
The Investigation of Classification Methods of High-Resolution Imagery

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Abstract.—As remote-sensing technology advances, high-resolution imagery, such as Quickbird and photography from the National Agriculture Imagery Program (NAIP), is becoming more readily available for use in forestry applications. Quickbird imagery is currently the highest resolution imagery commercially available. It consists of 2.44-m (8-ft) resolution multispectral bands ranging from blue to near infrared and a panchromatic band acquired simultaneously at 0.61-m (2-ft) resolution. In the near future, NAIP will provide annually updated, orthorectified, natural color, aerial photography at 1-m resolution across the continental United States. Our objective was to investigate two classification methods: an individual tree crown delineation and classification procedure and a technique using Feature Analyst software for classifying high-resolution Quickbird and NAIP photography. Both methods were found to be effective for discriminating different vegetation types using Quickbird and NAIP photography, although the Quickbird imagery proved to be superior to the NAIP photography according to visual and numerical assessments.

The numerical accuracy of the resulting maps ranged from 48 percent to 63 percent at the Level II classification, in which a class was determined based on the plurality of the species within approximately a hectare of the point. At the Level III forest and nonforest classification, the numerical accuracies ranged from 89 percent to 94 percent. The visual

assessments revealed good results, especially at Level III forest and nonforest classifications. We believe that these assessments show strong potential for their use as ancillary products in Interior West FIA's forest resource estimation procedures and should be further pursued.

Introduction

The U.S. Department of Agriculture (USDA) Forest Inventory and Analysis Program (FIA) strives to produce better information with lower costs and increased frequency. The objective of FIA is to estimate broad-scale forest population totals and to track trends and detect changes in our Nation's forests. In the past, inventories were conducted and estimates produced on a periodic basis (every 5 to 20 years). The 1998 Farm Bill, however, requires a proportion of all field plots to be measured (1 out of 10 in the Western United States and 1 out of 5 in the East) *each* year on *all* lands in the United States, and forest population estimates must be updated. In an effort to become more efficient, the Interior West (IW) region of FIA is investigating high-resolution remotely sensed products to assist in obtaining the information requirements of this legislation while reducing inventory costs.

With the technological advancement of satellite systems, high-resolution satellite imagery, such as Quickbird, is becoming more readily available for use in forestry applications. Currently, Quickbird imagery has the highest resolution commercially available. It consists of 2.4-m (7.9-ft) resolution multispectral bands ranging from blue to near infrared and a panchromatic band acquired simultaneously at 0.6-m (2.0-ft) resolution. The Quickbird satellite was launched in October

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2001 and is owned and operated by DigitalGlobe (<http://www.digitalglobe.com>). Quickbird has a geolocational accuracy within 23 meters, an imaging swath 16.5-km (10.2-mile) wide, 128 gbits image storage capacity onboard, and an off-axis unobscured design telescope with an 11-bit dynamic range (DigitalGlobe 2005). These characteristics present an opportunity to identify individual crowns of vegetation.

In addition to Quickbird, another high-resolution product we examined is aerial photography from the National Agricultural Imagery Program (NAIP), which is available for download from the Internet (<http://www.apfo.usda.gov>). The NAIP acquires digital ortho imagery during the agricultural growing season of the continental United States. The photography is orthorectified, natural color, 1-m resolution photography with a horizontal spatial accuracy matching within 3 m of an orthorectified reference digital ortho quarter quad (DOQQ). With resolution, timely acquisitions, and availability, this product is very desirable as a modeling tool or for identifying/locating vegetative features on the ground.

Numerous algorithms are being developed for delineating individual tree crowns (Culvenor 2002, Definiens 2003, Leckie *et al.* 2003, Pouliot *et al.* 2002). CLC-Camint, Inc., uses its own proprietary methodology for delineating and classifying tree crowns using Quickbird imagery. This methodology uses an automated individual tree crown (ITC) classification and object-based segmentation procedure (Gougeon 1995, Gougeon 1997) to generate a digital map of tree crowns integrated into a Geographical Information System. The ITC algorithm uses a valley-following approach (Gougeon 1995) to delineate unique tree crowns. This approach searches for the shaded areas between crowns and removes (masks out) these areas, leaving objects representing the crown of a tree. The method uses the Quickbird imagery to create a digital layer depicting each unique tree crown. These delineated crowns are further classified by species type based on identified training sites (or trees), along with multispectral, textural, structural, and contextual analysis tools. Signatures are developed for each individual tree crown, and a maximum likelihood decision rule assigns it to a species type class.

