Experimental assessment of supervised algorithms to classify targeted land-cover using ultra-high resolution multispectral UAS imagery

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Introduction

- Thematic land cover classification is one of the primary application used in remote sensing.
- Unmanned Aerial System (UAS) platform have provide potential for acquiring remote data more rapidly, with increased spatial resolution, increased site revisit time.
- Opportunity to create detailed maps of Michigan's wetland communities.

- **Objectives**
  1) Map vegetation zones in a wetland community.

  2) Compare classification algorithms for classification accuracy.

Study Area and Data

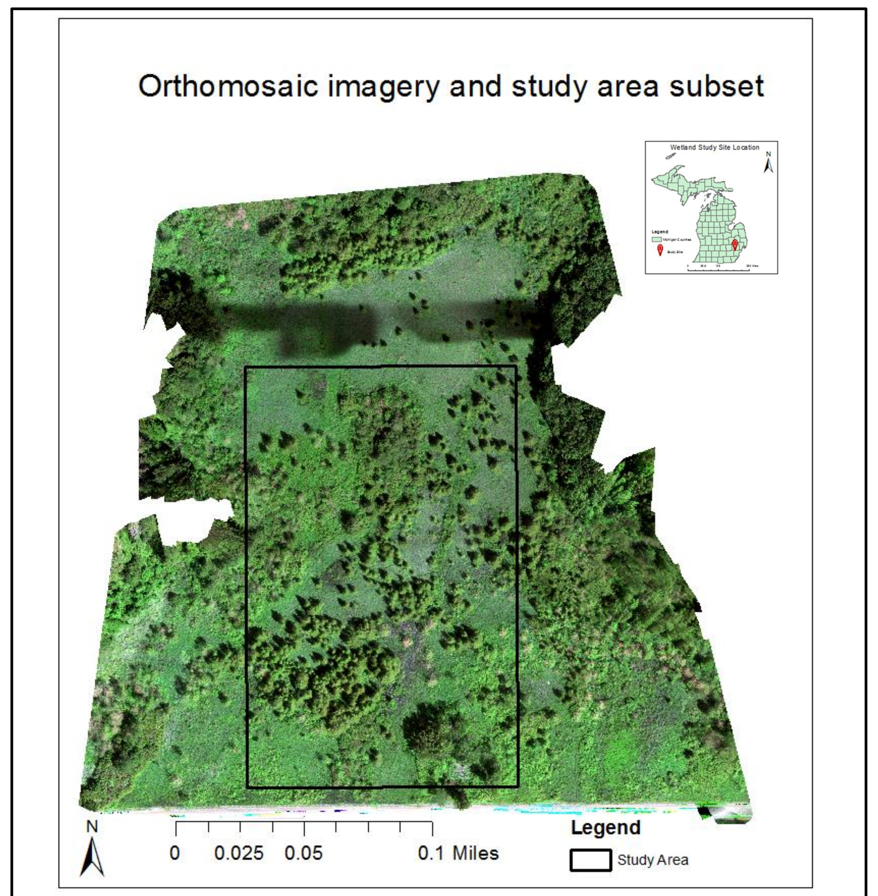

Figure 1. Orthomosaic image of prairie fen wetland study site and 12 acre rectangle subset used for analysis (above)—Study site was located in Oakland County Michigan, USA. [42°51'5.91"N, 83°28'7.84"W]

Figure 2: 3d Robotcs x8+ UAS mounted with dual Micasense Rededge multispectral cameras.

