Using Color Infrared Imagery and Remote Sensing Software to Classify Vegetation at Agassiz National Wildlife Refuge

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Abstract

The ability of remote sensing applications to accurately differentiate priority vegetation types was evaluated on a 664-hectare habitat management unit on Agassiz National Wildlife Refuge, located in Marshall County in northwest Minnesota. The Refuge is a diverse complex of wetland and upland habitats, largely inaccessible by foot. Its relative inaccessibility, coupled with the known occurrence of various non-native and invasive plant species, presents a critical need for inventory and monitoring of Refuge flora. Aggressive species such as narrow-leaved cattail (*Typha angustifolia)*, common reed (*Phragmites australis*), and willow (*Salix* spp.), all prevalent on the Refuge, are of special management interest. The ability to determine change in percent cover of priority vegetation types over time is important in evaluating the success or failure of habitat management practices and the Refuge's progress in meeting habitat objectives. This study was designed to measure the capabilities of Definiens eCognition and ERDAS™ software in delineating and classifying these vegetation types across both upland and wetland Refuge habitats.

Introduction

Refuge Overview

Agassiz National Wildlife Refuge (NWR), established in 1937, is situated in the tallgrass aspen parklands ecological province of Minnesota and lies between the coniferous forests to the north and east and the tallgrass prairie to the south and west. The Refuge itself is comprised of 24,890 hectare (ha) of wetland, shrubland, forestland, grassland, cropland, and black spruce-tamarack bog (U.S. Fish and Wildlife Service [USFWS], 2005). Its habitats are especially important for wildlife, such as migratory birds, moose, bear, wolves and deer, among a wide range of other fauna.

The Refuge has a complex water management system consisting of 26 pools, ranging from 16 to 4,047 ha in size, all of which are regulated by an intricate system of dikes and water control structures (USFWS, 2005).

Refuge habitats are primarily managed through water level manipulation, mowing, timber management, prescribed fire, and chemical application (USFWS, 2005). Agassiz NWR is managed to meet specific objectives, including the protection and production of migratory birds and other wildlife, and the provision of large-scale biodiversity. Vegetative inventory and monitoring must be completed to determine if management actions are achieving pre-defined Refuge objectives.

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Management Issues

Agassiz NWR, much like other Refuges within the NWR System, has been negatively impacted by aggressive invasive species, both native and non-native. Some non-native or "exotic" plant species were deliberately introduced to specific areas for specific purposes while other introductions were accidental. Exotic plants can cause drastic and expensive ecological (loss of biodiversity) and economic damage by outcompeting native species, causing shifts in both floral and faunal composition, and reducing the vegetative structural diversity that is important to wildlife. Reed canary grass (*Phalaris arundinacea*), Canada thistle (*Cirsium arvense*), and hybrid cattail (*Typha X glauca*) are particularly invasive at Agassiz NWR (USFWS, 2005).

Controlling the spread of aspen (*Populus tremuloides*), a native species, is one of the main habitat objectives on the Refuge. As aspen encroaches on historically open grassland areas it not only changes the floral and structural composition of the land, but it also alters bird community composition. For example, with less open grassland areas, certain grassland-dependant species (e.g., sharp-tailed grouse, Le Conte's sparrow, Nelson's sharp-tailed sparrow) are forced to locate more suitable habitat for breeding and nesting which, in some cases, are off-Refuge (USFWS, 2005).

Examples of two non-native species the Refuge is actively seeking to manage include narrow-leaved (*Typha angustifolia)* and hybrid cattail. These particular species, if left unmanaged, have the ability to out-compete other emergent wetland vegetation (e.g., sedge [*Carex* spp.], bulrush [*Schoenoplectus* spp.]), and convert open water to a cattail-choked marsh (Selbo and Snow, 2004). The repercussions of this would adversely affect many of the Refuge's over-water nesting birds (e.g., ducks, grebes, gulls). Most waterbird species find a 50:50 mix of open water and emergent vegetation (e.g., cattail [*Typha* spp.]), commonly referred to as "hemi-marsh," to be the ideal wetland condition (Weller and Spatcher, 1965; Fredrickson and Reid, 1988).

Historically, sedge meadows constituted more than three-quarters of Minnesota's original wetlands. However, abundance of sedge meadow habitat, both on and off Refuge, has been severely reduced due to human introduced hydrologic changes and encroachment by reed canary grass, willow (*Salix* spp.), and cattail. Although sedge meadow typically does not support the diversity of species usually associated with other wetland types, this rare and declining habitat type is indispensible for lilies, irises, native orchids, mallards, northern harriers, sandhill cranes, soras, Wilson's snipes, yellow rails, sedge wrens, among other species. On the Refuge, it is believed that prolonged high water stimulates the invasion of sedge meadows by cattails (USFWS, 2005).

Aggressive hybrid cattail also tends to out-compete important stands of emergent vegetation. Emergent habitat dominated by bulrush is found in Agassiz Pool and benefits species such as Franklin's gulls, grebes, diving ducks, black terns, and black-crowned night-herons (USFWS, 2005).

Vegetation Monitoring Techniques

Due to the vastness and inaccessibility of wetland habitats at Agassiz NWR, many ground-based vegetation monitoring techniques (e.g., plot frames, line transects) are not practical or cost effective. Therefore, the Refuge is exploring the possibility of utilizing color infrared (CIR) imagery, geographic information systems (GIS) and image processing software, such as ERDAS™ and Definiens eCognition, to classify, quantify, and accurately assess changes to vegetation composition over time. The ability to accurately quantify the increase or decrease of priority plant types (e.g., sedge, cattail) over time would allow Refuge staff to better evaluate the success or failure of their present management regime.

The main vegetation species of interest in this study include: aspen, bulrush, cattail, common reed, grasses (Family Poaceae), open water/submerged aquatic, reed canary grass, sedges, and willow.

Remote Sensing

Remote sensing is a broad field of study which can be described in various ways. According to Lillesand and Kieffer (1987), remote sensing is the science and art of collecting and interpreting data obtained by a device not in immediate contact with the phenomenon under investigation. Remote sensing, as it applies to this study, can be more narrowly defined as observation of the earth's land and water surfaces by means of reflected or emitted electromagnetic energy (Campbell, 2002). It is an invaluable tool which has improved substantially in recent years. Presently, remote sensing is commonly utilized in conjunction with GIS to link ancillary data to remotely sensed data (Campbell, 2002). One of the advantages of remote sensing is the nadir which provides a better understanding of spatial relationships and generates the ability to measure size, area, height, and depth (Campbell, 2002). Remotely sensed data can also aid in monitoring and detecting change over time. Utilized in combination with an appropriate field sample design, remote sensing is an efficient tool for landscape inventory and monitoring. Lastly, remote sensing, relative to photo interpretation (PI), allows more portions of the electromagnetic spectrum to be captured and analyzed such as the near infrared (IR), mid-IR, and even the thermal IR, rather than analyzing only the visible spectrum (Lillesand and Kiefer, 1987).

