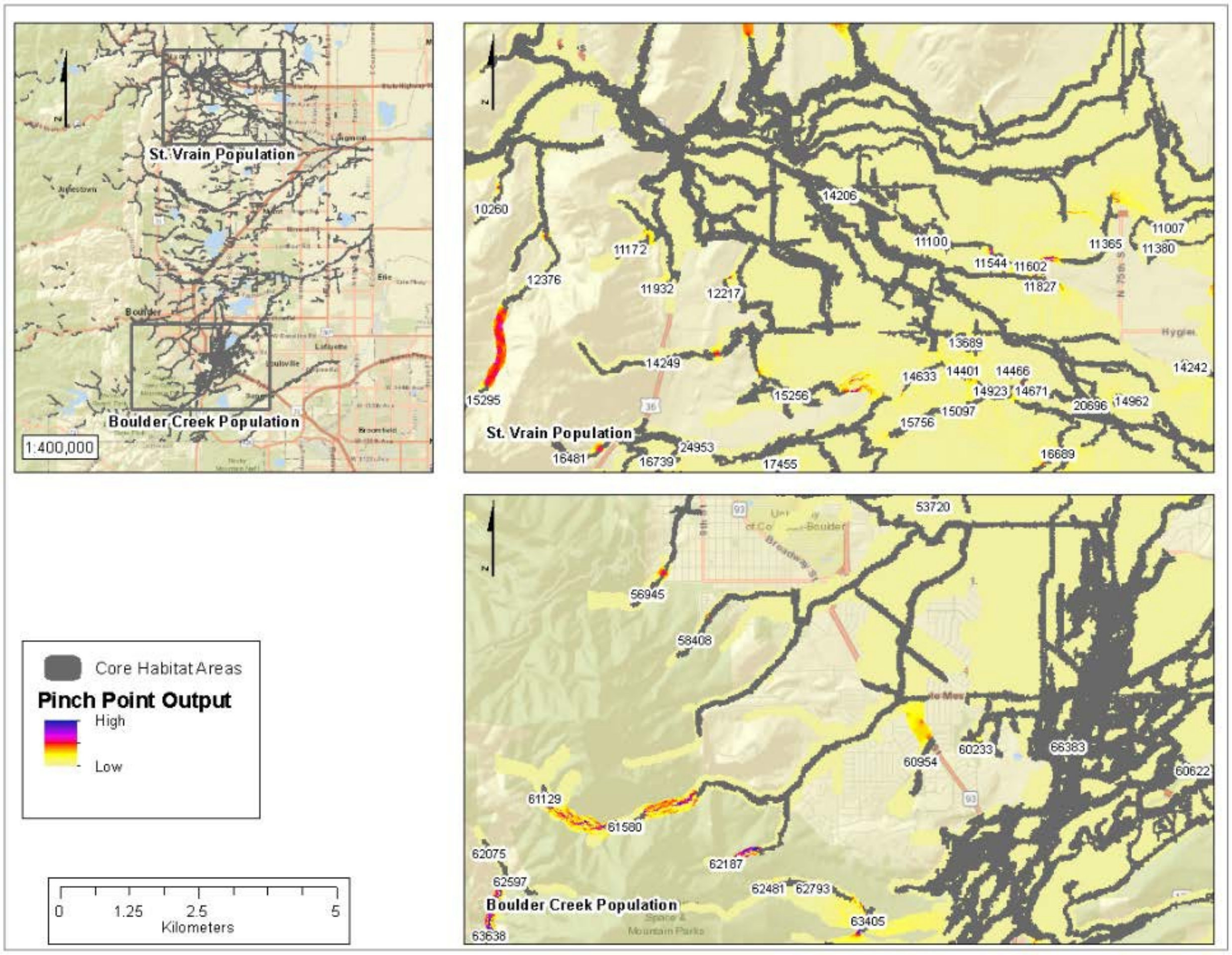

Figure 4-15. Pinch point analysis for core habitat corridors.

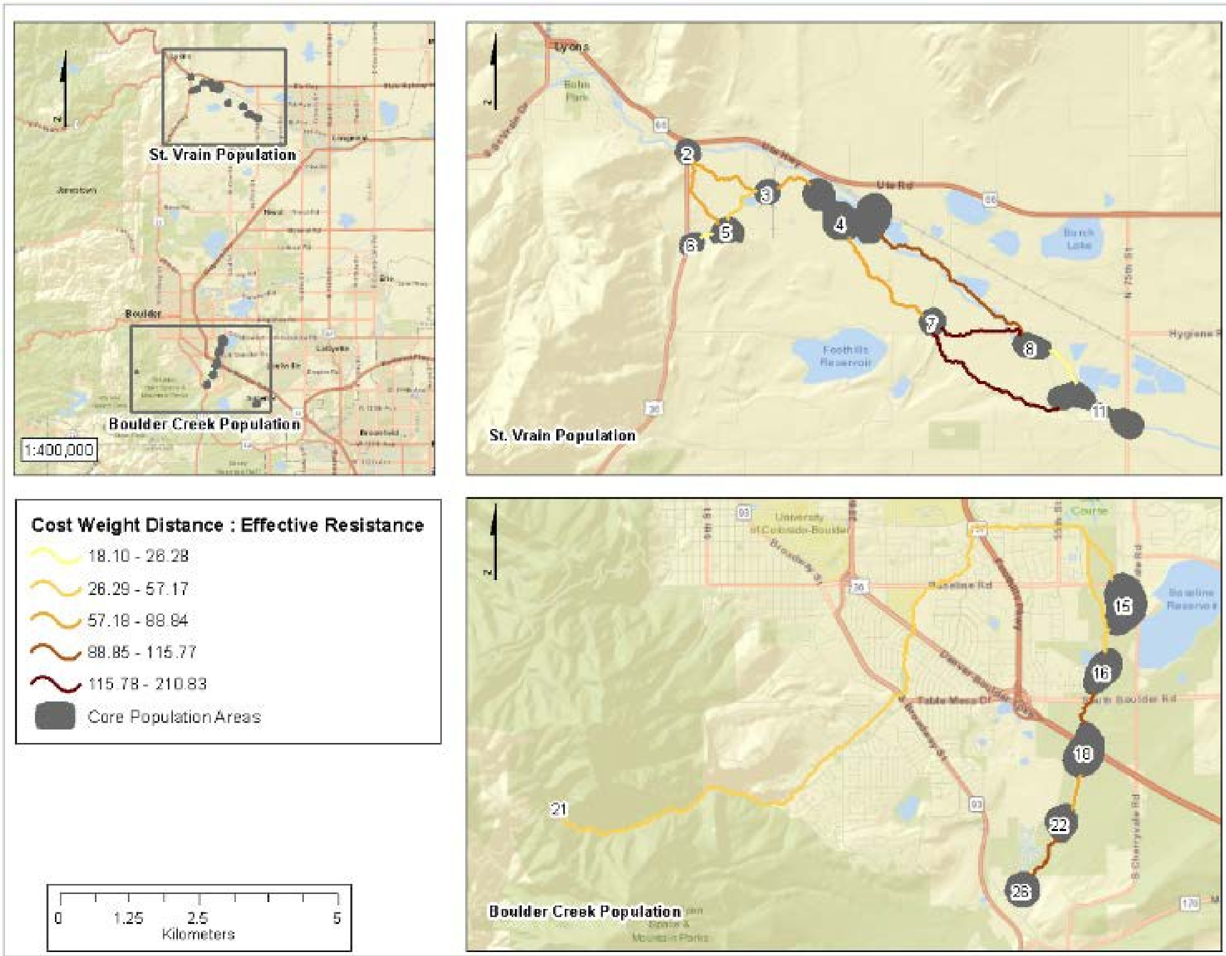

Figure 4-16. Effective resistance for core population least cost paths.

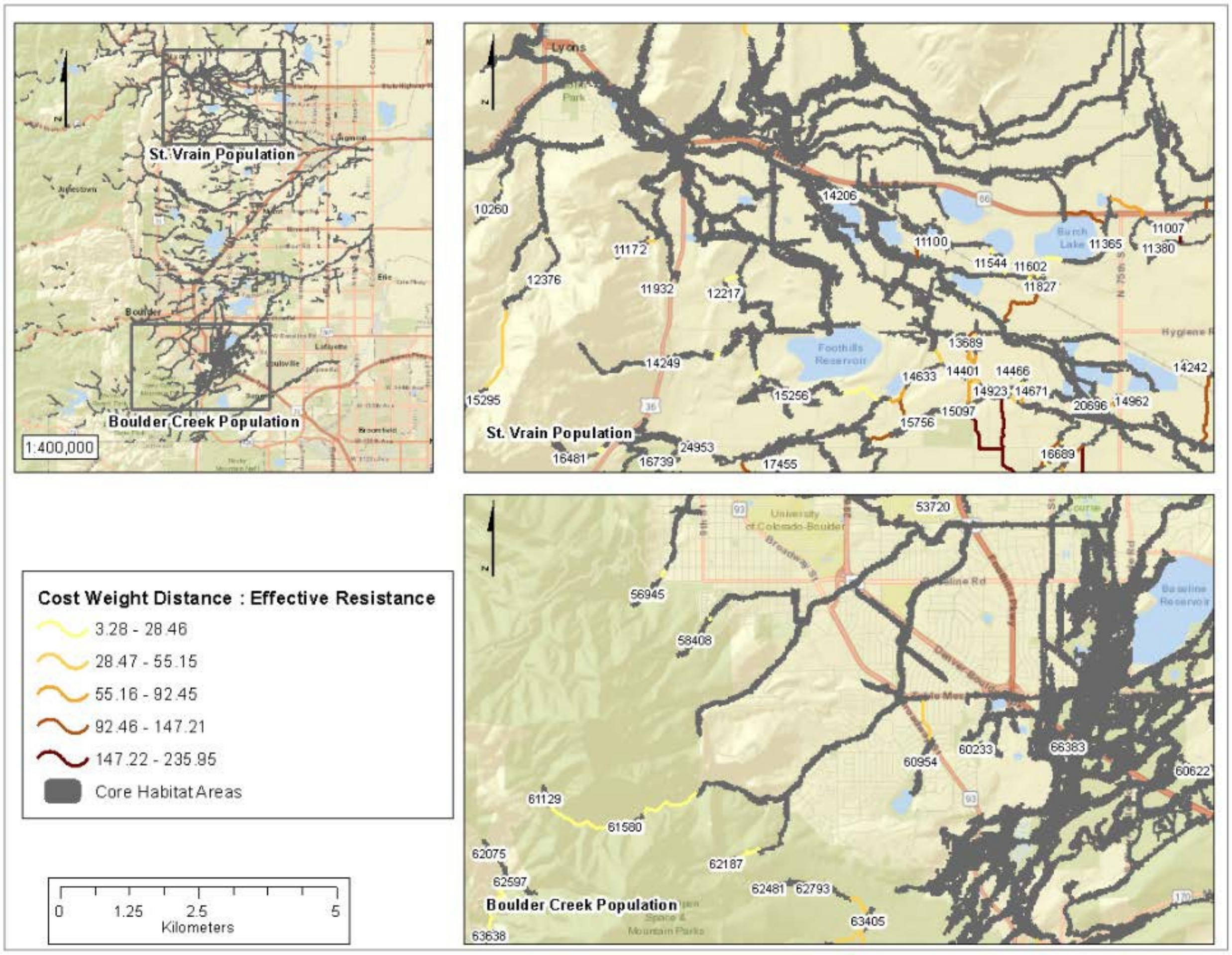

Figure 4-17. Effective resistance for core habitat least cost

paths. Barriers

Using the Barrier Mapper module within Linkage Mapper with a minimum search distance of 50 m and a maximum search distance of 1000 m, we produced barrier maps based on search distances at 50 m intervals. This tool predicts the strength of impact a barrier will have on movement at varying distances. Depending on the scale (i.e., size of the step), we see different results that indicate the relative effect on connectivity. Here to illustrate the differences, we present the results of the Barrier Mapper analysis using three different radii, a short travel distance of 150 m (Figures 4-19 and 4-20), moderate travel distance of 450 m (Figures 4-21 and 4-22), and a maximum travel distance of 950 m (Figures 4-23 and 4-24). Higher values indicate barriers that have the strongest impact on the least path corridors between habitat patches given a specific distance. For example, 450 m analysis is asking, within 450 m of a given patch using the cost weighted distance developed from the resistance layer, what and where are the relative barriers to movement. This analysis is applied to the entire radius (450 m), extending beyond the least cost pathways, and can be used to assist in interpreting the location of the least cost paths and how barriers have the potential impact the location of the path. Using the examples presented below, it is evident there that at a travel distance of 150 m (Figures 4-19 and 4-20) there is little resistance to movement for both the core population and habitat areas. While the least cost path between habitat patch 15 and 21 (Figures 4-19, 4-21, and 4-23) is presented, it is not likely a mouse would travel that pathway through the City of Boulder, nor is it realistic to assume that barrier removal is likely to take place along this route. The result is that mangers can disregard this route for consideration for restoration and focus resources on other areas, such as the vulnerable connections between patches 7 and 8 or 22 and 23 (Figure 4-17).

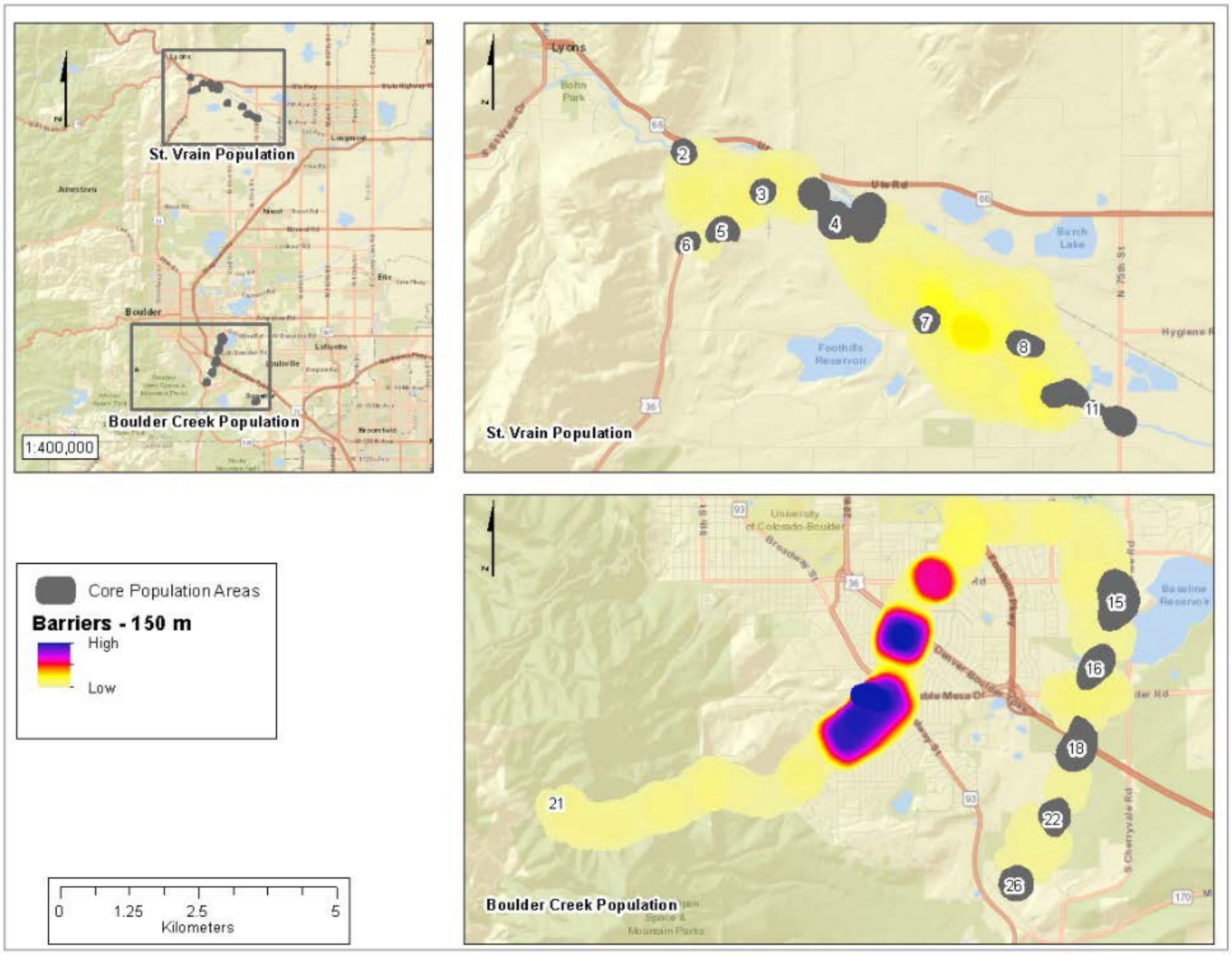

Figure 4-18. Potential barriers to core population connectivity using an analysis radius of 150 m.

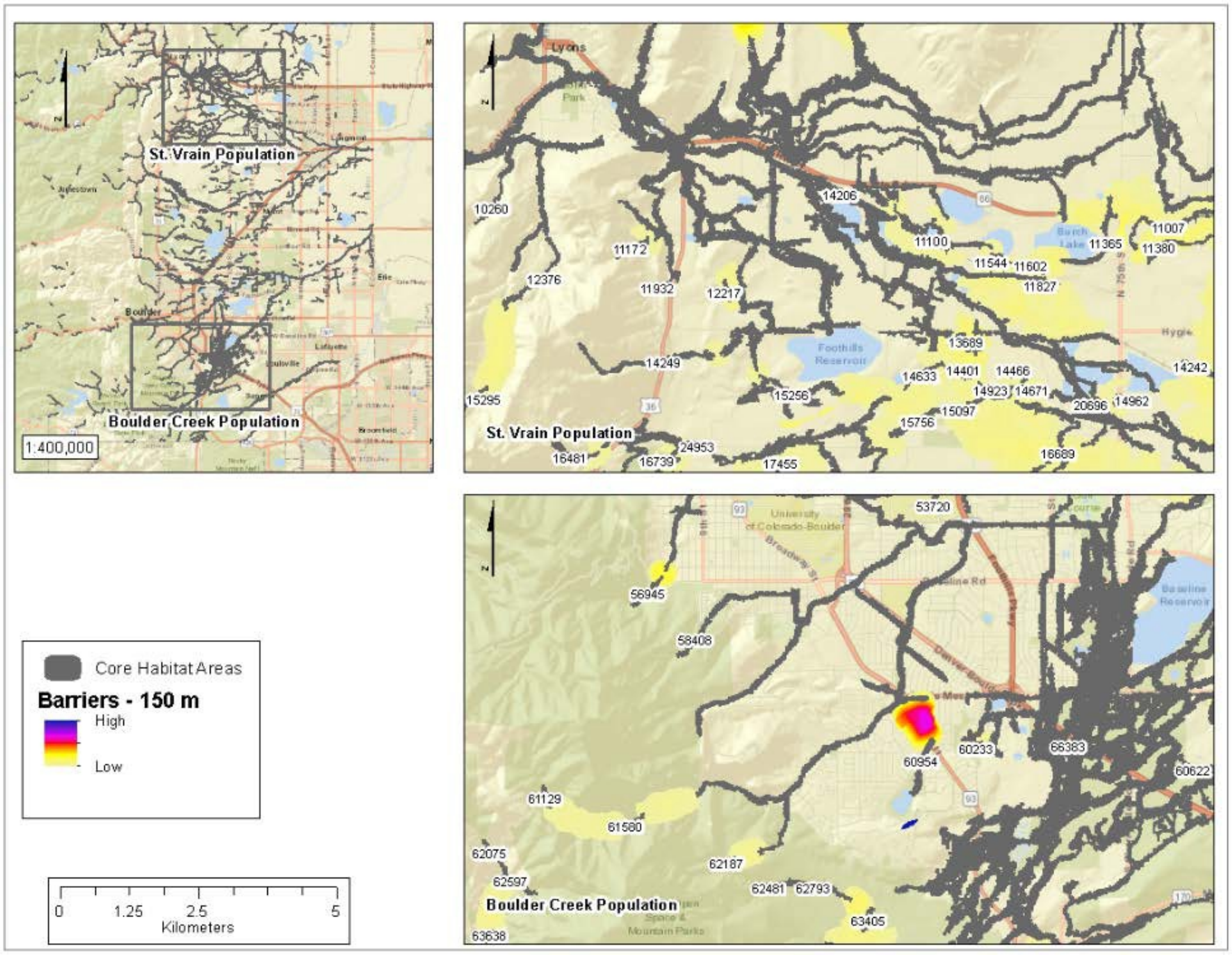

Figure 4-19. Potential barriers to core habitat connectivity using an analysis radius of 150 m.

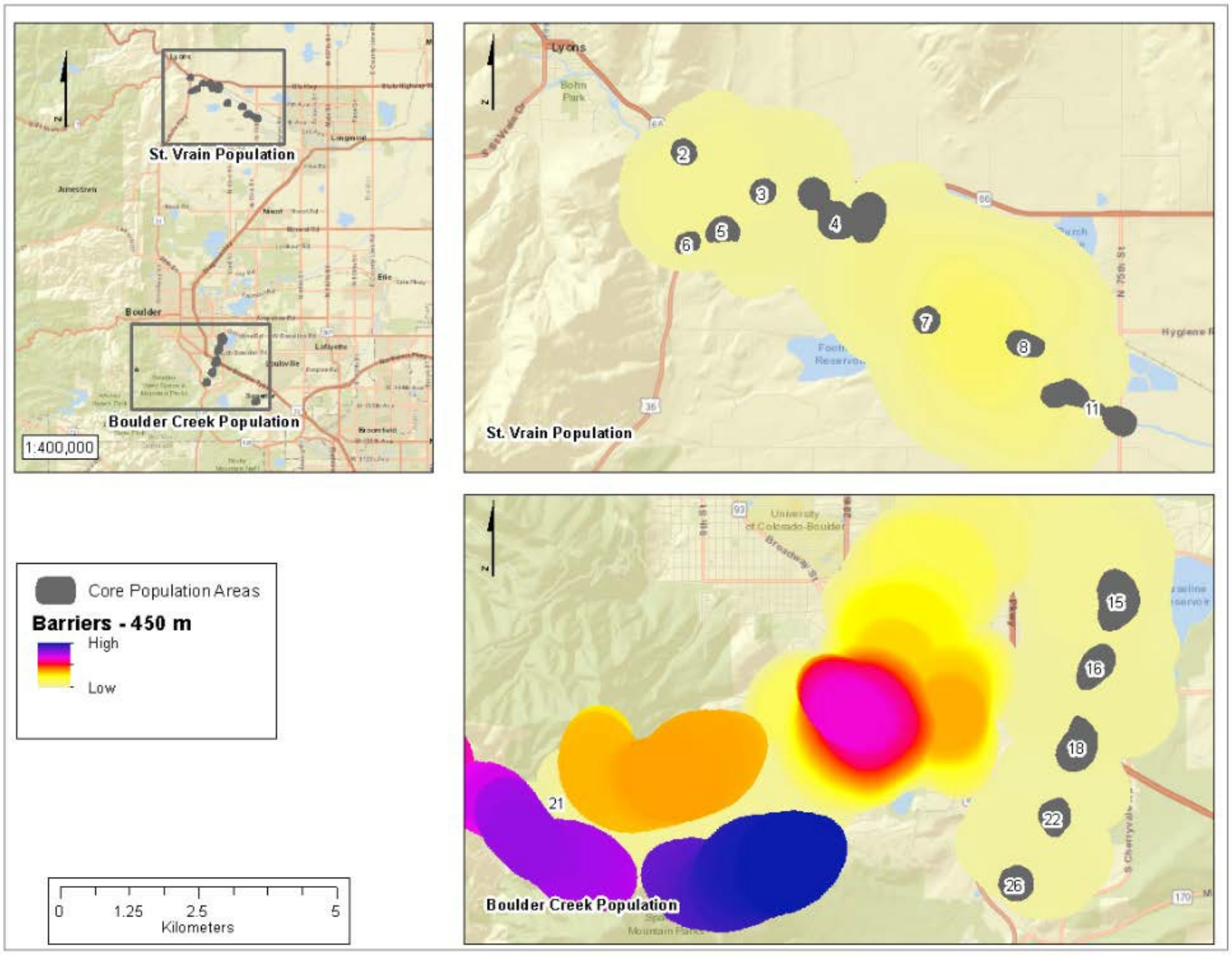

Figure 4-20. Potential barriers to core population connectivity using an analysis radius of 450 m.

