# Determining Ideal Parameters in Object Based Classification for Multiband UAS Imagery


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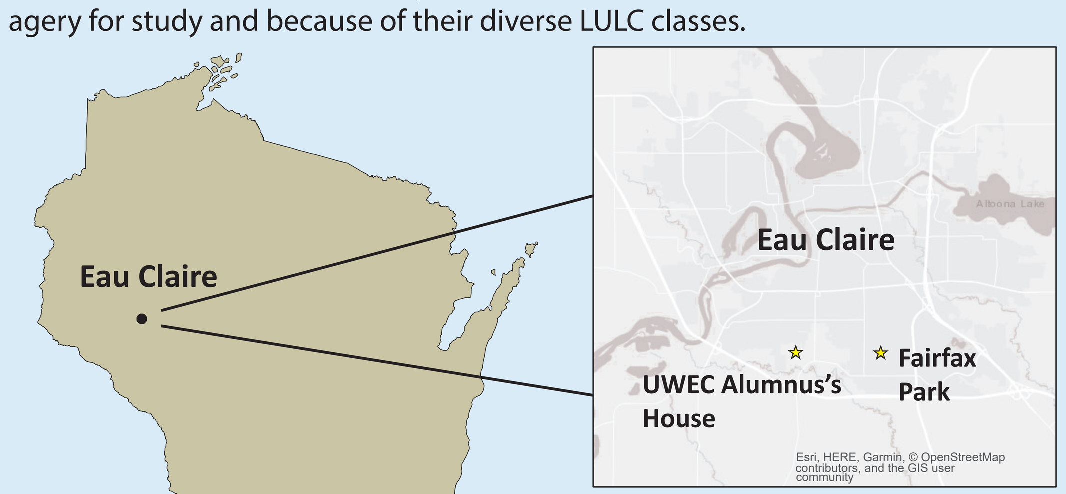
## Introduction:

As Unmanned Aerial Systems (UAS) are applied to an ever-increasing array of remote sensing applications, a greater value is being placed on added data analysis including object based classification. Imagery captured using a UAS platform has very high spatial resolution imagery (5.67cm and 3.97cm in this study) compared to the spatial resolution of traditional piloted aircraft (~1 m) and satellite imagery (30 m). This research investigates the ideal parameters in performing object based classification on UAS captured imagery. The imagery in this project was captured using a Red Edge sensor. The figure below shows the spectral resolution of the imagery collected by the Red Edge Sensor while the figure above shows what the sensor looks like itself. Many steps are needed to perform object based classification, and therefore ideal parameter selection is essential. The main steps include segmenting imagery, collecting and refining training samples, classifying the imagery, and assessing output accuracy. These parameters are beneficial to potential real-world applications, such as vegetation restoration in extraction-based industries, which could rely upon object based classification to lower overhead costs, improve survey accuracies, and streamline workflows.

| Band Number | Band Name | Center Wavelength (nm) | Bandwidth FWHM (nm) |
| --- | --- | --- | --- |
| 1 | Blue | 475 | 20 |
| 2 | Green | 560 | 20 |
| 3 | Red | 668 | 10 |
| 4 | Near IR | 840 | 40 |
| 5 | Red Edge | 717 | 10 |

## Study Areas:

Two study areas are used for this research. The first being a 19 acre area of Fairfax Park in Eau Claire, WI, and the second being a 9,075 m$^2$ area of a UWEC alumnus's house and surroundings also located in Eau Claire, WI. These areas can be thought of as case studies. Each case study has different land uses present in them. For example, Fairfax Park has herbaceous plants and bare soil where the UWEC alumnus's has neither of these. These study areas were chosen based on the available UAS imagery for study and because of their diverse LULC classes.




