# MAPPING VEGETATION CHANGE ON A RECLAIMED SURFACE MINE USING QUICKBIRD[1]

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**Abstract.** This paper looks at two methods for visualizing and mapping vegetation change on a large surface mining complex in southern West Virginia. Two Quickbird image sets, acquired in 2003 and 2007, were used to identify vegetation trends and to map significant change events manifested during the four year interval. Vegetation trends were visualized using Normalized Difference Vegetation Index (NDVI) difference images, which proved to be a simple and effective means of identifying vegetation change events for further investigation. The study then evaluated Feature Analyst—a commercial analysis package—for its ability to map and quantify two of the most significant change events identified in the study area.

A field investigation used handheld GPS receivers equipped with ArcPad software and GPS-equipped cameras to verify the cause of the two events—1) the defoliation of stands of black locust, and 2) a significant increase in area dominated by deciduous shrub vegetation, caused by rapid growth in autumn olive. Feature Analyst was able to delineate the extent of black locust defoliation, estimated at over 152 acres on several reclaimed permits. In the second case, the analysis estimated that deciduous shrub cover expanded from 32 acres to over 81 acres on one permit, representing an increase from 6.5% to 16.5% of the total permit area.

Feature Analyst showed significant promise for extracting vegetation features from the source images, including individual trees. Feature Analyst's ability to effectively utilize panchromatic and multispectral image sets suggests it is an effective tool for use with increasingly high resolution data available from commercial vendors.

**Additional Key Words:** Remote Sensing, feature extraction, object recognition, landcover classification.

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## Introduction

The deployment of commercial high-resolution satellite sensors has dramatically increased the availability of high quality remote sensing products. The spatial, and temporal, resolution of these sensors suggests new possibilities for monitoring surface mining activity at a more detailed, site-specific level. At the same time, the extent of surface mining has increased rapidly, creating new challenges for understanding cumulative impacts to the physical and biotic landscape of Appalachia. In West Virginia, entire complexes of a dozen or more adjacent interconnecting permits have evolved over the course of decades, making it increasingly difficult to quantify and visualize landscape changes over large areas, such as watersheds.

The West Virginia Division of Environmental Protection (WVDEP) and the Office of Surface Mining's (OSM) Charleston Field Office currently are investigating methods for analyzing high-resolution satellite image products to support the regulatory process. This project is focused on issues relating to vegetation—including mapping vegetation types, percentage cover, and change over time—within a broad goal of identifying core capabilities of data resources and analysis methods that can address regulatory questions. Phase one of the project (Shank, 2007) investigated the potential for calculating percent vegetative cover from satellite images, which is a factor in determining eligibility for bond release. This paper specifically investigates the issue of vegetation change over time. Central to this investigation are the use of vegetation indexes to identify specific change events, and the use of Feature Analyst software, by Visual Learning Systems, to identify and map change areas on a large surface mining complex in southern West Virginia.

## Study Area

The study area is a subset of a large mining complex located in southern West Virginia (Fig. 1) that includes 18 surface mining permits issued to Hobet Mining between 1977 and 2004. The total permitted area for this complex is approximately 18 square miles, and includes permits ranging in status from active to phase III release.

Older permits in this area have post-mining land uses that include rangeland, wildlife habitat, and pasture, while more recent permits have tended to favor forestland. There are relatively large areas of herbaceous grasses on reclaimed areas, interspaced with deciduous trees, pines, and shrubs. Deciduous plantings sometimes occur in blocks and rows, while other areas have been hydro-seeded and the pattern is indistinct. Dense patches of bi-color lespedeza are clearly visible in some areas, and autumn olive appears to be rapidly expanding in many areas. Based on final planting reports and reclamation plans, dominant non-herbaceous species include autumn olive, black alder, bicolor lespedeza, Virginia pine and white pine.

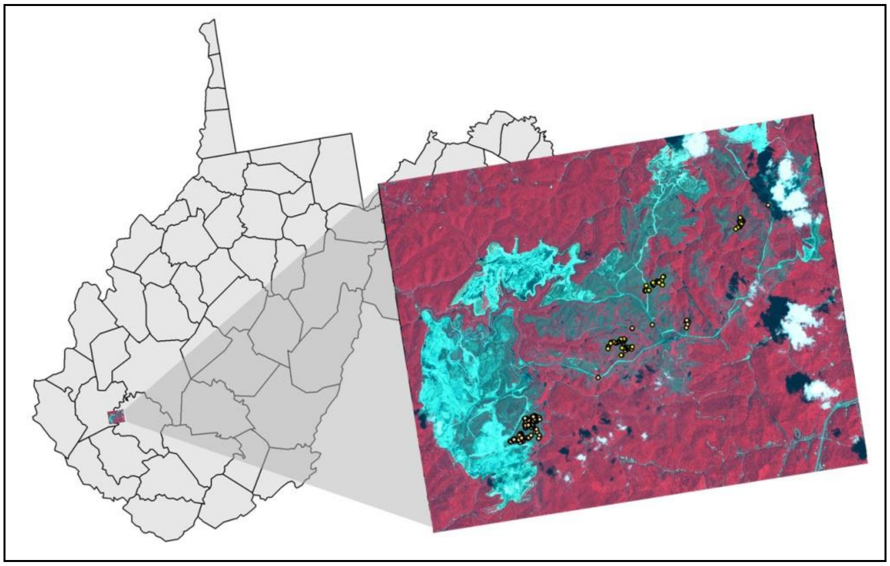

Figure 1. Study Area.

A site visit was made on August 1st, 2007. Trimble GPS receivers running ArcPad were used to locate the areas of interest identified from visual analysis of the satellite images used for the study. A GPS-equipped camera was used to record vegetation types found on the site, and to confirm the causes of unusual events observed in the images. Over 100 georeferenced digital photographs were acquired documenting vegetation types and patterns within the study area.

In addition to species identified on planting reports, the site visit identified additional volunteer species that included sycamore, black willow, red cedar, and ailanthus. Bristly locust and bi-color lespedeza were identified in concentrated patches, along with smaller patches of blackberry, and several small fields dominated by goldenrod. Several wetland areas contained dense concentrations of cattail, and often included black willow and sycamore nearby.

A visual comparison of two satellite images of the study area, acquired in 2003 and 2007, indicated general growth and expansion of vegetation throughout the reclaimed areas. Planted trees showed expanded crown diameter and more pronounced shadow characteristics due to increased height. Autumn olive appeared to be expanding into areas once occupied by grasses. The remaining barren areas showed reduced size as herbaceous species developed.

## Satellite Data

The study used images acquired in 2003 and 2007 by the Quickbird satellite. Quickbird is a commercial, high-resolution earth imagining satellite owned and operated by DigitalGlobe. The satellite collects both multispectral and panchromatic images simultaneously. The multispectral sensor produces a 4-band image, recording spectral radiance in the visible blue, green, red, and near infrared. Multispectral image resolution is 2.4m, whereas the panchromatic image resolution is 0.6m.

