Area Dependent Region Merging: A Novel, User-Customizable Method to Create Forest Stands and Strata

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Abstract
Remotely sensed high-resolution imagery and LiDAR data can be used to develop stand delineations and stratifications for forest inventory and management purposes. A new Area Dependent Region Merging method is introduced that uses LiDAR data and expert knowledge to develop forest stands and strata based on user-supplied constraints. This method uses an area-dependent scale parameter that allows for different merging criteria based on the size of the objects being merged. This method was used to develop a new forest inventory that showed improved accuracy with significantly fewer field plots. Compared to non-area-dependent region merging approaches, this method more effectively reduced within stand variability and more closely matched a manual stand delineation.

Keywords: Forest segmentation, object-based, GEOBIA, stand delineation, forest stratification, forest inventory.

Introduction
Global products acquired from satellites, such as the Moderate Resolution Imaging Spectroradiometer (MODIS – 250 m to 1 km pixels), Landsat (30 m), Quickbird (1 m pixels) and IKONOS (1 m pixels) have all been used to make inferences about forest stocks, fluxes, and structure across both large and small scales [Running et al., 2004; Hall et al., 2006; Heinsch et al., 2006; Zhang and Kondragunta, 2006; Potter et al., 2007a; Mildrexler et al., 2009; Song et al., 2010]. In recent years, Light Detection and Ranging (LiDAR) data products as well as higher resolution imagery products acquired from airplanes rather than satellites have been used to make inferences about forest ecosystems at smaller spatial scales and higher resolutions [Akay et al., 2009; Asner et al., 2011]. Some scientists have combined multiple remote sensing data products to generate wall-to-wall estimates [Potter et al., 2007b; Gonzalez et al., 2010; Ke et al., 2010; Golinkoff et al., 2011] or have used small samples of higher resolution remote sensing products combined with lower resolution data to reduce costs and improve the accuracy of estimates [Næsset, 2002; Wulder and Seemann, 2003; Wulder et al., 2012].
As higher resolution remote sensing data products become available, it is possible and
necessary to group small pixels into meaningful objects. The need to use objects as opposed to pixels arises when individual pixels are smaller than the features of interest (e.g., stands or individual tree crowns) in an image [Johansen et al., 2010]. The aggregation of pixels into objects allows object level properties to be summarized efficiently while reducing the amount of data required to be stored about the image [Ali et al., 2009; Hofmann et al., 2011; Sasaki et al., 2012]. Object-based analysis has also been shown to perform better than using pixel-based approaches in classifying images [Blaschke, 2010]. This improvement in classification using objects as opposed to pixels (the current approach) may also translate to improved performance of predictive models of future ecosystem state as well and may provide a better platform on which to run these models [Maselli et al., 2009; Golinkoff and Running, 2013].

Geographic Object Based Image Analysis (GEOBIA) is a relatively new field that uses objects as the fundamental unit of analysis when interacting with geographic imagery [Hay and Castilla, 2008; Blaschke, 2010; Addink et al., 2012]. How to best partition a landscape into objects and some of the implications of the segmentation chosen were first discussed within the context of the Modifiable Areal Unit Problem [Openshaw, 1984]. Openshaw explained that the location and boundaries of objects within a given area are in many cases arbitrary and that there are infinite possible combinations of non-overlapping objects, some more suitable than others, in defining reasonable divisions within the landscape. Many methods to optimally segment a landscape have been proposed to address this issue. These methods build upon years of image segmentation work in the computer vision and medical imaging fields [Fu and Mui, 1981; Pal and Pal, 1993].

Many authors have reviewed segmentation methods and discussed specific forestry applications of these methods. Cheng et al. [2001] provided a general overview of the many different approaches that can be used to segment a color image. Dey et al. [2010] related these techniques to the remote sensing field and reviewed the most commonly applied methods. Broadly, the results of image segmentation can be considered to fall on a spectrum from over to under segmented. Over-segmented images have too many segments and break objects into their component parts. Under segmented images have grouped relevant objects together and image fidelity and resolution is lost as a result [Möller et al., 2007; Marpu et al., 2010]. Segmentation methods can also be distinguished by those that create final objects by grouping similar pixels and/or sub-objects together versus those that create final objects by splitting larger objects apart based on discontinuities [Addink et al., 2012]. This concept is similar to agglomerative and divisive hierarchical methods of cluster analysis [Mardia et al., 1979]. Segmentation methods also vary based on the input data considered: spectral intensities or digital numbers of pixels, spatial attributes such as neighborhood relationships and texture, object shape and size, and prior knowledge of the image [Dey et al., 2010]. Segmentation can also vary based on the degree of user guidance or supervision versus automation as well as whether a model driven versus image driven approach is used [Baatz and Schäpe, 2000; Hay and Castilla, 2008; Dey et al., 2010]. In model driven approaches, an underlying image structure is assumed and used as a model that then drives the image segmentation.

