Animas River Removal and Replacement of Invasive Phreatophytes, Phase II Continuation and Strategic Mapping

Final Report


Prepared for:
Colorado Water Plan Grant Program
Attn: Chris Sturm

September 30, 2022

Mountain Studies Institute
SAN JUAN MOUNTAINS COLORADO

Grant Amount: $59,299.00

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Introduction

Building on the success of MSI's previous efforts to remove and replace invasive phreatophytes in the Animas River Subbasin, this project endeavored to complete several major objectives: 1) a continuation of the removal efforts in Phase II, working with private landowners, businesses, Southwest Conservation Corps (SCC), City of Durango (COD), and Southern Ute Indian Tribe (SUIT) to reduce populations of Russian olive (*Elaeagnus angustifolia*) and tamarisk (*Tamarix* spp.) in the Animas River Watershed, and 2) to implement a strategic approach to map the "state of the watershed," quantifying the extent of the Russian olive population by using object-based image analysis methods to create a distribution map in the Animas Subbasin in support of state-mandated noxious weed management goals. The intentions for this mapping effort are to be able to use it as an assessment tool to evaluate our progress in the basin, an outreach tool for recruiting landowners, and serve as a model for mapping efforts in other basins. This report covers the performance period for this Colorado Water Plan Grant program from July 30, 2020 to September 30, 2022.

Background

MSI began this effort with Phase I, under CWCB's Invasive Phreatophyte Control Program. During Phase I of this work, MSI built strong relationships with the community to engage landowners to remove invasive phreatophytes and encouraged replacement with native species. Approximately 290 acres were treated in Phase I from 2016-2018. MSI began the Phase II effort in 2019 and has since continued to engage additional landowners and the business community. We also expanded our partnership with the SUIT and were able to address populations of Russian olive that crossed the "checkerboard" of private property and tribal property boundaries.

Further, in 2020, MSI began a partnership with Four Corners Mapping and GIS. As a task within Phase I, MSI had attempted to map Russian olive within the Animas Subbasin with limited success using several methods and GIS tools. The proprietor of Four Corners Mapping and GIS introduced MSI to a new method for mapping Russian olive using remotely sensed imagery and object-based imagery analysis, which could be used to document the progress of removal efforts at a watershed-wide scale. This pilot study, titled "Supervised Classification of Russian Olive in the Animas Valley with NAIP Imagery and Object-Based Image Analysis", conducted in June 2019 on the Animas River in La Plata County, used USDA NAIP imagery to classify Russian olive, achieving accuracy of 91.3%. Based on the success of this pilot study, MSI subcontracted Four Corners Mapping and GIS to map the distribution and quantity of Russian olive for the entire Animas Subbasin in La Plata and San Juan Counties using these methods. Overall, our goal is to quantitatively document if the Russian olive populations in the Animas Subbasin are decreasing as a result of our efforts over time.

This project aligns with multiple stated goals in Colorado's Water Plan:
Colorado Water Plan, Section 6.2, pg. 6-15:
"Colorado's Water Plan uses a grassroots approach to formulate projects and methods that avoid some of the undesirable outcomes of the supply-demand gaps. The plan addresses the gaps from multiple perspectives—such as water storage, reuse, recycling, integrated water management, restoration, and conservation." This project supports this goal by working with private landowners and business owners, as well as tribal and local government to restore the watershed by removing invasive phreatophytes.

Colorado Water Plan, Section 6.6, pg. 6-157:
The policy of the State of Colorado is to identify and implement environmental and recreational projects and methods to achieve the following statewide long-term goals:

- Promote restoration, recovery, sustainability, and resiliency of endangered, threatened, and imperiled aquatic- and riparian-dependent species and plant communities.
- Protect and enhance economic values to local and statewide economies that rely on environmental and recreational water uses, such as fishing, boating, waterfowl hunting, wildlife watching, camping, and hiking.
- Support the development of multipurpose projects and methods that benefit environmental and recreational water needs as well as water needs for communities or agriculture.
- Understand, protect, maintain, and improve conditions of streams, lakes, wetlands, and riparian areas to promote self-sustaining fisheries and functional riparian and wetland habitat to promote long-term sustainability and resiliency.
- Maintain watershed health by protecting or restoring watersheds that could affect critical infrastructure and/or environmental and recreational areas.

This project supports these goals by removing invasive phreatophytes from a reach of the Animas River that is highly prized for recreational value, including boating and fishing, as well as environmental values, such as wildlife habitat. In Phase I of this project, removal efforts were focused on the upper reaches of the watershed, in an attempt to treat seed sources high in the watershed. In Phase II, efforts were focused on the lower part of the Animas River in Colorado, near the New Mexico state line. In these lower elevation areas, MSI and SCC encountered populations of Russian olive much denser than in Phase I, at higher elevations. It became apparent that additional labor would be needed to complete Phase II, which still continues into 2022 and will for several more years. We now focus on treating the denser populations, rather than the higher elevation seed source populations.

Additionally, this project aligns with the Southwest Basin Round Table, Basin Implementation Plan, 2015. This project addresses and contributes to the Measurable Outcomes of the following goals identified in the BIP.

- A5 Maintain watershed health by protecting and/or restoring watersheds that could affect critical infrastructure and/or environmental and recreational areas.
- D1 Maintain, protect and enhance recreational values and economic values to local and statewide economies derived from recreational water uses, such as fishing, boating, hunting, wildlife watching, camping, and hiking.
- E1 Encourage and support restoration, recovery, and sustainability of endangered, threatened, and imperiled aquatic and riparian dependent species and plant communities.
- E2 Protect, maintain, monitor and improve the condition and natural function of streams, lakes, wetlands, and riparian areas to promote self-sustaining fisheries, and to support native species and functional habitat in the long term, and adapt to changing conditions.

These goals are particularly important to MSI, as we view these efforts to control invasive phreatophytes as enhancing the overall resilience of our communities to adapt to future extended drought and a warming climate, which will promote rapid expansion of Russian olive populations in our watershed.

Methods

During Phase 2 of this project, MSI expanded on the work done during Phase 1. We concentrated our efforts in two areas: the Bodo Industrial Park in Durango, CO and the southernmost reach of the Animas River corridor in Colorado, which includes SUIT lands. MSI partnered with SCC, SUIT, and the COD to accomplish our goals. Together we accomplished the mechanical removal and herbicide treatment of Russian olive and tamarisk on 162 acres (Figure 1). Additionally, the SCC crews retreated approximately 18 acres that had been initially treated in 2019. We expect that retreatment may continue to be needed over the next 5-10 years to fully accomplish eradication of these species due to their persistence through resprouting and the longevity of the seeds in the seedbank. Through partnership with the SUIT's Division of Wildlife, we treated approximately 40 acres of tribal land (Figure 2), which complements approximately 100 acres in the Animas and La Plata sub-watersheds, which the SUIT restored with matching funding sources to pay for SCC's labor. While invasive species eradication is a long-term goal, MSI and our partners continue to work towards a fully restored upper San Juan watershed to create a sustainable future for Colorado wildlife and communities.

In the Bodo Industrial park, MSI obtained permission from 22 individual businesses that had Russian olive growing on their grounds. Due to limited time, Russian olive was removed from the grounds of 5 businesses. Due to the nature of where these Russian olive were growing, as part of landscaping, these trees were replaced with non-invasive species grown at local nurseries. This work was augmented by the City of Durango through purchase of additional trees, use of their chipper and truck, and the labor of their staff. One project site of particular note is the Juniper School, a charter elementary school in Bodo Industrial Park. The Juniper School grounds were populated with very large, mature Russian olive trees. MSI staff conducted a 5-week education program with the elementary students about why the trees were being removed and replaced. This work was supported through COD funds (not counted as match for this project). Eight replacement trees were planted from November 2020-April 2021. Students helped with the April 2021 plantings as part of the COD's Arbor Day celebrations. Replacement trees were also planted at several other businesses. MSI will continue to work with the remaining businesses with Russian olive on their property through additional funding from the Colorado Water Conservation Board.

The majority of the work in Phase 2 focused on the southernmost reach of the Animas River in Colorado. MSI was able to connect 13 landowners with adjacent or nearly adjacent private parcels, as well as SUIT lands to treat 0.93 linear mile of the river corridor.

An additional aspect of this project which provided a community benefit, while solving the problem of slash disposal was to work in cooperation with the Durango Daybreak Rotary club. The club operates an annual firewood assistance program to help low-income families and seniors to heat their homes. Rotarians volunteered their time and personal vehicles to pick up the firewood sized slash from project sites and hauled it to a staging area to dry. The Rotary club reported that they collected approximately 30 cords of woods from 2020-2021.

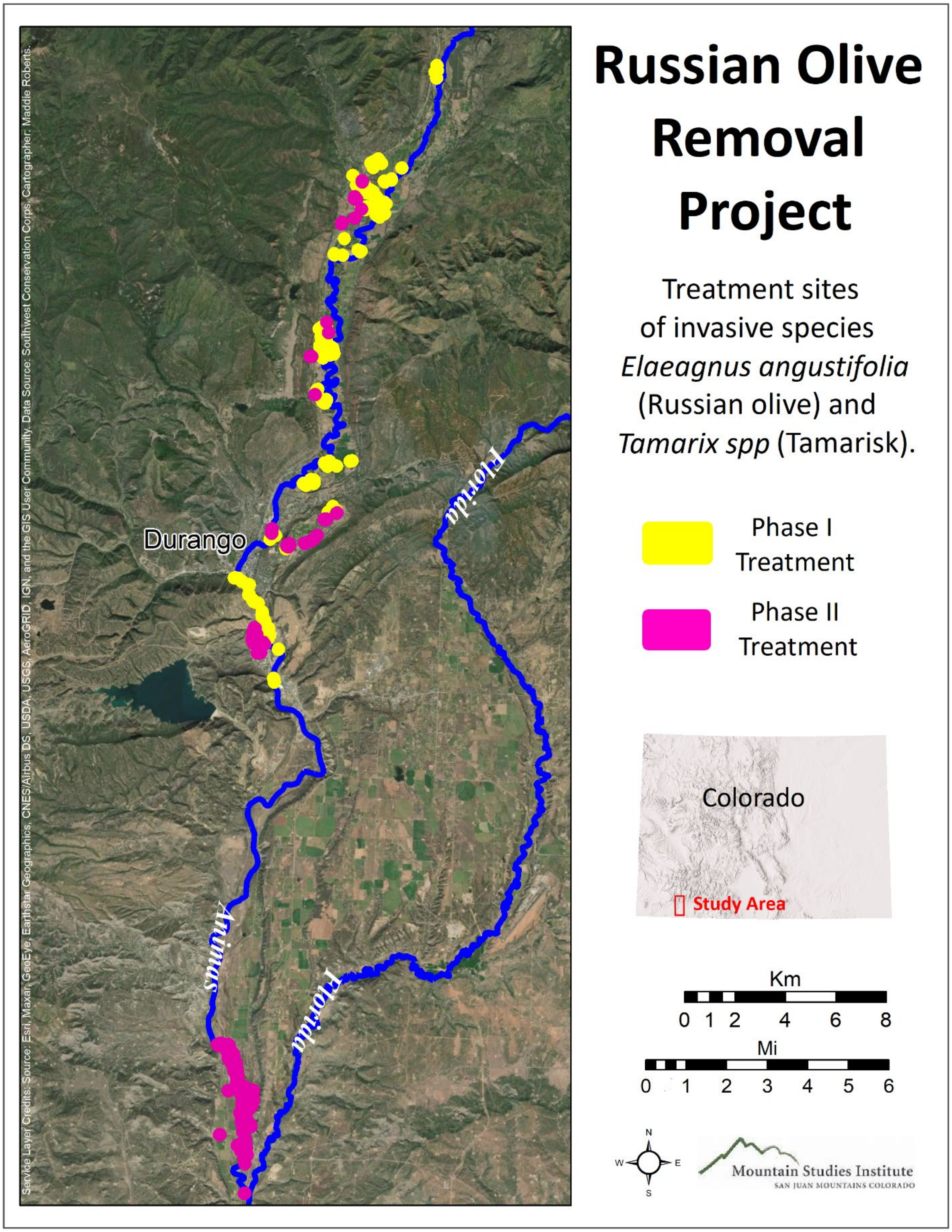

Figure 1. Acreage treated in Phase 1 (2016-2018) and Phase 2 (2019-2021).