The first image was a subset of an archival scene captured on June 6, 2003. The second image was contracted by OSM's Technical Innovation and Professional Services (TIPS) program, and acquired on June 14, 2007. The images were delivered in 'ortho-ready' format, which includes basic georeferencing and sensor corrections. The West Virginia DEP performed orthorectification for terrain displacement using the 1/9 Arc-Second National Elevation Dataset provided by the USGS, and was precision georeferenced using ESRI's ArcMap software. A total of 11 control points were used, including 8 points collected using a Trimble GEO-XH GPS in the field. Typically, the adjustments made by the precision georeferencing were relatively small, on the order of a few pixels. The 2003 scene was then matched to the 2007 scene. A spline adjustment was used in conjunction with 72 common tie points identified between the two scenes.

Quickbird follows a sun-synchronous orbit, which maintains the angle of illumination for successive passes over a particular location. Metadata for the images indicates both were collected between 16:00 and 17:00 GMT, or mid-morning local time. The original pixel values were not modified prior to analysis. However, the display software used to produce figures shown below performed a contrast stretch on each image individually.

The two scenes are shown as false-color infrared in Fig. 2 and 3. Significant new mining activity has occurred in the four-year interval, characteristically depicted as light blue areas in the center-west, and the northeast. Recent reclamation activity also has taken place to the southwest and northeast. The center of the scene contains numerous older permits in Phase I and Phase II release status with more established vegetation. Grasses in this area are a darker grey-blue, while shrub and tree species are mostly pink. Undisturbed deciduous forest surrounding the mining complex appears bright red. The 2007 scene also contains scattered clouds, and associated shadow, which typically are masked out prior to analysis.

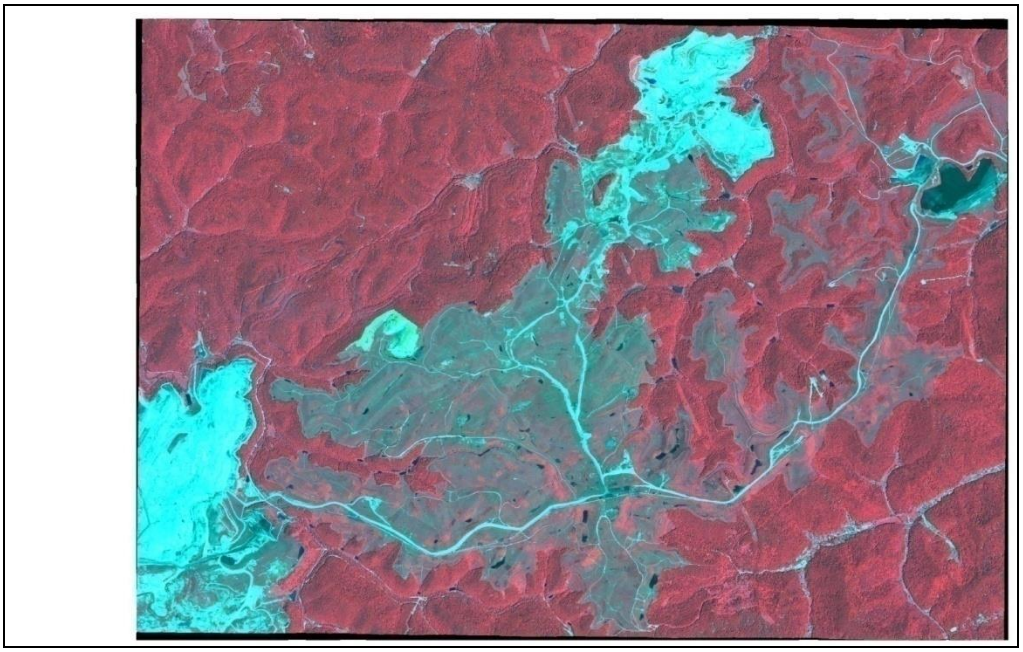

Figure 2. Quickbird scene from June, 2003.

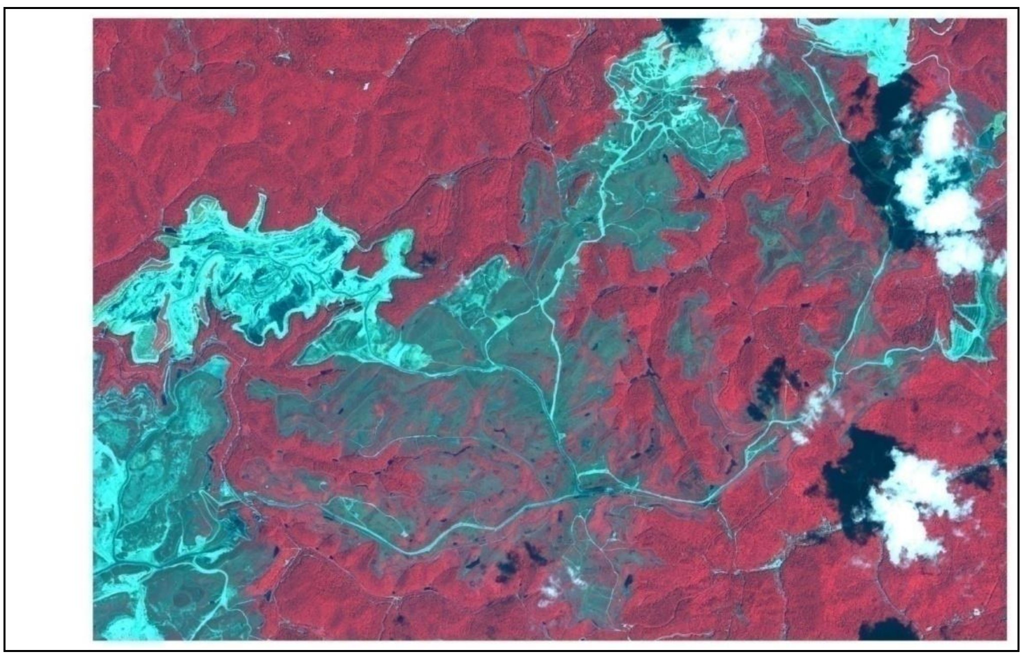

Figure 3. Quickbird scene from June, 2007.

## **Analysis**

Change Detection Overview

1. Analyzing change is a common topic in remote sensing research. The nature of the changes being investigated can vary considerably, from relatively short term events such as snow cover, flooding, and forest fires, to longer trends like suburban

development, deforestation, glacial retreat, or wetland loss. Analysis of vegetation change often is performed on image pairs from the same sensor, collected at approximately the same time of year to minimize seasonal variation and the effect of sun angle.

2. Methods for conducting change analysis vary widely, but most techniques can be characterized as either a visualization technique, or a mapping technique. Visualization techniques manipulate source data so that change events are revealed to an observer who can interpret them for some purpose. Mapping techniques, in contrast, attempt to automate the extraction of change events, producing a dataset that allows them to be mapped and quantified. This study applies both approaches in an attempt to identify and characterize significant vegetation trends within the study area.

