Forest Mapping Update: Automated Process for Forest Stand Delineation

Report to NRCS Oregon

In partial fulfillment of Grant No. NR19436XXXXG012
NRCS Oregon - USDA

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Submitted February 2021

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1. BACKGROUND

In this report, we provide an update on our work developing models and applications to map forest conditions for use by non-industrial forest owners in Oregon.

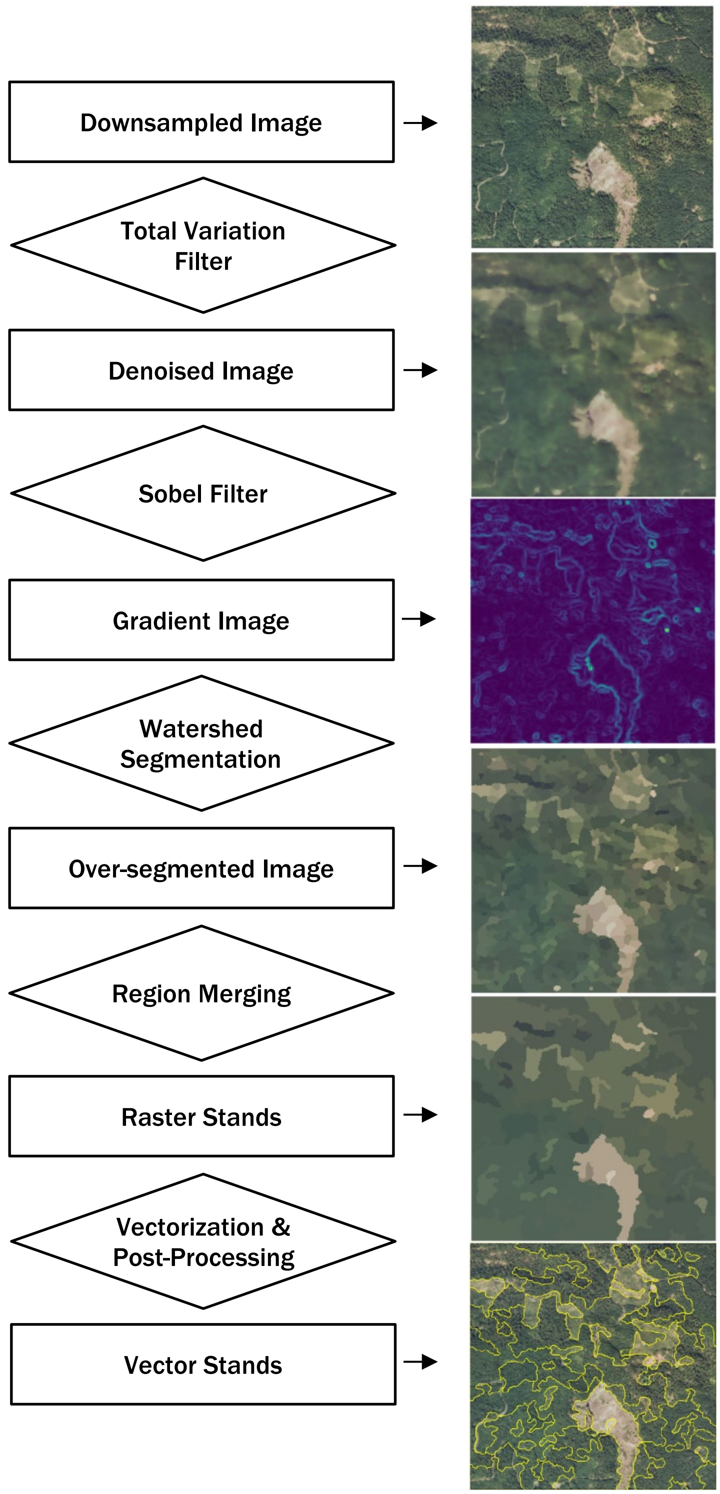
We report on the process we have implemented to automate the process of delineating management-relevant units by tuning the process to learn from stand delineations completed across millions of acres by state and federal forest managers on public lands. We provide several examples of delineations of forested scenes and discuss modeling choices to minimize the effort that may be involved for end-users to post-process the automated delineations.

Earlier reports have described and illustrated the data sources and attributes used to predict specific forest attributes (e.g., diameter class, cover class, species composition). In this report, we focus on the task of delineating areas on the landscape that are visually distinct from neighboring areas, without quantifying the vegetation conditions in each area. These two modeling systems to achieve stand delineation and forest attribute prediction will be combined in future work.