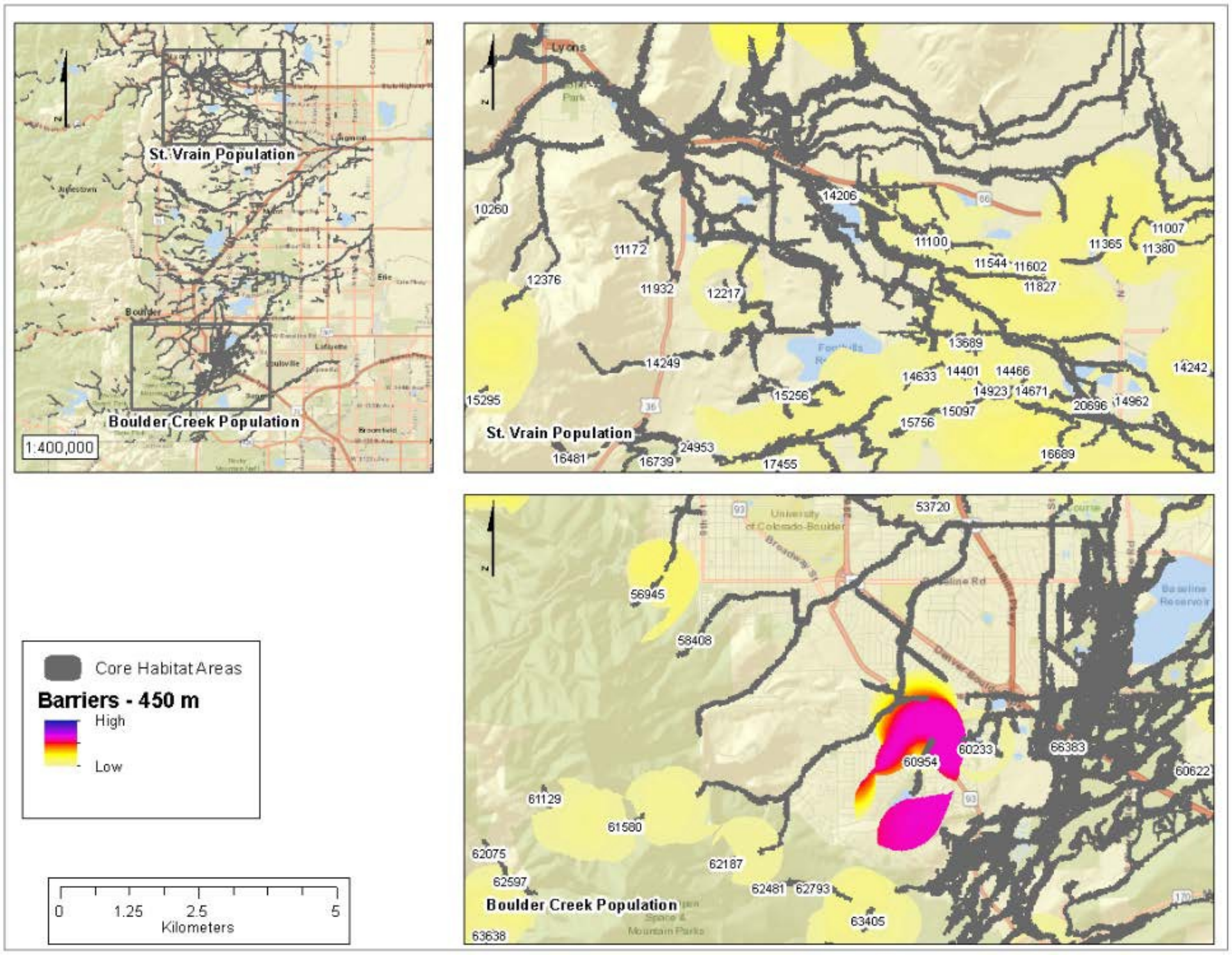

Figure 4-21. Potential barriers to core habitat connectivity using an analysis radius of 450 m.

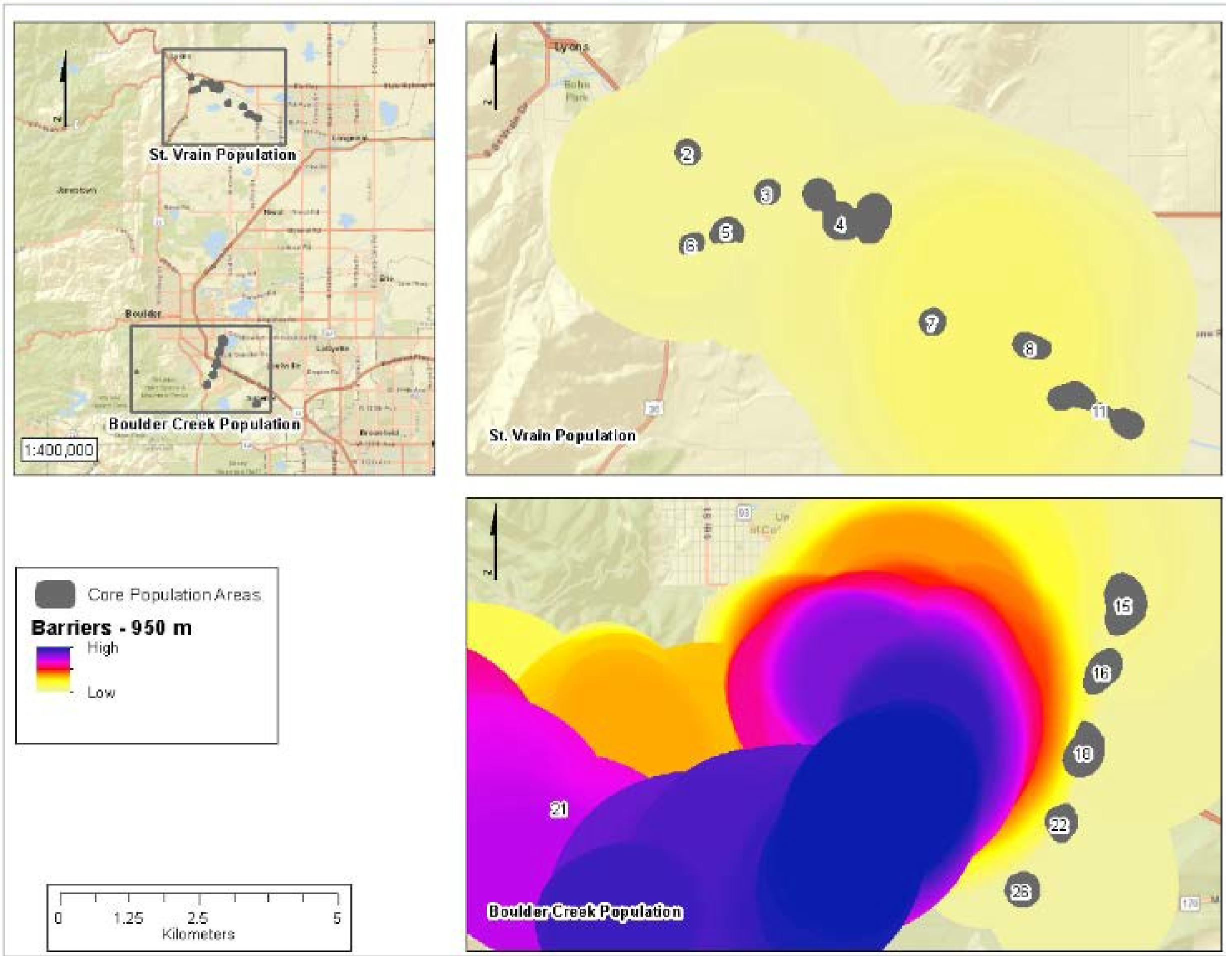

Figure 4-22. Potential barriers to core population connectivity using an analysis radius of 950 m.

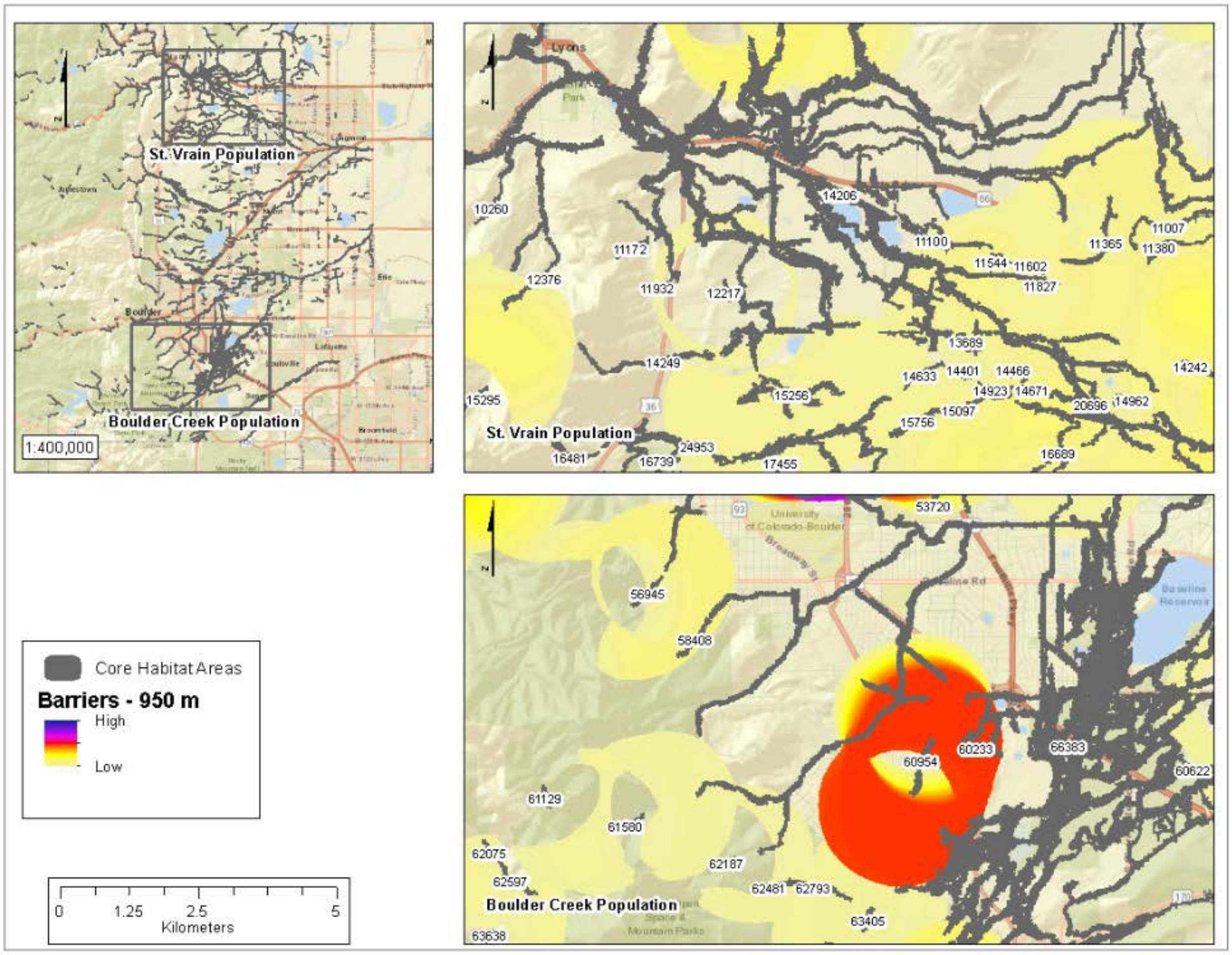

Figure 4-23. Potential barriers to core habitat connectivity using an analysis radius of 950 m.

Discussion

To our knowledge, this is the first attempt at creating a species distribution model and associated landscape connectivity analysis for PMJM at a broad scale. We created two connectivity models, one which represents known populations of PMJM, referred to as core population areas, and one that represents high quality habitat, referred to as core habitat areas that represent potential PMJM habitat.

Overall, the highest costs of connectivity (Figures 4-11 and 4-12) are located in the foothills at the western extent of the study area and near developed areas such as the cities of Longmont and Boulder. The riparian zones located in the steeper valleys of the foothills have naturally disjointed riparian vegetation that is further fragmented by small communities and roads, resulting in less connectivity. We acknowledge that setting a minimum mapping unit of 1 hectare may impact the connectivity analysis by excluding suitable habitat in the foothills. However, practical consideration of processing time and knowledge of PMJM ranges, we selected a reasonable size based on the extent of the study area.

The core population connectivity model identified two separate PMJM regions within Boulder County, a northern population in the St. Vrain watershed and a southern population in the South Boulder Creek watershed (Figure 4-8), and a third, unconnected, population south of Superior, which may have been connected to other populations outside of Boulder County before disappearing in the mid-2000's (personal communication, Tim Shafer). Genetic testing would need to be conducted to determine if any of the three populations were connected, however without further knowledge of PMJM inhabiting the areas between the three populations and/or improvements in connectivity through restoration efforts, these populations are likely unrelated and will remain isolated from each other.

The core habitat model, based on the SDM, suggests that Left Hand Creek and Fourmile Canyon Creek (within the City of Boulder) both have habitat that could and potentially does support PMJM populations. However, the Boulder County PMJM Habitat Conservation Areas Map (Boulder County Land Use Department 2017) does not identify these streams as potential mouse habitat (Figure 4-25). We suggest that Left Hand Creek drainage be added to the PMJM management plan as “suitable, noncontiguous habitat” and future trapping efforts be increased along Left Hand Creek. Trapping efforts have occurred over the past 20 years along Left Hand Creek, however based on the data provided, it appears no trapping has been conducted since 2014. If trapping efforts are successful, it would be best to update the core population connectivity models with the field work results. Fourmile Canyon Creek has the potential to support PMJM, however sections of the creek are located within developed areas of the City of Boulder and may not support PMJM. There have been two trapping efforts on Fourmile Canyon Creek, in 1997 and 2003. While we recognized that there are no BCPOS properties along the lower elevation reaches of Fourmile Canyon Creek, there are other publicly owned properties (e.g., Belgrove, Mckenzie, and Mary Moore owned by City of Boulder Open Space and Mountain Parks) that may serve as trapping locations. We recommend working with other agencies to increase trapping efforts on Fourmile Canyon Creek, however this would be a second priority after increasing trapping on Left Hand Creek, and potentially adding Fourmile Canyon Creek to the PMJM Habitat Conservation Areas (Boulder County Land Use Department 2017).

The PMJM Habitat Conservation Areas map (Boulder County Land Use Department 2017) identifies three locations as possible linkages between PMJM habitat: on South Boulder Creek between Eldorado Springs and Gross Reservoir, on an intermittent stream between Highway 36 and Highway 66, and a third location on Swede Ditch (Figure 4-25). Our core habitat model identified the core habitat and linkages along each of these corridors (Figure 4-26) and suggests additional potential linkages in several locations: North St. Vrain Creek upstream of Button Rock Reservoir, along both Dry Creeks located north and south of Highway 119, along Lykins Gulch Ditch, along an intermittent stream located between Left Hand Valley Reservoir and Boulder Reservoir, and an intermittent stream located between Panama Reservoir No. 1 and Boulder Creek. Although the CWD to LCP ratio (Figure 4-26) suggests that there is moderate to high resistance along each of these linkages, there is suitable habitat and the effective resistance is high on the majority of linkages identified by the PMJM Habitat Conservation Areas map (Boulder County Land Use Department 2017). Further investigation, including field work, would be necessary to confirm if these modeled linkages have the potential to support PMJM movement.

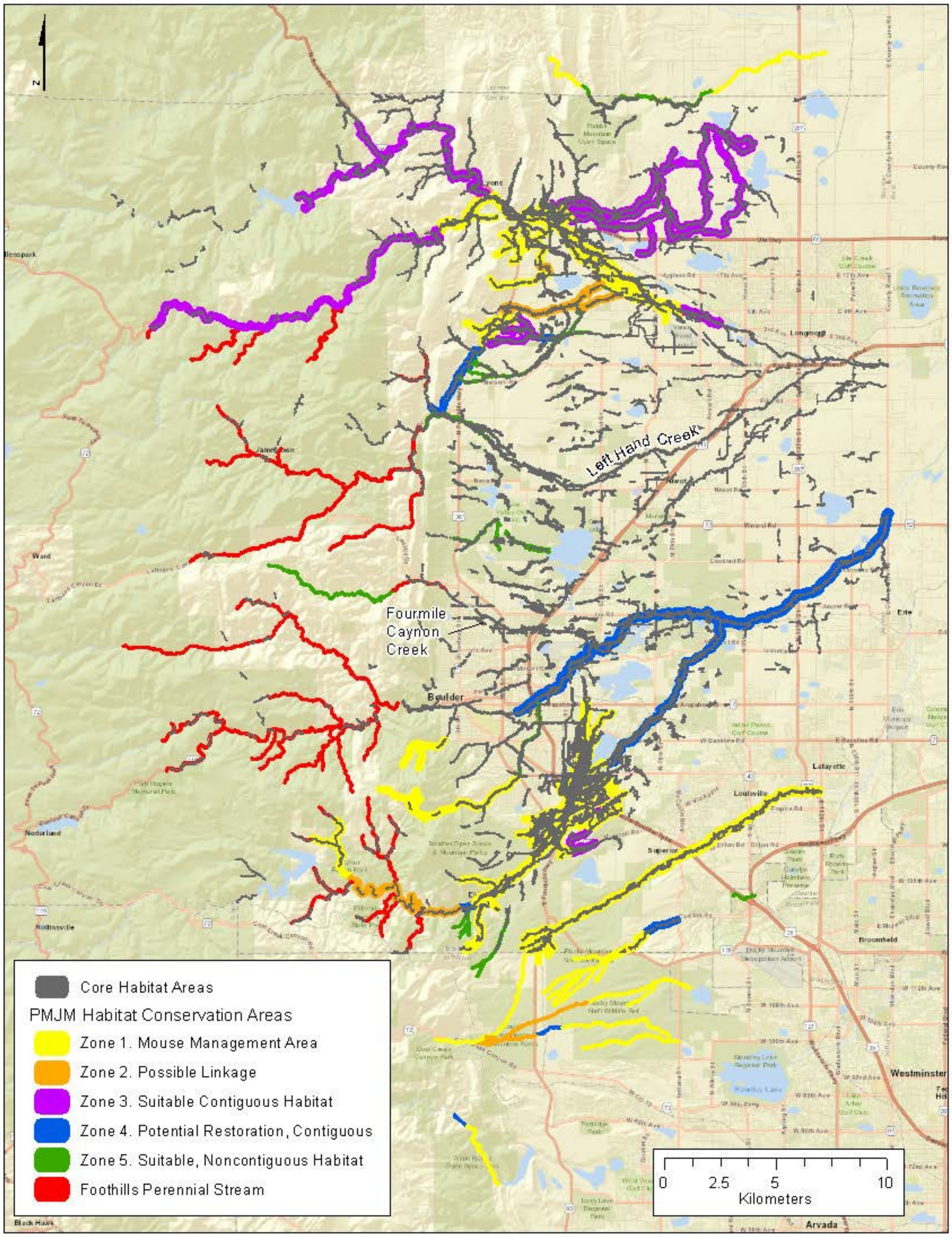

Figure 4-24. PMJM Habitat Conservation Areas (Boulder County Land Use Department 2017) and core habitat identified by the SDM. The SDM suggests that Left Hand Creek and Fourmile Canyon Creek could support PMJM.

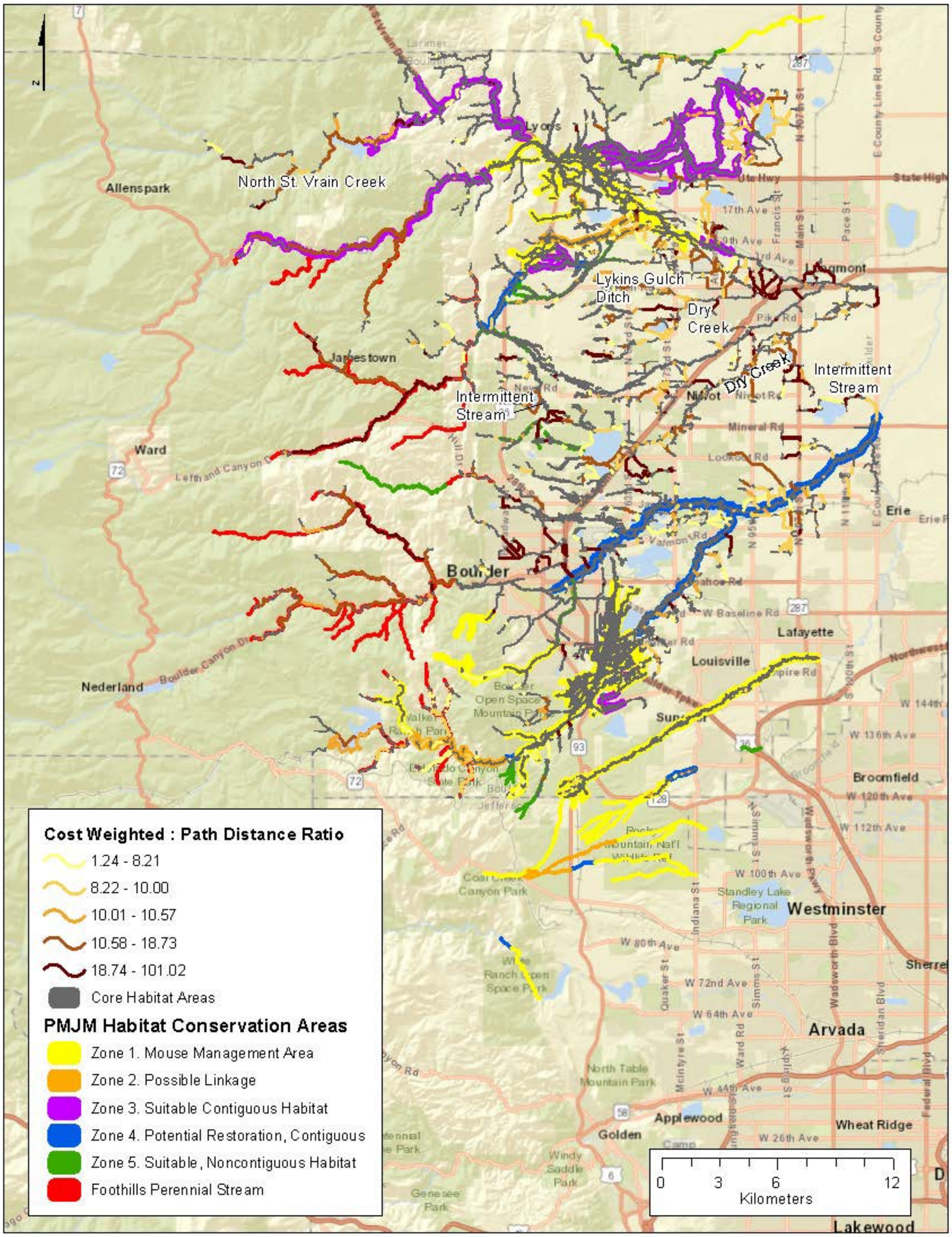

Figure 4-25. PMJM Habitat Conservation Areas (Boulder County 2013), core habitat identified by the SDM, and least cost paths.

Of the newly identified potential links (Figure 4-26), the Lykins Gulch Ditch link has the lowest effective resistance, is relatively close to known PMJM habitat, and may be a good candidate for restoration. The existing grazing exclosures on private land near Gage Open Space can serve as a template for creating PMJM habitat areas every few hundred meters to increase connectivity between core habitat located on Bangell NUPUD and Coyote Ridge NUPUD and

Carpenter NUPUD (Figure 4-27). The output of the 150 m barrier analysis (Figure 4-28) indicates relatively low resistance to movement in this area at a distance of 150 m, making it a good candidate for focused restoration using exclosures to protect or restore riparian vegetation along ditches on private land and public land currently used for agriculture. Between Bangle and Coyote Ridge, the SDM has modeled suitable habitat but, field investigation would be needed to verify this result. Likely, an investment in restoration would be necessary in order to establish a true habitat corridor in this location. An additional connection between the core habitat in Carpenter NUPUD and known PMJM habitat in Pella Crossing would further expand potential connections to suitable habitat and known PMJM populations through an area with relatively low resistance to movement.