<u>NDVI differencing</u>

Vegetation indices, particularly the Normalized Difference Vegetation Index (NDVI), have been applied to a wide variety of remote sensing vegetation studies. Vegetation indices exploit the characteristic of vegetation to reflect significantly more light in the near-infrared portion of the electromagnetic spectrum than adjacent red frequencies (Fig. 4). In contrast, substrate materials tend to reflect similarly in both segments.

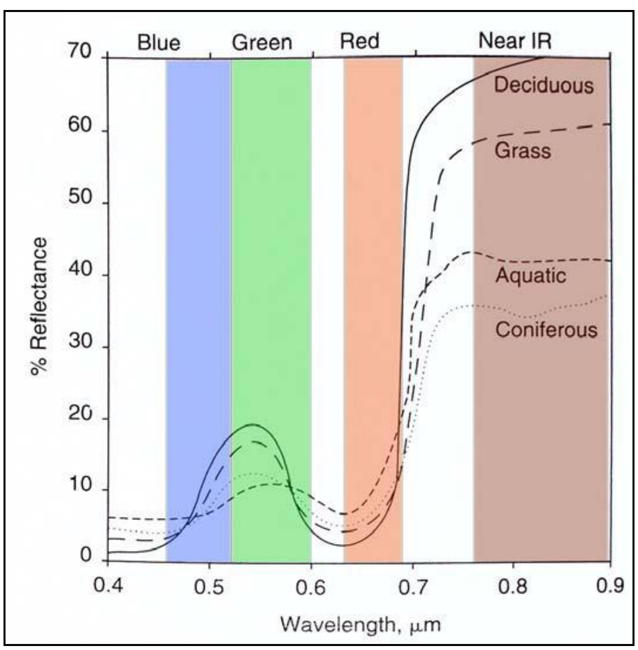


Figure 4. Typical vegetation reflectance patterns, superimposed with sensor bands associated with the Quickbird multispectral sensor

NDVI has been used to estimate leaf area index, to reveal stressed vegetation, to identify deforestation, and to monitor desertification (Avery and Berlin, 1992). It also has been used to identify trace quantities of vegetation (Elvidge *et. al.*, 1993) and estimate percent vegetation cover (Purevdorj *et al.*, 1998) using satellite data. Shank (2007) related NDVI to field measurements of vegetation cover on a recently reclaimed surface mine in order to estimate the overall percentage of the area that had been revegetated.

NDVI is specified as:

$$NDVI = (NIR - RED) / (NIR + RED) \qquad \textbf{(1)}$$

Where *NIR* is the recorded radiance in the near infrared, and *RED* is the recorded value in the red portion of the spectrum for a particular image pixel. NDVI values for non-vegetation typically produce small or slightly negative values, while vegetated areas produce values starting around 0.4 and approaching 1.0.

On a basic level, direct comparison of NDVI values at two time intervals can be used to visually analyze vegetation changes within a study area. Simple subtraction ($NDVI_{2007}$ – $NDVI_{2003}$) can be used to map the magnitude of change in the interval spanned by the two scenes. Assuming there are no systemic impacts affecting one of the images, it is reasonable to interpret significant positive values as an increase in vegetation density, and negative values as a reduction.

Of course, real-world measurements are often more complicated. NDVI changes also can be indicative of a significant increase or decline in vegetation health due to stress conditions, such as drought, infestation, or herbicide. Gong *et.al.* (2006) suggested adjusting the NDVI values of the latter scene to account for systemic impacts before comparing values. A multiplicative term was applied, based on the mean difference in NDVI in the two scenes, calculated for areas in the image that were not subject to significant change:

$$\text{Adjusted\_NDVI}_{post} = \text{NDVI}_{post} * \text{Ratio\_C} \qquad \textbf{(2)}$$

Where:

$$\text{Ratio\_C} = \text{Mean\_NDVI}_{pre} / \text{Mean\_NDVI}_{post} \qquad \textbf{(3)}$$

Initial comparisons of the two Quickbird scenes indicated that some vegetation may have been affected by moderate drought conditions ongoing in 2007. Drought impact was investigated by selecting ten sample areas lying outside the permit boundaries where no apparent changes had occurred. The results, shown in Table 1, indicate that forested areas showed no significant difference between the two dates, in fact having less variation than water and road samples. Samples taken from grassy areas did show significant variation in some cases. However, these differences can be hard to interpret. Though none of the fields appeared to be in use for agricultural production, they may have been cut periodically by their owners. Similarly, grassy areas associated with residential areas may have been subject to watering or fertilization.

In summary, while drought conditions may have contributed to an overall decrease in NDVI values for some grassy areas, this condition did not predominate across the scene, as evidenced by the lack of change for forested areas. While it is considered valid to adjust NDVI values prior to comparison when warranted, it was not performed for this study.

Table 1. Mean NDVI values for sample areas representing no-change areas.

| **Cover Type** | **2003 NDVI** | **2007 NDVI** | **Change** |
|---|---|---|---|
| Forest | 0.75 | 0.76 | 0.01 |
| Forest | 0.78 | 0.77 | -0.01 |
| Forest | 0.76 | 0.77 | 0.01 |
| grass, field | 0.71 | 0.53 | -0.18 |
| grass, field | 0.56 | 0.56 | -0.01 |
| grass, field | 0.57 | 0.45 | -0.11 |
| grass, large lawn | 0.72 | 0.64 | -0.09 |
| grass, large lawn | 0.70 | 0.57 | -0.13 |
| Road | 0.10 | 0.12 | 0.03 |
| Water | 0.13 | 0.17 | 0.03 |

The NDVI difference image is shown in Figure 5. Broad trends are easily visible throughout the scene, including an large drop in NDVI caused by the transition from forest to active mining at locations 1 and 2, and a large increase in NDVI due to the change from active mining to reclamation activity at 3 and 4. Location 5 indentifies a forested area that did not change between the two dates. Area 6 results from cloud cover in the 2007 scene, and area 7 represents cloud shadow. Location 8 is a high voltage transmission line showing a significant reduction in vegetation, due to the application of herbicide and tree cutting.

Locations 9-11 in Fig. 5 show areas of NDVI loss in reclaimed areas. Results in area 9 may be due to drought conditions. It also is possible that grasses have replaced brushy species that exhibited a larger total leaf area. However, since field work was not performed for the first image, this is not known for certain. Finally, areas 10 and 11 were confirmed by field investigation to be caused by a die-off event, which will be investigated in detail below.

