A MULTI-RESOLUTION APPROACH TO FOREST SEGMENTATION AS A PRECURSOR TO ESTIMATION OF VOLUME AND BIOMASS BY SPECIES

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ABSTRACT

Accurate and efficient measurement of vast forest resources has always been a challenge. Remote sensing offers exciting possibilities because of its ability to cover large tracts of land and its applicability to the estimation of carbon sequestration in forest areas. This study explored the implementation of a multiresolution segmentation approach as a precursor to volume and biomass by species estimation. The study area is located in the Appomattox Buckingham State Forest (Appomattox County, Virginia) in the Virginia Piedmont physiographic region. The area consists of a variety of pine, upland hardwood, and mixed stands. The eCognition segmentation algorithm was chosen because of its ability to accurately delineate real-world objects, its widespread use, and because modeling results can be hierarchically scaled. Segmentation was performed through (i) structural segmentation of forest types using small-foot-print, multiple return lidar data and (ii) spectral segmentation using high spatial resolution (1 m) AISA hyperspectral data. Between- and within-segment variances of a canopy height model were used to gauge ideal segmentation results. Results indicated that such a variance comparison is ideally suited to selection of the segmentation result that should be used for subsequent model fitting. It seems likely that using a combination of lidar and hyperspectral data to segmentation, followed by extraction of volume-by-species on a per-segment basis, will afford large area, precise, and cost-effective inventories. Application in both scientific and managerial contexts is promising, since remote sensing data are readily available and results are applicable to net primary productivity or carbon sequestration modeling.

INTRODUCTION

Accurate prediction of forest biomass and volume by species has long been an ideal of natural resource managers. Not only does such a prediction have far reaching implications for the financial aspects of any forest company, but it also is of global ecological importance with regards to monitoring carbon sequestration. The traditional way to gauge forest resources involves large-scale, labor-intensive forest inventories, often incorporating intricate sampling schemes and extrapolation efforts. At a local scale the accurate classification of volume by species is important to commercial and environmental forest management, aiding in forest inventory (yield-per-species or group), pest and environmental stress management (dying, decaying, or drought-stressed trees), assessing wildlife habitat ranges, and managing human impacts on a forest environment. Location of forest species or forest taxonomic groups and assessment of biophysical parameters subsequent to species or group identification, are therefore crucial to our ability to effectively manage forests and assess forest conditions.

Remote sensing has come to the fore as one of the most effective tools for forest inventory and natural resource assessment. Hyperspectral sensors make discernment of an area's composition through spectral response discrimination more effective than is possible with broader band, multispectral sensors. Hyperspectral sensors have prepared the way for a new set of applications to be explored by providing data in high enough temporal and spectral resolution to resolve the natural variability in features such as minerals, vegetation, and atmospheric gases (Curran, 1989; Wessman *et al*., 1989; Birk and McCord, 1994; Yoder and Pettigrew-Cosby, 1995; van Aardt and Wynne, 2001, 2003).

Light detection and ranging (lidar) technology is an even more recent development than hyperspectral sensing. Lidar involves the emission of a laser pulse from an airborne sensor, the measurement of the pulse's returntravel time from sensor to target, and the calculation of the distance traveled by the laser beam. Applications in forestry include the measurement of canopy height, sub-canopy topography, and the vertical distribution of intercepted surfaces in forested areas. Above-ground biomass, stem counts, and crown widths can in turn be modeled from the measured characteristics (Dubayah and Drake, 2000; Lefsky *et al*., 2002). Lidar data have been used by many groups to accurately gauge aboveground biomass of both temperate and tropical forests, as well as relating biomass to merchantable volume estimates (Lefsky *et al*., 1999a; Lefsky *et al*., 1999b; Means *et al*, 1999; *Means et al*., 2000).

The combination of lidar and hyperspectral technologies seems inevitable given the challenge of both unbiased and precise estimates of forest volume and carbon sequestration by species. Forest structural information such as tree height, basal area, biomass, and volume can be extracted using lidar data, while genus or species specific informational content can be derived from hyperspectral data. The result of coupling these data sources is a group- or species-specific volume assignment, the core of any mensurational attempt. This type of approach is of particular importance to the modeling of net primary productivity (NPP), which is crucial to the question of how much carbon is sequestered where and by which species. One of twelve critical application areas in NASA's Earth Science program is in fact "Sequestration capacity monitoring for carbon management". These application areas are deemed as being of "high national priority, have significant potential for increased socio-economic value from the application of Earth science…" (NASA Webcast, Research Community Update, 2002). Hence applicability of a seemingly forest inventory-only tool is extended to possible regional, national, or even global application.