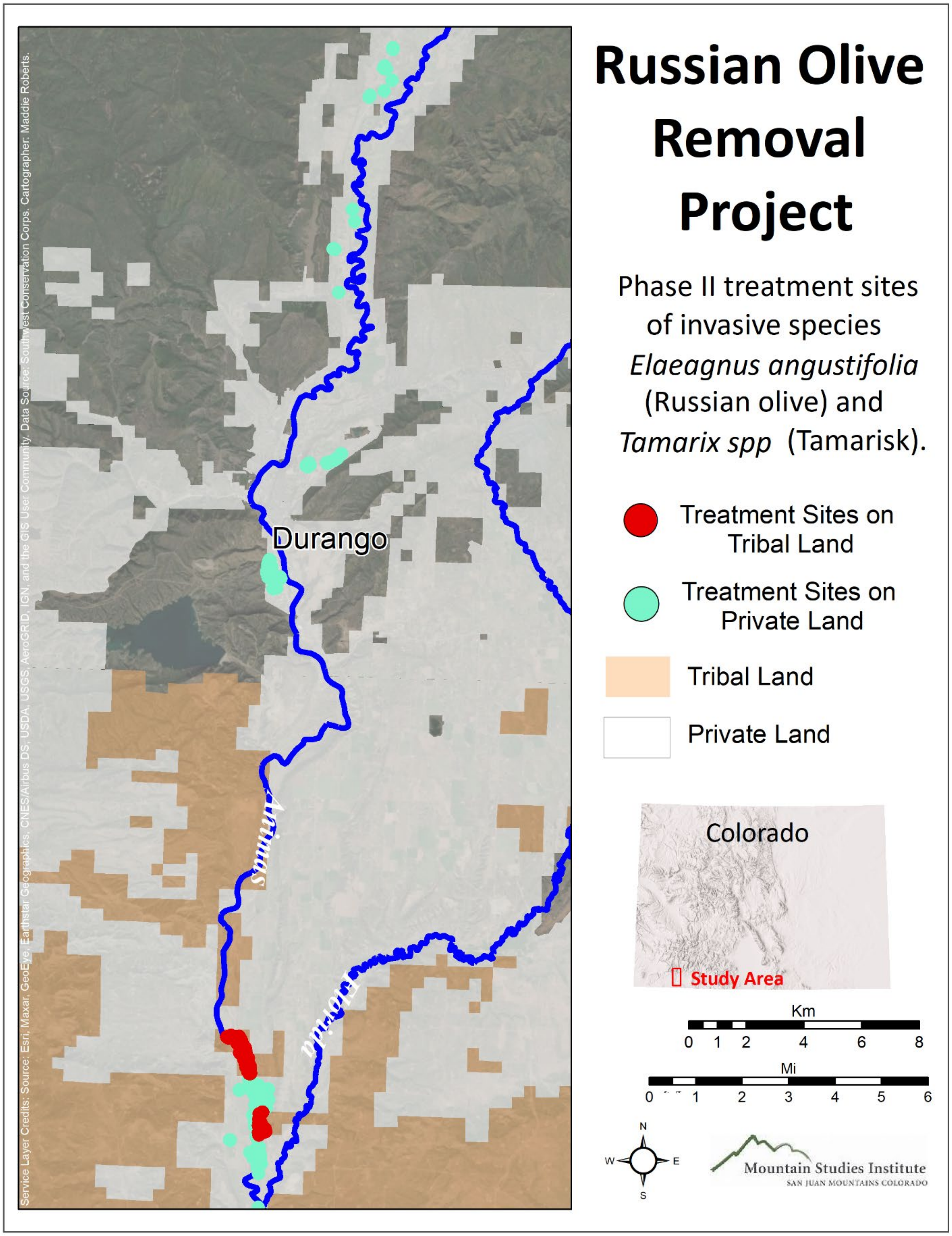

Figure 2. Acreage treated on private and tribal lands.

Invasive Phreatophyte Treatment Methods

Cut-Stump treatment method

The cut-stump technique involved cutting the trees and shrubs to ground level and spraying stumps with herbicide (Garlon 4 or Rodeo) and JLB oil. Chain saws, brush cutters, lopping shears and other hand tools were used. Stumps were sprayed using hand-held spray bottles, sprayers, or "painted on". The herbicide was applied to the stump immediately following cutting to maximize efficiency of the herbicide treatment.

Frill cut treatment method or "hack-and-squirt"

Using a hatchet, machete, or similar device a frill cut was made at a downward angle at intermittent spacing around the trunk (not completely girdling the tree). After striking, the hatchet was pulled backwards to produce a "cup" to hold the herbicide. Cuts were made to penetrate through the bark into living cambium tissue. Herbicide (Garlon 4 or Rodeo) mixed with JLB oil, according to the label specifications, was sprayed into the frill cuts using a sprayer. This method was used to control individual trees greater than five inches in diameter. This method was used in areas where it was difficult to fell trees and is beneficial for wildlife habitat, as standing dead trees become good habitat trees.

Basal bark treatment method

This method was used to address younger plants and re-sprouts with stems no larger than 6 inches in diameter. Herbicide was sprayed onto 12-15 inches of bark around entire stem near the base of the plant.

All treatment methods were applied after the phreatophytes had bloomed and prior to dormancy, between September and November for maximum effectiveness and to reduce re-sprouting, and in order to be outside of the migratory bird nesting season.

Once trees were removed, the wood material was either piled on site for later burning by the landowner, hauled away by the Durango Daybreak rotary club volunteers, or chipped and hauled away for incineration by the City of Durango (funded by in-kind match).

Mapping Methods

Methods for the strategic mapping of Russian olive portion of this project are described in detail in Appendix A: *Mapping the Distribution of Russian Olive in the Animas Valley A Workflow using Object-Based Image Classification, NAIP Imagery, and LiDAR* (pp 6-21).

Results

Through this project, and additional matching sources, the mechanical removal and herbicide treatment of Russian olive and tamarisk was accomplished on 162 acres (Figure 1), which included approximately 40 acres of tribal lands (Figure 2) and complements an additional approximately 100 acres in the Animas and La Plata sub-watersheds, which the SUIT restored with matching funding sources to pay for SCC's labor.

The mapping component of this project found that Russian olive covers 36.2 acres across the valley bottom of the Animas Subbasin, accounting for 0.03% of the project area. Russian olive was found at elevations ranging from 5,929 ft (1,807 m) to 7,340 ft (2,237 m). Please see Appendix A: *Mapping the Distribution of Russian Olive in the Animas Valley: A Workflow using Object-Based Image Classification, NAIP Imagery, and LiDAR* for a complete, detailed description of the results of this component of the project.

Conclusions and Discussion

The methods for removal of invasive phreatophytes continue to prove effective overall. We detect some resprouting from year to year, which is to be expected for these species, particularly Russian olive. By retreating the resprouted individuals before they become established as mature trees with a large seed crop, we continue to diminish the population overall.

The collaborative effort that MSI has developed by partnering with SCC, private landowners, SUIT, and COD, has proven to be effective. By working across boundaries of land ownership, we have created a comprehensive approach to reducing the impact of invasive phreatophytes overall. We still encounter landowners that are unwilling to work with our program. However, as the public perception of the detrimental effects of invasive phreatophytes grows, and the "word of mouth" communication between landowners amplifies, we are seeing more cooperation in key areas for removal.

MSI intends to keep this program going for several years. Funding has been secured through SCC, in partnership with MSI, to be able to employ SCC crews for several additional years. MSI has been unable to complete project work on all potential project sites each year that we have been working on this project. In other words, we have more work available than we have capacity to complete in a season. We continue to work towards eradication of invasive phreatophytes year after year.

The conclusions and discussion of the mapping effort are discussed in great detail in Appendix A (pp 25-32). In summary, the overall accuracy ranged from 84.30% to 93.59%. One major concern of this method is that there is no ability to discern Russian olive from the native species silverleaf buffaloberry (*Shepherdia argentea*), which has similar leaves to

Russian olive. This may require a further additional study to determine any differences in reflectance between the two species. Even with this limitation, the product of the mapping effort will extremely useful in future project planning and as an outreach tool. This method may be useful for mapping additional subbasins throughout the state, as well.

Actual Expense Budget

Table 1 shows the actual budget including all cash match and in-kind match funding and the total amount spent. MSI underspent our proposed budget by $236.**Table 1. Proposed**

COLORADO
Colorado Water Conservation Board
Department of Natural Resources

Colorado Water Conservation Board								
Water Plan Grant - Budget Actuals								
Date:	**28-Sep-22**							
Name of Applicant:	**Mountain Studies Institute**							
Name of Water Project:	**Animas River Removal and Replacement of Invasive Phreatophytes, Phase II Continuation and Strategic Mapping**							
Budget								
PERSONNEL								
Task	**Item**	**Hourly Rate**	**# Hours**	**Total**	**CWCB CWP Funds Proposed**	**CWCB CWP Funds Actual**	**MSI Cash Match**	**Matching Inkind**
Task 1- Outreach/Coordination								
	MSI Staff (Finance, GIS support, etc)	$ 50.00	20				$ 1,000.00	
	MSI Project Coordinator	$ 55.00	100	$ 5,500.00	$ -		$ 3,500.00	
	MSI Conservation Intern	$ 25.00	40				$ 1,000.00	
Task 2- Strategic Mapping								
	MSI Project Coordinator	$ 55.00	20	$ 1,100.00	$ 1,100.00	$ 11,634.20		
	La Plata County GIS							
Task 3 - Removal/Replacement								
	MSI Project Coordinator	$ 55.00	100	$ 5,500.00	$ 3,000.00	$ 2,713.03	$ 2,500.00	
Task 4- Monitoring/Reporting								
	MSI Project Coordinator	$ 55.00	100	$ 5,500.00	$ -		$ 5,500.00	$ -
	Landowner Monitoring	$ 28.02	100	$ 2,802.00	$ -			$ 2,802.00
Personnel Total				**$ 20,402.00**	**$ 4,100.00**	**$ 14,347.23**	**$ 12,500.00**	**$ 2,802.00**
DIRECT EXPENSES								
Expense	**Item**	**Unit Cost**	**Units**	**Total**	**CWCB CWP Funds Proposed**	**CWCB CWP Funds Actual**	**SUIT Cash Match**	**Matching Inkind**
Task 2- Strategic Mapping								
Remote Sensing Analyst	Subcontractor	$ 78.00	480	$ 37,440.00	$ 37,440.00	$ 27,784.00		
Software	Trimble eCognition (monthly)	$ 638.33	3	$ 1,915.00	$ 1,915.00	$ 1,110.00		
Hardware	HP Z6 G4 Workstation	$ 3,300.00	1	$ 3,300.00	$ 3,300.00	$ 3,625.82		
Hardware	Extra Ram for Workstation	$ 494.20	1	$ 494.20		$ 494.20		
MSI GIS License		$ 1,000.00	1	$ 1,000.00				$ 1,000.00
Task 3 - Removal/Replacement								
Southwest Conservation Corps	8 Person, 40h Crew	$ 8,000.00	5	$ 40,000.00	$ 8,000.00	$ 8,000.00	$ 32,000.00	
Mileage						$ 12.95		
SUIT Removal Efforts	Lump sum	$ 30,000.00	1	$ 30,000.00	$ -			$ 30,000.00
SCC Volunteer Inkind Contribution	All weeks	$ 10,000.00	1	$ 10,000.00	$ -			$ 10,000.00
TOTAL				**$ 124,149.20**	**$ 50,655.00**	**$ 41,026.97**	**$ 32,000.00**	**$ 41,000.00**
Other Direct Costs								
Units:	**Item**	**Unit Cost**	**Units**	**Total**	**CWCB CWP Funds Proposed**	**CWCB CWP Funds Actual**		**Matching Inkind**
MSI Subcontractor Fee	10% Administrative Cost on Sub	10%	45,440	$ 4,544.00	$ 4,544.00	$ 3,688.80		
TOTAL Other Costs				**$ 4,544.00**	**$ 4,544.00**	**$ 3,688.80**		**$ -**
TOTAL COSTS				**$ 149,095.20**	**$ 59,299.00**	**$ 59,063.00**	**$ 44,500.00**	**$ 43,802.00**

Budget vs Actual Expenses, with matching cash and in-kind, by task.

Appendix

Appendix A: *Mapping the Distribution of Russian Olive in the Animas Valley: A Workflow using Object-Based Image Classification, NAIP Imagery, and LiDAR*.

