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HABITAT ANALYSIS FOR BREEDING WHITE-TAILED KITE (*ELANUS LEUCURUS*) ALONG THE AMERICAN RIVER IN SACRAMENTO COUNTY, CALIFORNIA

INTRODUCTION

White-tailed kites (*Elanus leucurus*) (Figure 1) were once predicted for extinction due to large scale population decline as a consequence of habitat loss, hunting, and egg collection (Polite 2005). In response to this decline, in the 1940s and continuing through the 1970s, white-tailed kite populations had begun to rebound in a number of areas as a result of hunting and egg collection restrictions and an increase in agriculture, which subsequently increased small mammal abundance, the primary food item of kites. In 1957, the white-tailed kite was afforded fully protected status in California. Although protected status aided in the recovery of the white-tailed kite population, the white-tailed kite range was much reduced over its former range. In California, the white-tailed kite primarily inhabits the coastal and valley lowlands near pastureland and along riparian corridors.


Figure 1. Adult white-tailed kite (*Elanus leucurus*).

White-tailed kites are generally believed to be a non-migratory falcon, heavily dependent upon a reliable food source, especially during the breeding season (Dunk 1995). The main prey items of kites are voles, and other small mammals, and less often small birds, insects, reptiles, and amphibians (Dunk 1995). Kites require relatively undisturbed, open grasslands and meadows for foraging, but also will utilize pastureland and emergent wetlands. Another, key component of suitable kite habitat are trees and shrubs that can be used for roosting and nesting. Nests are often situated near the top of oak, pine, or other tree stands adjacent to foraging areas.

In the Sacramento Valley, white-tailed kites utilize both agriculture and riparian corridors year-round. The riparian corridor along the American River is known to support a relatively high density of white-tailed kites due to its comparatively open grasslands and dense tree stands amongst its urban surroundings. However, due to the continuing threats of urban development and increased human disturbance impacting our remaining natural areas, it is important to monitor protected species like the white-tailed kite to identify what types of habitat are critical to their persistence. As a first step in this process, this project was undertaken to broadly classify habitat features along a selected portion of the American River that may support breeding white-tailed kites. Habitat classification enables biologists to identify which areas are most likely to support kites as well as identify locations that might be a candidate for restoration to facilitate increased use by kites, which subsequently would benefit a variety of other wildlife species in addition to supporting improved human recreational opportunities.

The primary objective of this project is to classify habitat into five broad categories along the American River between Highway 160 and Howe Avenue. Habitat categories were based on their importance to breeding white-tailed kites and included grasslands, shrubs, woodlands, water, and unsuitable. The unsuitable classification includes barren land and urban areas such as business parks and housing developments or any other area generally unsuitable for use by white-tailed kites. At the conclusion of this project I hope to have developed an image that broadly classifies habitat along the riparian corridor of a section of the American River that can begin to identify important habitat features that are likely to be utilized by white-tailed kites. The resulting classification can then be used as a model to classify other, similar, areas along a riparian corridor.

METHODS & RESULTS

An image of a portion of the American River riparian corridor (SAC_31) was selected from the Sacramento 2009 imagery provided by the instructor. SAC_31 was selected because the image included a significant proportion of riparian habitat in addition to the adjacent urban development. The image roughly includes the area from Highway 160 east to Howe Avenue and Exposition Boulevard to the north and R Street to the south, Sacramento, California. The image consists of three bands with 0.5 meter resolution in MrSID compressed format; uncompressed image size is 2.01 GB with an 8 bit pixel depth.

Since I was aiming to classify habitat features, I first identified the broad habitat classifications I wanted to utilize for the project. Using the California Department of Fish and Game's California Wildlife Habitat Classification Scheme (CWHR 1988) as a guide, I reduced the 25 habitats listed for Sacramento County into five broad classifications. The classifications included grasslands which incorporated annual and perennial grasses; shrubs including chaparral species such as scrub oak, ceanothus, chamise, and manzanita; woodland which included tree species such as oak, buckeye, cottonwood, sycamore, walnut, willow, and eucalyptus; water including the river, wetlands, and seasonal ponds; and unsuitable which encompassed all urban features as well as barren ground.

Next, I began the habitat classification process utilizing Feature Analyst in ArcMap. I brought the image into an ArcMap document and ensured that the Feature Analyst extension was functioning. I created five new feature classes, each named for one of the five habitat classifications. Then I selected training sets for each of the five feature classes (Fig. 2). For all the feature classes, I selected training sets that were representative of the habitat feature, for example grass fields for grasslands, trees for woodland, etc. However, for the unsuitable feature class I choose a wider variety of training sets including buildings, houses, roads, parking lots, and other areas that were basically not going to be utilized by white-tailed kites.