Color Infrared Imagery

Scanned CIR aerial photography was chosen for this study over both color and black and white film because of its broader spectral resolution and ability to better distinguish between vegetation types. CIR imagery delves into both the visible and the near IR spectrum, allowing more in depth analysis of the absorption and reflectance of light (Figure 1).

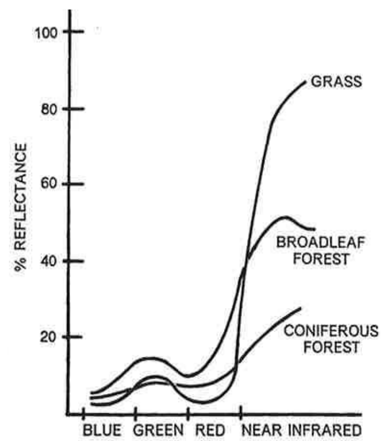

Figure 1. Depiction of increased spectral differentiation of vegetation in the near IR spectrum. Figure obtained from Campbell (2002).

The ability to go further into the electromagnetic spectrum is key for separation of vegetation classes (Campbell, 2002). According to Campbell (2002), the absorption and reflection of light in the near IR spectrum is determined by the structure of the spongy mesophyll tissue, not the plant pigments. Therefore, the bright IR reflectance observed from living vegetation is a result of the cavities within the leaf and internal reflection of IR radiation within the leaf's structure (Campbell, 2002).

Software

Definiens eCognition 4.0

eCognition is an object-based image processing software with capabilities of feature extraction and classification. This software implements the use of multi-resolution segmentation; a means of knowledge-free extraction of image objects. This bottom-up technique constructs hierarchical networks of images by merging smaller image objects into larger image objects (Definiens eCognition Professional Version 4.0 Manual, n.d.). Although eCognition has the capabilities to perform image classification, its main purpose in this project was multi-resolution segmentation.

ERDAS™ 9.2

ERDAS™ is a raster-based image processing software utilized for feature extraction and classification of satellite and aerial images. Capabilities include preparing, displaying, and enhancing digital images for use in GIS. Although this software has many applications, its primary purpose for this project was supervised image classification.

Objectives

1) Determine the ability of using both eCognition and ERDAS™ software to accurately classify priority vegetation classes from analysis of fall color IR imagery.

2) Determine if, in the future, Agassiz staff can analyze infrared imagery and obtain desired results.

Study Area

The original scope of this project was to generate a vegetation classification and evaluate accuracy levels for priority vegetation types on multiple Refuge habitat management units (HMUs). This included collecting ground truth data for 441 training sites and 276 randomly distributed accuracy sites across the 24,890-ha Refuge.

Due to time and resource (e.g., availability of and access to necessary software and computer hardware) constraints during the classification and analysis process, the scope of this project was reduced from a focus on the majority of the Refuge’s land base to a single 664–ha HMU (hereafter referred to as the Headquarters HMU). The Headquarters HMU is located in the south-central portion of the Refuge and was selected because of its suspected high (compared to other Refuge HMUs) diversity of priority plant species (Figure 2). Each priority vegetation class (see Methods section) was believed to have been represented within this HMU, making it a suitable study site.

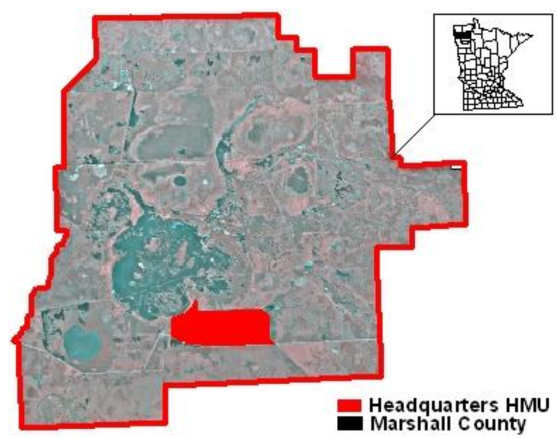

Figure 2. CIR image of Agassiz NWR showing Headquarters HMU study area.

Methods

Vegetation Classes

The vegetation classification was comprised of 10 vegetation classes; eight priority and two non-priority. Priority vegetation classes included bulrush, cattail, common reed, other grasses, reed canary grass, sedges, and willow. The two non-priority vegetation classes included open water/submerged aquatic and 'other.' The 'other' class included vegetation common to non-agricultural disturbed areas, like goldenrod (*Solidago* spp.), thistle (*Cirsium* spp.), and sweetclover (*Melilotus* spp.).

Data Acquisition

CIR imagery was acquired on 9 August, 2007 by an LMK 2000 aerial survey film camera made by Zeiss. This camera system used a 152 mm lens and 9X9 inch format. The imagery was flown at a scale of 1:15,840 and processed and scanned at 800 dots per inch (DPI) by the USFWS, Region 3, Division of Conservation Planning. A File Geodatabase (FGDB) containing Refuge data was obtained from the Division of Conservation Planning. The main purpose of the FGDB was data storage.

Agassiz NWR provided the remaining vector datasets for this project. These datasets included a Refuge boundary, roads, dikes, ditches, pools, prescribed fire boundaries, HMU boundaries, State Soil Geographic (STATSGO) and Soil Survey Geographic (SSURGO) data, national wetland inventory (NWI) data, Minnesota watershed data, and a 1997 vegetation classification of the Refuge completed by the U.S. Geological Survey – Upper Mississippi River Environmental Sciences Center (USGS-UMESC).

Although Agassiz NWR spans both zones 14 and 15 of the Universal Transverse Mercator (UTM) projection, all datasets were designated as North American Datum (NAD) 1983 zone 14N. Newly created vector datasets were also projected in NAD 1983 zone14N. The FGDB, however, was projected in GCS_North_American_1983.

Data Processing

eCognition Segmentation

Segmentations were created using eCognition Software. Multiple test segmentations were created for the Headquarters HMU by assigning different values to the following parameters: scale, color, and shape (compactness and smoothness). As stated by Thomas, Hendrix and Congalton (2003), scale is the most important parameter as it is the heterogeneity tolerance. This parameter determines the size of each individual polygon generated by the segmentation process. According to the (Definiens eCognition Professional Version 4.0 Manual, n.d.), the color parameter, can either increase or decrease the spectral homogeneity. By defining a color weight of 1.0, all emphasis is placed on the spectral homogeneity and the shape homogeneity is not taken into consideration. Changing the weight of the shape parameter can either increase or decrease the shape homogeneity of the resulting polygons. A high weight value for compactness outputs amorphously shaped feature polygons that do not adhere to major features, and defining a high weight value for smoothness allows for polygons that follow natural features (Thomas, Hendrix and Congalton (2003). The aforementioned parameters should be balanced on a per study basis and will depend on the specified objectives (Thomas, Hendrix and Congalton (2003).

The final segmentation for the Refuge was selected based on highest correlation between the delineated segments generated by eCognition and the actual vegetation transition zones observed on the ground. The segmentation which proved to have the highest correlation was generated using a scale parameter of 20, color set to 0.9, shape set to 0.1, compactness set to 0.7, and smoothness set to 0.3. The above parameters were utilized to generate the final segmentation for the entire Agassiz NWR. The final segmentation was exported as a shapefile and 717 polygons were selected from the segmentation and ground truthed.

