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MULTI-CRITERIA WETLANDS MAPPING USING AN INTEGRATED PIXEL-BASED AND OBJECT-BASED CLASSIFICATION APPROACH

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September 2008

COLORADO DEPARTMENT OF TRANSPORTATION
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16. Abstract
The Colorado Department of Transportation (CDOT) has the challenging task of protecting the environment while developing and maintaining the best transportation systems and services possible for the citizens of Colorado. Among these tasks, a wetland inventory database is a key component required to meet the environmental protection mandate. The subject research project is directed to developing a semi-automated method to identify and classify inland wetlands in the northern Front Range area of Colorado. A goal of the project is to produce a database that accurately records wetland locations based on the classification system that is commonly used by many organization and institutions. The methodology is based on satellite imagery, high resolution aerial photos, and digital elevation model data in conjunction with field global positioning system data collections. Satellite imagery being used includes moderate resolution LANDSAT 7 ETM+, Terra ASTER, and EO-1 Hyperion/ALI. The aerial photography is from the National Agriculture Imagery Program and is mainly used for validation and sample collection purposes. The EO-1 imagery has high spectral resolution and is used to develop a wetlands spectrum signature library which is then used to observe the correlations between EO-1 and LANDSAT 7 and ASTER image bands. The image processing approach being applied uses both pixel-based and object-based classification techniques; the object-based technique accounts for the pattern of neighboring pixels and wetland boundary shapes. The variables generated for object-based classification algorithm are extracted from multi-spectral imagery and include image texture, wetland shapes, greenness, wetness, brightness, normalized difference vegetation index, principal components, stream networks, biological soil crust index, and land thermal fluctuation. In the final stage, these variables are incorporated into a hierarchical rule creation for facilitating the wetland classification operation. To complete the tasks, the software used include ArcGIS®, ENVI®, DEFINIENS® Professional. Results of the research indicate a high correspondence with wetlands mapped by field biologists and identification of additional wetlands not previously recognized.

17. Keywords
USACE Wetlands Delineation Manual, wetland inventory databases, remote sensing, geographic information systems (GIS), global positioning systems (GPS), land use change, hydrological analysis

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EXECUTIVE SUMMARY

One of the major issues when attempting to conduct environmental assessments in Colorado and elsewhere is the lack of information on wetlands. Functionally, wetlands serve a critical role in benefiting the state's water resources by providing flood and erosion control, water quality maintenance, and habitat and other ecosystem functions. But wetlands are vanishing rapidly. Over the past two centuries, approximately 40% to 60% (0.4-1.2 million ha; 1-3 million ac) of the original wetland areas of Colorado has been lost (Dahl 1990, Wilen 1995). The subject research project is directed to developing a semi-automated method to identify and classify inland wetlands in the northern Front Range area of Colorado. A goal of the project is to develop an effective wetland mapping methodology so that a database that accurately records wetland locations can be created. The methodology is based on satellite imagery, high resolution aerial photos and digital elevation model data in conjunction with field global positioning system data collections. Satellite imagery used includes moderate resolution LANDSAT 7 ETM+, Terra ASTER, and EO-1 Hyperion/ALI. The aerial photography is from the National Agriculture Imagery Program. The EO-1 imagery has high spectral resolution and is used to develop a wetlands spectrum signature library which is then used to establish correlations between EO-1 and LANDSAT 7 and ASTER image bands. The image processing approach being applied uses both pixel-based and object-based classification techniques; the object-based technique accounts for the pattern of neighboring pixels (i.e. context) and wetland boundary shapes. The variables generated for object-based classification algorithm are extracted from multi-spectral imagery and include image texture, wetland shapes, greenness, wetness, brightness, normalized difference vegetation index, principal components, stream networks, biological soil crust index, and land thermal fluctuation. Software used in the process includes ArcGIS®, ENVI®, and DEFINIENS® Professional remote sensing software. Results of the research indicate a high correspondence with wetlands mapped by field biologists and identification of additional wetlands not previously recognized. The results of this research are expected to be supportive to transportation planning by the Colorado Department of Transportation.

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1. INTRODUCTION

1.1. The Importance of Wetland Information

In Colorado, wetlands are recognized as one of the most productive ecosystems by virtue of their abundant moisture in an otherwise arid environment. In recognition of the multitude of ecological functions and human values provided by wetlands, government agencies are seeking to establish wetland protection programs. The Colorado Department of Transportation (CDOT), Colorado Division of Wildlife (CDOW), US Army Corps of Engineers (USACE), Colorado Division of Water Resources (CDWR), local governments, and various conservation organizations are all among the institutions that could use a wetland inventory database, so that land use decision quality can be maintained and enhanced.

1.2. Regulatory Background

The Federal Water Pollution Control Act Amendments of 1972, amended in 1977, was established to maintain and restore the biological, chemical, and physical integrity of the waters of the United States. In practice, the Secretary of the Army, acting through the Chief of Engineers, was authorized by Section 404 of the Act to issue permits for the discharge of dredged or fill material into the waters of the United States, including wetlands. However, to accomplish wetland regulatory functions requires knowing where the wetlands are located. Creating a wetlands inventory database has thus become an urgent mission for Colorado. Responding to the Clean Water Act, US Army Corps of Engineers established the “Wetlands Delineation Manual” (USACE 1987) to provide guidance for identification and delineation of wetlands potentially subject to regulation under Section 404. This manual is viewed as the mandatory approach for public and private sectors to legitimately identify wetlands. The technical guidelines for wetlands delineation in the Corps manual do not specify a strict wetland classification system. Rather it provides guidelines for determining whether a given area is a wetland or not for legal regulatory purposes; such determination typically requires a field delineation of the wetland boundary by a professional trained in wetland delineation techniques.

The use of remote sensing for wetlands mapping has been established by a number of state agencies as a guide for planning purposes. A notable example in this regard is the Wisconsin wetland inventory program developed to augment the USACE procedures. For our work, the wetland classification system of Wisconsin Wetlands Association (WDNR 1992) was used for wetland categorization.

1.3. Objectives

The wetlands mapping research project has been motivated by requirements of the Safe, Accountable, Flexible, and Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU). SAFETEA-LU authorizes the Federal surface transportation programs for highways, highway safety and transit for the 5-year period 2005-2009. SAFETEA-LU addresses the many challenges involved in transportation system development, such as improving safety, reducing traffic congestion, improving efficiency in freight movement, increasing intermodal connectivity, and protecting the environment. The provisions include a new environmental review process for highways, transit, and multimodal projects, with increased authority for transportation agencies such the CDOT.

The wetland identification methods developed in this research are considered highly accurate and appropriate for transportation facilities planning purposes. The generated wetland inventory will therefore become a valuable component for developing cumulative impact assessments, inform transportation planning, stewardship of natural resources, and land use allocation decisions.

The objectives of this research are to:

1. Establish a highly reliable database of wetland occurrences and distributions to assist planning level activities.
2. Develop procedures for wetland identification using inexpensive data.
3. Create algorithms that accurately identify wetlands in a wide area.
4. Simulate the delineation method established in the USACE Wetlands Delineation Manual by applying recent advances of geospatial technology.

1.4. Incorporation of Object-Based Classification Algorithm

Traditional pixel-based classification algorithms, such as parallelepiped and ISODATA (Iterative Self-Organizing Data Analysis Technique), are carried out based on the spectrum information of each individual pixel. With a pixel-based algorithm, the pixel is classified according to the composition pattern of the radiation in various wavelengths emitted from that pixel location. This type of clustering, however, doesn't involve the evaluation of the geographic aspects of the pixel and its contextual relationship with the surroundings. Thus, the pixel-based classification is likely to generate many salt-and-pepper type classifications that do not represent contiguous wetland areas. Especially when there are not enough spectral bands in the imagery, the separation capability between classes would be dramatically reduced by using traditional pixel-based approaches. To overcome this deficiency, other techniques have been proposed, mainly consisting of three categories: (a) image pre-processing, (b) contextual classification, (c) post-classification processing, such as rule-based processing and morphological filtering. These techniques increase classification accuracy, but their disadvantages are evident when applied to high spatial resolution images, such as EO-1 Advanced Land Imager imagery, IKONOS, and NAIP (National Agricultural Imagery Program) data. These methods either require intensive computation or produce inaccurate results at the boundaries of distinctive land cover units.

Considering the complexities of mapping wetland occurrences, the object-based classification algorithm was developed in this project to supplement the capability of the traditional pixel-based classification algorithms. Instead of analyzing the pixel spectrum information for classification purposes, the mechanism of object-based classification algorithm is able to categorize the imagery by evaluating the geometric and textural characteristics of wetland areas as objects. Simply stated, objects are formed by grouping contiguous pixels with homogeneous aspects of ancillary conditions, such as smoothness, spectrum, or shape, as guided by the imagery analyst. Within objects the local spectral variation caused by gaps, shadows, and crown textures is mitigated by the creation of the objects at various scales. Furthermore, with objects as the minimum map units, the object-based algorithm is able to appraise many spatial properties of wetlands; such as shape, size, direction, density, distance, compactness, and texture of wetlands. Thus the object-based approach employed in this research is not limited to the evaluation of spectral characteristics of the hydrophytic vegetation and hydric soils, but makes maximum use of the spatial contextual variables of wetlands, such as the wetland distribution pattern and distances to the stream courses. This greatly enhances mapping accuracy and completeness. The object-based classification procedures developed in this research were executed with DEFINIENS® image processing software.

2. WETLANDS DEFINITION AND PARAMETERS

Successful identification of wetlands starts with a clear definition of wetlands. According to USACE (1987) wetlands are defined as:

> *Those areas that are inundated or saturated by surface or ground water at a frequency and duration sufficient to support, and that under normal circumstances do support, a prevalence of vegetation typically adapted for life in saturated soil conditions. Wetlands generally include swamps, marshes, bogs, and similar areas.*

2.1. Parameters of Wetland Delineation of USACE

The USACE (1987) wetland definition induces three mandatory environmental characteristics for wetland detection; vegetation, soil, and hydrology. Within the manual, these three diagnostic environmental characteristics are further characterized to provide guidelines of this study.

