Imputing Forest Inventory Data to Stands Formed by Image Segmentation in Maryland's Green Ridge State Forest

Andrew Lister
USDA Forest Service, Northern Research Station
National Inventory and Monitoring Applications Center
Forest Inventory and Analysis Unit
11 Campus Blvd, Suite 200
Newtown Square, PA 19073
E-mail: alister@fs.fed.us

Harry Kahler
Maryland Department of Natural Resources
Green Ridge State Forest
28700 Headquarters Dr, NE
Flintstone, MD 21530
E-mail: hkahler@dnr.state.md.us

Alexander Clark
Maryland Department of Natural Resources
Green Ridge State Forest
28700 Headquarters Dr, NE
Flintstone, MD 21530
E-mail: aclark@dnr.state.md.us

Francis Zumbrun
Maryland Department of Natural Resources
Green Ridge State Forest
28700 Headquarters Dr, NE
Flintstone, MD 21530
E-mail: fzumbrun@dnr.state.md.us

Jack Perdue
Maryland Department of Natural Resources
Maryland Forest Service
580 Taylor Ave, C-1
Annapolis, MD 21401
E-mail: jperdue@dnr.state.md.us

Abstract

Making stand-based forest management decisions is difficult for landowners of large tracts because creating, managing, and updating stand maps is expensive and time consuming. Recently, advances in image processing in the area of image segmentation have made this task easier. The goal of the study reported here was to develop a method to delineate forest stands using image segmentation, assign to them forest characteristics, and assess their quality. We

---

In Proceedings of the 6th Southern Forestry and Natural Resources GIS Conference (2008), P. Bettinger, K. Merry, S. Fei, J. Drake, N. Nibbelink, and J. Hepinstall, eds. Warnell School of Forestry and Natural Resources, University of Georgia, Athens, GA.

combined Landsat satellite and National Aerial Imagery Program (NAIP) aerial imagery to create a multispectral, 5-m resolution dataset, used image segmentation to delineate homogeneous landscape polygons, and used these polygons to aggregate a pixel-based map that imputes plot data to each pixel on the Green Ridge State Forest in Maryland. We also developed a quality assurance assessment method for the resulting stands and pixel-based maps.

Keywords. Image classification, eCognition, stand delineation, classification validation.

Introduction

A key to sound forest management for landowners of large tracts, such as local, state and federal governments, timber companies, and other nongovernmental organizations, is balancing economic, ecological, and recreational needs associated with their lands. Recognition of proper management by third-party certification bodies, such as the Sustainable Forestry Initiative, requires landowners to have full accountability of their lands at the forest stand level (Sustainable Forestry Board, 2004).

Landowners of large tracts often conduct stand-based management in which groups of adjacent trees with similar characteristics, such as age or species composition, are managed the same, such as with thinning, pruning, harvest, or understory herbicide application. This is often done to increase efficiency in preparation for harvesting, yet it also ensures overall forest health by mimicking natural disturbance patterns across the landscape through appropriate silvicultural management (Hicks, 1998).

A problem that frequently occurs with large land holdings, however, is that the creation of maps of stands and their characteristics is very time consuming and can require extensive field reconnaissance and perhaps manual photointerpretation (Brohman and Bryant, 2005; Hamilton et al., 2007). Over the past 15 years, as geographic information systems (GIS), remote sensing statistical methods and software, and digital aerial imagery have become cost effective and easy to use, significant progress has been made in automatic image segmentation procedures (Haralick and Shapiro, 1985; Pal and Pal, 1993). Image segmentation is the process whereby sets of contiguous pixels in images are grouped based on the spectral composition of the image. For example, in the context of remote sensing imagery, image segmentation can draw polygons around features such as clearcuts in forests, roads, individual tree crowns that a manual photointerpreter might choose to delineate. For example, van Aardt et al. (2006) successfully used image segmentation to segment forests in Virginia to improve aboveground biomass modeling results. Makela and Pekkarinen (2001) used image segmentation to improve plot-level estimates of timber volume using Landsat imagery. Dorren et al. (2003) found that segmenting Landsat images with digital elevation model-based data improved classification accuracy in mountainous areas. Finally, Wang et al. (2004) used image segmentation to improve maps of mangrove stands relative to results obtained from pixel-based classification.