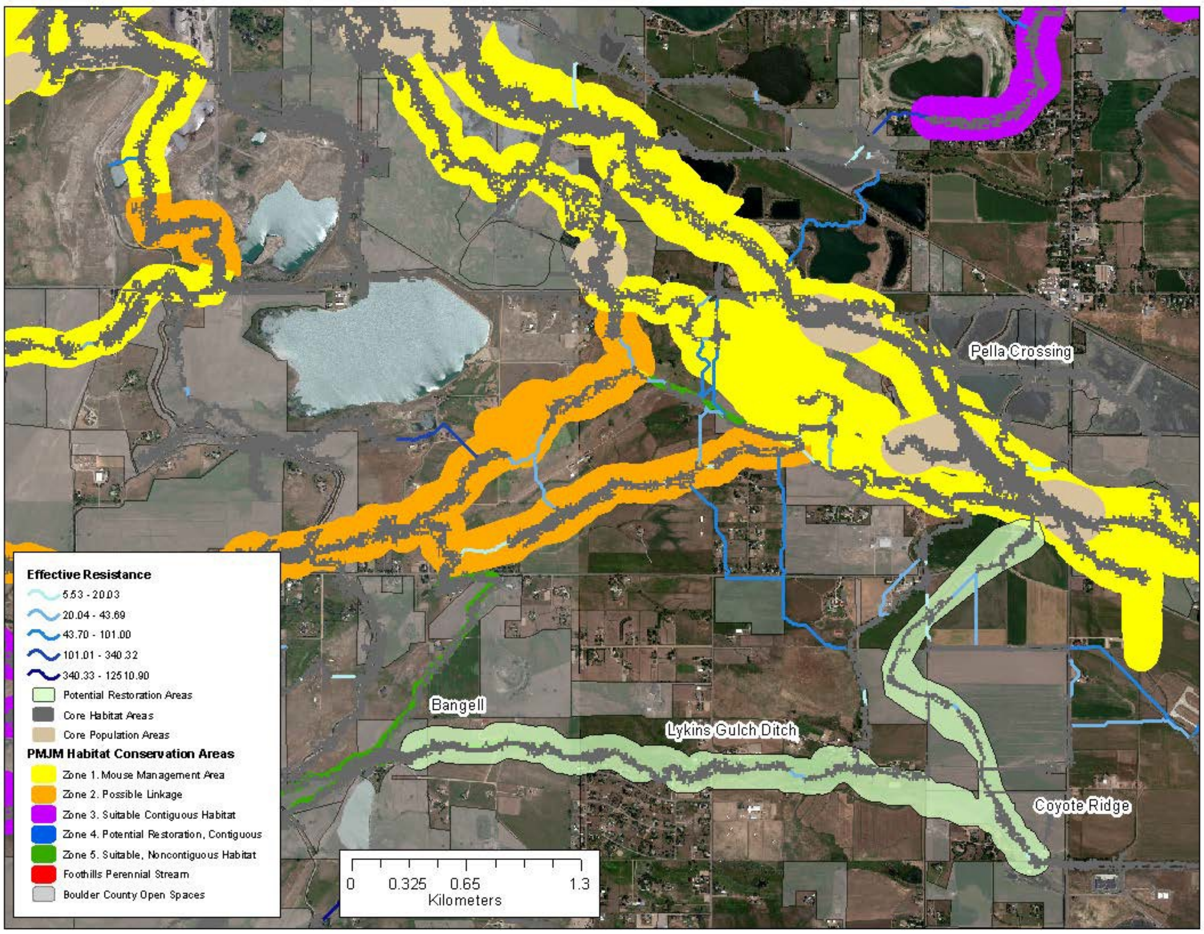

Figure 4-26. Potential restoration areas using core habitat effective resistance modeling links.

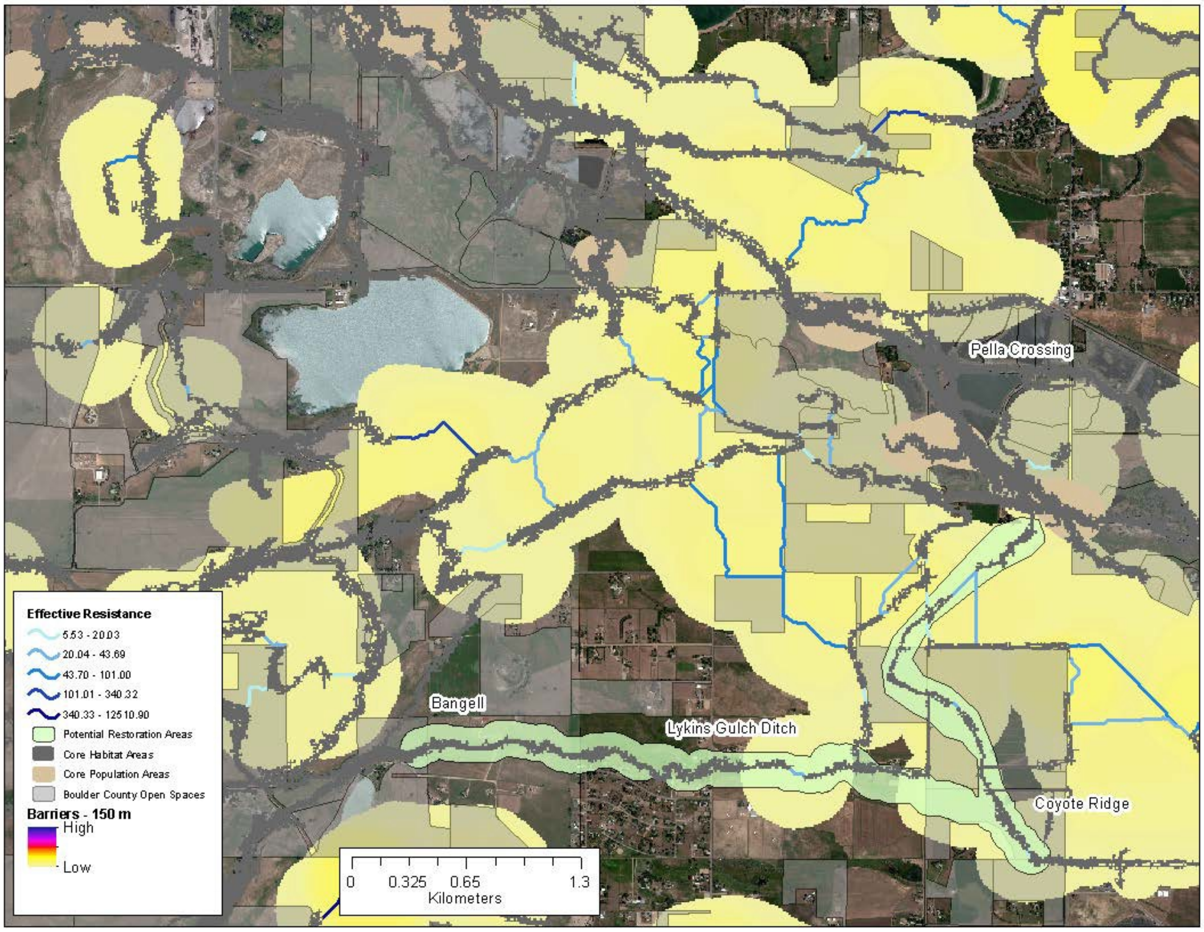

Figure 4-27. Barrier modeling for potential restoration using a 150 radius.

In examining the core population connectivity models, pinch point analysis, and barriers (Figures 4-13, 4-15, 4-17, 4-19, 4-21, and 4-23) we identified a second area for potential restoration and riparian vegetation enhancement between Pella Crossing, Gage, and the Western Mobile Complex (Figure 4-29). These linkages have moderate effective resistance (Figure 4-29) and moderate barrier values at both a 150 m and 450 m radius (Figure 4-19 and 4-21), suggesting that restoration to riparian vegetation in this location would improve PMJM habitat and mobility. Other potential restoration areas exist throughout the county (e.g, Left Hand Creek) to increase the connection between the northern and southern populations, but without confirmed PMJM occupation, restoration efforts may be ineffective.

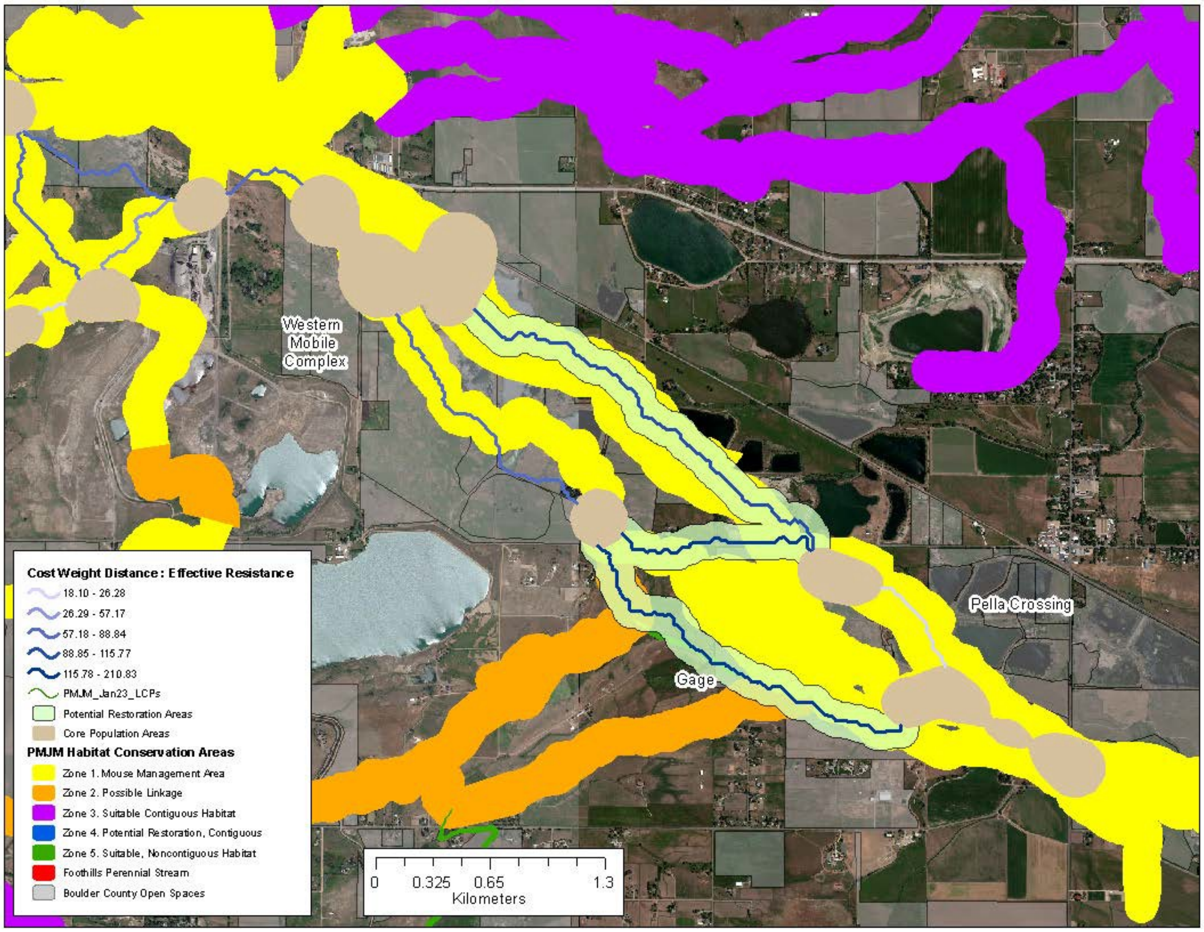

Figure 4-28. Potential restoration areas using core population effective resistance modeling links.

Conclusions

We created a species distribution model and modeled population and habitat connectivity for PMJM using the land cover classification developed in Chapter 2, LiDAR derivatives, and USFWS (2016) PMJM trapping data. SDMs provide a broad-scale tool for conceptualizing habitat across the Boulder County riparian area. Variable importance measures highlight the narrow geographic context in which PMJM occurs–the dominating influence of the distance to streams layer especially makes this clear. While less accurate as a prediction tool, the reduced model provided more insights in other variables that are also important. The importance of the land cover classification emphasizes general habitat affinities of PMJM, while the relative importance of HAG standard deviation highlights the importance of vertical heterogeneity. Our landscape level connectivity analysis provides insight into potential riparian habitat, movement corridors and, barriers to movement for PMJM by identifying suitable habitat using the species distribution model, identifying habitat PMJM are currently using kernel density estimates, and modeling the least cost paths between habitat patches. Overall, there is considerable suitable PMJM habitat (Figure 4-9) outside of the habitat that is currently being utilized (Figure 4-8). The suitable habitat is connected to known habitat in both the St. Vrain and Boulder Creek PMJM populations, indicating that PMJM has the potential to expand beyond its current distribution. However, we understand that there are additional biological variables (e.g., predation, disease) that may impact PMJM's ability to inhabit new areas. Additional habitat areas, such as private land on Left Hand Creek or Fourmile Canyon Creek has the potential to support PMJM but, trapping efforts have not been able to successfully verify PMJM occupation. Further research, such as increasing trapping efforts in suitable habitat (e.g., Left Hand Creek), completing landscape genetic studies to determine if populations are interbreeding to have a better understanding of PMJM interconnections, and increasing effort to understand PMJM movement using telemetry will better inform researchers and managers of habitat use and movement patterns.

Overall, the connectivity analysis illuminates several key points and recommendations related to PMJM habitat and management:

1. As modeled by the SDM, Left Hand Creek supports habitat suitable for PMJM and has the potential to form connectivity between the St. Vrain watershed and the Boulder Creek watershed. We recommend adding Left Hand Creek to the PMJM Habitat Conservation Areas map and increasing efforts to trap PMJM on Left Hand Creek. These efforts should be considered in conjunction with BCPOS aquatic and vegetation monitoring that is occurring at open spaces along Left Hand Creek.
2. PMJM habitat exists on Fourmile Canyon Creek. We recommend adding Fourmile Canyon Creek to the PMJM Habitat Conservation Areas map and, if resources exist, working with other agencies to increase efforts to trap PMJM on Fourmile Canyon Creek.
3. We have identified several potential linkages for PMJM, including Dry Creek, Lykins Gulch Ditch, two intermittent streams, and North St. Vrain Creek (Figure 4-26). We recommend conducting fieldwork to investigate the viability of these connections and to determine if PMJM are using habitat in these areas.
4. We have identified two locations (Figures 4.27 - 4.29) for restoration based on proximity to known PMJM populations, effective resistance, and barriers within short (150 m) to moderate (450 m) distances. The following chapter identifies areas for overall riparian restoration and flood recovery efforts and can be used in conjunction with the results from this chapter for a broader understanding of the condition of riparian ecosystem within Boulder County.

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CHAPTER 5. A LANDSCAPE-SCALE ASSESSMENT OF RIPARIAN VEGETATION STRUCTURE USING REMOTE SENSING DATA

Introduction

The structure of riparian vegetation critically influences many ecological processes and functions (Knopf and Samson 1994, Shaw and Bible 1996, Lyons et al. 2000, Bergen et al. 2009). Various field-based approaches for quantifying structure emphasizing different characteristics have been developed, but methods are time-intensive, costly, and poorly suited for assessing large landscapes (McElhinny et al. 2005, Korhonen et al. 2006, Haara and Leskinen 2009). Advances in remotes sensing, especially light detection and ranging (LiDAR) technology, allows analyses at scales not possible using traditional field methods (Means et al. 1999, Lefsky et al. 2002, Dassot et al. 2011).

Vegetation structure varies in horizontal and vertical dimensions and each is important to habitat quality and ecological function (Bergen et al. 2009, Coops et al. 2016). Assessment of horizontal structure usually focuses on attributes of land cover composition focusing on variables such as cover, patch size, or other landscape pattern metrics (Turner et al. 2001, Latterell et al. 2006). In contrast, analyses of vertical structure often focus on characteristics such as canopy height, biomass, or vertical heterogeneity (Shugart et al. 2010, Coops et al. 2016). Airborne LiDAR (ALS) can provide information on both vertical and horizontal structure at high resolution and broad spatial extents, providing valuable insights into habitat quality and ecological functions providing so are important for monitoring and assessment.

LiDAR data have been used to characterize vegetation structure in a wide variety of ecosystem types including riparian areas (Johansen et al. 2010, Caynes et al. 2016, Jeong et al. 2016). Data provide information useful for improving the accuracy of land cover mapping as well as providing direct information on structure useful for understanding habitat (Vierling et al. 2008, Alexander et al. 2014, Coops et al. 2016). While providing a powerful tool for ecological assessment, like any remote sensing approach, there are limitations to what LiDAR data can provide. For example, vegetation composition is difficult to ascertain from vertical structure data alone, although some of these limitations can be addressed by incorporating multispectral or hyperspectral data (e.g., see chapter 2) (Jeong et al. 2016, Luo et al. 2016). Another challenge in working with rich data sets like LiDAR is effective communication of results. Structure is not a single variable, rather it encompasses numerous different characteristics. The importance of any aspect of structure is context specific and no single mode of presentation can communicate all relevant aspects of structure.

Objectives

This chapter used airborne LiDAR (ALS) to quantify landscape-scale patterns of riparian structure across Boulder County using multiple complimentary approaches and presents a novel framework for analyzing structure and other variables for assessment and monitoring. The data and results provide insights into structural variability that have broad applications to riparian management. These include not just applications to PMJM habitat, which were extensively explored in the previous chapter, but to a broader set of resources and questions. The specific objectives included the following:

- Quantify continuous patterns of vegetation canopy height and structural complexity across major watersheds using a variety of ALS-derived metrics.

- Develop a discrete spatial framework for representing continuous ALS-derived structure information useful for identifying areas with particular structural attributes and for guiding future field assessment and monitoring.
- Use this framework to identify potential sites for restoration or management intervention based on lack of desired vegetation structure or cover characteristics.

Methods

Overview

Riparian structure was analyzed using multiple methods, including approaches representing structure as continuously-varying quantities and an approach that discretized patterns across the landscape. Both have advantages and disadvantages. Continuous representations reflect the reality that structure continuously varies across the landscape, but are more difficult to summarize. By discretizing structure, some resolution is lost, but data are more easily synthesized, offering advantages for summarizing patterns and integrating products into monitoring and management.

ALS data processing

We used small-footprint multiple-return LiDAR point cloud and intensity data collected in October and November 2013 to generate continuous raster layers depicting different aspects of structure (see Chapter 3). Using processing algorithms in the lastools library (Rapid Lasso, GmB; www.rapidlasso.com), raw LAS datafiles were cleaned and classified into ground and non-ground points and height normalized. Data were then used to generate continuous raster layers representing different statistical point cloud derivatives including the maximum, average, standard deviation, and various percentiles of canopy height above ground (HAG). In general, rasters were generated at 10 m resolution, an appropriate scale for conducting landscape-scale assessments that balances raster resolution with practical considerations like storage and processing requirements. For a subset of key variables used in analyses (e.g., principle components analysis), ALS-derivatives were produced at a finer 3 m resolution.

Continuous analyses of vegetation structure

Single and multiband derivatives

Data layers for each of the individual ALS derivatives were produced to provide insights into different aspects of riparian structure. These have been provided in a geodatabase to enable BCPOS or other users to view and analyze data. As a complimentary approach for visualizing landscape patterns in structure, we combined select variables into a multi-band raster that can be viewed as a false-color image (Stoker 2010). The red band was assigned ALS-derived cover (a measure of horizontal pattern), the green band was assigned 95th percentile height above ground (a measure of vertical structure), and the blue band was assigned the HAG standard deviation (a measure of vertical heterogeneity)(Coops et al. 2016). The value of such an approach is that it allows for qualitative assessment of variation in multiple variables simultaneously. For example, two areas with similar canopy cover but differing in vertical heterogeneity will appear differently in the composite.

Principle Components Analysis

While each of the individual ALS-derived rasters has value for assessing specific aspects of structure, the large number of variables possess a challenge for data interpretation. Principle components analysis (PCA), a statistical data reduction technique, was used to reduce HAG derivatives into a smaller number of bands capturing the main patterns of structural variability for visualization. The Principal Components tool in ArcGIS pro was used to transform the 10 HAG input bands into a new multivariate attribute space with the axes rotated with respect to the original space so that they are uncorrelated, thereby by eliminating redundancy. The output was a 3-band raster with each band corresponding to an individual component in the new multivariate space. The first principal component in a PCA explains the greatest amount of variance in inputs, with each successive component explaining less of the variance.

Discrete analyses of vegetation structure

Tessellation of study area

The study area was tessellated using a hexagonal grid to provide a discrete sampling frame for evaluating structure and to aid in future monitoring. Hexagons were chosen because they are the most circular-shaped polygon that can form an evenly spaced grid and because any point inside a hexagon is closer to the centroid than any given point in an equal-area square or triangle (Birch et al. 2007). This makes hexagons preferable when analysis includes aspects of connectivity or movement paths and can reduce sampling bias due to edge effects because of their low perimeter-to-area ratio (Birch et al. 2007).

Hexagons 0.283 ha in size were used, equivalent in area to a circle with a 30 m radius or a square with 53 m sides. The size of hexagons was chosen to represent an area on the ground sampleable using plot level methods in the field or imageable in a single scan using a TLS unit. By reference, the Forest Inventory and Analysis program uses plots measuring 0.4 ha (assessed using subplots). The area used represents a reasonable tradeoff between creating sampling units of fine enough detail to represent structure and be sampleable in the field, yet course enough to allow landscape scale statistical analyses.

The full tessellation of the study area produced over 120,000 hexagons. (See chapter 2 for a detailed description how the study area boundary was delineated.) To avoid spurious effects on structural metrics from buildings or roads, all hexagons intersecting Boulder County's building footprints and roads GIS layers were dropped, yielding a total 92,377 hexagons for analysis.

Summary statistics were calculated for each hexagon using the zonal statistics tool in ArcGIS Pro with various data layers (Table 5-1). Results were used as input into the cluster analysis described below and as a source of information for conducting queries of different measures of structure across the county. The distance of each hexagon to features in the County streams layer was calculated in ArcGIS and additional information was attributed to each hexagon including its watershed and the Open Space property in which it occurred (if applicable). The proportional area of each hexagon with different land cover classes (see Chapter 2) was calculated using the tabulate area function in ArcGIS. Lastly, the distance to PMJM travel corridors and predicted habitat were calculated (see Chapter 4 for details).

Table 5-1. List of variable names and descriptions in the hexagon layer.

Variable	Description
HEXID	Unique identifier for each hexagon
ELEV	Mean elevation above sea level (m) from ALS-derived bare earth
HU_10_N	10th level hydrologic unit basin (HUB) name
HU_12_N	12th level hydrologic unit basin (HUB) name
HUC_12	12th level hydrologic unit basin (HUB) code
AVG	Mean zonal value: HAG average
COV	Mean zonal value: ALS-derived cover
DEN	Mean zonal value: ALS-derived density
MAX	Mean zonal value: HAG maximum
P05	Mean zonal value: HAG 5th percentile
P10	Mean zonal value: HAG 10th percentile
P25	Mean zonal value: HAG 25th percentile
P50	Mean zonal value: HAG 50th percentile
P75	Mean zonal value: HAG 75th percentile
P90	Mean zonal value: HAG 90th percentile
STD	Mean zonal value: HAG standard deviation
AVG_Z	Mean zonal value: HAG average-0-1 normalized version
COV_Z	Mean zonal value: ALS-derived cover-0-1 normalized version
DEN_Z	Mean zonal value: ALS-derived density-0-1 normalized version
MAX_Z	Mean zonal value: HAG maximum-0-1 normalized version
P05_Z	Mean zonal value: HAG 5th percentile-0-1 normalized version
P10_Z	Mean zonal value: HAG 10th percentile-0-1 normalized version
P25_Z	Mean zonal value: HAG 25th percentile-0-1 normalized version
P50_Z	Mean zonal value: HAG 50th percentile-0-1 normalized version
P75_Z	Mean zonal value: HAG 75th percentile-0-1 normalized version
P90_Z	Mean zonal value: HAG 90th percentile-0-1 normalized version
STD_Z	Mean zonal value: HAG standard deviation-0-1 normalized version
CLUSTER	Cluster group produced from k-means cluster analysis
BARE	Percent of hex with bare land cover class
DEVELPD	Percent of hex with developed land cover class
RPFORST	Percent of hex with riparian forest land cover class
IRRGTDA	Percent of hex with irrigated agriculture land cover class
RPHRBCS	Percent of hex with riparian herbaceous land cover class
SHRUB	Percent of hex with shrub land cover class
UPFORST	Percent of hex with upland forest land cover class
UPHRBCS	Percent of hex with upland herbaceous land cover class
WATER	Percent of hex with water land cover class
STR_DIST	Distance to nearest stream (m)
CHA_DIST	Distance to the nearest habitat as predicted by the SDM & 95% of PMJM occurrence points
CPA_DIST	Distance to the nearest habitat from kernel density
LCPCHP_DIS	Distance to nearest least cost path from kernel density analysis
LCPCHA_DIS	Distance to nearest least cost path from SDM analysis
PROP_NAME	Property name from Open Space properties layer
OWN_SUBTYP	Owner type from Open Space properties layer

Cluster analysis

A statistical clustering of hexagons was run to provide a simple synthetic measure of structural similarity. Zonal statistics calculated for three different ALS-derived layers (cover, 95th percentile HAG, and HAG standard deviation) were standardized to a 0-1 range and used as input to the k-means clustering algorithm in R. K-means clustering is a form of unsupervised learning that looks for groups in data by assigning each data point to one of a number of groups (k), calculating its distance to the nearest cluster centroid based on the squared Euclidean distance, then iterating the process until the sum of the distances is minimized (Han et al. 2012). The algorithm requires specification of the number of clusters, determined in this analysis by running different clustering solutions using different values of k, and evaluating trends in the total within sum of squares across the number of clusters values.