Sample Design

Determining Total number of Training and Accuracy Sites

The total number of sample sites was determined by following Congalton and Green's (1999) calculations; however, the total number of recommended accuracy sites was doubled. Congalton and Green (1999) recommend multiplying the number of vegetation classes in the classification by 65 to establish a total number of sample sites. According to Congalton and Green (1999), this accepted (overall) level of accuracy was first described in Anderson et al. (1976) and has since been considered (by most) an adequate standard for assessing the accuracy of vegetation classifications. For this study, the open water/submerged aquatic class was not included in the calculation due to its unique (and easily photo-interpreted [PI'd]) spectral signature. Campbell (2007) explains that water absorbs light in the near IR versus vegetation which reflects highly in the near IR. The lack of light reflectance in water generates a uniquely dark signature making it easily identifiable. However, to obtain spectral signatures for the training and classification process in ERDAS^{TM}, 15 training sites were generated and ground truthed for open water/submerged aquatic. Also, the "other" class was not included in this calculation, as it was used as a "catch-all" for classifying vegetation encountered that did not match one of the priority vegetation types previously defined.

The total number of sample sites was calculated by multiplying the remaining eight classes by 65. Congalton and Green (1999) break the calculation down further; identifying the total number of training and accuracy sites per class. Following this methodology, 50 of the 65 sites from each vegetation class were used as training and the remaining 15 were used as accuracy.

In an attempt to increase the level of statistical validity, the total number of accuracy sites was doubled (instead of multiplying the number of priority vegetation classes by 15, the eight priority vegetation classes were multiplied by 30).

Excluded Areas

Prior to data collection and scope reduction of this project, specific areas of Agassiz NWR were excluded from the study. The northern two-thirds of the Agassiz pool were excluded because open water signatures are comparatively spectrally unique and show relatively little variability making it an easy class to PI (Congalton and Green, 1999). Due to the relative ease of PI of this class, training sites would be more valuable if distributed throughout other areas of the Refuge. The 1,619-ha Wilderness Area was not included because it is not an actively managed HMU. Remaining excluded areas (about 5,260 ha) were removed from the study because they had undergone active management (e.g., prescribed fire) after the 2007 CIR images were acquired, but prior to the collection of this study's ground truth data (Figure 3).

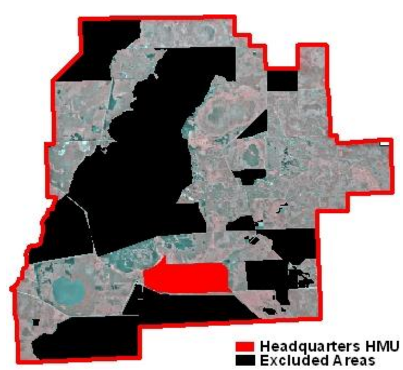

Figure 3. Map of Agassiz NWR showing areas excluded from study.

Training and Accuracy Site Selection

A 1,000 X 1,000-meter (m) grid was created using Hawth's Tools extension in ArcMap. The grid was utilized to stratify training polygons across the Refuge in order to obtain a good spectral representation of all vegetation classes.

Polygons were hand selected from the segmentation and attributed as training sites based on an observer-perceived diversity of spectral signatures. Figure 4 depicts how some cells (1,000 X 1,000 m) contained portions of excluded areas which were not allowed to contain training sites. Therefore, the number of training sites per cell was based on a set ratio. Cells containing 75 percent or more of excluded lands were allotted one training site, cells containing 50-74 percent were allotted two training sites and cells containing 25 percent or less were allotted three training sites. Cells not affected by the Refuge boundary or by the excluded areas could receive two or three training sites. A total of 441 training sites were selected.

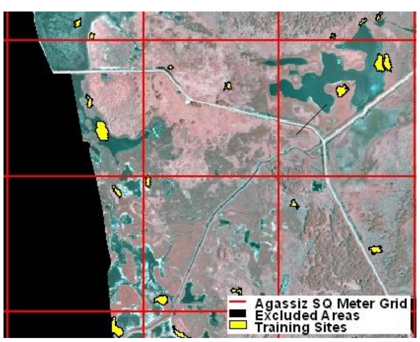

Figure 4. Example of training site distribution using a 1,000 X 1,000-m grid.

Accuracy sites were randomly generated using the Hawth's Tools extension in ArcMap. Only one point was assigned per individual segmentation-derived polygon. Polygons that received a point were attributed as accuracy sites. A total of 276 accuracy sites were randomly generated.

Training and accuracy sites were loaded onto a Trimble GeoXT global positioning system (GPS) receiver using ESRI's ArcPad software and Microsoft ActiveSync version 4.5. All data were collected in the field and stored directly in a Trimble GeoXT.

Field Methods for Assigning Vegetation Classes to Training and Accuracy Sites

Accuracy and training polygons were entered into the Vegetation Feature Class in the RLGIS Landscape and Habitat GeoDatabase. The RLGIS geodatabase has attributes and predefined domain values or pick lists for priority vegetation classes, non-associated plant species, and percent cover. The polygons, attributes and pick lists in the feature class were checked out to an ArcPad map. The ArcPad map was transferred to a Trimble GeoXT GPS using ActiveSync software. Training sites and accuracy sites were assigned the same symbology. This allowed sites to be ground truthed quickly and concurrently without introducing bias during the field data collection process.

Each training or accuracy polygon was transected along its longest straight line and an inventory of the vegetation present and associated percent cover was conducted by the observer. This information was immediately recorded in a Trimble GeoXT. Each polygon was then assigned to one of 10 vegetation classes based on a greater than 50 percent cover majority. If the dominant (≥50%) vegetation type was not one of the eight specific priority vegetation classes or open water/submerged aquatic it was recorded in the "other" class.

Sites not comprised of a dominant species (none ≥50%) or sites located in Refuge agricultural fields were discarded and replacement sites were generated within the corresponding cell. A total of 717 sites were ground truthed.

If the previously described method of assigning a polygon to a vegetation class was not successful, the polygon was transected as many times as necessary until the polygon could be assigned a vegetation class.

The majority of sites were ground truthed on foot; however, a portion of the sites were ground truthed via airboat, all terrain vehicle, or Marsh Master. Although different means of transportation were utilized, the same protocol for assigning a class to a polygon was followed.

Checking Data back into the FGDB

Data collected in the field was downloaded daily to a computer using ActiveSync software and checked back into the RLGIS FGDB using ArcPad Software. This ensured multiple days of data would not be lost or erased. After all study sites had been ground truthed and the data collection process was complete, the two FGDBs (two Refuge staff collected field data) were compiled into a single FGDB using the load objects option in ArcCatalog.