However, viable and homogenous units for volume extraction need to be established in order to derive accurate volume by species estimates for any given region. One very likely approach is that of forest segmentation or delineation of a composite forest area into spectrally or structurally uniform areas. Lidar volume estimation and hyperspectral species assignment can then be effectively performed on a per-segment basis. Segmentation for delineation of uniform stand units, followed by parameter estimation per defined unit, has been implemented successfully in many studies (Woodcock *et al*., 1994; Makela and Pekkarinen, 2001; Pekkarinen, 2002; Engdahl *et al*., 2003; Kellndorfer and Ulaby, 2003). More reliable parameter estimates can be obtained from homogenous, data-derived stand units, instead of using traditionally defined forest stands as units for parameter extraction. Although existing forest stands are often based on site (soil, topography, micro-climate) and species composition, it cannot be assumed that such stands are in fact spectrally or structurally homogenous. The use of ancillary spectral and structural (lidar) data in defining the units of measurement is therefore crucial if accurate, scalable estimates are required for large tracts of land using remotely sensed data. Ryherd and Woodcock (1996) found that textural information was the single most important component for accurate forest segmentation. The authors highlighted the importance of structural information contained in layers such as canopy models, height models, digital elevation models, and even high spatial resolution imagery.

METHODS

Objectives for this study include (i) development of an multiresolution approach to forest geographical differentiation whereby unique structural or spectral segments can be used for subsequent inventory analysis, (ii) establishment of a protocol for using hyperspectral data to delineate type specific segments for volume and biomass model development, and (iii) development of lidar-based methods for estimating species volume and biomass on a per-segment or stratum basis. This paper will focus exclusively on multiresolution segmentation as a precursor to volume and biomass per species estimation.

The study area is located in Appomattox Buckingham State Forest (Appomattox County) in the Piedmont physiographic province of Virginia, southeastern U.S.A at 78°41' W, 37°25' N. Vegetation is composed of various coniferous (*Pinus taeda, P. virginiana, P. echinata*, and *P. strobus*), deciduous (*Quercus coccinea, Q. alba,* and *Liriodendron tulipifera*), and mixed forest stands. Available data include summer 2003 AISA hyperspectral and 2002 small-footprint DATIS II lidar acquisitions. The AISA imagery consists of 16 visible and near-infrared wavelengths, while the lidar data are characterized by first, last, and intermediate returns. DATIS II lidar data specifications are given in Table 1, while AISA data characteristics are listed in Table 2.

Segmentation of the study area was done using the eCognition hierarchical, multiresolution algorithm. Advantages of the eCognition algorithm, as compared to alternative approaches to segmentation, include its ability to (i) take whole image information into account and produce segments of comparable size that are related to how humans perceive texture, (ii) form a hierarchical segmentation (statistically proven to produce better up-scaling results than cubic convolution, bilinear interpolation, nearest neighbor, and non-overlapping averaging), and (iii) take the relationship between pixel size and image-objects from which original object-specific analysis was developed into account (Hay *et al*., 2003). The underlying idea is the minimization of the weighted heterogeneity of image objects. In each step adjacent objects that define the smallest growth in heterogeneity are merged, but only if the heterogeneity growth is smaller than a user-defined scale parameter. This process is simultaneously applied across the whole image to obtain objects of comparable size and quality (Baatz and Schäpe, 2000; Willhauck *et al*., 2000; Schiewe, 2002). By mixing the spectral heterogeneity criterion with a spatial criterion, one can actually smooth the resultant object, thereby eliminating branched segments or fractal shaped borderlines. The user defines the scale parameter (heterogeneity criterion), single layer weights, and mixing of spectral and shape criteria.

