Remote Sensing of Southern Appalachian Spruce-Fir Forests

Rudi W. Boekschoten

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Biology Department
University of North Carolina at Chapel Hill
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Approved:
Dr. Alan Weakley, Thesis Advisor
Dr. Alan Hurlbert, Reader
Dr. Brian Taylor, Reader

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Abstract:

Southern Appalachian spruce-fir forest is a restricted and imperiled habitat characterized by two evergreen species, Red Spruce, *Picea rubens*, and endemic Fraser Fir, *Abies fraseri*, found at high elevations in North Carolina, Virginia, and Tennessee. This habitat contains rare and imperiled species such as the Federally Endangered spruce-fir moss spider. Spruce-fir forests have been severely impacted by historical logging, acid rain, and invasive balsam wooly adelgid. The forests are likely to be severely impacted by warming climates, as they are restricted to a narrow climatic window. Remote sensing utilizing LandSat 8 surface reflectance data is an important and effective tool for identifying and mapping evergreen ecosystems such as spruce-fir forest. GIS layers and maps produced from this data can help researchers and conservation practitioners gain a greater and more nuanced knowledge of the ecosystem as a whole. Currently no published research is available outlining a comprehensive and statistically sound validation of spruce-fir habitat classifications or derived population level statistics. The purpose of this study is to develop an understanding of the effectiveness of classification algorithms for identifying spruce-fir Forests and utilize this classification to understand the coverage and environmental parameters of these forests. Careful consideration of choices made in the classification and validation process establishes a methodology for both producing and using remotely sensed presence/absence maps. Three machine learning habitat classification algorithms, Support Vector Machines, Random Forest, and MaxEnt, were compared, as was the addition of EVI and NDVI vegetation indices. A proportional validation scheme was developed to produce relevant and comparable measures of classification accuracy. Machine learning classifications of spruce-fir forests were found to be an effective and efficient method to produce presence-absence classifications and population level parameters for spruce-fir forests, with Support Vector Machines classification performing best.

1. Introduction:

The Southern Appalachian spruce-fir ecosystem is a rare and restricted habitat type found at high elevations (>1155m) of the Southern Appalachian Mountains in North Carolina, Tennessee, and Virginia. The habitat is characterized by two evergreen species, Red Spruce, *Picea rubens*, and endemic Fraser Fir, *Abies fraseri*. Spruce-fir forests are considered a relic of what was once a more widely spread habitat during the last ice age, harboring many species known from more northern latitudes. The spruce-fir ecosystem as a whole is considered highly imperiled (Schafale and Evans, 2014). Many species found in these habitats are endemic, rare, endangered and threatened. These include the spruce-fir Moss Spider, Northern Flying Squirrel, Saw-Whet Owl, among many others (USFS, 2010). Eleven sub-habitats within the spruce-fir ecozone are recognized by their floristic characteristics (Schafale and Evans, 2014), however no attempt is made here to differentiate sub-habitats.

Spruce-fir forests have been and continue to be severely impacted by the introduction of the Balsam Wooly-Adelgid and acid rain (Ragenovich 2006, USFS 2010, Kaylor et al. 2017). Additionally, historical logging a century ago has reduced total area significantly (White, 1984). Spruce-fir forests have been classified as cloud forests by some and are understood to be highly dependent on a specific climatic niche comprising a combination of humidity, temperature, and soil moisture (Berry & Smith, 2014). As such, warming temperatures could push many populations to higher elevations, or off mountaintops entirely (Koo, 2015). These factors can be highly variable across the landscape on both local and regional scales and are determined by topographic traits such as elevation, latitude, location, and aspect (Cogbill & White, 1991). As such, methods for capturing the complete state of spruce-fir forests would both improve our understanding of the habitat and provide tools to inform conservation and research.