Analysis of hexagon-based structure metrics

Tables created from individual geoprocessing operations (e.g., zonal statistics on ALS-derived layers) were joined to the hexagon layer using a unique hexagon identifier. The resulting data layer, provided to BCPOS as a shapefile, was used to make queries of data and for creating statistical summaries using various grouping variables including hydrologic unit basins (HUB10), Open Space properties, and elevation zones. In addition, potential sites for restoration were identified by selecting hexagons dominated by bare ground from the land cover classification (Chapter 2), with low canopy cover and height from ALS data, and occurring near streams.

Results

Analysis of continuous structure data

Ten distinct continuously-varying structural variables were calculated across the study area. These include measures of horizontal structure such as cover, as well as multiple metrics characterizing vertical structure (Figures 5-1, 5-2). Metrics such as the height above ground (HAG) mean, maximum, and percentiles (p10, p95, etc.) provide information about canopy height characteristics, while the standard deviation provides insights into vertical heterogeneity. Each of these data layers is provided in geospatial format for use in a GIS. Large format maps have also been provided as supplemental material. Because the best spatial scale and resolution of a map is determined by the purpose, it was not feasible to provide every permutation possible. If the maps provided are unsuitable to a user's needs, the raw data have been provided to BCPOS to allow creation of output in whatever format is desired. If such as a user lacks basic GIS experience, they should consult staff with such knowledge for assistance. False-color images, created by assigning different data to the red, green, and blue channels of a standard, true-color image, were also created, providing additional way to examine structural variation in riparian areas (Figure 5-3).

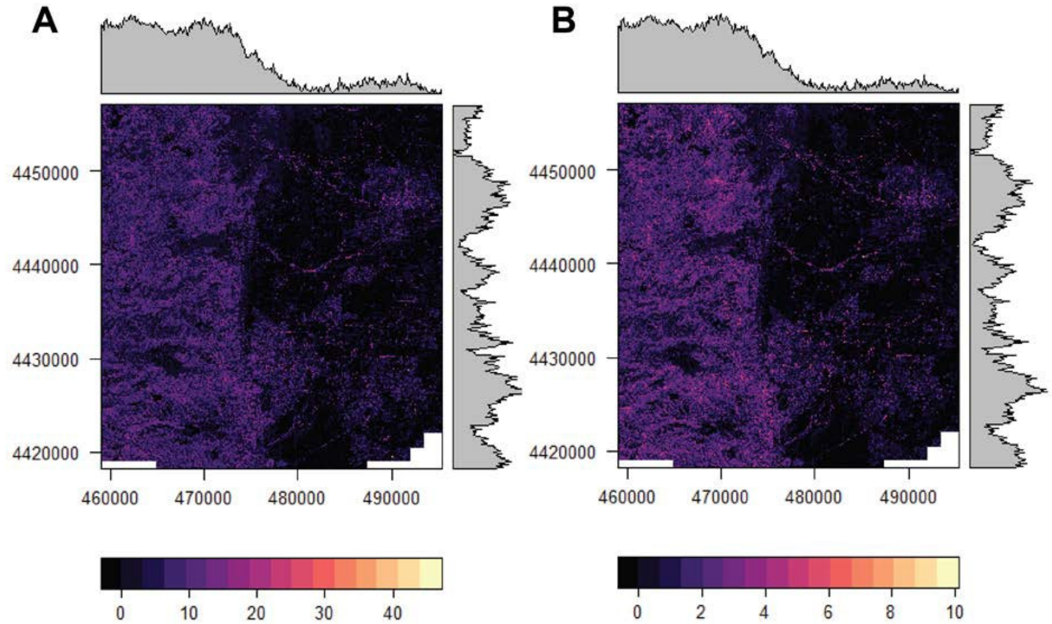

Figure 5-1. Examples of two of many ALS-derived structural data layers created for the study area: 95th percentile HAG (panel A) and HAG standard deviation (panel B). Axes refer to UTM coordinates, color scales to HAG in m. Fine detail is not observable at these broad spatial scales and small level of reproduction. The reader is directed to large format supplemental maps and GIS data provided with deliverables.

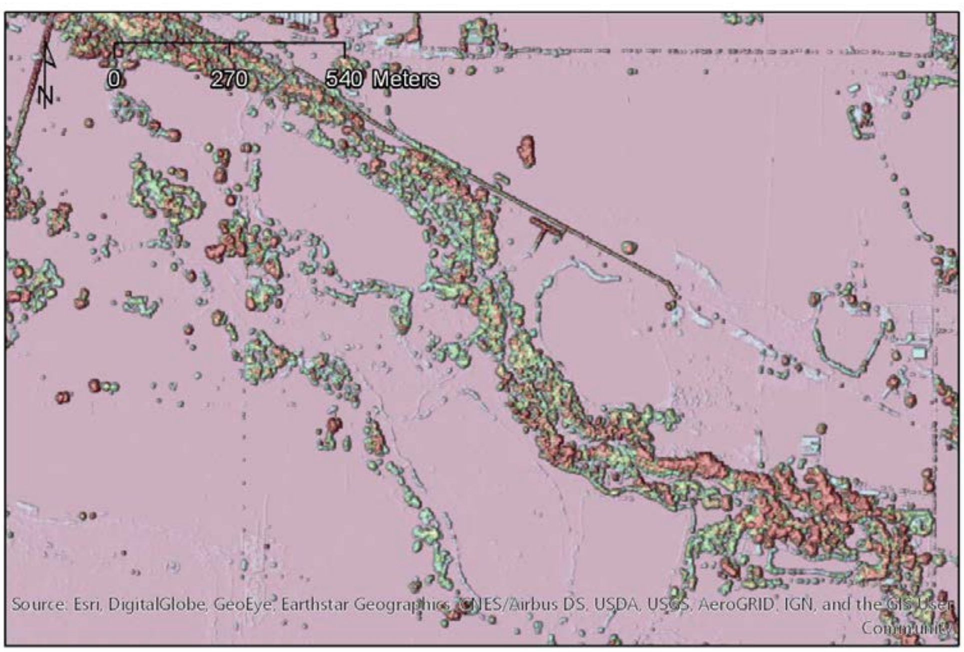

Figure 5-2. Map of 95th percentile height above ground output for a portion of the Western Mobile property. Large format versions of key single-band.

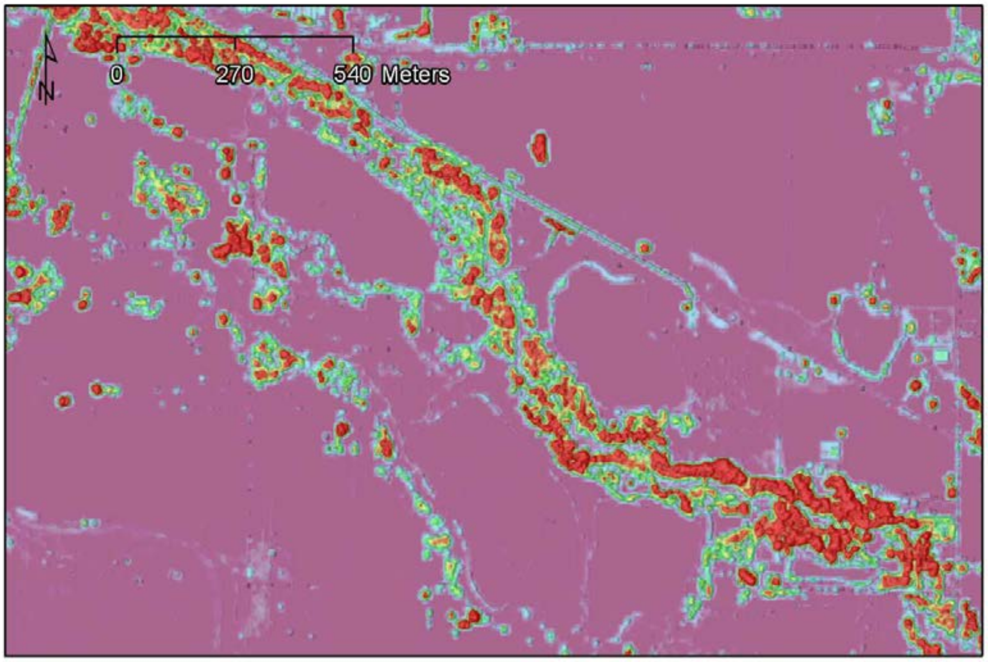

Figure 5-3. False color image of a portion of the Western Mobile property created by combining the 95th percentile HAG (red channel), HAG standard deviation (green channel), and ALS-derived cover (blue channel). A large format version is provided for the study area as supplemental material.

Principle components analysis

Results of the PCA showed that the first component accounted for 96.1% of the covariance Table 5-2). Adding in the second principal component accounted for 99.3% of covariance, while the third component added little extra information (0.7%) and is slightly redundant with principal components 1 and 2. The resulting raster output was used to visually evaluate variation in the 10 ALS-derived variables in a single map (Figure 5-4). Data have been provided to BCPOS as both geospatial data layers and large format maps.

Table 5-2. Results of principal components analysis on ALS-derived structure metrics.

Component	EigenValue	Percent of EigenValues	Accumulative of EigenValues
1	30.24	96.05	96.05
2	1.02	3.25	99.30
3	0.22	0.70	100.00

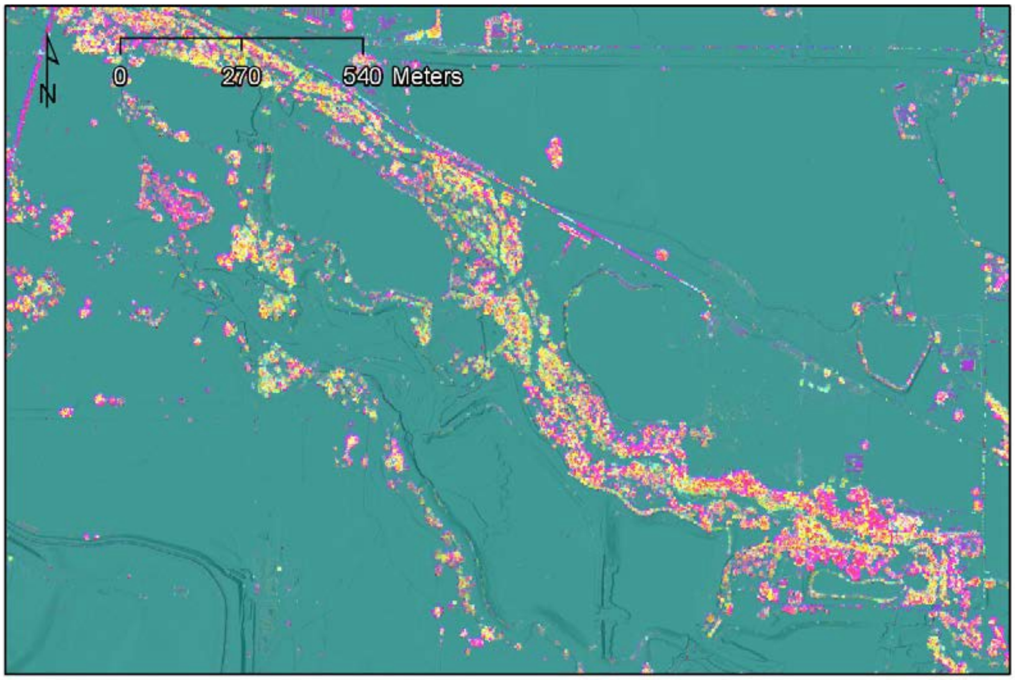

Figure 5-4. Map of principal components analysis output for a portion of the Western Mobile property. Scaling is in component space, so is not directly interpretable. The purpose is to qualitatively illustrate variation in structure along multiple dimensions.

Tessellation and cluster analysis

The number of hexagons in each watershed varied widely, with the greatest number in the Boulder Creek-Saint Vrain Creek HUB10, and the fewest in the headwaters of the little Thompson (Table 5-3). Hexagons were most abundant at lower elevations owing to the more expansive riparian areas there, decreasing in abundance in the foothills (Figure 5-5). Most hexagons occurred on non-Open Space lands (57,770, 62%), with 15,833 hexagons (17.1% of the total) occurred on County-owned Open Space (COS) lands, and the remaining hexagons distributed among other OS ownership classes (Figure 5-5).

Table 5-3. Count of hexagonal cells in each 10th level hydrologic unit basin (HUB10).

Watershed (HUC10)	**Count of**
Boulder Creek-Saint Vrain Creek	41740
Coal Creek-Boulder Creek	14791
South Boulder Creek	10150
Headwaters Boulder Creek	9276
Left Hand Creek	7572
North Saint Vrain Creek	4509
South Saint Vrain Creek	3092
Dry Creek-Little Thompson River	1094
Headwaters Little Thompson River	153

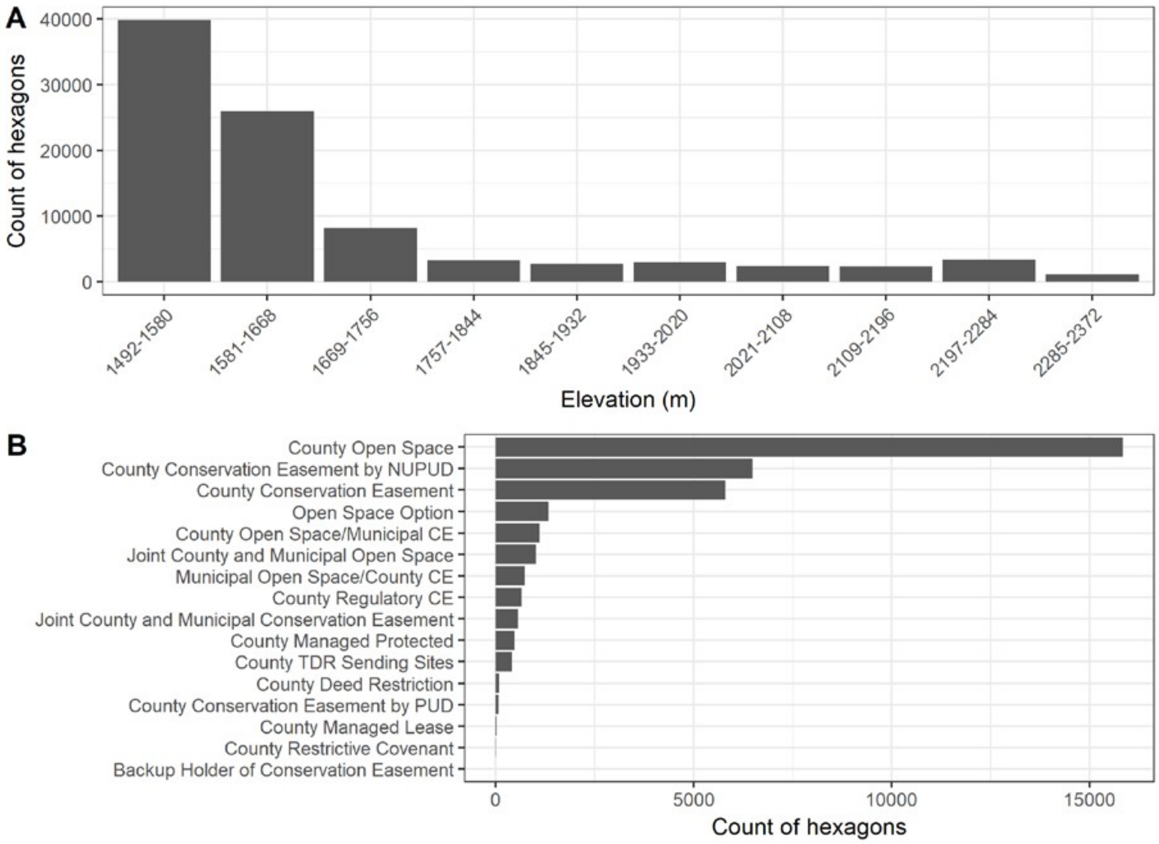

Figure 5-5. Count of hexagons by elevation band (panel A) and Open Space ownership class (panel B).

Mean canopy cover generally increased with elevation, although there was variability within any given elevational band (Figure 5-6). This trend reflects the generally higher tree density seen in foothills and montane life zones compared with the plains. However, there was significant variability at any given elevation, a reflection the inherent heterogeneity of riparian areas.

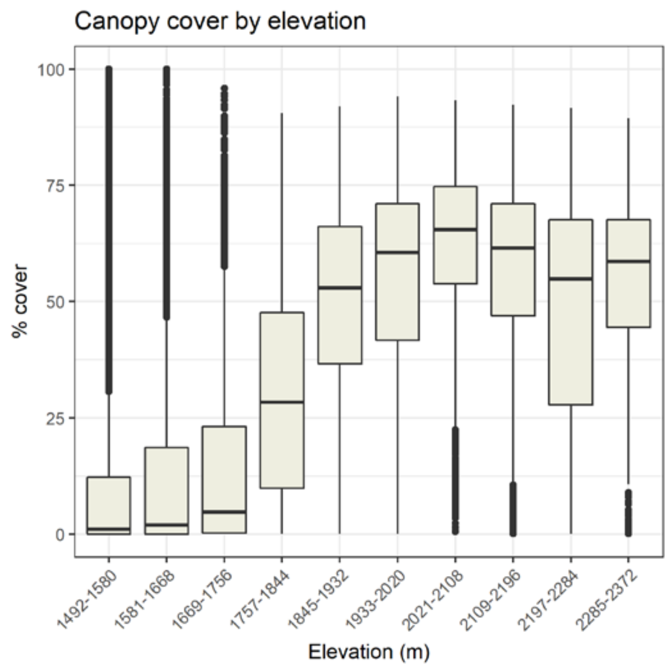

Figure 5-6. Boxplots of mean canopy cover for each 0.2 ha hexagon within different elevation above sea level bands.

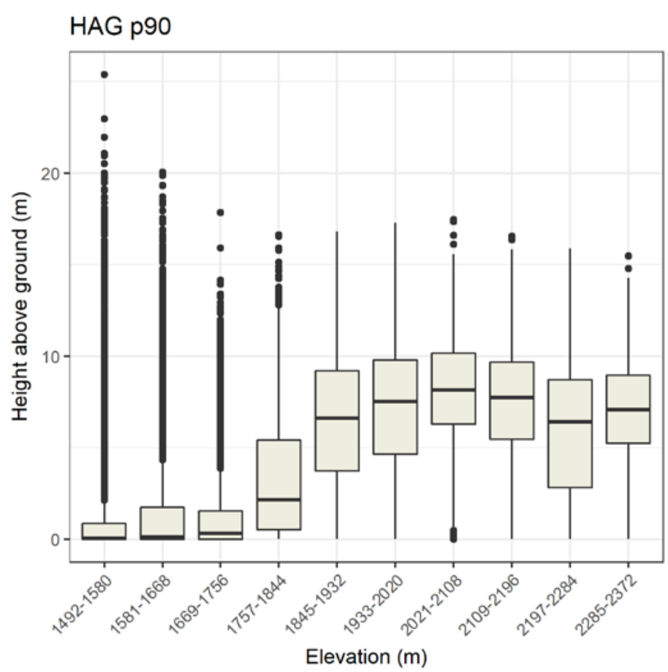

Figure 5-7. Boxplots of ALS-derived mean 90th percentile height above ground for hexagons versus elevation.

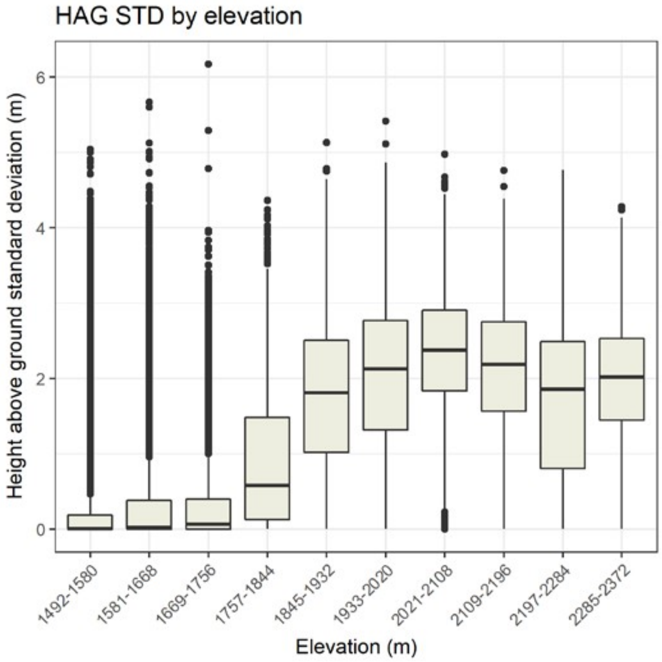

Figure 5-8. Boxplots of ALS-derived mean height above ground standard deviation for hexagons versus elevation.

Cluster analysis

Based on changes in total within sums of squares, 4 clusters were chosen for analysis (Figure 5-9). Cluster 1 was the most abundant, accounting for 61.3% of all hexagons (n=56,657), followed in abundance by cluster 2 (16.1%), cluster 3 (12.6%), and cluster 4 (10.0%). Clusters were clearly differentiated in basic structure (Figure 5-10), with cluster 1 showing lowest canopy cover, height, and variation and cluster 4 the highest (Figure 5-11).

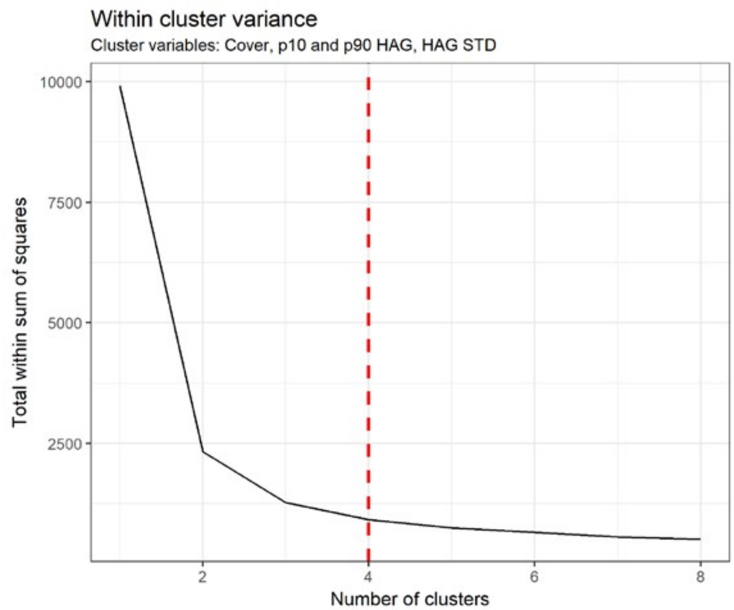

Figure 5-9. Plot of total within sum of squares as a function of the number of clusters (k) defined. Based on the inflection in the curve, a value of k=4 was selected.

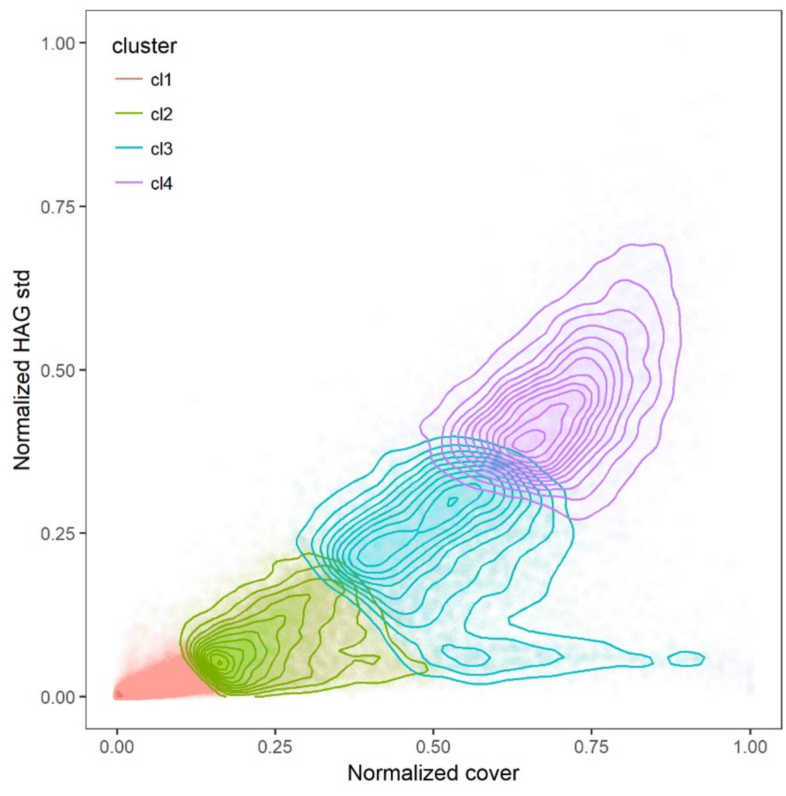

Figure 5-10. Two-dimensional density contours for normalized (0-1) canopy cover and HAG standard deviation illustrating clear differentiation of clusters.

