Using Multispectral Aerial Imagery to Map the Vegetation of Cheyenne Bottoms Wildlife Area

Project Summary and Final Report

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Executive Summary
In an effort to map the current vegetation communities within Cheyenne Bottoms Wildlife Area (CBWA) in Barton County, Kansas, the Kansas Applied Remote Sensing (KARS) program at The University of Kansas acquired and analyzed aerial imagery from the DuncanTech MS3100 digital multispectral camera. This work was conducted at the request of Mike Mitchener and Karl Grover of the Kansas Department of Wildlife and Parks (KDWP) as part of the cooperative agreement between the KARS Program and KDWP. On October 8th, 2005, imagery was acquired over the Cheyenne Bottoms Wildlife Area. Post processing was performed to geo-register and rectify the individual images then merge them into a seamless mosaic.

Previous mapping efforts that utilized near infrared film and relied exclusively on visual interpretation and the manual digitizing of vegetation communities were necessarily subjective in nature and hard to repeat. This project utilized multispectral digital imagery and examined multiple analysis and classification techniques in an attempt to develop a more quantitative and repeatable methodology for classifying the imagery.

Project objectives
1) Acquire digital multispectral aerial imagery over the Cheyenne Bottoms Wildlife area (one meter spatial resolution).

2) Conduct field-sampling to collect ground truth data. Resulting vegetation data will be used to assist with vegetation identification and classification efforts.

3) Process imagery and create a landcover map delineating vegetation communities of interest to park managers.

Deliverables
1) CD(s) containing the geo-registered and rectified aerial images.

2) Summary report detailing the methods used and the results of the analysis.

3) Two poster size graphics (1. aerial imagery, 2. vegetation map).
Flight Planning

The importance of timing

Our experience at KARS has shown that there are certain times of the year when it is very difficult to discriminate among some vegetation types, and other times when classification accuracy is greatly increased. We have found that due to the differences in phenological stages between species, it is difficult to spectrally discriminate among cool and warm season grasses in the middle of the summer, while spring and fall imagery provide better data for identifying these particular plants.

Due to the impact that phenological stage can have on classification, it was important to identify the optimal date for separating the wetland species such as cattail, bulrush, and spikerush as well as the upland plant communities of wheatgrass and cordgrass. Previous mapping efforts conducted between 1998 and 2002 indicated that a late summer acquisition date might provide the best separation between vegetation communities. After much consideration, an acquisition date of early September was scheduled to maximize spectral separation of both wetland species and upland plant species. Unforeseen circumstances and technical difficulties delayed the image acquisition date until October 8th, 2005. Preliminary analysis of the data showed a reasonably high level of contrast in vegetation patterns despite the late imaging date.

Spatial resolution

Due to the highly heterogeneous nature of the vegetation at CBWA, it was decided that any aerial imagery acquired needed to have a high spatial resolution (less than or equal to 1 meter). To maximize the spatial resolution and minimize the number of flight lines, a flight plan was created based on the plane flying at 9,700 feet above the ground (11,500 feet above sea level) for a pixel size of 0.85 meters. A total of ten flight lines were delineated, each spaced 1,000 meters apart.

Field sampling to gather ground truth data

To assist with interpreting the aerial imagery and classification efforts, field observations were conducted September 15-19, 2005, a date that was supposed to closely match the image acquisition date. Field observations were conducted by driving and walking to predetermined locations via GPS unit and recoding vegetation conditions at that site or recording new locations selected to document the occurrence of specific vegetation types at a given location. At each sample location the GPS coordinates were recorded (as UTM zone 14, NAD 83), a visual survey of vegetation types present was conducted, the site was assigned to a land cover class, and a digital photograph may have been taken. Interviews with CBWA personnel referencing LC maps from previous years were also conducted to learn about management actions and details not observed during four days of field observations. The majority of field points were located along the outer perimeter, though some observations were also made from the levees that transect the wetland (Figure 1).
Pre-processing

After the imagery was acquired, an image index map was made using the GPS center coordinates for each image (Figure 2). The forward overlap between images was sufficient enough that only every other image was needed to provide complete coverage of the area. Images were georegistered against a 2001 NIR digital orthophoto using Leica Photogrammetry Suite. Due to the relatively small image footprint, there were some areas (open water, mud flats) where there were not enough features to collect control points. For these areas, a sequence of images was manually and visually aligned in Adobe Photoshop to create an image chain long enough to span the featureless area. The image chain was then georegistered using photogrammetry suite by placing control points at the ends (where there were a sufficient number of features for control points) and at the occasional locations in the middle where control points could be found. Once georegistered, the images were projected to UTM zone 14, using the NAD 83 datum. The Leica mosaic tool was then used to assemble all the individual images and small image chains into one large seamless image.