UWEC Alumnus's House

Fairfax Park

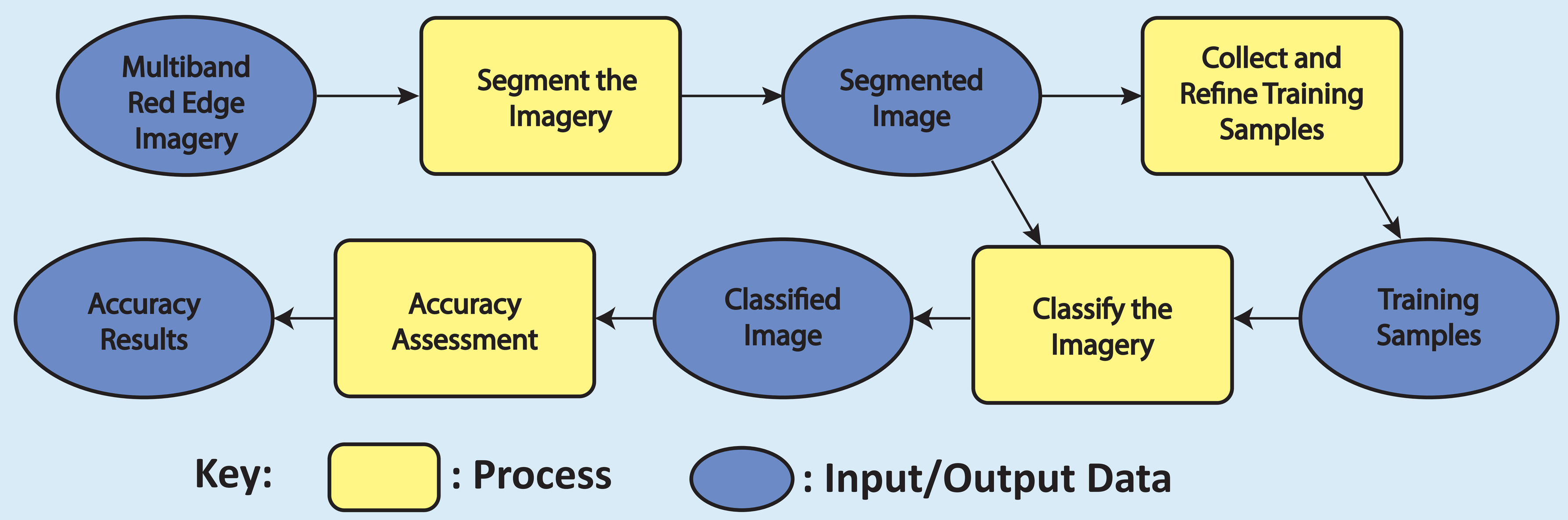
## Methods:

The raw imagery for this study was collected with a Micasense RedEdge sensor using a DJI Matrice 600 multirotor. The mission for both sets of imagery was executed using the Pix4d Capture Application. The imagery for the UWEC alumnus's house was collected on August 3rd, 2016, and the imagery for Fairfax park was collected on June 26th, 2017. The step by step process below was used to get the collected data ready for object based classification:

1. Generate a digital surface model (DSM) and the multiple raster bands (blue, green, red, red edge, and near infrared) using data using Pix4Dmapper .
2. Use the generated raster bands to create a near infrared (NIR), red, and green false color composite raster using the Composite Bands tool in ArcGIS.
3. Mask this composite raster to a digitized area which removes the outer edges of the raster. This improves the quality of the imagery to be used in the classification.