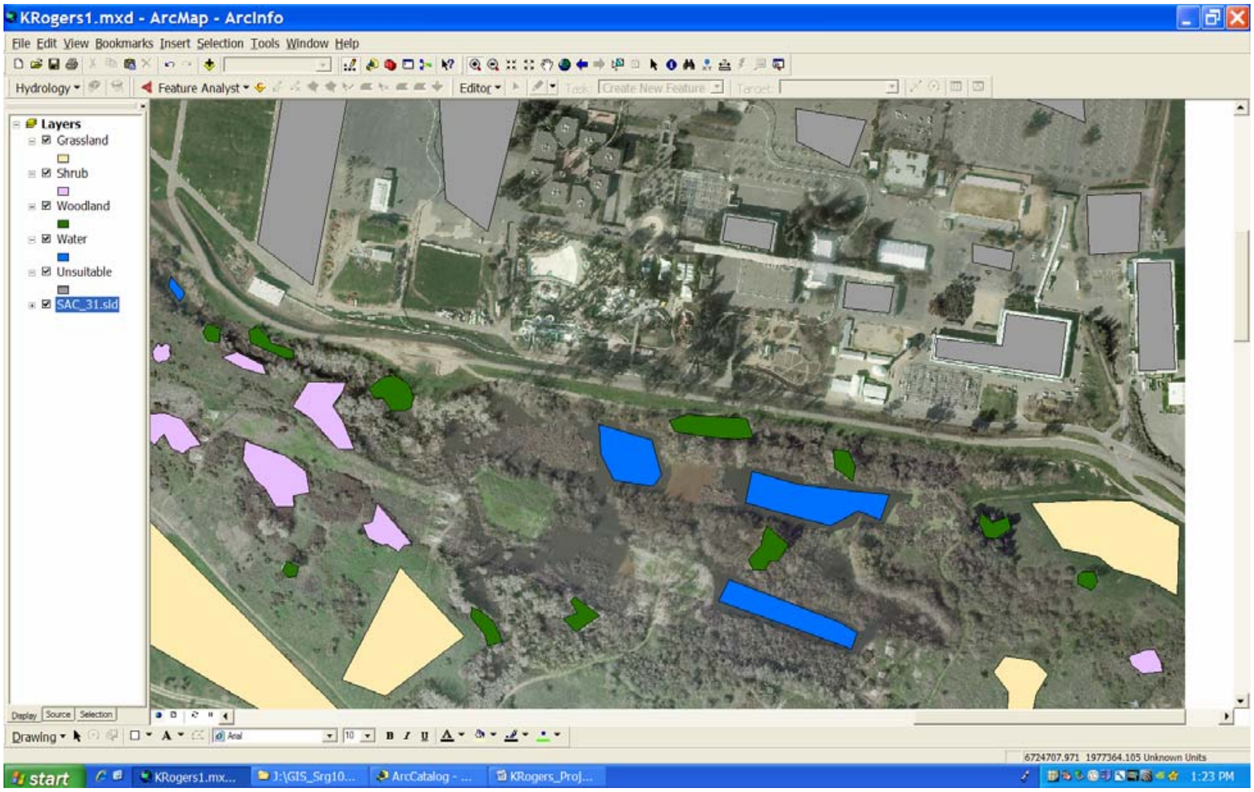

Figure 2. Training sets for each of the five habitat classifications: grasslands (tan), shrubs (pink), woodland (green), water (blue), and unsuitable (grey).

After I selected the training sets for each classification, I combined the individual classes into a single layer called MulticlassInput1. Then I set up the learning parameters for Feature Analyst. I selected the following parameters: Feature Selector is Land Cover Features, Image Resolution is 0.5 meters, Resample Factor is 3, Input Representation is Manhattan with a Pattern Width of 5, Learning Algorithm is Approach 1, Learning Options Aggregate Areas is 50 pixels, Wall to wall classification, and Output Format is Vector (Fig. 3). I clicked on One Button Learning, naming the output classification OneButtonLearning1. However, because there was no progress in the progress box for at least ten minutes, indicating this was going to be a very long process, I decided to cancel the classification and change the parameters.

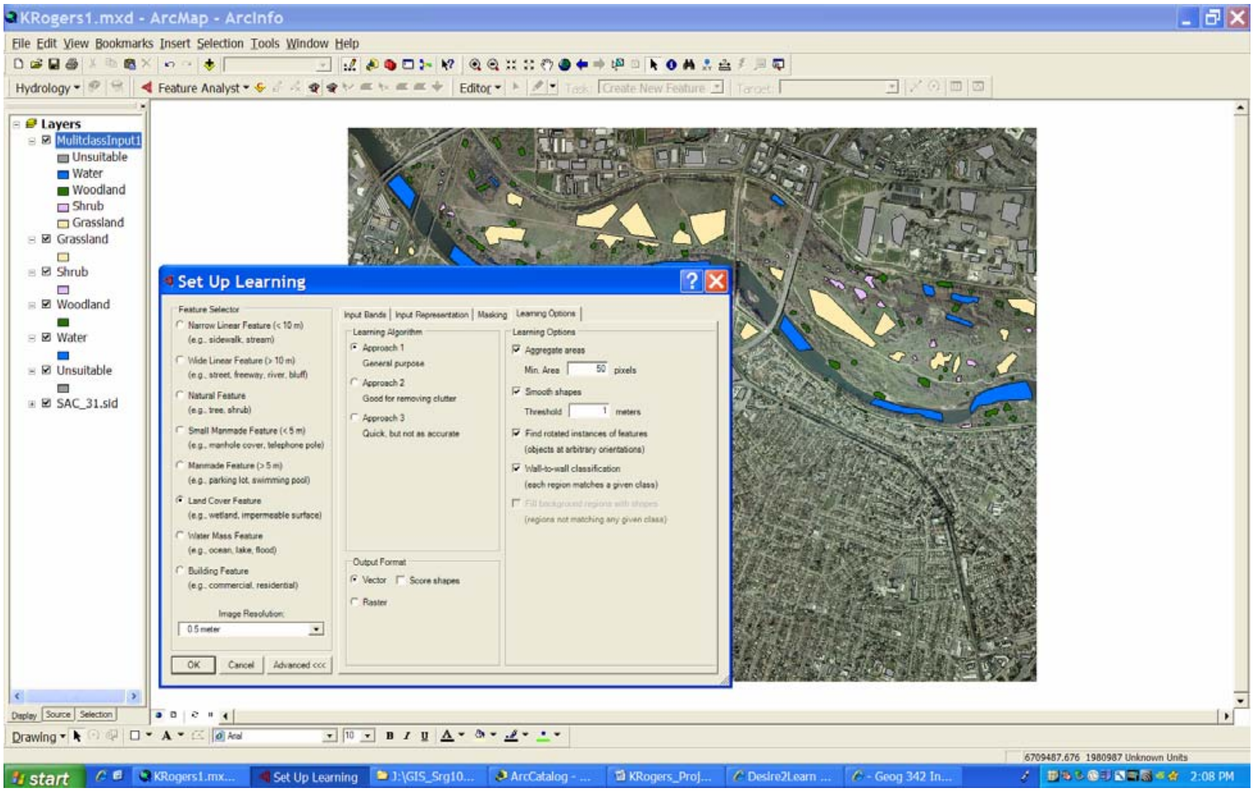

Figure 3. Setting up the learning parameters for One Button Learning.