An alternative automated procedure for extracting features is implemented in Feature Analyst, software developed by Visual Learning Systems, Inc. (<http://www.vls-inc.com>). Feature Analyst is a user-friendly, automated machine learning approach for extracting land cover features, or objects based on user-specified examples. Feature Analyst uses spectral and spatial pattern recognition techniques to extract features from high-resolution digital imagery. Where traditional classifiers use color and tone to extract features, Feature Analyst uses characteristics such as size, shape, color, texture, shadow, association, and pattern to extract features of interest. Although Feature Analyst has the functionality of delineating individual tree crowns, only stand-level classifications were generated for this study.

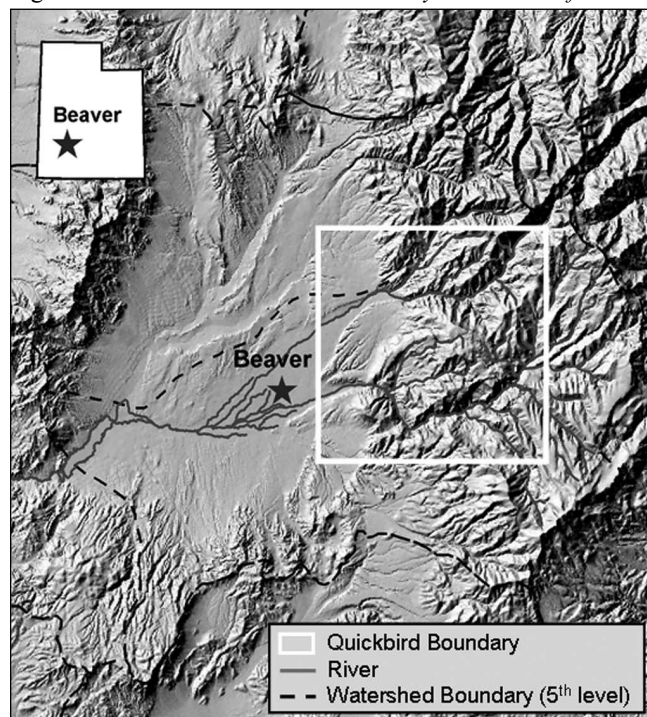
Our interest for this study was to investigate the capabilities of Feature Analyst and how it compares with CLC-Camint's ITC process for producing map products using high-resolution Quickbird imagery and high-resolution NAIP photography. Three analyses were conducted in this study. First, we tested the accuracy of the ITC algorithm for delineating and classifying crowns in a diverse forest area in the southern Rocky Mountains of Utah using Quickbird imagery. Second, we tested the accuracy of Feature Analyst for classifying forest stands in the same area applied to Quickbird imagery. Third, we once again tested the accuracy for classifying forest stands using Feature Analyst, but this time applied to NAIP photography.

Methods

Area of Interest

IW-FIA staff identified a 100 km² area of interest (AOI) within the southern Rocky Mountains of Utah that represented a diverse number of forest and species types. The AOI is east of Beaver, UT, within the Fishlake National Forest (fig. 1). The area was selected for its diversity of species types and altitudinal range with the intent to examine the performance of the ITC and Feature Analyst methods across multiple ecosystems that occur in the Western States. Within this area, elevation values range from 1,920 m (6,298 ft) to more than 3,000 m (9,840 ft). The species types reflect this elevational gradient with pinyon pine and juniper species at the lower

Figure 1.—The AOI in the southern Rocky Mountains of Utah.



AOI = area of interest.

elevations, oak and mahogany hardwood species at mid ranges, and aspen, Douglas fir, subalpine fir, and Engelmann spruce at higher elevations. The area also encompasses the Beaver River, which typically includes riparian vegetation types.