The goal of the this study is to develop a method with which to create vector (polygon) GIS layers representing stand-scale management units for the state forest holdings administered by the Maryland Department of Natural Resources (MDNR). The technique should be general enough to be applied across all state forests in Maryland and not require large amounts of user intervention. Finally, there should be a way to assess the quality of the resulting maps and thus their potential usefulness to resource managers.

Methods

Study Area

The study was conducted using imagery covering a portion of the Green Ridge State Forest, located in eastern Allegany County, Maryland (Figure 1). The 18,600-ha area is mostly forested and consists of mixed oak-hickory forest types with small patches of conifers intermingled with hardwoods.

Plot Data

Continuous Forest Inventory (CFI) data were collected on approximately 440 inventory plots spaced uniformly, approximately 600 m apart during the summer months between 1999 and 2001. The objective of the CFI is to periodically collect data on growth, volume, and other forest conditions to assist in making decisions relative to short- and long-term forest resource planning and operations. Each CFI plot consisted of a 16.7-m radius circular area within which species, diameter at breast height (DBH), and several other measurements were recorded on trees greater than 12.7 cm DBH. Total plot basal area by species was calculated, as well as relative basal area of conifer and hardwood species. A global positioning system (GPS) was used to record the latitude and longitude of the center of each plot; these position points were remeasured in the summer of 2007 to verify accuracy.

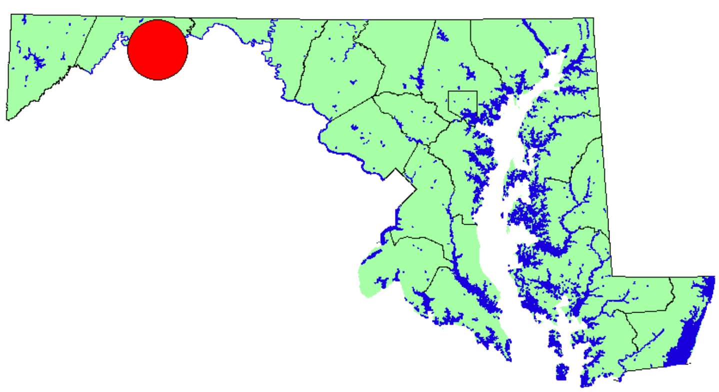

Figure 1. The Green Ridge State Forest is located in Allegany County, MD.

Imagery and Predictor Data

Figure 2 gives a methodology overview of the data preparation and modeling procedures. We used the following data in the study: brightness, greenness, and wetness layers derived from tasseled cap transformations (Huang et al., 2002) of 30-m pixel size Landsat imagery from circa 2000; 1-m pixel size natural color National Aerial Imagery Program (NAIP) 2006 photography; and 30-m pixel size digital elevation model (DEM) derivatives, including elevation, slope, aspect, and a position index (Homer et al., 2004). The Landsat and DEM-based data were obtained from the USGS NLCD 2001 consortium data archive (Homer et al., 2004), and the NAIP imagery was obtained from the U.S. Department of Agriculture Internet Data Gateway (http://datagateway.nrcs.usda.gov/). Prior to preparing the Landsat and DEM data for segmentation, the first (red) band of the 1-m NAIP imagery was aggregated to 5 m by assigning to each resultant 5-m pixel the average value of the 1-m pixels falling within it. To prepare the data for segmentation, the "resolution merge" procedure in Leica Imagine[1] was used to increase the resolution of the Landsat and DEM data by combining them with the first band of the derived 5-m NAIP imagery. We chose the first band of the NAIP imagery for this process because it exhibited the most visual detail. We acknowledge that the time difference between the 2000