Mapping the Distribution of Russian Olive in the Animas Valley

A Workflow using Object-Based Image Classification, NAIP Imagery, and LiDAR

Prepared for:

Mountain Studies Institute

Prepared by:

Four Corners Mapping & GIS

June 2022

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Executive Summary

Russian olive (*Elaeagnus angustifolia*) is an invasive species prevalent in the Animas Valley in southwest Colorado and is typically readily distinguished visually in aerial imagery due to its silvery-green canopy. Object based image analysis (OBIA) incorporates not only spectral but textural and spatial elements of a class and avoids the “salt and pepper” effect of pixel-based classification with high resolution imagery. This study used 0.6-meter, 4-band National Agricultural Image Program (NAIP) imagery from 2019 to segment and classify Russian olive in the Animas Subbasin in La Plata County, Colorado. This regional effort built upon and utilized in part the methodology from a similar pilot study conducted for a portion of the Animas Subbasin, which used NAIP imagery from 2017 (Riling 2019).

Valley bottom of the Animas Subbasin was approximated based upon a 10-meter digital elevation model and using topographic position index. Utilizing Trimble eCognition 10.2, a ruleset was developed to segment NAIP imagery within the valley bottom and classify Russian olive as a land cover class. To mitigate data processing times and file size, the 170 square mile (441 square kilometer) study area was divided into several smaller scenes via USGS National Hydrography Dataset 10-digit hydrologic unit category. The overall accuracy for these scenes ranged from 84.30 to 96.59 percent. The user’s accuracy for Russian olive ranged from 85.94 to 100 percent. Russian olive producer’s accuracies ranged from 33.33 to 72.22 percent.

Russian olive covers 36.2 acres across the valley bottom of the Animas Subbasin, accounting for 0.03 percent of the project area. Russian olive was found at elevations ranging from 5,929 ft (1,807 m) to 7,340 ft (2,237 m).

Nationally, NAIP imagery is collected every two to three years, and has been collected in Colorado in 4-bands since 2009. Depending on the quality and availability of aerial imagery, fine-scale mapping as represented in this study could be repeated for the Animas Subbasin for other years, or in other areas of interest.

Introduction

The following is a brief summary of Russian olive in general, as well as its introduction to Colorado and the Animas Valley. For a discussion of RO, OBIA, multispectral imagery, and the hydrological characteristics of the Animas watershed, please refer to the aforementioned pilot study report (Riling 2019).

Riparian ecosystems in the US account for less than 5 percent of the land surface but represent habitat and migration corridors for 80 percent of animal species. They are highly susceptible to changes in hydrology and have been heavily impacted by invasive species, which outcompete native plants for water and soil resources, increase soil salinity, dry up streams and water bodies, and contribute to the risk of wildfires (Walker et al. 2017; Narumalani et al. 2009). Habitat suitability models and distribution maps of invasive species are vital to the management strategy of invasive species, including Russian olive (*Elaeagnus angustifolia*).

The Russian olive (RO) tree is flood, drought, shade, cold, and heat tolerant, can grow in poor and infertile soils, and rapidly colonizes lowland fields and dries up irrigation ditches; birds that consume its fruits spread its seeds to areas not yet invaded by the tree, and seeds are viable for three years (Colorado Parks and Wildlife 2005; Colorado Department of Agriculture -Conservation Services 2015). In the early 1900s, it was introduced to the US as an ornamental and windrow plant due to its attractive silver leaves and broad canopy (Colorado Parks and Wildlife 2005; Colorado Department of Agriculture -Conservation Services 2015). It was even sold by the Colorado State Forest Service to encourage landowners to plant the tree for windbreaks on the Great Plains, but in 2003 the sale of Russian olive became illegal in Colorado and this species is now a designated noxious weed (Staff 2003; Colorado Department of Agriculture 2015).

RO was introduced as an ornamental to the Animas Valley north of Durango, La Plata County, Colorado in the 1970s. The non-native tree has since become a nuisance, pushing out native trees and consuming 75 gallons of water per day, and contributing to the deterioration of wetlands (Rupani 2017; Kuenzi 2018a). The plant is now the target of state-sanctioned management plans designed to stop the spread of the species (Colorado Department of Agriculture 2018).

Figure 1 Russian olive on the bank of the Animas River. Its silvery leaves and broad canopy make it distinguishable in both the field and remote sensing imagery (Photo: Amanda Kuenzi, MSI Staff).

Since 2016, Mountain Studies institute (MSI), a Durango-based non-profit research and education center, has cleared approximately 300 acres and removed over 2,700 stems of RO under grants from the Colorado Water Conservation Board and Colorado Parks and Wildlife (CPW) (Kuenzi 2018a).

Figure 2. A Student Conservation Corps member under the direction of MSI removes a dense stand of Russian Olive. (Photo: MSI)

Existing vegetation mapping in the Animas Valley consists of generalized, low resolution classifications of vegetative communities (Gergely and McKerrow 2013; "Basinwide Layer Package" 2013; "CPW Riparian Data - La Plata County" 2012). These classifications are inadequate for the needs of MSI, which requires up-to-date canopy-scale delineation of RO to monitor spread and efficacy of treatment applications. Because quantitative, comprehensive documentation of RO distribution does not exist in the Animas Valley, MSI has no ready means of evaluating efficacy of removal efforts or determining which locations to focus those efforts. MSI has identified the need for large-scale distribution mapping of RO in the Animas Valley as vital to the management strategy of this invasive species.

Russian olive and other invasive species have been successfully classified using 1-meter resolution US Department of Agriculture (USDA) Farm Service Agency (FSA) Aerial Photography Field Office (APFO) NAIP imagery with object-based methods incorporating ancillary data such as texture and shape (Hamilton et al. 2006; Li and Shao 2014; Tobalske and Vance 2017). NAIP imagery is free, multitemporal, high resolution, and has been flown with four bands (visible and near infrared) in Colorado since 2009 (USDA 2018). NAIP imagery represents an acceptable source for low-cost data with proven efficacy in mapping RO. It was used in this study to assist MSI in facilitating this and future RO mapping efforts at a lower cost than commercially acquired imagery.

Project Area

The project focused on the valley bottom of the Animas River valley in southwestern Colorado. The project area lies within the USGS 10-digit Hydrologic Unit Category (HUC) Animas Subbasin and measures approximately 170 sq mi (441 sq km). Details regarding the delineation of the project area extent are described in the Methods Section, below. Figure 3 depicts the project area.

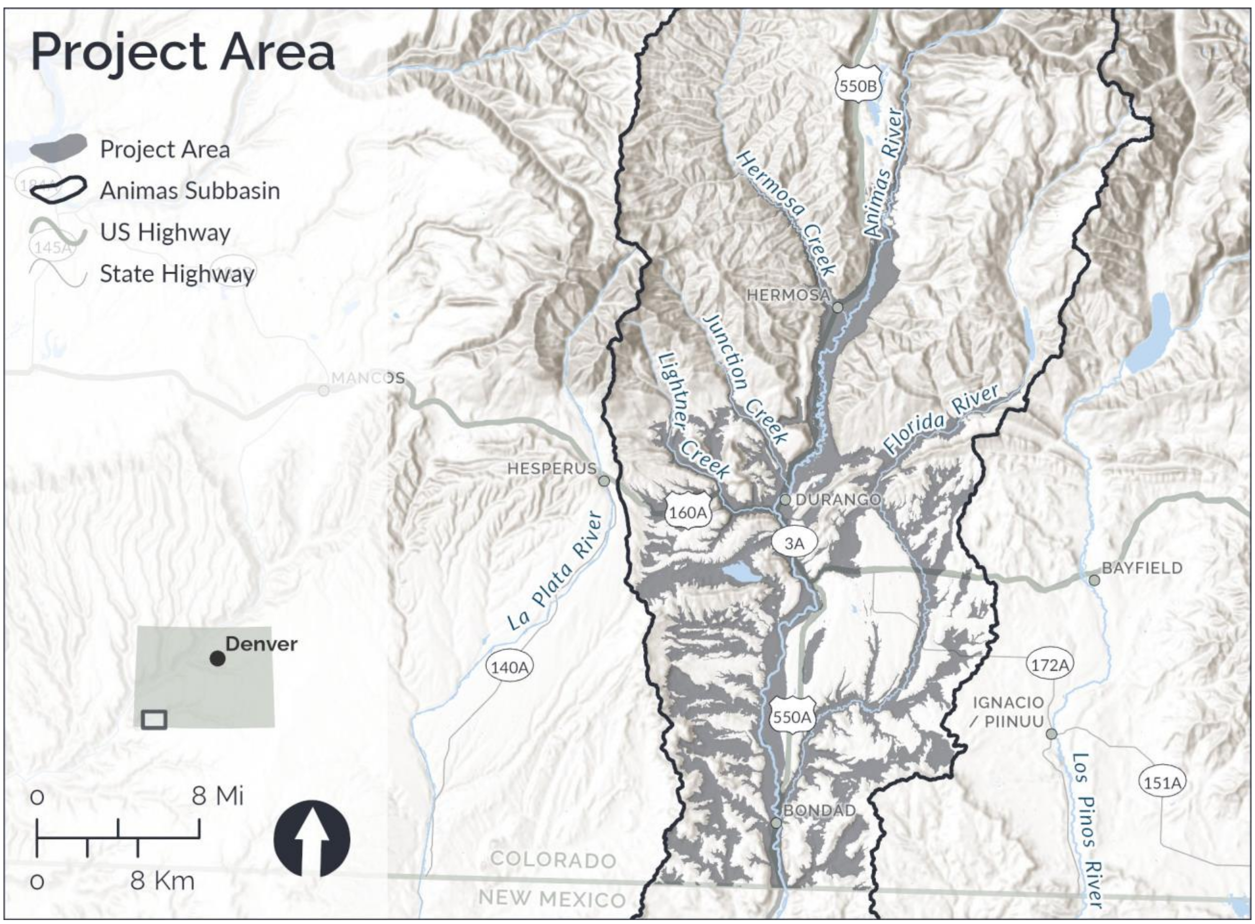

Figure 3 Project area: the valley bottom of the Animas Subbasin below 8,000 ft (2,440 m) in elevation.

Methods

The intent of this study was to generate a map of Russian olive distribution in the Animas Subbasin with a goal of 85 percent user's accuracy for RO using free, readily available NAIP imagery in the hopes that future classification efforts by MSI using NAIP imagery would be financially feasible and repeatable.

Valley Bottom Delineation

Approximate valley bottom for the Animas watershed was delineated to confine the pilot study area to potential riparian zones associated with the Animas River. This study used the topographic position index (TPI) tool developed by Jenness, Brost, and Beier (2013). TPI is the "difference between a cell elevation value and the average elevation of the neighborhood around that cell" and assigns a positive or negative value to a cell if it is higher or lower than its surroundings, respectively. The degree to which the cell is higher or lower, combined with the slope value of the cell, are used to classify that cell into one of three broad topographic categories; ridge, valley bottom, or slope (Jenness, Brost, and Beier 2013b).

In ArcGIS for Desktop 10.8, the TPI tool was used with a 10-meter resolution USGS DEM with a circular neighborhood of 200 cells to delineate approximate valley bottom for elevations less than 8,000 ft (2,440 m) (the upper range of RO habitat) within the Animas Subbasin. The result was exported to a project area feature class and reviewed by MSI staff for confirmation of project area extent.

Data Sources and Preparation

Imagery

NAIP imagery was sourced from the 2019 color infrared (CIR) and natural color compressed county mosaic orthophotos for La Plata County. Prior to distribution, color balancing was applied to the imagery mosaic and the imagery was orthorectified using the National Elevation Dataset (USDA FSA Aerial Photography Field Office n.d.). The imagery was collected in September 2019 with a ground surface distance (spatial resolution) of 0.6 meters.

In addition to NAIP, 3-band aerial imagery was also available via ArcGIS server through La Plata County. This high-resolution imagery dated from late spring/early summer 2017, 2019, and 2021, and was used as a tool for visual inspection, however it was not used in the segmentation process, and was not included as a band in classification.

LiDAR

The US Geological Survey has made LiDAR discrete-return point cloud data available in the American Society for Photogrammetry and Remote Sensing (ASPRS) LAS format. LAS format is a standardized binary format for storing 3-dimensional point cloud data and point attributes. Millions of data points are stored as a 3-dimensional data cloud as a series of x (longitude), y (latitude) and z (elevation) points. For this project, the data was collected between October 2018 and September 2019. The average point density is 2 points per square meter and average point spacing is 2.57 square meters (US Geological Survey 2020).