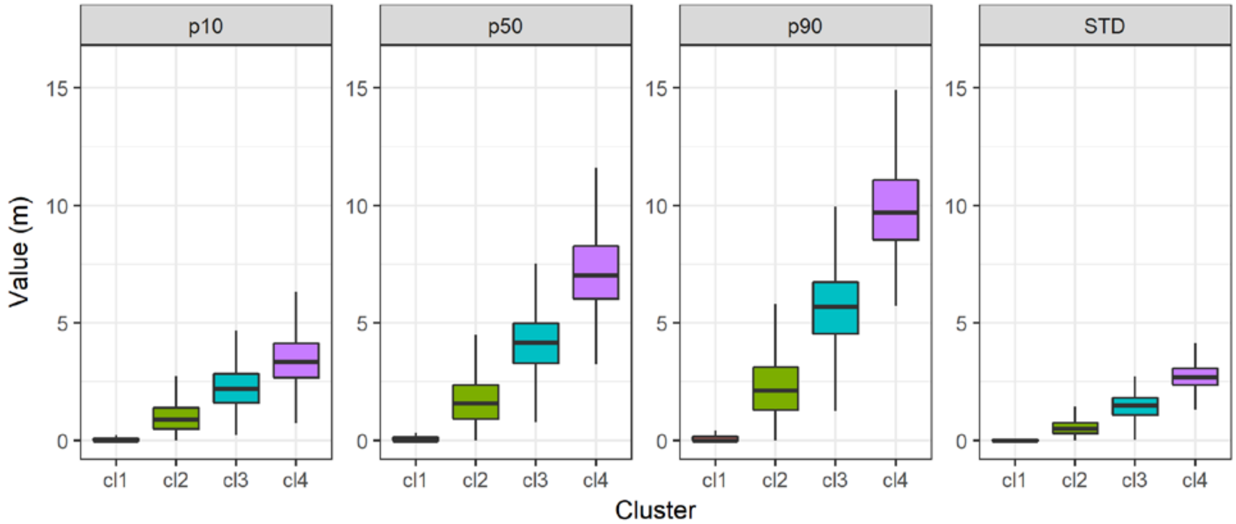

Figure 5-11. Boxplots illustrating height above ground variables for different clusters.

Map of clusters clearly differentiated structurally distinct areas of study area riparian corridors (Figure 5-12). Patterns are especially pronounced when viewed across broad extents (see supplemental maps). Geographic differences were also evident in plots of cluster count by elevation. Cluster 1–the most abundant class overall–and cluster 2 were most common at lower elevations, while cluster 4 reached peak abundance at higher elevations. This in part reflects the narrower riparian zone in the foothills and the structural influence of adjacent upland forests (Figure 5-13).

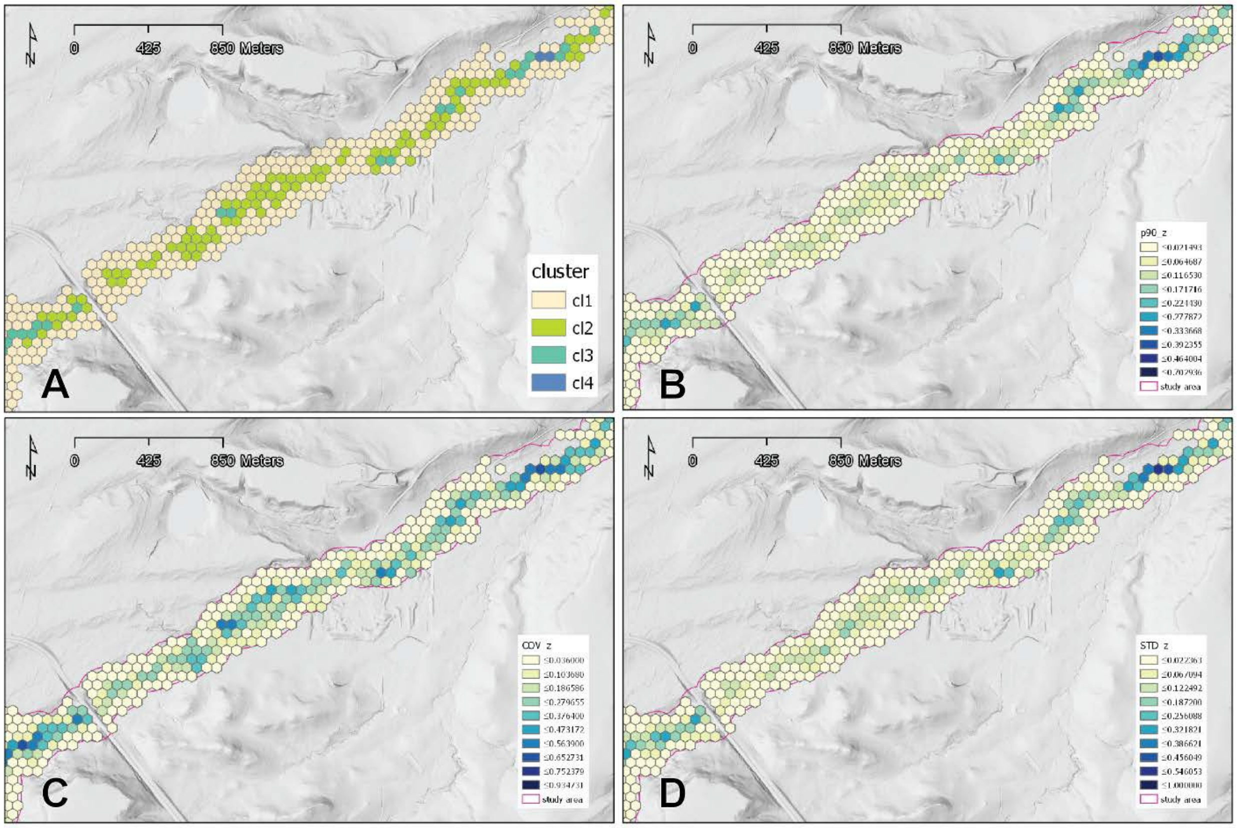

Figure 5-12. Example centered on a section of Coal Creek illustrating the results of the kmeans cluster analysis (panel A), the 90th percentile height above ground (HAG, panel B), ALS derived canopy cover (panel C), and HAG standard deviation (panel D).

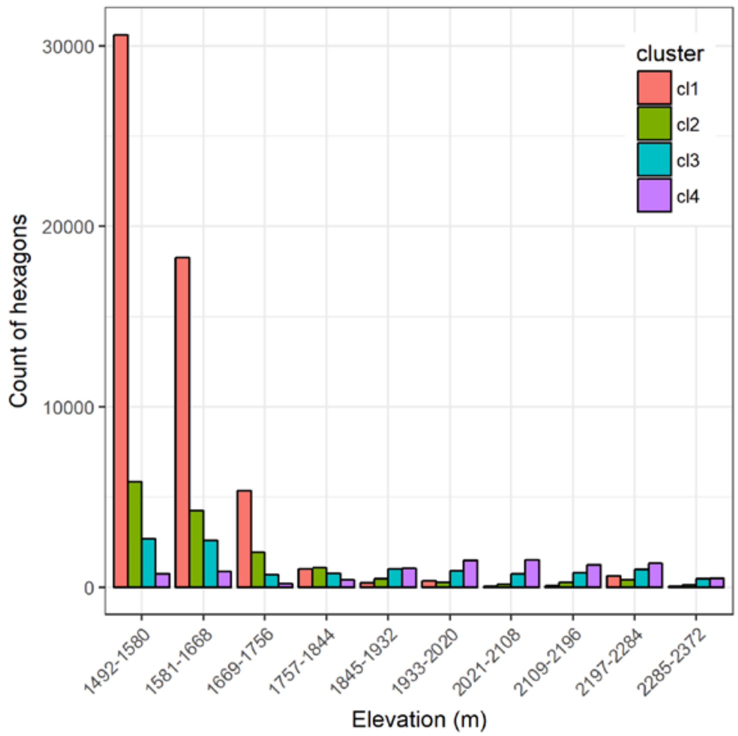

Figure 5-13. Counts of hexagons in each cluster and elevation class.

Summary by OS properties

Hexagons occurred in all ownership contexts, but within the context of different open space types, the greatest number occurred in County-owned properties (n=15833), followed County Conservation Easements by NUPUD (Figure 5-14, Table 5-4). Structural characteristics differed by ownership type. For example, the County Restrictive Covenant ownership type had the highest proportional cover of the Shrub land cover class, while the County Managed Lease type had the highest HAG max value, but both types represent a small fraction of total hexagons across the study area.

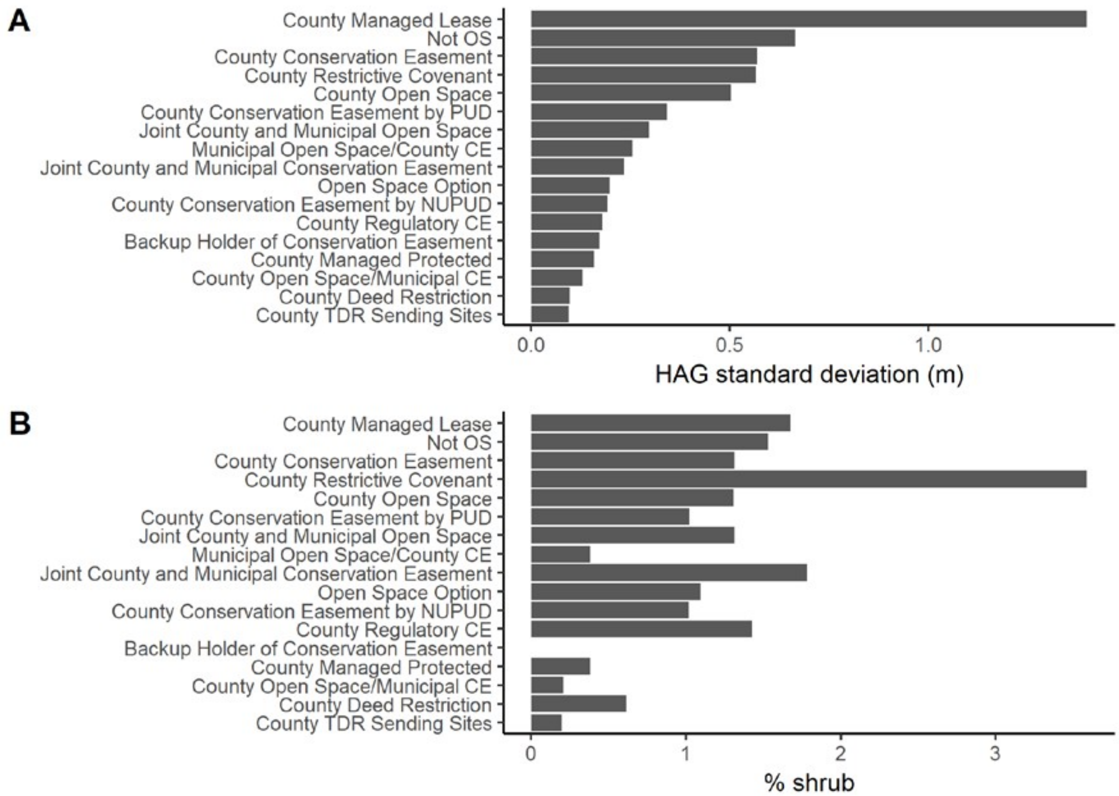

Figure 5-14. Mean height above ground (HAG) standard deviation for hexagons in different ownership classes (panel A). Mean proportional cover by the shrub land cover class by ownership type (panel B).

The proportion of hexagons in cluster 1 was slightly higher for County Open Space properties compared to other ownership classes, and the reverse was true for clusters 3 and 4, but differences were not significant (Table 5-4, Figure 5-15). Small difference between COS properties and other ownership classes were also observed. For example, maximum HAG was lower on COS for clusters 2 and 3 than other ownership classes, but again, differences were minor.

Table 5-4. Count of hexagons and summary statistics calculated for all hexagons in a given ownership type from the County Open Space layer.

OWN_SUBTYP	count	HAG STD	Cover	HAG Max	% Shrub
Not Open Space	57700	0.7	22.1	2.7	1.5
County Open Space	15833	0.5	17.5	1.9	1.3
County Conservation Easement by NUPUD	6491	0.2	8.3	0.8	1.0
County Conservation Easement	5801	0.6	18.4	2.2	1.3
Open Space Option	1331	0.2	7.4	0.9	1.1
County Open Space/Municipal CE	1105	0.1	4.6	0.6	0.2
Joint County and Municipal Open Space	1024	0.3	8.5	1.2	1.3
Municipal Open Space/County CE	748	0.3	9.2	1.0	0.4
County Regulatory CE	663	0.2	6.4	0.8	1.4
Joint County and Municipal Conservation Easement	569	0.2	8.2	1.0	1.8
County Managed Protected	480	0.2	9.0	0.7	0.4
County TDR Sending Sites	419	0.1	4.8	0.4	0.2
County Deed Restriction	87	0.1	10.5	0.4	0.6
County Conservation Easement by PUD	75	0.3	10.7	1.4	1.0
County Managed Lease	33	1.4	42.6	5.2	1.7
County Restrictive Covenant	14	0.6	19.9	2.4	3.6
Backup Holder of Conservation Easement	4	0.2	11.2	0.7	0.0

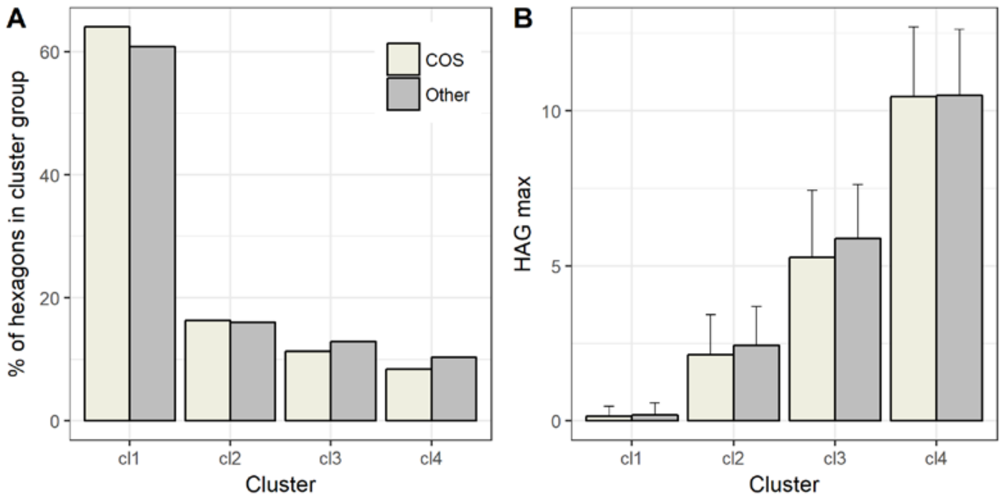

Figure 5-15. Barplot comparing the proportion of hexagons in each cluster for County Open Space (owned, COS) and other property ownership settings (panel A); barplot comparing maximum HAG (bars represent means, error bars standard deviation) within each cluster for COS and other settings (panel B).

Selection of potential restoration sites

To demonstrate the utility of the hexagon framework for management and planning, we queried the data set using multiple criteria to identify potential sites for restoration. Hexagons within 15 m of streams, with >50% of their area as bare ground, a 90th percentile HAG value <1 m, and ALS-derived canopy cover <10% were extracted, yielding 126 hexagons across the study area. All occurred in cluster 1. Sites were distributed among different watersheds, but were most abundant in the Boulder Reservoir, Indian Mountain-Saint Vrain Creek, and Dry Creek 12th-level HUBs (Table 5-5). Using statistics generated in the PMJM habitat modeling and connectivity chapter, this list can be further refined to focus on sites important for Preble's habitat. This is a simple demonstration of how these data can be used to identify areas of interest.

Table 5-5. Count of hexagons meeting criteria described above.

Watershed (HUB 12) name	n
Boulder Reservoir	38
Bullhead Gulch-Boulder Creek	6
Calkins Lake-Saint Vrain Creek	2
City of Boulder-Boulder Creek	3
Dry Creek	24
Dry Creek-Boulder Creek	2
Indian Mountain-Saint Vrain Creek	27
Ish Reservoir-Little Thompson River	3
Lower Left Hand Creek	4
McIntosh Lake-Saint Vrain Creek	11
Middle Left Hand Creek	1
Outlet North Saint Vrain Creek	3
Outlet South Saint Vrain Creek	2

Discussion and management implications

The analyses in this chapter provide a broad perspective of vegetation structure in Boulder County riparian areas. Multiple different ways of characterizing structure were presented, providing end users flexibility in applying data and analyses for different goals. The results and data products complement the land cover product presented in Chapter 2 and the Prebles Meadow Jumping Mouse (PMJM) habitat analyses and products (SDMs, connectivity layers) presented in Chapter 4, but purposefully does not duplicate these analyses. Results highlight both the diversity of riparian structural characteristics across Boulder County and the varied ways they can be assessed using airborne LiDAR data. The remote-sensing analyses used provide a valuable synoptic perspective of the structural characteristics of BCPOS riparian cover and structure.

No single variable captures all aspects of vegetation structure and the relative value of any particular metric varies depending on the issue being addressed (Kane et al. 2010, Coops et al. 2016). Categories of ALS metrics of importance to forest structure include metrics describing vegetation height, metrics describing the horizontal arrangement of vegetation (e.g., canopy cover), and metrics describing the vertical distribution of vegetation within the forest canopy (Lefsky et al. 2005). The latter includes variables such as canopy height or the standard deviation of HAG returns in the canopy. This chapter characterizes each of these to provide different insights into riparian structure across Boulder County.

We used data to identify potential restoration sites by identifying areas dominated by bare ground, with low canopy cover and height, and occurring near streams. However, there are important caveats to this approach. Because it relied exclusively on characteristics identifiable from remote sensing data, additional information such as vegetation composition data from field assessments would be needed to determine whether restoration is in fact appropriate. For example, one site dominated by saplings of a non-native species such as Siberian elm (*Ulmus pumila*) could show similar structure to another dominated by young native cottonwoods, with the former an appropriate target for restoration, but not the latter. Identifying and prioritizing restoration is more complex process than simply querying a GIS data layer and requires thought by managers.

The attributed hexagons produced in this study provide a rich source of information and a flexible tool for making queries of data. For example, we identified potential sites for restoration by querying hexagons dominated by bare ground, with low canopy cover and height, and occurring near streams, but other criteria such as parcel ownership or watershed could also be used. Similarly, the data can be queried to identify sites with desirable structural characteristics. For example, hexagons with well-developed structure near watercourses could be potential PMJM trapping sites.

The data provided to BCPOS conveniently provides information specific to PMJM, such as distance to travel corridors (see Chapter 4). The framework can also be updated with new information by somebody with sufficient knowledge of GIS and remote sensing. By using the basic geoprocessing steps used in this study (e.g., zonal statistics), new data can be joined and made accessible for queries. This could include updated versions of data already included (e.g., new LiDAR data) or totally different types of information. For example, point clouds can be extracted from hexagons (Figure 5-16) and compared between LiDAR acquisition dates to assess changes from factors like flood disturbance.

The framework can also be used for field sampling. The area of each hexagonal cell is large enough to capture essential habitat structure, but small enough to allow field sampling using plot-based methods. Grid cells are appropriately sized for scanning using TLS technology or for forest measurements using approaches like those used by the National Forest Health Monitoring and Forest Inventory and Analysis programs (Dunn 1999, Bechtold and Patterson 2005). For measuring herbaceous plant cover, hexagons can also be used as part of clustered sampling designs employing smaller plots (Bonham 1989). The coordinates each grid cell's center can be easily navigated to using a GPS, facilitating repeat sampling. Effective monitoring is a critically important component of natural resources management (Lindenmayer and Likens 2010). Because riparian ecosystems are spatially and temporally dynamic, monitoring must be able to capture the effects of both discrete disturbances such as floods and to allow assessment of long-term ecological changes such as vegetation succession. Remote sensing analyses like that presented here can be an important part of such efforts.

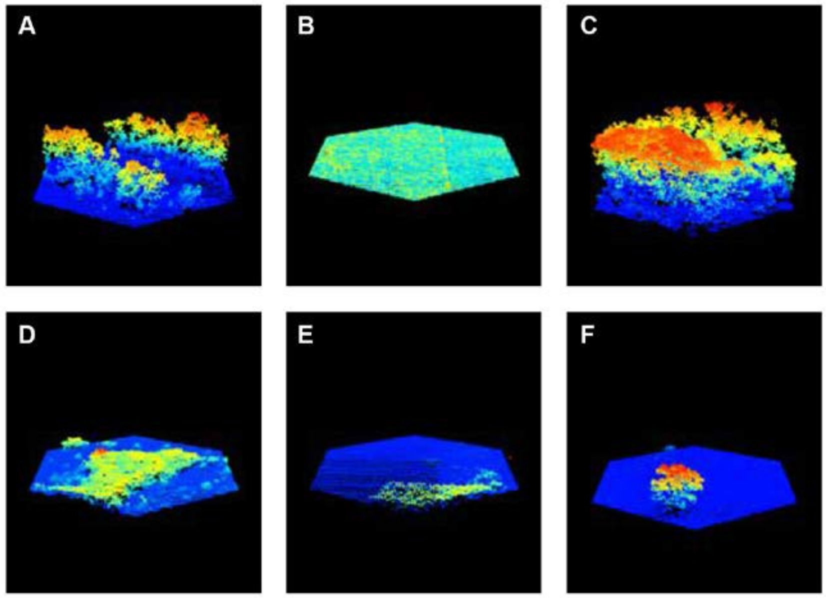

Figure 5-16. Examples of ALS point clouds extracted using hexagons. Mixed tree and shrub community supporting PMJM (panel A), bare sediment lacking vegetation (panel B), dense forest with well-defined understory (panel C), shrub dominated community (panel D), meadow with encroaching shrubs (panel E), golf course with lone open-grown tree (panel F).

However, remote sensing is not a silver bullet (Peterson et al. 1999, Disney 2016) as there are limitations to what can be observed from an airplane or satellite. For example, occlusion of laser pulses by overstory vegetation limits information on understory structure. Lidar technology is rapidly evolving, so the ability of future data to resolve different aspects of vegetation structure will likely improve (Hyde et al. 2005, Heinzel and Koch 2011, Hancock et al. 2017), but even so, there will always be a need for local knowledge and field assessment.

This study encompassed riparian areas across the county, but depending on sampling objectives and resources for implementation, smaller areas can also be examined (e.g., just BCPOS properties; see appendix 1). The tessellation has been provided as a geospatial data layer, so BCPOS, other managers in the county, or researchers can utilize it as a sampling frame for many different statistical sampling designs. For instance, the framework could be used in the development of paneled sampling designs using spatially-balanced sampling designs like GRTS (Stevens and Olsen 2004, Schweiger et al. 2015).

The September 2013 floods dramatically altered Boulder County riparian areas. Some effects (e.g., stimulation of new native woody plant establishment) were positive, other effects, such as an increase in erosion and geomorphic instability, were negative. Riparian areas are by their nature dynamic. The data and methods from this study provide a useful baseline from which to evaluate the continued evolution of BCPOS riparian areas and focus management and monitoring efforts.

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CHAPTER 6. REVIEW OF RIPARIAN AND AQUATIC MONITORING

Chapter goals

Currently, three BCPOS groups (Plant Ecology, Wildlife/PMJM, and Aquatic) are engaged in monitoring efforts that include a riparian vegetation component. In addition, there have been several recent riparian assessments completed by funded researchers (e.g., Biohabitats 2009, Backus and Sherrod 2014, AloTerra 2015, Gage and Cooper 2015). Based on the RFP for this project, as well as discussions with Tim Shafer and other BCPOS staff, the primary objective of this review is to compare the goals, protocols, site selection methods, and site locations for the BCPOS monitoring efforts and the funded projects. Key questions motivating this review are: (1) Is there overlap in the data needs of all three BCPOS programs (Wildlife/PMJM, Aquatic biomonitoring, and Plant Ecology) that might be met with a single protocol, or shared field efforts? (2) Could monitoring sites be co-located in order to increase efficiency and/or depth of ecological understanding at these locations? Note: This review focuses on riparian vegetation monitoring only, and not on other aspects of the various BCPOS monitoring efforts and funded projects.

BCPOS monitoring

BCPOS PMJM Habitat Monitoring

Goals/objectives. The main objective of PMJM monitoring efforts is to monitor riparian small mammal populations, documenting post-flood distribution and population status, with special focus on PMJM (Shafer and Beebe 2014). Because small mammal presence/absence and population status is strongly related to habitat conditions, riparian vegetation/habitat data are also being collected. The goals of the vegetation/habitat monitoring are to describe riparian habitat structure, emphasizing attributes of relevance to PMJM, and to provide data that can be used to track changes over time (e.g., in response to disturbance, post-flood natural recovery, and/or restoration activities). The management goals for the vegetation monitoring are to (1) relate PMJM population estimates (density, survival) to vegetation/habitat data in order to draw conclusions about relationships between habitat condition and PMJM population status, and to (2) use this information to identify target conditions and locations for restoration (Agenda 6/23/16). Note: the PMJM monitoring work includes two efforts – presence/absence data collection, and a mark/recapture study.