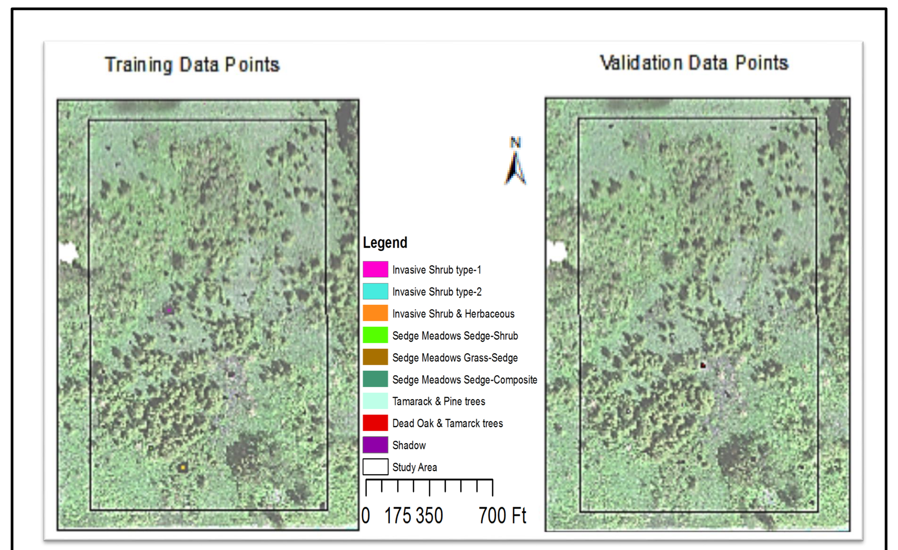

Figure 3. Training data (left) created for classification and validation data from GPS (right) used to compute classification accuracy.

Table 1. Spectral bands of multispectral camera system

Band	Wavelength (nm)	FWHM
Blue - 1	440	25
Blue - 2	475	20
Green - 1	540	18
Green - 2	560	20
Yellow	645	17
Red	668	10
Rededge - 1	700	10
Rededge - 2	717	10
Rededge - 3	740	20
Near-Infrared	840	40

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Dr. Benjamin W. Heumann supervised this research with assistance from Rachel Hackett. Data was provided by Rachel Hackett and John Gross, Center for Geographic Information Science. Special Thanks to the Nature Conservancy and the Michigan Department of Natural Resources.

Methods

- Step 1: Compute Class Spectral Separability
  - Estimates ability to distinguish classes using spectral data
  - Jefferies-Matusita (JM) distance
    - > 1.9 = Good Separability – classes well defined
    - < 1.0 = Poor Separability - classes should be merged
    - 1.0 – 1.9 = Medium Separabiltiy – Potential Confusion
- Step 2: Supervised Classification
  - Identify spectral characteristics for each class and create resulting map
  - Compare 4 common algorithms
    1) Maximum Likelihood: Statistical classifier based on spectral mean and variance in n-D space
    2) Spectral Angle Mapper (SAM): Classifier based on angle between bands in n-D space
    3) Support Vector Machine (SVM): Machine learning algorithm that optimizes non-linear boundaries between classes in n-D space.
    4) Neural Networks: Machine learning algorithm that simulate human learning process
- Step 3: Accuracy Assessment
  - Compare classification maps with validation data from field
  - Create confusion matrix (tabulation of errors)
  - Calculate accuracy statistics
    - Overall accuracy
    - Kappa statistic - accounts for relative abundance of each class
    - Omission error – number of validation points incorrectly classified
    - Commission error – number of pixels incorrectly classified