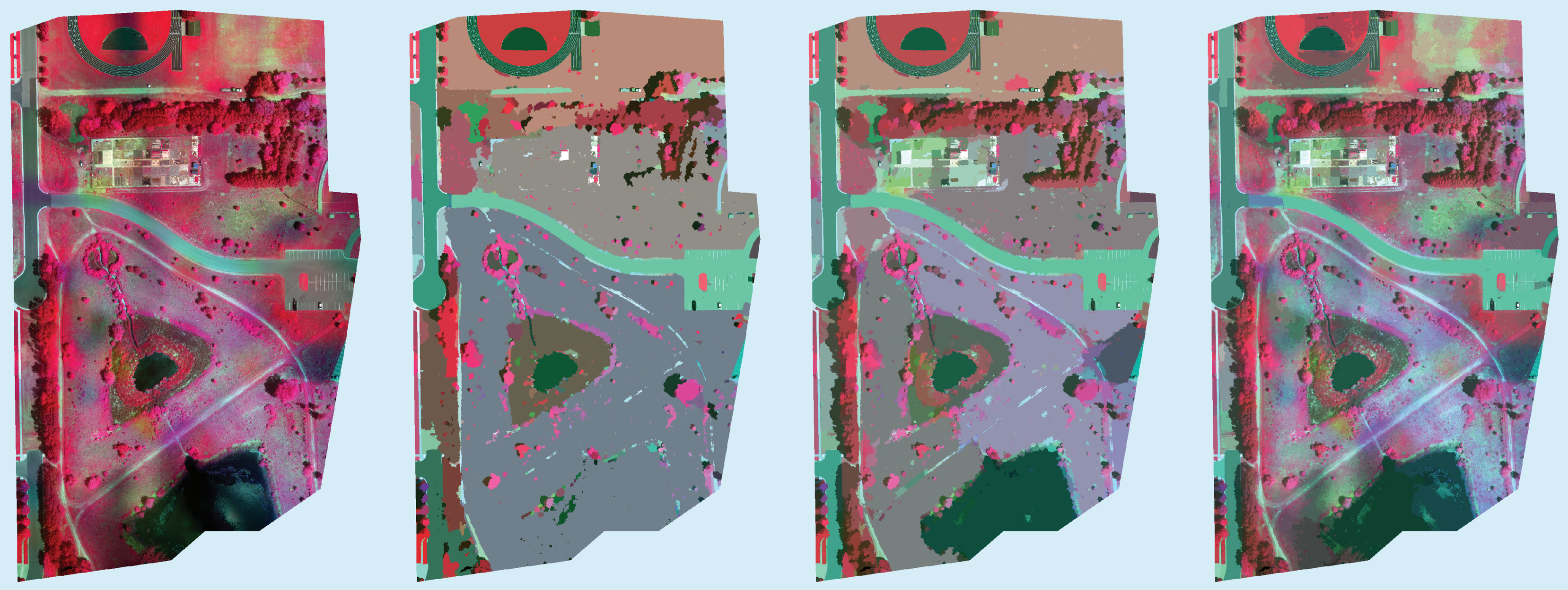
After preparing the imagery using the three steps above, in order to achieve ideal paramers, the following steps outlined in the data flow diagram shown at the top of the next column were executed over 20 times for each study to test different parameters. What is executed in each process is described in its corresponding section.

## Data Flow Model:




## Segment the Imagery:

Segmenting the Imagery was performed using the Segment Mean Shift tool. There are three parameters in this tool: spectral detail, spatial detail, and minimum segment size. The spectral detail ranges from 1.0 to 20.0 where higher values are appropriate for when differentiating objects with similar spectral characteristics and lower values are for differentiating between objects with dissimilar spectral characteristics. The spatial detail ranges from 1 to 20 and takes into account the location of objects. Higher values cause there to be more objects and lower values cause there to be less objects. Lastly, the minimum segment size sets the minimum size a segment can be in pixels. The ideal parameters for this are found by trial and error and the ideal parameters are unique to each dataset.



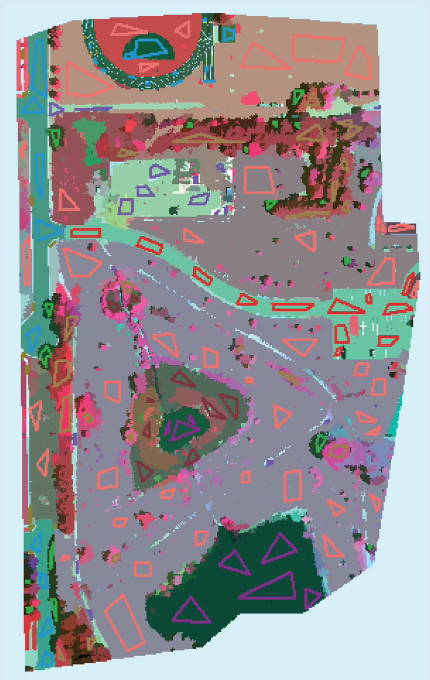
Original Image | Too Few Segments | Good Amount of Segments | Too Many Segments

## Collect and Refine Training Samples:

Collecting and refining training samples was done through the use of the Training Sample Manager. Training samples must be collected carefully as each sample should be homogeneous to a LULC. Training samples are very important as they are used to help in training the classifier to classify the imagery into the desired LULC classes. Training samples also should represent the full spectral characteristics of a LULC. Therefore, it is important that training samples are collected evenly across the image. Training sample quality is assessed by using histograms, scatter plots, and with statistics about the training samples. The figures to the right shows one set of training sample collected for Fairfax Park along with the Training Sample Manager window. LULC classes are determined in this step as training samples are collected for each class. It is okay to collect training samples for more than the number of final classes as training sample classes can be merged later.