EcoloGIS, a firm that specializes in automated LiDAR processing, was subcontracted by Four Corners to compile, download, mosaic, and process the LAS files to produce a Canopy Height Model (CHM) for use in classification. EcoloGIS also used NAIP imagery to produce combine the imagery into a 4-Band raster using its component bands (Red, Green, Blue, NIR). The CHM and NAIP bands were clipped to each of the 10-digit HUC shapes within the project area (see Table 1 and Figure 4).

Project Area Watersheds	HUC10
Cascade Creek	1408010402
Animas River Canyon	1408010403
Hermosa Creek	1408010404
Electra Lake-Animas River	1408010405
Lightner Creek-Animas River	1408010406
Headwaters Florida River	1408010407
Outlet Florida River	1408010408
Middle Animas Valley	1408010409
City of Farmington-Animas River	1408010410

Table 1 Project area Watersheds in the Animas Subbasin and their 10-digit Hydrologic Unit Codes (HUC)

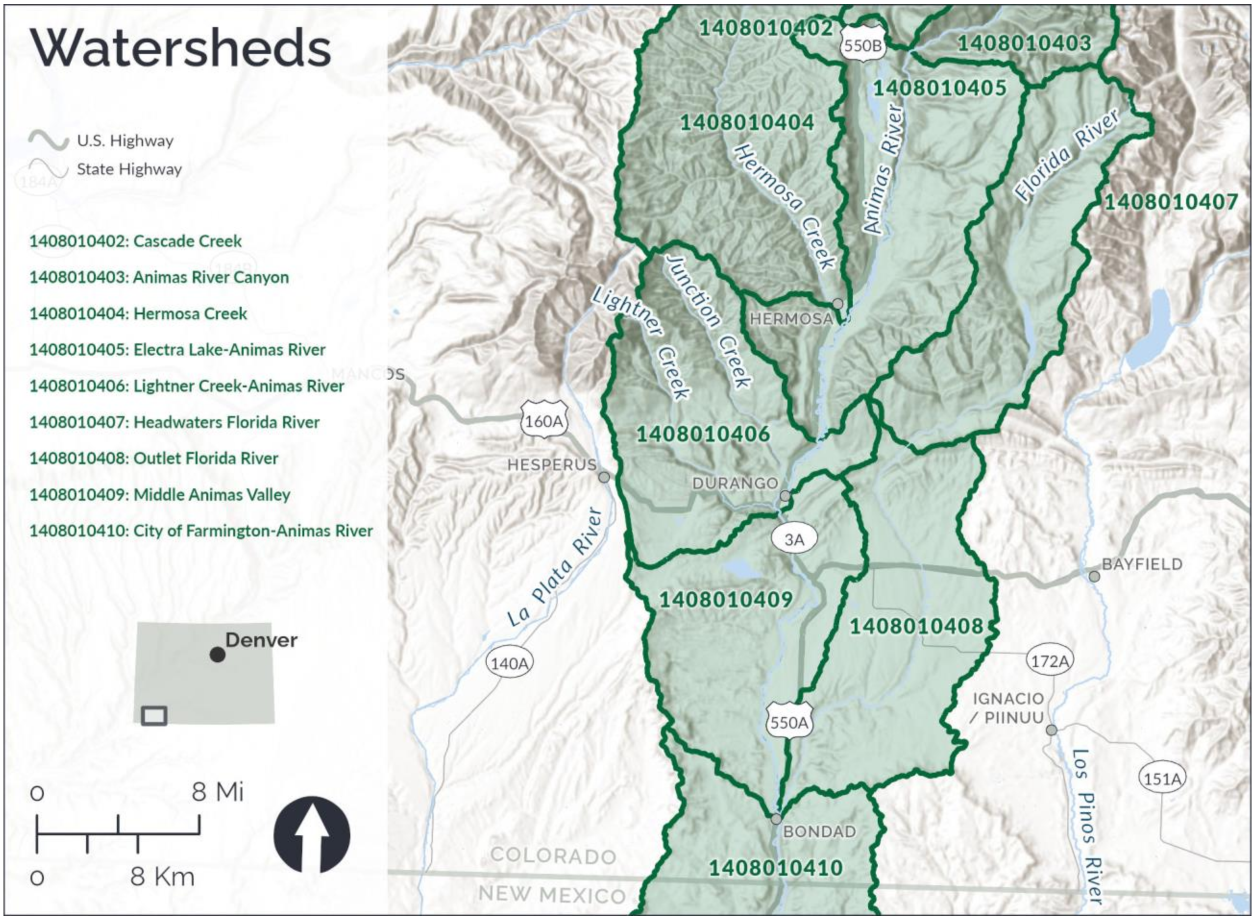

Figure 4 Map of project area Watersheds in the Animas Subbasin and their 10-digit Hydrologic Unit Codes (HUC).

These smaller areas were used to create subset scenes of the larger project area for use in segmentation and classification. The pixel size of the NAIP imagery for 2019 is 0.6 m; this cell size was also used for the CHM. In eCognition, the CHM was labeled “Height”.

Additionally, a slope band “(Slope_lidar”) was created in ArcGIS Pro based upon the CHM and was used in segmentation and classification. Alternatively, the *surface calculation* algorithm can be used in eCognition to create the slope band(s) but it adds to the processing time of the rule set.

Other Bands

In ArcGIS Pro, NDVI was created from the 4-band NAIP imagery mosaic and used as an imagery band in segmentation and classification in eCognition (see the Segmentation Section for details). NDVI can alternatively be created via the *index layer calculation* algorithm in eCognition, but this adds to the processing time of the rule set. NDVI was calculated as follows:

$$NDVI = [(NIR - R) / (NIR + R)]$$

where:

NIR = near infrared (band 4 in NAIP imagery)

R = red band (band 1 in NAIP imagery)

Lastly, from the USGS 10-meter DEM, elevation ("DEM") and slope ("Slope") rasters were resampled to match the NAIP cell resolution of 0.6 m, snapped to the NAIP imagery, and used in segmentation and classification.

Segmentation

Segmentation and classification were performed with Trimble eCognition 10.2. The first step is to create a "scene" by importing the imagery and other bands and any vector files into eCognition. Several scenes were created for this study, based upon the footprint of the project area and the 10-digit HUCs. These are Electra-Cascade-Animas River Canyon, Hermosa Creek, Lightner Creek-Animas River, Florida River, Middle Animas Valley (see discussion below), and City of Farmington-Animas River.

One 10-digit HUC, Middle Animas Valley, was subdivided into two scenes for processing in eCognition: Basin Creek – Animas River (12-digit HUC 14080104090) and Indian Creek – Animas River (12-digit HUC 140801040903). Basin Creek – Animas River included the Bodo Park, Jenkins Ranch, Horse Gulch, and Grandview areas. The Indian Creek – Animas River scene extended from Wilson Gulch to Bondad. The western boundary of the Indian Creek – Animas River scene is the west boundary of the Sections in the easternmost third of Townships 33 and 34 North, Range 10 West, and extends to the Ridges Basin dam (which dams Lake Nighthorse). No RO was observed in aerial imagery west of this boundary, or in Ridges Basin beyond the access to Lake Nighthorse. The area west of this boundary was included in the segmentation and preliminary classification of Canopy but was excluded from RO classification to improve accuracy of the remaining scene and limit processing time to those valley bottom areas where RO was observed and validation could be performed effectively. Figure 5 illustrates these scenes.

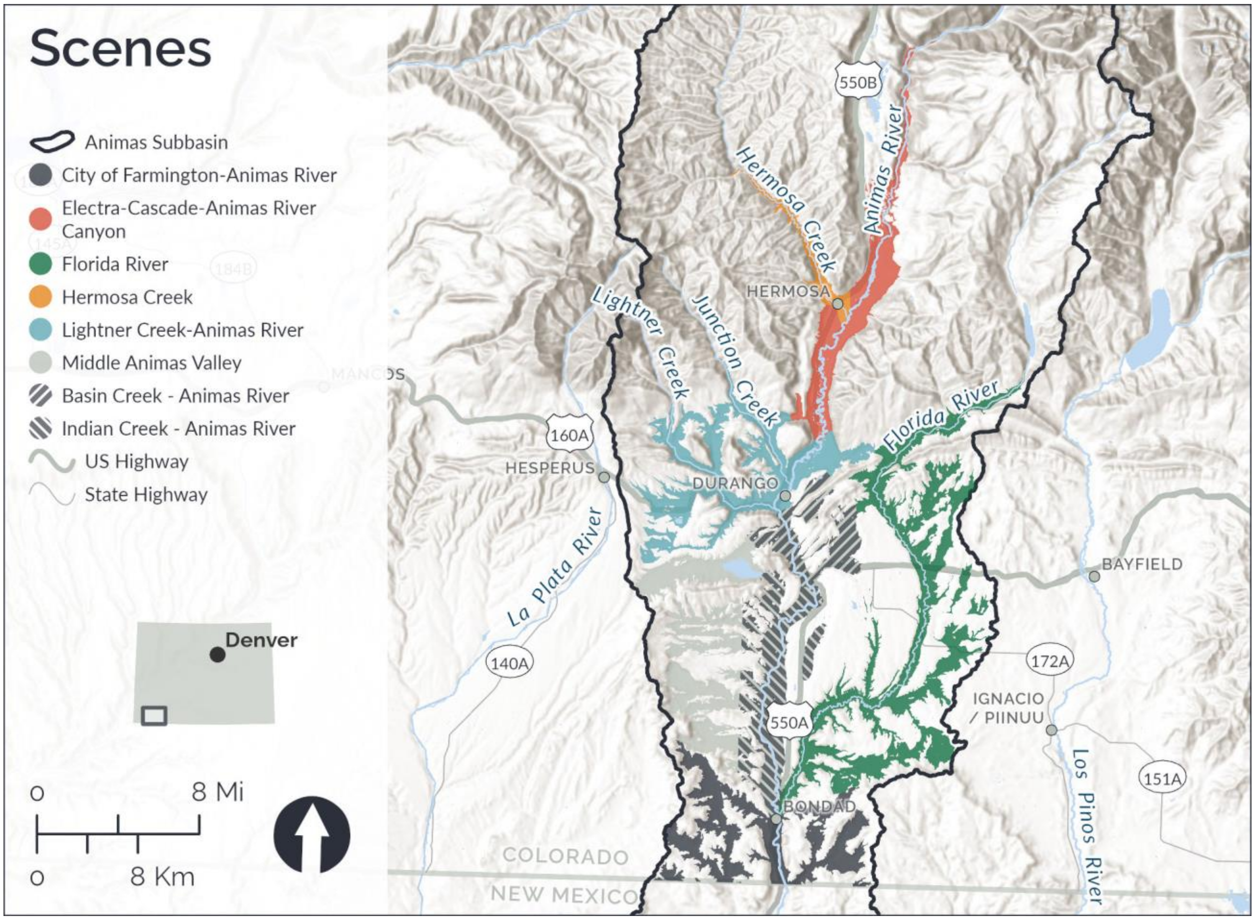

Figure 5 Project scenes used for processing in eCognition. Scenes were based upon HUC boundaries and PLSS Sections.

To process and analyze a scene in eCognition, a rule set must be developed. Rule sets are a combination of single processes, or algorithms. Each process can operate on two domains or levels; the image object level or the pixel level. For each object, a process will run sequentially through each target, applying an algorithm to each. Because of the long processing times typical of image segmentation, a smaller subset scene was created to develop, test, and run the rule set, after which the rule set was applied to all scenes.

Firstly, a background mask was created to limit processing to the area of the scene in which there are NAIP pixels. This was done via the *multi-threshold segmentation* algorithm on the pixel level by assigning all values of 0 for one of the NAIP bands to the class “background”, and all other values “unclassified”. Note that the NAIP raster was prepared using a NoData value of 0; if another value is used, then the algorithm parameters would need to be adjusted accordingly. Figure 6 depicts the algorithm window for this process, which used the Red band (but any of the four NAIP bands could be used because the NoData value for all is 0).