2. OVERVIEW OF THE DELINEATION WORKFLOW

In this project, we have reproduced a series of steps described in several previous research and how-to articles focused primary on the community of forest scientists in academic research and analysts at federal land agencies. Our approach closely follows the steps described by Castilla et al. (2008) and Hamilton et al. (2007), which described workflows which relied upon the use of proprietary image processing software. In particular, we reproduce the general workflow described Castilla et al. (2008) as "Size-Constrained Region Merging" (see Figure 1).

Figure 1: Illustration of Segmentation Workflow



Notes: Diamonds indicate algorithms/processes; rectangles represent raster or vector products. Adapted from Figure 1 in Castilla et al. (2008)

In brief, an aerial or satellite image is used as input, and downsampled to a coarser resolution (e.g., 5, 10, 15 meters) using the local mean value. This downsampling, along with the denoising filter, help limit the potential for the segmentation algorithms to produce convoluted boundaries which are overly sensitive to small variations. A total variation filter (Rudin et al., 1992; Chambolle, 2004) smooths/denoises the downsampled image to remove local variations while preserving edges. A gradient image, which quantifies the change in values between neighboring pixels is then generated using the Sobel-Feldman filter. Local minima spaced 20-30 meters apart on the gradient image are identified and used as seeds for the Watershed algorithm resulting in an over-segmented image comprised of “basins” which represent areas with similar pixel values. These basins are then subject to a graph-based region merging algorithm which combines neighboring basins with the most similar pixel values while obeying several size constraints (Castilla et al., 2008). The boundaries of regions generated from this region-merging process are then vectorized into polygons. These vector boundaries are then simplified using the Douglas-Peucker algorithm (Douglas and Peucker, 1973) and the smoothed using the Chaikin corner-cutting algorithm (Chaikin, 1974). The resulting vector layer can then be exported into standard formats used in Geographic Information Systems and web applications (e.g., shapefile, GeoJSON).

3. TUNING THE SEGMENTATION MODEL

3.1. Ground Truth Data

Hand-drawn stand delineations prepared by state and federal forest agencies have been collected across Oregon and Washington. These stand delineations cover several million acres and across several years. They have been subdivided into USGS Quarter-Quadrangles (each of which covers a 5,000 x 7,000-meter area). These Quarter Quadrangles are treated as distinct “tiles” which we use to gather additional data layers, such as NAIP aerial imagery, LANDSAT composite imagery from the leaf-on and leaf-off timeframes, topographic and hydrologic data, etc. (see Figure 2).

In this document, we report on results where segmentation models have been trained only using NAIP and LANDSAT leaf-on imagery. With additional funding and collaborators (e.g., a USDA Western SARE Grant, University of Washington eScience Institute’s Winter Incubator Program), we are exploring the use of this robust regional dataset with additional model types (e.g., neural networks). These co-occurring efforts include an explicit research orientation that it outside the scope and intent of the applied forest mapping and application development we are pursuing under the Oregon NRCS Conservation Innovation Grant.