Because of the myriad options available to segment images and the inherent subjectivity of the final segments, the method chosen depends heavily on the goals of the segmentation and the spatial characteristics of the forest. In forestry operations, the final object of interest is often a stand. The definition of a stand may vary but in general it refers to a contiguous area of forest that is managed as a unit and that has trees that are homogenous.
relative to surrounding stands [Sullivan et al., 2009]. Traditionally, forest stands were defined by human photo interpreters. However, as high-resolution remote sensing data and powerful microprocessors have become ubiquitous, it has become possible to remove some of the human labor and subjectivity from the stand delineation process by developing repeatable algorithms to complete this task [Leckie et al., 2003]. Generally, when devising forest segmentation, it is preferable to have some limits on the sizes of polygons. Forest stands are used to manage for inventory and harvest operations and stands that are too large or too small become difficult from a data management perspective and impractical for operations. Forest stands have been delineated using many different approaches and the method described here is an extension of some of the work that has already been done in this field. One of the most widely used approaches to the creation of objects is the eCognition program (see http://www.ecognition.com/). This commercially available software uses fuzzy logic and incorporates user-defined variables to define the importance of object shape and as well as a merge stopping criteria (scale parameter) [Baatz and Schäpe, 2000; Benz et al., 2004]. This software has been used in many studies and has been show to be a powerful tool to segment forests into stands and into individual tree polygons [Van Aardt et al., 2006; Pascual et al., 2008; Riggins et al., 2009; Ke et al., 2010]. Although powerful, this program is not freely available and requires users to iteratively choose the scale parameter that is optimal for their work. This scale parameter is a constant that will change the sizes of polygons. However, this parameter is not directly a constraint on forest stand size and instead defines a degree of dissimilarity that causes merging to stop. This is problematic, as many managers would like area constraints to limit the results of a stand delineation method more directly.

Other researchers have designed and used different approaches to segmentation. Leckie et al. [2003] built individual tree crown polygons from high resolution multi-spectral imagery and then combined these individual crown polygons into larger stands based on crown closure, stem density, and species composition. This approach smoothed individual tree crown data and used a minimum size constraint to guide stand creation. Another approach designed by Haywood and Stone [2011] for Eucalyptus stands in Australia uses a single minimum area constraint but also included a similarity metric that can incorporate data from a user specified number of remote sensing layers. Other approaches to forest segmentation use an iterative nearest-neighbor approach that selects regions to merge in several iterations based on relaxing the difference constraint. These algorithms proceed by increasing the amount of difference between neighbors that will trigger merging to occur until either a final mean polygon size is reached or until a maximum difference in feature space is reached [Hay et al., 2005; Castilla et al., 2008; Wang et al., 2010]. By using single global targets for mean polygon size and/or a constraint on minimum size, there may be small stands that are quite different from their neighbors that are merged instead of retained. For example, if a stand is smaller than the minimum size constraint and much different from its neighbors, these algorithms will force this polygon to be merged. Similarly, if a stand is larger than the minimum size constraint but more different than the feature space difference constraint, this polygon will be merged with its neighbors.

All of these methods show varying levels of success in defining stands that accurately partition forest systems. However, a forest manager or inventory planner may need more control over the final stand delineation and how important stand area should be in determining when objects are merged. An increase in control should allow managers to specify both minimum
and maximum stand sizes, stand shape, the variables used to define stand boundaries, and the differences between objects that allow for objects to remain distinct stands. In particular, unlike existing region merging area controlled segmentation methods, an area-dependent region merging approach allows for more control over final stand size. To address these needs, an area-dependent, region-merging (ADRM) method is proposed that allows users to select relevant real world sub-object characteristics (as opposed to spectral or textural properties) and specify polygon sizes given user-defined feature space distances. To evaluate the success of this result, a novel, scaled-variability metric is introduced to compare stand delineation outcomes. This evaluation method is a fast and intuitive approach that can allow analysts to understand the effectiveness of any given stand delineation model run compared to other model runs or against a reference case.

**Study Site / Data**

**Study Site**
The Big River and Salmon Creek Forests are located in Mendocino County, CA near Ft. Bragg and owned by The Conservation Fund (TCF) (see location map Fig. 1). TCF is a non-profit organization whose mission is to conserve threatened and important ecosystems and promote rural economies across the United States of America (see [http://www.conservationfund.org](http://www.conservationfund.org)). Both forests are dominated by Redwood (*Sequoia sempivirens*) and Douglas Fir (*Pseudotsuga menziesii*). The Big River forest is ~4,700ha and the Salmon Creek forest is ~1,700ha. These forests are currently managed as a unit and together are a verified and registered forest carbon offset project under the Climate Action Reserve Forest Project Protocol version 2.1 (CAR FPP v2.1) [CAR, 2007]. The Big River / Salmon Creek (BRSC) ownership has been extensively managed in the past using both even- and uneven-aged harvesting. This has resulted in a patchwork of old clear-cuts dominated by one size and age class as well as mixed-size and age stands. It is currently actively managed for both timber production and carbon offsets, in addition to watershed restoration and public recreation.