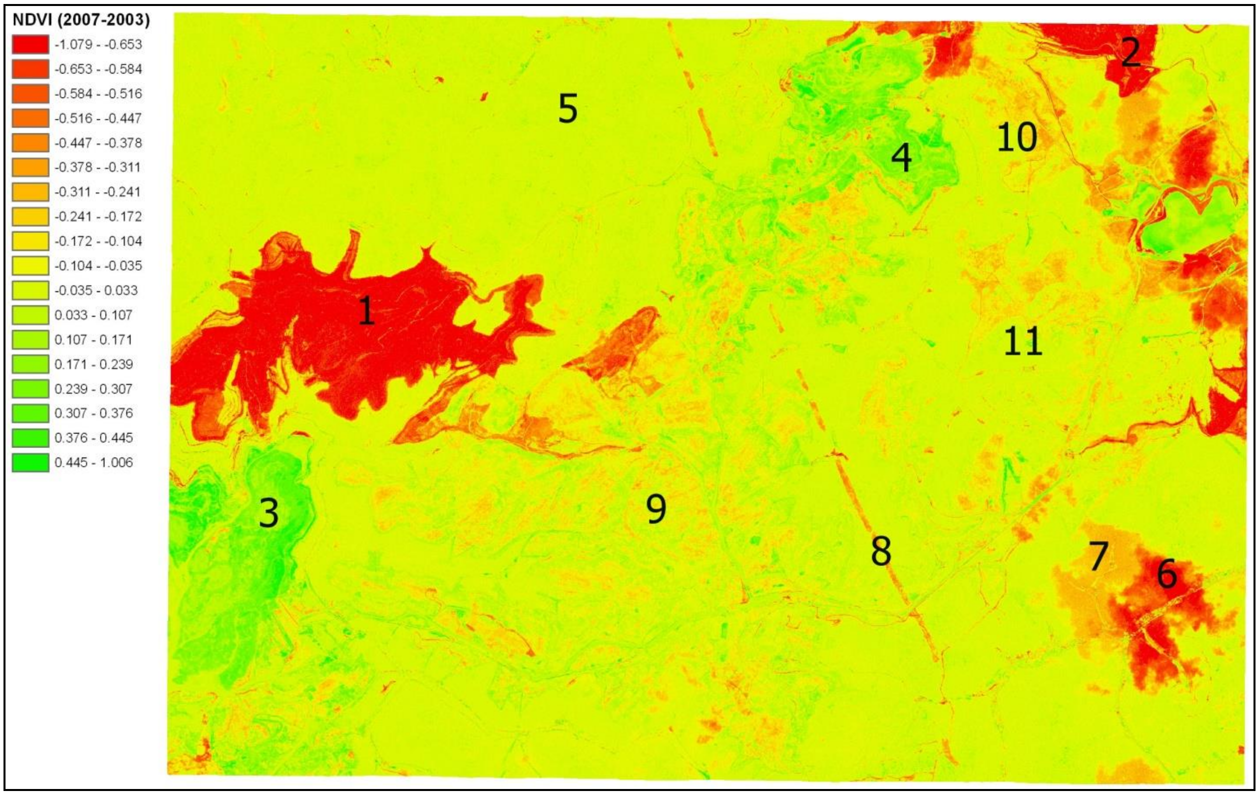


Figure 5. NDVI difference image of the entire area, where red indicates a reduction in NDVI and green represents an increase.

Close examination of the NDVI difference image suggested two areas for further investigation. Figure 6 shows an area of exceptional NDVI loss, which field investigation revealed was due to canopy defoliation of black locust. Visual examination of individual trees in the field indicated infestation by a boring insect, consistent with the locust borer, though a positive identification was not made. At the time of the investigation, many of the affected trees had regenerated new growth near their base. Figure 6(a) indicates a reduction in NDVI of more than 3 times the standard deviation between the two dates, relative to the "no change" samples collected for Table 1. Figures 6(b) and 6(c) show the same area in 2003 and 2007, respectively, and Fig. 6(d) is a GPS-tagged photo of the area taken during the field investigation. In the second part of the analysis, we will attempt to map the extent of this infestation and quantify the affected area.

Figure 7 reveals an area of vegetation growth, which field investigation identified as primarily autumn olive. Figure 7(a) shows areas of +2 and +3 times the standard deviation in green, with the corresponding areas from 2003 and 2007 in Figures 7(b) and 7(c), respectively. Figure 7(d) is a GPS-tagged photograph from the field investigation that confirmed the source of this increase in vegetation. As with the previous example, a more advanced analysis was designed to map the extent of this increase, which will be discussed below.