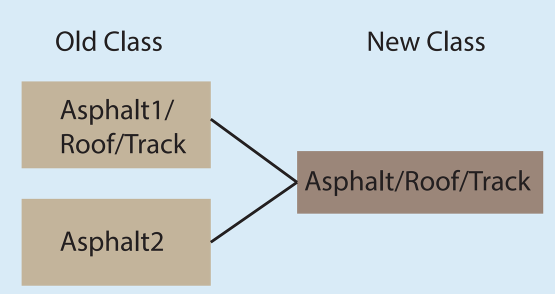
Training Sample Manager

| ID | Class Name | Value | Color | Count |
| --- | --- | --- | --- | --- |
| 1 | Grass | 1 | | 1109937 |
| 2 | Tree | 28 | | 215294 |
| 3 | Shadow | 49 | | 55729 |
| 4 | Concrete/Paint | 50 | | 6723 |
| 5 | Bare Earth | 66 | | 87159 |
| 6 | Herbacious | 85 | | 80104 |
| 7 | Water | 108 | | 242810 |
| 8 | Asphalt2 | 109 | | 184032 |
| 9 | Asphalt1/Roof/Track | 121 | | 236273 |



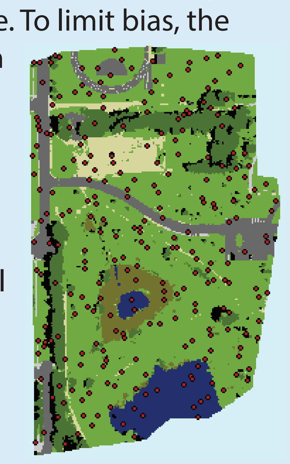
## Classify the Imagery:

In this research, only the Random Trees and Support Vector Machine classifiers were used. The first step in classifying the imagery is to train the classifier. This is done using either the Train Support Vector Machine Classifier tool or the Train Random Trees Classifier tool. Each time the Random Trees classifier was trained, the number of trees was set to 300 and the tree depth was set to 90. Also, the DSM was used as an ancillary raster to help in the classification and to calculate raster attributes. After this, the Classify Raster tool was used to classify the raster. Then, the Reclassify tool was used to combine classes such combining Asphalt2 with Asphalt1/Roof/Track to become Asphalt/Roof/Track. This tool also computes the pixel count for each new LULC class. The figure shown below helps to visualize this step.




## Accuracy Assessment:

Accuracy assessment is done by making a series of accuracy assessment points by using the Create Accuracy Assessment Points tool and then making an error matrix from those points. For each classified image, a stratified random sampling scheme was used to collect between 250 and 260 points. This tool creates a point feature class which contains a field for the classified and truth values. The tool automatically fills the classified values, while the truth values are entered in manually using the NIR composite image as a reference. To limit bias, the classified values were hidden when the truth values were entered. The figure to the right shows the accuracy assessment points for one of the many classified images. Lastly, an error matrix was created using the Compute Confusion Matrix tool which was then exported to Excel for easier analysis.

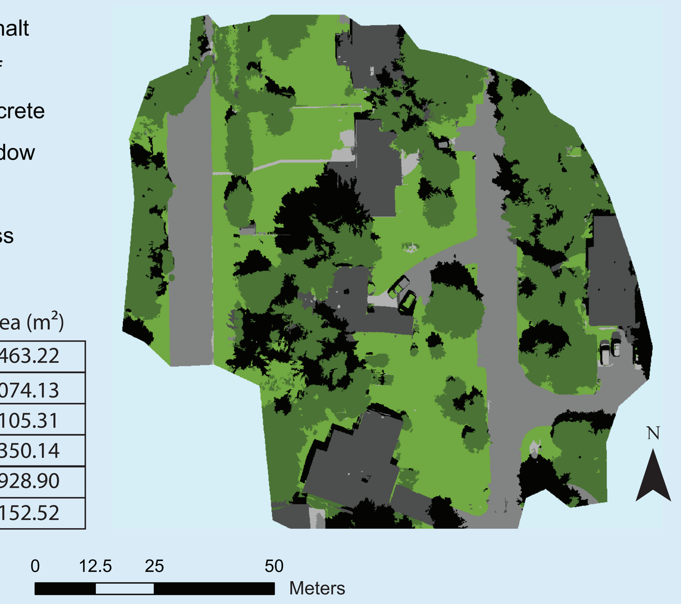


## Results:

Below are the best classified outputs achieved by entering in the ideal parameters for each classification. On the right side of each classified image, there is an error matrix which shows the various accuracies for the different classes within the images. The producer's and user's accuracy is displayed here for each LULC class. On the left side of the classified images, the area for each LULC class is displayed in a table. For the Alumnus's house image, the tree LULC class had the largest area. In the Fairfax Park image, the grass LULC had the largest area.