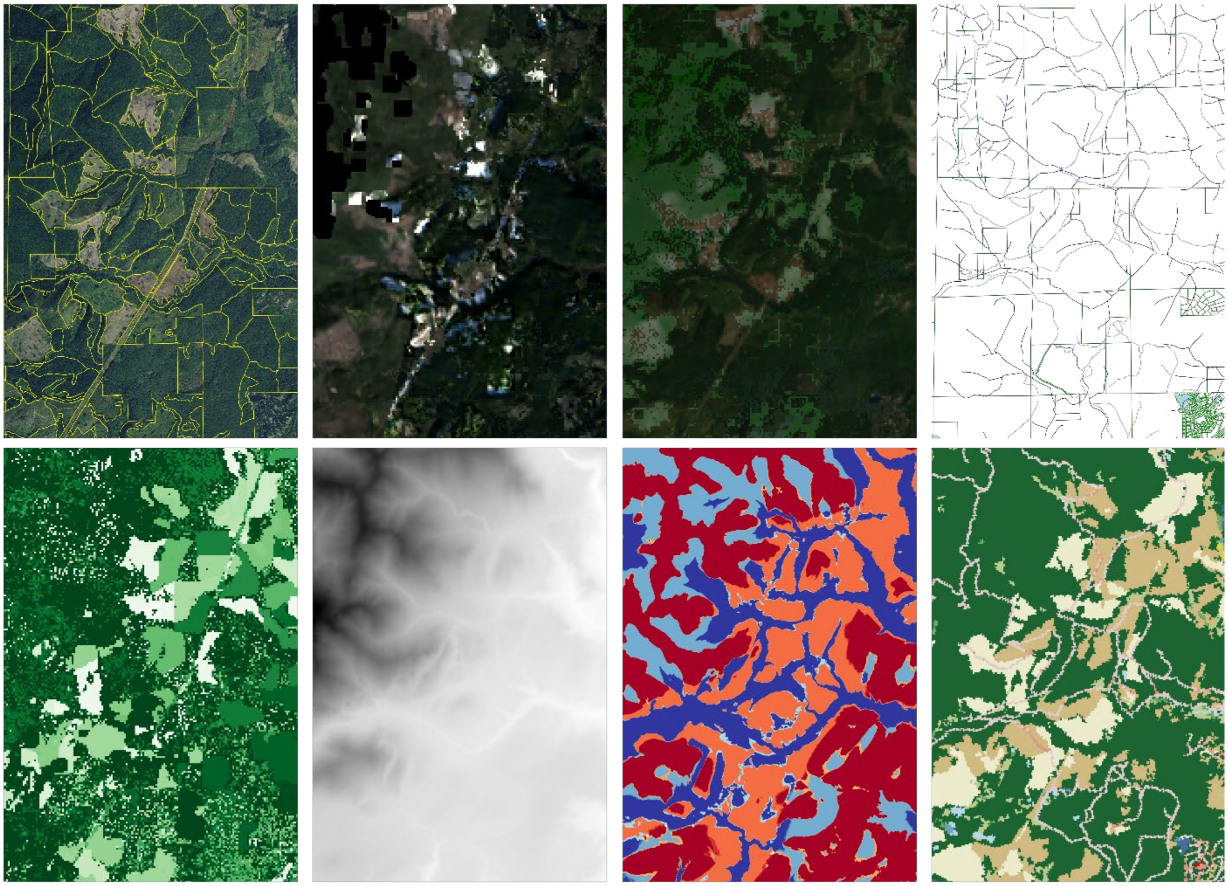
3.2. Finding Good Parameters for the Segmentation Models

There are several adjustable parameters for the algorithms involved in the segmentation workflow. These parameters can be tuned to control the level of detail in stand boundaries and the characteristics of stands. The primary tuning parameters include: whether to utilize natural color imagery and/or to include near-infrared or a vegetation index (e.g., NDVI) in the image to be segmented; the resolution to which the imagery is downsampled; and the constraints employed in Size-Constrained Region Merging, which include the Minimum Mappable Unit area, the Desired Mean Size, and the Maximum Allowable Size.

To identify a good set of default parameters to use in any of Oregon’s ecoregions, we are evaluating which parameter settings provide the best correspondence with stand boundaries that were hand-drawn by professional foresters, one scene at a time.

From each tile, we select a large scene or sample. The figures further below show square scenes with a footprint of just over 4,000 acres. A Bayesian optimization algorithm is employed to search through the various combinations of these parameters. At each step, the goodness of fit between the automated and hand-drawn stand boundaries is calculated, and as the optimization algorithm progresses, it learns which parameter settings are yielding better results and increasingly concentrates future searches in these ranges of parameters. Over 20-50 iterations, the search process usually converges on a good set of parameters for that scene. To quantify the goodness of fit, we calculate the average distance of each computer-drawn stand boundary from the nearest human-drawn stand boundary. This scoring approach increasingly penalizes lines drawn the further and further they get from the human-drawn boundaries.

Figure 2: Example Tile and Corresponding Stack of Data Layers



Notes: For each USGS Quarter Quad, we have gathered (top row, L to R): NAIP aerial imagery (stand delineations overlayed in yellow); LANDSAT leaf-off imagery; LANDSAT leaf-on imagery; vector layers of waterways and waterbodies, parcel boundaries, and roads; (bottom row, L to R): years since most recent distrubance (as detected using the LandTrendr algorithm on a LANDAT time series); Digital Elevation Model; topographic position; National Land Cover Dataset classification.