Table 1. DATIS II lidar data set characteristics

Characteristics	Specification
Laser altitude	6,562 ft. (2,000 m) above ground level
Laser scan FOV	75° maximum
Swath width and overlap between adjacent swaths	2,625 ft. (800 m)
Scan rate	25 Hz
Laser pulse rate	35 kHz
Scan angle	± 13.5°
Returns	≤ 5
Resolvable distance between returns	0.75 m
Footprint	1.51 ft. (0.46 m)
Spacing across / along track	3.3 ft. (1 m) / 6.6 ft. (2 m)
Accuracy (X,Y,Z)	X,Y: 1.6 ft.; Z: 0.49 ft. (X,Y: < 0.5 m; Z: < 0.15 m)
Post-processed GPS accuracy	< 0.05 m

Lidar-derived canopy height models (CHM) were used along with AISA spectral data to segment the forested area. First and last return lidar data were interpolated to 1, 3, 5, and 10 m grids using regular Kriging. The CHM for each resolution was by extension the difference between the first and last return surface. AISA data were used at 1m and resampled 3, 5, and 10 m resolutions. AISA data, the first return surface, and the CHM were used in combination and as stand-alone layers for segmentation at each resolution. Structural data (first return and CHM surfaces) were weighted more heavily by a factor of 10 when used in conjunction with the AISA imagery. This is because structural data are more important to subsequent volume estimation than spectral data. Segmentation results were evaluated based on the relationship of between- and within-segment variances (Oderwald, 2003). Segments where between- exceeds within-segment variance are ideal candidates for species differentiation and model fitting. The formulae for between- and within-segment variances, as derived from the variance formula for clusters of unequal size are:

$$s^2_{\text{cluster}} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M_i}\left(y_{ij}-\bar{\bar{y}}\right)^2}{\sum_{i=1}^{N} M_i - 1} = \underbrace{\frac{\sum_{i=1}^{N}\left[(M_i-1)s_i^2\right]}{\left(\sum_{i=1}^{N} M_i - 1\right)}}_{\textbf{Within-segment variation}} + \underbrace{\frac{(N-1)}{\left(\sum_{i=1}^{N} M_i - 1\right)} * \frac{\sum_{i=1}^{N} M_i\left(\bar{y}_i-\bar{\bar{y}}\right)^2}{N-1}}_{\textbf{Between-segment variation}}$$

where

N = # of segments; M_i = # of elements per segment; y_{ij} = observation j in segment i; $\overline{y}_i$ = mean of segment i; $\overline{y}$ = overall arithmetic mean; s_i^2 = variance for segment i

Table 2. AISA hyperspectral data set characteristics (X_{min} = 703,963 m, X_{max} = 707,459 m; Y_{min} = 4,142,217 m, Y_{max} = 4,145,626 m)

Band Number	Spatial Resolution (m)	Wavelength (nm)	Bandwidth (nm)
1	1 m	480	± 9.8
2		520	± 9.8
3		550	± 5
4		575	± 5
5		600	± 5
6		610	± 5
7		620	± 5
8		631	± 2
9		638	± 2.5
10		656	± 5
11		680	± 2.5
12		700	± 2.5
13		720	± 2.5
14		740	± 2.5
15		750	± 2.5
16		840	± 9.8

RESULTS

Results were very promising, with definite trends in the between- and with segment variance graphs. Figure 1 shows the between- and within-segment variances for the CHM using AISA 5 m data as segmentation input. Figure 2 shows the variance graph for the first return surface using AISA 5 m data as segmentation input Figure 3 shows the variance output for the 720 nm wavelength, located in the near-infrared region important to vegetation studies, also using AISA 5 m data for segmentation. From these figures it is clear that the within-segment variance is generally smaller than between-segment variance only at relatively large segment numbers, or small segments. The intersection of between- and within-segment variances occurred at > 450 segments for both the CHM and 720 nm wavelength variance cases. It should be note that the current, "operational" number of stands is 181. The fact that in the first return data the intersection occurred at fewer (larger) segments can be attributed to the fact that first return data are less indicative of stand height than a CHM. This could result in adjacent stands having the same first return "height" due to topographical differences, even if actual stand height is substantially different.

Figures 4-6 show the same set of variances, but for cases where AISA and CHM 5 m data were used as input to the segmentation algorithm. From these figures the same trend emerged, namely between- and within-segment variances intersection at relatively large segment numbers (small segments) for the CHM and 720 nm as variance variables. The variance intersect for the first return data occurred at a much larger segment-level, fewer segments.

