Automated Mapping of Invasive *Phragmites australis* from Remotely Sensed Imagery Using an Object-Based Machine Learning Algorithm

Erik M. Neemann

Department of Geography, University of Utah

Introduction

The invasive species *Phragmites australis*, or common reed, causes numerous problems and poses a significant threat to Utah wetlands, including the Great Salt Lake (Figure 1). The tall reed grows very densely into invaded regions, crowds out native species, disrupts migratory bird habitats, and negatively impacts recreation. It also alters the surface water regime, often converting submerged or saturated soils to dry land [1]. As a result, the Utah Department of Natural Resources, Division of Forestry, Fire, and State Lands (FFSL), has taken an aggressive approach to mitigating the *Phragmites* problem. A big component of *Phragmites* mitigation includes spraying a wetland-safe herbicide to kill the plant and allow native species to return (Figure 2) using GPS-guided equipment. Efficient spraying requires accurate geographic data representing *Phragmites* boundaries, but it is currently unavailable. This project generates *Phragmites* maps from remotely sensed imagery, including satellite and unmanned aerial system platforms (UAS), using a prototype, automated Python script.

Figure 1. Image of *Phragmites* along the Great Salt Lake (K. Hambrecht, personal communication, Apr 15, 2019.

Figure 2. Image of *Phragmites* spraying operation by PMG Vegetation [2].

Methodology

Remotely sensed imagery was collected from three different platforms to facilitate DNR's *Phragmites* mitigation work in the Howard Slough Waterfowl Management Area (Figure 3). The image platforms (Table 1), include the European Space Agency's Sentinel-2 satellite, DigitalGlobe's WorldView-2 (WV-2) satellite, and PMG Vegetation's UAS. Each platform collects imagery in different wavelength bands and spatial resolutions. These images are then passed into an automated Python script (workflow depicted in Figure 4) that exports a shapefile for use in GPS-enabled *Phragmites* spraying equipment.

	Sentinel-2	DigitalGlobe WV-2	UAS
Spectral Bands	13	8	3
Spatial Resolution	10 m	1.9 m	0.5 m
Image Dimensions	247 x 231	893 x 1276	4433 x 6421
Total Pixels	57,057	1.14 million	28.46 million

Table 1. Remote sensing imagery platforms used in study and their attributes.

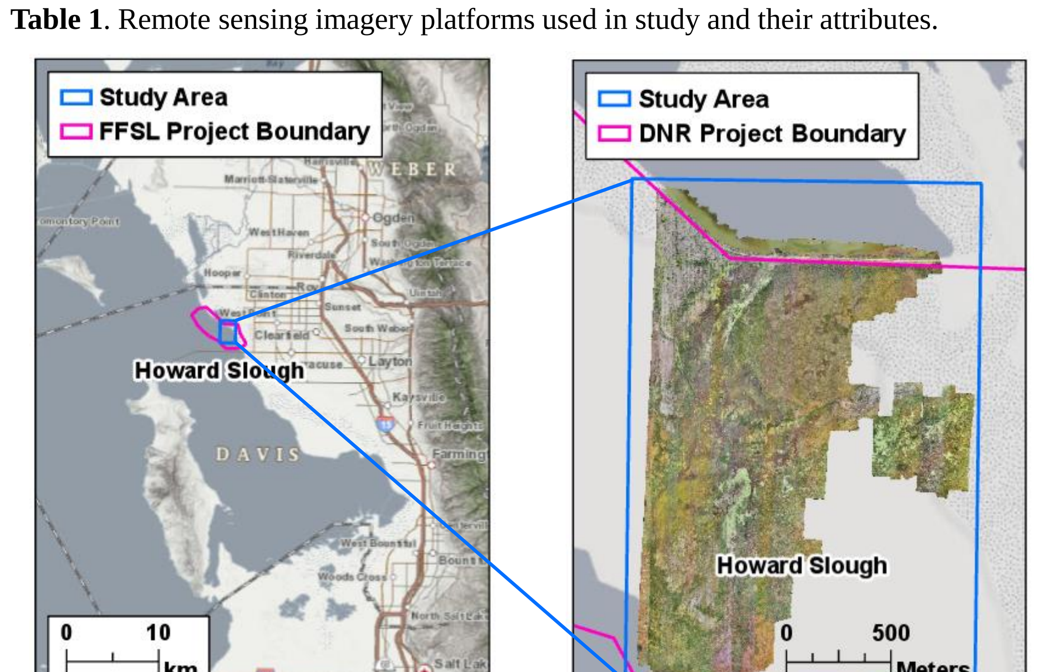

Figure 3. Reference map of Howard Slough *Phragmites* mitigation area (left) and study area for this project, including the UAS imagery (right).

