Supervised Classification of Russian Olive in the Animas Valley:

A Pilot Study Using Object-Based Image Analysis and NAIP Imagery

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RESEARCH QUESTION

Can feature extraction and Object Based Image Analysis (OBIA) successfully be used to classify Russian olive (RO) in the Animas Valley in southwestern Colorado with free, 1-meter, multi-spectral National Agricultural Image Program (NAIP) imagery?

BACKGROUND

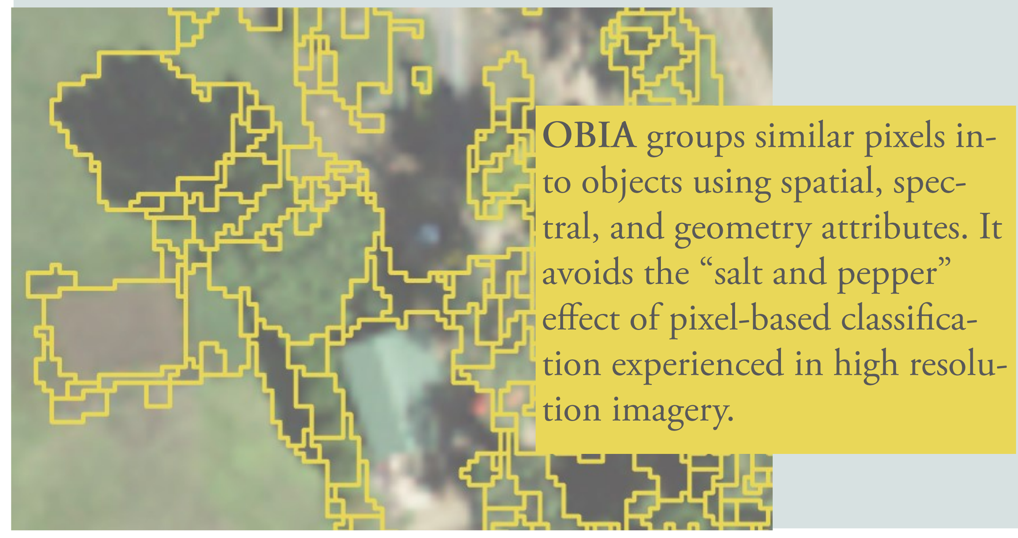
Mountain Studies Institute (MSI)

MSI is an environmental research and education non-profit based in Durango with state funding to remove RO. Quantitative distribution mapping of RO does not exist in the Animas Valley, and MSI has no ready means of evaluating the success of mitigation efforts.

Russian olive is an invasive species that pushes out native species and changes hydrology. It was intentionally planted as windrow plantings to control dust. It is a state-designated noxious weed in Colorado, and the focus of state-mandated mitigation.