Models will eventually be fitted to (i) segments that correspond to existing stands in size and shape and (ii) segments which may be substantially smaller than operational units, although both scenarios have to meet the selection criterion (between > within variance). In the latter case volume and biomass models might produce a better fit due to small within-segment variation, but results will have to be scaled to meet operational demands. The multiresolution, hierarchical segmentation procedure is ideally suited to this task. Therefore the results showed great promise since models fitted to smaller, and therefore more numerous segments will likely have a better fit due to small within-segment variance. These models subsequently can be applied to similar segments, based on structural (lidar) and spectral (hyperspectral) similarities.

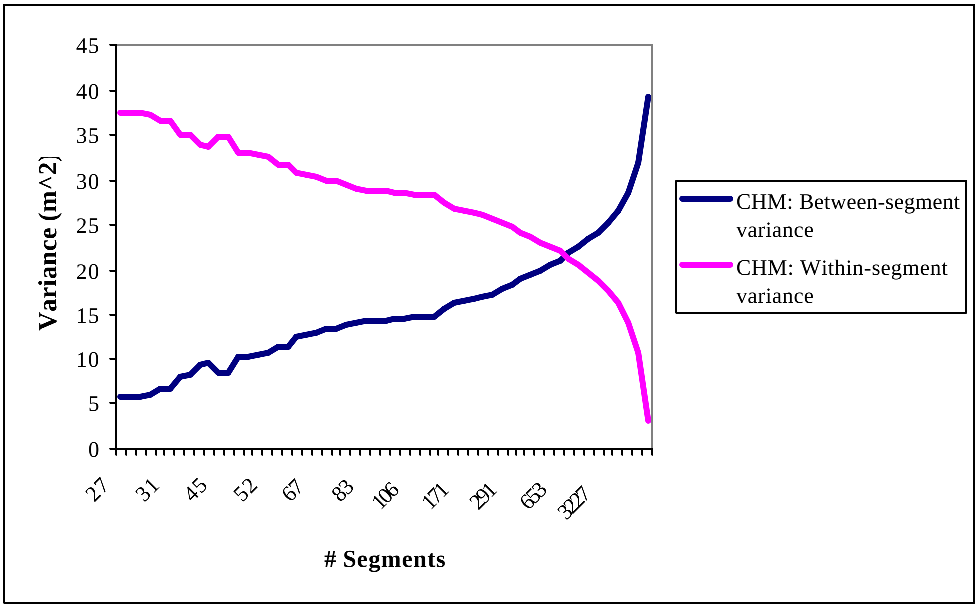

Figure 1. Segmentation using AISA 5 m data; between- and within-segment variance assessed using canopy height model (intersect: 819 segments)

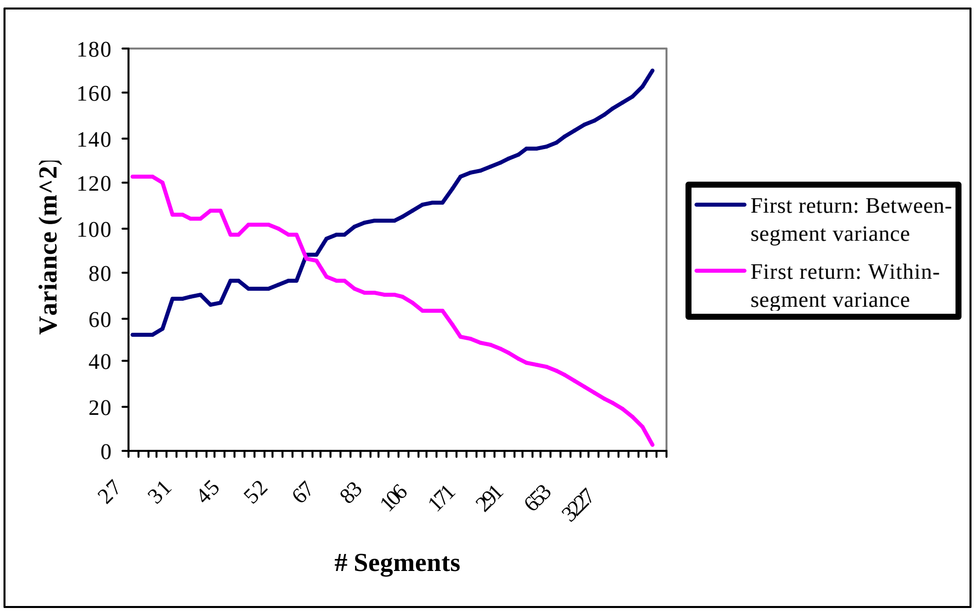

Figure 2. Segmentation using AISA 5 m data; between- and within-segment variance assessed using lidar first return surface (intersect: 65 segments)