ITC Delineation and Classification/Quickbird

A map of individual tree crowns, with species identified, was produced using the ITC process over the AOI. The process of producing this map involved multiple steps carried out by staff at IW-FIA and CLC-Camint, as outlined in table 1.

The Quickbird imagery for the AOI was provided as courtesy of DigitalGlobe CLC-Camint defined the specifications of the Quickbird scene and preprocessed the imagery. The acquired scene was approximately 300 km² in size, surrounding the AOI. This scene increased the range of altitudinal gradient to more than 1630 m (5,346 ft), from approximately 1,815 m (5,953 ft) to more than 3,450 (11,316 ft) at Mount Baldy Peak. The scene was received from DigitalGlobe radiometrically calibrated and corrected for sensor- and platform-induced distortions. CLC-Camint performed an orthorectification procedure based on a 1:24,000 map and mapped the scene.

At this stage, CLC-Camint applied an initial unsupervised classification technique to delineate sites with unique, homogenous signatures occurring on the image, with the help of aerial photographs. These areas were identified as potential training sites, which were delineated by a georeferenced point shapefile. A total of 170 training sites were identified. These sites were then located by IW-FIA on aerial photographs and labeled according to nine classes (table 2) of homogenous species or predominant mix of species based on the area around the sites. Each label was then given a number ranging from 0 to 100, indicating the percent confidence of the interpretation. The 170 labeled training sites were sent back to CLC-Camint for use in their ITC delineation and classification procedures.

CLC-Camint next performed the automated ITC delineation and classification procedure. The ITC valley-following algorithm does not work well in areas with sparse crowns (i.e.,

Table 1.—The process between IW-FIA and CLC-Camint to develop a map product delineating individual tree crowns.

Main activities	Group in charge
Acquire Quickbird scene	CLC-Camint
Unsupervised classification, identify training sites	CLC-Camint
Assign labels to training sites	IW-FIA
ITC delineation and classification	CLC-Camint
Review results and field check training sites	IW-FIA
Refine classification	CLC-Camint
Accuracy assessment	CLC-Camint/IW-FIA
Delineate stands	CLC-Camint
Accuracy assessment	CLC-Camint/IW-FIA
Cost assessment	CLC-Camint/FS-RMRS

FS-RMRS = Forest Service, Rocky Mountain Research Station; ITC = individual tree crown; IW-FIA = Interior West-Forest Inventory and Analysis.

Table 2.—The list of classes used for classification in the individual tree crown process.

Code	Species type
1	Spruce/fir
2	White fir
3	Aspen
4	Mahogany
5	Pinyon
6	Juniper
7	Oak/maple
8	Other hardwoods
9	Nonforest

pinyon and juniper species types) where there are no shadows between the trees (Gougeon and Leckie 2001). Consequently, an eCognition (Definiens 2003) procedure was applied to these areas prior to running the ITC algorithm. The ITC classification process involved two steps: a first-run classification based on the 170 training sites, and a second-run classification performed after reviewing the results of the first classification. For the second classification, ancillary information and/or new training information may be added in areas having many misclassifications. The results for this paper include output from the first classification. Currently, we are running the second classification, after reviewing the results of the first classification, field checking the original set of training sites, and identifying and labeling 130 additional training sites. The second classification will therefore use 300 correctly identified training sites along with ancillary data from a 10-m digital elevation model.