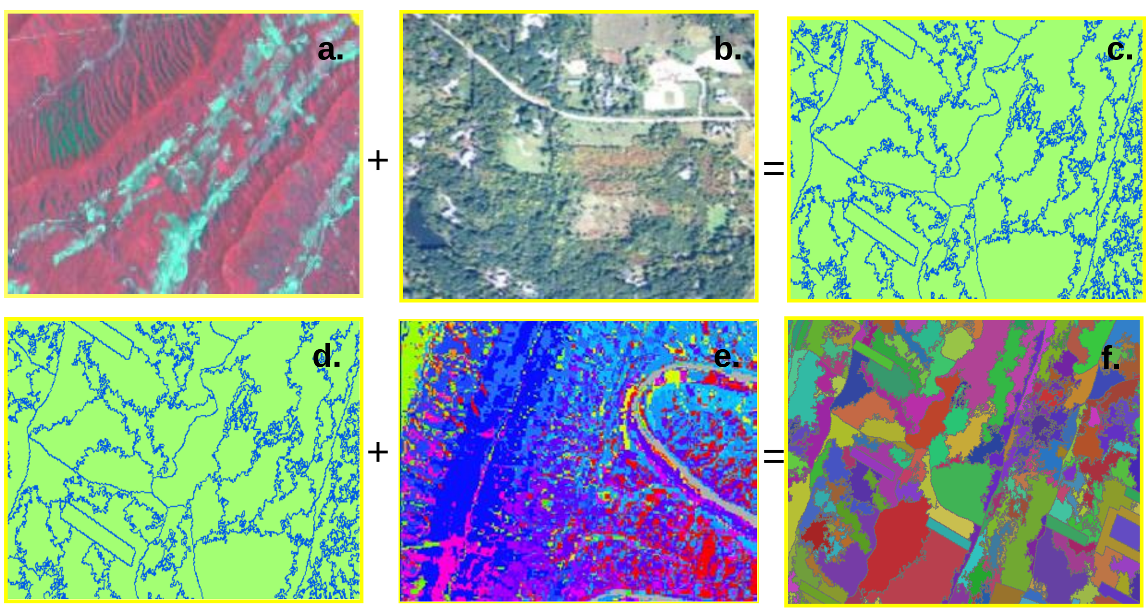

Figure 2. Methodology overview. 30-m Landsat imagery (a) was combined with 1-m NAIP imagery (b) using the resolution merge procedure to create a 5-m multispectral input image for segmentation. ECognition software was used to segment this image (c). The polygons from image segmentation (d) were combined with a 30-m output from a WEKA-based image classification (e) to produce the final, classified stand map (f).

[1] The use of trade, firm or corporation names in this publication is for the information of the reader. Such use does not constitute an official endorsement or approval by the USDA or the Forest Service of any product or service to the exclusion of others that may be suitable.

Landsat and the 2006 NAIP imagery will result in anomalous regions on the output maps in areas with land disturbance since 2000, but the MDNR has kept GIS files covering areas that have been harvested during that time period, allowing for post-processing to be performed.

Segmentation

Definiens (Munich, Germany) eCognition[1] software was used to produce homogeneous landscape polygons from an arbitrarily chosen spatial subset of the resolution merged imagery. The segmentation methodology in eCognition involves changing certain program parameters related to size, shape, and spectral composition of the resulting polygons, as well as to combinations of the input layers and associated weights. This unique combination will generally vary by dataset, so we will not elaborate on the specifics of parameter choices and band combinations made; details of parameter choices are on file at the Green Ridge State Forest Office, 28700 Headquarters Dr NE, Flintstone, MD 21530.

After various segmentation iterations and subjective comparison of results with local knowledge, field visits, and digital aerial photography interpretation, MDNR staff chose a combination of layer weighting, scale, and other segmentation parameters that yielded polygons which closely approximated useful stands. The polygonal segmentation results were exported as an ESRI shapefile.