The parameters for the next classification were based upon the parameters outlined in one of the lab exercises and were as follows: Feature Selector is Land Cover Features, Image Resolution is 6 inches, Resample Factor is 3, Input Representation is Manhattan with a Pattern Width of 5, Learning Algorithm is Approach 1, Learning Options Aggregate Areas is 100 pixels, and Output Format is Vector. The name of the output layer was OneButtonLearning2 (Fig. 4). This classification process took approximately 2.5 hours to complete. It was at this point, I decided to reduce the area of the image to focus more on the riparian corridor. I used the Clip tool in ArcMap to reduce the area of the image. To complete the clip, I created a polygon feature class in ArcCatalog named Focus which I then added to the ArcMap document. In ArcMap I started an edit session and used the draw tool to draw a rectangle that encompassed the area of focus. I then clipped the image using the Focus polygon. The image was clipped in the south to roughly E Street/McKinley Boulevard. The uncompressed image size was now 2.51 GB with a 16 bit pixel depth. I also clipped the output layer OneButtonLearning2, the initial classification of the habitat features, by the same extent as the image (Fig. 5).

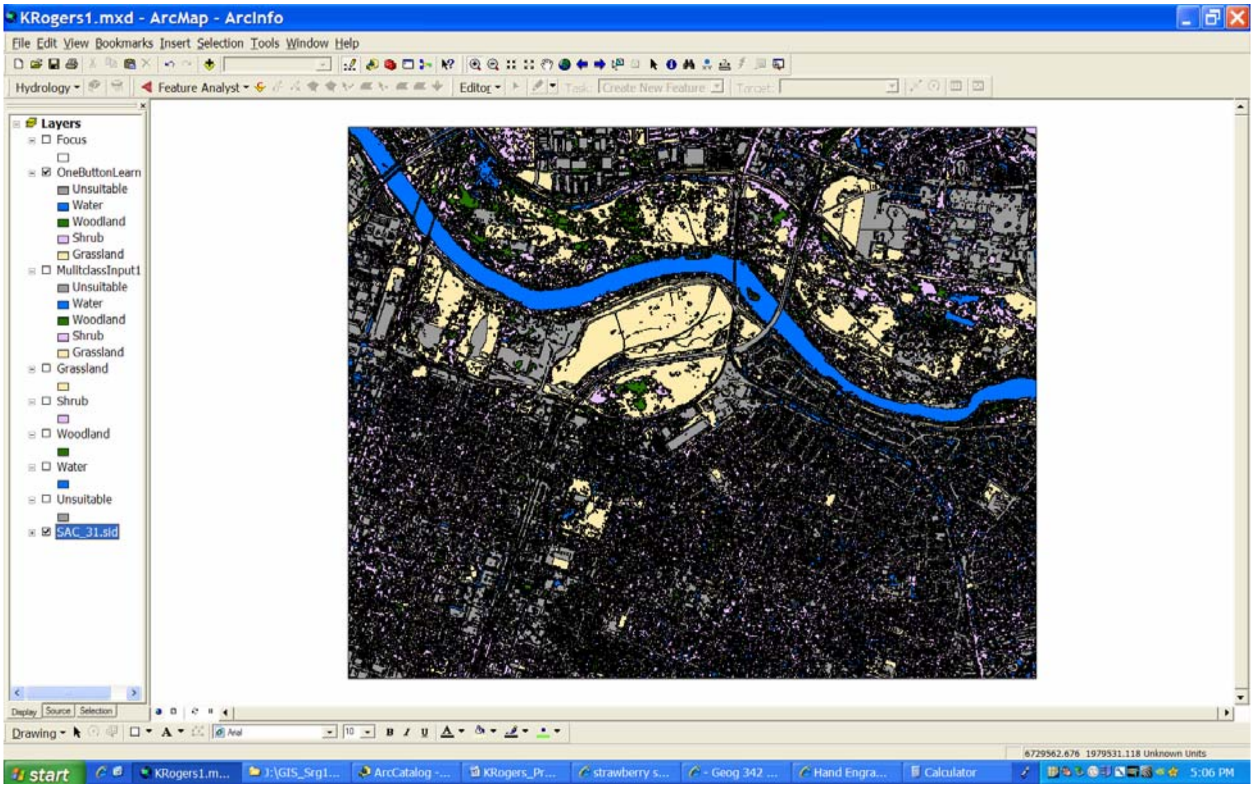

Figure 4. Results of the One Button Learning classification.