Results: Classification

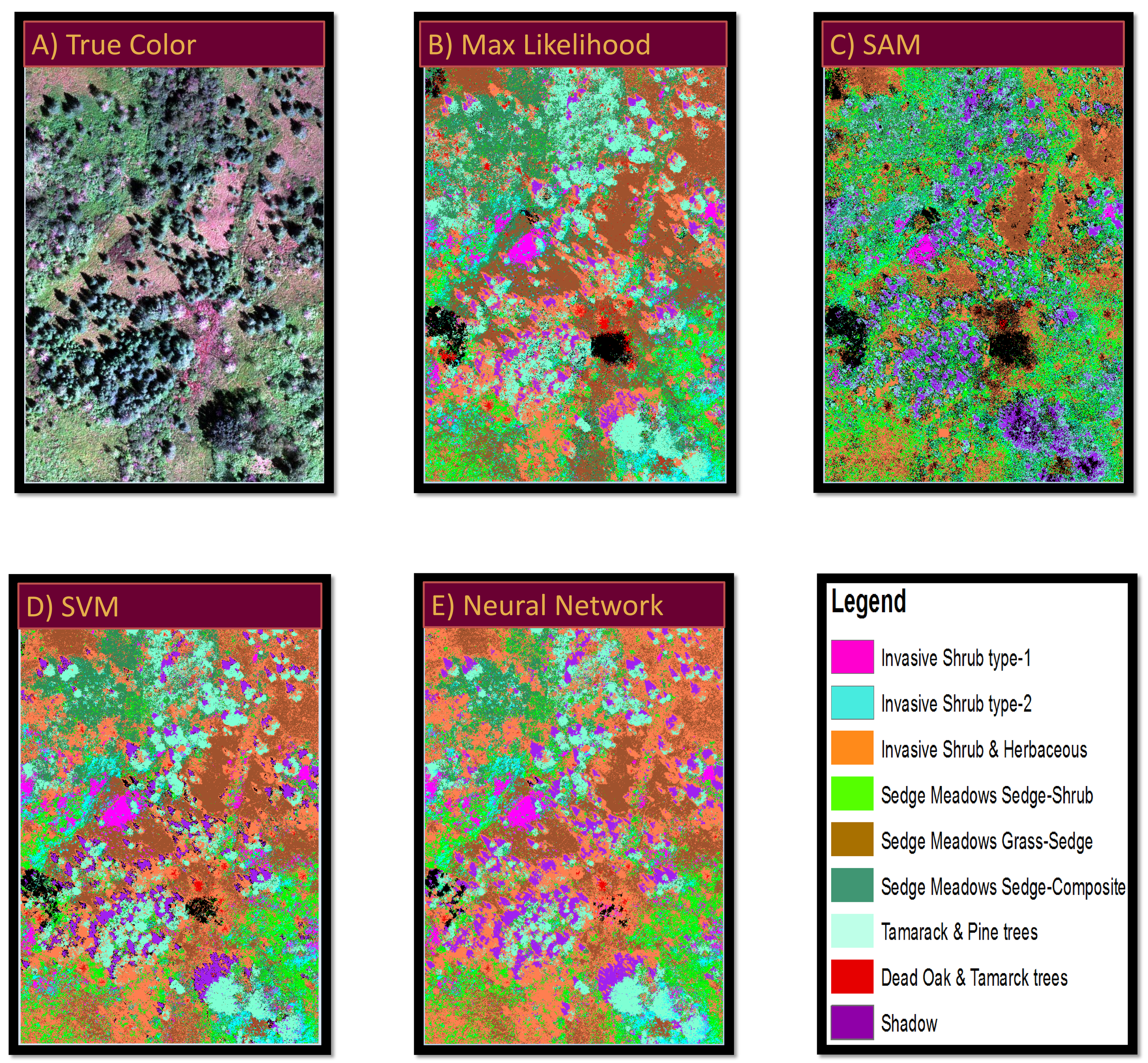

Figure 4. Supervised classification output for ultra-high multispectral imagery

Results: Spectral Separability

Table 2. List JM distance between given pair of training class file. Values 2.0-1.9 indicate strong spectral separability, 1.9- 1.0 indicate moderate separability & values less than 1 indicate poor separability among training data

Training Data: Class 1	Training Data: Class 2	JM Distance	Training Data: Class 1	Training Data: Class 2	JM Distance
Sedge Meadows Sedge-Composite	Sedge Meadows Sedge-Shrub	1.350	IH_1 Saturated	Dead Oak & Tamarck trees	1.986
Invasive Shrub type-2	Sedge Meadows Sedge-Shrub	1.514	Sedge Meadows Grass-Sedge	Dead Oak & Tamarck trees	1.989
Invasive Shrub type-2	Sedge Meadows Sedge-Composite	1.522	Invasive Shrub type-1	Invasive Shrub & Herbaceous	1.991
Invasive Shrub & Herbaceous	Sedge Meadows Sedge-Shrub	1.692	IH_1 Saturated	Invasive Shrub type-1	1.991
Sedge Meadows Sedge-Composite	Tamarck & Oak trees	1.812	IH_1 Saturated	Sedge Meadows Grass-Sedge	1.994
Sedge Meadows Sedge-Composite	Invasive Shrub & Herbaceous	1.889	Sedge Meadows Grass-Sedge	Tamarck & Oak trees	1.995
Sedge Meadows Grass-Sedge	Invasive Shrub & Herbaceous	1.908	Dead Oak & Tamarck trees	Sedge Meadows Sedge-Shrub	1.996
Invasive Shrub type-1	Sedge Meadows Sedge-Composite	1.908	Dead Oak & Tamarck trees	Tamarck & Oak trees	1.996
IH_1 Saturated	Sedge Meadows Sedge-Composite	1.915	Invasive Shrub type-1	Sedge Meadows Grass-Sedge	1.998
Invasive Shrub type-2	Tamarck & Oak trees	1.916	Sedge Meadows Sedge-Composite	Dead Oak & Tamarck trees	1.998
IH_1 Saturated	Tamarck & Oak trees	1.929	Sedge Meadows Grass-Sedge	Invasive Shrub type-2	1.998
Tamarck & Oak trees	Sedge Meadows Sedge-Shrub	1.942	Invasive Shrub type-1	Dead Oak & Tamarck trees	2.000
Tamarck & Oak trees	Invasive Shrub & Herbaceous	1.947	Shadow	Invasive Shrub & Herbaceous	2.000
Invasive Shrub type-1	Sedge Meadows Sedge-Shrub	1.952	Shadow	Tamarck & Oak trees	2.000
Dead Oak & Tamarck trees	Invasive Shrub & Herbaceous	1.954	IH_1 Saturated	Shadow	2.000
Invasive Shrub type-1	Invasive Shrub type-2	1.954	Invasive Shrub type-1	Shadow	2.000
Sedge Meadows Grass-Sedge	Sedge Meadows Sedge-Composite	1.957	Invasive Shrub type-2	Dead Oak & Tamarck trees	2.000
IH_1 Saturated	Sedge Meadows Sedge-Shrub	1.958	Shadow	Sedge Meadows Sedge-Shrub	2.000
IH_1 Saturated	Invasive Shrub & Herbaceous	1.959	Shadow	Dead Oak & Tamarck trees	2.000
Invasive Shrub type-2	Invasive Shrub & Herbaceous	1.966	Sedge Meadows Sedge-Composite	Shadow	2.000
IH_1 Saturated	Invasive Shrub type-2	1.972	Sedge Meadows Grass-Sedge	Shadow	2.000
Sedge Meadows Grass-Sedge	Sedge Meadows Sedge-Shrub	1.973	Invasive Shrub type-2	Shadow	2.000
Invasive Shrub type-1	Tamarck & Oak trees	1.975			