- ***Vegetation***. The widespread vegetation in wetlands is normally macrophytes that are typically adapted to areas with hydrologic and soil environmental conditions of saturation (USACE 1987). Hydrophytic species are the vegetation which have the ability to grow, compete, reproduce, and/or persist in anaerobic soil conditions. The delineation manual places emphasis on the assemblage of plant species that are a controlling influence on the character of the plant community rather than on indicator species. For this project characterization of the hydrophytic plant communities in Colorado were based on data from National Wetland Inventory website and associated field observations.

- ***Soil.*** The USACE Wetlands Delineation Manual (1987) set up a few criteria for determining the presence of hydric soils. Normally, these soils possess characteristics that are connected with anoxic soil conditions. They can be organic soil, histic epipedons, sulfidic material, or soils of the aquic/peraquic regime. These soils are the products of prolonged anaerobic soil conditions, which exist when soil is inundated or saturated for sufficient duration, and will result in chemical reduction of some soil components (e.g., iron and manganese oxides). Soil colors and other physical characteristics thus become the indicators of hydric soils. For the remote sensing approach, biological soil crust index accompanied by the generated emissivity or Thermal Response number, was used to emulate the soil identification process specified in the USACE delineation manual.
- ***Hydrology.*** According to the USACE manual (1987), wetland identifications should include the hydrologic characteristics that result in inundation either permanently or periodically at mean water depths ≤ 6.6 ft. Otherwise, at some time during the growing season of the prevalent vegetation, the soil is saturated to the surface. Topographically, the areas of lower elevation in a floodplain or marsh have more frequent periods of inundation and/or greater duration than most areas at higher elevations. For plant cover factors, areas of abundant plant cover make additional water drain more slowly and thus increase frequency and duration of inundation or soil saturation. Conversely the transpiration rates of the sites may give the investigated field an entirely opposite effect. The evapo-transpiration rates may be higher in areas with abundant plant cover and reduce the duration of soil saturation. This plant canopy factor, associated with other indicators such as drainage patterns, drift lines, sediment deposition, watermarks, stream gage data and flood predictions, historic records, visual observations of saturated soils and inundation, bring a rigorous criteria for wetland hydrological process evaluation. In this research, the use of Tasseled Cap transformation techniques, hydrological analysis on topographic data, and the concept of surface temperature, some of the field hydrologic indicators mentioned above can be incorporated using remote sensing techniques.

2.2. Wetland Types Adopted for Classification

As summarized in the previous section, wetland types are characterized by vegetation, soil type, and degree of saturation or water cover. According to the USACE (1987) wetland definition, all of the three diagnostic environmental characteristics need to be satisfied to classify an area as wetlands. In contrast the Classification of Wetlands and Deepwater Habitats of the United States (Cowardin et al., 1979) from the US Fish and Wildlife Service (USFWS) classify a wetland by requiring only one attribute fulfillment among the three diagnostic attributes. Considering that some inconsistency exists between these two systems and that the USACE wetland definition had been adopted for this research, a more general wetland classification system was used to categorize the wetland types found in the field. However, the corresponding wetland classes of the Wetlands and Deepwater Habitats Classification hierarchy from the USFWS were also contained in the texts for comparison. Some of the prominent wetland types are listed below; these form the wetland classification system for this research.

- **Aquatic Bed**

  Plants grow entirely on or in a water body for most of the growing season in most years. Aquatic beds in the NFRMPO area can be found in the sheltered areas of reservoirs or ponds that have little water movement. They generally occur in water no deeper than 6 feet. Plants include pondweed, duckweed, lotus and water-lilies. They can be classified into the Aquatic Bed class in the Lacustrine, Palustrine, or Riverine system if the hierarchy of the Wetlands and Deepwater Habitats Classification of the USFWS is used.

Fig. 1 Aquatic bed

Fig. 2 Marshes

- **Marshes**

Marshes are characterized by emergent aquatic plants growing in permanent and seasonal shallow water with water depths of less than 6.6 feet (2 meters). The counterparts of Marshes in the Wetlands and Deepwater Habitats Classification hierarchy of the USFWS is Palustrine / Emergent or Lacustrine / Littoral / Emergent. In the NFRMPO area, the marsh size can vary from a one-quarter acre pond to a long oxbow of a river or shallow bay of a lake. The species are dominated by cattails, bulrushes, pickerelweed, lake sedges and/or giant bur-reed.

- **Wet Meadows**

Wet meadows normally have saturated soil rather than standing water. Meadows are essentially closed wetland communities (nearly 100% vegetative cover) and often act as a transition zone between aquatic communities and uplands. Sedges, grasses and reeds are the governing species with the possible presence of sneezeweed, marsh milkweed, mint and several species of aster and goldenrod. Plants occurring in meadows include species found in other communities, such as the annuals of seasonally flooded basins and emergent aquatic plants of marshes. With the USFWS Wetlands and Deepwater Habitats Classification hierarchy, wet meadows can be categorized as Lacustrine/ Littoral/ Emergent class or Palustrine/ Emergent class.

Fig. 3 Wet meadows

- **Scrub/Shrub**

These areas, which include bogs and alder thickets, are characterized by woody shrubs and small trees less than 20 feet tall such as bog birch, willow, and dogwood. This type of wetland in the NFRMPO area mainly exists along rivers, but does not belong to a riverine system. Instead, Scrub/Shrub is categorized as

Fig. 4 Scrub/Shrub

Palustrine/ Scrub-Shrub class according to the wetland hierarchy of the USFWS.

- **Floodplain Forest**

The floodplain forest has its equivalent in the USFWS wetland hierarchy: Palustrine/ Forested. These forested floodplain complexes are characterized by trees 20 feet or more in height such as Cottonwood, Elm, Salix spp., Water Birch, and Big-tooth Maple. Grass cover underneath the trees is an important part of this system and is a mix of tall grass species, including Panicum virgatum and Andropogon gerardii. There are not many flood plain forests in the NFRMPO area; most of the forested floodplain complexes exist along the Cache La Poudre River.

Fig. 5 Floodplain forest

3. METHODS

3.1. Study Area and Image Acquisition

This research was conducted in the northern Front Range of Colorado covering an area from north of Fort Collins to the north of Loveland, with I-25 crossing through the middle from north to south (Fig. 6). The area is delimited by a trapezoid with the corners of 105 6′6.275 W, 40 39′56.001 N; 104 53′51.055 W, 40 39′56.001 N; 104 53′51.055 W, 40 26′45.949 N; 105 10′27.332 W, 40 26′45.949 N. The study area is about 60 miles away from Denver, Colorado. There is approximately 500 km² of area within the project research boundary. This area consists of agriculture, urban, and suburban zones. Most of the study area is located within the watershed of the Cache La Poudre River. The Cache la Poudre in northern Colorado is renowned for its canal development heritage in importing, storing and conveying water. Originating from above the tree-line in Rocky Mountain National Park, the Cache la Poudre has become Colorado's first and only national Wild and Scenic River. As the river and its tributaries wander through the terrain, numerous fens, marshes, potholes, and wet meadows are dotted through the area. Agricultural irrigation project have also created incidental wetlands.

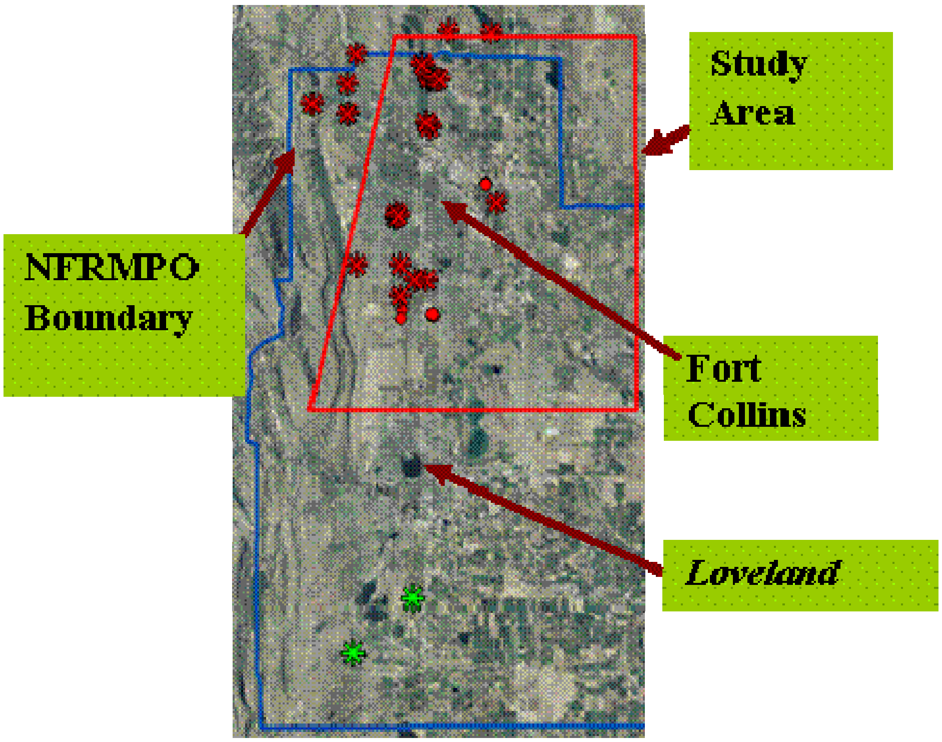

Fig. 6 Study area in vicinity of Fort Collins, CO

To cover this area, several satellite images were used:

- ASTER (Advanced Space-borne Thermal Emission Radiometer)

 The ASTER obtains high-resolution (15 to 90 square meters per pixel) images of the Earth in 14 different wavelengths of the electromagnetic spectrum, ranging from visible to thermal infrared light. The ASTER imagery used for this research was captured from the dates of 08-13-2003 and 03-15-2003. For the date of 08-13-2003, the L1B data, high-level kinetic temperature data, and surface radiance data all had been acquired. Data purchased for the date of 03-15-2003 are mainly L1B data and kinetic temperature data for thermal infrared bands. The data from these two dates possess all of the 14 bands of ASTER.