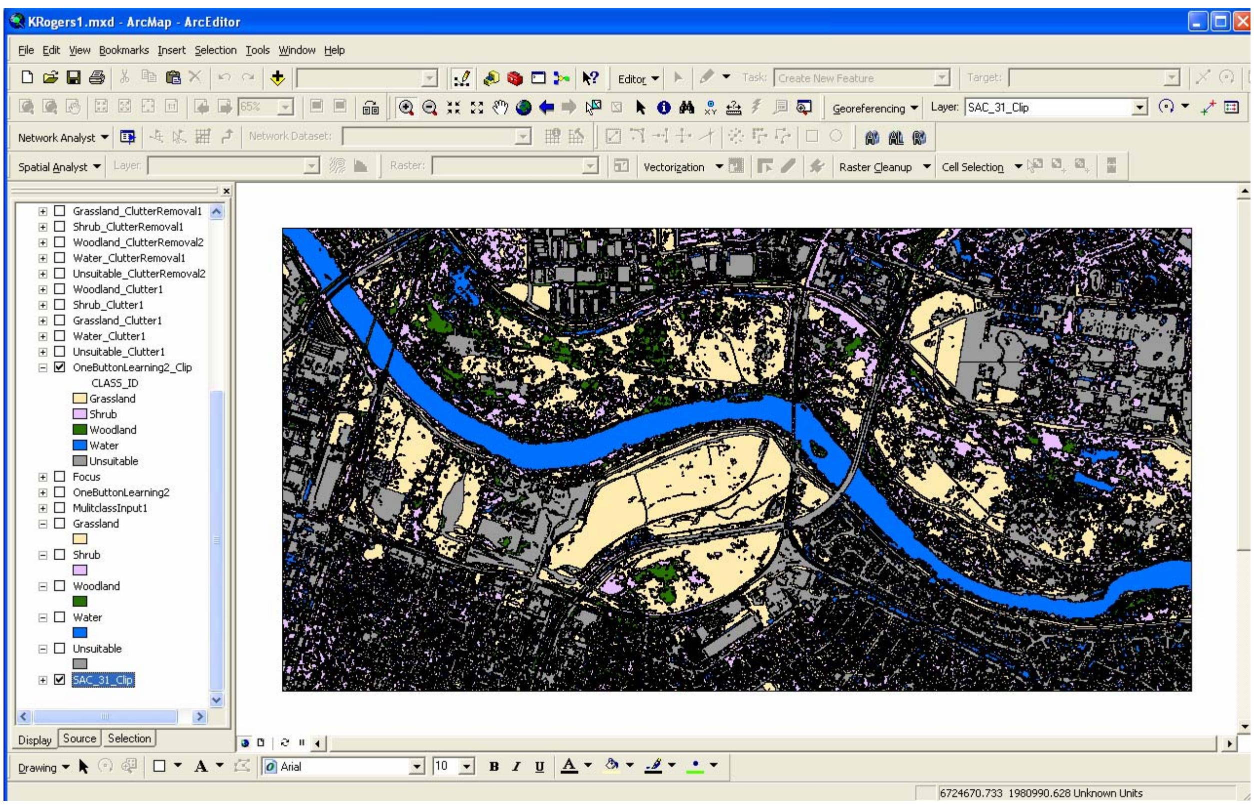

Figure 5. Image classification after performing the Clip to reduce processing time.

Next, I examined the results of the initial classification. For all of the classes there were features that were misidentified. I noted shadows were most frequently misidentified as other habitat features such as water. The woodland class was probably the most misidentified. It appeared as if trees were included in the shrubs class rather than in the woodland class. Therefore, I began the process of clutter removal. First, I split out the classes to examine them individually and attempt to improve the errors in classification. For each class I selected a representative sample of features that were either classified correctly or incorrectly (Fig. 6 & 7). I then reran the classification for each class using the One Button Learning tool and reevaluated the classification. The parameters for the classification for each of the classes were as follows: Land Cover Features, Image Resolution 0.5m, Resample Factor 5, Approach 2 at 25 pixels. Since time was a critical factor, I had to opt to choose parameters that would not take too long to process. Obviously, this affected the accuracy of my classification results, and is not ideal in real-world situations.

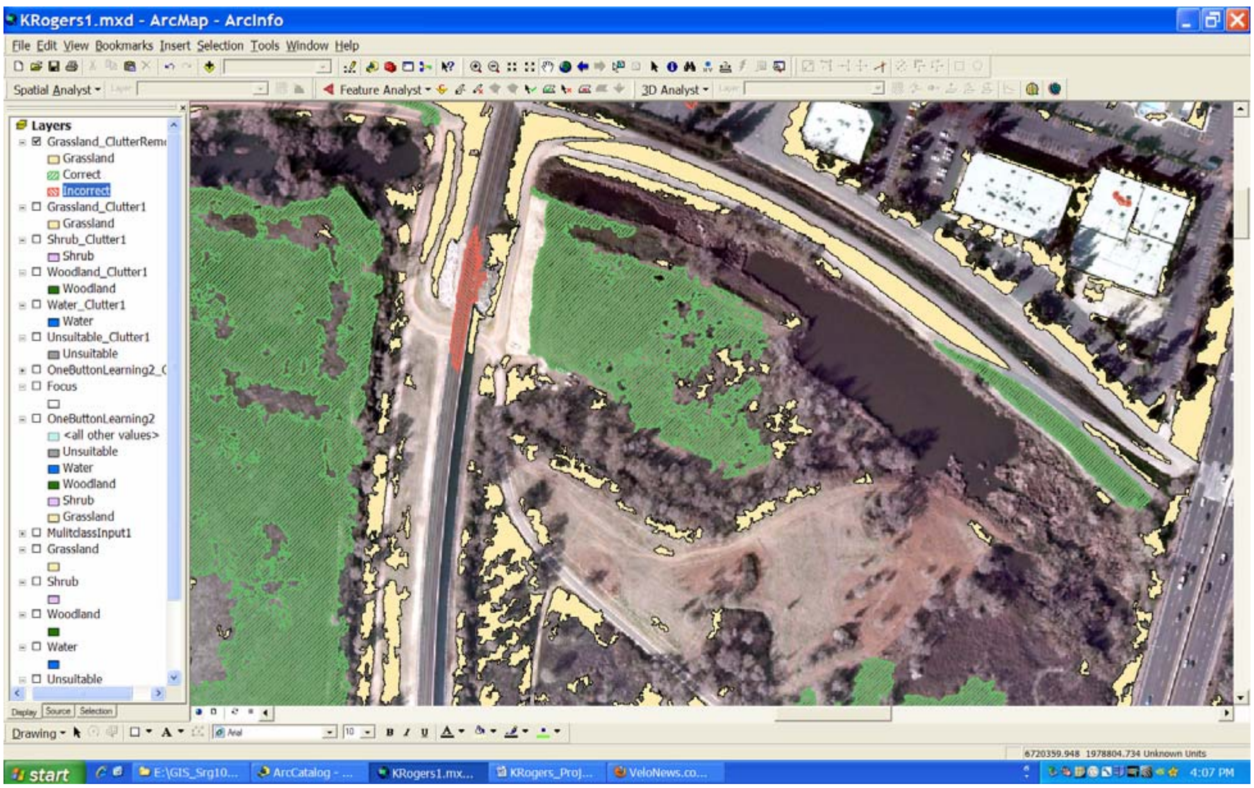

Figure 6. Example of clutter removal process for the Grasslands feature class, note the correctly identified features are in green and the incorrectly classified features are in red.