Generating a Vegetation Classification using Image Processing Software

Training sets were selected by vegetation class from the original FGDB and exported to new shapefiles. Each class shapefile was loaded into eCognition and re-segmented at a scale parameter of 10 to delineate spectrally homogeneous sub-polygons (Figure 5, Image A) within each training polygon (Figure 5, Image B). The emphasis of the re-segmentation was spectral homogeneity, therefore, the shape factor (compactness and smoothness) was given a weighted value of zero. The purpose of the re-segmentation was to increase the possibility of spectral separation during the classification process. Spectral separation can be maximized by removing signatures of one or more sub-polygons that are not spectrally representative of the majority class assigned to a training polygon.

Image A. Image B.

Figure 5. A re-segmented (scale parameter 10) training polygon depicting sub-polygons (Image A) and training polygon derived from the original eCognition segmentation (Image B).

A unique polygon ID was assigned to each re-segmented polygon (Figure 5, Image A). The re-segmented class shapefiles were then loaded into ERDAS™ and corresponding signatures and their unique IDs were extracted using the Signature Editor Tool under the Classifier Menu. Linking the unique polygon ID to the spectral signature enabled individual signatures to be identified both in ArcMap and in ERDAS™. This was a vital step which allowed specific spectral signatures to be added to, or removed from, the training signature set and the classification as needed. Once the training signature sets were generated for each vegetation class they were merged into one signature set using the Signature Editor Tool and a maximum likelihood classification was completed in ERDAS™ using the supervised classification tool under the classifier menu. During this process ERDAS™ analyzed each individual pixel within the Headquarters HMU and matched it to a corresponding class based on the statistics of the training signatures (i.e., brightness values).

A majority was then run on the classified image using the Zonal Attributes to Polygon Attributes Tool under the Vector Utilities Menu. All polygons from the eCognition-generated segmentation were then classified based on the most prominent class found within each segment (the majority).

Generating maximum likelihood classifications was a repetitive process. For each individual classification a new signature set was created by studying the vegetation and percent cover within each polygon in conjunction with visually analyzing the corresponding spectral signature. Signatures were plotted and histograms were generated to determine the level of spectral confusion between individual signatures, as well as different vegetation classes. Figures 6 and 8 illustrate good spectral separability between the signatures as shown by histograms and plots of mean brightness values. Figures 7 and 9 illustrate poor spectral separability between the signatures as shown by histograms and plots of mean brightness values. Plots and histograms were analyzed to determine spectral signatures with minimum spectral confusion and maximum spectral separation between vegetation classes (Donnelly, 2007). Signatures with good spectral separability were kept and used to generate a classification. Signatures with poor spectral separability were not included in the signature set used to generate a classification.

Dividing the HMU into Subsets

Headquarters HMU was divided into east and west subsets and classifications were generated for each subset. Unique signature sets were used for each of the classifications in order to decrease spectral confusion. The east half of the HMU, because of its drier condition, was classified using spectral

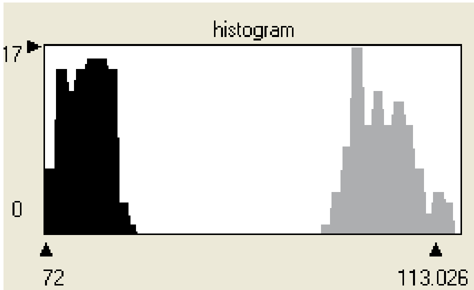

Figure 6. An illustration of good spectral separability between cattail (black) and common reed (gray).

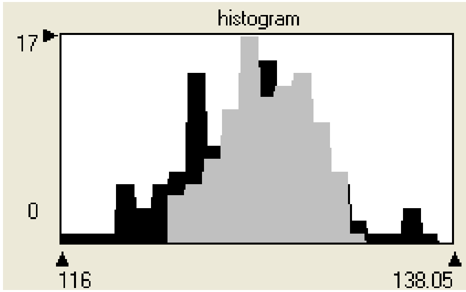

Figure 7. An illustration of poor spectral separability between reed canary grass (black) and grass (grey).

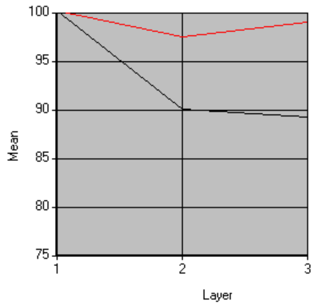

Figure 8. An illustration of good spectral separability between common reed (black) and sedge (red).

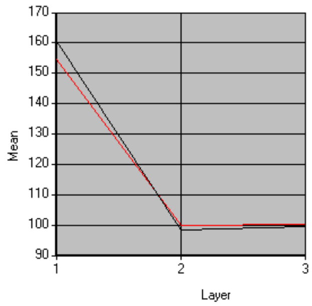

Figure 9. An illustration of poor spectral separability between sedge (red) and grass (black).

signature sets for common reed, other grasses, "other," reed canary grass, sedges, and a greatly reduced cattail signature set. Due to the west half of the HMU being much more hydric, the classification was generated using the spectral signature sets for common reed, other grasses, open water/submerged aquatic, sedges, and a much more diverse signature set for cattail. Bulrush was included in some classifications; however, the final classifications were generated without bulrush signatures, because it could not reliably be spectrally separated from other vegetation classes.

Photo Interpretation

Signature sets for willow and aspen were omitted from classifications to reduce spectral confusion with shadows and other vegetation classes (specifically cattail). Areas of willow and aspen were PI'd and assigned to the appropriate class (willow or aspen) by changing the majority values previously assigned to the eCognition-generated polygons during the classification process in ERDAS™.

Further Analysis

Data Collection

A second set of training and accuracy data were collected on 17-18 October, 2009, to help mitigate a lack of accuracy sites resulting from the study scope reduction to classify the Headquarters HMU only. These data were collected using the same protocol as the original set of data; however, centroids were also collected within the ground-truthed polygons.

Assessing Imagery

An unsigned eight-bit continuous (enhanced) mosaiced image of the Refuge with 2-m resolution was the initial base layer for this study. An unenhanced single eight-bit continuous image covering the extent of Headquarters HMU, with 2-m resolution was also classified. The 2-m unenhanced image was added to the study and classified as a means of assessing how classifications generated on enhanced images (altered pixel brightness values) compare to classifications generated from original pixel values.

Training Set Development from Seed Pixels

In an attempt to increase the accuracy of individual vegetation classes, as well as the overall accuracy of the classification, seed pixels were used to generate regions of pixels with homogenous and separable spectral response. Training points were collected on 17-18 October, 2009 and were used to identify seed pixels in ERDAS™.

A seed pixel, as defined by ERDAS™ Imagine (1997), is a single pixel that is representative of a training set. Contiguous pixels are compared to the seed pixel and are included in a region (the training polygon) if spectral parameters are met. These parameters include Euclidian distance of spectral values and number of pixels.

The unenhanced east subset image was loaded into an ERDAS™ viewer. Points representative of a homogeneous vegetation class were selected and exported to a training points shapefile and used for growing regions. The parameters for growing a region were set to a minimum of 50 pixels and a maximum of 100 contiguous pixels and the spectral Euclidean distance varied from seed to seed (because it had to abide by the minimum and maximum pixel parameters).