Spectral reflectance remote sensing is a tried-and-true method for landscape scale identification and classifications of ecosystems, especially those characterized by evergreen species (Fassnacht et al, 2016). Remotely sensed classifications are an effective tool for understanding large scale patterns across the entire range of ecosystems. With classifications we can answer questions of area, location, and environmental parameters determining presence - such as aspect, elevation, slope, and soil moisture. Optimization and validation of classifications is a vital step to understanding the effectiveness of the tool and justifying any resultant conclusions. When developing a validation and classification scheme, numerous factors must be considered and weighed, including sample size, data collection methodology, classification algorithm, and validation dataset proportionality (Congalton, 2019).

In this study LandSat 8 reflectance data is used to create, validate, and optimize a spruce-fir forest presence/absence classification. In doing so necessary guidelines, considerations, and protocols unique to this ecosystem such as sample size, classification algorithms, and validation schemes are established to guide conservation practitioners when working with spruce-fir classifications. Furthermore, this classification is utilized to develop an understanding of ecosystem parameters of Spruce Fir forest on a population level for eight populations. These parameters include area, occupancy, elevation profile, and aspect profile. Spruce-fir forest is found to be distributed unevenly across the southern Appalachians, with the Smokies comprising 68% of total area. Additionally, some populations were found to be restricted to much higher elevations than others, and the majority of populations show a strong affinity for northwesterly slopes. Occupancy of available land is also not consistent throughout populations suggesting some populations have yet to recover from logging and wildfires.

2. Methods:

LandSat 8 collection-2 level-2 data for row 18, path 35 for June 14, 2020 was acquired from USGS EarthExplorer (https://earthexplorer.usgs.gov/). This single image encompasses the entire range of spruce-fir forests. Bands 1-7 were retained and digital numbers were transformed to reflectance. 1 arc-second DEM files were downloaded from the National Map (https://apps.nationalmap.gov/downloader/#/) and resampled to LandSat pixels.

Training and validation data were collected through manual interpretation of high resolution (0.15m) ESRI world satellite imagery collected no earlier than 2018. All points were interpreted as presence or absence for spruce-fir forest. All points were collected within a 3x3 LandSat pixel size (90x90m) bounding box of consistent and entire spruce-fir coverage to avoid location accuracy discrepancies between data sources (Congalton, 2019). Spruce-fir presence points were individually collected in a manual, pseudorandom manner across all populations. Due to the large number of absence points required, points were collected in bulk as randomly distributed points spaced 90m apart within high elevation regions (>1155m) without spruce-fir forest.

All data manipulation and plotting was performed in R (R Core Team, 2021). Classifications were performed in both R and MaxEnt. Training data was identical for all classifications, with 392 presence points and 1000 absence points randomly selected from the presence/absence dataset. Three presence-absence classifications were conducted utilizing default parameters. Support vector machine (SVM) classification was conducted utilizing the e1071 package in R (Meyer et al. 2020). Random forest (RF) classification was performed utilizing the RF package in R (Ishwaran et al, 2021). MaxEnt classification was conducted utilizing the MaxEnt 3.4.1 Java package (Phillips et al, 2020). NDVI was calculated per Rouse, 1974, and EVI per Liu and Huete, 1995, added in addition to band 1-7 and classified with SVM.

Validation set sample size was verified experimentally by visualizing variability of accuracy results at increasing sample sizes (Figure. 1). Accuracy was assessed with a separate subset of 10,000 presence/absence points randomly selected from the presence/absence dataset. Accuracies are calculated as dual producer's and user's accuracies as is convention (Congalton, 2019). A proportional validation scheme was utilized as is appropriate for classifications of low proportion (Yadav and Congalton, 2019), making accuracy values relevant to the user. A preliminary unvalidated SVM classification was produced and a 7.5% spruce-fir coverage was estimated. This value was later determined to be below the proportion produced by the best classification (8.5%) resulting in slightly conservative user's accuracy estimates. To increase the proportion of spruce-fir forest the classifications and all training and validation points were restricted to elevations above 1155m (~3800ft), effectively increasing the proportion of spruce-fir from 0.5% to 7.5%.