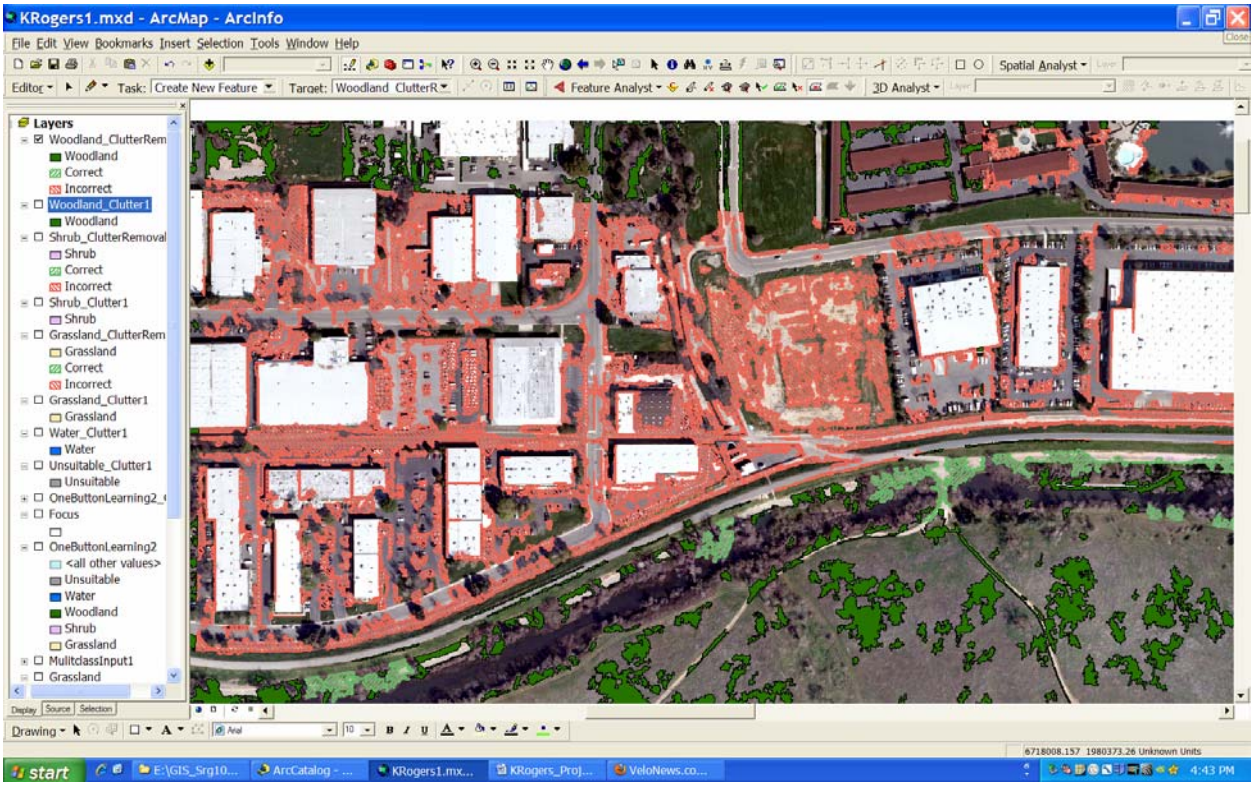

Figure 7. Example of clutter removal process for the Woodlands feature class. Note the high degree of misclassified features in red.

After rerunning the classification, I reevaluated the accuracy of each class. The Grasslands and Unsuitable classes look fairly accurate. Shadows are still being misclassified as Water and Shrubs. Also, Shrubs are close to what the Woodland class should be. I guess it's difficult for the program to distinguish between shrubs and trees, indicating that their spectral signatures are similar, or my training sets were not as precise as they could have been. Given these misclassifications, I attempted to remove more clutter on all the classes except Grasslands and Shrubs.

First, I manually deleted some misclassified features in the Water feature class. I did this by starting an editing session, Task: Modify Feature, Target: Water_OneButtionLearning3. I simply selected features that were misidentified and deleted them. I repeated this process for Unsuitable and Woodlands.

Next, I used the Add Missed Features tool to add features to the Woodland class (Fig. 8). I saved the new feature class as Woodland_AddMissedFeatures1. Using this tool, I added additional training set features (blue) that were missed in the first classification session. When I finished, I saved my edits and stopped the editing session. I then ran One Button Learning again to reclassify the feature class. The class was saved as Woodland_AddMissedFeatures2. Next, I ran One Button Learning for Woodland_AddMissedFeatures2 and named the new layer Woodland_AddMissedOneButton1. The result was not what I had expected; almost every habitat feature was classified as woodland (Fig. 9). I tried the process again, changing the parameters to 0.5m, resample factor to 3, Approach 2 at 25 pixels. The result was not improved, so I decided to stop here and move on due to time constraints.