As this model-tuning process is repeated across multiple scenes, the optimal parameter settings across the scenes can be summarized to indicate what parameter settings tend to lead to the best performance for those scenes, and how sensitive the fit is to those parameters. By running these tuning steps independently in each ecoregion and by each agency, the best-fitting default parameters for each ecoregion and forester can thus be defined. For example, in the drier forests east of the Cascade Crest, there are often clearer boundaries between forest and non-forest areas that intermingle in finger-like patterns related to aspect and topographic position. In these regions, there are often large non-forest “stands” in the hand-delineated maps, which may justify higher setting for variables like Desired Mean Size and Maximum Allowable Size for the Size-Constrained Region Merging algorithm. In the moist forests west of the Cascade Range, the ideal parameter settings seem to vary more widely depending upon whether the scene has many harvest blocks included or whether there is continuous forest cover. In general, there also appears to be clear differences between agencies and regions that seem related to whether the stand-delineator was more of a “lumper” or a “splitter” and whether parcel boundaries and the presence of roads are consistently used to divide stands even when there is not a clear transition in vegetation.

3.3. Practical Considerations for End-Users

Based on previous examples of automated stand-delineation intended for practical use within agencies (Hay et al., 2005; Hamilton et al., 2007; Castilla et al., 2008; Dappen, 2011) as well as initial conversation we have had with consulting foresters and Extension foresters in Oregon, we anticipate that some end-users of the forest type maps we produce (particularly professional foresters and Technical Service Providers who are assisting a landowner to develop a Forest Management Plan) will want or need to modify the forest stand boundaries. This may be motivated by poorly drawn automated stand boundaries in certain areas, the desire to lump or split polygons together, and the ability to adjust boundaries that may be shared between multiple polygons.

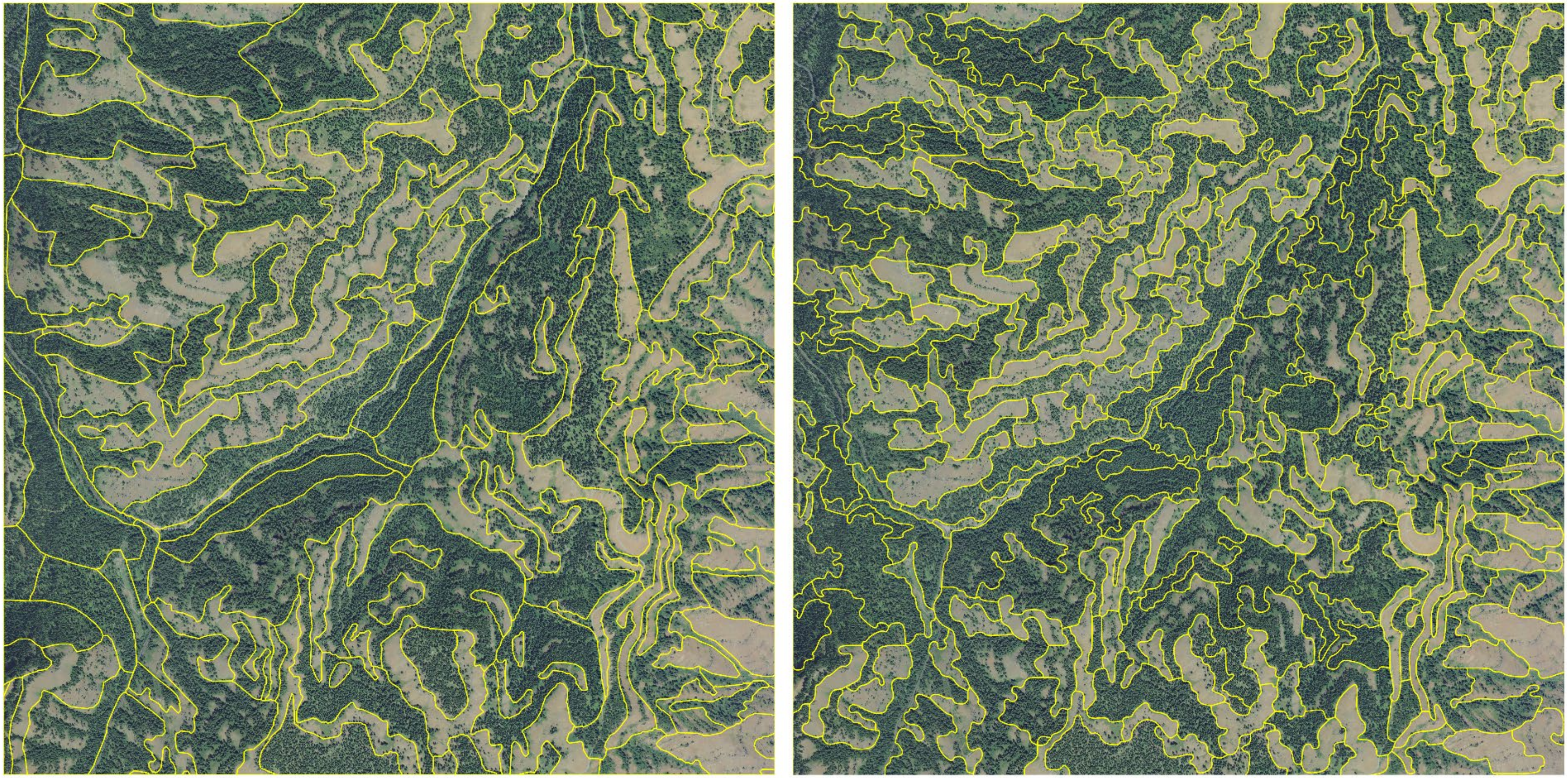
The safeguards and processes to allow interactive modification of geospatial layers are complex and challenging to ensure that gaps, overlaps, and other topological errors are not introduced which could cause areas to be over- or under-estimated, double-counted, etc.