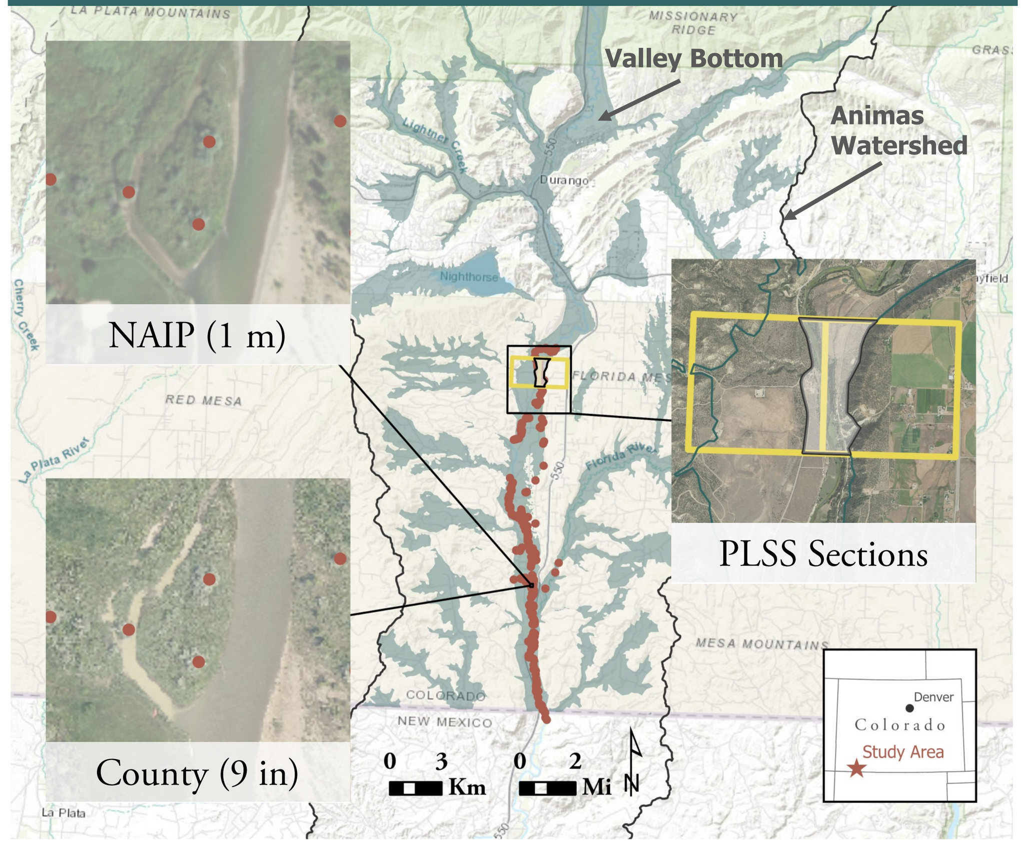
Object Based Image Analysis

Traditional pixel-based classification assigns each pixel to a land cover class, with no influence from neighboring pixels. OBIA groups similar pixels into objects using spatial and geometry attributes, and mimics what the human eye does extremely well. Previous studies have used OBIA and NAIP imagery to successfully to classify Russian olive. [2,3,4]



OBIA groups similar pixels into objects using spatial, spectral, and geometry attributes. It avoids the "salt and pepper" effect of pixel-based classification experienced in high resolution imagery.

STUDY AREA



Digitize Sample Points

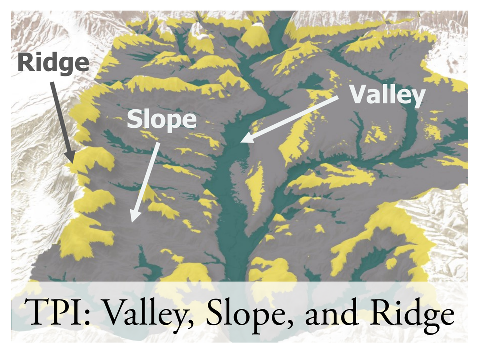
I digitized sample points of Russian olive trees for the Animas Valley south of Durango based on interpretation of aerial imagery (NAIP and La Plata County 9-in). RO has several distribution patterns, including windrow plantings, landscaping, and riparian settings.

Windrow distribution of RO

Riparian distribution of RO

Valley Bottom Delineation

By calculating topographic position index (TPI) using the Land Facet Corridor Tool[1], I delineated valley bottom to confine the analysis to riparian areas within the Animas Watershed. TPI is the difference between a cell elevation value and the average elevation of the neighborhood around that cell; it classifies a DEM into ridge, valley bottom, and slope.