Due to the history of management on this property, most stands are made up of second and third growth trees. Although there are some past clear-cuts where stand boundaries are easy to detect, much of the forest has heterogeneous stand conditions that grade into other stand conditions making traditional air photo interpretation or automated stand delineation difficult. The result of these conditions results in highly subjective stand boundary creation and large stands that make management planning difficult.

**Remote Sensing Data**
The BRSC forests were flown for full coverage Light Detection and Ranging (LiDAR) in August 2011. The LiDAR data was collected along east-west flight transects flown at ~900 m altitude with at least 10% overlap between flight lines. The LiDAR data was collected using an ALTM Gemini from Optech Incorporated sensor with up to 4 returns per point and on average 4 points per square meter. The data was binned into 1 m$^2$ pixels to create a digital elevation model (DEM) and a canopy height model (CHM). The CHM bins were based on the highest hit within the 1 m$^2$ pixels and the DEM was created using the ground point returns. The CHM is the total height of each pixel minus the bare earth DEM elevation and represents the top of the tree canopies. The stand delineation method described here relied primarily on the LiDAR data but could also incorporate imagery as well.
Ground Inventory Data
Existing Inventory
The existing inventory on the BRSC forests prior to the acquisition of the remote sensing data contained plots collected over the previous 11 years. The initial inventory sampling design was a multi-staged probability proportional to stand area list sample within a broader stratified inventory. This means that stands within each strata were selected with replacement with probability proportional to their area [Borders et al., 2005]. The plots in this inventory were variable radius basal area factor prism plots. The prism factor varied depending on the age and stocking of the stand with the target of 4 to 8 count trees included in each plot [Shiver and Borders, 1996; Bell and Dilworth, 2007]. In 2011, the existing inventory relied on 2597 plots and resulted in 3.43% estimated inventory accuracy at the 90% confidence level (estimated inventory accuracy = (z-statistic * SE) / mean where the z-statistic for the 90% confidence level = 1.645). Estimates of carbon density are calculated using the approved biomass and carbon equations required by the CAR FPP v2.1 and most are based on national scale biomass estimators developed by the US Forest Service [Jenkins et al., 2004; CAR, 2007]. The stands were stratified using three variables: dominant species (by the percentage basal area), dominant size class (by percentage basal area), and canopy closure.

As areas of the forest were harvested, these locations were delineated by hand on the stand map and re-inventoried as new stratum. Table 1 shows the summary of the plot data used. As can be seen, the majority of plots are at least 8-years-old and this, paired with changing on-the-ground conditions due to harvest and forest growth, created a need for a complete re-inventory of the entire forest area.

2012 Inventory
The updated 2012 inventory was installed after the final stand delineation and stand stratification was completed. The sampling design used was exactly the same as the prior
inventory — a multi-stage probability proportional to area within strata list design [Borders et al., 2005]. All inventory plots were installed with variable radius basal area prisms as in the previous inventory. A total of 677 plots were installed in 2012.

Table 1 - Existing inventory plots used by year. As is often the case in forest inventories, plots are collected on a rolling basis in between full forest re-inventory efforts. In this case, data from plots collected over 11 years were considered for the original inventory estimates. All plot data has been grown forward for final inventory results.

| Year | 2011 Plots used | % of Total |
|------|----------------|------------|
| 2000 | 21             | 4.7%       |
| 2001 | 59             | 2.3%       |
| 2002 | 1271           | 48.9%      |
| 2003 | 26             | 1.0%       |
| 2004 | 371            | 14.3%      |
| 2005 | 73             | 2.8%       |
| 2006 | 0              | 0.0%       |
| 2007 | 336            | 12.9%      |
| 2008 | 102            | 3.9%       |
| 2009 | 80             | 3.1%       |
| 2010 | 146            | 5.6%       |
| 2011 | 12             | 0.5%       |
| Total| 2597           |            |

**Method**

The method proceeds in four steps (Fig. 2). In the first step, the CHM of the forest is partitioned into management compartments. By first partitioning the property in this way, the final results can be controlled more easily and will more closely relate to the management constraints of the forest [see Leckie et al., 2003]. This step was done by a local forester and divided the forest along major roads and streams to create large areas that would share logging infrastructure. Within each compartment, small objects—microstands—are then created using an appropriate method (a watershed algorithm applied to a smoothed CHM, as detailed in section Microstand Creation). This step is designed to create sub-objects that correspond to similarly sized clumps of trees but are smaller than stands. The third step involves the user iteratively selecting the optimal constraints for stand creation. This involves selecting and weighting the variables adopted in the region merging algorithm and selecting the stand shape and size constraints. In the final step, the stands within each compartment are merged together and stratified to create a full property level stand delineation and stratification. The input and output formats for this method are shape files and the program is written in Perl using the GDAL/OGR module [GDAL Development Team, 2012]. Please contact the author for access to the source code.