Feature Analyst/Quickbird

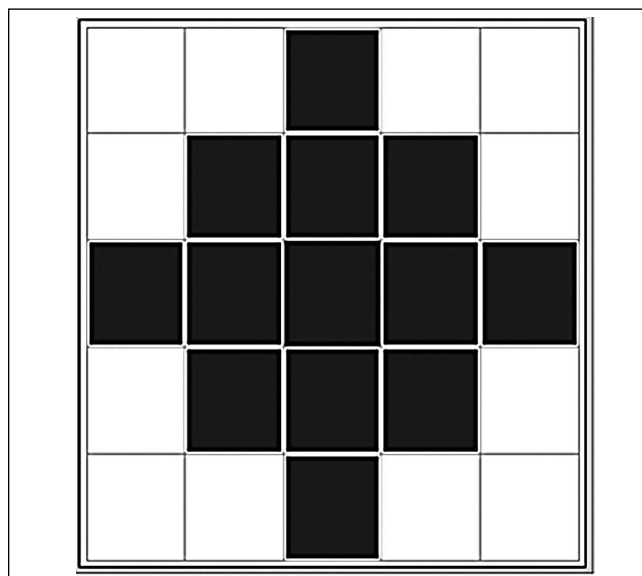
A map of forest stands, with forest types identified, was produced using Feature Analyst over the same area of the Quickbird image. This process was carried out by IW-FIA staff. Although the same point training sites as the ITC procedure were used, we created polygons surrounding these points for use as training sites in the Feature Analyst classification because Feature Analyst uses characteristics such as shape, texture, association, and pattern. Additional training polygons, determined from our field visit, were also delineated and resulted in a total of 300 sites for classification. Labels were assigned at a stand level based on Level I class assignments representing the dominant species, the dominant species associations, or a nonforest type (table 3).

The color infrared Quickbird imagery was used, including green, red, and near infrared bands as well as a 10-mr, U.S. Geological Survey digital elevation model (DEM) obtained from the Automated Geographic Reference Center Web site (<http://agrc.its.state.ut.us/>). All bands were resampled to a pixel size of 4.8 m, the smallest pixel size. For feature recognition, we set the pixel search pattern to a "Manhattan" style with a width of five pixels (fig. 2). Feature Analyst was set to run a wall-to-wall classification of the Level I classes resulting in a map with a minimum map unit size of 24 pixels (about 1 hectare).

Table 3.—*The list of Level I classes used for Feature Analyst classification and for assessing accuracy.*

Code	Species type	Number of training sites
1	Spruce-fir	8
2	Spruce-fir/aspen	9
3	Aspen/spruce-fir	15
4	Aspen	20
5	Aspen/white fir	9
6	White fir/aspen	3
7	White fir	16
8	White fir/mahogany	9
9	Mixed conifer	9
10	Cottonwood	9
11	Mahogany	18
12	Mahogany/pinyon-juniper	10
13	Pinyon-juniper/mahogany	11
14	Pinyon-juniper	19
15	Pinyon-juniper/oak	12
16	Oak/pinyon-juniper	12
17	Oak	19
18	Oak/mahogany	9
19	Chained woodland	14
20	Nonstocked timberland	11
21	Meadow	18
22	Agriculture	7
23	Road	10
24	Water	6
25	Barren	7
26	Shadow	10

Figure 2.—*The five-pixel, Manhattan search pattern used for feature recognition.*



Feature Analyst/NAIP

A map of forest stands, with forest types identified, was produced with Feature Analyst using NAIP photography within the study area. This process was also carried out by IW-FIA staff. The same 300 polygon training sites as the Feature Analyst/Quickbird process were used, but because of the misregistration between the NAIP photography and the Quickbird imagery, all polygon training sites were individually shifted to match the corresponding area.

The natural color NAIP photography was used, including blue, green, and red bands, as well as the 10-m USGS DEM. All bands were resampled to a pixel size of 1.0 m, the smallest pixel size. We set the pixel search pattern to a “Manhattan” style with a width of five pixels (fig. 2) for feature selection. Feature Analyst was set to run a wall-to-wall classification resulting in a map with a minimum map unit of 24 pixels (about 1 hectare).

Accuracy Assessment

Map accuracy and map comparisons were based on visual and numerical assessments at a stand level. A visual assessment was performed for each map to determine the reliability of the results of the ITC crown delineation and classification and the Feature Analyst results using Quickbird imagery and NAIP photography. For the ITC procedure, the visual assessment was based on the accuracy of the crown delineation and the classification of each crown. For the results of the Feature Analyst stand classifications using Quickbird and NAIP products, visual assessments were examined at three class levels: Level I included all 26 classes that were used for training (table 3); Level II included nine classes based on the plurality of species including one class with all nonforest classes (table 4); and Level III included two classes representing forest and nonforest.