Once the mosaic was completed, it was time to take advantage of the multispectral properties of the imagery and classify the data into a landcover map. Two complicating factors were immediately evident upon completion of the mosaic and visually assessing the image. First, the imaging date appeared to be a little too late for maximum separation of landcover classes, and second, the high spatial resolution was providing too much detail and was actually complicating the classification procedure by including large amounts of inter-class variation. Despite these initial observations, it was
believed that by using image-processing software to analyze the reflectance signatures, a more quantitative and repeatable methodology could be developed to create a landcover map instead of the visual interpretation and digitizing of landcover polygons that had been done in the past. Since this was a new and experimental approach, the methodology was iterative and the unsuccessful approaches proved almost as valuable as the final successful method.

![Figure 2. Plot of image locations and reference numbers.](image)

**Pixel Based Classification**

Using Leica Imagine software, ISODATA and maximum likelihood unsupervised classifications was initiated to generate 100 classes. The results of these classifications were, as expected, full of mixed classes that needed to be further classified through cluster-busting techniques, however the degree of spectral overlap between many of the classes was so great that it was not possible to accurately separate some of the main classes such as wheatgrass, cordgrass, spikerush, and undifferentiated emergent wetland (Figure 3). This mixing is both the result of acquiring the imagery in October, a time when most vegetation types are going through senescence or dying, and partly due to regional variation where a given class may appear drastically different between wetter, dryer, or weedier locations. Thinking that vegetation classes within a localized region would show less variability, an attempt to reduce the amount of spectral variation within classes was made by sub setting the image by management pools. Although this method did reduce the inter-class variation some, the new problem became matching landcover classes between pools, especially at the seams.
Another approach was initiated that, instead of relying on the computer to statistically “tease out” landcover classes, a supervised classification was tried. Using this method, the user provided training sites of each land cover type to “train” the software what the spectral characteristics of each class were, then it identified pixels with a similar spectral pattern. As with the unsupervised approach, the large amount of interclass variation prevented an accurate classification of landcover classes.

Looking closely at the imagery, it became apparent that due to the high resolution of the imagery (one meter) it was hard to “see the forest through the trees” or rather see the wheatgrass through the weeds. Part of the problem was that the camera was detecting minor variations in the vegetation due to localized differences in plant community composition. Wheatgrass areas with more or less ragweed, annual sunflowers, or saltgrass appeared spectrally different from one another even though they should have been categorized as the same class (Figure 4). To try to remove some of this spectral variation, the image was resampled to a five-meter resolution. By doing this, the general spectral characteristics of the different vegetation patches were maintained while the details from particular plants were removed. The unsupervised and supervised classification techniques were tried again using this five-meter data, and while the results were better, there was still a significant amount of mixed classes.
Advanced Statistical Analysis and Classification

Figure 4. An example of the spectral diversity found within landcover classes with the dotted line representing the approximate boundary between these three classes. The central portion is all wheatgrass, with the darker portions containing more annual weeds and the brighter blue areas indicating a more pure stand of wheatgrass. The greenish color in the lower left is spikerush, and the mottled green, brown, red mix in the upper right is undifferentiated emergent wetland, with the pink being cordgrass.

Object Orientated Cluster Classification

It was becoming clear that a totally new approach was needed to analyze and classify the imagery, one that would not be compromised by the high level of heterogeneity. Cluster analysis and classification using E-Cognition software was the next logical step. E-cognition used object orientated image analysis techniques that first grouped similar pixels into clusters (in a nested hierarchy of sizes), then analyzed and classified the clusters based on user defined training clusters. It was found that larger cluster sizes worked well for regional patterns, but small vegetation patches were under represented. This generalization had the greatest impact on spikerush patches, which were generally small and easily included in larger clusters of wheatgrass, cordgrass, or undifferentiated emergent wetland. Smaller clusters separated out the smaller vegetation patches, but also fragmented would be large single class patches. Since it was important to be able to identify the small patches, a smaller cluster size was selected knowing that the numerous small clusters that comprised a large single-cover patch could be aggregated (Figure 5).