**Microstand Creation**

The first step in creating stand polygons requires creating small regions across the full forest extent. There are many methods that have been put forward to move from an initial set of pixel-based layers to small microstand objects. For this particular case, microstands consisting of clumps of similarly sized trees were desired.
To build these microstands, the 1 m² resolution CHM was first up-sampled to 4 m² cells. A 5 by 5 median filter was applied, to preserve the edges in the image, as median filters have been shown to be edge preserving smoothers [Hay et al., 2005]. A morphological gradient image was then created from this up-sampled, smoothed CHM layer. The morphological gradient is a measure of local variation in an image and has edge enhancing effects. The morphological gradient image was then further smoothed using a 3 by 3 median filter. The smoothed morphological gradient image was converted to a microstand map using the watershed algorithm (Fig. 3). The watershed algorithm finds areas of pixels within contours (analogous to how a watershed is defined in nature using the flow of water) [Gonzalez et al., 2009]. Microstand creation was done using the MATLAB Image Processing Toolbox and ArcGis software [MATLAB Image Processing Toolbox, 2011; ArcMap 10.1, 2012].

The intent of this work is to highlight the region merging approach using an area-dependent scale parameter. This approach requires that small regions – microstands – are first created and then merged. As described above, a smoothed, gradient image was processed using a watershed segmentation algorithm to create the initial microstands. However, any appropriate method could be used to generate the microstand objects that will be used as the basis for the final stand creation. These microstand polygons should ideally range from a single tree crown to a collection of several tree crowns that are of similar type and species. Alternatively, microstands can be made to be plot sized and sampled prior to region merging.

Area-Dependent Region Merging (ADRM)
Once microstands are created, these regions can be merged together based on a set of user specified constraints. Regions are labeled using characteristics of importance to forest managers. Using this approach, managers have a better understanding of the factors that drive the final stand delineation and more control over the outcome.
For example, using LiDAR data, each region was assigned an average canopy height defined as the mean of the maximum heights of trees based on a tree crown segmentation. The tree crown segmentation was done using the watershed method on the inverted, unsmoothed CHM layer for areas taller than 3 m. Each microstand was also assigned a percent canopy cover metric defined as the percentage of LiDAR returns occurring above 2 m in height. These metrics closely relate to volume and stand vigor and are therefore important when trying to map merchantable timber and carbon stocks [Nilsson, 1996; Popescu et al., 2003; Ioki et al., 2009; Latifi et al., 2010]. Additional metrics (e.g. species composition) can be
considered on an as needed basis. However, it is recommended that at most three variables are used to avoid problems associated with high-dimensional neighborhood calculations. This “curse of dimensionality” leads to excessively large neighborhoods for each individual variable and reduces the skill of the results in predictions and classifications [Hastie et al., 2009].

Once a set of attributes is assigned to each microstand, the manager weights each attribute depending on the importance of the attribute for the final stand delineation. The manager also chooses an optimal shape weight as well. In this case, the shape constraint used was the ratio of polygon perimeter to the square root of the polygon area. This is equivalent to the compactness variable as defined by Benz et al. [2004]. Other possible shape constraints that have been discussed in the literature are the simple perimeter to area ratio, the object smoothness defined as the ratio of the polygon perimeter to the bounding box perimeter, or the object rectangularity defined as the ratio of object area to the bounding box area [Turner et al., 2001; Benz et al., 2004; Wang et al., 2010].

The next step in the ADRM process is to define the area constraints that should limit the stand creation results. The size of stand polygons is important to forest managers for several reasons. First, from an operational perspective, stands should be units that fit practical harvesting requirements, such as large enough to meet certain economies of scale (typically at least 2 ha) while at the same time not being too large to be operationally infeasible to manage. Second, from a sampling perspective, variability is introduced if there is a wide range of variability in stand size. Therefore, it is important that most stands are similarly sized [Shiver and Borders, 1996]. The most suitable stand areas are often well known by forest managers with experience in the field. Thus, this method enables managers more control over the outcome of the stand delineation process to meet these needs.

The final user-defined parameters to set is/are the scale parameter(s) that will define the difference thresholds that drive polygon merging, as well as the type of scale parameter to use. There are three types of scale parameters that can be chosen: 1) a standard, non-area-dependent scale parameter (ADSP), 2) a stepwise, discontinuous area-dependent scale parameter, or 3) a continuous area-dependent scale parameter. A standard, non-ADSP uses one difference for all merging regardless of polygon size. A stepwise ADSP uses one or more area / scale parameter pairs to define different merging criteria given different area limits. A continuous ADSP uses a smooth boundary to define different merging criteria given different areas. A continuous ADSP is any equation that connects the points (areaMin, maxDiff) and (areaMax, minDiff) (see Fig. 4 for a set of example ADSPs).

Figure 5 shows a comparison between traditional region merging approaches and the ADRM method. All microstand attributes and the shape attribute are standardized using a range standardization approach as this has been shown to result in better outcomes during clustering [Milligan and Cooper, 1988]. Variable standardization was used to insure that the absolute variable size was normalized so all variables might have equal weight in the analysis, allowing user defined weights to be applied appropriately.