The spectral signatures created using the Region Growing Properties Tool were saved as a single signature set and used to generate a classification. Signatures were removed from the generated signature set based on the resulting classification and on spectral separability in order to increase the accuracy. Classifications were re-generated using different signature sets until accuracies could no longer be improved. This procedure was repeated for the west subset. Once a final signature set was established for the non-enhanced image, the seed pixels were loaded into ERDAS™ and used as seeds to generate signature sets for the mosaiced image.

Classification

A maximum likelihood classification was completed in ERDAS™ using the aforementioned tools and procedures (see Generating a Vegetation Classification using Image Processing Software section). A majority was then run on the classified image and was obtained in shapefile format.

Accuracy Assessment

The east and west subset majority shapefiles of the unenhanced image were merged together using the Merge Tool in ArcMap Data Management Toolbox in order to obtain one shapefile with the majority values for both the east and west subsets. The merged shapefile was then converted into a grid raster dataset using the Feature to Raster Tool from the Conversion Toolbox. Using the ERDAS™ Import/Export option under the Import Menu, the grid raster dataset was converted into .img format. This procedure was repeated for the shapefiles obtained from the mosaiced image classification.

Coordinates were generated for the accuracy points collected in October 2009. The coordinates along with the corresponding field data were exported from the attribute table as a text file.

The classified image file was opened in an ERDAS™ viewer and the layer type was edited from continuous type to a thematic type. An Accuracy Assessment Viewer was also opened and linked to the viewer containing the classified image. The Accuracy Points text file containing the x-y coordinates was imported into the Accuracy Assessment Viewer and the points were displayed in the ERDAS™ viewer containing the classified image. The Show Class Values option was selected under the Edit Menu to display the classified class value which corresponded to each individual accuracy point. An accuracy report was generated selecting the Accuracy Report option under the Report Menu.

Results

The overall accuracy of 51.9% for the unenhanced image proved to have a better overall accuracy than the mosaiced image's 48.1% (Table 1 and 2, Figure 10 and 11).

Accuracy per vegetation class varied significantly. Aspen and willow were PI'd for both the mosaiced and the unenhanced image. The PI eliminated errors of commission because it allowed for the exclusion of two signature sets from the classification. An error of commission identifies a polygon as belonging to a class when in reality the field data shows it belonging to a different class (Congalton and Green, 1999). The elimination of the aspen and willow signature sets made it impossible for an eCognition-generated polygon to be misclassified in the classification as either of those two classes. However, it did not automatically eliminate the possibility of an error of omission. An error of omission occurs when an area is not included in the correct class (Congalton and Green, 1999). PI of these two classes, not only yielded more accurate results on a per class basis than what would have been obtained had they been classified using ERDAS™, it also reduced the probability of spectral confusion between the remaining classes.

The open water/submerged aquatic class was more accurately classified using the unenhanced image, yielding an accuracy of 67% versus 33% obtained from the classification using the mosaiced image (Table 1 and 2).

Reed canary grass, common reed, 'other,' and other grasses were all classified more accurately using the unenhanced image than when utilizing the mosaiced image. Although the aforementioned vegetation classes were more accurately classified using the unenhanced image, the degree of accuracy varied greatly amongst vegetation classes. The 'other' class obtained the lowest accuracy (11%) from the above mentioned vegetation classes. This vegetation class was confused almost equally with reed canary grass, cattail, and other grasses (Table 1 and 2).

Although the enhanced image produced a higher accuracy for five of the 10 vegetation classes, as well as a 3.8% better overall accuracy, the mosaiced image generated better accuracy for the sedge and cattail vegetation classes. The mosaiced image produced 60% accuracy for sedge and 85% accuracy for cattail, whereas the unenhanced image obtained 40% accuracy for sedge and 77% accuracy for cattail.

Bulrush obtained 0% accuracy by default (in both classifications) as a result of the exclusion of its signature set from the classification. Also, it was not PI'd because of the complexity of its spectral signature.

The only vegetation class, classified by ERDAS ™, which met the pre-established acceptable level of accuracy (≥85% as per Congalton and Green, 1999) was the cattail class generated from the mosaiced image. Even with the aid of the PI, both vegetation classifications (unenhanced and mosaiced) failed to meet the overall ≥85% accuracy goal. Based on the results (i.e., accuracy assessments) of this study, the analysis of CIR imagery in conjunction with image processing software cannot be used to accurately (≥85%) classify priority plant groups and ultimately quantify percent change over time on Agassiz NWR without changes to imagery used and/or vegetation categories.

Discussion

Date of Field Data Collection

To complete the 2008 field data collection effort before vegetation senesced and snow covered the landscape, it was necessary to utilize and segment a 2007 CIR image of the Refuge. The 2007 imagery was used as the base layer for all data preparation and analysis. One-year-old imagery (from August 2007) allowed image segmentation and training site selection to be completed in May and June 2008 and ground truthing to begin in late July 2008. Photographs taken of the Refuge in August 2008 could not have been processed, scanned, and returned to Agassiz NWR with enough time to experiment with segmentation parameters, segment the imagery, and complete the data collection effort before winter arrived.

The utilization of one-year-old imagery may have led to unnecessary discrepancies and spectral confusion during the training process in ERDAS™. Conditions on the ground vary with time; therefore, an August image of the landscape may depict different conditions than ground truthed data collected months ahead or months after the imagery was taken.

For example, a study site photographed in early spring with the

Table 1. Accuracy assessment of the mosaiced image classification illustrating errors of omission and commission and the user's and producer's accuracy. Overall classification accuracy 48.1%.

Mosaiced Image Classification												
	Reference										User	
Classification	SDG	BUL	OWSA	RCG	CR	ASP	WIL	CAT	OTH	GRA	**TOTAL**	Accuracy
Sedge spp.	18	0	3	7	4	0	0	1	3	11	47	38%
Bulrush spp.	0	0	0	0	0	0	0	0	0	0	0	0%
Open Water / submerged aquatic	0	0	2	0	0	0	0	0	0	0	2	100%
Reed Canary Grass	2	0	0	3	0	0	0	0	1	1	7	43%
Common Reed	0	0	0	1	5	0	0	0	0	0	6	83%
Aspen spp.	0	0	0	0	0	6	0	0	0	0	6	100%
Willow spp.	0	0	0	0	0	0	12	0	0	0	12	100%
Cattail spp.	1	2	0	0	0	0	0	11	2	0	16	69%
Other	0	0	0	5	4	0	0	0	0	2	11	0%
Grass spp.	9	1	1	1	3	0	0	1	3	7	26	27%
Producer TOTAL	30	3	6	17	16	6	12	13	9	21	133	
Accuracy	60%	0%	33%	18%	31%	100%	100%	85%	0%	33%		