- LANDSAT7 ETM+

The purchased images are the scenes captured on the dates of 06-16-2002 and 04-16-2003. The LANDSAT 7 imagery is composed of four bands of 30 m * 30 m visible and near infrared data, two middle infrared bands, one band of thermal-infrared data with 60 m resolution, and a 15m* 15 meter panchromatic image. The ETM+ data was used to calculate various vegetation indices and the soil crust index as well. The scene of 04-16-2003 was mainly used for supplementary analysis for the spring season, when leaves hadn't totally turned green or there were fewer leaves present. Thus, the impacts of image signal noise from soil upon the vegetation radiation can be observed. Comparison of the wetland hydrology, vegetation, and soil conditions in the spring and summer increases the accuracy of the mapping.

- EO-1 Hyperion Hyper-spectral / Advance Land Imager

To further observe the hydrophytic vegetation into the species level, hyper-spectral data was employed to classify the vegetation species. Having only a 7.7 kilometer swath, the EO-1 Hyperion data was not used for directly delineating wetlands. Instead, it was used for the creation of the spectrum library of the various wetland classes and used for the comparison with the other overlapping imagery. The obtained Hyperion hyper-spectral image has more than 220 spectral bands (from 0.4 to 2.5 μm). The data was captured on 10-26-2001.

- NAIP (National Agriculture Imagery Program) aerial photographs

The one-meter resolution NAIP for Larimer and Weld Counties were downloaded from the following USGS (US Geological Survey) FTP site. ftp://rockyftp.cr.usgs.gov/ngtoc/colo_naip/

This data was mainly used for GPS data check and sample sites selection.

3.2. Field Survey

Field data collection is mandatory for successful wetland mapping. The wetland sample sites can be either used as training sites to collect the spectrum characteristics or used as the samples for validation purpose.

The sample sites of various wetlands were located using a Global Positioning System (GPS) unit. The possible wetlands were first identified on the NAIP imagery. The field visits were then planned accordingly. In the field, the pictures of the wetland samples were taken and their location information was collected by using the handheld Trimble Geo-Explorer GPS unit. In order to ensure that the accuracy of wetland locations is within ± 2m, the recorded GPS data was post-processed using differential corrections. In the U.S., a number of government and private agencies have made the base files for the differential correction purpose freely available online. The data collected at the base

Fig. 7 Field samples GPS data collection

station is used to calculate the generated differences accompanied with the GPS satellite signals (by finding the difference between the positions calculated from the satellite signals and the known reference position). In the Fort Collins area there are two base stations that continuously serve ready-to-download data every hour. Two of the collected wetland sample sites are shown in the Fig. 7.

3.3. Data Preparation

Some basic image processing operations are required to be performed on the raw images before obtaining the environmental indices and implementing classification processes. These steps include geo-referencing, sharpening, and conversion to reflectance.

3.3.1. Geo-Referencing

First, since the images are collected from multiple satellite platforms, they all need to be registered to the same projection and geographic coordinate system. This step is to guarantee that the subsequent operations are spatially accurately executed on the layers generated from the various satellite platforms and also to ensure that the pixel offset between the images is constrained to the minimum. The registration accuracy is targeted at smaller than 0.35 pixels of root mean square error (RMSE). All of the geo-referencing operations were set up for a third-order polynomial transformation. More than 80 ground control points were collected for each registration effort to achieve such a high accuracy RMSE standard. In some cases, more than 100 ground control points were collected for registering an image.

NAIP, with its high geographic accuracy, was chosen as the reference map for geo-referencing the other satellite images. NAIP data uses UTM North America Datum 1983 as its coordinate system, thus the NAD83, UTM zone 13N was used as a common spatial reference system for all of the images in this research. The registration processes were executed using the ENVI® software. Most of the images were registered using the cubic convolution algorithm in recognition that wetlands normally are located in the edge between water bodies and uplands.

3.3.2. Gram-Schmidt Spectral Sharpening

Image fusion remote sensing techniques aim at integrating the information from multiple images having differing spatial and spectral resolution from satellite and aerial platforms. Given that the number and kind of satellite platforms are increasing, image fusion techniques are increasingly important for data development by remote sensing. The literature of image fusion shows that an optimal quality for a fused image is defined as having *Minimum Color Distortion* (containing all the spectral property of Multi\Hyper spectral images), *Maximum Spatial Resolution* (containing all the spatial property of high resolution image) and *Maximum Neutrality* (the best integration of spectral and spatial quality of input data). But this ideal situation only can be obtained theoretically (Zhou, 1998). For example, the most straightforward fusion method, Intensity-Hue-Saturation (IHS) transformation, has been shown to have a large spectral distortion when displaying the fusion product in color composition.

To achieve an optimal quality for the image sharpening process, the Gram-Schmidt spectral sharpening algorithm, one of the most sophisticated methods for performing fusion on multi-spectral and panchromatic bands, was applied in this project. This algorithm is based on the component substitution strategy developed by Laben and Brover (2000) and patented by Eastman Kodak. This algorithm is the method adopted by the ENVI® package and is thus used by this research.

Basically, Gram-Schmidt spectral sharpening extracts the high frequency variation of a high resolution image and then inserts it into the multi-spectral framework of a corresponding low resolution image. In this algorithm, algebraic procedures operate on images at the level of the individual pixel to proportion spectral information among the

Fig. 8 ETM+ imagery after pan-sharpening

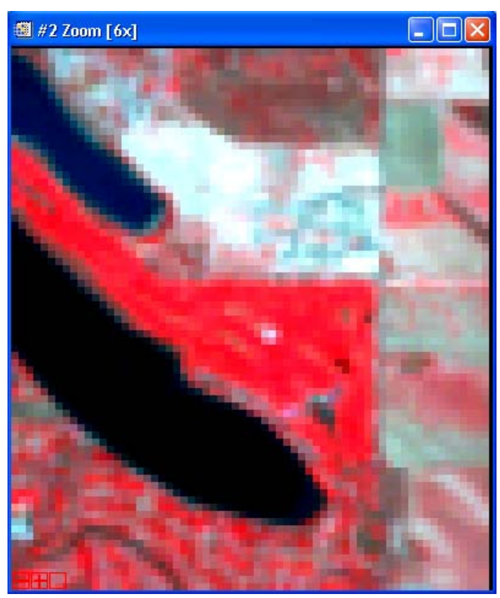

Fig. 9 Raw ETM+ imagery (30m)

bands of the multi-spectral image. The replacing (high resolution) image substitutes one of the bands of the original image and can then be assigned correct spectral brightness. A comparison of raw image and post sharpening of LANDSAT 7 ETM+ 06/16/2002 data by the Gram-Schmidt sharpening method is shown below. The comparison exhibits a considerable improvement of spatial quality after sharpening, while enduring little spectral distortion.

3.3.3. Transferring Digital Number to Reflectance

To successfully generate the vegetation and soil indices, the digital numbers of LANDSAT 7 ETM+ need to be transferred to the reflectance. This process actually includes two steps. The first step is to transfer the Digital Number of each band to its radiation detected at the sensor. This process involves the calibration process of calculation that brings the 8 bit integer data into the 32 bit floating point. The equation used is listed below.

Lλ = "gain" * QCAL + "offset"

which is also expressed as:

Lλ = ((LMAXλ - LMINλ)/(QCALMAX-QCALMIN)) * (QCAL-QCALMIN) + LMINλ

where:

Lλ = Spectral Radiance at the sensor aperture in watts/(meter squared * ster * μm)

"gain" = Rescaled gain (the data product "gain" contained in the Level 1 product header or ancillary data record) in watts/(meter squared * ster * μm)

"offset" = Rescaled bias (the data product "offset" contained in the Level 1 product header or ancillary data record) in watts/(meter squared * ster * μm)

QCAL = the quantized calibrated pixel value in DN

LMINλ = the spectral radiance that is scaled to QCALMIN in watts/(meter squared * ster * μm)

LMAXλ = the spectral radiance that is scaled to QCALMAX in watts/(meter squared * ster * µm)

QCALMIN = the minimum quantized calibrated pixel value (corresponding to LMINλ) in DN

= 1 (LPGS Products)

= 0 (NLAPS Products)

QCALMAX = the maximum quantized calibrated pixel value (corresponding to LMAXλ) in DN

= 255

All of the above variables can be obtained from the metadata accompanying the file. The second step is to translate from surface radiation to reflectance at the sensor. The LANDSAT scenes in this step were actually normalized for solar irradiance by converting spectral radiance, as calculated above, to planetary reflectance or albedo. This is a combination of surface and atmospheric reflectance of the Earth. It was computed with the following formula:

$$\rho_p = \frac{\pi \cdot L_\lambda \cdot d^2}{ESUN_\lambda \cdot \cos\theta_s}$$

Where:

ρ_p = Unitless planetary reflectance

L_λ = Spectral radiance at the sensor's aperture

d = Earth-Sun distance in astronomical units from nautical handbook or interpolated from values listed in Table 2. In order to get a correct distance in astronomical units, the Julian Day of the image capture date needs to be figured out.

$ESUN_\lambda$ = Mean solar exo-atmospheric irradiances from Table 1

θ_s = Solar zenith angle in degrees

Table 1 ETM+ Solar Spectral Irradiances	
Band	watts/(meter squared * µm)

1	1969.00
2	1840.00
3	1551.00
4	1044.00
5	225.70
7	82.07
8	1368.00

The Julian Day / Calendar Day Conversion information can be found from the related page provided by NASA Goddard Space Flight Center.

http://rapidfire.sci.gsfc.nasa.gov/faq/calendar.html

Table 2 Earth-Sun Distance in Astronomical Units

Julian Day	Distance	Julian Day	Distance	Julian Day	Distance	Julian Day	Distance	Julian Day	Distance
1	.9832	74	.9945	152	1.0140	227	1.0128	305	.9925
15	.9836	91	.9993	166	1.0158	242	1.0092	319	.9892
32	.9853	106	1.0033	182	1.0167	258	1.0057	335	.9860
46	.9878	121	1.0076	196	1.0165	274	1.0011	349	.9843
60	.9909	135	1.0109	213	1.0149	288	.9972	365	.9833

The generated LANDSAT band-4 reflectance of a portion of the study site based on the above formula is displayed in the figure 10.