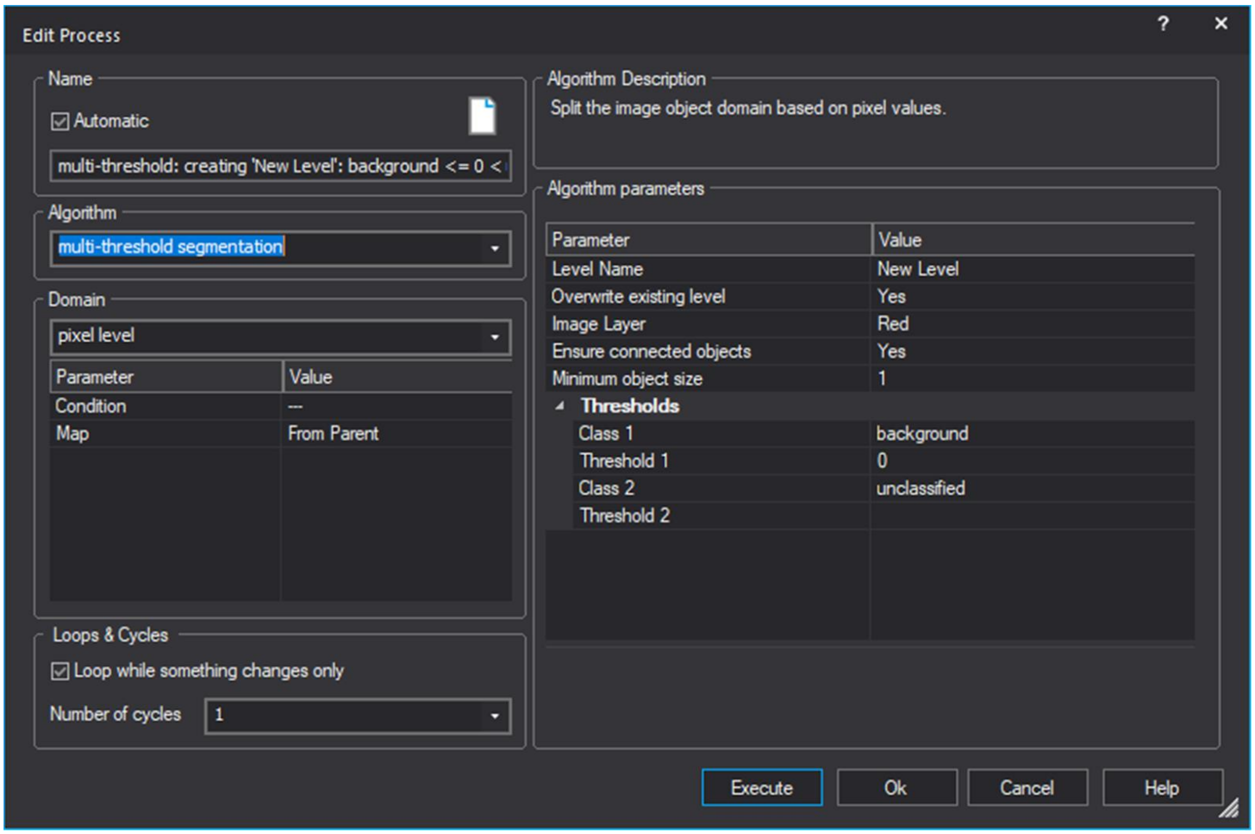

Figure 6 The multi-threshold segmentation algorithm was used to assign a class of "background" to pixels with a value of 0 in the Red band.

The next step was to create a “vegetation” class based on the NDVI band. Again, the *multi-threshold segmentation* algorithm was used, this time based on the image object level created in the previous step. Due to the observed very low NDVI values of RO, 0.1 was used as the threshold; values of the class “unclassified” less than 0.1 were assigned the class “non-vegetation”, and values greater than 0.1 were assigned the class “vegetation”. Alternatively, the *automatic threshold* algorithm can be used in eCognition to automatically compute a threshold from the histogram of the NDVI. This creates a scene-specific variable that can be used in other processes. This was attempted with intermittent success, but the value of 0.1 was used instead to ensure no vegetation was excluded from processing. Figure 7 depicts the use of the *multi-threshold segmentation* algorithm on the NDVI band to create the vegetation class.

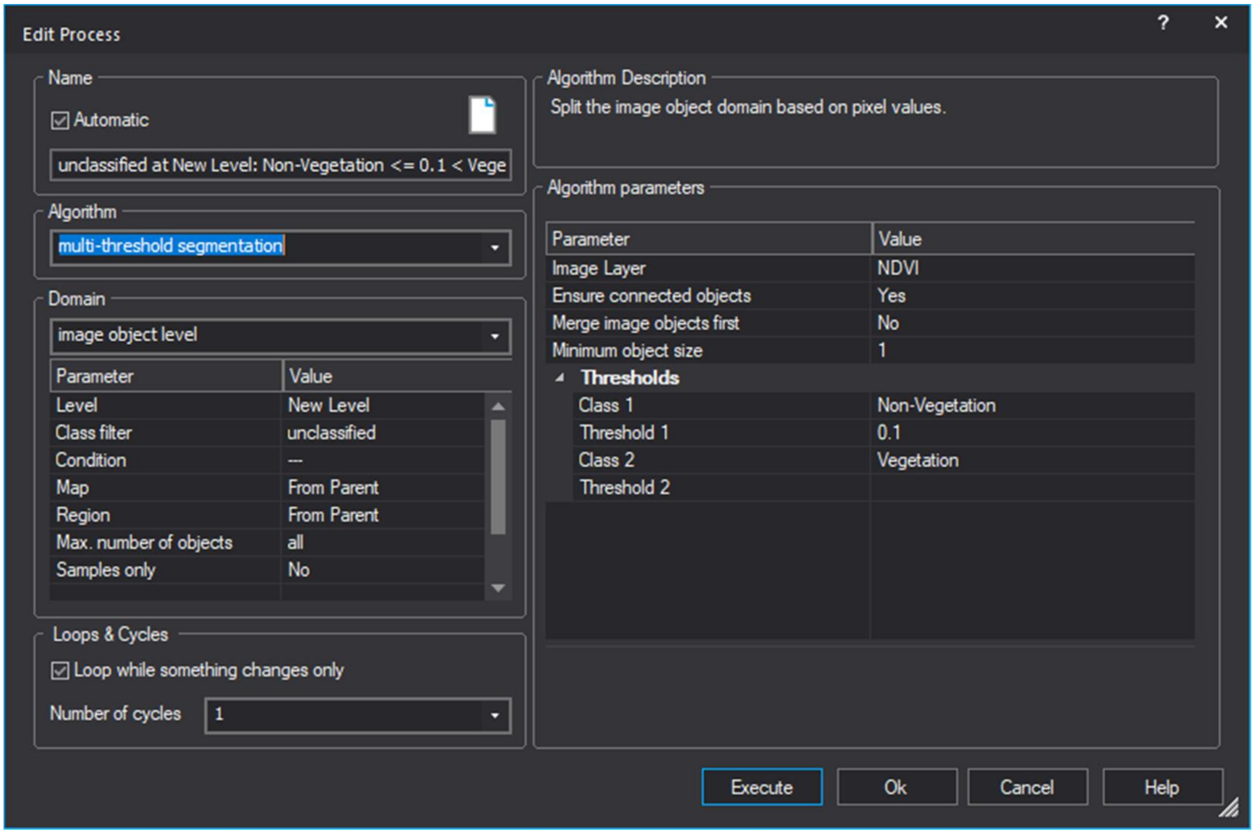

Figure 7 The multi-threshold segmentation algorithm was used to assign a class of "vegetation" for NDVI values greater than 0.1.

The vegetation class was then classified into “canopy” and “non-canopy” based on the Height band, again using the *multi-threshold segmentation* algorithm. A height of 1-meter was chosen as the threshold, meaning that any pixels greater than 1 meter were classified as Canopy. See Figure 8.

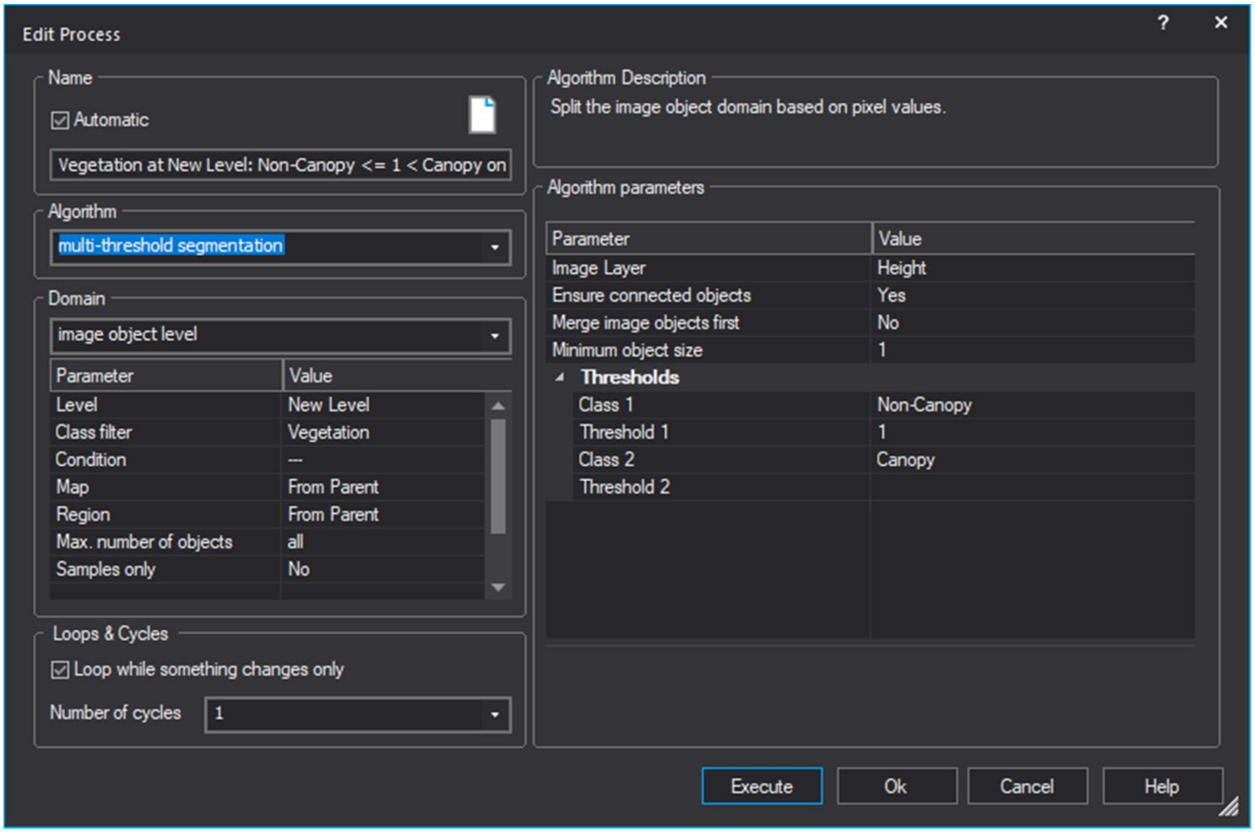

Figure 8 All pixels with a height greater than 1 meter were classified as Canopy.

The next step in the rule set was to segment the Canopy class. This was done using the *watershed segmentation* method applied to the inverted Height band. This algorithm is used to isolate tree crowns and is a region-based segmentation that uses seed objects, with the objects growing with rising intensity levels in the neighborhood until they touch objects growing from neighboring seeds. A visualization to understand the algorithm is that of water rising from valleys until the whole area is “flooded”; object borders are formed in places where the rising water levels from different valleys meet. In this case, a “top-down” method was used, starting from the highest pixels in the height band. For this project, several neighborhood types and seed criterion were evaluated, and each scene required slightly different parameters. For the final algorithm, a neighborhood of “8-connected” and the Overflow Area seed criterion were utilized, with a threshold of between 2 and 8; any objects with an area of less than threshold number of pixels were merged with neighboring objects/seeds. This algorithm was applied at the image object level with a class filter of Canopy. See Figure 9.