Pixel and Stand Classification

The IB1 classifier in the WEKA data-mining software[1] was used to create a model that calculated unweighted Euclidean distances between each instance in the modeling dataset and unlabeled instances for which predictions were desired, using the rescaled (minimum of 0, maximum of 1) 30-m Landsat and DEM-based layers as the distance defining axes (Aha and Kibler, 1991; Witten and Eibe, 2005). After attempting various data-reduction strategies, we decided to use the full set of 30-m predictor data for the modeling because results varied by only a few percent when comparing results from different subsets of the variables or composite layers such as principal components. Furthermore, our goal was not necessarily to produce the best possible map for an individual attribute, but rather to develop a general technique that can be applied with minimal user intervention to a suite of attributes.

Leica Imagine's "pixel to ascii" procedure was used to decompose the stack of Landsat and DEM predictor data into a text format matrix in which each row represented an unclassified instance. The text matrix was reformatted for use by WEKA by creating an appropriate header and delimiting it with commas. The IB1 model from WEKA was then used to assign the CFI plot identifier value (PID) to each row of this text matrix (pixel location) in the Green Ridge Forest study area based on the Euclidean distance between each observation with known PID (the CFI plots and associated vector of predictor data) and each row in the WEKA-formatted text matrix of predictor data (pixels with unknown CFI data). The resultant vector of predictions was then converted to a PID image using Imagine's "ascii to pixel" procedure. The PID image was then joined to the CFI dataset via the PID attribute, in effect attaching to each pixel of the PID image the entire associated CFI plot record.

Finally, ArcMap's "summarize zones" procedure was used to calculate the mean pixel value for the "percent conifer basal area" CFI attribute from the pixels falling within each eCognition-derived stand polygon. Final maps of this attribute were produced for quality assurance assessment.

Quality Assurance

To assess the quality and potential usefulness of the resulting classified image and stand, three methods were applied. First, a 20-fold cross validation of the IB1 model was applied in WEKA. For each of 20 iterations, a different 5 percent of the training data was withheld (without replacement), the IB1 model was created using the remaining 95 percent of the data, and predictions of percent conifer basal area for the remaining 5 percent of the instances were created. To assess the relationship between the set of actual and predicted values, a scatterplot was created and we calculated the R^2, slope, and intercept of the simple linear regression line passing through the cloud of actual vs. predicted points. We consider these three metrics, when used together, to serve as an index of confidence in the model outputs at the individual pixel level. A perfect model would have an R^2 of 1.0, a slope of 1 and y intercept of 0; the proximity of the observed values for these metrics to the ideal model can be used as a subjective quality assurance metric.

The second quality assessment was a window-based geographic aggregation and comparison of the actual and predicted data. First, a 2 x 2-km vector grid covering a subset of the study area was generated in ArcMap (Figure 3). Within each vector grid cell that contained at least six plots (a number we arbitrarily chose), the average predicted value and the average actual value were calculated, and the set of results were plotted and assessed as described previously. The intent of this assessment was to look at the actual vs. predicted relationship at a coarser scale than the previously described plot-pixel comparison.

Finally, to understand the relationship between actual plot data and the distribution of estimates of an attribute from the stand within which they sit, we determined the percent of the plots that fall within the middle 10, 20, 30, 40, 50, 60, 70, 80 and 90 percent of the distributions of estimates (e.g., Figure 4). If a larger proportion of the plots than would be expected by chance fall within a given region of the distributions of estimates, this suggests that there is logical agreement between the set of pixel-based estimates and the stands, giving the map consumer more confidence in the map's quality.

Results

Patterns in the pixel-based map of percent conifer basal area in a subset of the Green Ridge Forest (Figure 5a) and the classified stand map (Figure 5b) generally reflect patterns seen in the original plot data (Figure 5c). The plot-pixel quality assurance comparison of actual vs. predicted values is shown in Figure 6. For this attribute the R^2 value was 0.3, the slope of the regression line was 0.5, and the y intercept value was 0.08. When assessing the actual vs. predicted relationship using the 2-km window-based averaging approach, the R^2 improved to 0.5 and the y intercept improved to 0.06, but the slope worsened to 0.4 (Figure 7).