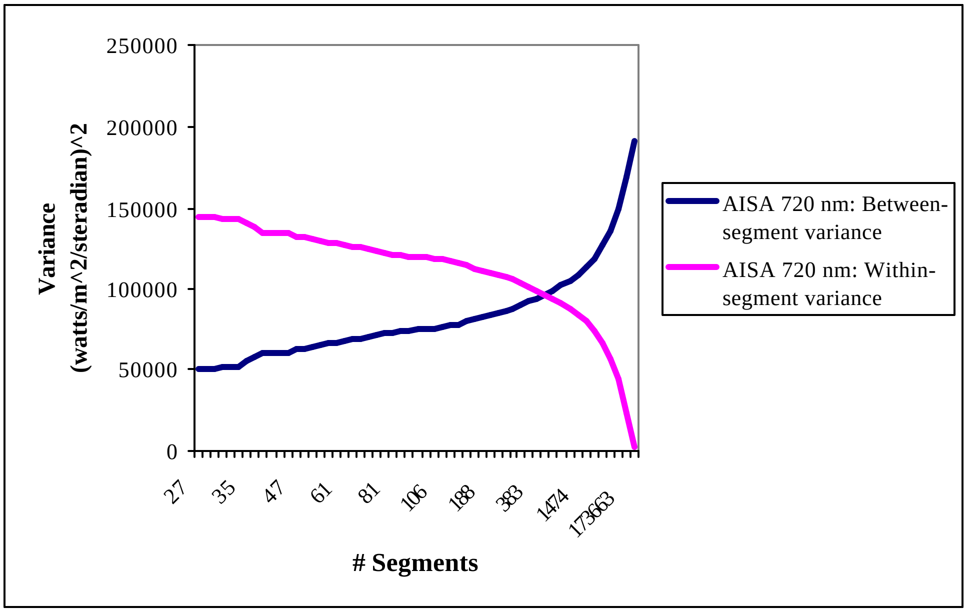

Figure 3. Segmentation using AISA 5 m data; between- and within-segment variances assessed AISA 720 nm band (intersect: 452 segments)

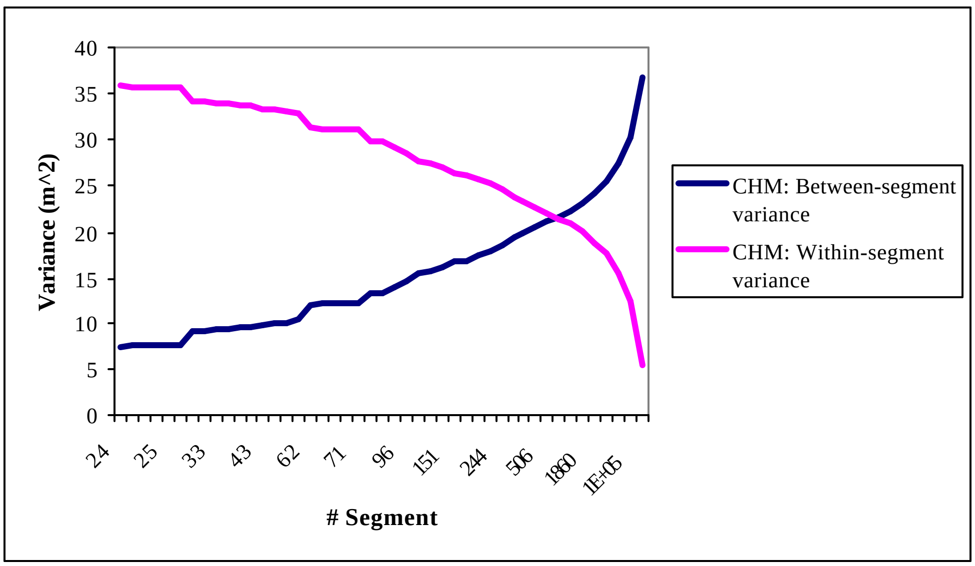

Figure 4. Segmentation using AISA and CHM 5 m data; between- and within-segment variance assessed using canopy height model (intersect: 652 segments)

A visual segmentation result is shown in Figure 7, where AISA 5 m data were used as segmentation input. The segmentation level was extracted for 160 segments to roughly match operational stand size (181 stands) for the study area. It is noticeable that the algorithm seemed successful in delineating unique forest areas, such as young stands with high texture in the northern part of the image.