Site selection. For the presence/absence study, 100 sites were selected using a spatially balanced random sampling design. Of these, 13 (+ 1 subjectively chosen site) were monitored in 2014 (Shafer and Beebe 2014), and another 14 monitored in 2015 (Tim Shafer, personal communication). The sites will be re-sampled every five years. For the mark/recapture study, sites were selected subjectively based on past PMJM occurrences and existence of apparently suitable habitat (Agenda 6/23/16). This was done to maximize the number of captures for better PMJM population estimates. These sites were monitored in 2016 and 2017.

Sampling locations. Summer 2014 (14 sites): Erin Arsenault, Lindsay, Montgomery, Peck, Gage, Golden-Fredstrom, Western Mobile, Caribou Springs Ranch, Alexander Dawson, F/Golden Farm, Doniphan, Heil Valley Ranch, Pella Crossing, Carlson-Lastoka. Summer 2015 (14 sites): Imel, Gage, North Pointe, Loukonen Outlots, Western Mobile, Hall Meadows, Hall 2, Bullock/Wallce, Parrish, Walker Ranch, Trevarton (Dorothy Ellen), Hall 2, Braly/Sadar, Loukonen Dairy Farm. 2016 and 2017 (8 sites): Western Mobile – St. Vrain (WMSV), Western Mobile – South Branch (WMSB), Pella Crossing (PC), Golden-Fredstrom, Gage 1 (G1), Gage 2 (G2), Gage 3 (G3), Braly-Sadar (BS). See Figure 6-1 for an overview of monitoring locations.

Protocols. The PMJM vegetation/habitat monitoring methods are adapted from Ruggles et al. 2004. Presence/absence study: Approximately five habitat monitoring transects are sampled at each study site, at the start point of each trapping line, oriented perpendicular to the stream channel. Approximately six 10 m diameter circular plots are sampled per transect, at specified distances up to 150 m from the stream. Data collected include visual estimates of cover in five height/growth form classes (tree, shrub, graminoid, forb, litter/bare ground), and a list of dominant species in each class. Tree canopy cover is measured with a densiometer. Photos are also taken at each plot. Mark/recapture study: Three habitat monitoring transects are laid out at each trapping line (at 0, 250, and 500 m). As above, these habitat monitoring transects are oriented perpendicular to the stream and data are collected within 10 m diameter plots placed at specified distances along each transect up to 150 m from the stream. Data collection methods are similar to the presence/absence study, except that a census of tree stems by size class is conducted. Anthropogenic impacts are also recorded, using the same protocol for both the presence/absence and mark/recapture studies. At a subset of habitat monitoring plots, observations are made regarding non-native plants, erosion, various human activities, etc.

BCPOS Aquatic Biomonitoring Program

Goals/objectives. The overall goals of the aquatic biomonitoring program are to assess short and long term response of aquatic life and water quality to regeneration and/or restoration activities, to provide data in support of BCPOS land management planning, and to provide ecological health reports for BCPOS lake and creek properties (Kobza, 2017). Within this context, the goals of riparian monitoring are to assess terrestrial vegetation conditions that support aquatic organisms. This includes provisioning of shade over the water column, leaf and nutrient inputs, large and small woody debris inputs, terrestrial insect (prey) habitat, and terrestrial habitat for larger animals. Note: Fine-scale empirical data are desired, that can be quantitatively analyzed and related to aquatic observations. This was not achieved by the existing rapid assessment protocol, which yields a coarse scale assessment of site conditions (Kobza, personal communication).

Site selection. Ten sites/reaches were subjectively chosen on Saint Vrain Creek based on the following criteria -- (1) representative of riverine habitat on Saint Vrain Creek within BCPOS fee-owned properties, and (2) in/near reaches that experienced large 2013 flood impacts. Thus, sites were selected for both practical reasons (i.e., post-flood monitoring, relevant to stream restoration assessment and permitting) and to achieve scientific outcomes (e.g., assessment of aquatic ecosystem response to a historic flood). All sites are on Saint Vrain Creek (Figure 6-1). Data were collected in 2014 as a pilot year, with full data collection in 2015, 2016, and 2017. In addition, fish data (points and transects) have been collected at 44 Boulder County sites, some of which are outside of the elevation zone of relevance to PMJM (Figure 6-1).

Sites. Two sites are located on the South Branch of Saint Vrain Creek, and 10 sites are located on the Saint Vrain Creek mainstem, all on BCPOS fee-owned riverside properties.

Protocol. Reach length is determined as 20 x the wetted creek width. At each reach, aquatic biomonitoring includes macroinvertebrate sampling, native and game fish identification, and water quality monitoring. In addition, stream survey data are collected at 10 points per reach -- densiometer measurements of canopy cover at stream center, wetted width and bankful width, and thalweg depth. Photos are taken at the start and end of each reach. Habitat and river condition are assessed at the reach scale using the 'PFC Modified Habitat Assessment Field Data Sheet' developed by Biohabitats (2009). This assessment is a modification of the Proper Functioning Condition (PFC) protocol developed by the Bureau of Land Management (US Department of Interior, 1998, 2013). The method evaluates a reach and assigns points in three categories – hydrology, erosion potential, and vegetation. The Biohabitats (2009) field sheet also contains a checklist of sites features (e.g., raptor nests, rip rap) and information on possible restoration or maintenance opportunities. With respect to riparian vegetation, each reach is scored (in four categories) based on width of riparian plant community, percent cover of non-native tree species, percent cover of non-native shrub species, percent cover of non-native herbaceous species, woody debris and leaf supply, and vegetation structure and diversity. The riparian assessment includes the entire width of the vegetated riparian zone (usually narrow), though width is not measured. Note: use of this protocol by BCPOS has been discontinued, as it did not yield data of sufficient detail to necessitate annual surveys. Instead, minimal riparian observations are being recorded, using the EPA Habitat Assessment data sheet.

BCPOS Post-Flood Vegetation Monitoring

Goals/objectives. The objectives of the post-flood vegetation monitoring being conducted by BCPOS plant ecology staff are to (1) observe vegetation changes over time, and (2) collect data to inform restoration management decisions to increase native species diversity and vegetation (Post Flood Vegetation Monitoring Protocol). The monitoring focuses on areas directly impacted by the 2013 floods (i.e., areas of avulsion and deposition), in order to track post-flood recovery over time (DeLeo et al. 2016). As such, data collection is targeted within 50 m of the active stream channel, in areas highly impacted by the 2013 floods.

Site selection. Study sites were chosen subjectively, focusing on areas directly impacted by the 2013 floods. Data were collected at six properties in 2015. Three of these properties (Hall Meadows [5 plots], Brewbaker-Sorenson [1 plot], and Keyes [1 plot]) were re-sampled in 2016.

Sampling locations. 2015: Braly, Brewbaker-Sorensson, Bullock, Gage, Hall, Keyes. 2015 and 2016: Hall Meadows, Brewbaker-Sorensson, Keyes. Monitoring was not conducted in 2017.

Protocol. One to five monitoring plots are located at each study site. Plots are 50 m by 50 m, located adjacent to the stream channel. Plots consist of one 50 m point intercept transect oriented perpendicular to the stream (Transect A), and three 50 m line intercept transects 15 m apart parallel to Transect A. On Transect A, the following data are collected: point intercept data, woody vegetation density (by species and size class) in 0.5 m^2 frames at 7 points, and canopy cover data using line intercept and densiometer methods. On the three additional line intercept transects, the following data are collected: substrate cover (bare soil/sand, cobble, boulder, water, forb/grass, sedge, woody debris, and litter), woody plant cover by species and size class.

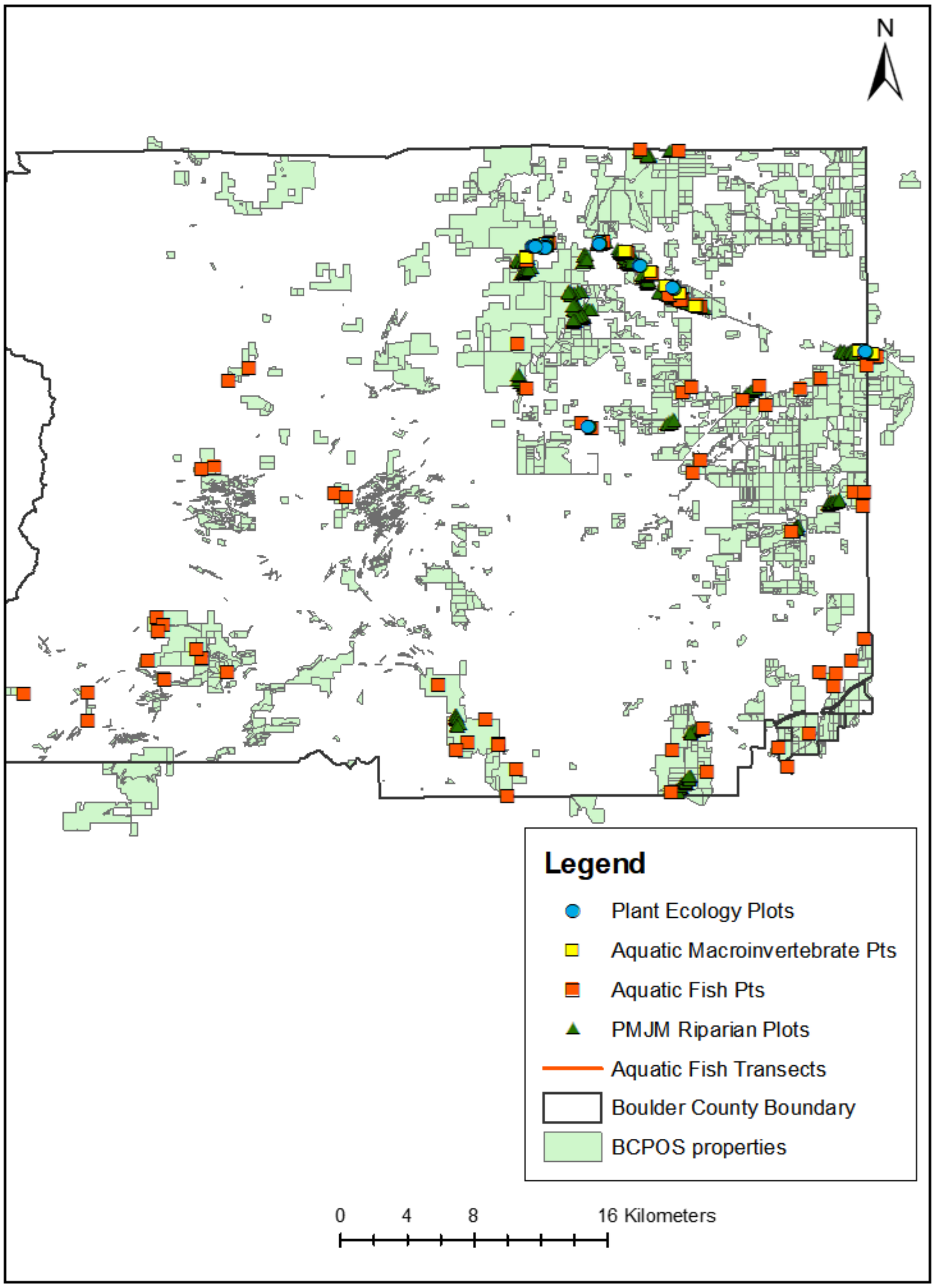

Figure 6-1. Overview of BCPOS riparian monitoring locations.

Funded projects

Biohabitats (2009)

Goals. The purpose of this project was to evaluate riparian condition at the reach scale. Reaches were scored relative to desired conditions, similar to the Bureau of Land Management's "proper functioning condition" concept (US Department of Interior 1998, 2015). In this framework, desirable stream and riparian conditions include the ability to dissipate streamflow energy, reduce erosion, improve water quality, promote floodplain geomorphic development, improve floodwater retention, and stabilize banks. In addition, a wide riparian community, with good physical structure and high native species diversity, is desired (Biohabitats 2009).

The Biohabitats (2009) approach is based on the Bureau of Land Management Proper Functioning Condition (PFC) assessment method (US Department of Interior 1998, 2015). The original PFC method was developed to qualitatively evaluate physical stream processes, considered to be the foundation for chemical and biological processes in riparian zones. In this framework, a stream in PFC should be able to withstand a moderately high flow event (e.g., a 10- or 25-year flood), or can recover quickly following such an event. Reaches are evaluated by an interdisciplinary team, using 17 stream and riparian attributes. Each reaches is then placed into a category (High Functioning, Moderate Functioning, or Low Functioning).

Site selection. BCPOS identified priority reaches for assessment on Saint Vrain Creek, Left Hand Creek, Coal Creek, and Rock Creek.

Sites. Biohabitats (2009) assessed riparian conditions at 47 reaches distributed among 39 BCPOS properties. Coal Creek: Armstrong a & b, Adler/Fingru, Haselwood, Bailey/Kenosha Ponds, Madrigal, Mayhoffer/Singletree, Serrano, Stephenson Nelson, Telleen 1, Telleen 2a & 2b, Warembourg, Warembourg-Lafayette Farms. Left Hand Creek: Brewbaker/Sorenson, Imel. Rock Creek: American Pacific, Carlson/Lastoka 1, Carlson/Lastoka 2, Carlson/Lastoka 3, Eberl , Imel/NWP a & b, Lindsay, Roberts (Simi), Rock Creek Farm 1, Rock Creek Farm 2, Rock Creek Farm 3, Rock Creek Farm 4, Rock Creek Farm 5, Rock Creek Farm 6, Ruth Roberts, Scriffany (Carlson), Stephenson Nelson, Thompson (Tommy), Zaharias/Thomas. Saint Vrain Creek: Bullock, Wallace, Braly, Gage, Golden Farms & Keyes, Golden Fredstrom, Golden Gravel & Fairgrounds, Martenson a & b, Montgomery, Pella West 1, Pella West 2, Peschel, Ramey, Western Mobile.

Protocol. Biohabitats (2009) developed a riparian assessment protocol for plains streams in Boulder County, based on the Bureau of Land Management Proper Functioning Condition (PFC) approach (US Department of Interior 1998, 2015). The Biohabitats (2009) protocol utilizes a 4- page semi-quantitative field form with rankings in three categories – hydrology, erosion potential, and vegetation. The field sheet also contains a checklist of sites features (e.g., raptor nests, rip rap) and information on possible restoration or maintenance opportunities. Thus, the assessment results consist of (1) a reach level ranking, which indicates the PFC category of the reach (High Functioning, Moderate Functioning, or Low Functioning), (2) identification of major reach characteristics that influence its score (e.g., channelization, gravel mining, high species diversity), and (3) management opportunities for reach improvement (e.g., areas for revegetation, invasive plant removal). With respect to riparian vegetation, the field forms contain information on width of the riparian plant community, tree age classes present and vigor, percent cover of non-native tree species, percent cover of non-native shrub species, percent cover of non-native herbaceous species, woody debris and leaf supply, and vegetation structure and diversity.

Backus and Sherrod 2014

Goals. The goals of this 2014 BCPOS grant-funded study were to (1) identify high-priority Boulder County Noxious Weed infestations, (2) document changes in riparian vegetation, hydrology, and stream geomorphology following the 2013 floods, and (3) provide a summary report comparing current stream and riparian conditions with those existing before the 2013 floods (based on Biohabitats 2009 data).

Site selection. The Backus and Sherrod (2014) report does not indicate how sites were selected, but presumably based on BCPOS priorities for sites impacted by the 2013 floods.

Sites. Saint Vrain Creek: Custode, Hall 2, Hall Meadows, Triangle, Bullock, Wallace, Montgomery, Western Mobile W, Western Mobile E, Braly, Ramey, Sadar, Gage, Pella West/Marlatt, Golden/Fredstrom, Keyes/Golden Farm, Peschel. Left Hand Creek: Brewbaker/Sorensen, IMEL, Bielins/Hock, Russell/Anderson/Schmidt. Boulder Creek: MMS Partnership, Dawson W, Dawson E, Doniphan, Bailey Ponds/Kenosha.

Protocol. Reaches were assessed by walking the entire length of the reach (laterally including the pre-flood riparian zone extent), and completing an assessment based on the Biohabitats (2009) field form. Backus and Sherrod (2014) modified the Biohabitats (2009) field form to better account for effects of the 2013 floods. For the riparian vegetation component, they added five additional scoring criteria – presence and prevalence of post-flood native woody seedlings or saplings, presence and prevalence of post-flood non-native woody seedlings or saplings, percent abundance of Boulder County noxious weeds, percent of riparian area experiencing 2013 flood deposition (e.g., cobble deposits), and percent of riparian area lost to erosion or flood deposition (Backus and Sherrod 2014).

AloTerra 2015

Goals. This project employed and tested a visual-based stream stability assessment (SSA) developed by Aloterra, LLC. The specific objectives of the project were to characterize the stability of two stream reaches at BCPOS foothills properties, identify areas of instability, and field test and refine the SSA protocol. The focus of this project is geomorphic assessment, which includes a vegetation component from that perspective.

Site selection. The AloTerra (2015) report does not indicate how sites were selected, but presumably based on BCPOS priorities for assessment of sites impacted by the 2013 flood.

Sites. The SSA was applied at Hall-II on South Saint Vrain Creek, and Western Mobile on Saint Vrain Creek.

Protocol. Longitudinal profiles and channel cross sections were surveyed at three locations (sub-reaches) at Hall-II, and two locations at Western Mobile. Cross section locations were benchmarked with rebar and GPS locations recorded (for possible re-sampling). For each sub-reach, visual observations were made describing the percent length of the reach characterized by specified conditions within the following assessment categories: bank and channel material, bank angle, bank and riparian vegetation type and cover, recent bank erosion, bed morphology, and vertical incision. Photos are also taken at the middle of each sub-reach. With respect to riparian vegetation, the SSA includes estimation of the percent cover of bare earth, nascent vegetation (annual and perennial herbs, juvenile perennial vegetation), perennial grasses and forbs, shrubs and trees at each sub-reach.

Gage and Cooper 2015

Goals. The overall goal of this study was to develop baseline data and maps of post-flood recovery of BCPOS riparian areas. Specific objectives were to (1) use remote sensing (i.e., Lidar data, multispectral imagery) to quantify changes to the extent and three-dimensional structure of BCPOS riparian areas resulting from the 2013 flood, (2) develop a spatially balanced design for field sampling to characterize riparian areas, evaluate flood impacts, and provide a baseline for monitoring riparian area recovery, and (3) apply a rapid assessment protocol for basic aspects of physical structure and condition (Gage and Cooper 2015).

Site selection. This project focused on BCPOS properties east of the Peak to Peak highway, on Boulder Creek, Saint Vrain Creek, Left Hand Creek, and their major tributaries. For field sampling, one thousand point locations were identified, using a spatially balanced random sampling design. Of these, ninety-five sites (sample points) were visited for field data collection.

Sites. See Gage and Cooper (2015) Appendix 1 for the list of sites where field data were collected.

Protocol. The GIS and remote sensing portion of this project involved analysis of LiDAR data from 2011 (pre-flood) and 2013 (post-flood) in order to detect channel and riparian change. Lidar data were classified and processed to create 0.5 m resolution models of ground surface (bare earth), and canopy height. These models were used to detect geomorphic (bare earth) changes resulting from the 2013 floods, as well as changes in riparian tree occurrence and height.

Field data were collected along a transect perpendicular to the stream channel at each sample point. To assess riparian cover, at least three 1 m x 1 m square plots were placed at equal intervals along the transect line. Within each plot, the percent cover of soil-surface features, geomorphic surface type, vegetation cover by physiognomic class, and weed cover were recorded. Tree diameter, species, and canopy condition were recorded in a 5 m wide belt along the transect line, and photographs were taken. Additionally, riparian condition was assessed in the reach surrounding each sample point, using a rapid assessment field protocol. The protocol evaluated riparian cover, channel and bank physical characteristics, native seedling establishment, tree damage/mortality, cover of exotic plant species, and riparian canopy structure. The field protocol was adapted from existing riparian condition protocols developed by the US Forest Service (Forest Service National Riparian Technical Team 2014), the Colorado Natural Heritage Program (Lemly and Gilligan 2013), and the New Mexico Natural Heritage Program (Muldavin et al. 2011).

Comparison and synthesis

BCPOS monitoring approaches and goals

Based on this review, the BCPOS monitoring efforts and funded projects fall into two general categories – (1) qualitative or semi-quantitative reach- or site-level assessments, and (2) quantitative localized data collection. For example, the Biohabitats (2009) protocol is a semi-quantitative assessment method that employs rankings to produce an overall site/reach level score indicating functional level. The AloTerra (2015) protocol is similar, though more narrowly focused on geomorphic stability. In contrast, the vegetation data being collected by BCPOS for PMJM monitoring and post-flood vegetation monitoring are more quantitative in nature, employing more detailed plot- or transect-level data collection. These two approaches are not mutually exclusive, and can be combined when appropriate. For example in the field component of their project, Gage and Cooper (2015) combined plot level data collection with reach level rapid assessment. The utility and appropriateness of each approach depends on BCPOS monitoring objectives and data needs with respect to riparian vegetation, which seem to vary somewhat by program.

Although rapid assessment protocols probably do not provide sufficient quantitative detail for the PMJM and post-flood vegetation monitoring programs, they do fill an important management need for BCPOS. These methods are designed to rapidly assess reaches or sites to identify areas of concern, and to allow BCPOS staff to target areas for treatments (e.g., weed control) or protection. Although these approaches are qualitative or semi-quantitative in nature, they do produce site scores or rankings that can help BCPOS set management priorities. Further, they can be used to qualitatively assess changes at a site following disturbance (e.g., Backus and Sherrod 2014).

Cleary stated goals and objectives are critical components of natural resources monitoring (Fancy et al. 2008, Kennedy et al. 2009). In a general sense, the BCPOS PMJM and post-flood vegetation riparian monitoring efforts share similar objectives. The goals of PMJM habitat monitoring are to (1) describe riparian habitat structure, emphasizing attributes of relevance to PMJM, and (2) provide data to track changes over time. Similarly, the stated goals of the post-flood vegetation monitoring are to (1) collect data to inform restoration management decisions to increase native species diversity and vegetation, and (2) observe vegetation changes over time. Thus, both programs aim to describe current conditions, and to track changes over time.

BCPOS monitoring site locations

Despite some general similarities in riparian monitoring goals, there are important differences in focus among the three BCPOS programs. For the plant ecology post-flood vegetation monitoring and the aquatic biomonitoring programs, the focus is on flood impacted sites. In contrast, PMJM riparian monitoring includes both sites impacted and not impacted by the 2013 flood (Table 6-1). This creates the opportunity for co-location of monitoring sites, at flood impacted properties that may be of interest to all three programs.

Table 6-1. Comparison of site types for BCPOS monitoring.

	2013 flood impacted sites	Non-flooded sites
PMJM Habitat Monitoring	X	X
Post-Flood Vegetation Monitoring	X	
Aquatic Monitoring	X	

Examination of BCPOS monitoring locations indicates that some monitoring is taking place at shared sites, with sample points/plots in close proximity (Figures 6-1 to 6-7). All three programs are collecting data in close proximity at Hall Ranch and Bullock on Saint Vrain Creek (Figures 6-2 and 6-3), and relatively near to one another at Gage and Keyes (Figures 6-5 and 6.7). The PMJM riparian monitoring program and the aquatic biomonitoring program are collecting data in close proximity at Hall Ranch 2, Western Mobile, Gage, Pella Crossing, and Golden- Fredstrom on Saint Vrain Creek (Figures 6.2-6.7). There are also fish sampling points and PMJM riparian transects near to one another at Heil Valley Ranch, at BCPOS properties (i.e., Bielins-Hock to Peck) on Left Hand Creek, at Alexander Dawson on Boulder Creek, at Erin Arsenault on Coal Creek, and at BCPOS properties on Rock Creek. The plant ecology and aquatic biomonitoring programs are collecting data near each other at Brewbaker-Sorensson on Left Hand Creek (Figure 6-8). Please note: The following maps (Figures 6.2 through 6.8) target BCPOS properties where monitoring is being conducted by multiple programs. Not all monitoring locations are shown on the maps.