Script Workflow

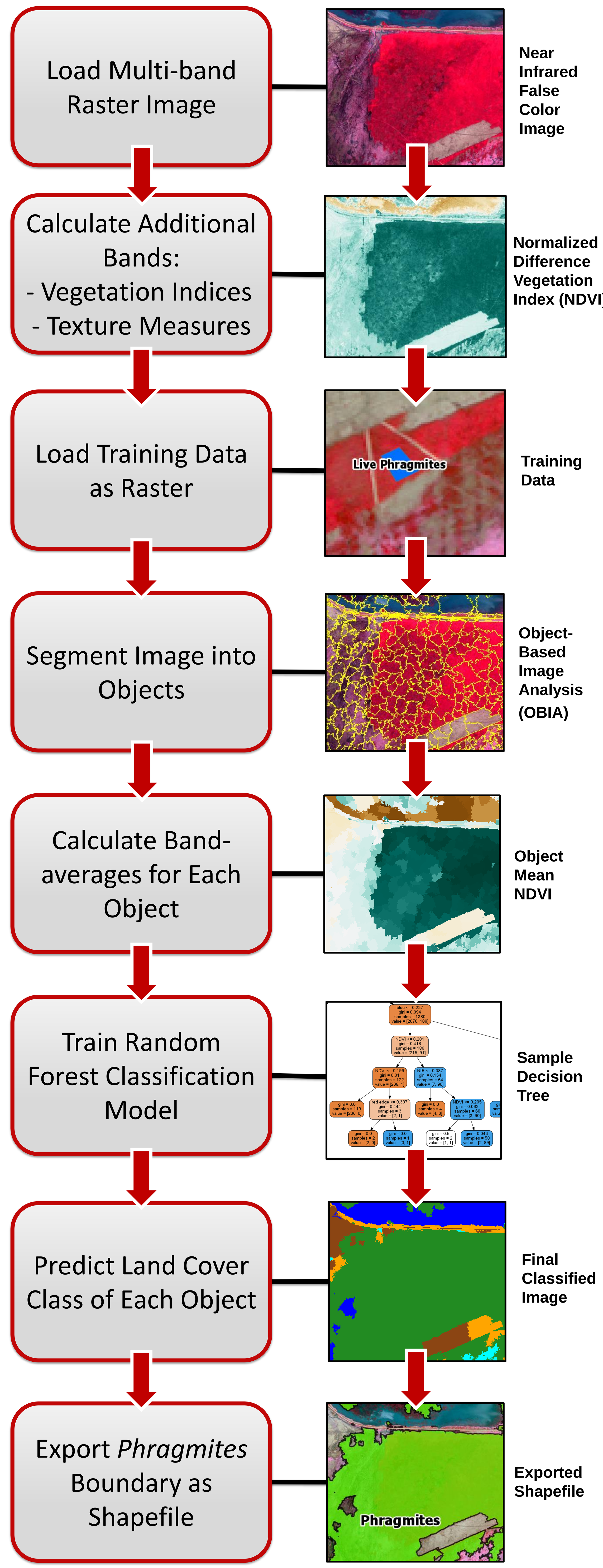

Figure 4. Diagram of automated script workflow. The left column describes the script's primary functions, the right column represents a snapshot of each function's output.

Results

The final classified images show quite different results (Figure 5), but each platform scored well (above 0.9) on several validation metrics (Table 2). While classification differences are expected for a complex wetland scene, the high scores for each platform may indicate that the training/validation data samples were unambiguous and easy to classify. Sentinel-2 even had a perfect score for producer's accuracy with the live *Phragmites* class. Both objective accuracy metrics and subjective assessment indicate that WorldView-2 performed the best. It appears to have the most probable and coherent classification, with the best representation of dead *Phragmites* in previously-treated areas. The UAS results are much less coherent, but the higher resolution may better capture small pockets of water and native emergent vegetation. All platforms appear to over-classify live *Phragmites* and may have difficulty in distinguishing it from other forms of live vegetation. Generally, both higher resolution data and additional wavelength bands appear to improve image classification.