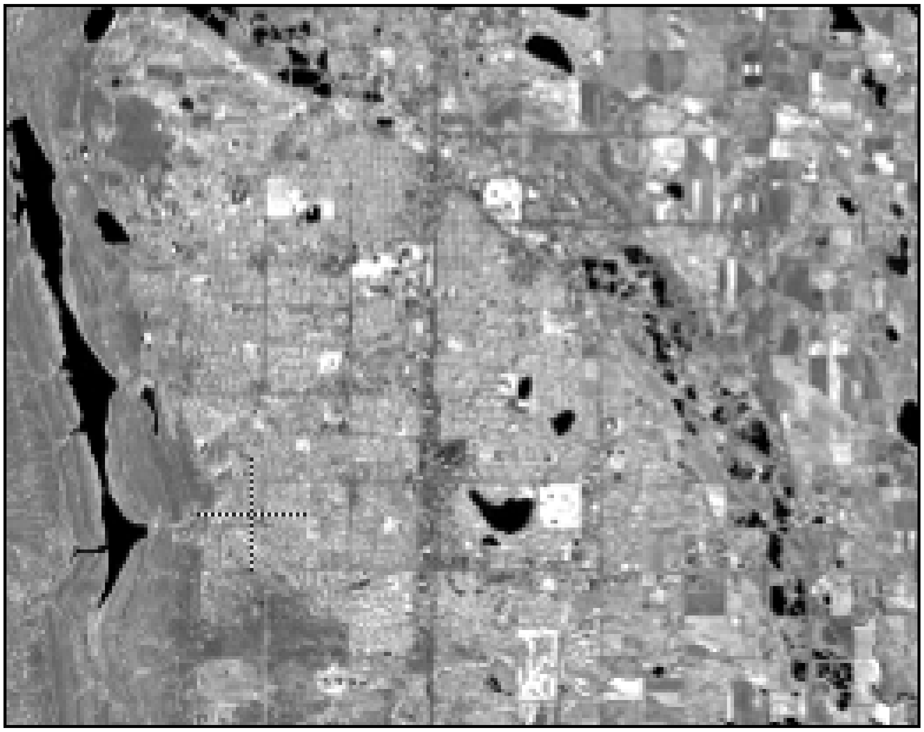

Fig. 10 LANDSAT Band 4 reflectance

After transferring Digital Number of ETM+ Band 6 digital number to radiance as the process described above, the ETM+ Band 6 imagery can also be converted from spectral radiance to a more physically useful variable. This is done under an assumption of unity emissivity and using pre-launch calibration constants listed in the Table below. The effective at-satellite temperatures of the viewed Earth-atmosphere system in Fort Collins area on the date of 04/16/2003 is displayed below. The conversion formula used in this research is:

$$T = \frac{K2}{\ln\left(\frac{K1}{L_\lambda} + 1\right)}$$

Where:

T = Effective at-satellite temperature in Kelvin

K2 = Calibration constant 2 from Table below

K1 = Calibration constant 1 from Table below

L = Spectral radiance in watts/ (meter squared * ster * μm)

Table 3 ETM+ Thermal Band Calibration Constants

	Constant 1- **K1** watts/(meter squared * ster * µm)	Constant 2 - **K2** Kelvin
Landsat 7	666.09	1282.71
Landsat 5	607.76	1260.56

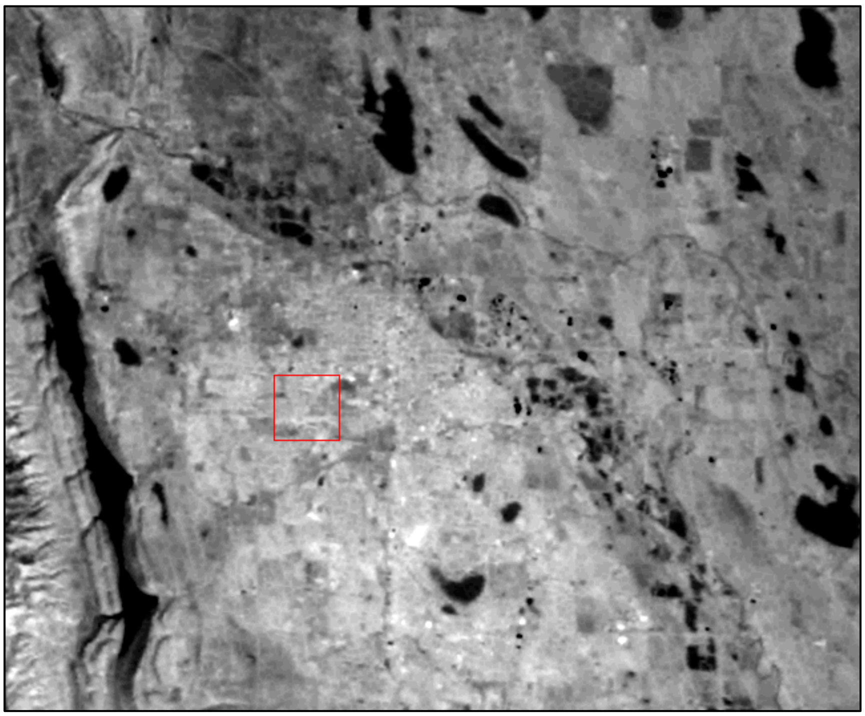

Fig.11 At-satellite surface temperature generated from ETM+ of 04/16/2003 data for Fort Collins and adjacent area

From the at-satellite surface temperature image shown above, the difference of the surface temperature of the urban/suburban, agricultural, and wetter areas is clear. This data is helpful for identifying wetlands as they are normally cooler in comparison with bare soil or artificial structures.

3.4. Vegetation Indices

The acquired hyper-spectral data (EO-1 Hyperion) only covers a portion of the study area; this makes a thorough differentiation of wetland vegetation species across the study area impossible. Therefore, instead of relying completely on EO-1 imagery, the vegetation and soil biophysical variables extracted from the ASTER and LANDSAT imagery were used in a supplemental manner to increase the accuracy of the wetland identification. In this research, these vegetation indices, complemented with the spatial attributes of the image objects generated in the object-based classification process, will create the thresholds for various classification categories. The vegetation indices are able to:

- Maximize sensitivity to plant biophysical parameters,
- Normalize the external effects, such as atmospheric effects, Sun angle, and viewing angle,
- Validate the classification results,
- Normalize internal effects such as canopy background variations, such as soil noise, differences in senesced vegetation, and topography.

Several indices were extracted from the images. They are NDVI, Wetness, Brightness, and Greenness. Some of the generated indices are displayed below. They are accompanied with NAIP photograph for comparison.

3.4.1. Kauth-Thomas Tasseled Cap Transformation

Kauth and Thomas (1976) produced an orthogonal transformation of the original LANDSAT MSS data space to a new four-dimensional feature space. This is the inauguration of the application of Kauth-Thomas Tasseled Cap Transformation. Through the years, the Kauth-Thomas tasseled cap transformation continues to be widely used and has been reformed for ETM+ image application. The derived brightness, greenness, wetness can provide subtle information concerning the occurrence status of the wetland environment.

- **Greenness**

 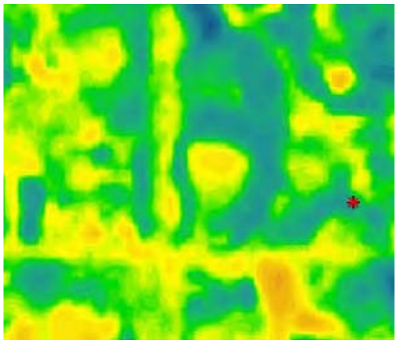

Fig.12 The greenness layer has been found highly corresponding to the existence of wetland locations. The dark blue color on the right is correspondent to the vegetation on the left

- **Wetness**

 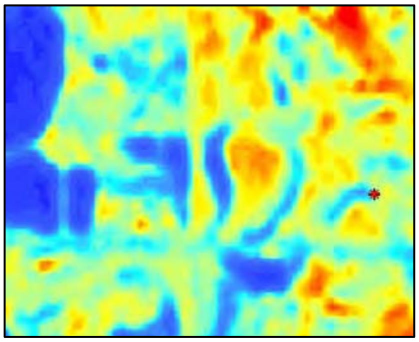

Fig. 13 Wetness, the bluer the color is the wetter the place is. These wet locations correspond to the wetlands and ponds on the left NAIP image

- **Brightness**

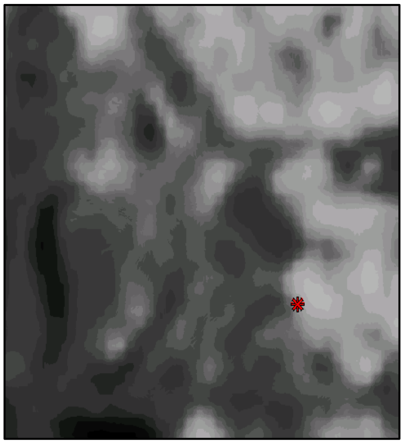

Fig. 14 The brightness layer of the same sample site shows that the grey and medium dark areas are likely to be wetlands

The coefficients developed by Huang et al. (2002) were used for executing the Kauth-Thomas Tasseled Cap Transformation and were listed below. This Tasseled Cap transformation was performed on the LANDSAT ETM+ data by using the Band Math function in ENVI®.

- Brightness
  - 0.3561*B1+ 0.3972*B2+ 0.3904*B3+0.6966*B4+0.2286*B5+0.1596*B7
- Greenness
  - -0.334*B1-0.354*B2-0.456*B3+0.6966*B4-0.024*B5-0.263*B7
- Wetness
  - 0.2626*B1+0.2141*B2+0.0926*B3+0.0656*B4 – 0.763*B5 - 0.539*B7

3.4.2. NDVI (Normalized Difference Vegetation Index)

NDVI can be used to discriminate herbaceous and hard wood vegetations and other non-vegetation land covers. The discrimination is based on differences in reflectance in the NIR and red bands for vegetation and other land covers. The equation is listed as below.