For a more objective, numerical assessment and comparison of the three maps, an independent test set of 100 points was randomly selected within the extent of the Quickbird image and applied to each map. The points were assigned classes based on interpretation of 1:16,000 stereo aerial photographs and expert knowledge. These classes were compared to the maps

Table 4.—*The list of Level II classes used for Feature Analyst classification and for assessing accuracy.*

Code	Species type	Number of training sites
1	Spruce-fir	17
2	Aspen	44
3	White fir	25
4	Mixed conifer	9
5	Cottonwood	9
6	Mahogany	28
7	Pinyon-juniper	42
8	Oak	40
9	Chained woodland	14
10	Nonstocked timberland	11
11	Nonforest	58

based on the three class levels mentioned above for the visual assessment of the Feature Analyst classifications. For the maps generated using Feature Analyst, the test points were compared directly to the intercepted pixel class of the map. The ITC map involved two steps. First, the individual tree crowns were evaluated at each point and a stand-level class was assigned based on approximately a hectare or more area surrounding the point. Then, these class assignments were compared to the class assignment of the test set.

Error matrices were generated for each map and a percent correctly classified (PCC) and a Kappa statistic were calculated to provide a numerical statistic of accuracy. The accuracy and comparisons were evaluated at the three different class levels.

Results

ITC Delineation and Classification/Quickbird

Based on a visual evaluation of the ITC product compared to the panchromatic Quickbird image, the ITC procedure performed fairly well delineating individual tree crowns. In areas of low crown densities with pinyon and juniper species, the delineation process generally picked up most of the tree crowns (fig. 3). In some of these areas, though, it seemed like larger pinyons and junipers were split into more than one crown and smaller trees were not captured at all (e.g., the gray circles

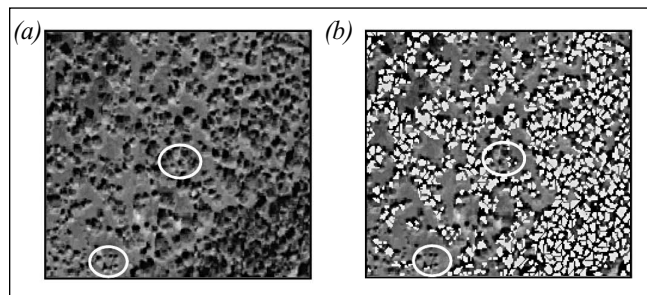
in fig. 3). These conditions were a result of the eCognition procedure completed on the lower density areas prior to the ITC valley-following approach. The ITC valley-following algorithm performed adequately in depicting changes in stand densities, such as the different aspen stands shown in figure 4. This process did not perform well in areas having steep terrain, where tree shadows were long and narrow and/or there were many downed trees. For both of these conditions, the ITC algorithm placed trees incorrectly (fig. 5).

Although the ITC classification performed well in some areas, overall it needs improvement. Most of the classification difficulties were related to changes in elevation and aspect. For example, pinyon and juniper species on northern slopes were typically misclassified as spruce/fir and white fir species. Also, in the higher elevations, spruce/fir and aspen species tended to be misclassified as pinyon, juniper, and mahogany species.

The results of the numerical assessment for each class level are shown in table 5. When comparing the Level I class values interpreted from the first iteration ITC product to the 100 randomly selected test point values, 32 percent of the points were correctly classified with a Kappa value of 0.25. For the Level II class values, 48 percent of the points were correctly classified with a Kappa of 0.37. For the Level III classes, 90 percent of the points were correctly classified and a Kappa of 0.56.