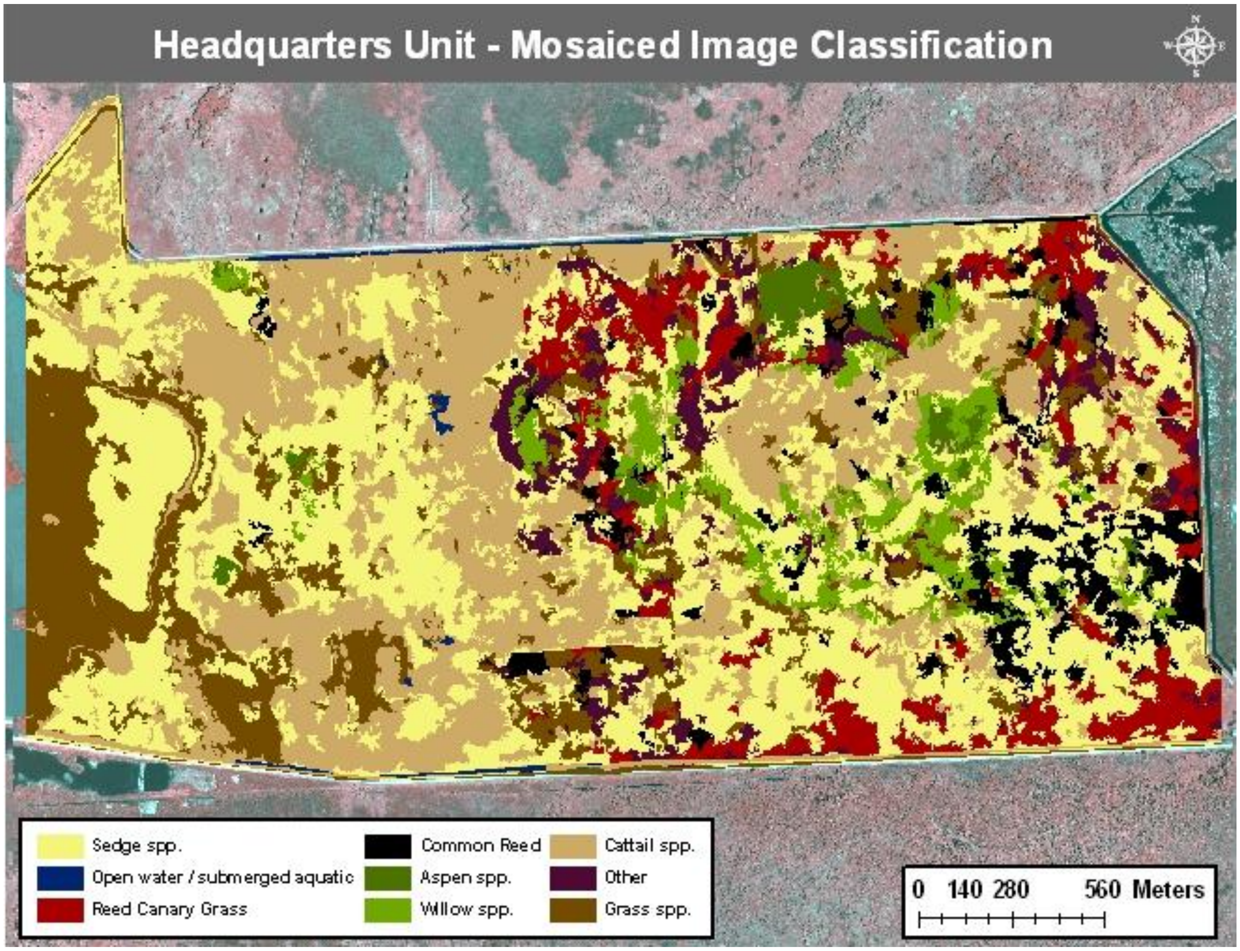

Figure 10. Final ERDAS™ classification of the mosaiced Headquarters HMU.

Table 2. Accuracy assessment of the unenhanced image classification illustrating errors of omission and commission and the user's and producer's accuracy. Overall classification accuracy 51.9%.

Unenhanced Image Classification												
	Reference										User	
Classification	SDG	BUL	OWSA	RCG	CR	ASP	WIL	CAT	OTH	GRA	**TOTAL**	Accuracy
Sedge spp.	12	0	0	5	1	0	0	1	0	2	21	57%
Bulrush spp.	0	0	0	0	0	0	0	0	0	0	0	0%
Open Water / submerged aquatic	0	1	4	0	0	0	0	0	0	0	5	80%
Reed Canary Grass	4	0	0	5	1	0	0	1	2	1	14	36%
Common Reed	2	0	0	0	8	0	0	1	1	4	16	50%
Aspen spp.	0	0	0	0	0	6	0	0	0	0	6	100%
Willow spp.	0	0	0	0	0	0	12	0	0	0	12	100%
Cattail spp.	2	2	2	0	0	0	0	10	2	0	18	56%
Other	1	0	0	6	4	0	0	0	1	3	15	7%
Grass spp.	9	0	0	1	2	0	0	0	3	11	26	42%
Producer TOTAL	30	3	6	17	16	6	12	13	9	21	133	
Accuracy	40%	0%	67%	29%	50%	100%	100%	77%	11%	52%		