NDVI $=(\boldsymbol{\rho}\text{nir} - \boldsymbol{\rho}\text{red}) / (\boldsymbol{\rho}\text{nir} + \boldsymbol{\rho}\text{red})$

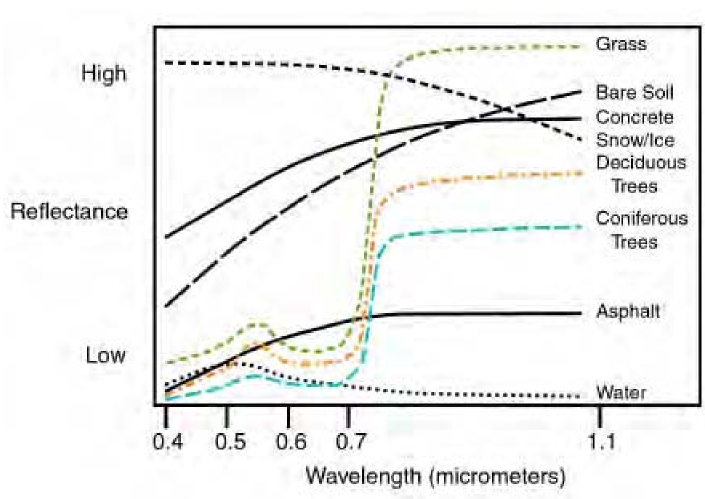

Fig. 15 Reflectance of different vegetation category and materials

In this research, the NDVI was generated from the ASTER imagery of August and EO1 ALI imagery of October. The purchased ASTER data is high level surface radiance data corrected for atmospheric effects, having higher radiometric resolution with 16 bits. The generated NDVI layers are shown in Figure 16 below.

Fig. 16 NAIP photo with the generated stream network in blue lines

Compared with the NAIP photograph above, the generated NDVI from ASTER and EO1 ALI imagery shown below were found to have potential to differentiate herbaceous plants, woody plants, and non-vegetative area. These land covers have different NDVI values, making them easy to be distinguished.

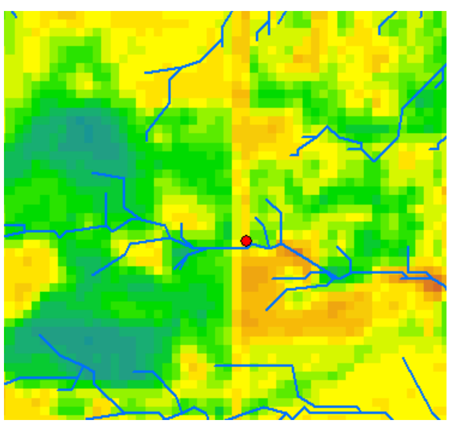

Fig.17 NDVI of August from ASTER 08132003 imagery

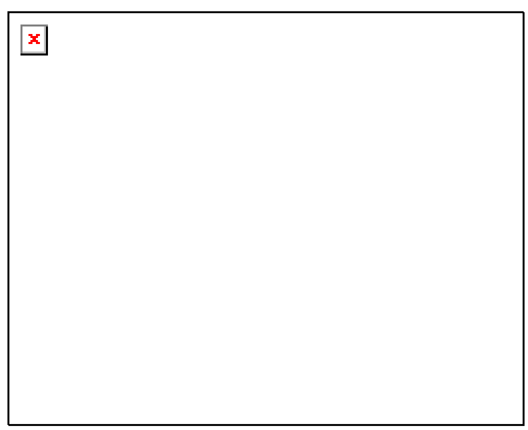

Fig.18 NDVI generated from EO1 ALI shows that most of the vegetation has become brown in October except the irrigated Agriculture Land

3.5. Hydrological Analysis

Surface depressions and areas along stream courses are locations where wetlands and riparian often occur. To discover the depression storage areas and the stream network, a sequence of operations on DEM data were implemented using hydrological analysis functions. The functions of hydrology analysis can be found in the Spatial Analyst Tools in ArcGIS®. The hydrology analysis starts from the flow direction function. Drainage flow directions are determined by the prevalent “D8” algorithm, which assigns the drainage value from one point on the DEM grid to one of its eight bordering neighbors. The possible assigned value are “1”, “2”, “4”, “8”, “16”, “32”, “64”, and “128” as shown in Figure 19. This FLOW_DIR raster is next used to execute Flow Accumulation analysis (Figure 20). In the flow accumulation analysis, the amounts of cells that will flow into each cell in the FLOW_DIR grid along all the possible direction are calculated and accumulated to produce a new raster of FLOW_ACC. After flow accumulation operation, The Map Algebra function is employed as the final step to generate the stream network.

32	64	128
16		1
8	4	2

Fig. 19 Available assigned value in D8 algorithm

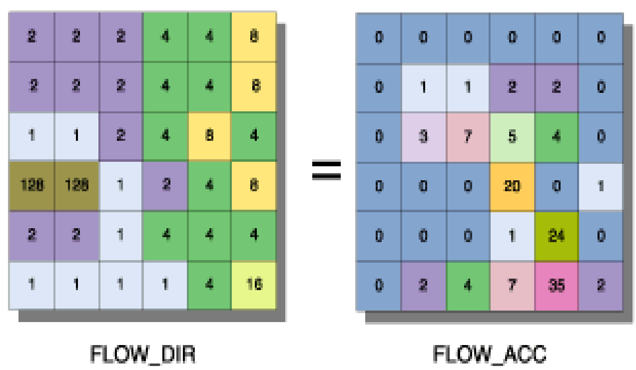

Fig. 20 Flow accumulation operation concept

The sequence of hydrology operations is quite articulate. In the process from flow direction to flow accumulation operation some confining hydrologic depressions will be generated making the network interrupted at these depression spots. In the real world, these spots are the area where water stops flowing. Though some of these depressions exist in the real world, most of them are data assimilation errors when converting the floating point values in the DEM to integer values. This incurred error may cause problems in establishing the stream networks because in the real world terrain water flow fills small depressions and then additional water will continue to flow along its course.

Therefore, depressions in the 10M DEM needs to be filled to insure drainage continuity through flat spots and out of depressions. But some of the sinks are real depressions in the terrain. To avoid erasing these real depressions these sinks were filled back to the elevation of the outpour point of that specific drainage area. The retained depression areas are prone to be flood detention sites and potential sites for wet soils and where wetland vegetation can build up.

The condition that was set up for stream network flow accumulation in this study was 45 pixels. In other words, only the grids which possess more than 45 pixels of progressive accumulation after flow accumulation operation were counted as members of the network. The CON tool syntax is listed as below:

- ***streamnet = con (flowacc > 45, 1)***

  or
- ***streamnet = setnull (flowacc < 45, 1)***
- ***threshold set at 45***

The results of the hydrology analysis were quite accurate (Figure 21). The generated synthetic stream network was overlain on NAIP data and was found to be very close to the real world network configuration. Meanwhile, the locations of depressions also proved to be accurately mapped except that the true range of the depressions may not be precisely as depicted, particularly in flat areas. The differences may be caused by the coarse resolution of the elevation data; a 10-meter DEM grid was employed in this study.

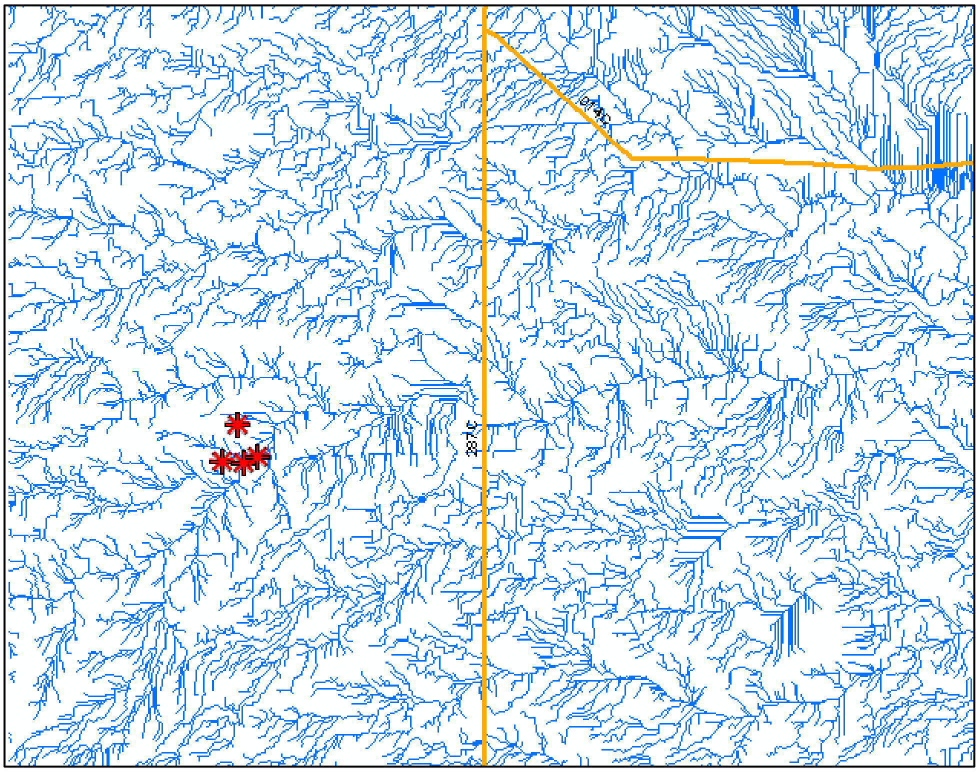

Fig. 21 Generated stream network from 10-meter DEM

The stream network is a very important layer for the later object-based classification. As land developments encroach into the stream buffers, identification of wetlands in neighborhoods has become more difficult. This is due to hydrophytic vegetation being confused with plants in residents' backyards or vice versa. In this research, the creation of the stream network helps to resolve these mapping challenges. Buffering of the stream network increases the capability to identify areas where water is likely to stagnate and where wetlands have a tendency to occur (Figure 22).