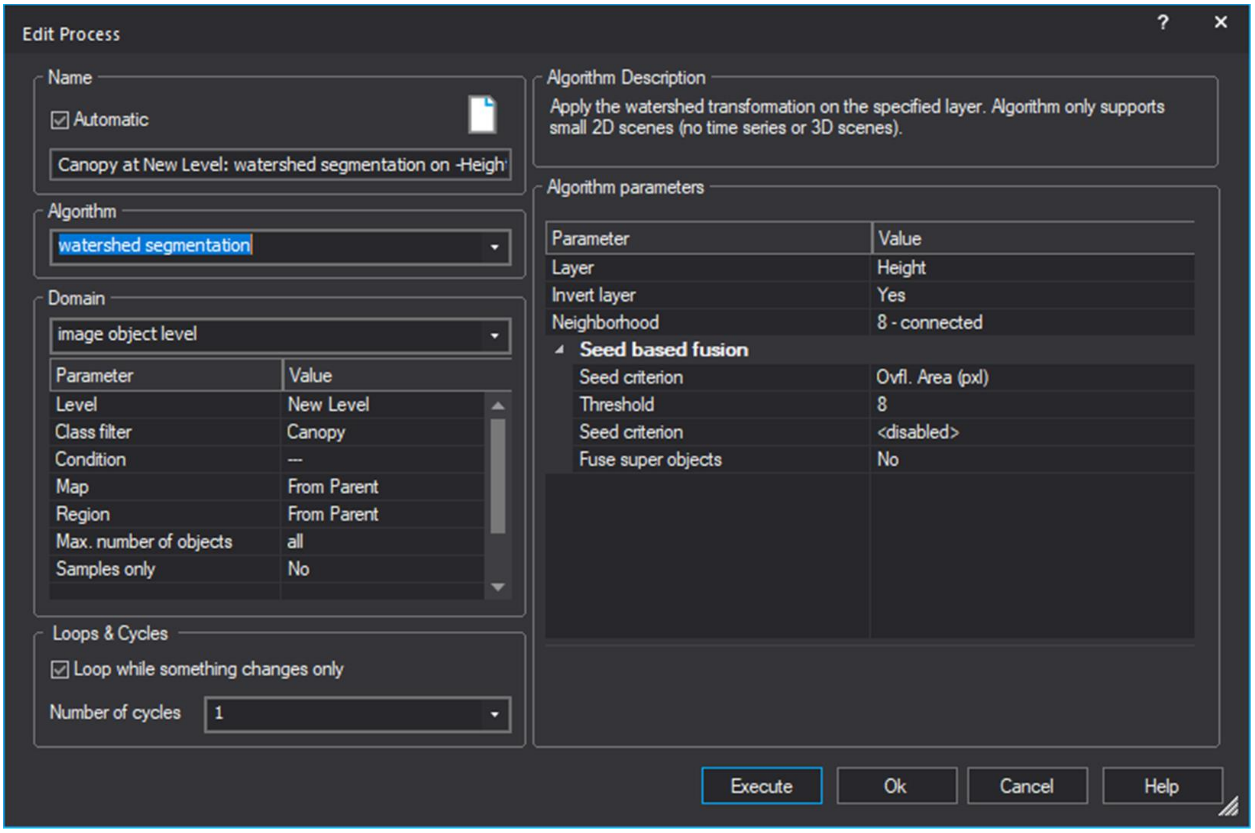

Figure 9 Watershed segmentation on the Height band with an Overflow Area seed criterion with a threshold of 8.

Following segmentation, the *pixel-based object resizing* algorithm was applied to refine the segmented objects. Based on visual observation of the imagery, there were several roof tops with NDVI greater than 0.1 that were misclassified as Vegetation and/or Canopy. These roof tops typically had a Blue value of greater than 105. Pixels in these objects with a Blue value of greater than 105 were “shrunk” from the Canopy class and assigned to the class “Structure”. See Figure 10 and Figure 11.

Figure 10 Several roof tops misclassified as Canopy.

Figure 11 Misclassified roof tops with Blue values greater than 105 reclassified as Structure.

Additionally, using the *remove* objects algorithm, very small objects, very small holes within objects, and linear objects with a shape not representative of RO were removed.

Following the *watershed segmentation*, the result was exported to a shapefile for developing the training and testing samples.

An example rule set file will be provided to MSI.

Prior to the use of the *watershed segmentation* algorithm, the *multi-resolution segmentation* algorithm was evaluated, which locally minimizes the average heterogeneity of image objects for a given resolution of image objects. It consecutively merges pixels or objects based on spectral and shape homogeneity, with user-defined parameters for scale, shape, and compactness. Image layers can be selected and weighted differently; for instance, greater weight may be assigned to the NDVI and/or Red bands. This algorithm has higher memory requirements and significantly slower performance than other segmentation algorithms.

Many variations of user-defined parameters with the *multi-resolution segmentation* algorithm were evaluated for this project. Depending on these parameters, the resulting imagery was typically either "over-segmented" based on spectral characteristics, creating hundreds of thousands of objects for very bright and very dark areas (i.e. leaves reflecting sunlight and, conversely, shadowed areas) or under-segmented based on a higher shape or scale parameter, with distinct trees of different types, including RO and others, lumped together into one object. Additionally, the memory requirements of this algorithm resulted in a processing time of several hours for some scenes. The *watershed segmentation* algorithm typically provided a better segmentation result of tree crowns with fewer, more compact objects in a fraction of the time than *multi-resolution segmentation.* For instance, in the case of a single tree in a field, the watershed segmentation usually produced a single object, while the multi-resolution segmentation produced several based on spectral intensity. For these reasons, *watershed segmentation* was used for this project. Examples of these segmentation algorithms are depicted in Figure 12 through .

Figure 12 Russian olive trees adjacent to trees of a different species (La Plata County 2019 imagery).

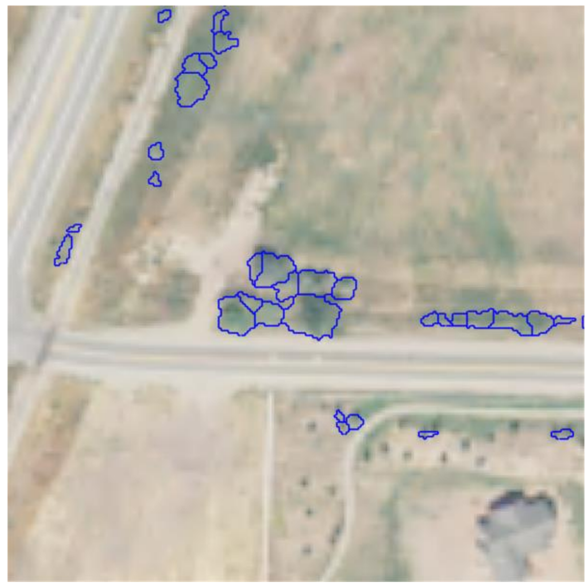

Figure 13 Canopy segmentation using the watershed algorithm applied to the Height band. Individual tree crowns are delineated.

Figure 14 Canopy segmentation using the multi-resolution segmentation algorithm (scale = 25, shape = 0.1, compactness = 0.5). Objects are spectrally grouped, causing other classes to be grouped with RO.

Figure 15 Canopy segmentation using the multi-resolution segmentation algorithm (scale = 25, shape = 0.4, compactness = 0.5). Shaded and bright areas occupy their own objects regardless of if the areas represent the same tree.

Training and Testing Samples

This study utilized a supervised classification method, which requires the use of user-selected training samples following segmentation, consisting of representative areas that represent the unique makeup of a particular class. In general, the greater the number and diversity of training samples for each class, the better the results of classification. For this study, the Canopy class was classified into two classes: Russian olive (RO) and Other Tree (OT); OT samples consisted of every other object within the Canopy class aside from RO. This methodology was similar to that of the pilot study, with the exception that the Grass and Shrub classes from the pilot study were negated in this study by classifying the Canopy class based on height, leaving just the two classes within the Canopy class (RO and OT).

RO sample points that were used in the pilot study were reviewed via visual inspection of 2019 NAIP and La Plata County imagery to assess any change between 2017 and 2019. Additional RO sample points were delineated for the entire current study area and a point feature class was created.

The segmented Canopy class for each scene was brought into ArcGIS Pro 2.9.0 and overlaid on top of NAIP and County imagery. The RO points were reviewed to ensure that no object had more than one RO point; the presence of multiple testing samples within the same object might skew accuracy assessment by producing duplicate results. Using Model Builder, a model was created ("Create Random Other Tree Samples"), where the Create Random Points tool was used to generate random points within a dissolved Canopy that did not contain RO sample points. A user-defined parameter was specified to enable the selection of the number of points. An attempt was made to digitize enough points to cover as much of the spectral variability of each class as possible. The model is illustrated graphically in Figure 16.

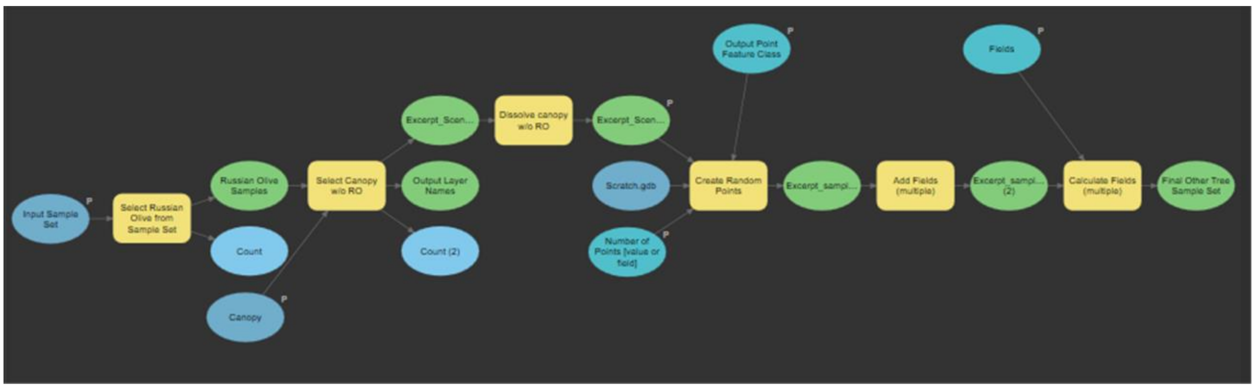

Figure 16 Create Random Other Tree Samples Model.

Next, another model was created ("Select Training and Testing Samples") to combine the RO and OT sample feature classes, then partition those into training and testing datasets. Twenty percent of the samples were reserved for testing samples for use in assessment of classification accuracy.

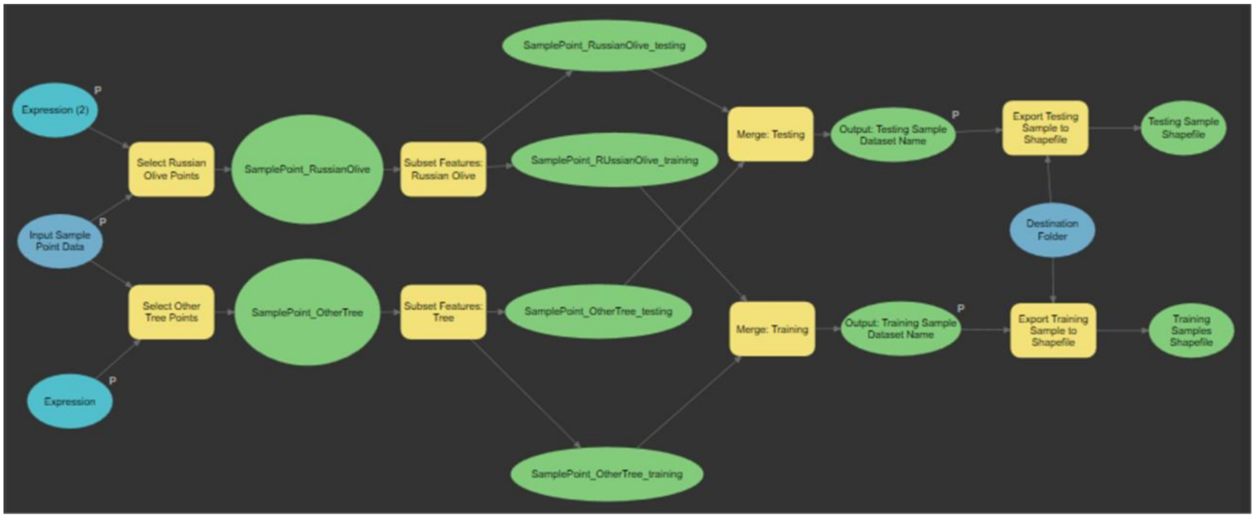

Figure 17 Select Training and Testing Samples Model.

The resulting Training Samples feature classes were used to train the classification algorithm each scene, and the Testing Samples were used to generate confusion matrices, as discussed in the Results Section.

Classification

Following the creation of the training and testing samples, these datasets were added as vectors to eCognition and then used to create and save sample statistics. The *assign class by thematic layer* algorithm was used to convert training samples into classified image objects, because sample statistics currently can only be created using classified image objects. This process was followed by the *update supervised sample statistics* algorithm, which created feature statistics for each object of each class.