In our ongoing coordination and consultation with FMP-writers including family forest owners, consulting foresters, and extension agents, we will continue to adjust our segmentation workflow to minimize the effort required for additional post-processing of these automated stand boundaries. In the current approach, we begin by acknowledging that it is quicker and easier for end-users to merge existing polygons together than it is for them to add or adjust existing polygon, which would usually involve manually drawing new lines or moving individual vertices. In terms of the automated workflow, this suggest that it is better to err on the side of drawing too many boundaries rather than drawing too few. As such, the examples we present here impose constraints on the Desired Mean Size and Maximum Allowable Size and reduce the penalty associated with drawing new boundaries when those boundaries are drawn in areas where there is a strong gradient or transition in spectral values. Essentially, the tuning algorithm rewards the automated drawing of lines close to human-drawn boundaries, as well as in areas of high contrast. This balancing act between these two components of the scoring function used to the tune the optimization model generates modestly over-delineated stands compared to human-drawn versions to ensure that areas of high contrast, many of which are not captured in the human-drawn versions, are delineated and left for the end-user to decide how much of a lumper or splitter they want to be.

4. ILLUSTRATIVE EXAMPLES OF AUTOMATED STAND DELINEATION

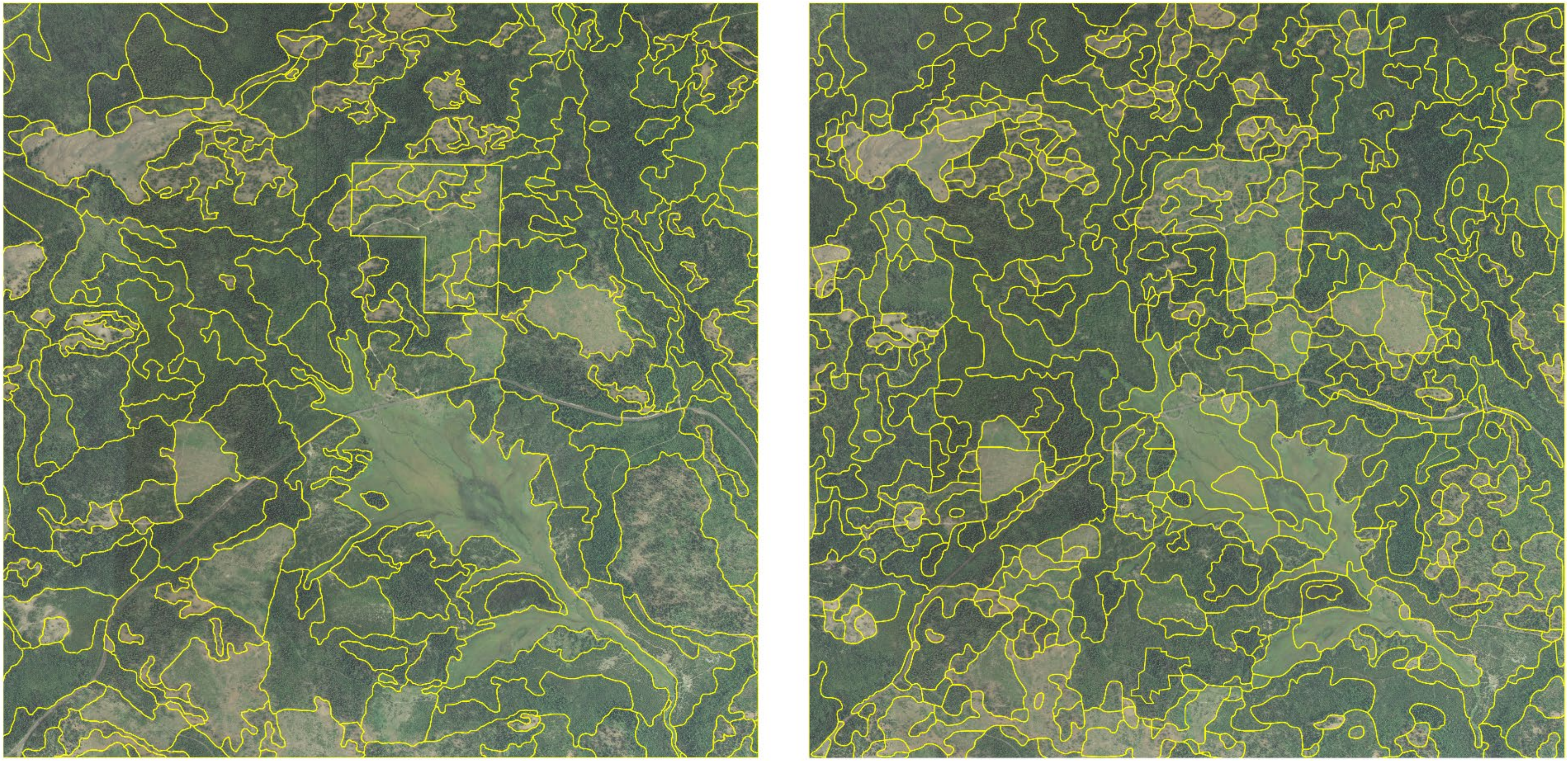
On the pages that follow, several examples of stand delineations are presented. These are randomly selected scenes from the collections of tiles in several National Forests across Oregon. We present delineations from Wallowa-Whitman, Umatilla, Mt. Hood, and Willamette National Forests to offer illustrative examples of the varied ecological and topographic conditions across Oregon’s forested landscapes and how the segmentation algorithm behaves.