Fig.22 Involvement of stream layer in delineating wetlands in the neighborhood (shown on the left) is aided by inclusion of the stream network layer into the DEFINIENS® software as an analysis feature

3.6. Unsupervised Pixel-Based Classification

Rapid assessment of the land cover distribution pattern for the study area was accomplished using an ISODATA (Iterative Self-Organizing Data Analysis) technique. This approach was chosen as a classification technique to classify the imagery of EO1 ALI 10/26/2001, LANDSAT 7 ETM+ 04/16/2003, and LANDSAT 7 ETM+ 06/16/2002. ISODATA is actually an unsupervised classification and consists of three steps: (a) classification into spectrally distinct clusters, (b) post-clustering treatment, and (c) assignment of labels to the clusters. Since unsupervised classification clusters pixels into spectral clusters it is possible that classes not known a priori can be discovered. This is an iterative practice; the cluster properties are defined from the pixels belonging to that cluster at any iteration and then all pixels are appointed to the "closest" cluster.

One of the properties of unsupervised classification algorithms is that they always implicitly assume that the initial assignment of the clusters does not influence the outcome of the classification. This is not always true. In this project, the ISODATA operations set with the same thresholds had been tested upon EO1 ALI 10/26/2001 imagery for several times. The classification result is slightly different for every operation. In other words, the classification results cannot be exactly reproduced. If working on a relatively wide area, this classification uncertainty problem can become noticeable. However, the ISODATA technique still provides a preliminary land cover classification which can greatly enhance the accuracy of the object-based classification operation in the later steps.

3.6.1. Minimum Noise Fraction Transformation

When imagery is captured by the sensors there can be considerable variability (i.e. “noise”) implanted into data due to the problems of band overlap and irradiance from adjacent pixels. In this project, a minimum noise fraction (MNF) transformation algorithm was used to segregate noise in the data and to determine the inherent dimensionality of image data. MNF consists of the two steps of separate principal components analysis rotation:

- By using the principal component analysis on the noise variance/covariance matrix, the noise in the data was whitened. Thus the noise in the transformed data only has unit variance.
- After the above operation, only the derived principal components with large eigenvalues were used for further spectral processing.

Figure 23 is the MNF transformed band 1 of EO1 ALI data. After checking the MNF images and eigenvalues spectrum, the first 6 MNF bands were found to contain the coherent variability. The MNF operation was performed by using ENVI® software.

Fig. 23 MNF Band 1 of EO1 ALI data

3.6.2. ISODATA Classification

After the MNF transformation had been performed on the three image sets, ISODATA classification was then executed. In this step, thirty five classes were set for ISODATA classification on EO1 ALI 10/26/2001, twenty classes for ISODATA operation on ETM+ 06/16/2002, and 18 classes for the ISODATA classification on ETM+ 04/16/2003 imagery. The categorization results from these images were then reclassified with a 1 to10 scale, depending on the potential rank to be wetlands of the generated classes. Figure 24, 25 and 26 are part of the reclassification of the ISODATA operations unto the three data sets; in these figures the bluer the color the higher a wetland potential.

- EO1 ALI 10/26/2001 Unsupervised Classification Results

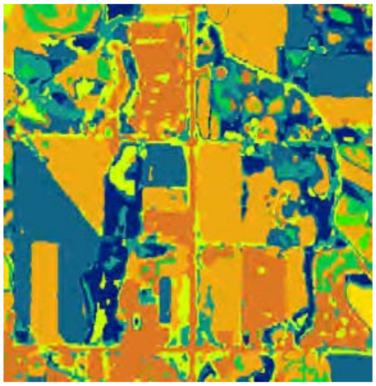

Fig. 24 From the ISODATA classification of EO1 ALI 10/26/2001 imagery, the wetland delineation is promising. The blue color in this thematic layer represents the high potential as a wetland

- <u>LANDSAT 7 ETM+ 04/16/2003 Unsupervised Classification Results</u>

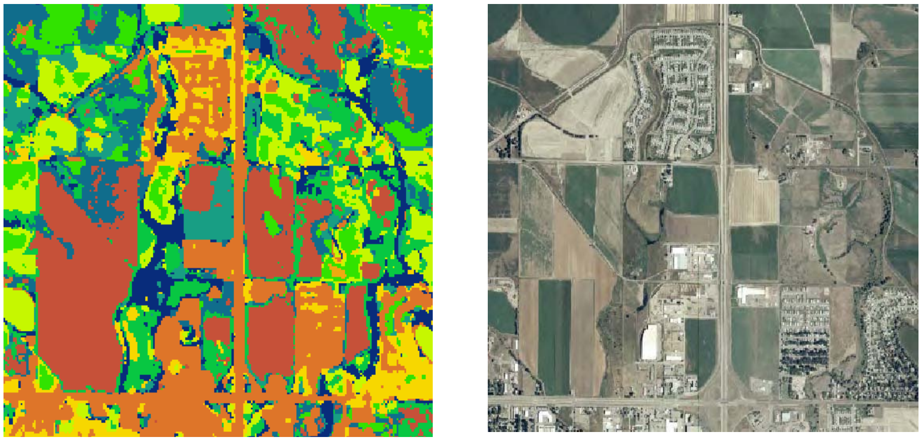

Fig. 25 ISODATA classification of April LANDSAT 7 data provides valuable supplement information of different season for wetland delineation

- <u>LANDSAT 7 ETM+ 06/16/2002 Unsupervised Classification Results</u>

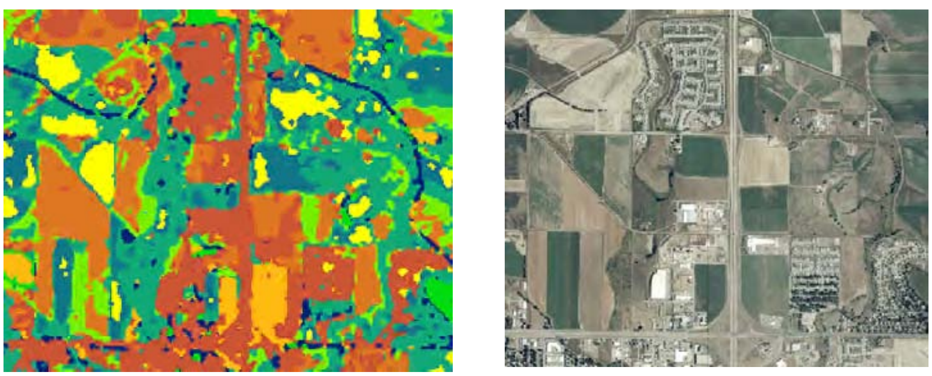

Fig. 26 A 3*3 majority analysis was applied to the ISODATA classification product of ETM+ 06/16/2002, reducing some salt-and-pepper effects from the classification results. A more generalized wetland distribution pattern can be found

Generally the individual ISODATA classifications on the image of the various seasons proved productive for locating possible wetlands. Still, some amount of misclassification and inconsistency were found in these three unsupervised classifications. Especially many irrigated agricultural lands were included in the wetland category. This misclassification problem is largely due to the generic limitation of the multi-spectral data and pixel-based classification approach. On the other hand, comparing the classification results for the three different season images, the classification of EO1 ALI 10/26/2001 was found to have the best quality. To overcome the inconsistencies of classifying the different season images and to make the best use of multi-temporal observations, the products from the ISODATA classification were overlaid with different weights to produce a final pixel-based potential wetland map (Figure 27). This map was later inserted into DEFINIENS® package as a layer for object-based classification.

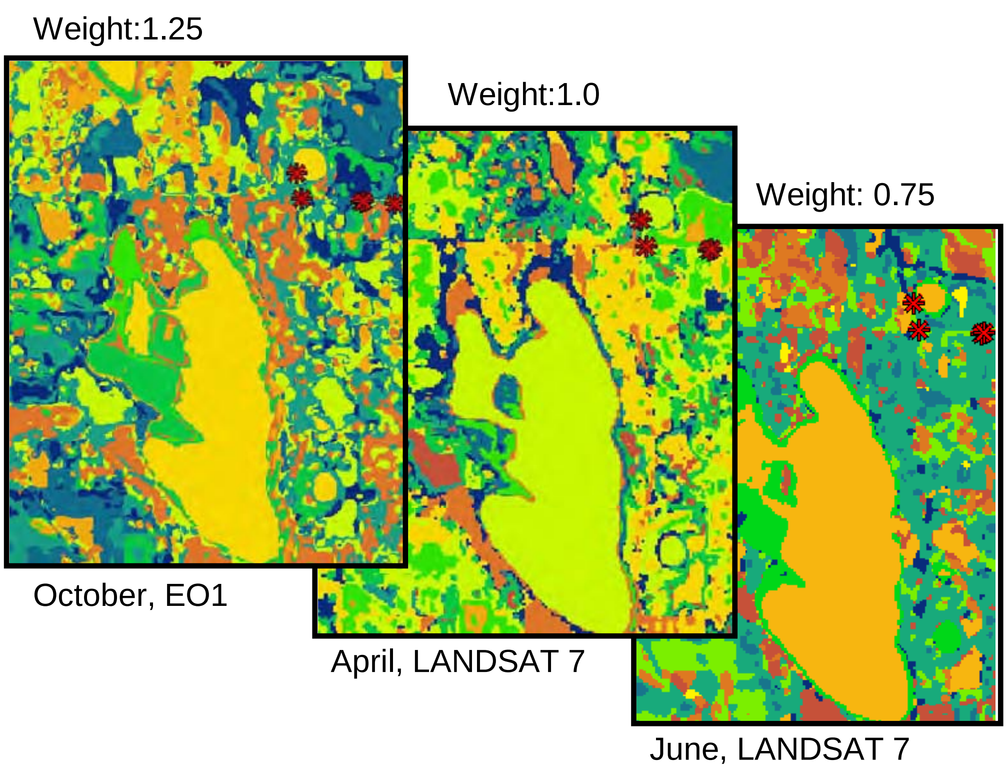

Fig. 27 Weighted overlay of ISODATA classifications from the three different season images

3.7. Object-Based Classification

The basic idea of object-based classification is to cluster the spatially adjacent pixels into homogeneous objects, and then perform classification on these objects. Hay et al. (2001) defined the objects as basic entities situated within an image; these objects possess an inherent size, texture, shape, and geographic relationship with the real-world scene component it represents. Essentially, object-based classification emulates human cognitive processes that extract intelligence from images. The workflow of object-based classification in DEFIENS Professional® consists of the following sequence of operations.