After all user-defined parameters have been chosen, the ADRM process can begin. The order of merging affects the final merging outcome and several region merging algorithms and optimizations have been discussed in the literature [Castilla et al., 2008; Wang et al., 2010; Haywood and Stone, 2011]. The region merging approach used in this method was an iterative relaxation of the difference constraint similar to that described in Wang et al. [2010].
Figure 4 - Example of area-dependent scale parameter for 5 different types. Any polygon and neighbor pair whose difference in feature and shape space is below these lines would be merged.

Merging of regions proceeds by first choosing the best neighbor if the best neighbor is less than the ADSP. A neighbor is considered “best” if for two polygons $p_i$ and $n_i$, $n_i$ is the least different from $p_i$ for all neighbors $n_i$ to $n_n$ and $p_i$ is the least different from $n_i$ for all of $n_i$’s neighbors $p_j$ to $p_n$ (where difference is calculated as the sum of the weighted attribute and shape differences). “Best” merging continues until no further merges can occur. At that point, the constraint is relaxed from the best constraint to a difference criterion that is some fraction of the maximum scale parameter allowed. The fraction is defined by a user selected number of iterations that by default is 5. For each potential merge, each polygon is first checked to see if the difference between itself and its neighbor is less than the tolerance of the current iteration and that the difference is less than the ADSP. Only if both constraints are met and both polygons are smaller than the maximum area is the polygon merged with its neighbor. A random ordered list [Fisher and Yates, 1948] of merge polygons is used at every iteration to avoid problems with clumping during the merging process.

**Strata Formation (Classification)**

Stratification is a well-known method to reduce sampling effort and improve inventory accuracy when estimating population characteristics [Thompson, 2002]. The last step in the method to develop stand delineations for a forest is to stratify these stands into similar forest types. The stratification is again user driven and is supplied by the user before running the merging tool.
The strata are defined by listing the variables that will be the basis of the strata and the breaks that define the different bins within each stratum. In this way, a full set of strata can be used to partition all the stands once they are made. The strata are applied based on the attributes of each final stand polygon and these attributes are based on the original microstand polygon attributes. In the example case where canopy height and canopy cover are used as the variables of interest, the strata were defined as 7.62 m (25 ft) height bins and 20% canopy cover bins (Open: <20%, Low: 20% to 40%, Medium: 40% to 60%, Dense: 60% to 80%, Extremely Dense: >80%).

A series of model runs using different parameters were experimented with to define a set of potential stand delineations. Table 2 summarizes the parameters chosen for each model run. To assess how these stand delineations and stratifications performed they were compared to a photo interpretation done by hand by the forest manager on a small portion of the Salmon Creek property. Even for a trained forester with experience in this geographic region, creating a stand map is difficult and subjective given the variability across the forest. A stratification accuracy assessment of the hand-done stratification versus a series of region merging processes was then conducted. Each model run with different input constraints was visually examined. The results were also compared to the number and the mean variability of the hand-created stand delineation.
Table 2 - Summary of stand creation model runs. “None” means no area-dependent scale parameter was used, “stepwise” used a discontinuous approach, “linear” used a form $\text{diff} = -a(\text{area}) + b$, “exponential” used a form $\text{diff} = a \times \exp(-b(\text{area}))$, “Neg. Parab” is a downward opening parabola and “Pos. Parab” is an upward opening parabola with equation form $y = (\text{area} – a)^2/4b + c$. “ShapeWt” is the user defined weight that shape parameters are given relative to the attribute similarity. “maxDiff” is the limit above which no merging between features occurs (unless the features are less than minArea). The (“areaN”, “diffN”) pairs are used to define either stepwise or continuous ADSPs.