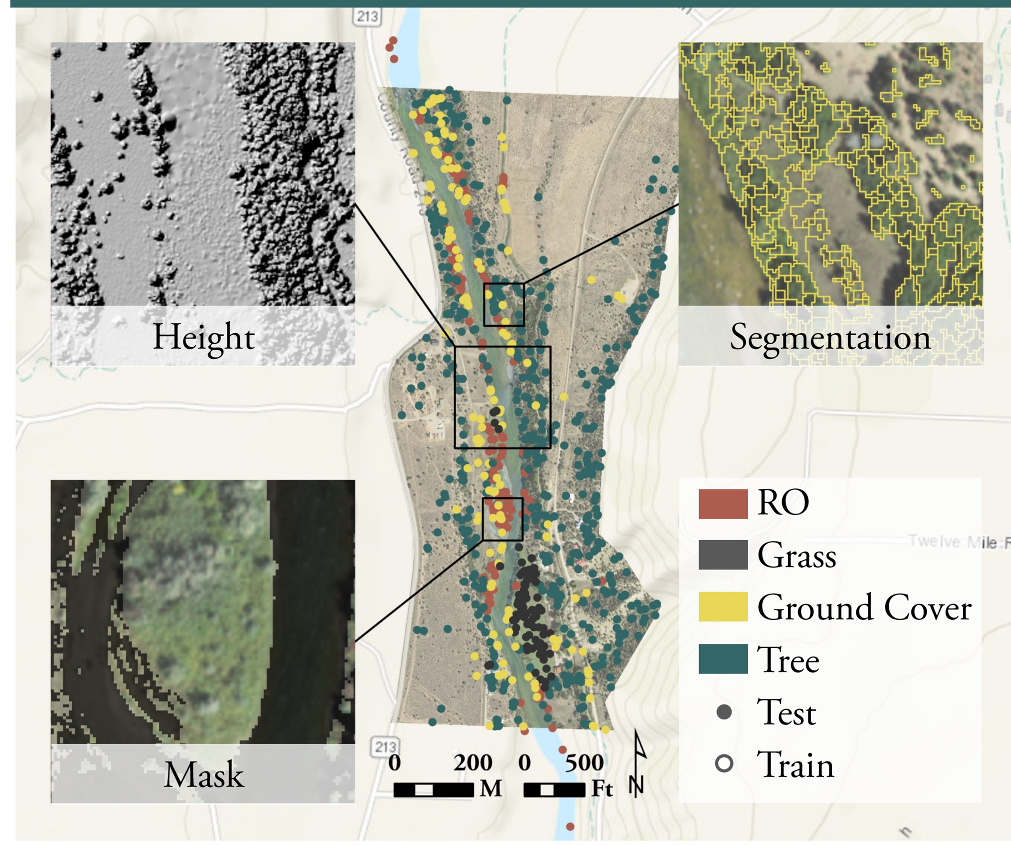


TPI: Valley, Slope, and Ridge

Clip to BLM PLSS Sections

I then selected the PLSS sections with the highest number of RO samples, and clipped them to the valley bottom on the east and La Posta Road on the west to create the 1 km² study area.

METHODS



Input & Ancillary Data

Ancillary data typically increases classification accuracy. I used multispectral, free, 1 m, biennial NAIP imagery for the input. I created a height band from LiDAR data[6] by subtracting the Digital Terrain Model from the Digital Surface Model. Height, NDVI, Hue, Saturation, and Intensity were used as input bands.

Masking

Masking eliminates areas of non-interest from analysis. NDVI was used as a mask by reclassifying as a binary raster: non-veg < 0.1; veg ≥ 0.1. NDVI=[(NIR-R)/(NIR+R)]

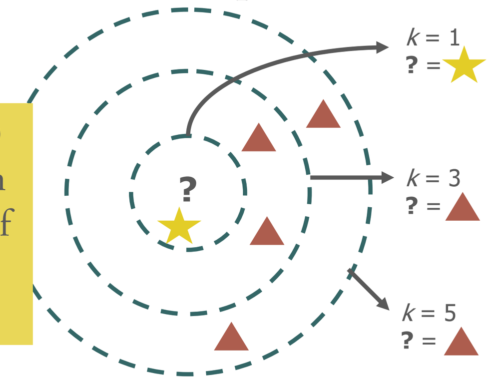
Sample Set

Training samples are used to train the classifier and testing samples are for model validation. Random sample points were classified into four (very) broad classes: Grass, Ground Cover, RO, and Tree.