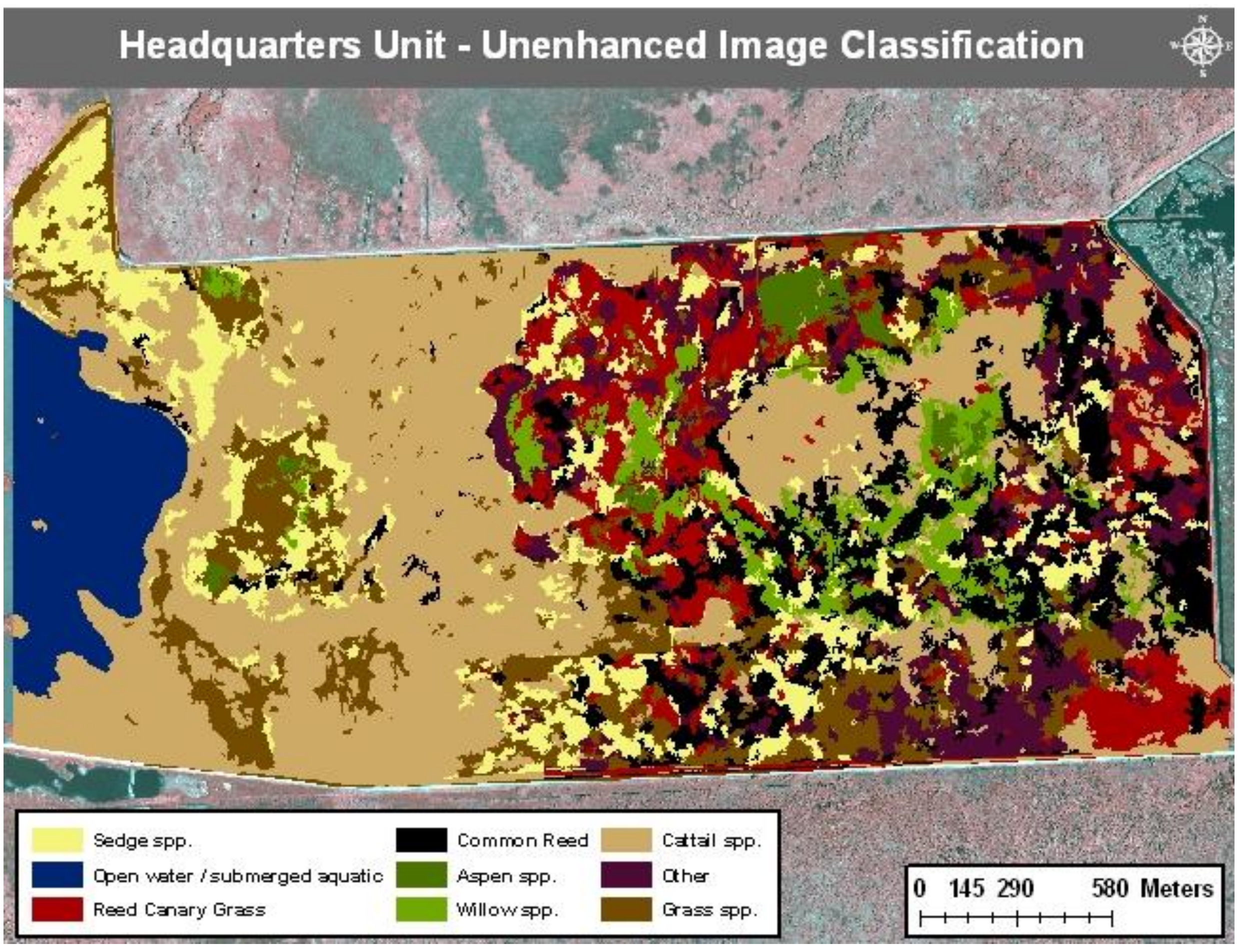

Figure 11. Final ERDAS^{TM} classification of the unenhanced Headquarters HMU.

appearance of water in a specific area may be identified as sedge when ground truthed in late summer. Data with such discrepancies introduce spectral confusion into a classification because the resulting signature sets are no longer representative of a homogeneous class; rather they are representative of a mixture of two or more classes. This specific example could result in open water areas being misclassified as sedge.

To decrease spectral confusion, data should be collected as close to the flight date as possible. However, if this is unfeasible, reference data should be collected within the same season. Obtaining imagery and collecting data at staggered time intervals increases the possibility of error and impacts the accuracy of the classification. Resulting misclassifications are not an accurate representation of the software's capabilities; rather they are caused by landscape change and misrepresentative reference data (Congalton and Green, 1999).

Film

The KODAK AEROCHROME III IR Film 1443 used in this study consisted of three bands: green, blue, and red/IR. This film is sensitive to ultraviolet, visible, and IR radiation to approximately 900 nm (KODAK, n.d.). Since the KODAK CIR film is only sensitive up to 900 nm, it may have been a limiting factor to spectral separability of plant groups. When sensor sensitivity encompasses more of the near IR spectrum, spectral separability increases for vegetation. In future studies, a CIR image encompassing more of the near IR spectrum may yield higher accuracies.

Image Enhancement

ERDAS™ Image Equalizer software was implemented to create an aesthetically pleasing CIR image mosaic from many individual 2007 CIR photographs. Image enhancement is conducted to improve the visual appearance of an image and its interpretability by amplifying slight differences in features, making them more apparent to the user (Lillesand and Kiefer, 1987). It is important to note that image enhancement is performed without regard for the integrity of the original pixel brightness values (Campbell, 2002). According to Campbell (2002), image enhancement will alter the original pixel values causing them to lose their relationship to the original brightnesses on the ground.

Image Equalizer calculated a histogram of brightness values for the 2007 CIR photographs utilized in this study. The histograms were then averaged and applied to each individual image which made up the final mosaic of the Refuge. Enhancing the image with this software resulted in altered pixel values; while some pixels were assigned new values other pixels retained their original values.

Enhancement of the 2007 Agassiz image resulted in vegetation classifications generated from altered pixel values. The alterations of the pixel values could have been responsible for some of the spectral confusion between various vegetation classes. Vegetation classifications and change detection should be generated from original pixel values (Campbell, 2002). If generating a classification on enhanced imagery, an increased number of training and accuracy sites and a well distributed sample design can mitigate for some of the introduced error.

Atmospheric Conditions

All energy must pass through the atmosphere before reaching a remote sensing instrument. According to Lillesand

and Kiefer (1987), the atmospheric effects on energy can vary throughout a flight and will usually vary substantially from mission to mission. Impacts of atmospheric conditions such as dust, smoke, haze, or clouds may also vary depending on the height at which the senor is carried; low flying aircraft may experience minor impacts in comparison to sensors carried by satellites (Campbell, 2002). Because light is altered (i.e., scattered, reflected, absorbed) in intensity and wavelength by particles and gases in the earth's atmosphere, pixel brightness values are altered, thus degrading the quality of the image (Campbell, 2007). However, these pixel value alterations can be mitigated for using the Atmospheric Adjustment Tool in ERDAS™. Adjustments to mitigate for atmospheric conditions were not made on the imagery utilized in this study. This may have introduced some degree of inaccuracy.

Multi-Temporal Imagery

Multi-temporal imagery was not available for this project and was a limiting factor. To help compensate for the lack of multiple dates of imagery, the August image was used in conjunction with the following ancillary data: STATSGO and SSURGO soils, NWI data, and a 1997 Refuge vegetation classification completed by USGS-UMESC.

Dates of multi-temporal data, which will prove most helpful, will vary from one study to the next depending on the vegetation being mapped and habitat types present (Ozesmi and Bauer, 2002). Because not all vegetation leafs out simultaneously, amount of litter varies from species to species, and chlorophyll amounts are dependent on individual species and time of year; having multi-temporal imagery available for this study would have improved the accuracy of the classification. A spring image of the Headquarters HMU may have reduced some of the spectral confusion between sedge, reed canary grass, common reed, and other grasses.

Multi-temporal imagery may have also better differentiated between warm season and cool season grasses. Species such as big bluestem (*Andropogon gerardii)* and reed canary grass mature at different times and therefore the time frame during which their spectral signatures are the most representative vary. Reed canary grass, being a cool season grass, would better exhibit spectral differentiation in spring and early summer. Big bluestem, as a warm season grass, is harder to spectrally differentiate until later in the summer. Other vegetation (for example different species of grass) matures in late spring or early summer and have their most unique spectral response at that time.

Change in Scope of Work

Specific research objectives must be pre-defined and understood prior to generating a sample design and establishing data collection methods. The objectives of a study will always be dependent upon the mission of the Refuge, the complexity of the landscape, time, and funding. Once the objectives have been established, detail of the classification and required precision of data and accuracy assessment can be determined.

The sample design and protocol will vary depending on whether the goal is to determine gross change across a refuge or to detect minute change in percent cover of less abundant vegetation species. Flying a specific area with an established goal or objective may yield more accurate data than analysis completed on imagery which was obtained for a different purpose (Cowardin, 1974). No matter what the objective, pre-defined qualitative and quantitative measures must always be in place prior to data collection.