| Run | ADSP used | max Diff | max Area | min Area | shape Wt | area1 | diff1 | area2 | diff2 | iters |
|-----|-----------|----------|----------|----------|----------|-------|-------|-------|-------|-------|
| 1   | None      | 30       | 50       | 3        | 0%       |       |       |       |       | 5     |
| 2   | None      | 20       | 50       | 3        | 0%       |       |       |       |       | 5     |
| 3   | None      | 10       | 50       | 3        | 0%       |       |       |       |       | 5     |
| 4   | None      | 15       | 50       | 3        | 10%      |       |       |       |       | 5     |
| 5   | None      | 15       | 50       | 3        | 5%       |       |       |       |       | 5     |
| 6   | Stepwise  | 20       | 50       | 3        | 5%       | 10    | 15    |       |       | 5     |
| 7   | Stepwise  | 15       | 50       | 3        | 5%       | 10    | 10    |       |       | 5     |
| 8   | Stepwise  | 20       | 50       | 3        | 5%       | 30    | 5     | 10    | 15    | 5     |
| 9   | linear    | 20       | 50       | 3        | 5%       | 10    | 15    |       |       | 5     |
| 10  | linear    | 15       | 50       | 3        | 5%       | 10    | 10    |       |       | 5     |
| 11  | linear    | 20       | 50       | 3        | 5%       | 10    | 5     |       |       | 5     |
| 12  | exponential | 20      | 50       | 3        | 5%       | 10    | 15    |       |       | 5     |
| 13  | exponential | 15      | 50       | 3        | 5%       | 10    | 15    |       |       | 5     |
| 14  | exponential | 20      | 50       | 3        | 5%       | 10    | 5     |       |       | 5     |
| 15  | Neg. Parab | 20      | 50       | 3        | 5%       | 10    | 15    |       |       | 5     |
| 16  | Neg. Parab | 15      | 50       | 3        | 5%       | 10    | 10    |       |       | 5     |
| 17  | Neg. Parab | 20      | 50       | 3        | 5%       | 10    | 5     |       |       | 5     |
| 18  | Pos. Parab | 20      | 50       | 3        | 5%       | 10    | 15    |       |       | 5     |
| 19  | Pos. Parab | 15      | 50       | 3        | 5%       | 10    | 10    |       |       | 5     |
| 20  | Pos. Parab | 20      | 50       | 3        | 5%       | 10    | 5     |       |       | 5     |

Results

The stratification accuracy of each stand delineation outcome was calculated by examining the area within each strata intersection of the manually delineated stands and the automatically delineated stands [Congalton, 1991]. This accuracy calculation is not a sample of classes but rather looks at the full forest area to see how many pixels were placed into the same class as the hand-delineated stand layer. It should be noted that because the hand stand delineation is highly subjective, this manual delineation serves as a benchmark to compare the performance of the ADRM method. The strata were derived for both the hand delineation and the automated delineation based on the average characteristics of all of the combined microstand polygons. In this way, these are more subjective classes rather than true forest types. Although different than a classical classification accuracy assessment, the classes of managed forests are difficult to define and subjective themselves so this was deemed an unbiased approach to assess the similarity of the results. Lastly, it should be noted that the stratification accuracy relates only to the stratification and not the forest segmentation stand boundaries.

In addition to the stratification accuracy results calculated, a new metric was designed to provide an estimate of the average variability within the created stands. The weighted, scaled total variance (WSTV) describes the skill of the stand creation routine based on the degree to which the stands minimize within stand variability. The WSTV was calculated for
each model run. This metric is based on the original microstand objects. Each microstand has attributes of interest based on the needs of the manager. These attributes are also given importance weights by the manager. Using these weights, the linear combination of the attributes is calculated for each microstand. Once final stands have been created, these linear combinations are aggregated to calculate the mean and variance of the microstands within the final stand delineations. Weighted, scaled total variance is defined as:

\[
WSTV = \left( \sum_{i=1}^{n} \frac{\text{area}_{i}}{\text{area}_{\text{tot}}} \cdot \text{IcVar}_{i} \right) \cdot n \quad [1]
\]

\[
\text{area}_{\text{tot}} = \sum_{i=1}^{n} \text{area}_{i} \quad [2]
\]

\[
\text{IcVar}_{i} = \sum_{j=1}^{m} \frac{(\text{IcMean}_{j} - \text{IcMean}_{i})^2}{m_i} \quad [3]
\]

\[
\text{IcMean}_{i} = \sum_{j=1}^{m} \frac{\text{IcMean}_{j}}{m_i} \quad [4]
\]

\[
\text{IcMean}_{j} = \sum_{k=1}^{n} w_k \cdot a_k \quad [5]
\]

Where \( n \) is the total number of stands created, \( m_i \) is the number of microstands within each final stand \( i \), \( p \) is the number of user-chosen merge parameters, and \( w_k \) is the user-defined weight of attribute \( a_k \). \( \text{IcVar}_{i} \) is the variance of the linearly combined, user-specific attributes. In this way, the \( WSTV \) represents the variability across all variables of interest and all final stands.

The estimates of stand level variability are area weighted by the stand area and summed across all stands to calculate a final metric of mean forest variability. This estimate of forest level within stand variability is highly dependent on the size of the stands. Larger stands will tend to have larger variability as they typically have more types of sub-objects. Because of this, stand creation routines that create more stands will necessarily have lower variability within stands (see Fig. 6). Therefore, to assess the skill of the stand creation routine it is necessary to remove the impact of the stand number on the estimate of within stand variability. This is done by multiplying the area weighted forest variability by the number of stands and results in the scaled, area weighted estimate of forest variability. The results of each stand creation run can be seen in Table 3 and Figure 7.

The horizontal black line in Figure 7 is the scaled variability metric for the hand delineated stands. As can be seen, the manual stand layer did not perform as well in terms of reducing within stand variability as the computer generated stands. For this reason, the stratification accuracy percentage should be viewed as a guide but not a definitive metric of the success of the stand delineation. Manual stand creation is highly subjective and may or may not represent the best partitioning of variability. The accuracy statistic does, however, allow for a comparison between the outcomes and how closely the automatic results match the manual results in terms of classification accuracy.
Area-Dependent Region Merging for Stand Creation

Figure 6 - Forest level variance as a function of the number of stands created. The red circle is the manual reference stand layer.

