# Object-oriented Classification of Wetland Vegetation in the Kissimmee River Floodplain

**Lawrence Spencer, Ph.D.**

**South Florida Water Management District, West Palm Beach, FL**

## Abstract

Object-oriented classification of imagery offers the promise of having a machine "see" images similarly to how humans do. Rather than as a series of pixels, an object-oriented classifier picks out groups of adjacent pixels that have color, texture, or other attributes of interest in common, and forms them into "objects" that can then be processed further or used directly to build a map. The importance of the attributes used to pick out objects is determined by a human operator, but the operations carried out by the machine can save a great deal of time when compared to traditional methods of photo interpretation.

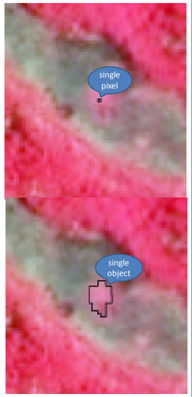
At South Florida Water Management District, we have applied object-oriented algorithms to the mapping of wetland vegetation as part of the Kissimmee River Restoration Project. This restoration, which involves filling parts of a large flood control canal and re-opening flow to quiescent river channels and to a wide floodplain, has been ongoing since 1999 and is set to be complete in 2019. To track wetland community response to restoration, periodic aerial photo surveys have been conducted since 1996. The resulting maps have been used to measure the distributions and relative abundances of wetland vegetation types of interest. Comparisons have been made to pre-restoration landscapes.

In 2011, we initiated a mapping effort using object-oriented algorithms developed through commercial software products. Field-identified signatures were collected concurrent with the imagery missions to act as signature definitions for classification and accuracy assessment. A unique algorithm was developed which used height of vegetation as a first criterion for broad classification and then used a Nearest Neighbor classification to separate wetland features. Initial accuracy was around 85% for this technique when applied to a map with ten classes. Further refining signatures allowed for higher accuracy. The original algorithm and the ways it was altered to increase accuracy will be discussed.

## Introduction

**Overview of Object-Oriented Classification:**

Traditional **pixel**-based classification methods (supervised or unsupervised) work on an individual **pixel** level and assign class values to each **pixel** separately based on spectral or other characteristics. **Object**-oriented classification differs from this by joining adjacent pixels with close spectral and textural signatures into **"objects."** This is known as segmentation, and creates numerous **objects** that can then be classified using a semi-automated procedure for placing each type of **object** into a particular class. Users can change the threshold for joining pixels and can also use other numeric attributes such as height, elevation, or NDVI as input signatures for machine-based **object** segmentations. For vegetation classification, segmented **objects** should mimic natural **objects** that can be seen in the images, such as natural populations or groupings of trees, shrubs, or herbs, or water courses.




## Methods

### 2011 Imagery Classification: From imagery to vegetation map using objects

**Methods:**

SFWMD acquired aerial imagery of the Kissimmee River floodplain in 2011 for the purpose of vegetation mapping (Figure 1). We decided to carry out the classification and mapping of vegetation with this imagery using object-oriented map classification. This was done using Trimble eCognition software, which allowed for iterative model creation and resulted in an algorithm that allowed coherent map classification throughout the Phase I area of the Kissimmee River Restoration, and the application of the algorithm with some adaptations to other floodplain areas to be mapped. The algorithm entailed the several steps, which resulted in a dichotomous (branched) classification of many of the broad classes:

## Step 1

Field Data Collection:

Field crews collected multiple field signatures for each map class throughout area to be mapped using airboats and helicopters. These samples were to be used for map classification and accuracy assessment. Accuracy assessment points were assigned randomly and set aside before mapping commenced. Classification points were used throughout the mapping process to assist both human- and machine-made class assignments.

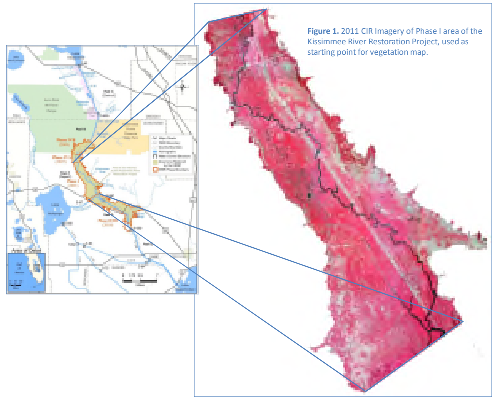


**Figure 1.** 2011 CIR Imagery of Phase I area of the Kissimmee River Restoration Project, used as starting point for vegetation map.

## Step 2

### Water and Land

Starting with a source image (a mosaic of ortho-rectified color infra-red (CIR) images) (Figure 1), we separated Land and Water objects using darker CIR spectral signature for water (Figure 2). This separator worked in 95% of open water areas.

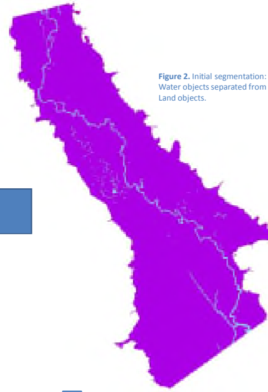


**Figure 2.** Initial segmentation: Water objects separated from Land objects.

## Step 3

### Land to Forest/Shrub and Herbaceous/Low

Using Land objects (Figure 2), we separated Forest/Shrub from Herbaceous/Low vegetation using height layer created from a terrain model of the area derived from stereo imagery (Figure 3). Accuracy assessment of this separation showed it had about 94% accuracy. Those areas not separated using this classifier were placed in an uncertain category, which were classed with a **Nearest Neighbor** classifier using samples of known sites from each class.