A series of training clusters was created for each vegetation class (about 20-30 clusters each) then a classification was performed. The classification was assessed and mis-classified clusters were re-assigned as training clusters for the correct class, then the classification was run again. The process of train, classify, assess, re-train, and re-classify was performed many times until the final classified image appeared correct. As with the pixel based classification attempts, the large amount of variation within a class created complications and made it necessary to create many more training sites than would have been necessary for an image with less inter-class variation and/or more
distinct reflectance patterns between classes (Figure 6). Once the classification was finished, the classified image was exported as an ESRI polygon shapefile that was plotted and mailed to CBWA personnel for a preliminary accuracy assessment. The original shapefile was edited extensively by first appending a digitized version of the roads and disked areas, then by removing sliver polygons and small landcover patches (less than 50 square meters), then when the classification edits were received from CBWA personnel, the shapefile was further edited to correct the numerous misclassifications (Figure 7). Once completed, a 1:12,0000 aerial image mosaic and landcover map was generated (Appendices A and B).
Figure 6. Plot of the mean, minimum and maximum reflectance values for the clusters of the dominant vegetation classes. With all the mean values so close, and within the ranges of the other classes, it became clear why it was difficult to classify the vegetation types.

Assessment

Conducting a field accuracy assessment of the CBWA landcover map one year later is not a practical or accurate method to assess the map. Because of the dynamic nature of the vegetation communities at CBWA any accuracy assessment could falsely create errors of omission or commission due to changing vegetation patterns. Vegetation changes quickly at CBWA due to management practices (burning, disking) and due to natural changes that occur along the ecotone of a wetland between seasons and between years due to differences in rainfall. As a result of this variation, the only accuracy assessment done was the mailing of a draft map to CBWA personnel for review.
In general, since the last landcover map was made in 2002, there have been some
dramatic changes. Recent years been extremely dry at CBWA and the pools are either
very low on water or completely dry. The drought has given managers great access and
as a result the cattails that once nearly covered pools 2 and 3 and were patchy elsewhere,
were almost gone from this latest map. Park managers have actually discovered that they
needed to keep some of the cattails present as buffers along the drainage ditches to keep
them from silting in. The perimeter uplands also got drier and areas that were spikerush were often mapped as undifferentiated emergent wetland indicating that more dry land species were present (though there may have been spikerush present under the annual litter). A direct comparison of land cover areas between this year and previous maps is not very accurate since the landcover classes are not the same as in previous years, however the areas from this year are listed in Table 1 along with those areas for the 2002 mapping effort for general reference.

<table>
<thead>
<tr>
<th>Landcover</th>
<th>Area (02)</th>
<th>Area (05)</th>
<th>Landcover</th>
<th>Area (02)</th>
<th>Area (05)</th>
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<td>Intro. Annuals</td>
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<td>877.2</td>
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<td>Cordgrass</td>
<td>587.5</td>
<td>707.3</td>
<td>Agriculture</td>
<td>867.4</td>
<td>821.9</td>
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<td>Spikerush</td>
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<td>295.3</td>
<td>Trees</td>
<td>66.1</td>
<td>97.9</td>
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<tr>
<td>Undif. Emerg.</td>
<td>707.9</td>
<td>2657.8</td>
<td>Indian hemp</td>
<td>10.6</td>
<td>7.9</td>
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<td>Cattail</td>
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<td>874.9</td>
<td>Water</td>
<td>3728.6</td>
<td>1458.0</td>
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<td>Bulrush</td>
<td>NA</td>
<td>1215.2</td>
<td>Bare ground</td>
<td>2826.2</td>
<td>2908.3</td>
</tr>
</tbody>
</table>

Table 1. Land cover area comparison between current map and 2002 map of CBWA. Areas are reported in acres.

*To approximate the current classes, several classes from the 2002 map were combined to better reflect the 2005 map classes. Wheatgrass 05 = wheatgrass + abandoned agriculture from 2002, cattail 05 = cattail + sparse cattail from 2002. Bare ground 05 includes naturally bare uplands, exposed mudflats, while bare ground 02 includes only exposed mud flats.

**Conclusions and Recommendations**

The 2005-2006 land cover mapping project for the Cheyenne Bottoms Wildlife Area turned out to be a more complicated task than originally anticipated. The suite of situations and issues that kept surfacing presented numerous learning opportunities and constantly encouraged researchers to investigate new approaches.