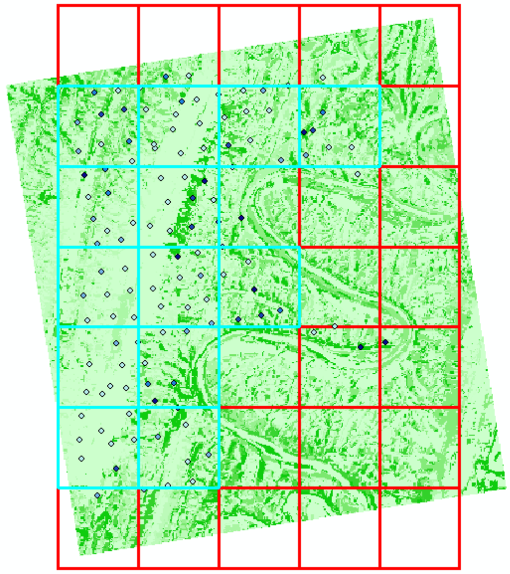

Figure 3. A vector grid was overlaid on a subset of the pixel-based map. For each grid cell within which six CFI plots fell (cells that are highlighted), the mean CFI value and the mean pixel value of percent conifer basal area were calculated and values were plotted (Figure 7).

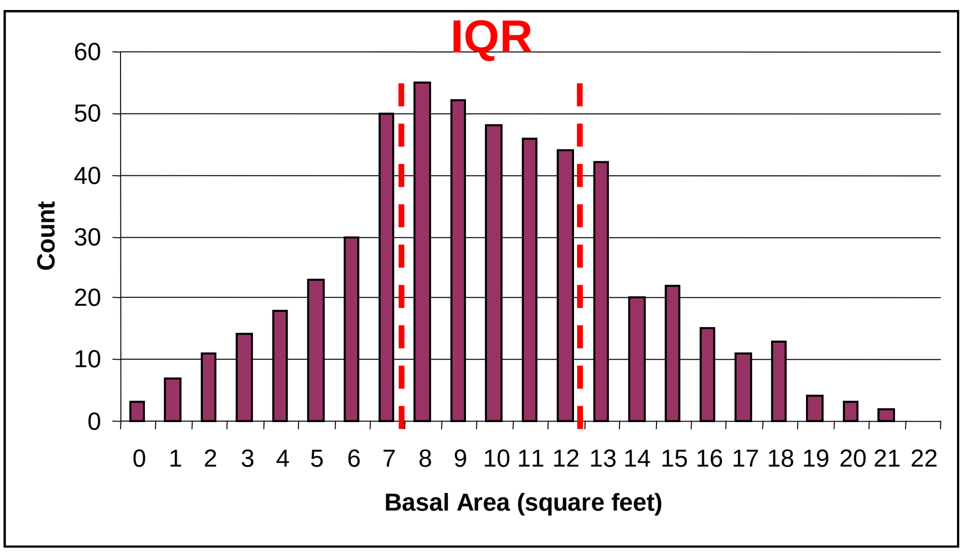

Figure 4. The area of the distribution of this contrived example between the dashed lines is the interquartile range (IQR), or middle 50 percent of the frequency distribution of estimates. If a given plot's value falls within that portion of the distribution 50 percent or less of the time, then the stands are not very homogeneous, or the plots have anomalous values compared to their neighbors in the stand. In either case, the usefulness of the stand results is questionable.

Figure 5. The pixel-based map of percent (proportion) conifer basal area(a); the classified stand map (b); and the CFI dot map (c). All estimates range from 0 to 1.