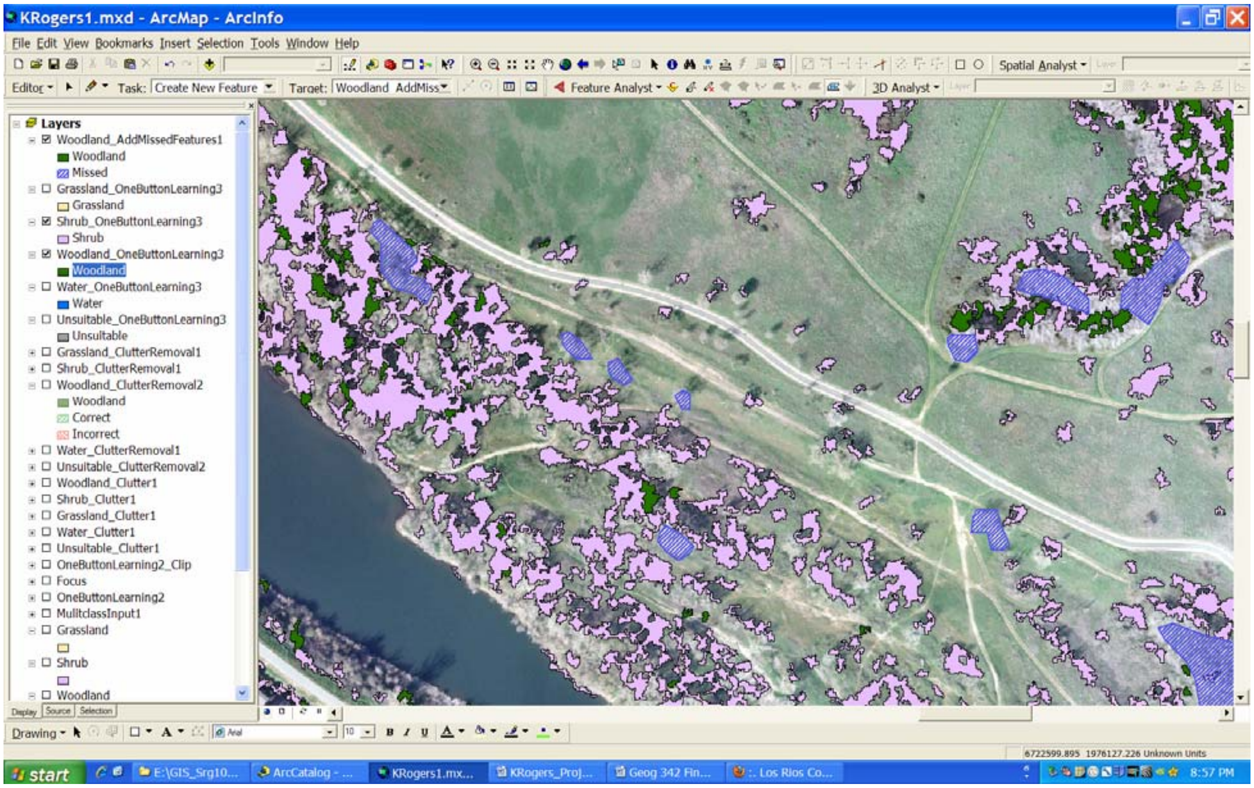

Figure 8. Add Missed Features tool was used to add missed features (blue) to the woodland class (green).

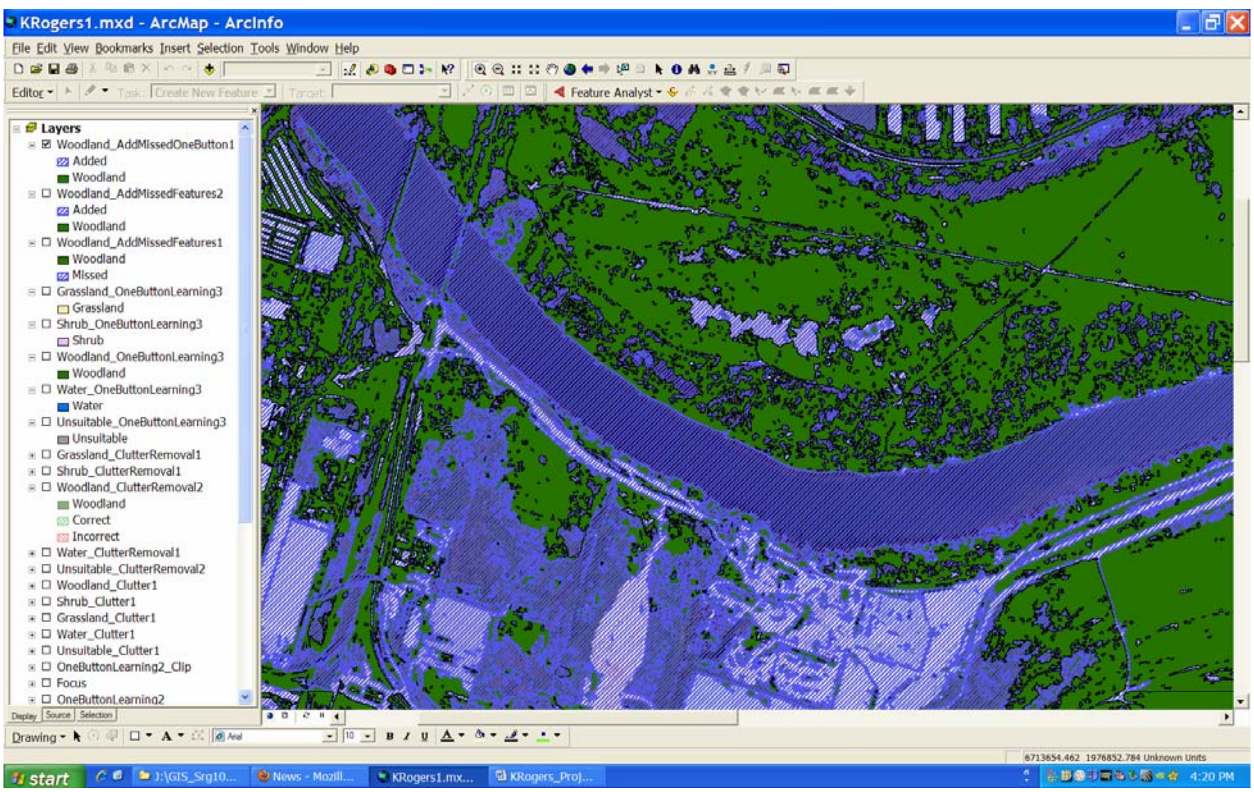

Figure 9. Result of One Button Learning for Woodland class using the Add Missed Features tool. Note the over classification of woodland features including water, buildings, shrubs, grasslands, etc.