Following much trial and error selecting different types and combinations of feature attributes to generate the best accuracy results, the following features were extracted for each object in each scene: image layer values (mean and standard deviation of each NAIP band, NDVI, Height, Slope, Slope_lidar), brightness; asymmetry, roundness, compactness, rectangular fit, hue, saturation, and intensity. The sample statistics were exported to csv for use in training the classification algorithm, and the RO and OT classifications were returned to the Canopy class using the *assign class* algorithm.

Next, validation samples were created from the Testing Samples vector input. Again, the *assign class by thematic layer* algorithm was used to assign objects to the class corresponding to the testing point located within them. The *convert classified image* *objects to samples* algorithm was used to create samples for each classified image object that was previously assigned a class based on the location of testing sample points. The classification of RO and OT were then removed, and those objects returned to the Canopy class.

In an effort to achieve the highest accuracy for RO classification, several different classification algorithms were tested, including K Nearest Neighbor (KNN), Support Vector Machine (SVM), Decision Trees, and Random Trees. Again, after trial and error, SVM was selected as the classification algorithm due to superior preliminary accuracy results.

SVM is a type of machine-learning classifier that separates classes with a decision plane that maximizes the margin, or separation, between classes. Points falling on either side of the plane are assigned to different classes. This plane, or surface, is called the *optimal hyperplane*, and the classes closest to it are called the *support vectors*. SVM was originally developed as a binary classifier and is adapted to be used as a multiclass classifier by creating a binary classifier for each possible pair of classes and projecting the feature space to a higher dimension, or kernel. There are several kernels used in remote sensing; common types include polynomial kernels and radial basis function (RBF) (Maxwell, Warner, and Fang 2018). Setting a penalty parameter allows for misclassification by allowing a certain number of *support vectors* to fall on the wrong side of the *hyperplane*; in eCognition, this is the C value, or *capacity constant*.

For this study, the *supervised classification* algorithm was used, with the operation set to Train, the Classifier type set to SVM, and the source of the training data set to use the sample statistics created previously. An RBF kernel type was used, with a C value of 100, and a gamma function of between 0.01 and 0.03 depending on the scene. See Figure 18, which shows the algorithm window and relevant settings.

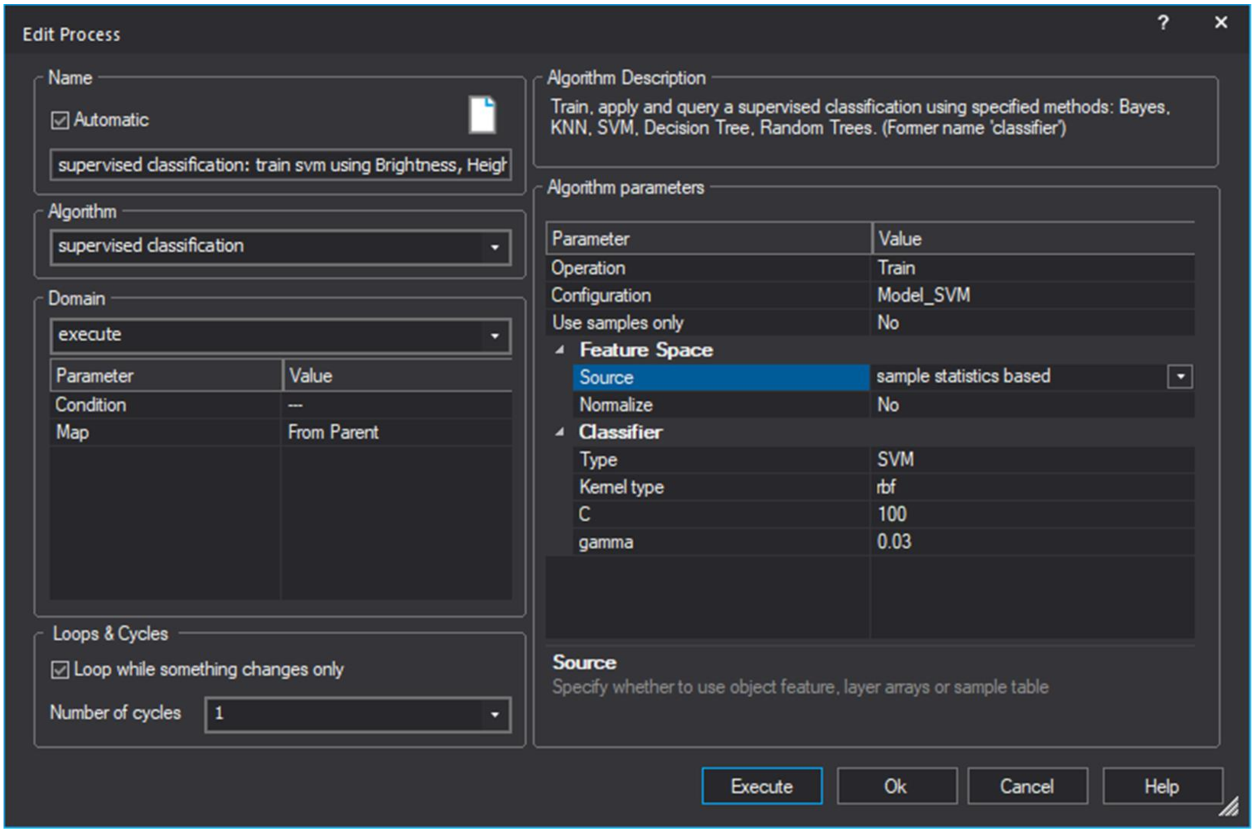

Figure 18 Training the SVM classification.

The same algorithm was used to apply the classification, with the operation set to Apply.

The classification result was exported to a shapefile for post-modeling editing. The confusion matrix was exported to csv for each scene.

Post-modeling

Post-classification editing of the classification results was performed in ArcGIS Pro to correct misclassified objects. All misclassifications were corrected manually by doing a "once over" of the entire project area using NAIP and County imagery as the background. A grid was created for the entire valley bottom of the project area, and once the manual edits in each approximately 250 m x 250 m grid square were completed, the grid section was marked as such. White tedious and time-consuming, this approach produced more satisfactory results than any automated method.

Results

To assess the accuracy of the classification results, prior to post-modeling, confusion matrices were generated in eCognition for each processed scene using the validation samples generated from the Testing Sample dataset. This study aimed for an overall accuracy of 85 percent or better, and a user's accuracy of 85 percent or better for Russian olive, as was achieved in a prior study mapping RO with NAIP imagery (Tobalske and Vance 2017).

The overall accuracy calculates the proportion of objects out of the testing samples (reference data) that were mapped correctly. It is expressed as a percent, with 100 percent being perfect classification–all reference objects were classified correctly. User's accuracy is the probability that a classified object is really of that class. In a practical sense, the user's accuracy is a measure of the likelihood of someone going to an area on the ground that has been classified as RO, and actually finding it to be RO in the field. Producer's accuracy is the probability that an object in a given class was classified correctly; for this study the RO producer's accuracy represents the likelihood that an area of RO will be correctly predicted. Cohen's Kappa is a measure of the difference between actual and chance agreement between reference data and classified data, with 0 being no better than chance, and 1 being a perfect agreement between classification results and ground truth samples.

Overall accuracies ranged from 84.30 percent (Indian Creek – Animas River) to 93.59 percent (City of Farmington – Animas River). Russian olive user's accuracies ranged from 85.94 percent (Indian Creek – Animas River) to 100.00 percent (City of Farmington – Animas River, Hermosa Creek, and Lightner Creek – Animas River). Russian olive producer's accuracies ranged from 33.33 percent (Hermosa Creek) to 72.22 percent (City of Farmington – Animas River). Cohen's Kappa ranged from 0.45 (Hermosa Creek) to 0.80 (City of Farmington – Animas River). Accuracy measures are summarized in Table 2.

Scene	Russian Olive User's Accuracy (%)	Russian Olive Producer's Accuracy (%)	Overall Accuracy (%)	Cohen's Kappa
City of Farmington-Animas River	100.00	72.22	93.59	0.80
Hermosa Creek	100.00	33.33	87.76	0.45
Lightner Creek – Animas River	100.00	65.79	86.73	0.70
Florida River	100.00	50.91	84.57	0.59
Basin Creek – Animas River	96.05	74.49	85.79	0.72
Electra-Cascade-Animas River Canyon	94.12	72.73	86.54	0.72
Indian Creek – Animas River	85.94	65.48	84.30	0.63

Table 2 Classification accuracy (overall and Russian olive user's and producer's accuracies) and Cohen's Kappa prior to post-modeling for seven scenes in the Animas Subbasin.

Overall, RO covers 36.2 acres across the valley bottom of the Animas Subbasin, accounting for 0.03 percent of the project area. RO was found at elevations ranging from 5,929 ft (1,807 m) in the City of Farmington-Animas River scene at the border with New Mexico to 7,340 ft (2,237 m) in the Florida River scene east of the Edgemont Highlands development. In terms of abundance and distribution, the Electra-Cascade-Animas River Canyon scene contain the most RO per acre, with approximately 0.09 percent of its valley bottom covered with RO. The distribution of RO is summarized in Table 3.

Scene	Russian Olive Area (Acres)	Scene Area (Acres)	Russian Olive (%)
Electra-Cascade-Animas River Canyon	11.0	12,492	0.09%
Middle Animas Valley	13.1	34,262	0.04%
Hermosa Creek	0.9	2,757	0.03%
Lightner Creek – Animas River	4.6	17,627	0.03%
Florida River	4.6	27,838	0.02%
City of Farmington-Animas River	2.0	14,178	0.01%
Animas Subbasin	**36.2**	**109,154**	**0.03%**

Table 3 Spatial distribution of Russian olive in the Animas Subbasin. Area is given in acres.

Mapped Russian olive based on the classification results for the project area is depicted in Figure 19.

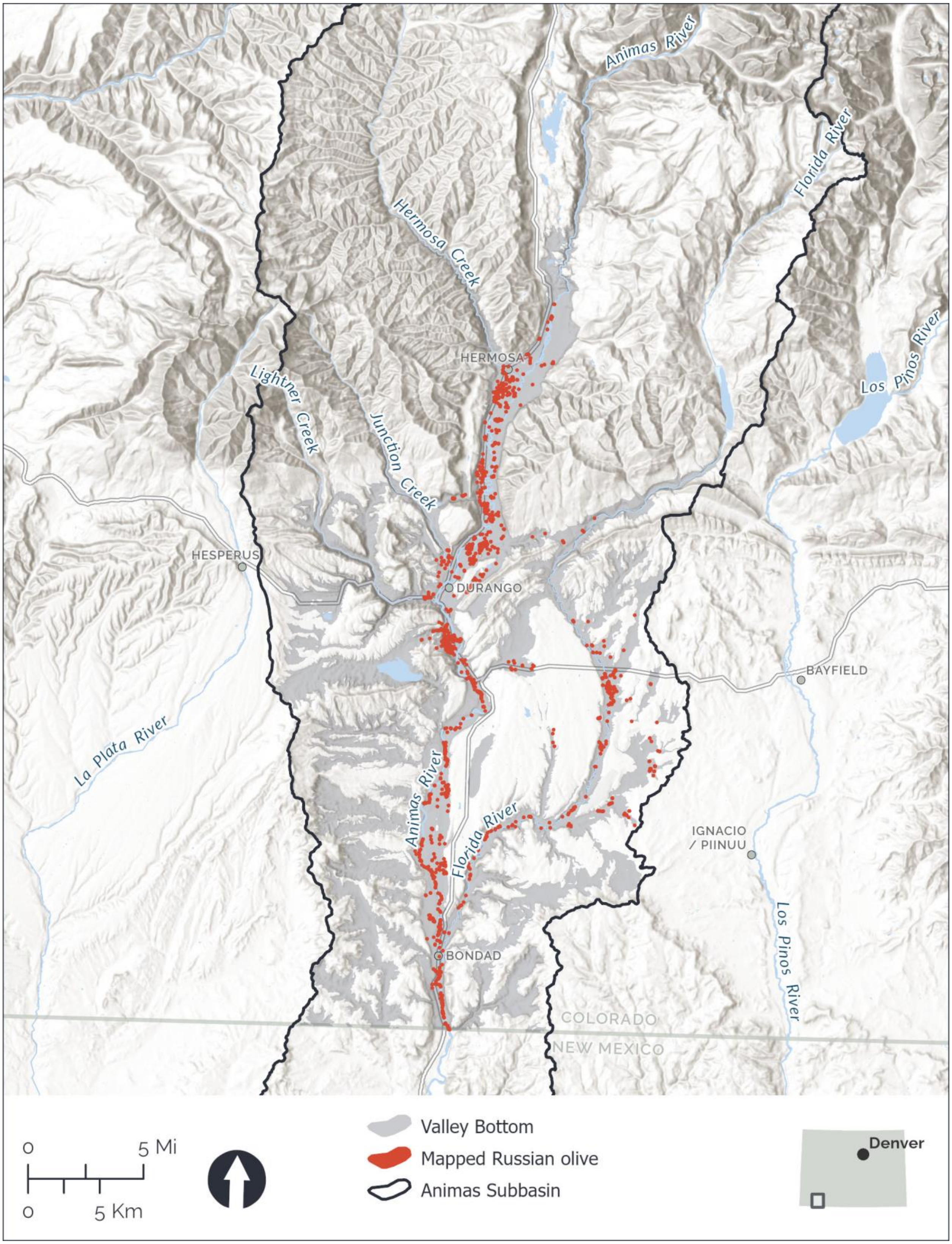

Figure 19 Mapped Russian olive in the Animas Subbasin.