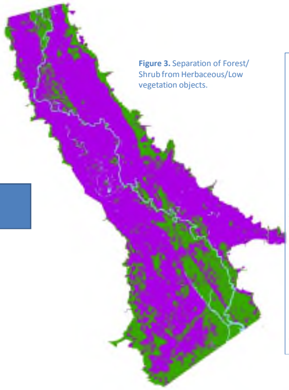


**Figure 3.** Separation of Forest/ Shrub from Herbaceous/Low vegetation objects.

## Step 4

### Forest/Shrub to separate Forest and Shrub

Within Forest/Shrub, Forest was separated from Shrub objects using the height layer a second time, assigning threshold heights to both trees and shrubs, based on sampling of the height layer within known regions of each class (see Figure 4). Areas of overlap in height were discovered, and dealt with using a combination of proximity mapping (classifying objects the same as other classified objects closest to or enclosing them) and nearest neighbor classifiers using samples of known sites from each class.

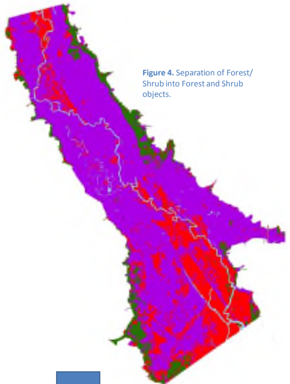


**Figure 4.** Separation of Forest/ Shrub into Forest and Shrub objects.

## Step 5

### Separating Wet Forest and Shrub from Upland Forest and Shrub

Within both Forest and Shrubland objects, Upland and Wetland classes of each were initially separated using elevation thresholds determined by sampling the elevation layer within known regions of each class, and assuming that upland areas are at a higher elevation relative to wetland areas. The elevation separator was supplemented with a previously classified map of Landscape classes, and with Nearest Neighbor classifiers using samples of known sites from each class (see Figure 5).

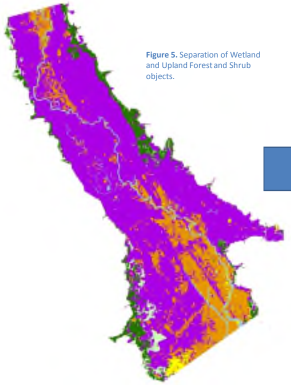


**Figure 5.** Separation of Wetland and Upland Forest and Shrub objects.

## Step 6

### Separating Wetland Herbaceous from Upland Herbaceous

Within Herbaceous/Low vegetation, separated Upland Herb from Wetland Herb using combination of spectral signature (upland appeared lighter in many cases) and elevation (Upland was at a higher elevation relative to wetland in same area). Spectral signature and Elevation were not, in some cases, coherent classifiers, especially in transition zones between upland and wetland areas, so had to be supplemented with a Nearest Neighbor classifier using samples of known sites from each class (see Figure 6).

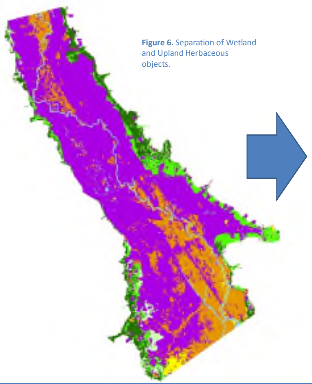


**Figure 6.** Separation of Wetland and Upland Herbaceous objects.

## Step 7

### Final Separations and Clean Up

Within Wetland Herb, separated Wet Prairie, Broadleaf Marsh, Standing Water Aquatics, and Miscellaneous Wetlands using Nearest Neighbor classifiers. Coherent class separation among these classes was achieved after a number of iterations of trial and error using various samples. This was the most time-consuming sample-dependent process and reinforced the requirement for an effective field sampling regime prior to the initiation of mapping.

Clean-up: Any objects smaller than 0.1 acres (the Minimum Mapping Unit or MMU) were merged with surrounding objects of larger size. Removal of shadow polygons, which showed up among forest and shrub polygons as open water, involved selecting disconnected water objects between 0.1 and 1.0 acres that were surrounded by or directly adjacent to shrub or forest objects (final product shown in Figure 7).

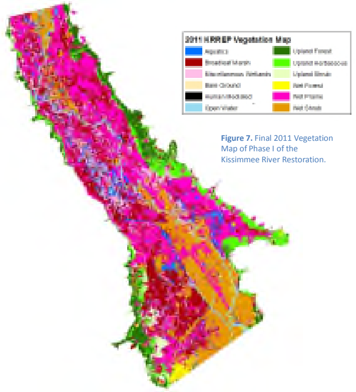


**Figure 7.** Final 2011 Vegetation Map of Phase I of the Kissimmee River Restoration.

## Conclusions

After classification, we carried out an accuracy assessment, which showed an overall accuracy of 86%. However, wetland vegetation alone reached a 93% accuracy level. Further refinements to the classification algorithm for upland types are expected to increase the final accuracy for all classes.

Overall, this vegetation mapping protocol using object-oriented vegetation classification algorithms iteratively shows promise for future mapping projects in the Kissimmee Basin. The project has made it clear that one of the most important parts of a mapping project such as this is the field verification point collection protocol. It is highly important to collect field data as close to the time of imagery acquisition as possible and that these data be accurate, match the level of detail of the classification scheme, and include enough points to be useful for both map signature generation and accuracy assessment. Supplemental points for accuracy assessment can also be collected directly from imagery, but should only be used if their signatures match directly with ground-verified points.