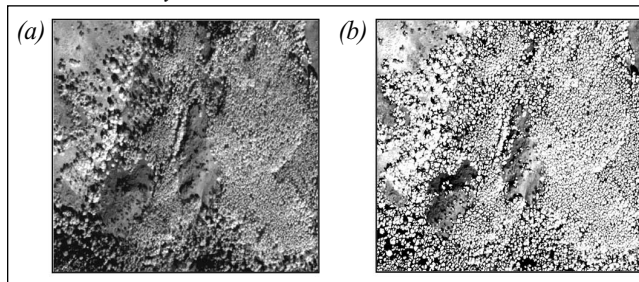
Feature Analyst/Quickbird

Figure 3.—Visual comparison of ITC product with Quickbird panchromatic image in a pinyon-juniper forest type. (a) Panchromatic image. (b) Panchromatic image with crown delineation product overlaid. The circles show examples where trees were not delineated using ITC process.



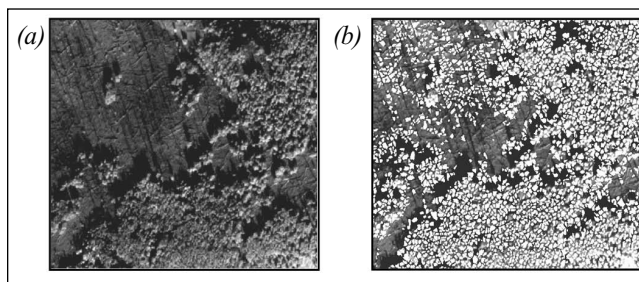
ITC = individual tree crown.

Figure 4.—Visual comparison of ITC product with Quickbird panchromatic image in an aspen forest type with different densities. (a) Panchromatic image. (b) Panchromatic image with ITC overlay.



ITC = individual tree crown.

Figure 5.—Visual comparison of ITC product with Quickbird panchromatic image in a mixed aspen-conifer forest type. (a) Panchromatic image. (b) Panchromatic image with ITC overlay.



ITC = individual tree crown.

Table 5.—Numerical assessment of ITC process, Feature Analyst using Quickbird imagery, and Feature Analyst using NAIP photography including PCC and Kappa.

Classification process	Statistic	26 classes	11 classes	2 classes
ITC/Quickbird	PCC	32	48	90
	Kappa	0.25	0.37	0.56
Feature Analyst/Quickbird	PCC	41	63	94
	Kappa	0.37	0.57	0.69
Feature Analyst/NAIP	PCC	23	51	89
	Kappa	0.19	0.43	0.50

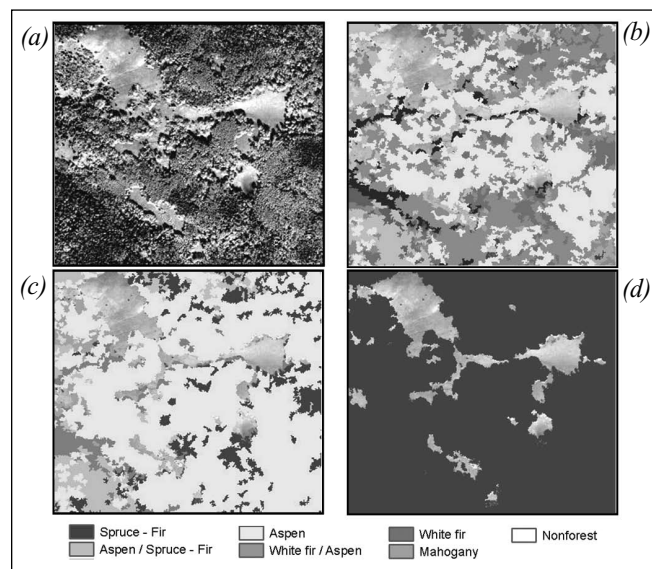
ITC = individual tree crown; NAIP = National Agricultural Imagery Program; PCC = percent correctly classified.

The visual evaluation of the Feature Analyst classification of the Quickbird image compared to the color infrared Quickbird image indicated fairly good results. Figure 6 shows an area with aspen and mixed white fir/aspen stands. In this example, the classification performed relatively well in distinguishing aspen and white fir/aspen stands but confused mahogany with some of the more dense white fir areas (figs. 6b, 6c). At the Level III forest and nonforest classification (fig. 6d), Feature Analyst performed very well.