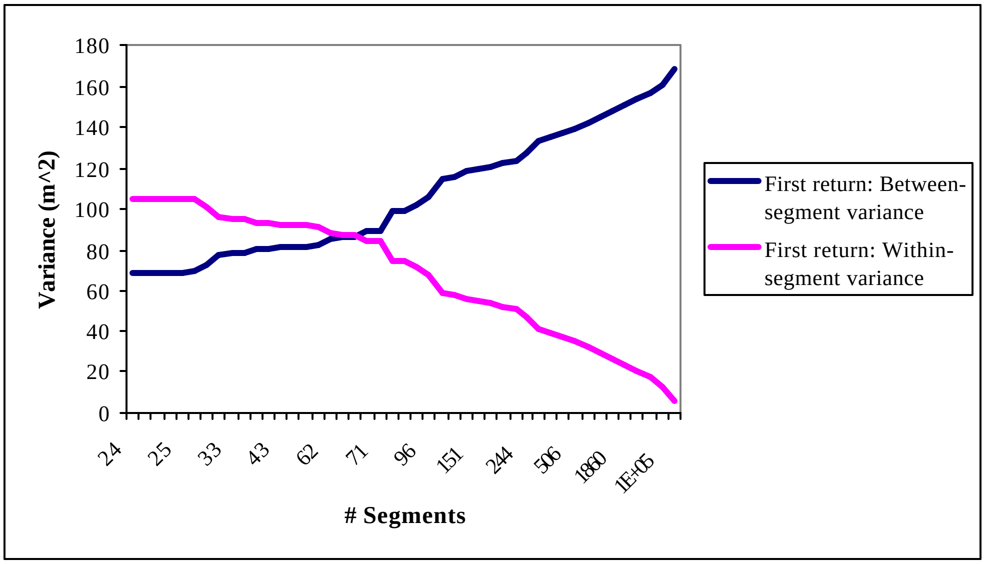

Figure 5. Segmentation using AISA and CHM 5 m data; between- and within-segment variance assessed using lidar first return surface (intersect: 66 segments)

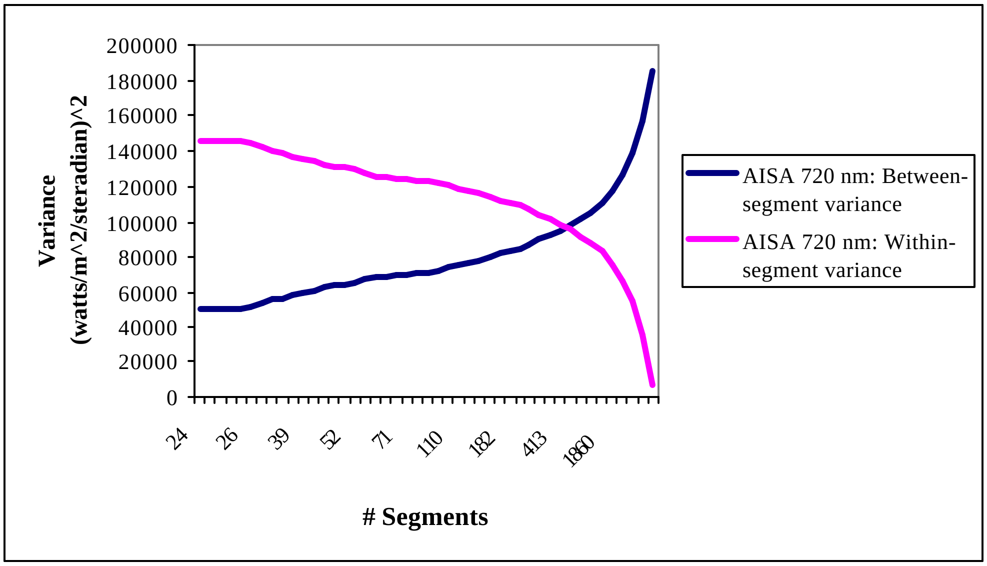

Figure 6. Segmentation using AISA and CHM 5 m data; between- and within-segment variance assessed using AISA 720 nm band (intersect: 506 segments)

CONCLUSIONS

It can be concluded that multiresolution segmentation of a forest landscape has potential in defining operational units for volume-by-species modeling. Evaluation of between- and within-segment variances could be an effective method for defining the segment size at which such volume models need to be fitted. Finally, the hierarchical nature of the approach lends itself to subsequent scaling to larger tracts of land. Such an integrated approach to forest inventory will be beneficial to forest managers and scientists.