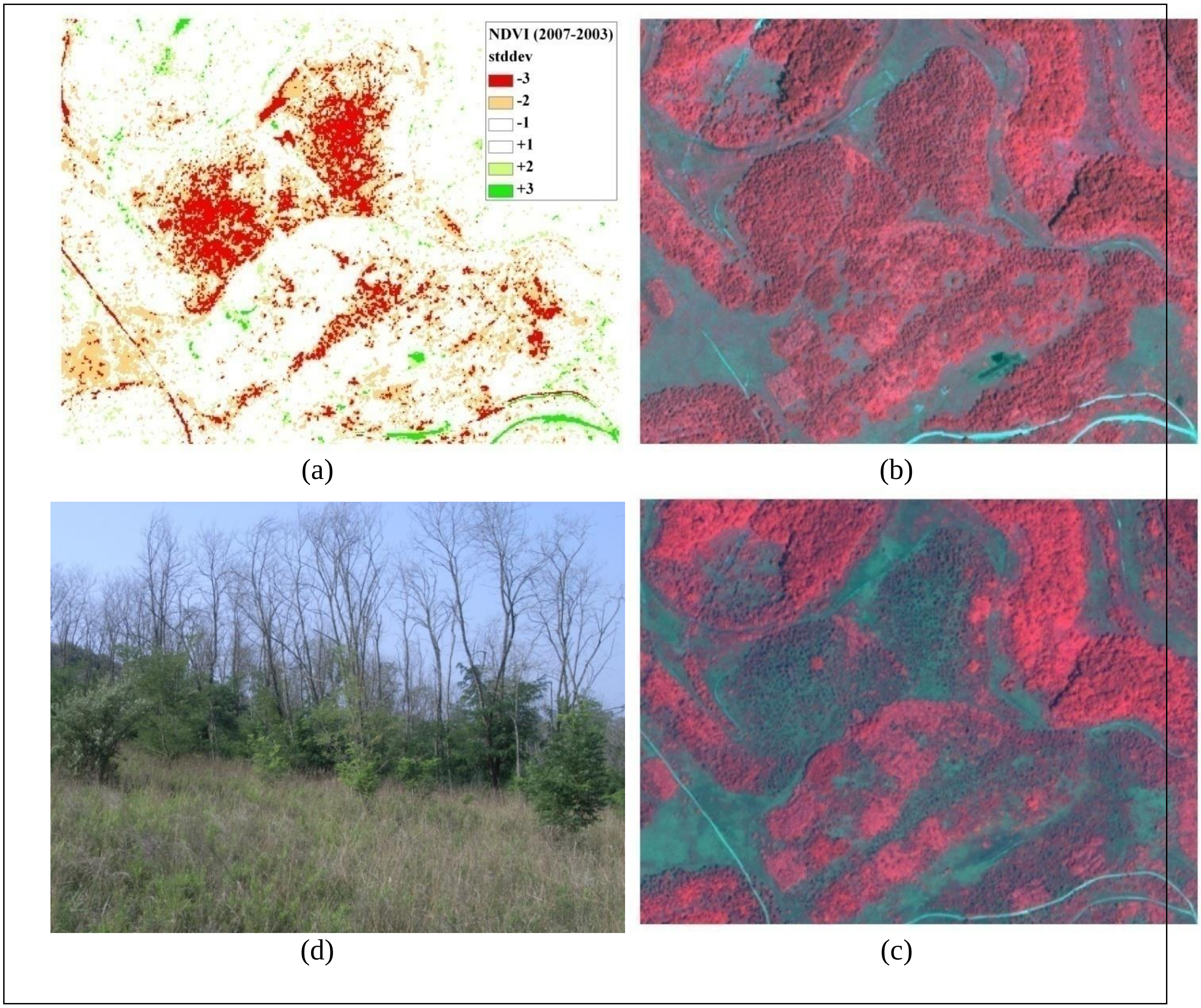


Figure 6. NDVI change analysis detected a significant loss due to defoliation of stands of black locust. (a) Red areas show a decrease of greater than 3 standard deviations from the mean, relative to unchanged areas. (b) Apparently healthy stands of black locust in 2003. (c) The same stands in 2007. (d) Defoliated trees captured using a GPS Camera. The trees have begun to regenerate near their base.

Also apparent in Fig. 7(a) are several areas that depict a net decrease in NDVI between the two scenes. This phenomenon is associated with areas dominated by grasses at the time of the field investigation. Close visual inspection of available images suggests the current grasses may have replaced other vegetation types that reflected significantly more infrared. The increased infrared response may indicate vegetation with significantly different leaf morphology, density, or both.  However, a conclusive identification of species occupying these areas in 2003 could not be made.

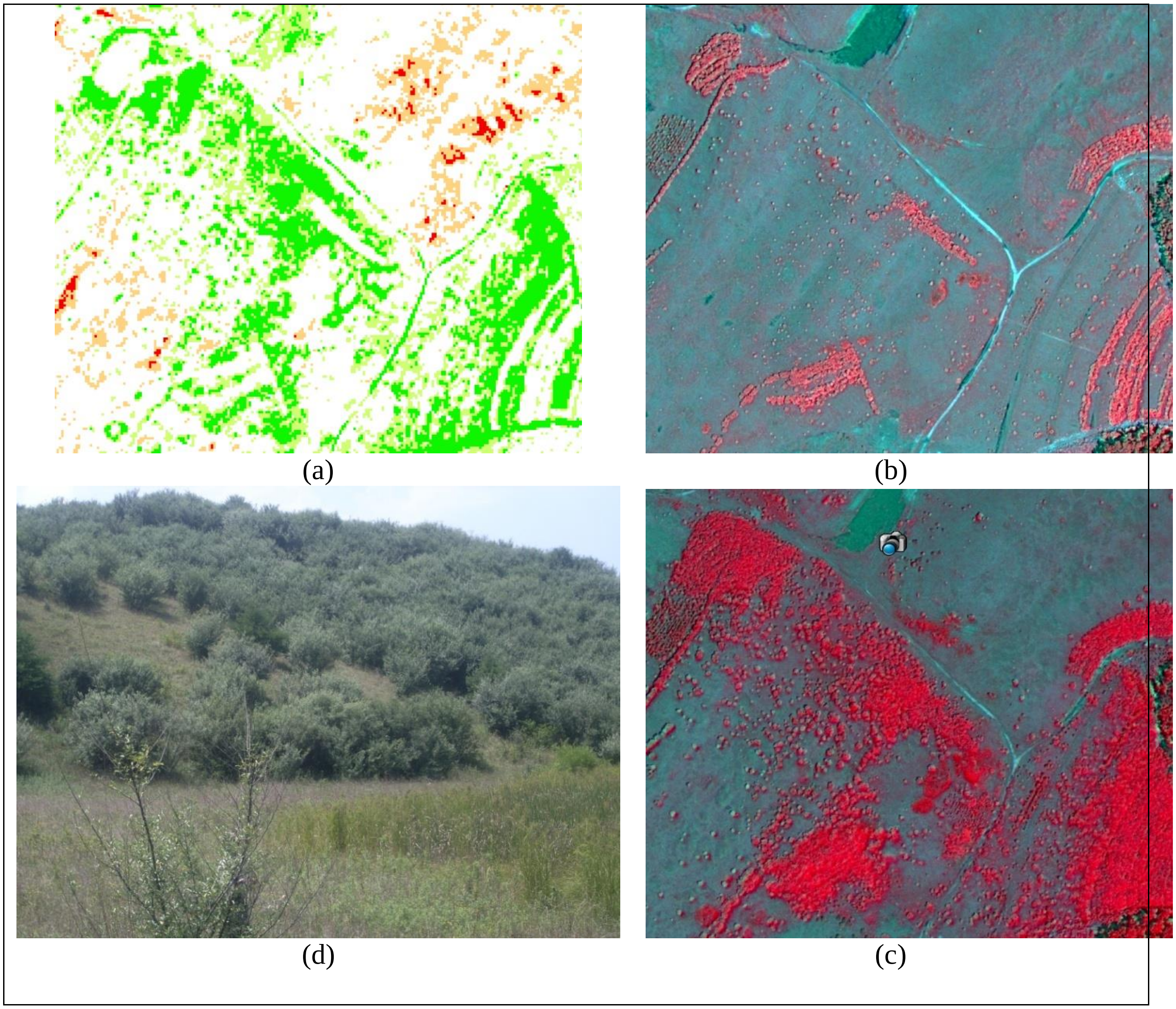

Figure 7. Detail of an area exhibiting a large increase in NDVI due to vegetation growth. (a) Green areas depict areas with an increase greater than +3 standard deviations from the mean. (b) Area as it appeared in 2003. (c) The same area in 2007. (d) GPS-coded field photograph showing the expansion was due to autumn olive.

Landcover Classification and Feature Extraction

NDVI differencing is an effective technique for visually analyzing changes in vegetation over time using matched image pairs, particularly since it can be easily symbolized to indicate both gain and loss in biomass or vigor. This technique was found more useful than examining single and multiband difference images. However NDVI differencing is not useful for mapping or quantifying specific types of change within a scene.

Historically, remote sensing research has devoted significant effort to developing and evaluating methods for extracting thematic information from images. The general goal is to improve on the manual process of identifying features such as buildings or trees, or delineating boundaries between types of landcover. This is because manual digitizing can be exceedingly slow, very expensive, and sometimes tedious.

Traditional research in this area focused on the creation of thematic maps depicting basic landcover types, *e.g.* conifer, hardwood forest, shrub, grass, water, etc. Methods usually relied on the degree to which these different landcover types exhibited distinct reflective characteristics in different bands of the electromagnetic spectrum. However, these routines failed in circumstances where landcover types were similar enough to mix, or overlap.