### Best UWEC Alumnus's House Classification

LULC: Asphalt, Roof, Concrete, Shadow, Tree, Grass




| LULC | Area (m$^2$) |
| --- | --- |
| Asphalt | 1,463.22 |
| Roof | 1,074.13 |
| Concrete | 105.31 |
| Shadow | 1,350.14 |
| Tree | 2,928.90 |
| Grass | 2,152.52 |

A = Asphalt
R = Roof
C = Concrete
S = Shadow
G = Grass
T = Tree
UA = User Accuracy
PA = Producer Accuracy

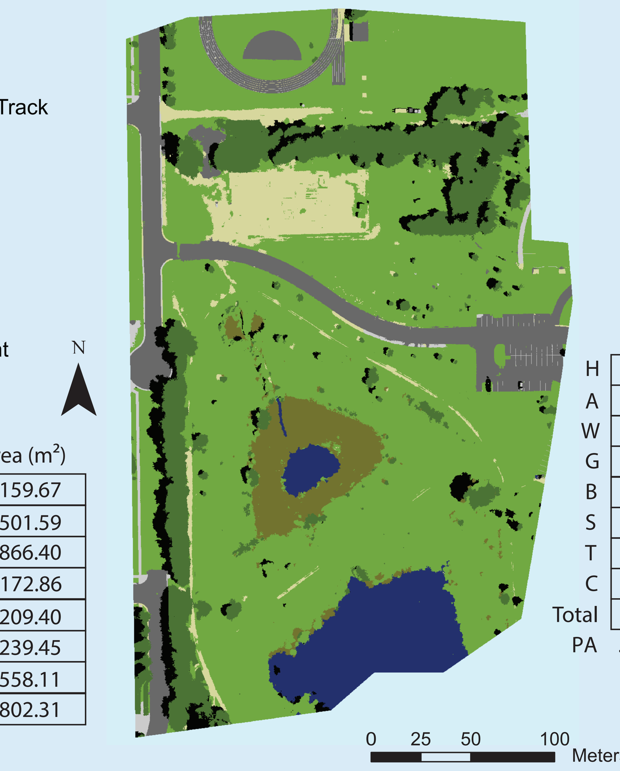
**Error Matrix**

| | A | R | C | S | T | G | Total | UA |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| A | 41 | 0 | 0 | 0 | 0 | 0 | 41 | 1.0 |
| R | 7 | 21 | 0 | 0 | 0 | 0 | 28 | .75 |
| C | 0 | 0 | 7 | 0 | 0 | 0 | 7 | 1.0 |
| S | 0 | 0 | 0 | 35 | 2 | 0 | 37 | .95 |
| T | 0 | 0 | 0 | 6 | 60 | 13 | 79 | .76 |
| G | 0 | 1 | 0 | 1 | 5 | 51 | 58 | .88 |
| Total | 48 | 22 | 7 | 42 | 67 | 64 | 250 | |
| PA | .85 | .95 | 1.0 | .83 | .90 | .80 | | |

.8225 Kappa Statistic
86.0% Overall Accuracy

### Best Fairfax Park Classification

LULC: Herbaceous, Asphalt/Roof/Track, Water, Grass, Bare Soil, Shadow, Tree, Concrete/Paint




| LULC | Area (m$^2$) |
| --- | --- |
| Herbaceous | 3,159.67 |
| Asphalt/Roof/Track | 7,501.59 |
| Water | 4,866.40 |
| Grass | 44,172.86 |
| Bare Soil | 4,209.40 |
| Shadow | 3,239.45 |
| Tree | 8,558.11 |
| Concrete/Paint | 802.31 |

H = Herbaceous
A = Asphalt/Roof/Track
W = Water
G = Grass
B = Bare Soil
S = Shadow
T = Tree
C = Concrete/Paint
UA = User Accuracy
PA = Producer Accuracy