All analysis and summaries were done individually for 8 populations of spruce-fir forest identified by their respective peak or range and chosen based on geographic isolation. These are the Great Smoky Mountains (Smokies), Balsam Mountains (Balsams), Black Mountains (Blacks), Roan Mountain (Roan), Unaka Mountain (Unaka), Grandfather Mountain (Grandfather), Long Hope Valley (Long Hope), and Mount Rogers (Rogers) (See Fig. 1).

3. Results:

3.1 Validated spruce-fir presence/absence classification

Here, a completed comprehensive classification of spruce-fir forest displays the entire range of the ecozone across 8 populations in NC, TN, and VA. Regions above 1155m with misclassifications due to roofs, asphalt, Christmas tree farms, and evergreen stands but known not to contain spruce-fir forest were manually removed but included in accuracy calculations.

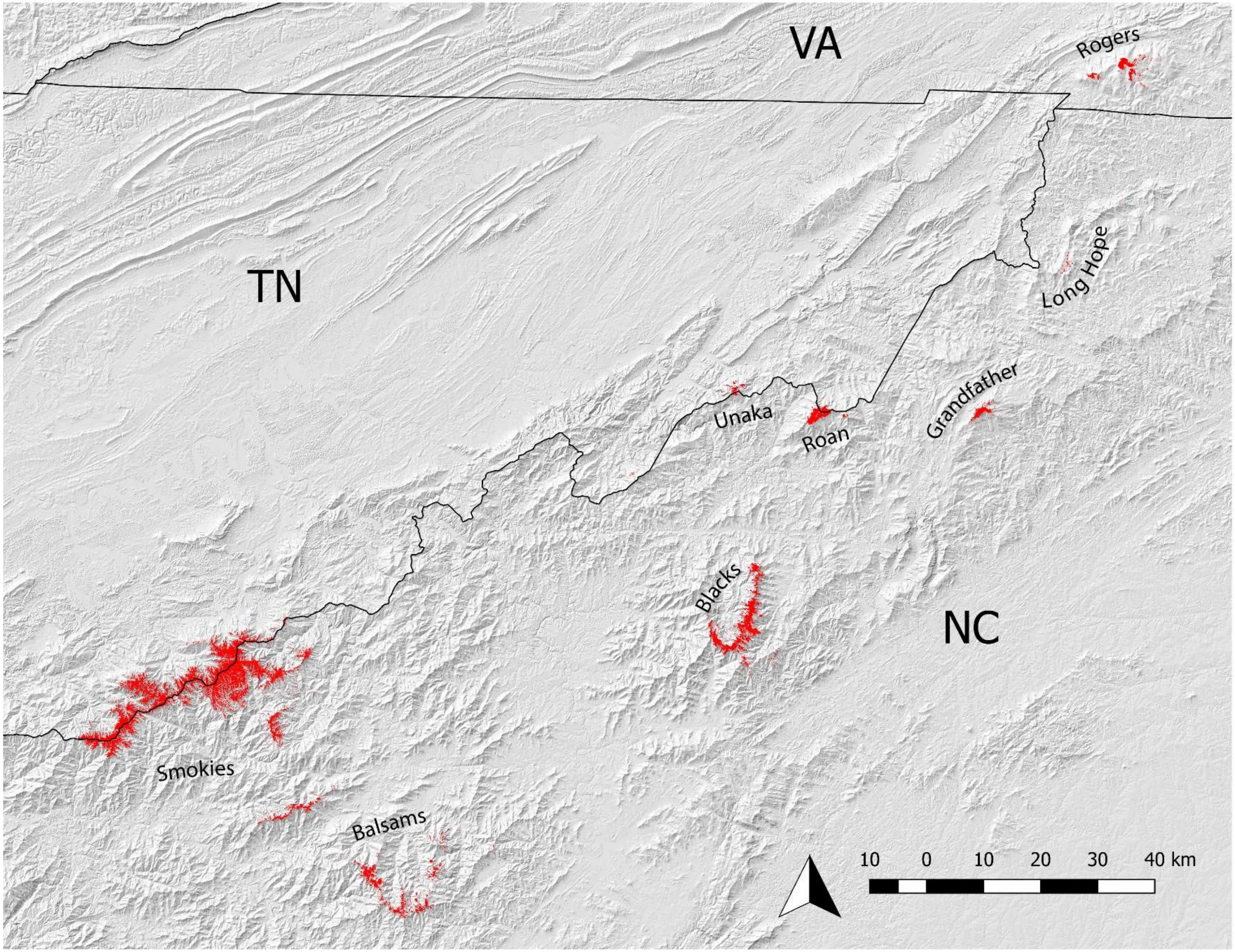

Figure 1. SVM classification of Southern Appalachian spruce-fir forests. Minor editing to remove misclassifications outside spruce-fir areas.

3.3 Validation sample size optimization