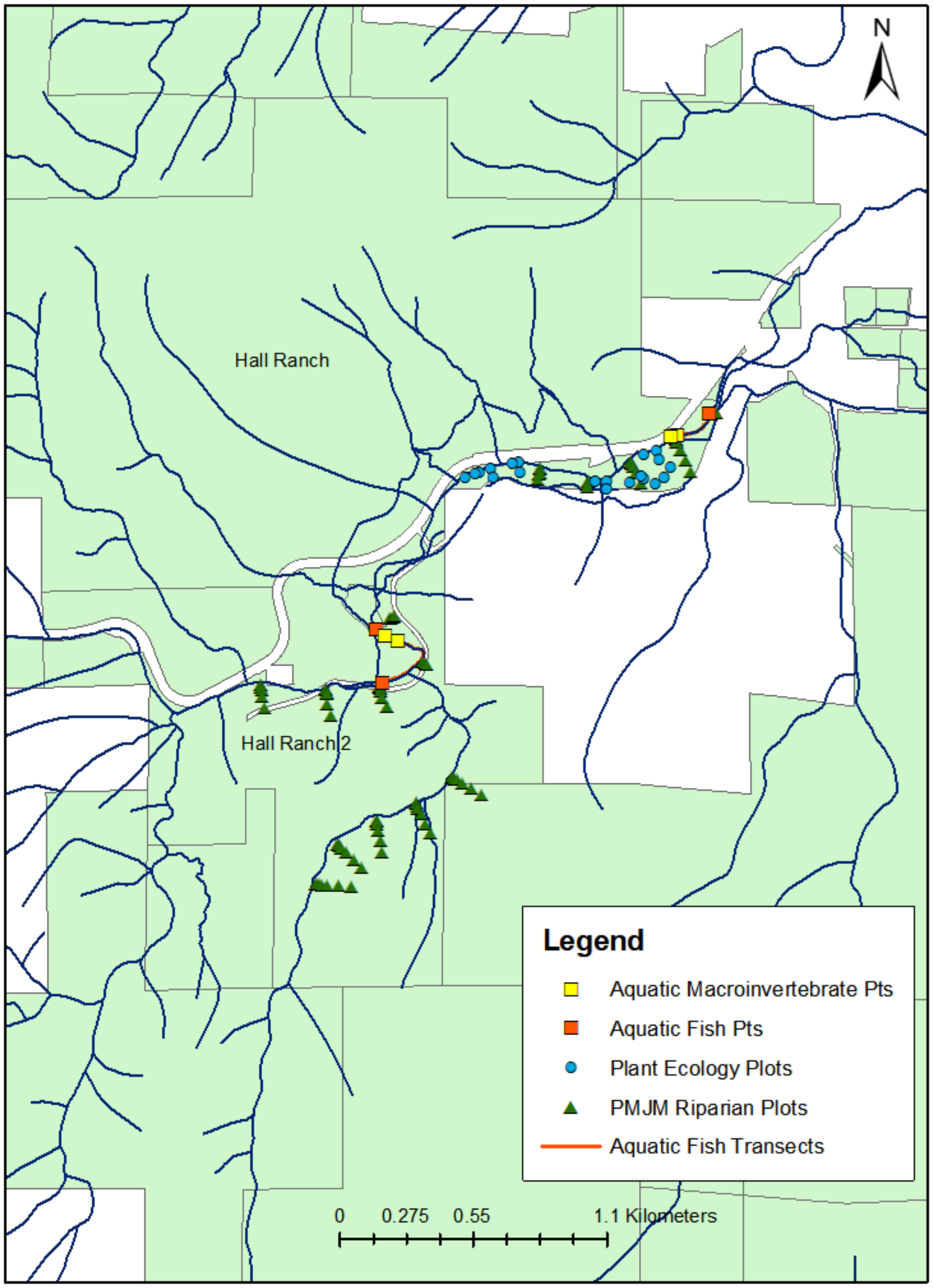

Figure 6-2. BCPOS monitoring locations at Hall Ranch and Hall Ranch 2.

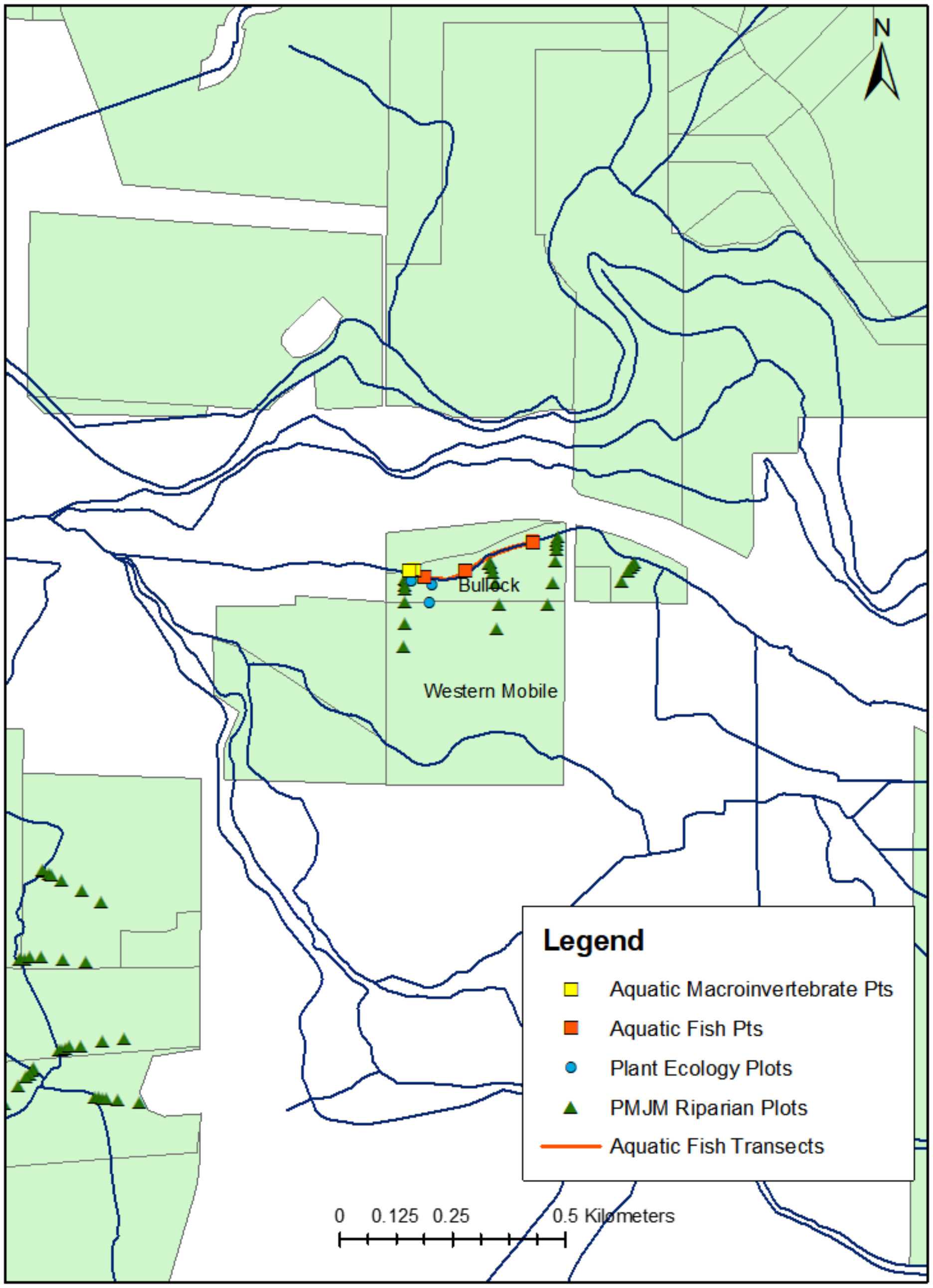

Figure 6-3. BCPOS monitoring locations at Bullock and Western Mobile on Saint Vrain Creek.

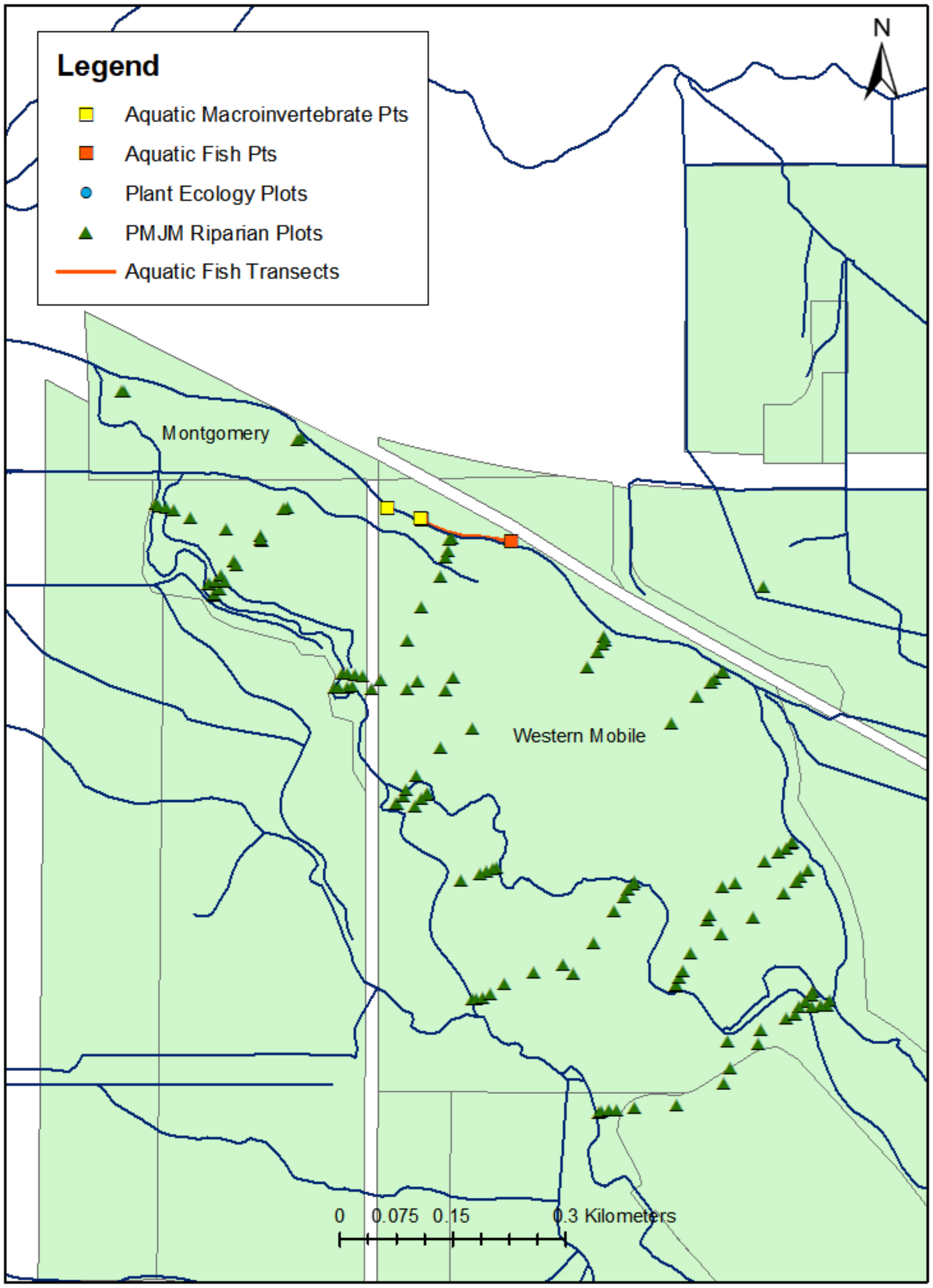

Figure 6-4. BCPOS monitoring locations at Montgomery and Western Mobile on Saint Vrain Creek.

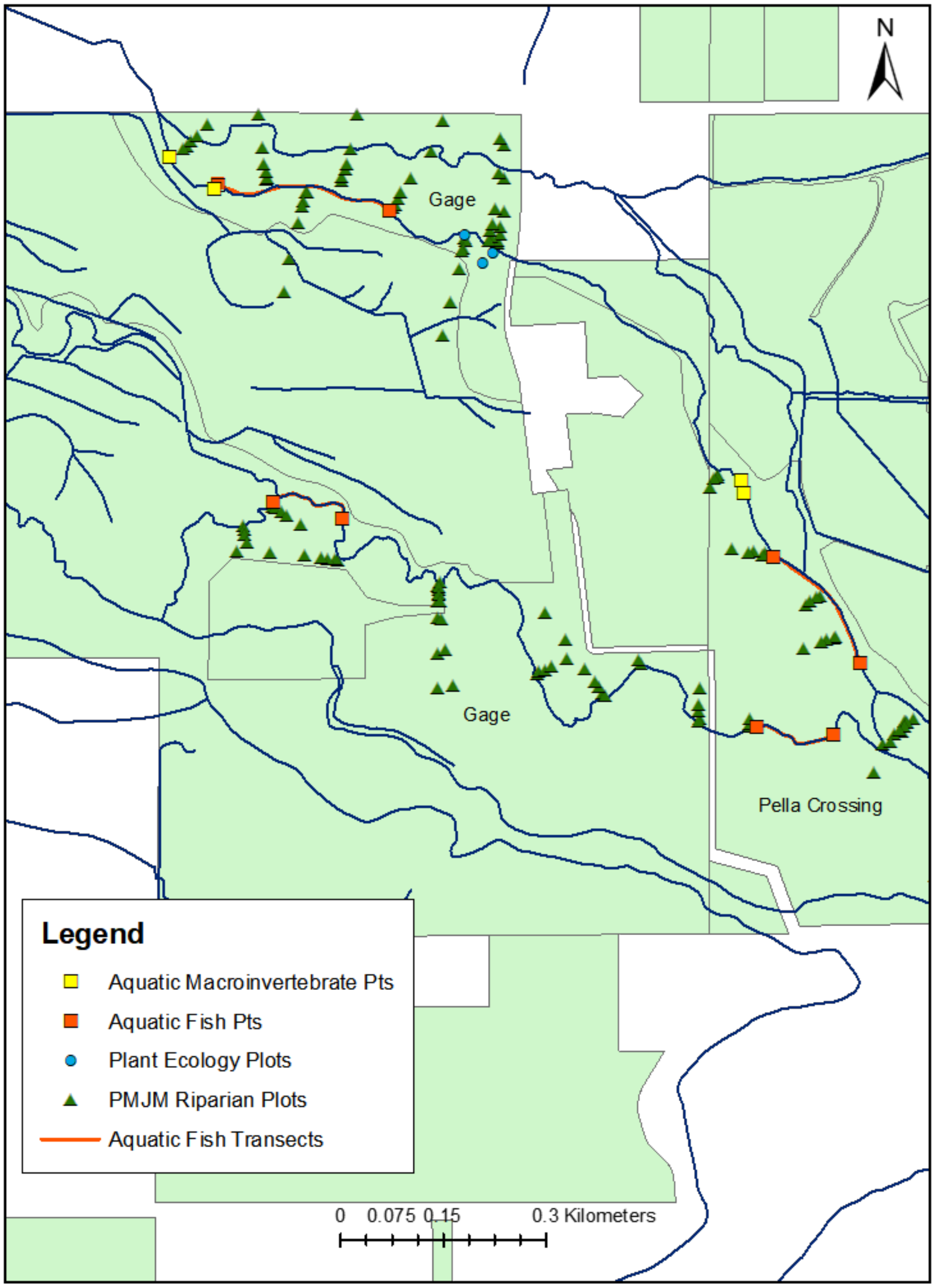

Figure 6-5. BCPOS monitoring locations at Gage and Pella Crossing on Saint Vrain Creek.

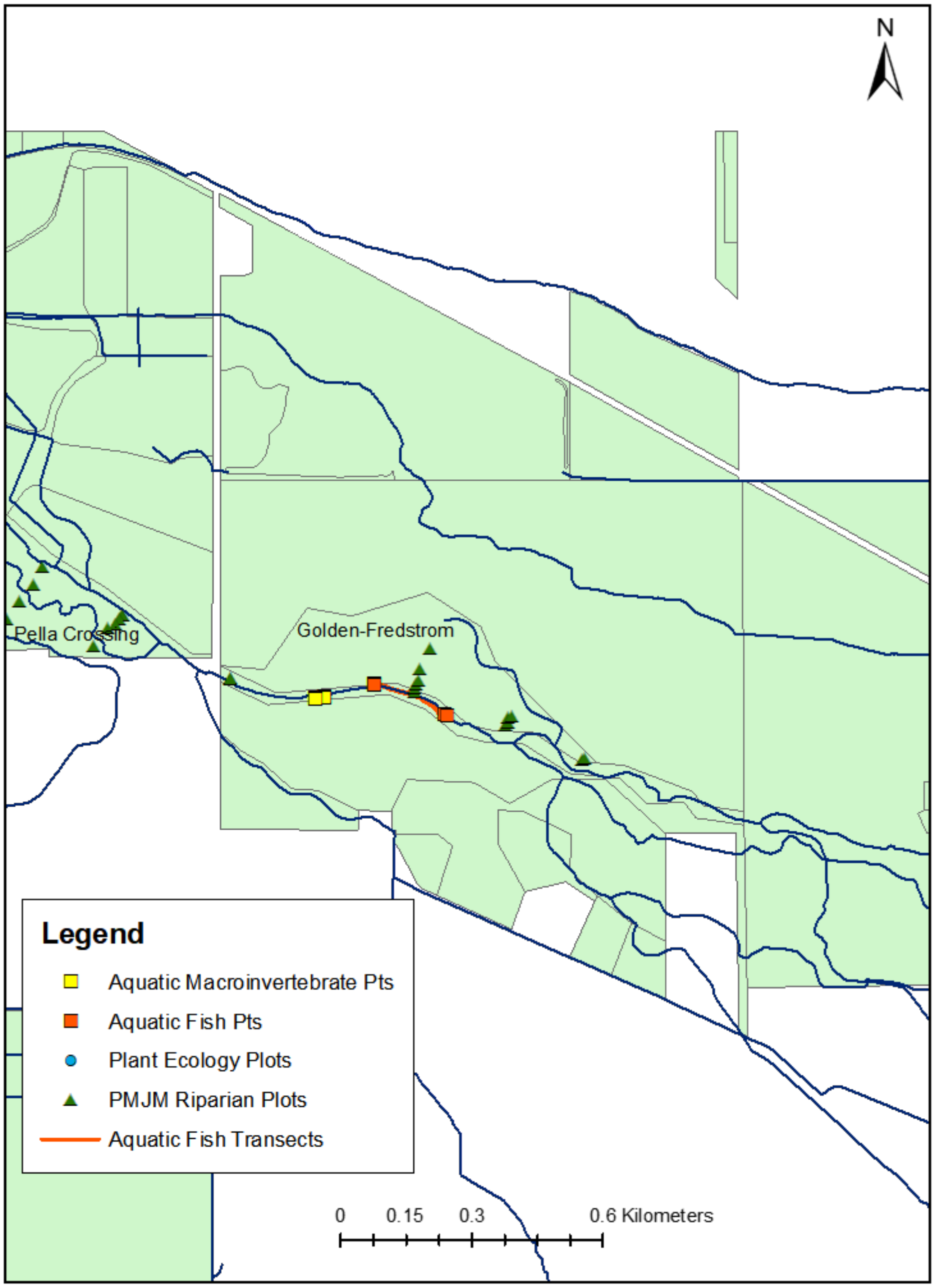

Figure 6-6. BCPOS monitoring locations at Golden-Fredstrom on Saint Vrain Creek.

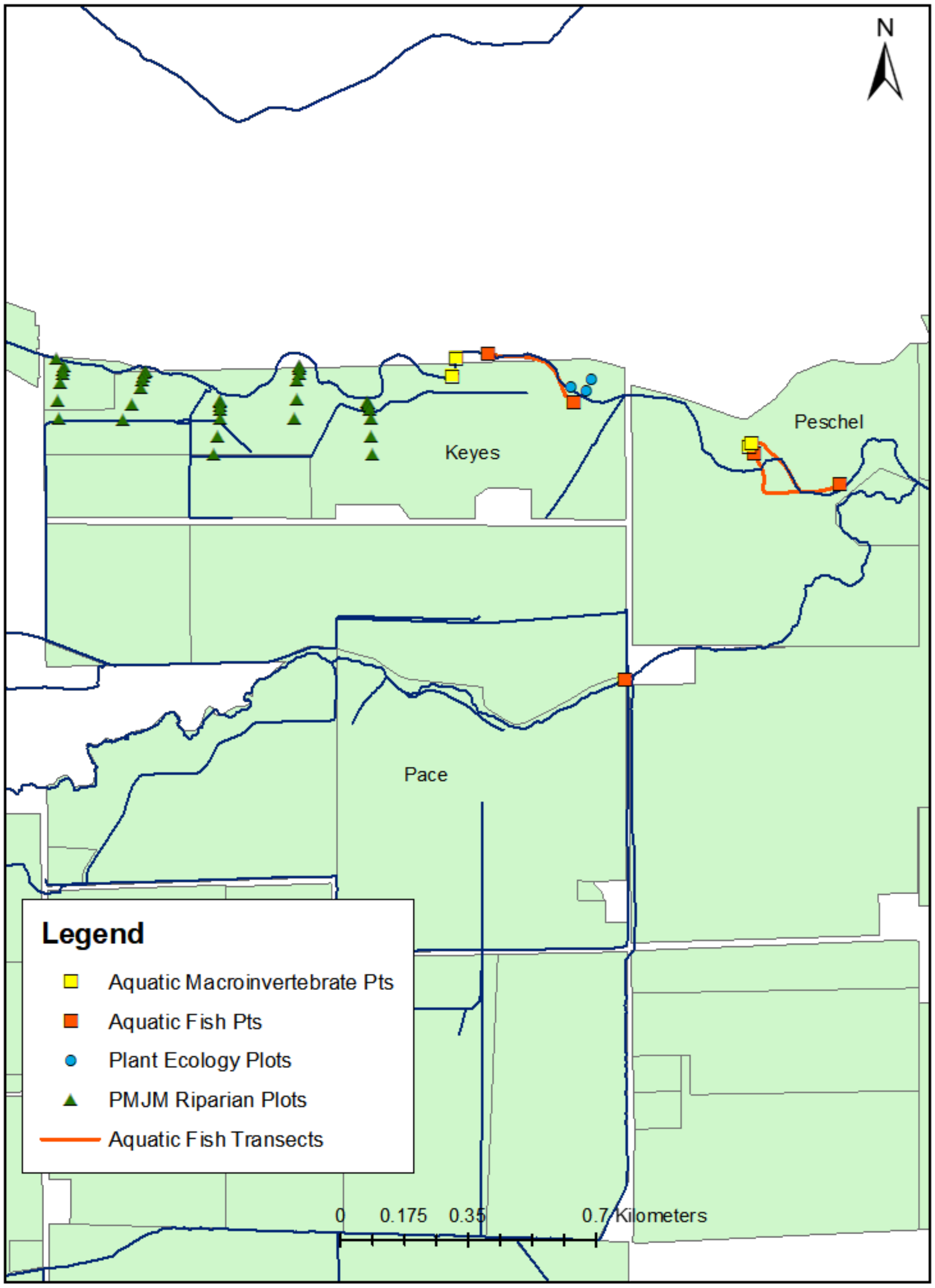

Figure 6-7. BCPOS monitoring locations at Keyes and Peschel on Saint Vrain Creek, and Pace on Dry Creek.