Metric	S-2	DG WV-2	UAS
Overall Accuracy	0.9730	**0.9876**	0.9623
Cohen's Kappa	0.9551	0.9611	**0.9693**
Live *Phrag.* User's Accuracy	0.8750	**0.9265**	0.9145
Live *Phrag.* Producer's Accuracy	**1.0**	0.9793	0.9182
Out-of-bag Accuracy	0.9346	**0.9819**	0.9779

Table 2. A sample of accuracy metrics for each platform's final classification. Metrics are calculated from independent validation pixels that were not used to train the model.

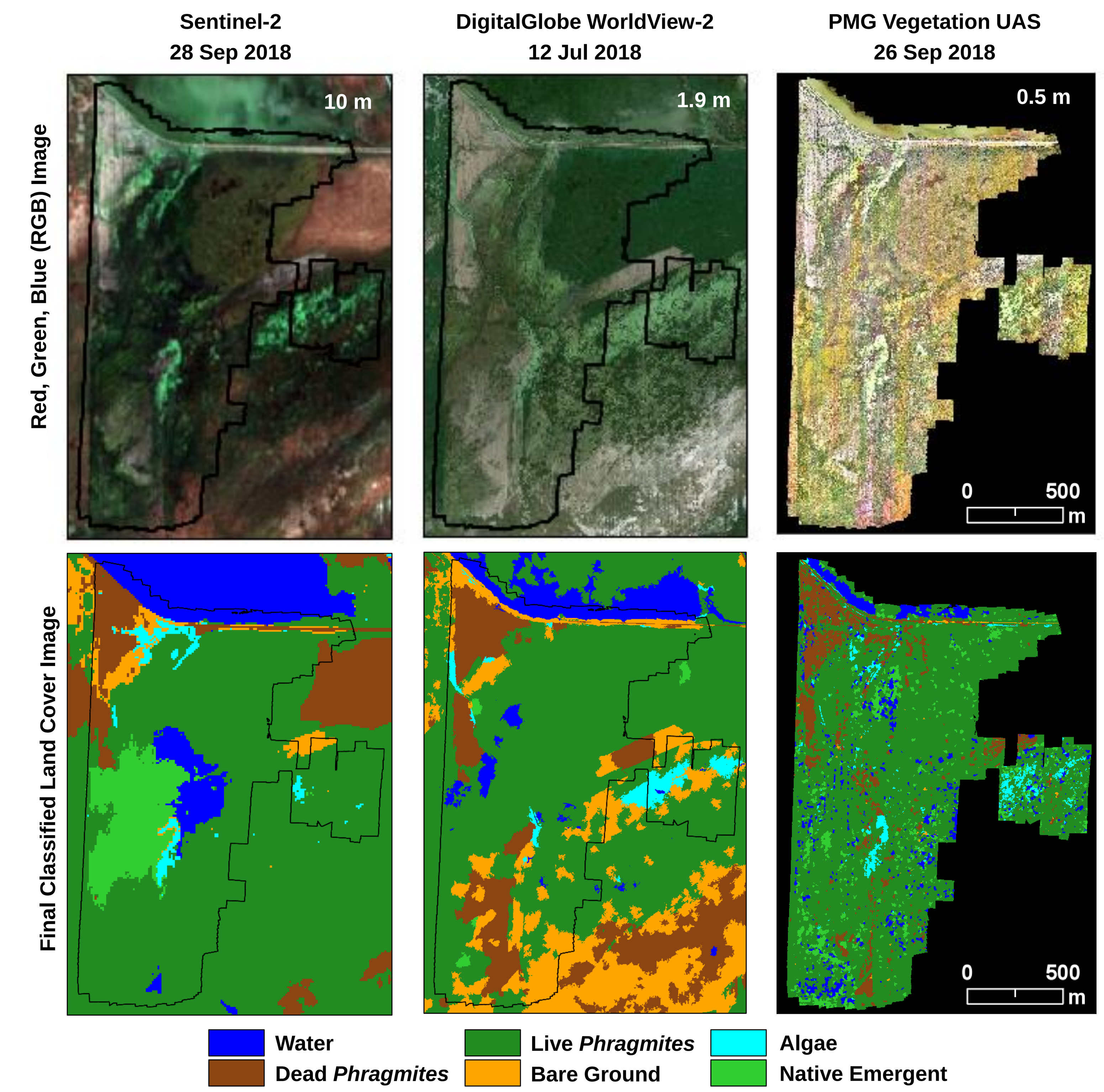

Figure 5. Standard red, green, blue (RGB) image from each platform (top row) and final classified land cover image using object-based random forest model (bottom row).