**Error Matrix**

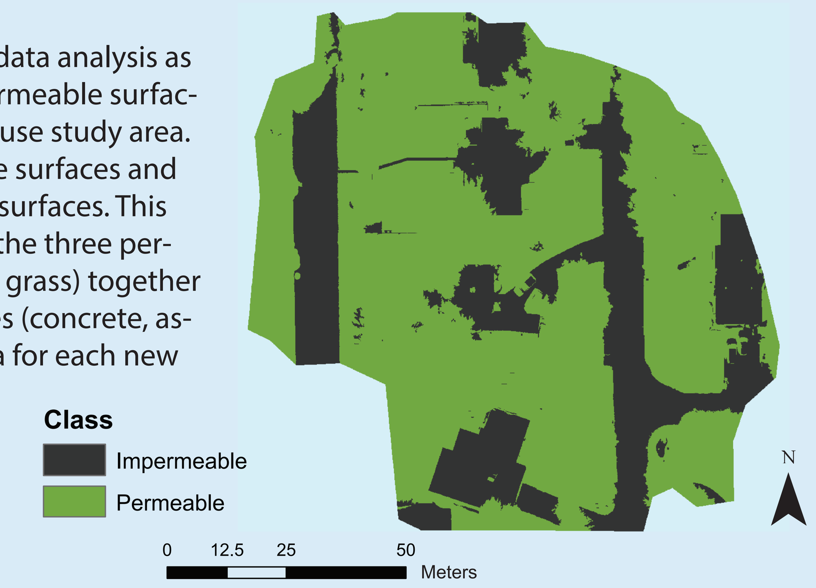
| | H | A | W | G | B | S | T | C | Total | UA |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| H | 8 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 9 | .89 |
| A | 0 | 23 | 0 | 0 | 0 | 0 | 1 | 0 | 25 | .92 |
| W | 1 | 0 | 15 | 0 | 0 | 0 | 0 | 0 | 16 | .94 |
| G | 0 | 0 | 0 | 128 | 5 | 1 | 6 | 0 | 140 | .91 |
| B | 0 | 1 | 0 | 2 | 10 | 0 | 0 | 1 | 14 | .71 |
| S | 0 | 0 | 0 | 0 | 0 | 8 | 2 | 0 | 10 | .80 |
| T | 0 | 0 | 0 | 1 | 0 | 0 | 25 | 0 | 26 | .96 |
| C | 0 | 0 | 0 | 1 | 2 | 0 | 0 | 7 | 10 | .70 |
| Total | 9 | 25 | 16 | 140 | 14 | 10 | 26 | 10 | 250 | |
| PA | .89 | .96 | .94 | .97 | .59 | .80 | .76 | .78 | | |

.8444 Kappa Statistic
89.6% Overall Accuracy

This map is an example of added data analysis as it shows the permeable and impermeable surfaces within the UWEC Alumnus's House study area. Gray areas represent impermeable surfaces and green areas represent permeable surfaces. This map was created by aggregating the three permeable classes (shadow, tree, and grass) together and the three impermeable classes (concrete, asphalt, and roof) together. The area for each new class is shown in the chart below.

| Class | Area (m$^2$) |
| --- | --- |
| Impermeable | 2,642.66 |
| Permeable | 6,431.97 |

Class: Impermeable, Permeable




## Conclusion:

In conclusion, the ideal parameters are unique to each individual dataset. For segmenting the imagery, the spectral similarities and difference between objects accross different datasets causes the need for different parameters. One should find ideal parameters for this step by qualitatively assessing the segmented imagery by looking at how well it segments objects. For training samples, they should be refined using histograms, scatter plots and statistics, and should pertain to a specific LULC class. Lastly, the ideal classifier is unique to the data set as well. In this project, the Support Vector Machine classifier resulted in higher accuracies for the UWEC Alumnus's house imagery while the Random Tree classifier resulted in higher accuracies for the Fairfax Park imagery.

As hinted at in the introduction and results section, object based classification can be used in added data analysis. Below is a list which includes potential applications and their importance or an example which the results of this project could be used in.

1. Wetland Deliniation: For development and construction projects as wetlands are often protected by federal, state, and local laws .
2. Impermeable & Permeable uses: Impermeable and permeable areas can be calculated which can be used to help with water runoff modeling and water quality modeling.
3. Mine Reclamation: The amount of land which needs to be restored can be measured as well as what LULC needs to or has already been restored.
4. LULC Change Detection: The growth of an urban area or othe LULC classes could be measured to be used in estimating local ecological impacts.

## Acknowledgments / References:


I'd like to thank the following people / organiztaions:
Dr. Cyril Wilson for helping determine the number of accuracy assessment points to use and for determining which classifiers would most likely provide the highest accuracy
Martin Goetll for helping with computer program difficulties
UWEC Geography and Anthropology Department



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