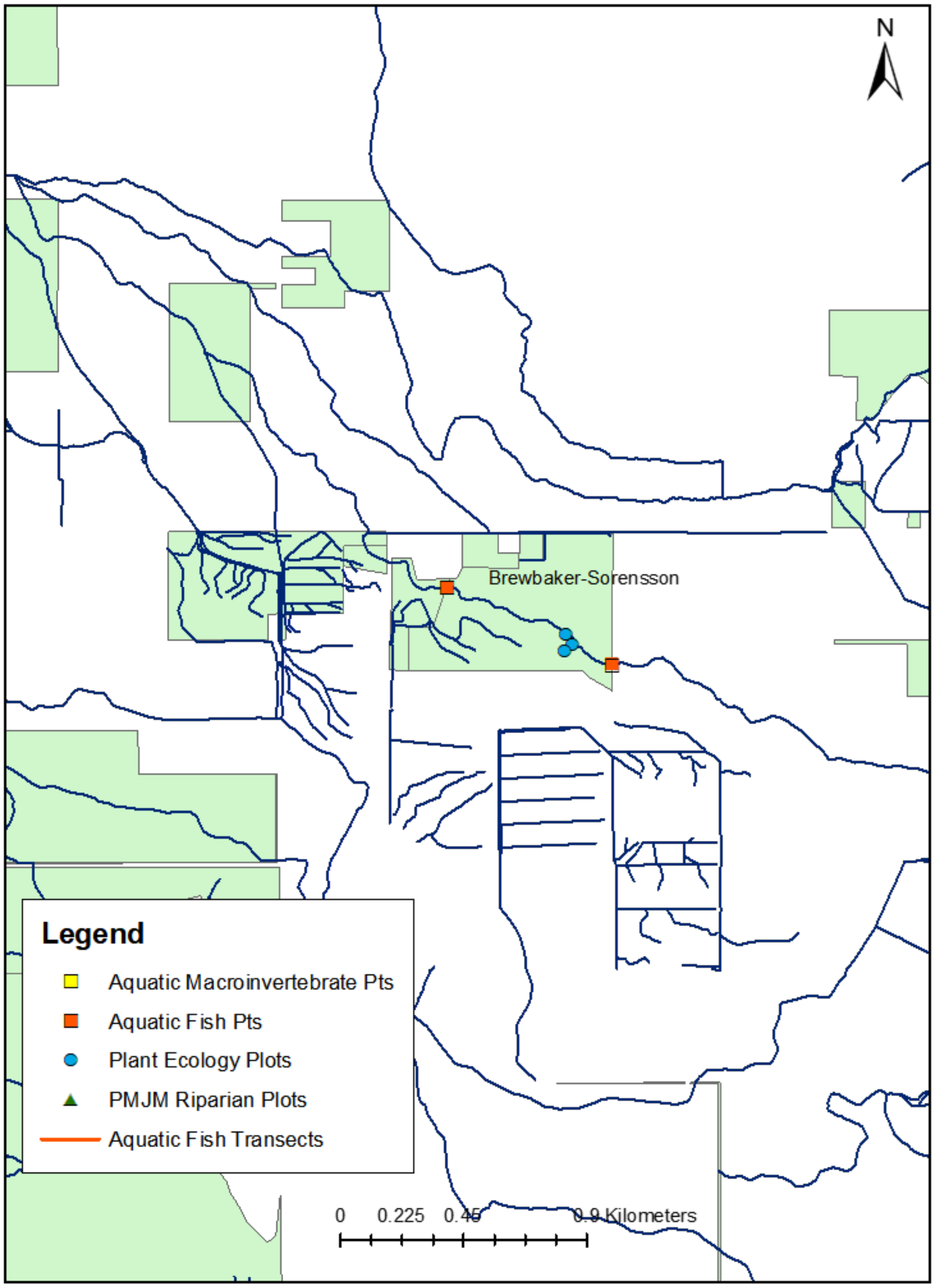

Figure 6-8. BCPOS monitoring locations at Brewbaker-Sorensson on Left Hand Creek.

Comparison of monitoring zones and protocols

An important difference in riparian vegetation monitoring among the three programs relates to the spatial extent of the riparian zone being monitored at each site (Table 6-2). For plant ecology post-flood vegetation monitoring, the focus is near-channel areas impacted by the 2013 flood. For aquatic biomonitoring, the collection of quantitative data is limited to the channel area, although a rapid assessment is used to describe the entire riparian area. In contrast, the PMJM habitat monitoring protocol entails plot data collection in the entire riparian zone (up to ~150 m from the stream channel).

Table 6-2 Comparison of monitored riparian locations for BCPOS monitoring.

	Near channel riparian (50 m)	Full riparian extent (150 m)
PMJM Habitat Monitoring	X	X
Post-Flood Vegetation Monitoring	X	
Aquatic Monitoring*	X	
*Rapid assessment is conducted for entire riparian width, but quantitative measurements are limited to near-channel area.		

There is some overlap in the plot data being collected for BCPOS PMJM habitat characterization and BCPOS post-flood vegetation monitoring (Table 6-3). PMJM habitat characterization requires localized (~10 m diameter plot scale) measures of (1) riparian vegetation structure (i.e., volume or cover in distinct height strata), and (2) riparian plant species composition, across the width of the riparian zone at a site. Although not its focus, the BCPOS post-flood vegetation monitoring project is collecting data that meets much of these needs, albeit in a smaller area (within ~50 m of the stream channel) than is needed for PMJM habitat monitoring (up to 150 m from channel edge). The post-flood plant monitoring protocol does not divide cover data into height/growth form categories (e.g., tree, shrub, graminoid, forb, litter/bare ground), but cover data are collected by species so this information is implicit and probably could be derived. Another substantial difference is that the plant cover data being collected for post-flood vegetation monitoring is significantly more detailed (i.e., point and line intercept data) than that being collected for PMJM habitat monitoring (i.e., plot level visual cover estimates). The aquatic biomonitoring data collection includes densiometer measurements of canopy cover at the center of the stream channel.

Table 6-3 Comparison of plot/point field data being collected for BCPOS monitoring.

	Bare ground cover	Herb cover	Shrub cover	Tree cover	Species comp.	Non-native species	Tree density
PMJM Habitat Monitoring	X	X	X	X	X	X	X
Post-Flood Vegetation Monitoring	X	X	X	X	X	X	X
Aquatic Monitoring				X			

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Agenda 6/23/16. Preble's Mark-Recapture Study: Final Design Meeting.

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CHAPTER 7. SYNTHESIS AND RECOMMENDATIONS

Background

Several BCPOS programs share an interest in mapping, assessing, and monitoring riparian vegetation in Boulder County. In particular, the BCPOS Plant Ecology, Wildlife and Aquatic groups are all engaged in some form of riparian vegetation monitoring (See Chapter 6). Further, a number of external projects have been funded to map and assess riparian habitat condition (e.g., Biohabitats 2009, Backus and Sherrod 2014, AloTerra 2015, Gage and Cooper 2015). Riparian monitoring efforts are also relevant to 2013 flood recovery and restoration efforts, which usually entail a commitment to at least three years of post-project monitoring. For the purpose of this report, we highlight aspects of riparian monitoring pertinent to the threatened Preble's meadow jumping mouse (PMJM) because its legal status necessitates particular consideration in the context of riparian management. Further, PMJM may be considered an 'indicator species' of riparian ecological integrity (Clippinger 2002), integrating key elements of ecosystem health and function.

Spatial scale is a key issue in the context of mapping, assessing and monitoring riparian habitat relevant to PMJM. An understanding of the spatial grain relevant to PMJM summer movement (e.g., for daily foraging and resting) and winter hibernation underpins effective habitat assessment and monitoring efforts. PMJM is a small animal (approximately 3 inches long, with a 6 inch long tail). However, individual home range sizes can be up to ~6,000 m^2, usually located within the 100 year floodplain (Trainor et al. 2012). At a given occupied site, individual home ranges overlap, resulting in varying intensity of habitat use within the occupied area. Individuals appear to frequent certain 'high use' microhabitats, including daytime nests and communal nighttime feeding areas (Trainor et al. 2007). Thus, a PMJM occupied site or habitat patch contains some microhabitats that are not used. However, presumably a PMJM occupied site must contain a sufficient number or density of microhabitats that meet the conditions for high-use, including sufficient food resources, cover from predators, and hibernation locations. Specifically, Trainor et al. (2007) found that high-use areas (defined as 9 m x 9 m grid cells used by radiocollared PMJM) were characterized by greater shrub cover, woody basal area, and woody debris cover compared to no-use areas at three sites in the foothills of the Colorado Front Range (Trainor et al. 2007).

In addition to the microhabitat scale, the landscape scale context is important to the identification and monitoring of PMJM habitat (Clippinger 2002, Ruggles et al. 2004). Important issues relevant at the landscape scale include the overall spatial distribution of habitat patches, the sizes of habitat patches, habitat connectivity, and the condition of adjacent land cover patches. Clippinger (2002) used the 30 m resolution National Land Cover Dataset (NLCD) and a PMJM trapping location database for Colorado to compare land cover in grid cells where PMJM had been captured and not captured. He found that forested/shrubland cover was strongly associated with PMJM presence, while residential development was strongly associated with PMJM absence. Similarly, based on classification tree analysis Keinath (2001) asserted that PMJM capture sites were negatively associated with human disturbance in Wyoming. Ruggles et al. (2004) suggested that landscape scale GIS and remote sensing analyses could be used to measure changes in habitat health (e.g., comparing NDVI between time steps), and measure important changes in land cover relevant to PMJM habitat (e.g., succession to upland vegetation types, or increases in impervious cover). Change detection could then be used to cue management actions, or to prompt ground-based assessments.

Recommendations for ground-based monitoring

Consider a probability design for selecting monitoring site locations. Depending on monitoring goals, it may make sense to employ a probability based method for selecting monitoring sites. These approaches enable unbiased inferences from monitoring sites to the larger population of resource elements the sample represents, and are the recommended approach to site selection in the Vital Signs Monitoring program developed for US National Parks (Fancy et al. 2008). Some BCPOS riparian monitoring efforts have employed these types of site selection methods: The PMJM presence/absence study used Generalized Random Tessellation Stratified Design (GRTS), a spatially balanced random design, to select a pool of 100 monitoring sites from which they sub-sampled for annual monitoring. Similarly, Gage and Cooper (2015) used the Reverse Randomized Quadrant-Recursive Raster (RRQRR) algorithm to generate a sequential list of 1000 point locations that can be used for monitoring. This method maximizes spatial independence of sample points, such that contiguous ranges of points on the list are approximately spatially balanced. The hexagonal sampling frame presented in Chapter 5 could be used as a sampling frame for such sampling designs.

On the other hand, a probability based method of site selection may not be appropriate or feasible for BCPOS monitoring programs. Existing monitoring efforts have been targeted to subjectively chosen areas due to specific needs (e.g., documentation of post-flood recovery or system response to restoration projects, monitoring of known PMJM populations). In this case, monitoring at subjectively chosen sites could be supplemented by less frequent assessments at an unbiased sample of sites, e.g., with a ground based rapid assessment protocol, and/or a remote sensing approach.

Consider co-locating monitoring sites. Although the various BCPOS monitoring efforts differ somewhat in their focal locations, objectives and protocols, there are still benefits to be gained from co-location of monitoring sites. Co-locating monitoring sites enhances opportunities for data sharing, to the extent that there are overlapping data needs. Further, monitoring multiple resource elements at a single site can lead to improved understanding of ecosystem status and trends, and the interactions among monitored elements. Indeed, the Vital Signs Monitoring program encourages the co-location of sampling sites at US National Parks in order to improve both efficiency and depth of ecological understanding (Fancy et al. 2008).

Currently, there are four study sites (properties) on Saint Vrain Creek where monitoring is being conducted by all three BCPOS monitoring programs. Data are being collected in close proximity at Hall Ranch and Bullock (Figures 6-2 and 6-3), and in relatively close proximity at Gage and Keyes (Figures 6-5 and 6-7). These sites, especially Hall Ranch and Bullock, could be used for a pilot project to determine whether riparian monitoring can be coordinated or integrated among the three programs. Initially, the three programs might meet to present monitoring results for Gage and Bullock, and discuss the feasibility of coordinating data collection or sharing data (reducing any redundancies in monitoring). At a minimum, it appears that the data being collected for PMJM habitat monitoring may meet the needs of the aquatic biomonitoring program, creating an opportunity for data sharing.

Consider a common protocol for all riparian monitoring. BCPOS currently has an extensive network of monitoring locations distributed on Boulder County waterways (Figure 5.1). If a shared protocol could be developed that met the needs of all three BCPOS monitoring programs, a large and consistent data set could be created for all areas of interest. This would enhance ecological understanding of BCPOS riparian areas, including the range of conditions present and changes over time. One idea would be to develop a common plot based protocol that would be used in the near channel zone (e.g., within 50 m of the stream channel) by all groups, since all three programs are interested in near-channel riparian data. Data plots could then be distributed further from the channel at sites of interest to PMJM habitat monitoring, which has a more explicit interest in the entire riparian width.

The process of developing a common ground-based data collection protocol would entail further discussion among the three BCPOS programs. This might start with sharing existing riparian monitoring results for the four currently shared monitoring sites (Hall Ranch, Bullock, Gage and Keyes). This would allow each program to see if and how data being collected by the other programs might meet their specific monitoring needs. A shared monitoring protocol would enhance future monitoring efficiency at sites that are already shared by the three programs, but could create difficulties in meshing newly collected data with existing data if protocol changes are substantial.

Consider a nested plot sampling design. For ground-based data collection, plots sizes ranging from 0.1 m^2 to approximately 80 m^2 have been used to describe microhabitat conditions relevant to PMJM (Clippinger 2002, Ruggles et al. 2004, Trainor et al. 2007). Clippinger (2002) used 1 m^2 quadrats distributed along transects to describe riparian vegetation at study sites. However, Ruggles et al. (2004) argued that a larger plot size is more appropriate for PMJM habitat monitoring since PMJM move over fairly large areas during the active season. They recommended a ~78 m^2 plot size (10 m diameter circular plot) for ground-based monitoring of PMJM habitat (i.e., riparian plant community characteristics and vegetation cover). This is the plot size that has been used for BCPOS PMJM habitat monitoring over the past few years. Although a larger plot size allows for description of larger habitat areas, it can be difficult to accurately estimate percent cover and density in plots this large, especially for herbaceous and shrub vegetation components.

One successful approach to vegetation monitoring is to use nested plots. This approach can be used to take into account spatial variability in vegetation conditions within a focal area (e.g., Trainor et al 2007), and to account for vegetation elements of differing sizes (e.g., USDA Forest Service 2005, USDA Forest Service 2011). Trainor et al. (2007) analyzed habitat conditions (i.e., vegetation and ground cover characteristics) by collecting data in 50 cm x 20 cm ‘subplots’, and then used subplot data to describe microhabitat characteristics of 9 m x 9 m (81 m^2) grid cells, employing 12 subplots per grid cell. The USDA Forest Service Forest Inventory and Analysis (FIA) program uses nested plots of different sizes to describe and monitor forest conditions.

Large circular subplots (radius = 24 feet [~7.3 m]) are used for tree sampling; Additional vegetation indicator data are collected in two plots sizes – some data are collected in the 24-foot radius subplots (e.g., total cover in height classes, species presence/absence and cover), and some data are collected in three smaller 1m x 1 m quadrats nested within the subplots (e.g., species presence/absence). Because of the time commitment required to collect field data, this level of detail may not be feasible for BCPOS monitoring. However, the approach of using nested subplots to describe larger microhabitat areas is worth considering, especially if there are challenges with the current data collection protocols.

Recommendations for remote sensing monitoring

Traditional riparian monitoring approaches have emphasized field-based data collection, however, remote sensing approaches are increasingly being used. This study highlights the tradeoffs inherent in the use of different remote sensing approaches for habitat assessment. ALS is useful because of its scale, low cost per acre, and accuracy, but because the temporal frequency of data updates is usually low, other methods can help fill gaps. Structure from motion proved unreliable for characterizing structure of vegetation in this study, but UAS imagery is extremely valuable even if the 3D models are lacking in quality. Repeat LiDAR data can be used to assess change in riparian tree height and/or extent at BCPOS properties, either at cross-sections of interest or continuously across an area.

Based on the large study area, we suggest landscape level monitoring modeling occur at 10 m resolution. Finer resolution data exist, but have proven to be problematic in both processing of the data and introducing considerable noise to land cover classification efforts. Following our recommendations for field based sampling, it may be good to incorporate a multiple scale, nested remotely based sampling design, using finer resolution (< 5 m) at localized sites and coarse resolution (~10 m) data for a landscape level analysis.

When new imagery is available or major events (e.g., floods or restoration efforts) have occurred, repeating the land cover classification and connectivity modeling analysis has the potential to highlight how changes may impact PMJM analysis. We recommend repeating this analysis after major events or every 5-8 years to capture how changes in the physical landscape may impact connectivity of PMJM populations and habitat. A second consideration, based on the feedback provided from the draft report regarding the accuracy of the land cover classification and the ability of the land cover classification to map riparian shrubs, is that BCPOS personnel may want to map land cover and vegetation in the field or to hand digitize land cover in and around BCPOS properties to increase the accuracy of the products.

Using the derived datasets. We have developed several remote sensing products that can assist in management and monitoring activities. Use of these products requires careful interpretation and consideration of the limitations and assumptions of the data. Here, we provide guidance on how to use the following products.

Land cover classification. The land cover classification provides useful landscape scale context for a single time period (2016) of observation. The accuracy of this dataset is 65%, which means that at any given pixel, there is a 35% chance of incorrectly classifying the land cover type. The kappa coefficient is 0.56, depicting a moderate agreement with the land cover classification and testing data, and indicating that the land cover classification outperforms a random dataset. Although this accuracy suggests moderate agreement with the testing data, it outperforms existing land cover classifications within the study area and those that map riparian zones. One must be careful to only compare the land cover classification with imagery that was capture during a similar time period (May – July 2017). If the land cover classification is compared to imagery from a different time period (e.g., pre-flood) additional discrepancies will be observed.

Through the use of geospatial tools in ArcMap (or other GIS applications) the land cover classification can be used to summarize land cover within the study area, in specific watersheds, or at individual open spaces, and to locate land cover of interest. The land cover classification can be used to evaluate the spatial arrangement of land cover classes, as an input to estimate connectivity for specific species or for a suite of species, and as a guide to locate land cover (e.g., bare ground) that may serve as a location for restoration. The land cover classification is a tool to guide field-based activity and any site-specific decisions must be verified on the ground before proceeding. Remotely sensed products provide a landscape level perspective, it is still very important that managers use their knowledge of the study area. For example, if one sees an agricultural area classified as riparian, they must understand that that is not an active riparian zone and can be excluded from their analysis.

Potential to integrate remote sensing and ground-based monitoring

There is great potential for natural resource monitoring programs to integrate remote sensing and field based protocols (e.g., Nagler et al. 2009, Lawley et al. 2016). Both site-based and remote sensing methods can be used independently to monitor compositional, functional and structural aspects of vegetation, but their integration has the potential to provide multi-scale information for ecologists and managers (Lawley et al, 2016). The development of effective ways to integrate the two monitoring approaches is currently an active area of research, and several challenges remain (Lawley et al. 2016, Tehrany et al. 2017). In particular, attention to the spatial and temporal match between the data sources is needed.

For the present time, we suggest the use of remote sensing analysis (i.e., using the workflows developed for this project) of the entire study area at regular intervals (5-8 years) or after major disturbance events. These analyses can be used to provide landscape context and to guide ground based data collection, for example if new areas of potential habitat importance are identified. Remote sensing analysis will be especially useful for monitoring general trends or abrupt changes in riparian physical structure and connectivity over time at the watershed/landscape scale, and for conducting species-specific modeling. In addition, remote sensing can be used to identify potential areas for restoration, according to criteria important to

BCPOS (e.g., areas lacking complex vegetation structure). However, due to the error inherent in remote sensing and GIS statistical modeling approaches, ground-based riparian habitat monitoring should continue at specific sites of interest to BCPOS. Ground-based monitoring is necessary both to track areas of desired riparian habitat condition (i.e., areas suitable for PMJM) as well as to track post-flood recovery and response to restoration at specific sites. Further research could compare carefully georeferenced field data (e.g., vegetation structure) with analysis of remote sensing products at select BCPOS study sites in order to further refine an integrated monitoring approach. The framework introduced in Chapter 5 is well suited for incorporating new remote sensing data sets (e.g., new LiDAR acquisitions)

Recommendations from habitat connectivity modeling

Overall, the connectivity analysis illuminated several key points and recommendations:

1. As modeled by the SDM, Left Hand Creek supports habitat suitable for PMJM and has the potential to form connectivity between the St. Vrain watershed and the Boulder Creek watershed. We recommend adding Left Hand Creek to the PMJM Habitat Conservation Areas map and increasing efforts to trap PMJM on Left Hand Creek. These efforts should be considered in conjunction with BCPOS aquatic and vegetation monitoring that is occurring at open spaces along Left Hand Creek.
2. PMJM habitat exists on Fourmile Canyon Creek. We recommend adding Fourmile Canyon Creek to the PMJM Habitat Conservation Areas map and, if resources exist, working with other agencies to increase efforts to trap PMJM on public land on Fourmile Canyon Creek.
3. We have identified several potential linkages for PMJM, including Dry Creek, Lykins Gulch Ditch, two intermittent streams, and North St. Vrain Creek (Figure 4-26). We recommend conducting fieldwork to investigate the viability of these connections and to determine if PMJM are using habitat in these areas.
4. We have identified two locations (Figures 4.27 - 4.29) for restoration to increase connectivity between PMJM based on proximity to known PMJM populations, effective resistance, and barriers within short (150 m) to moderate (450 m) distances.

Using the connectivity analysis. When using the data produced by the connectivity analysis, it is important to remember the output is limited by the accuracy of the input data and the assumptions made in creating the resistance layer. Many efforts were made to reduce the amount of error within the datasets, but error still exists in the inputs to the connectivity modeling. The data layers produced by the connectivity analysis are not a replacement for thinking, but rather a tool to assist in how to think about connectivity for PMJM (Spencer et al. 2010). The connectivity analysis presented here is PMJM specific and, without refinements to the resistance layer and habitat areas, cannot be extrapolated to other species or groups of species (e.g., other riparian obligates).

The connectivity analysis has produced three main datasets – the least cost pathways, the barriers to movement, and the pinch point analysis. The outputs of the pinch point analysis have been transferred to the attribute table of the least cost pathways for easy interpretation and use.

Least cost pathways. The least cost paths reflect the easiest modeled movement routes between adjacent habitat patches and are sensitive to our modeling assumptions and errors in our input data layers. These pathways provide our best estimates of potential movement between adjacent habitat patches and provide powerful tools to support connectivity planning. While the least cost pathways may appear to provide easy answers to PMJM connectivity questions, they must be used with caution as they are sensitive to modeling assumptions and errors in data inputs. These data are the most useful when approached with an understanding of how the models were developed and the assumptions and errors associated with the input data sources combined with firsthand knowledge of PMJM habitat requirements and behavior. Using these data in conjunction with other data, such as aerial photos and field records and observations, can provide additional insight. Managers must ask the following questions when interpreting the least cost pathways: (1) Does this pathway make sense given what we know about PMJM movement? If a least cost path transverses a large irrigated agricultural field, it is unlikely that a mouse would take that route. The model developed that least cost path because the agricultural field had the lowest cost of travel than the surrounding areas. One potential explanation for this is that the field was surrounded by higher resistance land cover (e.g., developed areas, roads, or lakes and reservoirs) and the pathway through the irrigated agriculture is the least costly path connecting the two habitat patches. (2) Have PMJM used the habitat areas, either historically or currently, that are modeled? We have modeled two types of connectivity – potential connectivity connecting suitable habitat as modeled by the SDM and known habitat modeled using kernel density estimates. Many of the areas in the potential habitat areas may not be currently used by PMJM or may not be realistic (i.e., riparian zones within the developed areas in Boulder and Longmont) and therefore, connectivity between these patches is not applicable. We recommend focusing on areas that are known to or have a high probability of supporting PMJM populations (e.g., St. Vrain Creek, South Boulder Creek, Coal Creek) when analyzing the connectivity data.

The least cost path data has several attributes that can be used to interpret the data. Two key attributes are the cost weighted distance (CWD) to path distance ratio (cwd_to_Path_Length) and the CWD to effective resistance ratio (cwd_to_Eff_Resist_Ratio). The CWD to path length ratio provides a measure of cost of travel normalized by the unweighted length of the path. The lower the values in this attribute, the lower the cost of travel along that specific pathway will be. This can be used to compare different least path costs and to prioritize corridors with high cost but, low travel distance. The effective resistance is a measure generated by the pinch point analysis which takes into account the number of alternative routes, using the cost weighted distance layer, between the two adjacent habitat patches and the width of a specific corridor. Using the normalized attribute (cwd_to_Eff_Resist_Ratio) allows for equal comparison of least cost paths. While the width of a corridor may make little difference to a PMJM, this is a measure of vulnerability of habitat along a least path corridor. If a corridor is narrow and the effective resistance is high, removing or altering preferred habitat within the corridor has the potential to have a larger impact on the movement of a mouse than in a wide corridor with multiple options for movement in preferred habitat. For example, several of the corridors near Gage and Pella Open Spaces are constricted by reservoirs and have high effective resistance values. If the riparian vegetation between the reservoirs was removed or degraded due to flooding or other disturbances, the connectivity between the habitat areas would be threatened. Managers can use the CWD distance to effective distance ratio to identify vulnerable corridors for further monitoring and potential restoration sites.

Barriers. The barrier analysis was conducted at 50 m intervals from 50 m to 1000 m to identify barriers to movement within a specific radius of a habitat patch, producing three data products. Barrier Centers which report the improvement, per cell, to the cost weighted raster layer if a barrier was removed, at a given window size. Barrier Circles (used in figures in Chapter 4) report the improvement expanded to fill the entire radius. Barrier centers and circles report the same information displayed in different ways. For an overall understanding of barriers, McRae et al. (2012) suggest using barrier circles to identify where barriers to movement occur within the specified distance. The final layer is the percent improvement scores in terms of the percentage relative to the original least cost distance of the corridor. High values in the percent improvement score indicate that if a barrier is removed, the cost of connectivity would decrease.

BCPOS riparian monitoring capacity

Considering the importance of riparian monitoring to BCPOS, and the diversity of ongoing and recent projects focused on this task, we suggest that BCPOS consider centralizing responsibility for and/or oversight of riparian monitoring within a single BCPOS staff position. Such a person could (1) lead discussions among the three programs (PMJM/wildlife, Plant Ecology, and Aquatic) to determine whether a shared riparian monitoring protocol is feasible and desirable, and (2) develop a plan for the integration of ground based and remote sensing based monitoring.

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