As researchers confronted the limits of spectral-based methods, the remote sensing landscape was radically altered by the launch of high-resolution digital sensors from commercial vendors, and by the introduction of laser-based elevation mapping systems. Data products from these systems suggested new possibilities for feature extraction, such as identifying individual objects. At the same time, research has suggested that increased resolution could be problematic for established methods, due to a consequent increase in spectral variability for particular landcover types (Cushnie, 1987). For example, the widely used Landsat sensor averaged radiance across an area about 30 meters square, whereas high-resolution sensors can capture partial canopies of individual trees, which can be oriented at any angle to the sun.

These developments have lead to increasingly complex routines for extracting information. Some of these techniques attempt to segment an image into a set of 'objects' (Carleer *et.al.*, 2005) , then use a variety of metrics calculated from the spectral, textural, and neighborhood attributes to identify the object (Thomas *et.al.,* 2003, Yu *et.al.,* 2006). Other approaches draw from developments in machine vision pursued by researchers in artificial intelligence. Most of these approaches seek to effectively incorporate additional characteristics for identifying objects that human analysts use as a matter of course, such as shape, size, texture, shadow, and association (Blundell and Opitz, 2006).

Feature Analyst

Feature Analyst was designed to leverage advanced processing techniques behind a relatively simple user interface. It is designed as a general purpose tool that can identify and extract objects from an image based on an exemplar set supplied by an analyst. Blundell and Opitz

(2006) relate broadly the Genetic Ensemble Feature Selection (GEFS) approach used by Feature Analyst. This approach employs a genetic algorithm to identify a set of neural networks that, working together, produce results that are significantly better than any single algorithm used alone. Initial results can be refined using a process they call hierarchical learning, which incorporates analyst-identified errors and omissions during a second and third pass. The Feature Analyst approach borrows from artificial intelligence research in machine vision, which is now being applied to high resolution satellite images.

Feature Analyst was used for this study because it provided relatively sophisticated feature extraction capabilities that could be applied quickly to the problems being studied. These capabilities were packaged as a general purpose tool that was relatively easy to use. The software was installed as an extension of ESRI's ArcGIS software, making the considerable visualization and analysis tools provided by this software accessible from a single user interface. While a custom-designed technique, or set of techniques, might have been developed that produced comparable results, the time needed for this development likely would have been excessive. And the approach may have had limited application, or would have been difficult and time consuming to adapt to new problems.

Mapping Black Locust Defoliation

Examination of the NDVI difference image indicated a significant defoliation event, confirmed by a site visit, to be affecting stands of black locust. The first test of Feature Analyst was to delineate the extent of this event. For the analysis, a ten-band composite image was used as input, which included the four original spectral bands from the 2003 and 2007 images, plus the two NDVI bands. The analysis process consists of selecting several training areas representing the feature of interest, setting a series of input parameters, and running the algorithm to produce an initial output that delineates similar features found within the scene. In the second phase, the analyst examines the results and identifies a subset of features that are either correctly or incorrectly identified. The algorithm is then run a second time to optimize the initial results. The typical result is a significant reduction in erroneous features. A third phase allows the analyst to add additional features that previously were missed. However, for this analysis the results were far too permissive—far too many additional erroneous features were added—to be considered useful, and this step was not used. Instead it was found more productive to add missed features to the initial training set and repeat the first step again.

Feature Analyst identified defoliation over an area totaling over 152 acres of reclaimed land. Most of the affected area occurred in a southern area, shown in Fig. 8, and a northern area shown in Fig. 9. Mapping the defoliated area was judged significantly faster than manual digitizing, considering the complex nature of the shapes involved. The software also identified areas that had not been identified previously by visual analysis.

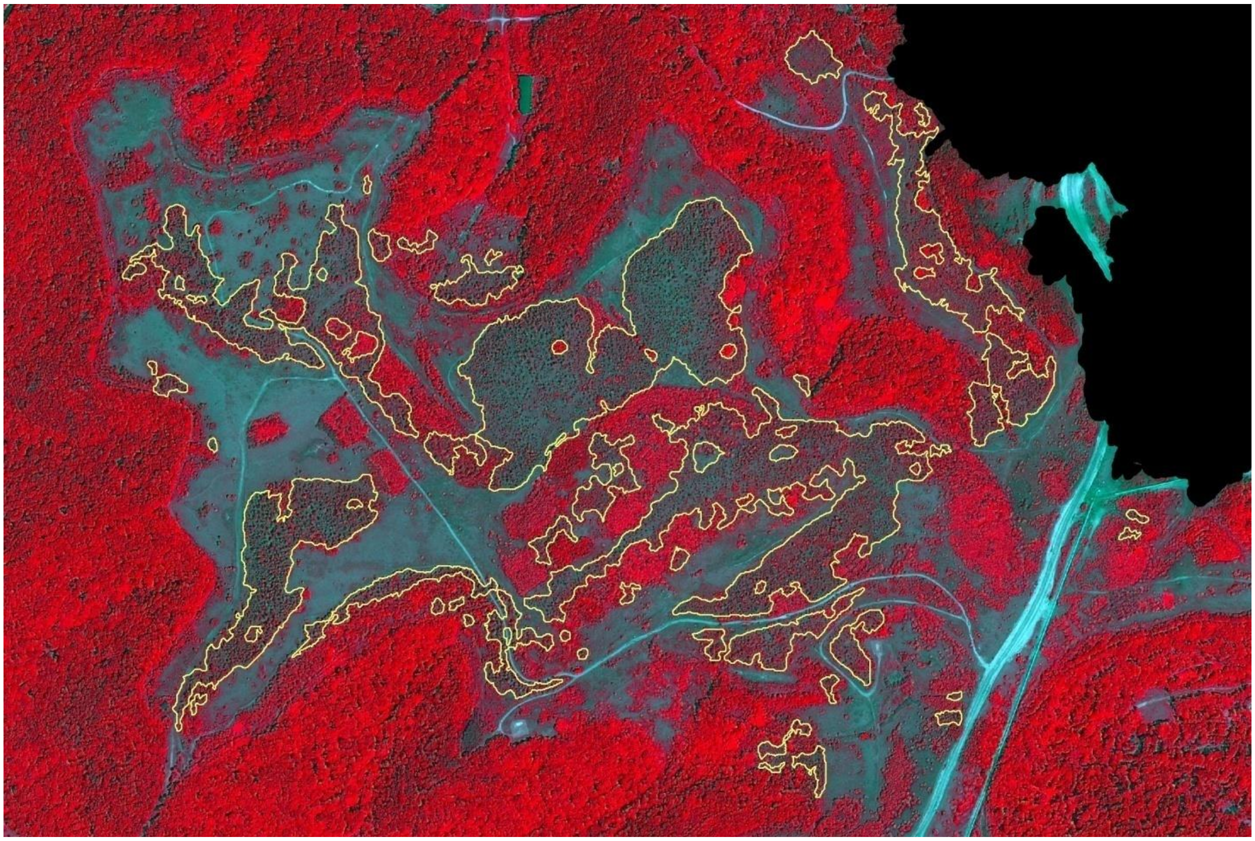

Figure 8. Southern defoliation area delineated by Feature Analyst.