The results of the numerical assessment are shown in table 5. For the Level I class, the PCC of the Feature Analyst map using Quickbird imagery was 41 percent with a Kappa value of 0.37. The Level II class had a PCC of 63 percent and a Kappa of 0.57 while the Level III class had a PCC of 94 percent and a Kappa of 0.69.

Feature Analyst/NAIP

Figure 6.—An example of the Feature Analyst classification using Quickbird imagery in aspen and mixed aspen/white fir stands. (a) Quickbird color IR image, (b) Quickbird color IR image with Level I classification overlayed, (c) Quickbird color IR image with Level II classification overlayed, and (d) Quickbird color IR image with Level III classification overlayed. Here, the forest class is colored black.

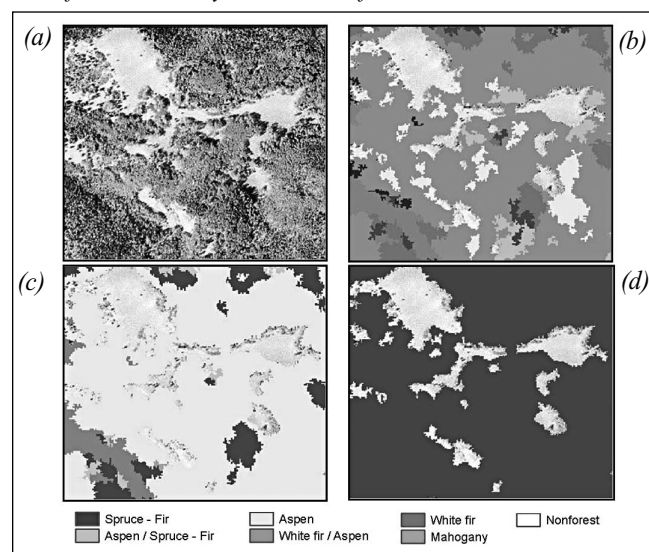


IR = infrared.

Figure 7 shows an example of the Feature Analyst classification of the NAIP photograph compared to the color infrared Quickbird image for the same area in Figure 6. Although the visual assessment of the results of the classification looks very different than that of the Feature Analyst classification of the Quickbird image, the results from the numerical assessment are fairly good. At the Level I classification, the PCC was only 23 percent with a Kappa at 0.19 (table 5). For the Level II classification, the PCC was much higher at 51 percent with a 0.43 Kappa value. The Level III class had a PCC of 89 percent with a Kappa of 0.50 (table 5). This increasing accuracy is noticeable visually as well.

The PCC and Kappa values of the Feature Analyst map using NAIP photography were generally lower than the map using Quickbird imagery. With many classes (Level I) the PCC and Kappa of the NAIP map were much lower than the Quickbird

Figure 7.—An example of the Feature Analyst classification using NAIP photography in aspen and mixed aspen/white fir stands. (a) NAIP natural color image, (b) NAIP image with Level I classification overlayed, (c) NAIP image with Level II classification overlayed, and (d) NAIP image with Level III classification overlayed. Here, the forest class is colored black.



NAIP = National Agricultural Imagery Program.

map at 18 percent and 0.18, respectively. With fewer classes (Level II), however, the PCC and Kappa of the NAIP map were only 12 percent and 0.14 lower, respectively, than the Quickbird map.

Discussion

Our investigation of high-resolution products was an initial test of the usefulness of the resulting map products in providing ancillary information to IW-FIA's forest resource estimation process. We based this investigation on both visual observations and numerical accuracy of the resulting map products as well as the time and costs devoted to the methods used to generate the products.

The visual evaluation of the map products revealed the conformity of the maps to expert knowledge and highlighted specific areas of concern. For the ITC delineation and classification product, most of the concerns were related to the species classification. As mentioned previously, the assessments were based on the first iteration of the classification effort. The final classification will most likely improve with the addition of the new training sites and ancillary information, such as elevation and aspect. Another issue discovered through the visual assessment was the consequences of long shadows in the areas of steep terrain and where there were many downed trees. These issues will need resolution within the valley-following algorithm.