The classification of RO as a feature class will be provided to MSI in the project geodatabase.

Discussion and Conclusions

NAIP imagery was used along with LiDAR-derived elevation products to develop a SVM model to generate a distribution of Russian olive in the valley bottoms of the Animas River in La Plata County, Colorado. Manual editing post-classification was performed to correct misclassified objects. Validation was performed prior to manual editing. Figure 20 represents a methodology flowchart.

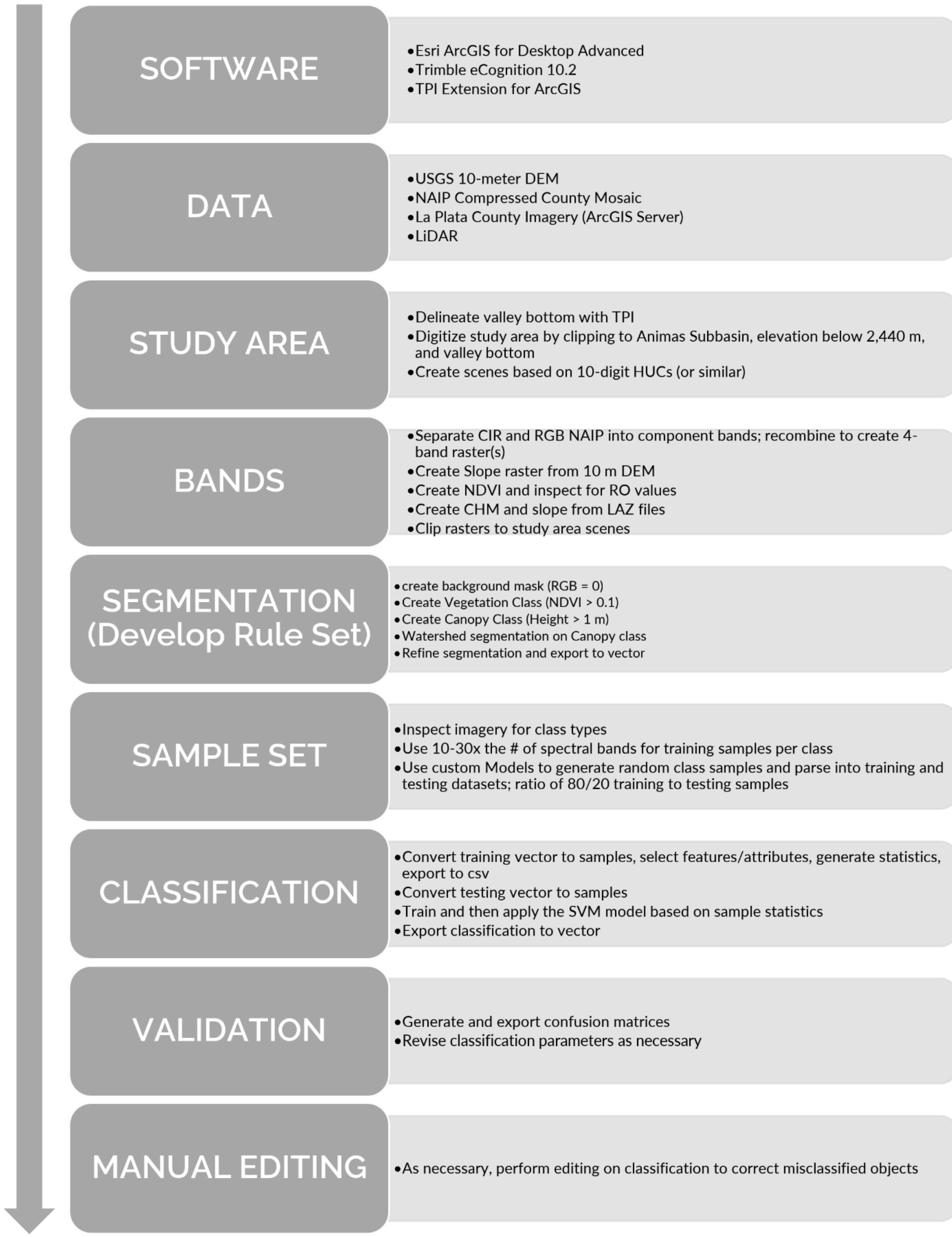

Figure 20 Flowchart of methodology and parameters.

The overall accuracy ranged from 84.30 to 93.59 percent. The Russian olive user's accuracy ranged from 85.94 to 100 percent; this translates to at least an 85.94 percent probability that each object classified as RO represents RO in reality. The Russian olive producer's accuracy ranged from 33.33 to 74.49 percent; this translates to up to a 74.49 percent probability that a location of RO will be correctly predicted depending on the scene. (It should be noted that the lowest producer's accuracy came from the Hermosa scene, which had only nine RO training sample points, which is typically too low to generate meaningful statistics but is included here for the sake of completeness.)

The practical goal of this study was to produce a regional distribution of RO. The most important quality of classification to an MSI staff member looking at a map of RO is whether it is there or not. The accuracy of the other classes (i.e. Other Tree, Non-Vegetation) derived during the development of the rule set are of relatively little importance in this effort.

The overall and user's accuracies in this study met the project goals and represent a satisfactory probability of accurately classified RO objects. The relatively lower producer's accuracy values are similar to that found in the pilot study and were reflected in the degree of manual editing that was required to correct misclassified RO objects. Further work aimed at improving the producer's accuracies might include differentiating the Other Tree class into different classes (i.e. tall vs low canopy), breaking out the RO class into multiple classes based on distribution patterns (i.e. riparian, windrow, and landscaping), raising the minimum height for determination of Canopy, ground-truthing some or all of the samples, or altering the sample statistics attributes.

A supervised classification is heavily dependent on the quality and quantity of training samples, and the confusion matrix is likewise a function of the classification results compared to the testing samples. The development of the sampling set and post-classification manual editing were completed primarily in ArcGIS Pro by a systematic review of aerial imagery, both NAIP as well as La Plata County high resolution imagery from 2017, 2019, and 2021. There was limited "ground truthing". The reliance on aerial imagery to determine if a sample is RO or not, or if a classified object is RO or not, means practically that if the image is unclear, or the RO tree doesn't appear as obvious in the imagery (i.e. heavily shadowed, leaf-off, or in mixed canopy or occluded by overstory), the RO tree will not be recorded as a sample and therefore its attributes not included in sample statistics for classification. Therefore, there may be RO trees in the project area that were not classified as such. Conversely, if an object was mistakenly recorded as an

RO sample but in fact was different species, for instance a tree or shrub with similar reflectance due to sun angle, time of day, or presence of light-colored flowers, the object's attributes would be included in the sample statistics for RO and used to train the classification algorithm. In this case, the possibility exists that objects classified as RO in reality represent other species. Perhaps future studies might incorporate a ground truth component to sample collection; however, for such a large area it represents a challenge of practicality. Finally, there is no defined consensus in the literature reviewed for the pilot study for number of training to testing samples, and classification results could potentially differ from those of this study with alteration of the number and location of each type of sample.

RO covers 36.2 acres across the valley bottom of the Animas Subbasin, accounting for 0.03 percent of the project area. RO was found at elevations ranging from 5,929 ft (1,807 m) in the City of Farmington-Animas River scene at the border with New Mexico to 7,340 ft (2,237 m) in the Florida River scene east of the Edgemont Highlands development. In terms of abundance and distribution, the Electra-Cascade-Animas River Canyon scene contain the most RO per acre, with approximately 0.09 percent of its valley bottom covered with RO.

Several distribution patterns of RO were observed, including riparian areas adjacent to rivers, streams, oxbows, and ponds; alongside manmade water sources such as ditches and stock ponds; as windrows at the edges of agricultural fields; and in landscaping applications. RO trees were also observed growing beneath overhead electric transmission lines, assumedly in a utility easement or alley where there might be disturbed ground or a fence. Aerial images (La Plata County 2019 imagery) of RO distribution patterns are depicted below in Figure 21 through Figure 30.

Figure 21 RO growing beneath overhead electric transmission lines in the Lightner Creek-Animas River scene in Durango northwest of the intersection of Holly Ave and Florida Rd.

Figure 22 RO growing beneath overhead electric transmission lines adjacent to US 550 in the Electra-Cascade-Animas River Canyon scene in the Animas valley north of Durango.

Figure 23 RO growing adjacent to the Citizens Animas Ditch in the Middle Animas Valley scene.

Figure 24 RO growing at the edge of a manmade pond in a golf course in the Electra-Cascade-Animas River Canyon scene in the Animas valley north of Durango.

Figure 25 Abundant RO as windrow plantings surrounding a home in the Animas River floodplain in the Lightner Creek-Animas River scene.

Figure 26 RO as windrow plantings at the edges of fields in the Electra-Cascade-Animas River Canyon scene in the Animas valley between CR 203 and US 550 north of Durango.

Figure 27 Riparian growth of RO along the banks of the Animas River upstream from the 32nd St boat launch in the Electra-Cascade-Animas River Canyon scene.

Figure 28 RO growing at the edges of an oxbow lake in the Animas River floodplain in the Electra-Cascade-Animas River Canyon scene.

Figure 29 RO as landscaping in a residential area west of Needham Elementary School in Durango in the Lightner Creek-Animas River scene.

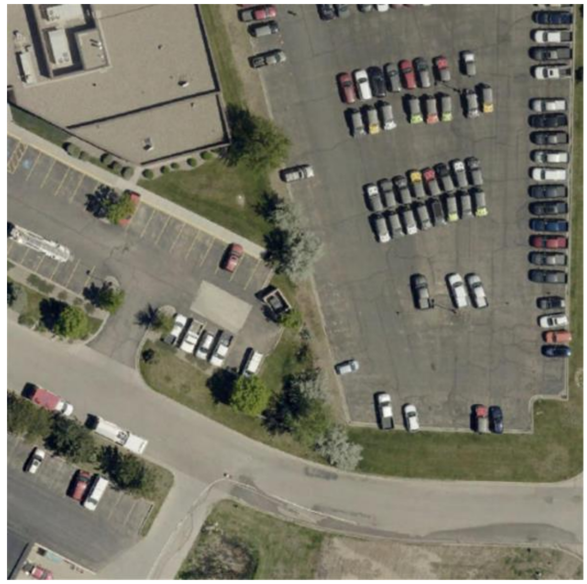

Figure 30 RO is used prolifically in the Bodo Industrial Park area as landscaping, Middle Animas Valley Scene.

Finally, the invasive RO tree is often confused both in the field and in aerial imagery with the closely related, native Silver Buffaloberry (*Shepherdia argentea).* The Silver Buffaloberry is a native species and its distinction from the invasive RO is vital to avoid accidental removal of an important native tree during RO mitigation efforts (Kuenzi 2018b). The leaves of both have a similar silver-green hue in visible imagery, and often can only be distinguished in the field by close inspection of plant characteristics (Figure 31 and Figure 32). It was not possible to distinguish the two types of trees from aerial imagery for this study, and there is a probability that some of the RO identified in this classification is in fact Silver Buffaloberry.

Figure 31 Russian olive: Alternate leaf pairs.

Figure 32 Native Silver Buffaloberry: Opposite leaf pairs.

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