Results: Accuracy

Table 3. Results of Confusion Error Matrix for each classifier using GPS validation data

Figure	Classifier	Kappa Statistic	Overall Accuracy
B)	Maximum likelihood	0.6674	70.8457%
C)	Spectral Angle Mapper	0.323	39.2539%
D)	Support Vector Machine	0.6242	67.0407%
E)	Neutral Net	0.5811	64.0297%

Table 4. Maximum likelihood supervised classification output confusion error matrix using validation data

Class	Maximum Likelihood Supervised Classification Error Matrix: IH_1 Saturated	Invasive Shrub type-1	Sedge Meadows Grass-Sedge	Invasive Shrub type-2	Sedge Meadows Sedge-Composite	Shadow	Dead Oak & Tamarck trees	Invasive Shrub & Herbaceous	Sedge Meadows Sedge-Shrub	Tamarck & Oak trees	Total	Commission error (%)
IH_1 Saturated	**1106**	0	0	2	10	0	0	7	0	258	1383	20.03
Invasive Shrub type-1	0	**741**	0	124	12	0	0	8	0	117	1002	26.05
Sedge Meadows Grass-Sedge	0	0	**5879**	0	27	0	4	0	49	5	5964	1.43
Invasive Shrub type-2	0	0	0	**1200**	7	0	2	15	57	448	1729	30.6
Sedge Meadows Sedge-Composite	0	0	19	456	**1981**	0	8	22	350	1144	3980	50.23
Shadow	0	0	0	0	0	**1439**	0	0	0	0	1439	0
Dead Oak & Tamarck trees	0	0	127	0	0	0	**1752**	24	7	42	1952	10.25
Invasive Shrub & Herbaceous	0	0	188	2	65	0	462	**1973**	639	1429	4758	58.53
Sedge Meadows Sedge-Shrub	0	0	0	806	284	0	5	63	**882**	306	2346	62.4
Tamarck & Oak trees	1	0	0	21	17	0	3	198	6	**2113**	2359	10.43
Total	1107	741	6213	2611	2403	1439	2236	2310	1990	5862	**26912**	
Omission Error (%)	0.09	0	5.38	54.04	17.56	0	21.65	14.59	55.68	63.95		

Overall Accuracy: **70.8457%**
Kappa Coefficient = **0.6674**

Conclusions

1) Major vegetation types can be distinguished using 10-band UAS imagery.

2) Maximum Likelihood was the best performing classifier.

3) Demonstrated potential to use UAS to map wetland communities.

4) Future research will examine use of object-based image analysis to classify groups of pixels