As a result of the reduction in scope, the number of training and accuracy sites within the Headquarters HMU did not meet the minimum number recommended by Congalton and Green (1999) for the Headquarters study area. In order to resolve this problem, training signatures were incorporated from adjacent areas and utilized for the maximum likelihood classification, as well as for the majority. Official accuracy assessments were not completed on these classifications due to the lack of accuracy assessment sites. However, based on knowledge of the area and time spent out in the field it was noted that the overall accuracy of these classifications were low.

A second set of training and accuracy sites were collected (17-18 October, 2009) and utilized to generate the vegetation classifications and carry out accuracy assessments. Although, the accuracy of the classifications increased, this could have been due to utilizing only spectral signatures from within the Headquarters HMU or from generating training sets from seed pixels, or from a combination of the two. Additionally, it cannot be overlooked that the data utilized in the final classification were collected two years post image acquisition. Therefore, the reference and accuracy data (collected in the field) could have been erroneous data yielding false accuracies.

Also, although training sets developed from seed pixels generate more spectrally homogenous signatures, it is a very time intensive task and can be a limiting factor when dealing with large sample sizes and when comparing multiple images' accuracies.

Sample Design

Distribution of Data Collection

Selection of a proper sample design is vital to any study and is often dictated by time and resources. Had the project not deviated from the intended scope, the total number of training and accuracy sites determined using Congalton and Green's (1999) calculation would have been sufficient to complete the vegetation classification and the accuracy assessment. However, the original training sites for this study did not equally represent all of the vegetation classes. For this particular study, an equal number of training sites per class, for the more commonly occurring vegetation classes, should have been collected and the total number of training sites for the less abundant vegetation classes (i.e., bulrush) should have been increased. More ground truthed sites should have been collected in the field during the initial data collection process after it was noted that some vegetation classes were underrepresented. The number of training samples per category can and should be adjusted based on the objectives of the study and on the variability and relative importance (Congalton and Green, 1999). Sample sites for each class must be distributed throughout the study area. Sheer number will not necessarily provide a representative distribution of vegetation classes among the training sites.

Sample Distribution

To reduce the time and cost of data collection, the use of a buffer around existing roads and trails to determine acceptable areas for training and accuracy sites would be acceptable. This method may only be implemented if the network of roads and trails covers the extent of the study area. If the only roads and trails within the study area are clustered in a certain area (i.e., the northwest corner), some off road and trail data collection will be necessary to obtain a good distribution and representation of spectral signatures.

Spectral Confusion within Training Polygons

Training polygons were assigned to a vegetation class based on a 50 percent cover majority. Following this protocol, training polygons could contain spectral signatures from multiple vegetation classes. For example: a polygon comprised of 55% sedge, 25% other grasses and 20% 'other', based on its vegetation breakdown and the 50 percent cover majority, would be classified as sedge. After completing the data collection, all spectral signatures from the training polygons identified as sedge would then be combined to generate a complete sedge signature set. This signature set would not be a homogeneous representation of the sedge signatures, because other classes were present within the sedge training sites. Some of this spectral confusion can be eliminated by PI, by adding and removing spectral signatures from sub-polygons, and with the aid of ancillary data. However, the final signature set may still be a misrepresentation of the actual spectral range of the specific vegetation class. Also, classifying an image using heterogeneous signature sets and outputting it to homogeneous vegetation classes will introduce error which cannot be mitigated.

Using this protocol, spectral confusion could also be introduced as a result of a polygon's percent cover breakdown being close to 50:50. For example: a polygon comprised of 52 percent sedge and 48 percent other grasses is incorrectly assigned to other grasses because of the lack of a definite dominant vegetation class. After completing a classification and running a majority on this polygon, ERDAS™ determined the majority to be sedge. The discrepancies observed when comparing the software-generated classification to the ground-truthed accuracy data, at times, were not representative of the software's capabilities. Rather, they were representative of the spectral confusion introduced as a result of the field methods implemented. Erroneous data collection in the field can decrease the accuracy of the vegetation classification, even though the software classified it correctly.

In future studies, erroneous data collection of both training and accuracy sites could be drastically reduced if the percent cover necessary to assign a polygon to a vegetation class is increased to 100% for a single class. Campbell (2002) states the most important property of a good training site is its uniformity. A training polygon must be representative of a homogeneous vegetation class. This however, can only be determined by ground truthing sites. If visited sites are not homogeneous they must be discarded and selection of replacement sites is necessary. If too many sites are discarded the image may be re-segmented or vegetation classes may be combined. These decisions are determined on a per study basis. If a polygon were truly representative of a homogenous class, spectral confusion between vegetation classes, as seen in figures 8 and 9, would not be as severe a problem during the classification procedures.

Photo Interpretation

During the creation of the signature sets, training polygons were PI'd and the spectral signatures were visually analyzed in an effort to reduce the spectral confusion within each of the class' signature sets. Also, willow and aspen were PI'd due to spectral confusion with other signatures, specifically cattail.

Had fine-scale elevation data such as Light Detection and Ranging (LIDAR) been available, the need to PI could have been reduced. The implementation of LIDAR has the potential to improve spectral separability by distinguishing between vegetation classes based on the differences in vegetation height (McCauley and Jenkins, 2005). The ability to distinguish vegetation types in wetland areas would have been helpful in differentiating between reed canary grass and common reed and between sedge and other grasses.

Management Implications

Defining the Scope of the Project

Aside from the specialized skill set required, access to software and adequate technology is also a limiting factor. This study was only doable because of time and resources offered by other USFWS personnel. Without Region 2, Division of Biological Service's Definiens eCognition software and Region 3, Division of Conservation Planning's ERDAS™ software, the cost of the remote sensing software alone would have surpassed the project's funding. Budgets for both field offices and the regional office could be a limiting factor for availability of image processing software in the future.

Alternatives to using remote sensing software would include hand digitizing and PI, the use of stereo imagery, or contracting these information needs out to the UMESC, or another agency or private firm with expertise in vegetation mapping.

Conclusion

The results showed vegetation classifications of upland and wetland habitats on Agassiz NWR cannot be completed accurately using only CIR imagery and image processing software. The accuracy of the vegetation classification may be improved by using multi-temporal data or by combining vegetation classes into physiognomically similar vegetation classes (i.e., mesic grassland, herbaceous, wetland shrub, shrubland, wetland forest, upland forest, freshwater marsh; Ozesmi and Bauer, 2002).

In future studies, the combined use of image processing software, PI, multi-temporal image data, imagery encompassing more of the near IR spectrum, and LIDAR is recommended to increase the accuracy of vegetation classifications. Classifications would also benefit from being divided into physiognomic classes, by masking out areas of known vegetation occurrence or which are easily PI'd such as water and forest (Ozesmi and Bauer, 2002).

A good representative sample design, accurate data collection, and knowledge of the area are also vital components of a study such as the one completed for Agassiz NWR.

Based on the accuracy results, the time necessary to generate a classification, and the remote sensing skills required to efficiently implement remote sensing softwares, it is unfeasible for Agassiz NWR to generate their own vegetation classifications on site and obtain acceptable levels of accuracy (>85%).

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