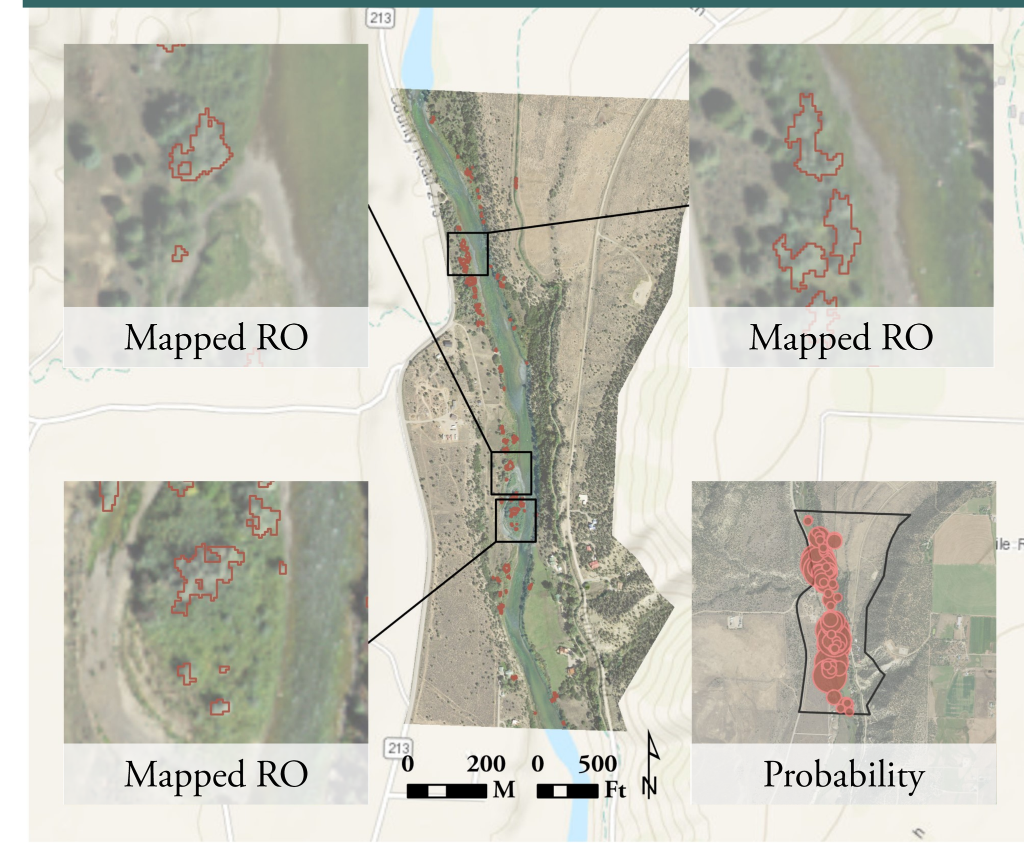
Segmentation & Classification

The image is partitioned into **segments of similar spectral intensities**. Each segment is assigned the mean spectral value of the pixels within that segment.

The K-Nearest Neighbor (KNN) classifier assigns the most common class of the user-defined number of training samples (k) that are nearest to it. This study used $k = 3$.



RESULTS



Post-Classification Editing

The results were manually edited in ENVI to exclude segments that were misclassified or too small to determine if they were Russian olive, resulting in 4,031 m² of mapped Russian olive in the 1 km² scene. It may be inferred that the probability increases with object size, and area may be used as a proxy for probability.

Confusion Matrix

A confusion matrix was used for model validation, and compares the relationship between reference data (testing samples) and classification results (training samples).

REFERENCE DATA

CLASSIFICATION DATA: Class	Grass	Ground Cover	Russian Olive	Tree	Total
Unclassified	2	47	36	148	233
Grass	**58**	0	0	1	59
Ground Cover	0	5	1	0	6
Russian Olive	0	2	**63**	4	69
Tree	60	54	100	**165**	379

Class	Producer's Accuracy (%)	User's Accuracy (%)
Grass	96.67	98.31
Ground Cover	9.26	83.33
Russian Olive	63.00	91.30
Tree	7.27	100.00