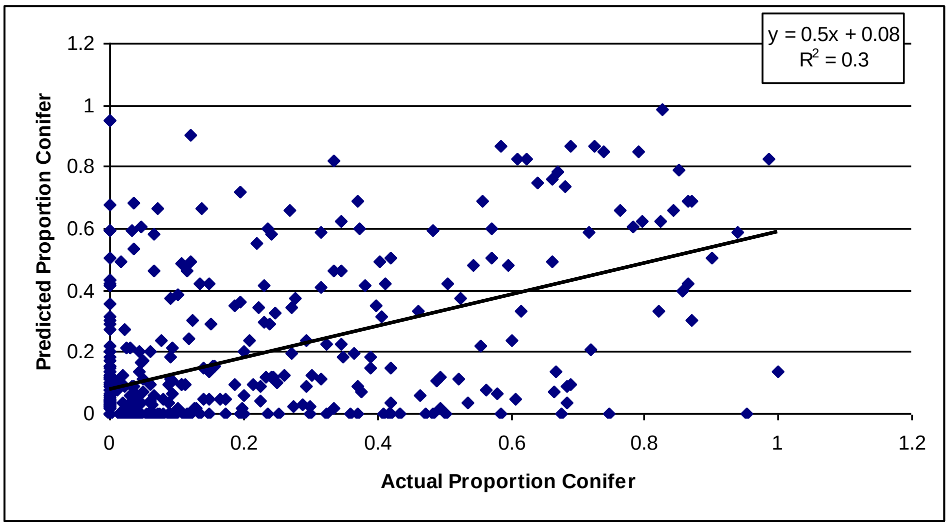

Figure 6. Scatterplot of actual vs. predicted proportion conifer basal area.

When examining the percentage of plots that fell within given regions of the distributions of estimates for the stands in which the plots fell, we found that for each region of the distribution, a larger percentage of the plots fell in the region than would be expected by chance (Figure 8). The relationship approached 1:1 as the region of the distributions examined approached the middle 90%.

Discussion

The intent of this study was to develop a general technique for using digital imagery and image segmentation software to create stand maps, and for labeling these with information from a classified pixel-based map. The particular attribute chosen for illustration of this technique, percent conifer basal area, was chosen because we have found through past experience that

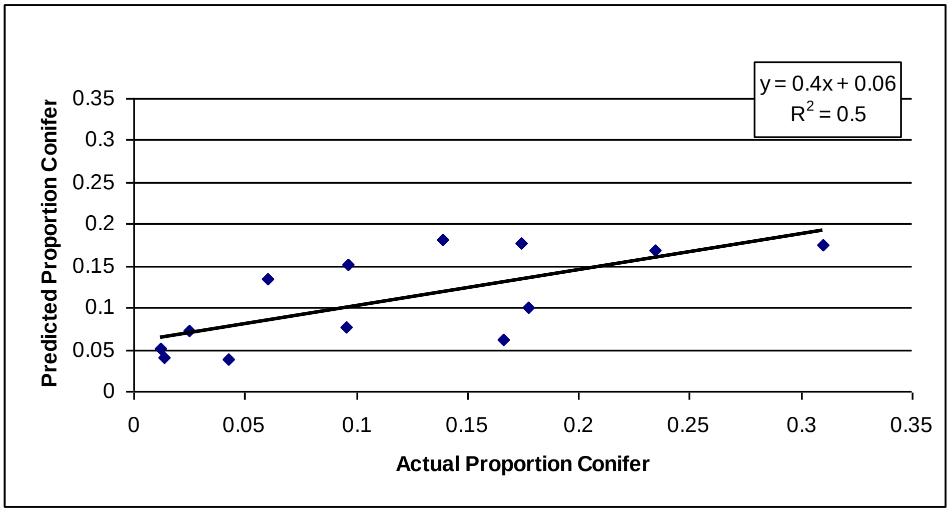

Figure 7. Scatterplot of actual vs. predicted proportion conifer basal area within 2-km windows.