Figure 8 shows the manual stand delineation compared to the three highlighted runs in Figure 7. It is interesting to note that the best performing stand creation runs all used an ADSP. This speaks to the importance of area dependency in stand creation. The final stand delineations also show less compactness of stands and more complicated boundaries as they more closely follow forest features than they would in a manual delineation. This difference is due to the nature of the region merging algorithm as well as the preference of this photo-interpreter to build smoother stand boundaries.

Based on these results, a stepwise ADSP was chosen for the full forest stand delineations. The results of the estimated inventory accuracy using the new stand layer were compared with the original estimated inventory accuracy. The new inventory achieved an estimated inventory accuracy of 3.81% at the 90% confidence level using a total of 677 plots. The prior inventory had an estimated inventory accuracy of 3.43% at the 90% confidence level but used 2597 plots – almost 4 times as many.

Discussion

A flexible, user-customizable, area-dependent region merging stand creation method has been described above. This method allows for fine grain control of the stand delineation process using real-world attributes that forest managers can understand. At the same time, it provides powerful, area-based merging criteria that can serve to better partition the variability of a forest. A stratification approach that allows for on-the-fly forest classification was also introduced to allow managers’ input both into the stand creation process and the final stratification results. This method was compared to a manually delineated stand map used as a reference and was also evaluated using an area-weighted, scaled metric of within-stand variability that can be easily generated and provides an accessible and rapid means of assessing the skill of a given stand creation model run. A large improvement in sampling efficiency was observed using this method. Over large areas, these improvements can result in substantial cost savings as field inventory is one of the most expensive elements of forest management.
Table 3 - Summary of model run results. The three models in bold represent some potential results with optimal stratification accuracy and weighted, scaled total variance. Please refer to Figure 7 for a graphical explanation of why three models were chosen.

| Run   | Type           | Stratification Accuracy | Mean Variance | Stand Number | Scaled Variance |
|-------|----------------|-------------------------|---------------|--------------|-----------------|
| Reference | by hand         | NA                      | 167           | 35           | 5,838           |
| Run1  | None           | 44.1%                   | 192           | 21           | 4,042           |
| Run2  | None           | 50.6%                   | 167           | 24           | 4,009           |
| Run3  | None           | 50.4%                   | 148           | 40           | 5,902           |
| Run4  | None           | 47.0%                   | 152           | 28           | 4,256           |
| Run5  | None           | 53.6%                   | 169           | 31           | 5,254           |
| Run6  | Stepwise       | **58.4%**               | **160**       | **30**       | **4.811**       |
| Run7  | Stepwise       | 55.7%                   | 164           | 34           | 5,583           |
| Run8  | Stepwise       | 50.3%                   | 169           | 30           | 5,071           |
| Run9  | linear         | 45.3%                   | 173           | 27           | 4,663           |
| Run10 | linear         | 48.9%                   | 156           | 36           | 5,611           |
| Run11 | linear         | 53.3%                   | 166           | 28           | 4,640           |
| Run12 | exponential    | 49.4%                   | 176           | 28           | 4,916           |
| Run13 | exponential    | 52.2%                   | 171           | 28           | 4,778           |
| Run14 | exponential    | **54.9%**               | **163**       | **28**       | **4.565**       |
| Run15 | Pos. Parab     | **52.3%**               | **185**       | **22**       | **4.080**       |
| Run16 | Neg. Parab     | 48.3%                   | 158           | 30           | 4,749           |
| Run17 | Neg. Parab     | 51.6%                   | 173           | 28           | 4,837           |
| Run18 | Pos. Parab     | 53.3%                   | 173           | 30           | 5,186           |
| Run19 | upParab        | 50.6%                   | 151           | 38           | 5,725           |
| Run20 | upParab        | 55.1%                   | 158           | 34           | 5,387           |

Figure 7 - Scaled, area-weighted forest level variability estimate versus the stratification accuracy of 20 different stand creation model runs (see Tab. 1 for a description of the model runs). The red circles correspond to the results found for the bold model runs in Table 3 and represent some of the best outcomes as they show the least variability but have the greatest accuracy when compared to the reference layer. The horizontal black line shows the weighted scaled forest variability estimate calculated for the manual reference stand layer.
The ADRM method described here was developed for use in an active working forest to meet the needs of forest managers to create reasonable stands for operations. There are several issues managers should consider when using this method. First, from an operational perspective, the boundaries created by the ADRM method are more complicated than stands created by humans. The more complicated boundaries may lead to difficulties in locating stand boundaries in the field. In general, boundaries created in an automated, rule-driven way will be more complicated than boundaries created by human interpreters. Photo-interpreters, especially those with experience managing timber harvests, are more likely to group dissimilar areas together to create smoother stand boundaries. The automated approach, even when shape constraints are imposed, is less likely to do this. In practice, this is not a major problem as the inventory estimates can be used to inform management even if the stand boundaries do not exactly line up with how a forest may be harvested in the future.