The equivalency value for producer's and user's accuracy shows high variability at small sample sizes. This is primarily driven by the relative rarity of misclassified presence pixels in absence regions. Figure 3 demonstrates the variance of absence samples of sample sizes from 100 to 50,000 taken from a 250,000-sample dataset. The percent of absence pixels misclassified as presence pixels determines the user's accuracy of the map. A higher percentage of misclassification for the same sample size would result in a lower user's accuracy. For example, the relative rarity of spruce-fir forest means 1% misclassification of a 9,250 site absence dataset would amount to 12% of a 750 site presence dataset. Figure 3 further demonstrates an absence sample size of 10,000 may not be sufficient to approximate the true proportion of misclassifications.

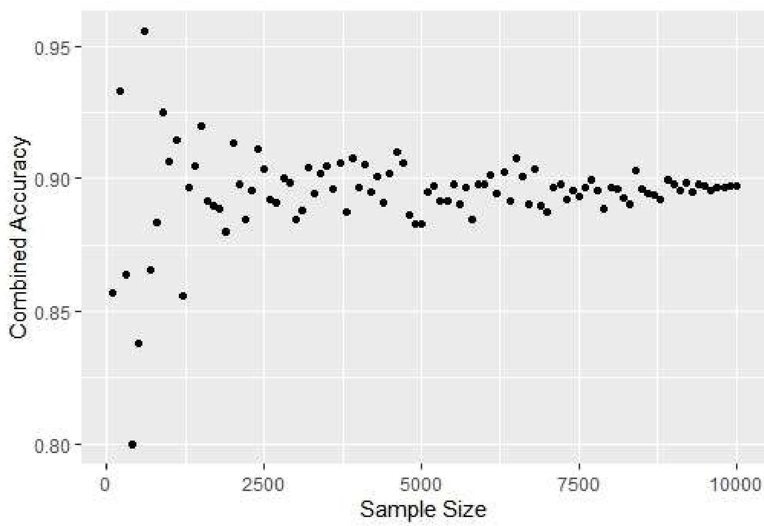

Figure 2. Producer's and user's accuracy equivalency values per combined sample size (7.5% presence + 92.5% absence).

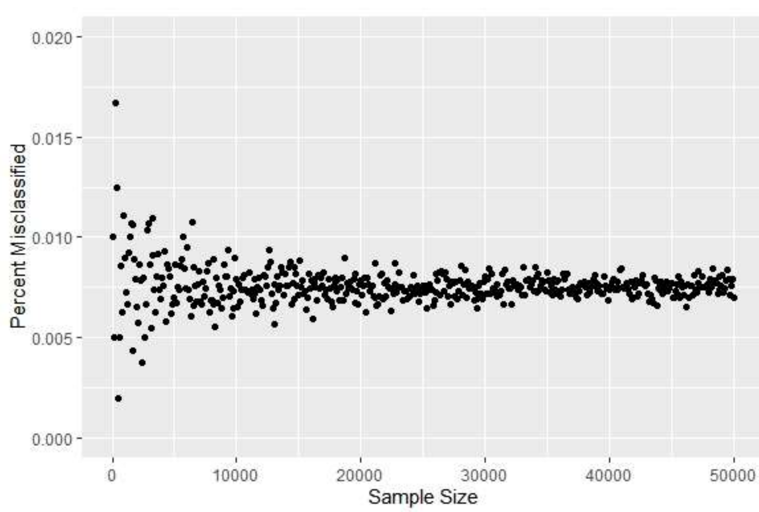

Figure 3. Percent of non-spruce-fir absence regions misclassified for sample sizes from 100 to 50,000