Mapping the defoliation event was considered a good fit for Feature Analyst because success depended on the unique texture produced by the loss of canopy leaves in the 2007 image. Methods that depend solely on spectral characteristics likely would have been confused by other change events occurring in other parts of the scene. While some ad hoc method of incorporating the use of texture could have been found, significant time would have been spent developing the method of analysis, instead of obtaining a final result.

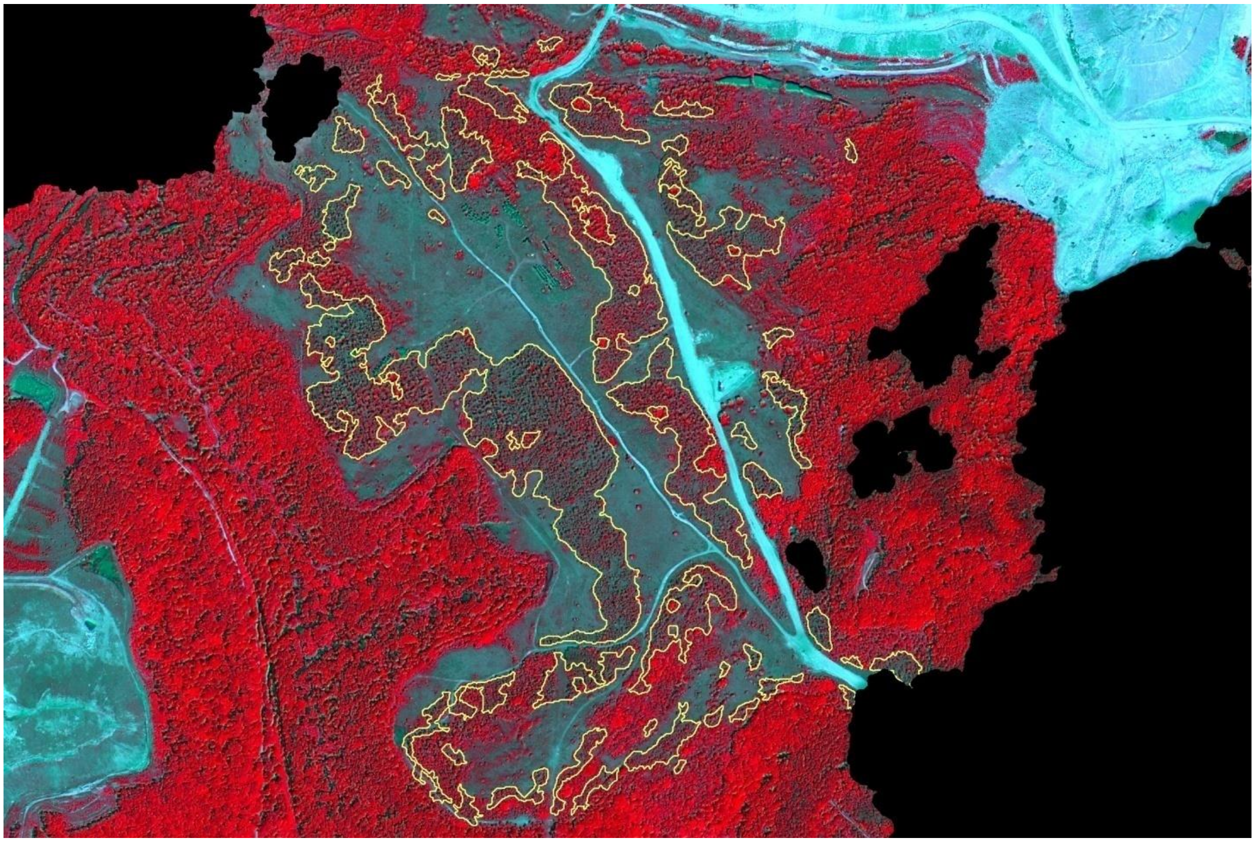

Figure 9. Northern defoliation delineated by Feature Analyst.

Mapping Autumn Olive Expansion

The second use of Feature Analyst involved mapping the rapid expansion of shrub species observed on the NDVI difference image in the previous section. Close examination indicated that this problem was more difficult than the previous example, because shrubs occurred both in solid blocks and as individual trees on both images. Therefore, the analysis was separated into two phases for each image, first by extracting solid blocks of shrub vegetation, and second by extracting occurrences of individual trees. The results then were merged to create a single map of shrub occurrence for each date.

Because Feature Analyst relies heavily on spatial pattern for extracting smaller features, it was decided to run the tree extraction process twice—once for smaller trees, and once for larger ones. This allowed the texture pattern used by Feature Analyst to be adjusted for each size category. Figure 10(a) shows a subset of the scene which includes several of the individual trees used for training Feature Analyst to identify larger trees. Figure 10(b) shows the pattern selected for use by Feature Analyst for identifying these trees. The presence of shadow to the upper left of individual trees was a key characteristic, making it important to size the training pattern within the shadow area. The pattern also should differentiate between the spectral response of the center pixel, made up of deciduous leaves, and surrounding pixels, which typically would be grass. Figure 10(c) shows the initial features returned by Feature Analyst for the same area. In Figure 10(d) these features have been converted into point locations and buffered by 3 meters,