Discussion

Overall, the methods employed in this study produced reasonable land cover classification results and successfully generated a shapefile identifying *Phragmites* boundaries from an automated workflow. However, there were several limitations to this study that prevent strong conclusions from being drawn, including:

- Ground truth data were not available; therefore, training and validation data were derived through visual interpretation of high-resolution imagery.
- Asynchronous images were assumed to be collected at the same time and the same set of training/validation data were used on images from all platforms.
- Image resolution differences resulted in a large discrepancy between platforms in the number of pixels available to train and validate the random forest model (Figure 6; Table 3). This limits the validity of strictly using the objective metrics to assess classification performance.

With these in mind, the study could be improved if ground truth reference data were gathered with a random sampling strategy at the time image collection. This would limit temporal differences and remove subjectivity from the data collection process.

	S-2	DG WV-2	UAS
Total Training Pixels	99	2,811	71,403
Total Validation Pixels	33	937	23,801

Table 3. Number of training and validation pixels for each imagery platform.

Future Work

- Collect ground reference data at the time of image collection
- Employ a 5-band multispectral sensor to gather high-resolution UAS imagery in red, green, blue, red-edge, and near infrared wavelengths
- Experiment with the number of land covers used in the classification
- Perform additional optimizations to the image segmentation and random forest algorithms

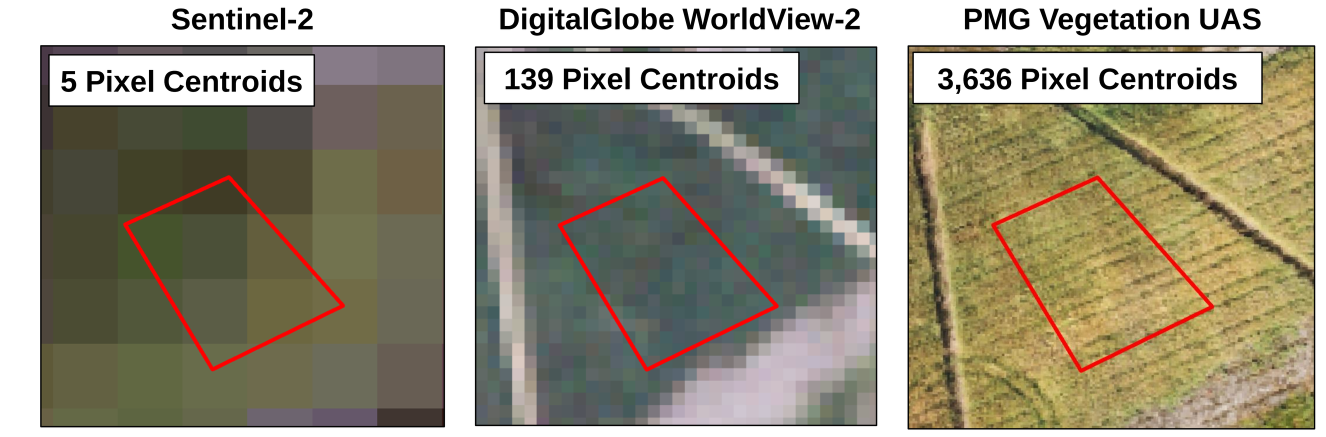

Figure 6. Example training/validation polygon (red outline) overlaid on RGB imagery from each platform to demonstrate the difference in the number pixels available for training and validation across platforms.

Acknowledgements

[1] Michigan Department of Natural Resources, Wildlife Division. (2014). *A Guide to the Control and Management of Invasive Phragmites*. Retrieved April 14, 2019, from https://www.michigan.gov/documents/deq/wrd-ais-guide-phragmites_622427_7.pdf

[2] PMG Vegetation. (2017, September 30). *Phragmites Spraying* [Video file]. Retrieved from https://www.youtube.com/watch?v=8JuxJi3Cq84

Buck Ehler, Michelle Baragona, and Keith Hambrecht at the Utah DNR-FFSL for background information and guidance throughout the project. Nate Elwood at PMG Vegetation for providing UAS Imagery and additional *Phragmites* spraying information. Phoebe McNeally at the University of Utah for general project guidance and feedback.