This issue of complicated boundaries may also make it difficult to be sure a given plot falls in the correct stand. For this work, it was found that plots should be located with
GPS coordinates using handheld GPS receivers to remove bias and cruiser subjectivity when locating plots. Although in some cases plots may fall in neighboring stands using this method, most plots will fall in the correct stand and the resulting inventory is still much more accurate than a traditional heads-up digitized stand layer. To further constrain the final stand layer, it may be beneficial for large forest ownerships to first manually delineate logical management compartments and then run this stand delineation within those compartments to constrain the outcome. Even with the best stand delineation (from the perspective of variability reduction), one stand may fall into multiple areas that in reality would never be managed simultaneously. To control for this, the use of management compartments to constrain the results is a critical step in this process. The use of logical management units will also reduce the complexity of stand boundaries in many areas.

In the example developed here, the stand delineation was applied first, a stratification was developed, and a field sample then proceeded within the delineated stands. However, it may be preferable to stratify and sample within microstands and then merge these microstands into larger stand units after sampling. By reversing the order, sampling may be conducted first, allowing the user to generate any number of post-sample stand layers. The inventory data may then be used to both inform the microstand attributes for merging purposes and to populate the final stand layer, which may be useful depending on monitoring or management goals. Sampling microstands first allows for flexibility in creating stand layers to meet these objectives. Any microstand layer can be used, although microstands should be at least as big as the plots that would be installed within them (see Golinkoff et al. [2011] for a discussion of finding the optimal microstand size).

An example of the reversed order approach mentioned in the prior paragraph was done using square microstands in a pixel-based stratification done by Golinkoff et al. [2011]. The original inventory was designed to minimize field effort while at the same time achieving a highly accurate inventory. However, future harvest planning was not considered during the design of this pixel-based inventory. For harvest planning, the square microstands were merged into larger stands that can now be used for management planning.

The models used in this work were chosen to illustrate some of the differences that different ADSPs produce when creating stand delineations and stratifications. This process of iterative variable selection and ADSP parameter tuning is time consuming but is important to provide managers more control of the final stand layer that is created. The area constraints chosen will vary based on management objectives and this may be the first variables that are experimented with to determine the spatial scale of the final forest segmentation. After this step, a series of maximum attribute differences and shape constraints can be examined to further constrain the outputs. The final step in this process is to experiment with different ADSP forms and parameterizations. This general framework for stand layer creation was followed for this work and can be seen in the ordering of models in Tables 2 and 3. Generally, exponential and positive parabolic forms will result in more stands. The linear ADSP form will result in slightly more stands created. The negative parabolic ADSP form will result in the fewest stands. The stepwise ADSP is more easily understood and was chosen in this case.

ADSPs provide finer grained control for managers in determining the final outcome of stand delineation. In some senses, this can be considered a model-based segmentation as it assumes a structure to the forest variability that varies with the stand area. Results show that this area-dependent approach performed better than a single non-area-dependent scale
factor. However, it is still difficult for a forest manager to choose the optimal parameters for this method and as a result many parameters must be examined before deciding on the best parameter set and area dependency approach to use. Because of this, more work is needed to develop a system that automates some of the variable selection and tuning.

Another future direction for this work may be to examine the area-dependent nature of the forest as a whole and how this might provide a model of forest variability. Woodcock [1988] proposed the use of variograms to model the spatial structure of remote sensing data but this assumes that the same variogram results apply to the full forest extent. Using this area-based approach, it may be possible to generate separate variogram models for different regions of a forest that correspond to the area-dependent differences observed in the stand creation process. This would have value in partitioning an ecosystem for process-modeling purposes particularly for future predictions [see Golinkoff and Running, 2013].

The ADRM method presented here provides several improvements to existing forest segmentation results. This method also builds upon much of the work that has already been done in this field. This method has incorporated many components of other object creation algorithms (e.g. – shape constraints, size constraints, iterative merging criteria relaxation, random seed regions, weighted attributes) but it has added to these methods in several key ways. First, by defining management compartments, assigning real-world attributes to each initial microstand, allowing managers to weight these attributes and define the forest stratification classes, this stand delineation and stratification method can be better controlled and understood by the managers who will actually use the results. Second, a new, scaled, within-stand variability metric has been proposed and used to provide a measure of how well a given stand delineation model run performs. This metric, when used in combination with a reference stand delineation and stratification, can be used to select the optimal merging parameters and structure. Last, the use of an ADSP to control the region-merging has been shown to improve the outcome of forest stand delineation. The improvement is seen in the stratification accuracy when compared to a reference stand delineation and stratification, in the scaled, within-stand variability metric, and in the drastic improvement in sampling efficiency when using this approach to guide a new forest inventory.

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