The final step was to combine the feature classes for each categorized habitat type and run the last classification (CombinedFeatures1) (Fig. 10). The resulting classification is somewhat correct. The grasslands include grasslands and meadows, but also features like some of the vacant lots and exposed dirt which should have been classified as unsuitable. Shrubs include shrubs and most of the trees. It was difficult to get the program to recognize shrubs and trees as different entities. As such the woodland classification included only a few of the tree stands, while the majority was included in the shrub classification. The reclassification and adding missed features process for the woodland feature class did not improve the woodland classification. The water feature class was classified correctly in most cases except for some misclassifications of shadows. The unsuitable classification was classified correctly in most cases, but I would have like to have seen some instances of barren ground classified as unsuitable rather than as grasslands. Also, roads and bridges were not always classified correctly, but rather as a vegetation type rather than unsuitable.

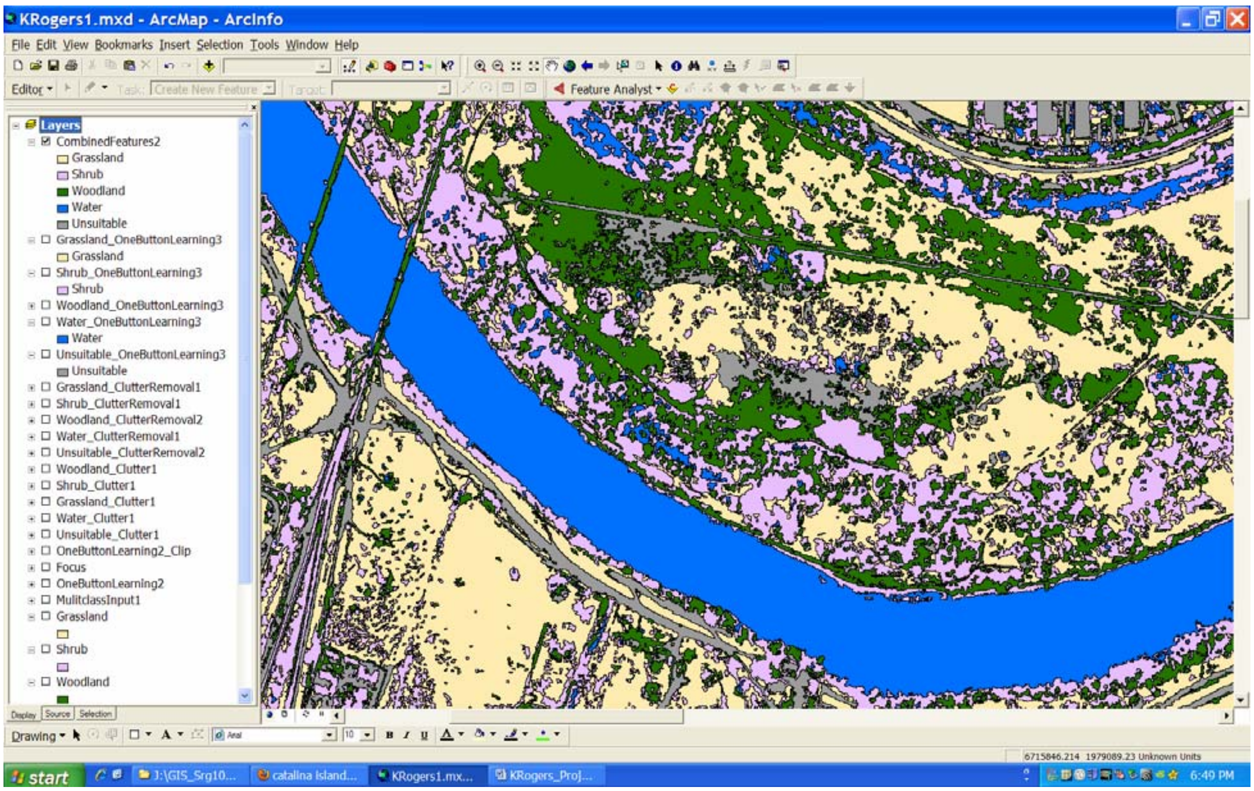

Figure 10. Result of Combined Features tool. This layer consists of a single layer that consists of the five habitat types.

DISCUSSION

The main issue was the limited amount of time I had to complete the project. Every step of the classification process such as the initial classification, clutter removal, adding missed features, and rerunning the classifications, can be extremely time consuming. Both the hands-on part of the process like selecting training sets and evaluating the output is time consuming, but equally as time consuming is the processing by the computer. It took two and a half hours to run the initial classification and I only selected 5 different classification types. I also used generic classification parameters. Careful planning both prior to and during the classification process is important to keep the project focused and manageable.

Cropping the image was helpful at reducing some of the processing time. However, if I had been performing this classification for real, I would have made the crop more meaningful if possible. For example, I would buffer the river by a certain distance meaningful to white-tailed kites. That is, my area of focus would have some biological reasoning like nest occurrence distance from the river, or riparian area. I also recently found out that you can perform the crop in Feature Analyst using the Crop Raster tool to only analyze a portion of the whole image.

Alternatively, I could have used the Mask feature in Feature Analyst to reduce the processing time and improve the results of the classification. Masks can be used to reduce the amount of the image used in processing or to remove some of the features, like buildings, that are not needed in processing. These methods are likely to reduce the occurrence of misclassifications, particularly of shadows.