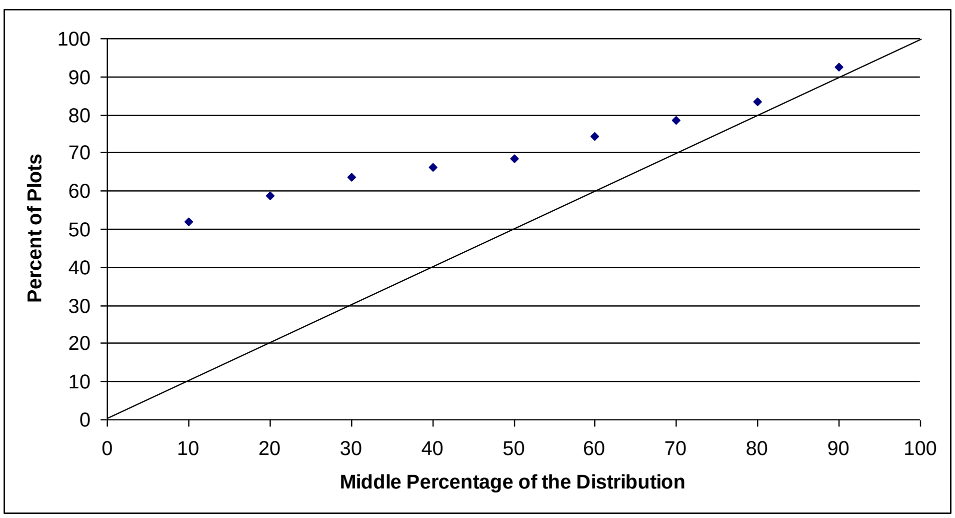

Figure 8. The relationship between the percentage of the plots that fall in a portion of the distribution of pixels within a stand, across all the stands, and that portion of the distribution. The 1:1 line is included for reference and represents the values that would be expected by chance.

separating conifers and hardwoods using Landsat imagery is relatively straightforward. The Green Ridge Forest, however, mostly consists of mixed oak-hickory forests with small patches of conifers intermingled with hardwoods. This heterogeneity of species composition could explain the unimpressive results from the plot-pixel assessment. While the relationship depicted in Figure 6 clearly is positive, there is significant spread seen in the actual vs. predicted scatterplot. The general landscape patterns of conifer appearance, as seen in Figure 5c, are reflected in the pixel and stand maps. This is reinforced by the improvement in some of the actual vs. predicted assessment metrics when the analysis is carried out within a set of 2-km windows (Figure 7). This suggests that use of the results at scales coarser than the pixel level might be most appropriate.

Both the plot-pixel, and the 2-km window based scatterplots show slopes that are much less than 1, indicating a truncation of the variance of estimates caused by an overestimation of small values and an underestimation of large values. This frequently occurs in prediction studies of this nature because neither the plot information nor the satellite data are collected without error, so with a weakened relationship between the predictors and the dependent data, estimation errors occur. The erroneous estimates due to random error are more likely to come from the center of the distribution of true data than from the extremes because there are more data that fall in the center (Curran and Hay, 1986; Lister and Lister, 2006). A number of sources of measurement error exist, including atmospheric contamination of the satellite measurements, poor spatial co-registration of the plots and pixels, errors in plot data accounting, and measurement error on the plots. For this particular case study, a general technique was desired and minimal outlier removal attempts were made. Once the technique is refined, future research will involve improved data cleansing and data reduction methods that optimize the relationship between the attribute of interest and the predictors.

The stands that were created appear to be at least partly effective at grouping pixels with similar levels of conifer basal area percentage together. Figure 8 shows that more than 50 percent of the plots fall within the middle 10 percent of the distributions of estimates found in the stands in which they sit. To interpret these results, it is helpful to consider a null model in which pixel estimates were randomized and then grouped by the stands. Chance would dictate that for a given stand 10 percent of the time, a given plot value would fall in the middle 10 percent of the distribution of estimates (between the 45^{th} and 55^{th} percentiles). However, the plots do seem to be more representative of the stands in which they sit than would be found by chance. In other words, groups of contiguous estimates of similar magnitude and the stand delineation (which was done independently of the classification using some of the same input data) seem to agree spatially. The magnitude of this agreement, as depicted on Figure 7, provides the map user an index of confidence in the stand attribution procedure.

This technique has drawbacks. For example, past experience has shown us that by tailoring data reduction and outlier removal methods to the prediction of a specific attribute, improvements can be made over the naïve, generalized approach we present here. However, for practical reasons, Maryland DNR might find our approach useful because the modeling procedure is performed once to create the PID image, and the production of other CFI attribute maps is accomplished by a simple recoding using PID as the lookup value. Similarly, one can summarize the attribute table of the PID image based on the stand identification number and join the summary table back to the vector GIS stands layer to create a stand map. The alternative to our approach is a time-consuming, high-overhead modeling procedure for each attribute of interest.