3.7.1. Load and Create Project

The data layers inserted into DEFINIENS® for object-based classification and segmentation are layers listed below:

- AST 09 Atmospheric Corrected Surface Radiance Data. There are 9 bands, including Visible, Near Infrared, and Short Wave Infrared, in this dataset.
- LANDSAT 7 ETM+ panchromatic band
- Brightness, Greenness, Wetness layers of 06/16/2002 and 04/16/2003 ETM+ imagery generated from Kauth-Thomas Tasseled Cap Transformation.
- Principal Components 1, 2, 3, and 4 of LANDSAT 7 imagery.
- Convoluted Thermal Infrared Band of LANDSAT 7 ETM+ 06/16/2002
- At-Satellite Surface Temperature of LANDSAT 7 ETM+ 04/16/2003 generated according to the algorithm described in the previous section.
- Five bands of AST09T 08/13/2003 Atmospheric Corrected Surface Radiance of Thermal Infrared data
- AST08 of 08/13/2003 Surface Kinetic Temperature. This is the high level ASTER data acquired from NASA. The data is obtained by applying temperature-emissivity separation algorithm to atmospherically corrected surface radiance data.
- NDVI of 08/13/2003 generated from AST09 surface radiance data
- NDVI generated from EO1 ALI 10/26/2001
- Nine bands of EO1 ALI of 10/26/2001 data. This dataset is a 16 bit data.

- Stream Buffer 165 meters raster layer. The raw stream layer was downloaded from CDOT website. The buffering of 165 meters is to identify the floodplain forest. These forests in the Front Range normally are present along wider rivers, such as Cache la Poudre or South Platte River.
- Stream Buffer of 32 meters raster Layer. The buffering of 32 meters is to consolidate the capability of identifying Marshes. As the stream network normally indicates the presence of inundated water, the addition of stream buffer data into object-based classification operation enhances the segregation of Marshes and Wet Meadows.
- Generated wetland raster layer using overlay and ISODATA classification method.

3.7.2. Create Image Object

Unlike the ISODATA technique applied in the previous step, the segmentation technique used in this action is a local behavior-based method which analyzes the data variation in a relative small neighborhood. In essence ISODATA produces clusters based on the similarity in the data space, whereas the segmentation technique used by DEFINIENS® not only lessens the variable heterogeneity of pixels within an object but also addresses the concern of spatial heterogeneity of the image space. The Fractal Net Evolution Approach is thus employed by DEFINIENS®. This approach initiates with 1-pixel image objects and grows regionally. Currently DEFINIEN Professional® provides four different image object segmentation algorithms, including 1) segmentation of chessboard, 2) quad tree based, 3) multi-resolution, and 4) spectral difference. Though the calculation may be time consuming, multi-resolution segmentation generates objects resembling ground features quite meticulously. Considering that wetlands are clusters of vegetation and water with genuine shape, the multi-resolution segmentation algorithm is therefore assumed in this research.

In the level 1 (the most basic level) image segmentation, the scale parameter was set at 15. The composition of homogeneity criterion was set as 0.7/0.3 for Color/Shape and 0.4/0.6 for Compactness/Smoothness. The level 1 segmentation result is displayed in

Figure 28. Close examination of the results showed that the objects corresponded well to the real situation. If an even smaller scale parameter is set, the segmentation results can be even better; but this can result in excessive computer processing time. The best scale parameter for the level one segmentation is thus recommended to be set between 12 and 15.

Fig. 28 Level 1 image objects

For the Level 2 image segmentation the scale parameter was set at 60. The composition of homogeneity criterion was set as 0.9/0.1 for Color/Shape and 0.4/0.6 for Compactness/Smoothness. The color parameter in the segmentation operation of Level 2 was set much higher than the shape parameter. This results in the spectral and data variables from the input layers making the greatest contribution to the formation of image objects in Level 2. The Level 2 objects were used to support the correct assignment of classes in the Level 1 classification; the involved layers for the creation of objects in the Level 2 were thus less than the layers used for Level 1 image segmentation. These layers include ASTER green and near infrared, ASTER band 7 and 9, ETM+ 06/16/2002 brightness and wetness layers, ETM+ 04/16/2003 at-satellite surface temperature, NDVI of ASTER 08/13/2003 layer, and 32 meters stream buffering. The Level 2 segmentation result is displayed in Figure 29. From the display, the object outlines can be found very close to community, farm unit, or water body boundaries. The classification executed on these larger objects will furnish more information to enhance the classification accuracy in Level 1 (child classes).

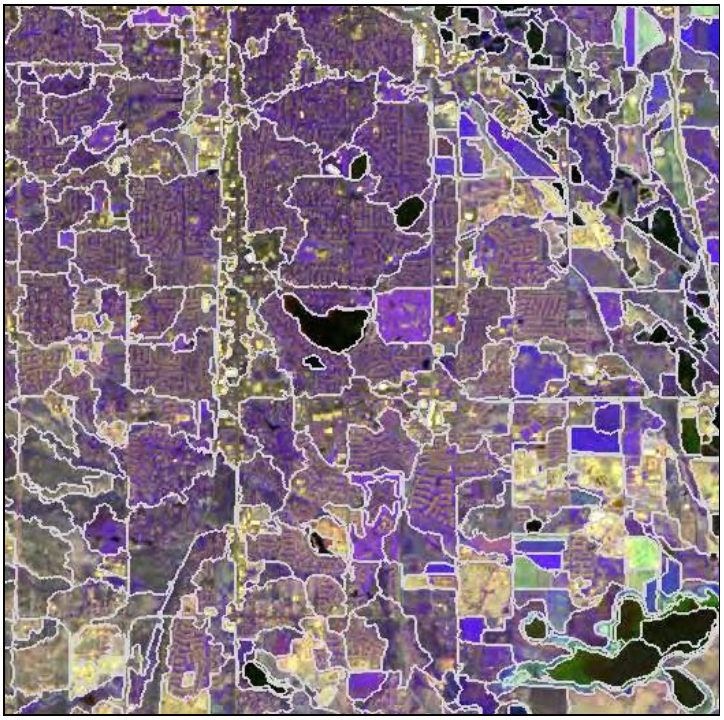

Fig. 29 Level 2 image object segmentation

3.7.3. Classification

Though intended for wetland identification, the classes created in this object-based classification are not limited to wetland related classes. The classes created are Aquatic Bed, Commercial/Industrial Zone, Farm Land, Floodplain Forest, Forest, Golf Course, Grassland, Marshes, Residential Area, Rocks, Scrub/Shrub, Water Body, and Wet Meadows. DEFINIENS® employs a nearest neighbor function as its main classification algorithm. This is a supervised classification process. The training sites selection is very similar to the traditional pixel-based supervised classification maneuver but the objects created earlier are used as the medium instead of pixels.

The most common features that can be applied for classification in object-based classification are layer mean and standard deviation. In addition to the layer mean and standard deviation, the features information that can be employed for wetland identification in the object-based classification process include: area of wetlands, length/width, density, compactness, distances to streams, relationship to super-objects, gray level co-occurrence matrix, and Shape Index of the wetland features. Use of these features dramatically increased the wetland classification accuracy. However, due to the concerns of computer capacity and the priority of exploring procedures for integrated pixel-based and object-based classification, only the feature of layer mean value and distances to other classes were adopted for classification in this pilot project.

Part of the classification results are displayed below (Figures 30, 31, and 32) which show a satisfactory result. The agricultural zone (peach color area) and residential zone (magenta area) in Fort Collins area are clearly segregated. The various wetlands are found to be present either along the water course or close to the water bodies. In addition the misclassification problem with wetlands and irrigated farms has been resolved. This result demonstrates the effectiveness of object-based classification approach.