3.4 Classification algorithm accuracy

Accuracy comparisons for each of the three tested classification algorithms clearly demonstrates that Support Vector Machines (SVM) classification provides the most accurate classification. This method of visualizing accuracy does away with the need for arbitrary cutoffs of classifier values, instead demonstrates the superiority of SVM classification across the entire range of cutoffs. The equivalence point between producer's and user's accuracy for the SVM classification is 89.7%. Proportional validation sampling at 7.5% makes these values relevant (i.e. 89.7% of points classified as spruce-fir are actually spruce-fir). The final proportional makeup of the SVM classification was 8.4% classified as spruce-fir. This is greater than the semi-arbitrary proportional validation choice of 7.5%, however accuracy values will be conservative if the validation proportion is less than the true proportion.

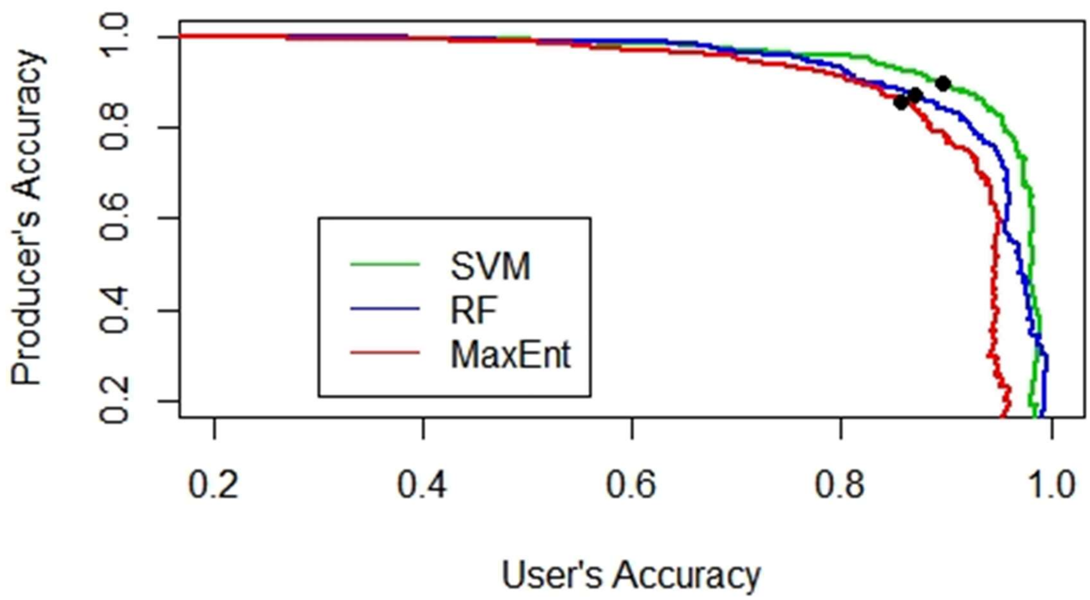

Figure 3. Accuracies of classification algorithms along a sliding cutoff clearly demonstrate the overall accuracies regardless of where cutoff is set. A perfect classifier falls in the upper right. Points show equivalencies between producer's and user's accuracy. Values below 0.2 removed due to arbitrary and confusing nature.

3.5 NDVI and EVI addition

The addition of NDVI and EVI to LandSat bands 1-7 prior to classification with SVM demonstrates neither NDVI nor EVI provide appreciable accuracy improvements and is an unnecessary step to take when classifying spruce-fir forest.