Another advantage of this approach to mapping PID values is that the entire plot record is imputed to each pixel. This avoids problems with logical inconsistency that often occurs in other modeling methods such as regression, in which the sum of the basal area predictions of all of the species at a pixel location might be a value that is impossible to find in nature. Using the nearest neighbor PID image approach, all of the interrelationships among the CFI data are maintained in the final pixel map.

In conclusion, MDNR must decide if the cost of accepting a less-than-optimal map product outweighs the benefit of a mapping procedure that allows for rapid, exhaustive mapping of any CFI attribute via a simple GIS recoding exercise. Future work will involve assessing the utility of maps produced using this method for making management decisions.

Acknowledgements

We would like to thank Robert Webster of the MDNR for logistical support. We would also like to thank Dale Weyermann, Sean Healey, John Stanovick and Susan Wright for their efforts to review this paper.

References

Aha, D., and D. Kibler. 1991. Instance-based learning algorithms. Machine Learning. 6: 37-66.

Brohman, R., and L. Bryant (Editors). 2005. Existing vegetation classification and mapping technical guide. General Technical Report WO-67. Washington, DC: USDA Forest Service, Ecosystem Management Coordination Staff.

Curran, P.J., and A.M. Hay. 1986. The importance of measurement error for certain procedures in remote sensing at optical wavelengths. Photogrammetric Engineering & Remote Sensing. 52(2): 229-241.

Dorren, L.K., B. Maier, and C. Seijmonsbergen. 2003. Improved Landsat-based forest mapping in steep mountainous terrain using object-based classification. Forest Ecology and Management. 183: 31-46.

Hamilton, R., K. Megown, T. Mellin, and I. Fox. 2007. Guide to automated stand delineation using image segmentation. RSAC-0094-RPT1. Salt Lake City, UT: USDA Forest Service, Remote Sensing Applications Center.

Haralick, R., and L. Shapiro. 1985. Image segmentation techniques. Computer Vision, Graphics, and Image Processing. 29: 100-132.

Hicks, R.R., Jr. 1988. Ecology and Management of Central Hardwood Forests. New York: John Wiley and Sons.

Homer, C., C. Huang, L. Yang, B. Wylie, and M. Coan. 2004. Development of a 2001 national landcover database for the United States. Photogrammetric Engineering and Remote Sensing. 70(7): 829-840.

Huang, C., B. Wylie, C. Homer, L. Yang, and G. Zylstra. 2002. Derivation of a tasseled cap transformation based on Landsat 7 at satellite reflectance. International Journal of Remote Sensing. 23(8): 1741–1748.

Lister, A.J., and T.W. Lister. 2006. Post-modeling histogram matching of maps produced using regression trees. In Proceedings of the sixth annual forest inventory and analysis symposium. General Technical Report WO-70. Washington, DC: USDA Forest Service.

Makela, H., and A. Pekkarinen. 2001. Estimation of timber volume at the sample plot level by means of image segmentation and Landsat TM imagery. Remote Sensing of Environment. 77: 66-75.

Pal, N.R., and S.K. Pal. 1993. A review on image segmentation techniques. Pattern Recognition. 26: 1277-1294.
Sustainable Forestry Board. 2004. Sustainable Forestry Initiative Standard (SFIS), 2005–2009 Standard. Available at: http://www.aboutsfb.org/miscPDFs/SFBStandard2005-2009.pdf. Accessed 15 April 2005.
van Aardt, J.A.N., R.H. Wynne, and R.G. Oderwald. 2006. Forest volume and biomass estimation using small-footprint lidar-distributional parameters on a per-segment basis. Forest Science. 52(6): 636-649.
Wang, L., W.P. Sousa, and P. Gong. 2004. Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery. International Journal of Remote Sensing. 25(24): 5655-5668.
Witten, I.H., and F. Eibe. 2005. Data Mining: Practical Machine Learning Tools and Techniques (Second Edition). New York: Morgan Kaufmann.