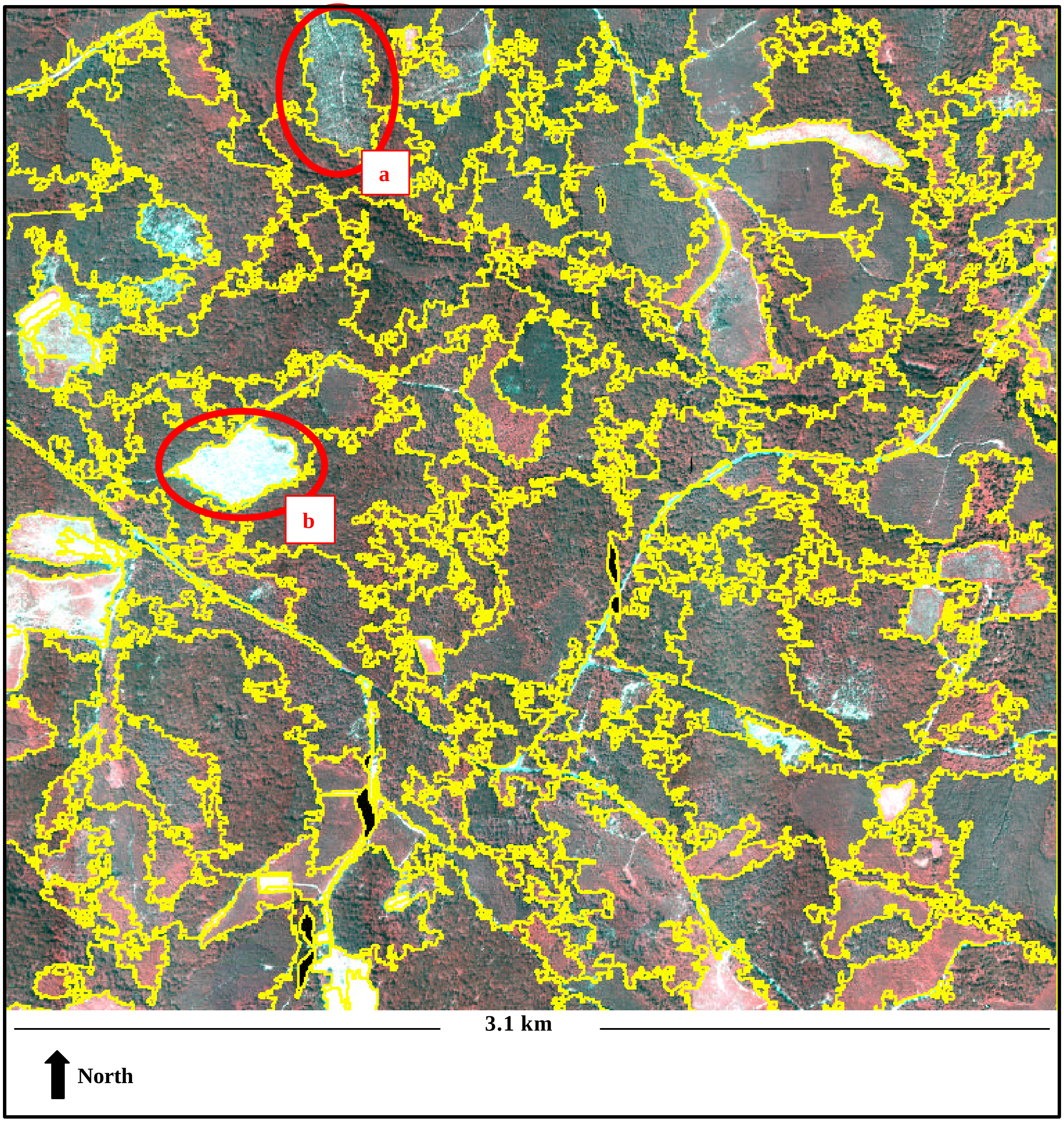

Figure 7. Segmentation result for AISA 5 m data used as input (160 segments) (Note the delineation of "unique" textural areas such as ***a*** and ***b***)

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