Figure 3: Stand Delineations for a Scene in the Wallowa-Whitman National Forest



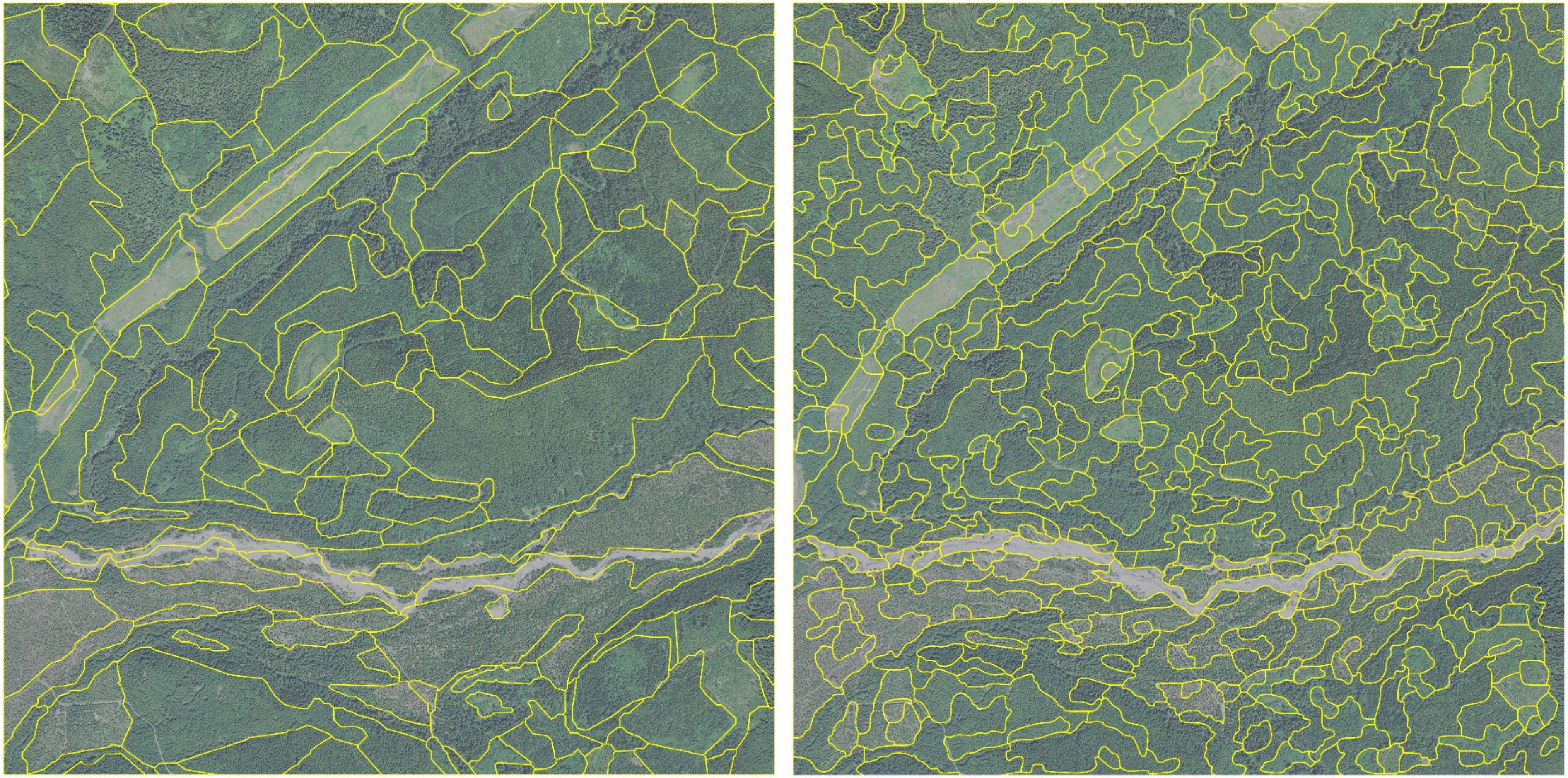
Notes: This scene covers 4096 x 4096 meters (4,147 acres). Human-drawn stand delineation is shown on the left, and the automated stand delineation is shown on the right.