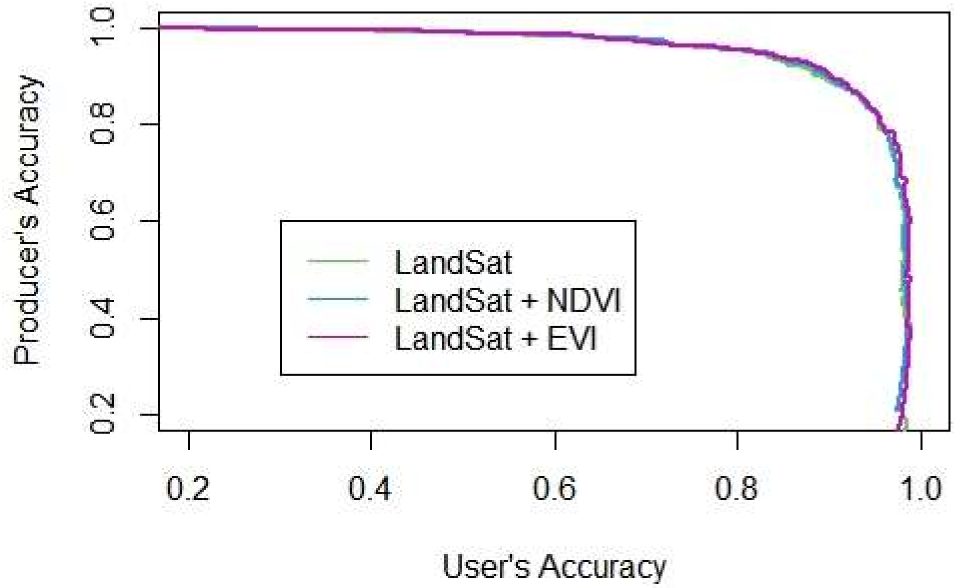

Figure 4. Addition of NDVI and EVI shows negligible difference from LandSat bands 1-7.

3.6 Population level spruce-fir area

Overall spruce-fir forests were found to occupy 22,151 hectares (54,736 acres) across North Carolina, Tennessee, and Virginia. Eight populations were focused upon, defined by their mountain or range and chosen for their relative isolation from other regions of spruce-fir. Of these, the Great Smoky Mountains represented some 15,074 hectares (37,249 acres), or 68% of all spruce-fir forests. Next in order of size were the Black Mountains, Balsam Mountains, Roan Mountain, Mount Rogers, Grandfather Mountain, Unaka Mountain, and Long Hope Valley. These results demonstrate the heterogeneity of spruce-fir distribution.

Table 1. Spruce fir coverage by population

Range	Hectares	Acres	Percent Total
Long Hope	77	190	0.35
Unaka	218	539	0.98
Grandfather	421	1040	1.90
Rogers	741	1831	3.35
Roan	754	1862	3.40
Balsams	1894	4681	8.55
Blacks	2972	7344	13.42
Smokies	15074	37249	68.05
Total	22151	54736	100.00

3.7 Population level spruce-fir elevation profile

The median elevations of each spruce-fir population are not consistent. Median elevation is variable, with the highest, Roan, 300m (~1000ft) higher than Unaka (considering Long Hope as an outlier), and 150m (~500ft) higher than the Smokies. Additionally, the minimum elevations of some populations are much higher (i.e. Roan and Balsams) compared to those in the Smokies, Grandfather, and Unaka.