When the imagery was finally flown in mid-October (due to technical delays), researchers were hoping they had not missed the optimal date for separating vegetation types. Early looks at the data showed high-resolution imagery with lots of detail and definable patterns, however, not far into the process it became apparent that this detail also include an abundant amount of within class variation, and that between class differences were less apparent. The large amount of variation found within classes, especially the wheatgrass and undifferentiated emergent wetland classes were primarily due to the high diversity of plant species associated with these communities (and the proportion of these species present at a given location). Since most vegetation types were going through senescence, most of the vegetation was looking “pretty dead”, especially after the hot and dry summer. Had it not been for the multispectral aspects of this camera, which created improved visual separation, this project would have been much harder. Though there was considerable overlap of spectral values that hindered computer classification, there were visual differences that aided interpretation (Figure 8). However, since the goal was to find a less subjective method than manual interpretation to classify the vegetation, we pursued the computer classification method.
Had the imagery been acquired earlier, at a time when there was better separation between classes, the more common pixel based classification methods first tried may have been more effective. Future efforts may want to investigate this, though researchers should not spend all their time on it and a re-sampling to five meters would be recommended. The classification effort using E-cognition also had its difficulties,

![Figure 8. NIR film from Aug. 2001 (left) and multispectral imagery from Oct. 2005 (right) over an area on the eastern edge of CBWA. Note the dramatic difference in appearance and how vegetation patterns are better defined in the multispectral image.](image)

with one downside being the ever-changing classification results due to the addition of training sites. When a classification error was found and corrected by turning that cluster into a training site for the correct class, that affected the broader classification parameters for the entire image and sometimes changed previously correctly classified clusters and created classification errors elsewhere on the image. Another limitation to the computer-based classification (pixel and cluster) was that it could not be used to map all the classes used in the previous years mapping efforts (33 land cover and land use classes). The distinction between land use types cannot be made using spectral information alone and is one advantage of manual interpretation and delineation.

Based on this effort, the recommended approach for future mapping efforts would be a hybrid approach where E-Cognition creates several hierarchies of clusters that are exported to shapefiles then manual photo interpretation would be performed with the shapefiles aggregated and labeled as necessary according to user interpretation. Using this hybrid approach would assist with landcover polygon delineation while allowing more control over the classification process and the inclusion of land use categories. The clusters generated provided an accurate delineation showing differences in vegetation conditions (classes), something that is often difficult to do with manual digitizing.
Additionally, if more detail were needed for a specific area, the finer level clusters could be used to guide a manual modification of the classification. Some management and infrastructure features like fireguards, levees, access roads and agricultural fields would benefit from manual delineation as well.

**Key points:**

Acquire imagery in late summer. Early summer may work as well as long as vegetation classes appear different from one another. Imagery acquired in mid summer or fall do not work well because everything is either “all green” or “all dead”.

Acquire coarser resolution imagery (1-2 meter, or resample). This will enlarge the image footprint (assisting geo referencing), reduce the total number of images, and reduce the amount of detail (spectral confusion) in the data to help with classification.

Take more field reference pictures and link to GIS with coordinates. Field notes should contain a list of common and occasional plant species present as well as a field based classification assignment.

The multispectral features of the DuncanTech imagery greatly enhance visual interpretation power, but due to the large amount of interclass variation, manual interpretation and digitizing may produce better results than pixel or cluster based classification methods.

**Appendices**

Appendix A:
Mosaic of aerial images

Appendix B:
1:15,000 scale landcover map

Appendix C:
Collection of natural color photographs over Cheyenne Bottoms
- C-1. View of northwest corner
- C-2. View of southwest pool 5
- C-3. View of southwest corner of pool 1B
- C-4. View of southwest corner of pool 5
- C-5. View of mitigation marsh
- C-6. View of northern 4A and 3B
Appendix A:

Mosaic of aerial images
Appendix B:

1:15,000 Scale landcover map
Appendix C-1. View of the Northwest corner of Cheyenne Bottoms showing the uplands of pool 5 and the disked and burned areas of pool 2.
Appendix C-2. The view looking north through the west edge of pool 5. The main office is in the upper left corner and the nesting islands are in the upper right.
Appendix C-3. The view looking north through the large cattail island in the Southwest corner of pool 1B. In this view it can be seen that the interior of the island is mostly dead cattail.
Appendix C-4. The view looking north across the southeast corner of pool 5. Central to this image is a teardrop depression of cattail with cordgrass to the north. The rectangles on either side of the teardrop are dominated by spikerush.
Appendix C-5. The view looking north across the mitigation wetland located in the southeast corner of Cheyenne Bottoms.
Appendix C-6. The view looking northwest across the northern edge of pool 4A (lower), 3B (upper), and the surrounding uplands. The pools are dry and bullrush (tan) is abundant.