Figure 4: Stand Delineations for a Scene in the Umatilla National Forest



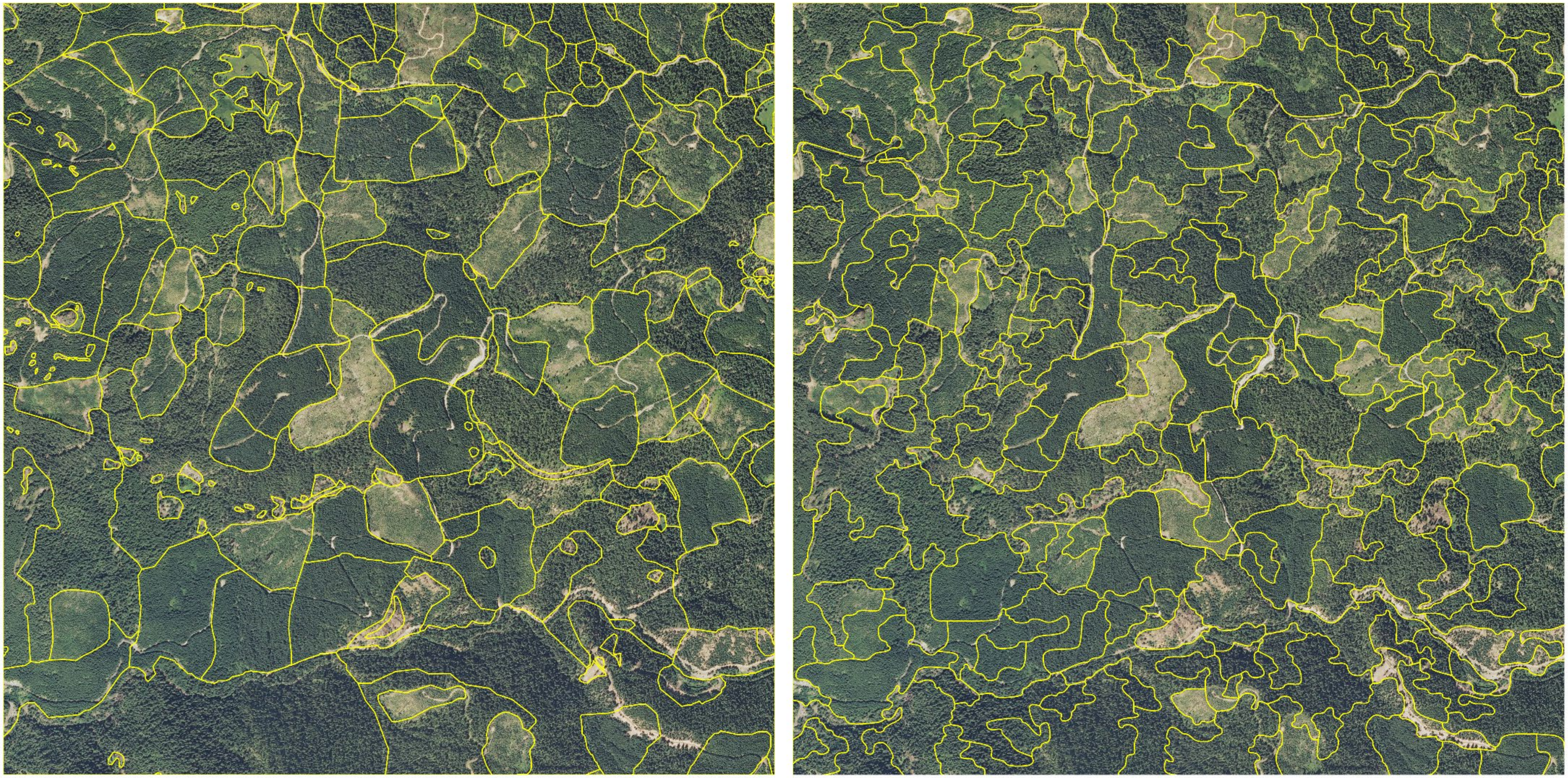
Notes: This scene covers 4096 x 4096 meters (4,147 acres). Human-drawn stand delineation is shown on the left, and the automated stand delineation is shown on the right.