Feature Analyst performed successfully as an alternative automated procedure for classification at a stand level, using both Quickbird imagery and NAIP photography. Most of the issues involved sensitivity of the classes defined, the number of classes, and the training samples used for classification. We created a fairly comprehensive list of classes based on the species occurring in the area and common associations that occurred in a stand. Common types with many training sites, such as aspen and pinyon and juniper, were well classified, but less common types, such as cottonwood and

water, were overestimated. One characteristic of Feature Analyst that was not explored in this study was its learning ability. Classifications can be refined by delineating areas that were misclassified or classified correctly and rerunning the algorithm. This process is more time consuming but may be worth pursuing, especially for classes that are less common.

The numerical assessment showed that the Feature Analyst classification using Quickbird imagery had the highest percentage of correctly classified points and the highest Kappa at all class levels. Again, these were preliminary comparisons to the first iteration classification of the ITC process including fewer training sites and no ancillary data. Also, the stand-level comparisons were based on visual interpretations of classes defined by individual crown delineations, not the automated stand delineation process included with the ITC product. Still, Feature Analyst proved to be competitive with the ITC process at a stand level. Further investigations at a crown level are necessary.

The Quickbird imagery proved to be superior to the NAIP photography both visually and numerically, most likely because of its availability at a higher resolution, as color infrared, and at a higher bit size. Notably, the characteristics of NAIP including accessibility, resolution, and acquisition frequency make NAIP more appealing than Quickbird imagery for future analyses.

Although the ITC process and Feature Analyst are automated procedures, the generation of training sites is not yet automated. Defining the classes and delineating training sites is a tedious and time-consuming step that is essential for high-quality classifications. The level of detail and number of classes needed should be considered when defining the classes. Time allocated to photo interpretation and field visitation should be considered when delineating the training sites. The accuracy and experience of the photo interpreters should also be considered when delineating the training sites.

Conclusions

The objective of this study was to evaluate CLC-Camint's automated ITC delineation and classification approach and to investigate and compare two alternative automated methods for classifying stands within a diverse forested area near Beaver, UT. The numerical accuracy of the resulting maps ranged from 48 percent to 63 percent at the Level II classification, in which a class was determined based on the plurality of the species within approximately a hectare of the point. At the Level III forest and nonforest classification, the numerical accuracies ranged from 89 percent to 94 percent. The visual assessments revealed good results, especially at Level III. We believe that these assessments show strong potential for their use as ancillary products in IW-FIA's forest resource estimation procedures and should be further pursued.

Literature Cited

- Culvenor, D.S. 2002. TIDA: an algorithm for the delineation of tree crowns in high spatial resolution digital imagery of Australian native forest. Melbourne, Australia: University of Melbourne. Ph.D. thesis.
- Definiens. 2003. eCognition software version 3. Germany. <http://www.definiens.com>.
- DigitalGlobe. 2005. http://www.digitalglobe.com/product/basic_imagery.shtml. (2 December 2005).
- Gougeon, F.A. 1995. A system for individual tree crown classification of conifer stands at high spatial resolution. In: Proceedings, 17th Canadian symposium on remote sensing. Saskatchewan, Canada: 635-642.
- Gougeon, F.A. 1997. Recognizing the forest from the trees: individual tree crown delineation, classification and regrouping for inventory purposes. In: Proceedings, third international airborne remote sensing conference and exhibit. Copenhagen, Denmark: 807-814.
- Gougeon, F.A.; Leckie, D.G. 2001. Individual tree crown image analysis—a step towards precision forestry. Proceedings, first international precision forestry symposium. Seattle, Washington.
- Leckie, D.G.; Gougeon, F.A.; Walsworth, N.; Pardine, D. 2003. Stand delineation and composition and estimation using semi-automated individual tree crown analysis. Remote Sensing of Environment. 85: 355-369.
- Pouliot, D.A.; King, D.J.; Bell, F.W.; Pitt, D.G. 2002. Automated tree crown detection and delineation in high-resolution digital camera imagery of coniferous forest regeneration. Remote Sensing of Environment. 82: 322-334.