In retrospect, it is apparent that spending the time to select high quality training sets for each habitat classification is critical to reduce misclassifications. Training sets should clearly encompass the feature you are trying to capture as well as depict the variety of the features for each sample training set. For example, for the woodland classification in my project, I should have selected training sets that represented the variety of tree species present including trees of different shape, color, contrast, and size. However, I found it difficult for myself to distinguish between some of the tree and shrubs in the image. As such, utilizing actual on-the-ground, real-world information to verify what I think I'm seeing in the image would be helpful to validate my training sets thus making them more accurate and useful for image classification. Using the hierarchical process to continually refine the training sets helps to improve the classification. Also, it is important to start with predefined learning parameters, run the classification, evaluate the classification, and then adjust the parameters again and again until you are getting the most accurate results for your classification. Adjusting both the Input Representation and Aggregate Area (minimum polygon size) for each feature is crucial to developing a precise classification. These parameters attempt to focus the learning for features to specific spatial context and size. For the purposes of this project, it just wasn't possible to run through all the possible variations in learning parameters due to time constraints. However, along with choosing high quality training sets, trial and error with the various learning parameters is time well spent to ensure your classification will be accurate. Once the parameters are identified for a portion of the project area you can utilize the parameters for similar projects, ultimately saving time. For instance, if I planned to classify habitat elsewhere for white-tailed kites, I could use the same parameters identified in the initial project for all subsequent projects substantially reducing the amount of time spent on setting up the learning process.

CONCLUSIONS

Overall, I think the classification I developed for this project was a good start (Fig. 11). The output of the classification process for this project was a single layer that depicted the five habitat classes I initially chose to identify white-tailed kite habitat. The resulting layer combined the Grassland, Shrub, Woodland, Water, and Unsuitable features into a final classified image consisting of polygons that identify each of the five habitat classes. Learning was used to place unclassified areas and areas of overlap into a class. This layer can then be used to identify areas that are likely utilized by kites and areas that are likely avoided by kites. Unfortunately, I was limited by time. If more time were available I would have selected better training sets and adjusted the parameters for multiple iterations to determine the best combination for this project. Feature Analyst is a powerful tool for image classification that can ultimately save the analyst time. However, the process is not automatic, it is imperative the analyst take the time to select high quality training sets, set up the learning process as precisely as possible, review each classification, make adjustments, and rerun the classification until the desired results are achieved.

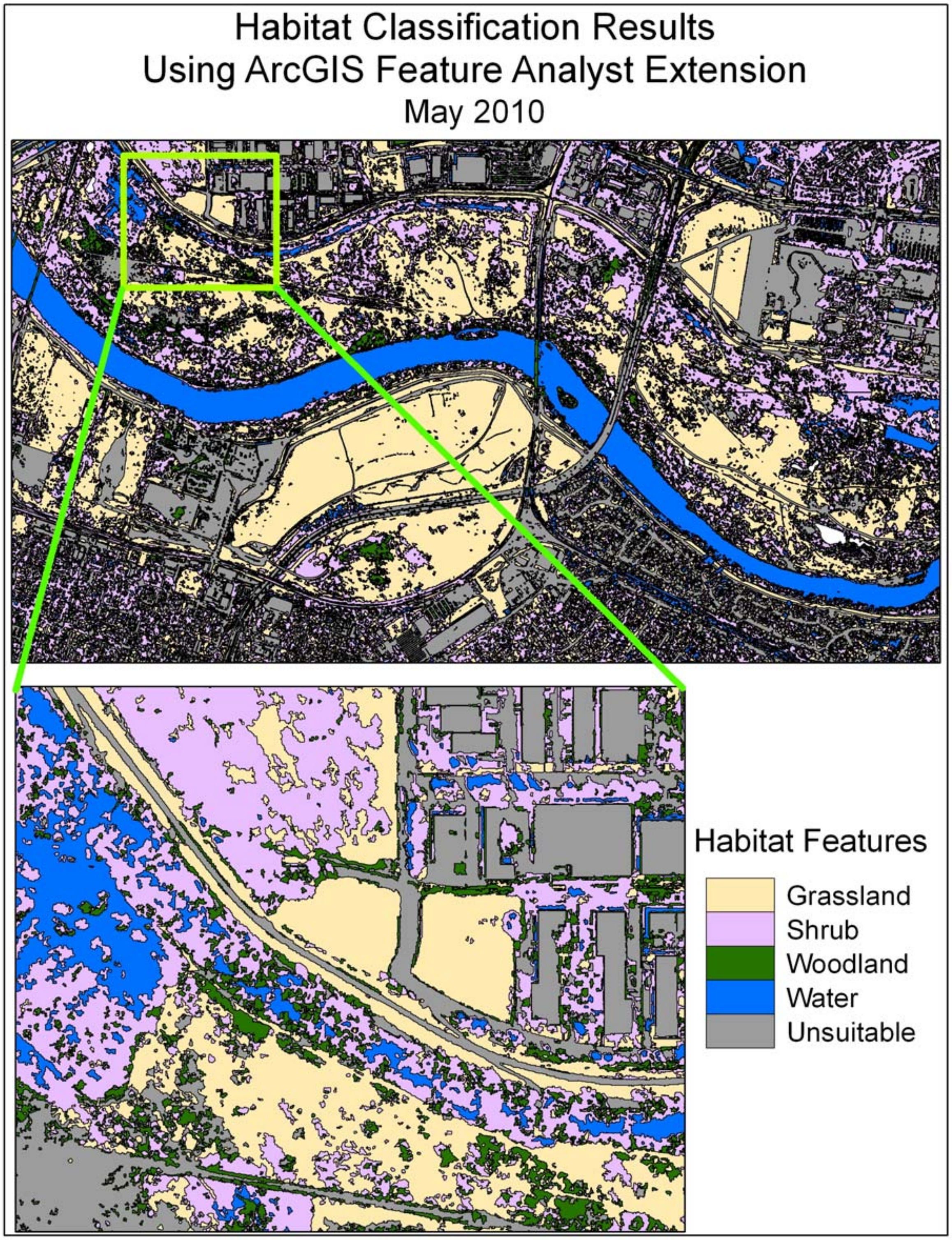

Figure 11. Final classified layer for the five habitat features selected for classification using the Feature Analyst extension for ArcGIS.

References

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