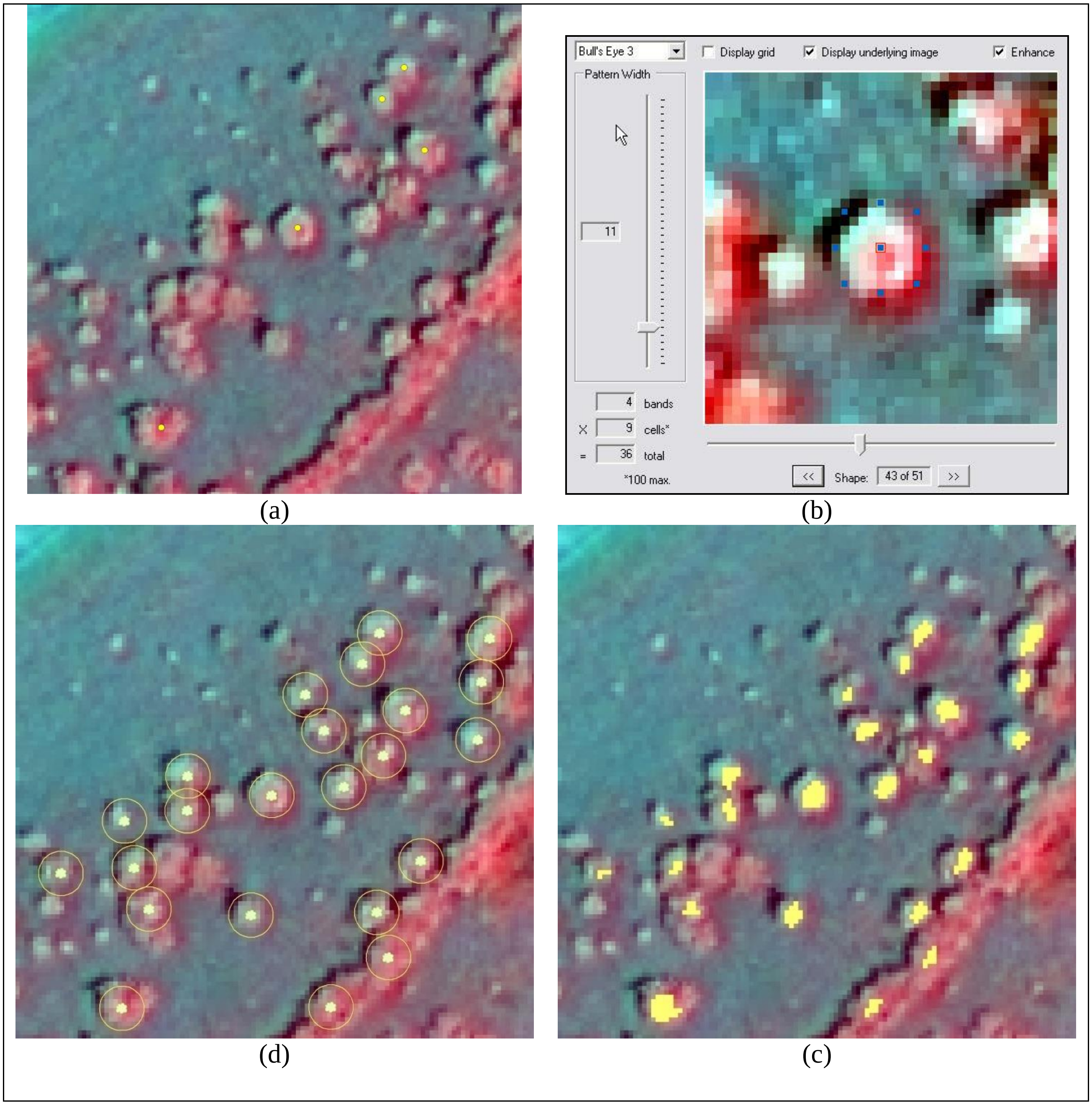


Figure 10. Extraction of medium-large trees from the 2003 scene. (a) Close-up, with training examples identified by yellow circles. (b) Pattern selected for training Feature Analyst. The shadow thrown by individual trees was a critical feature for identification. (c) Results returned from the initial extraction. (d) Initial extraction results converted to point features and buffered by 3 meters.

suggesting the ease with which basic GIS tools could be used to develop datasets for modeling tree canopy or attempting stem counts.

Individual tree extraction was performed on four-band pan-sharpened images. Pan-sharpening was seen as a way to incorporate the superior resolution of the panchromatic image captured by the sensor, with the advantages of the multispectral image for discriminating between many types of landcover.

Visual examination of the tree extraction results suggested the software has good potential for identifying individual trees and shrubs when sufficiently isolated. The second pass, which trained on smaller exemplars, identified most of the remaining trees shown in Fig. 10. Because shadow pattern was so critical, Feature Analyst also tended to identify tree objects within tightly packed rows, and occasionally other objects with a similar shadow pattern.

During the analysis, it was discovered that the multispectral and panchromatic scenes were not always in perfect alignment, so that the color information became offset relative to the object in the panchromatic scene (see Fig. 10(b)—the color information is offset to the lower right). This misalignment should have negatively impacted the quality of the results, and it was considered remarkable that the software performed as well as it did under these circumstances. There currently are plans to correct this problem and run the analysis again, after which the results will be compared to manual delineation in order to provide more rigorous guidance in the use of the software for estimating the extent of deciduous canopy.

Output from the individual tree extractions was combined with output from the extraction of solid blocks of deciduous plantings, creating composite maps of shrub cover for both dates. Figure 11 shows the composite cover for permit S502991, with the 2003 composite in light green against the darker green for 2007. Figure 11 reveals the extent of expansion in deciduous shrub canopy during this period. Over the time interval between the two images, deciduous shrub canopy increased from 32.2 acres in 2003 to 81.7 acres in 2007. This represented an increase from 6.56% to 16.63% of the entire permit area.

Results from this analysis are considered preliminary, in that the results suggest significant possibilities for mapping vegetation on a fairly detailed scale. An examination of the results indicates no large-scale error sources that would significantly modify the basic conclusion—that the area within the permit occupied by shrub canopy, overwhelmingly consisting of autumn olive, has more than doubled in four years. On the other hand, significant work remains to be done to refine the analysis, for example, by doing a better job of aligning the panchromatic and multispectral images. More work also needs to be done to investigate the impact of modifying some of the parameters set within Feature Analyst, and in developing a procedure for evaluating the accuracy of the results.

Figure 11. Permit S502991, showing deciduous shrub canopy in 2003 (light green) and 2007 (dark green). Canopy cover expanded from 32.2 to 81.7 acres between acquisition of the two images.

## Conclusion

This paper attempts to address one facet in a broader question of the role of remote sensing in monitoring surface mining and reclamation activity. This question has evolved significantly in the last decade, as new sensors have become available, and new techniques have been developed to analyze them. These developments have coincided with rapid expansion in the size of surface mines in the Appalachian region, and new questions about the quality of landscape being constructed in the wake of mining activity.

Specifically, this study examined the utility of two methods for identifying vegetation change events on surface mines. The first technique, NDVI differencing, was found to be a simple and effective method for visually identifying significant changes in vegetation using a matched pair of satellite images. Feature Analyst was evaluated as a second technique for producing detailed, quantifiable data of change events. Feature Analyst's close integration with ArcMap GIS provided seamless access to extensive GIS analysis and visualization capabilities, which simplified and accelerated the analysis process. Preliminary results demonstrated Feature Analyst's effectiveness at extracting features with distinct texture. The software appears to be particularly effective at integrating the panchromatic and multispectral images produced by commercial satellites, leveraging the advantages of higher spatial resolution and detailed texture information in the panchromatic scene, and the more detailed spectral information contained in the multispectral image.

Despite its established promise, a significant amount of investigation is still necessary for understanding the affect of varying individual parameter settings associated with Feature Analyst, including resample level, training pattern selection, and whether or not to apply a histogram stretch. There is an obvious need to devise objective metrics for evaluating the software's capabilities for producing accurate results. The case of extracting individual trees appears to be one area that deserves further investigation, since stem counts are an integral measure of reclamation success.

Further work also remains in evaluating the software's capability for identifying other distinctive vegetation types, which would help build a more detailed model of large reclaimed areas. It was noticed during the extraction of autumn olive that the classifier skipped blocks of conifer and alder, which the software may be trained to identify, along with other distinctive features common on reclaimed and active sites

Advances in spatial data gathering are not limited to commercial satellites. A revolution is underway with the deployment of integrated sensors that capture laser elevation data (LIDAR) in conjunction with high resolution multispectral images with 20cm resolution. Features that cannot be resolved from spaced-based sensors now fall within the capabilities of these aircraft mounted sensor packages. More advanced, flexible tools are essential for rapidly and efficiently extracting useful information from these data sources.

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