Overall Accuracy (%)	Kappa Coefficient
36.41	0.30

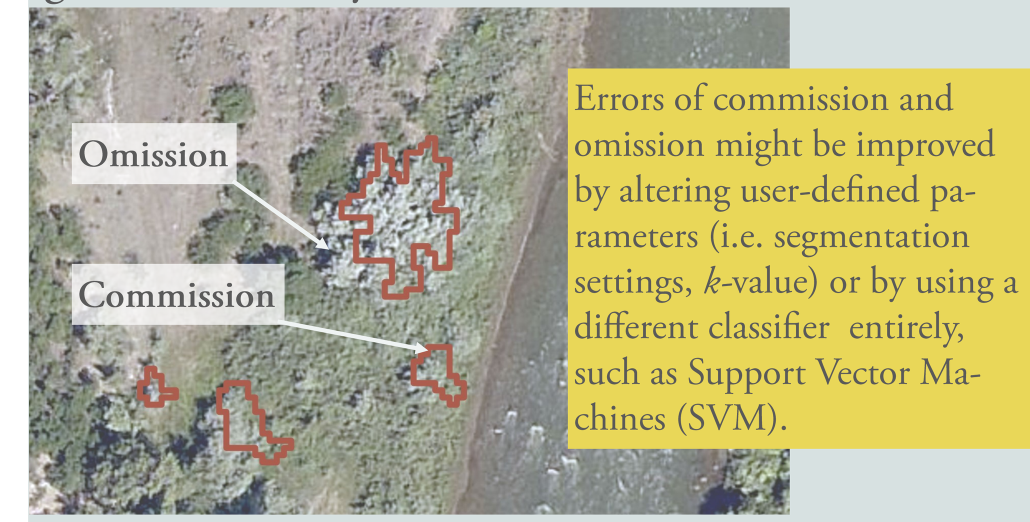
User's accuracy: If I go to an area on the ground that has been classified as RO, there is a 91.30% chance of finding a Russian olive tree at that spot in the field (measure of commission).

Producer's accuracy: If I am standing at a RO in the field, there is a 63.00% probability that the classification will correctly identify that object as RO (measure of omission).

DISCUSSION

Accuracy

The most important quality of this classification is whether RO is actually there or not, and the accuracy of other classes was not as important. The very low Overall accuracy and Kappa would be unacceptable in a land cover classification, but in the case of rare classes, they matter less, an argument made by others[7].



Errors of commission and omission might be improved by altering user-defined parameters (i.e. segmentation settings, k-value) or by using a different classifier entirely, such as Support Vector Machines (SVM).

Good Sample = Good Result (and Vice Versa)

Any classification is dependent on quality and quantity of training samples, and the confusion matrix is a function of results compared only to reference data. All samples were identified based on aerial imagery, and some could be wrong!

Native Lookalike

Potential confusion with Silver Buffaloberry (*Shepherdia argentea*), a native lookalike.

RO: Alternate leaf pairs.

SB: Opposite leaf pairs.

MORE INFORMATION

Contact me!

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Check out the Story Map!

Don't have time to read this?
http://bit.do/russianolive

CONTACT

STORY MAP

References: [1]Jenness, Jeff, Brian Brost, and Paul Beier. 2013. "Land Facet Corridor Designer." USFS Rocky Mountain Research Station. http://www.jennessent.com/downloads/Land_Facet_Tools.pdf.; | [2]Hamilton, Randy, Kevin Megown, Henry Lachowski, and Robert Campbell. 2006. Mapping Russian Olive: Using Remote Sensing to Map an Invasive Tree. | [3]Li, Xiaoxiao, and Guofan Shao. 2014. "Object-Based Land-Cover Mapping with High Resolution Aerial Photography at a County Scale in Midwestern USA." Remote Sensing 6 (11): 11372–90. http://dx.doi.org.du.idm.oclc.org/10.3390/rs61111372; | [4]Tobalske, Claudine, and Linda Vance. 2017. "Predicting the Distribution of Russian Olive Stands in Eastern Montana Valley Bottoms Using NAIP Imagery." 95815401. University of Montana; | [5]La Plata County GIS Department 9 inch aerial imagery was acquired 7/23/17; | [6]LiDAR was acquired 4/17-7/17, La Plata County; [7]Maxwell, Aaron E., Timothy A. Warner, and Fang Fang. "Implementation of Machine-Learning Classification in Remote Sensing: An Applied Review." International Journal of Remote Sensing 39, no. 9 (May 3, 2018): 2784–2817. https://doi.org/10.1080/01431161.2018.1433343.