Figure 5: Stand Delineations for a Scene in the Mount Hood National Forest



Notes: This scene covers 4096 x 4096 meters (4,147 acres). Human-drawn stand delineation is shown on the left, and the automated stand delineation is shown on the right.

Figure 6: Stand Delineations for a Scene in the Willamette National Forest



Notes: This scene covers 4096 x 4096 meters (4,147 acres). Human-drawn stand delineation is shown on the left, and the automated stand delineation is shown on the right.

5. NEXT STEPS

In general, we are very pleased with the speed and quality of automated stand delineations we have been able to generate to date. These delineations have been executed with very limited consideration of data layers beyond true color aerial imagery and a vegetation index (NDVI).

For inclusion in stewardship plans, maps of forest conditions will need to include both boundaries between types, and the classification of each stand. In terms of predictive modeling, this means that we will need to combine outputs from models presented in earlier reports which predict basic forest attributes (e.g., canopy cover, size class, species composition) with the boundary delineating models presented in this report.

There are two primary ways we will explore the integration of forest attributes and boundary delineation:

1. **Summarize pixel-based predictions within auto-delineated stands.**
   This approach would apply the pixel-based forest condition predictions and the automated stand-delineation independently. The pixel-based predictions are then summarized (e.g., mean, variation, range) within the stands that contain them. This is similar to how forest stand delineation and inventory stratification is actually done, whereby the landscape is delineated based on high-resolution imagery, and then updated with field observations to characterize what is in each of the management units.
2. **Execute stand delineation using pixel-based forest conditions as the input.**
   This approach would apply pixel-based predictions first, and then use those pixel-based predictions of canopy cover, tree size, etc. as inputs to the segmentation algorithm. This approach is more similar to the conceptual definition of forest stands as "a contiguous community of trees sufficiently uniform in composition, structure, age, size, class, distribution, spatial arrangement, site quality, condition, or location to distinguish it from adjacent communities" (Nyland et al., 2016, p. 23) and does not directly employ segmentation on raw spectral data.

In consultation with the landowners and foresters we have been involved with for this CIG grant focused on extension and delivery of the maps, the previous Oregon NRCS CIG which demonstrated proof-of-concept for this work, and through a closely-aligned USDA Western SARE project, we will begin presenting automated stand delineations to these advisors for areas they are familiar with and gather feedback about the qualities of the delineations they prefer and dislike. Through this consultation, we will determine the most-desirable default settings for forest stand delineation and forest type classification and then apply that workflow to allow it to be applied to any area in Oregon using the Landmapper web application.

6. REFERENCES CITED

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