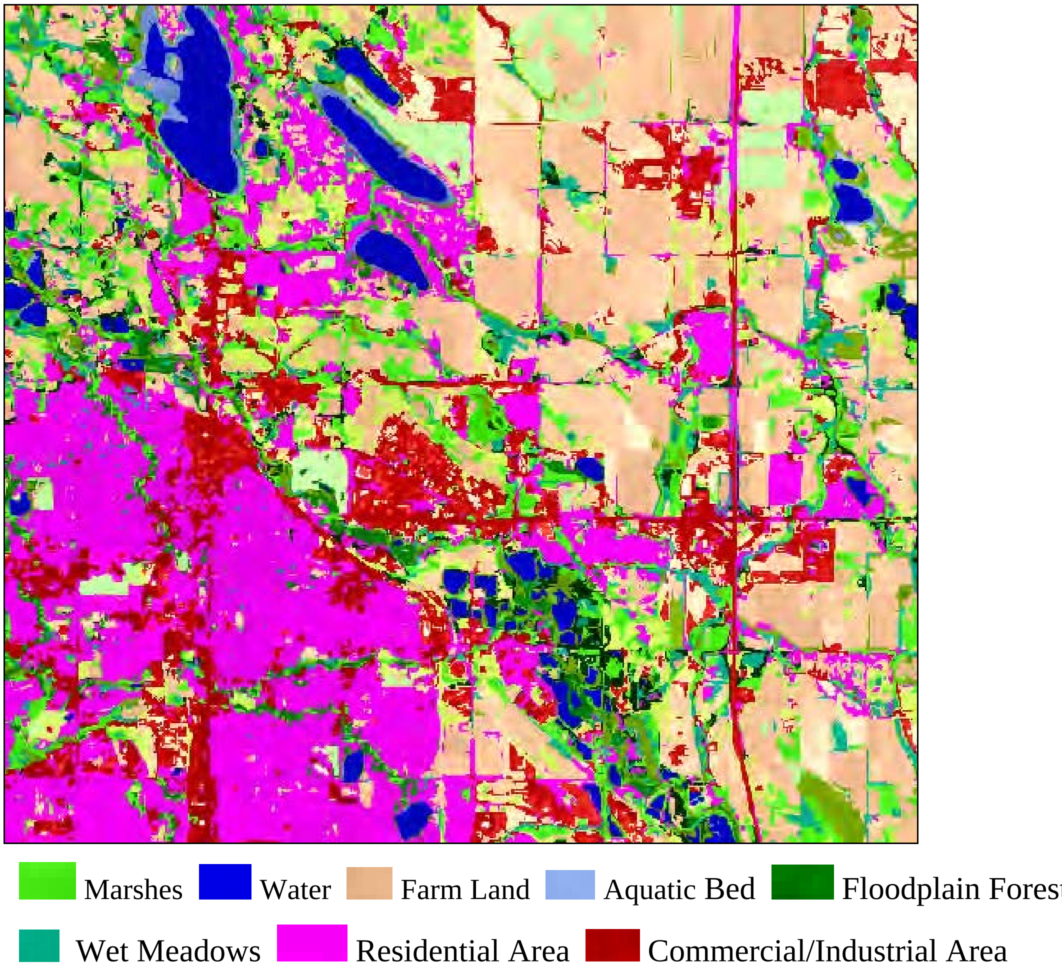

Fig. 30 Level 1 classification results shows the crossing out of salt-and-pepper effect

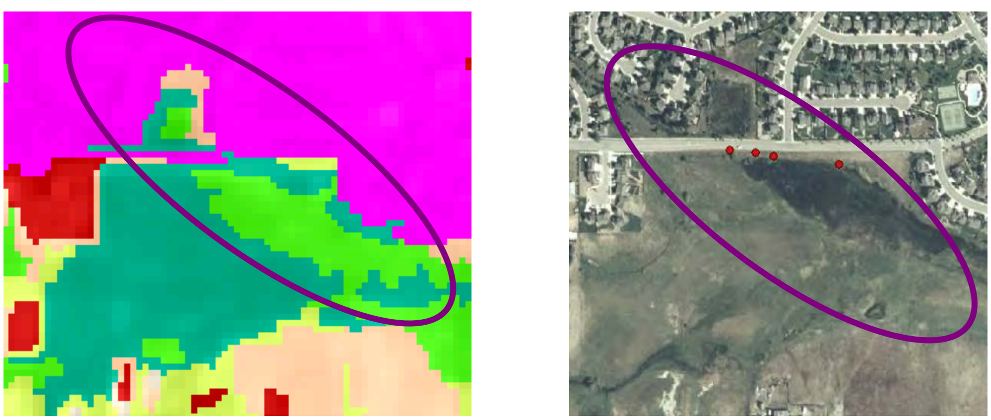

Fig. 31 Comparison of individual marsh identification and its location in the real world shows the success of this wetland mapping method

Fig. 32 Photograph of the above mapping example

4. RESULTS AND DISCUSSION

4.1. Areas of the Wetlands Identified

The areas of the wetlands in the study area which have been mapped in this research are listed as below:

- Marshes: 37.6 km²
- Scrub/Shrub: 10.3 km²
- Floodplain Forest: 5.2 km²
- Aquatic bed: 5.5 km²
- Wet Meadows: 17.6 km²

Total: 76.2 km²

The above statistics shows that the mapped wetlands occupy around 15.3% of the research area (500 km²). These figures can be a slightly higher than the real world situation due to a small portion of irrigated farms that were misclassified as marshes and scrub/shrub. These minor misclassification problems can be easily resolved if more object features and another level of classification can be executed with the object-based classification methods.

4.2. KAPPA Analysis

Final accuracy assessment of classification results were based on the KAPPA analysis and error matrix. Results are shown below (Table 4). The referenced classification is based on the 42 samples collected during the field work and 79 samples directly extracted from NAIP data. The speculated samples from NAIP are believed to have high reliability given field visits to areas having similar wetland formation characteristics.

Table 4 Error Matrix

	Classified Data						
Reference Data	Marshes	Wet Meadows	Aquatic Bed	Scrub/Shrub	Floodplain Forest	Water	Row Total
Marshes	29	2	0	2	0	0	33
Wet Meadows	2	11	0	2	1	0	16
Aquatic Bed	1	0	5	2	0	0	8
Scrub/Shrub	1	1	0	12	3	0	17
Floodplain Forest	1	0	0	2	19	0	22
Water	0	0	0	0	0	25	25
Column Total	34	14	5	20	23	25	121
Overall Accuracy	**0.83**						

- **Producer's Accuracy (Omission Error)**

  Marshes 29/33 = 87.88%

  Wet Meadows 11/16 = 68.8%

  Aquatic Bed 5/8 = 62.5%

  Scrub/Shrub 12/17 = 70.6%

  Floodplain Forest 19/21 = 86.4%

  Water 25/25 = 100.0%

  Overall Accuracy = (29 + 11 +5 +12 + 19 + 25)/121 = 0.83

- **Khat Coefficient**

Khat=(N*∑Xii - ∑(Xi+*X+i)) / (N^2-∑(Xi+*X+i))

N = 121

∑xii = 29+11+5+12+19+25 = 101

∑(Xi+*X+i) = 33*34 + 16*14 + 8*5 + 17*19 + 22*23 + 25*25 =2857

Khat= 79.5%

4.3 Findings and Conclusions

This study examined the effectiveness of an integrated pixel-based and object-based classification method on wetland mapping. Many variables were generated to enhance the wetland identification process. Some of the variables, such as stream networks, Greenness, Wetness, NDVI, surface temperature and the leading two Principal Components, were more influential than others for the wetland detection. These influential variables represent real world wetland factors; vegetation, soil, and hydrology. Incorporating the geometric features extracted from the segmented objects, these influential variables contributed greatly to the accuracy of wetland mapping using inexpensive imagery.

The integrated classification method described in this research began with pre-processing the image to obtain spectrally and spatially adequate data. The preprocessing steps included geo-referencing, Gram-Schmidt spectral sharpening, and transferring the digital number to reflectance. The final phase of the wetland classification process involved synthetic analysis using the DEFINIENS® software. Through this research, the integrated approach has proved to be an effective and efficient method for high accuracy wetland mapping.

In natural communities small changes to one or more local conditions of altitude, hydrology and climate could result in an entirely different suite of soils, plants or animals. This complexity is one of the things that make wetlands so difficult to classify into distinct categories. Wetlands have not only variability of natural communities but also exist on a gradual continuum in the field. Considering that the USACE (1987) wetland definition was adopted for this research, a general wetland classification system, instead of the classification system of the U.S. Fish and Wildlife Service, was applied in classifying the wetland types discovered in the study area. The classes of the wetlands are aquatic bed, floodplain forest, marshes, scrub/shrub, and wet meadows. A similar categorization system was used in Wisconsin and can be found at the following link. http://www.wisconsinwetlands.org/wetlofwisc.htm

As can be seen from the accuracy assessment the classification approach developed performed especially well at locating inland marshes throughout the study area. To achieve a high accuracy of wetland mapping for all the wetland types, more field observations would need to be done so that the factors relevant for wetland identification can be collected and transferred into variables for data analysis. Nevertheless, the results shown in this research indicate that a high quality wetland mapping can be achieved using inexpensive multi-spectral LANDSAT ETM+, ASTER, and EO1 Advanced Land Imager images.

Methodologically, regardless of the computer capacity, the developed image processing procedures are suitable for the wetland mapping work in an even wider area. But to identify wetlands in an extremely large area some of the processes proclaimed in this research need to be automated and customized as tools. In addition, this research demonstrated the possibilities for classifying wetlands by setting up classification rules. For example, the segregation of sub-emerged vegetated wetlands (aquatic bed) and low marshes depends on the rules which can single out areas where vegetation appears in the dry season but disappears in the wet season.

5. FUTURE EFFORTS

Overall, the wetland mapping accuracy is quite good. Though the mapping accuracy for wet meadows and aquatic bed categories are only 68.8% and 62.5% respectively, the accuracy can be improved by additional research. For aquatic beds classification, the accuracy can be improved by doing more field work and observing their geographic relationship with rivers, seasonal water inundation, and the NDVI standard deviation. For the wet meadows class, to achieve higher accuracy mapping could be difficult because this category is often confused with general grassland. The accuracy of wet meadows identification can be resolved by employing multi-temporal satellite images. In addition, some ancillary data such as SSURGO soil data and distances to other wetland types and water bodies could be useful for enhancing the mapping accuracy. These are all activities which deserve our future efforts.

The integrated pixel-based and object-based classification approach developed in this research can be improved by developing a decision tree model to simulate the wetland occurrence logic in the real world and applying such logic as a mathematical model in the classification process. To successfully apply these mathematical models within a large geographical area requires a computer system with exceptional calculation capacity. A parallel computer processing system is a way for the future exploitation.

An accurate and smooth vector format of the wetland boundaries layer covering a large area is always demanding. The completed research provides a solid foundation for future work pertaining to this purpose. As most of the images used here are commonly used data and cover the whole State (except the EO1 ALI data), the feasibility for mapping wetlands across the whole state is considered quite feasible. The methods and parameters developed here are repeatable and can be written as processing functions by using the IDL scripting language. DEFINIENS® software allows users to create a process so that repetitive tasks can be automated. Creation of such a wetland identification process would lessen the burden for wetland mapping in a wide geographic area.

There are some cautionary notes and guidance. First, a large area should be divided into numerous operation units with less than 1000 km^2 to overcome the possible limitation of computer calculation capabilities. Second, for the mountainous areas, more time for data collection and validation may be required for each sampling site. Thirdly, additional remote sensing software license seats should be purchased for production level operations. Though there are some challenges we are optimistic about the capability of the developed methodology in mapping wetlands for the whole State and are hopeful that this can happen in the near future.

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