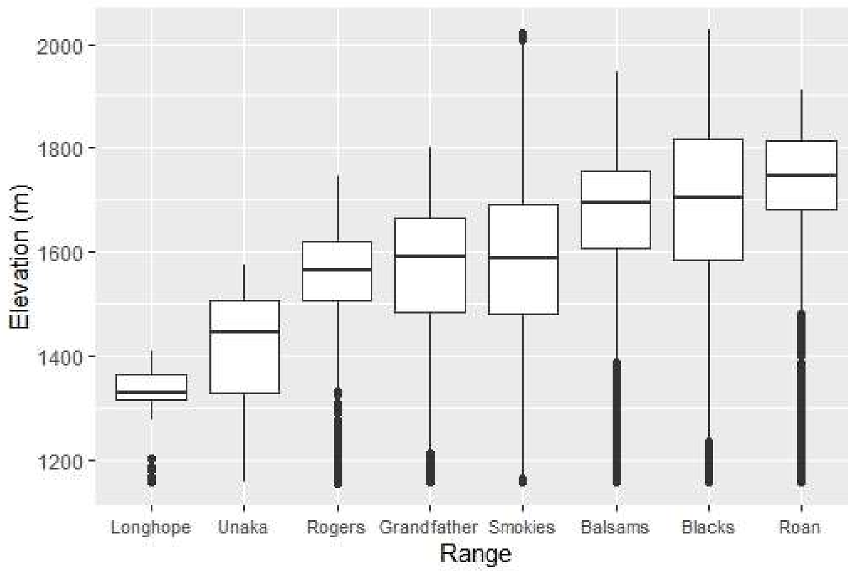

Figure 5. Spruce-fir elevation profile by population. Points are primarily misclassification outliers.

3.8 Population level aspect profile

Here the elevation 2 standard deviations below the mean for each population was used as the minimum elevation for each population. The aspect of all presence pixels (spruce-fir only) in the population was subsequently calculated and divided by the aspect of all pixels (spruce-fir and not spruce-fir) above the minimum elevation. This gives us the occupancy of spruce-fir at all aspects. All values were normalized out of 1 for relative frequency.

These results show spruce-fir forests display a distinct affinity for northwest facing slopes. Some variability in these results exists among those peaks with large planted areas of spruce-fir such as Unaka. The Smokies, which represent 68% of spruce-fir forest show the pattern distinctly.

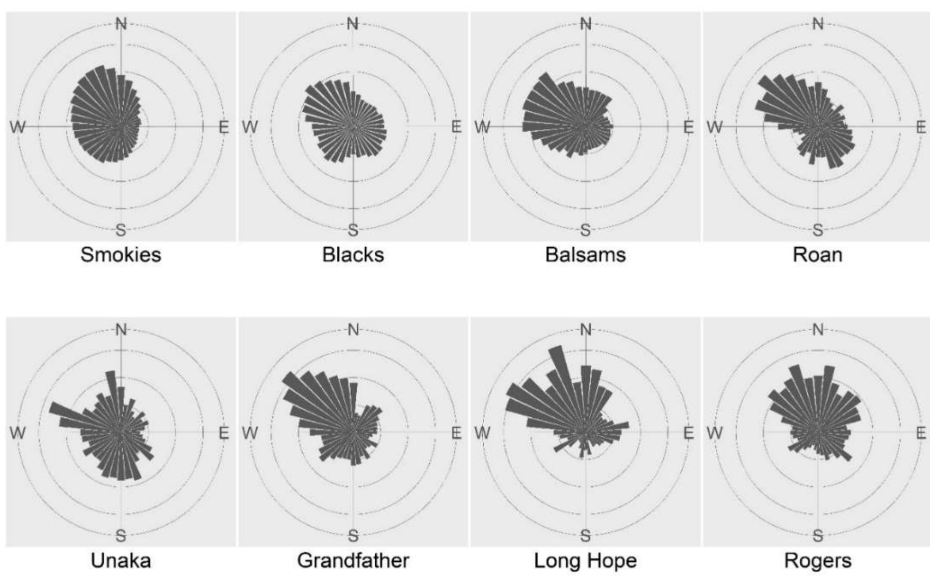

Figure 6. Relative frequency of aspect for each population. Bar heights are frequency.

3.9 Population level occupancy

Spruce-fir occupancy is a measure of the proportion of available land occupied by spruce-fir forests. This value depends on where you draw your elevation cutoff. Thus, local occupancy is defined as spruce-fir occupancy of elevations greater than two standard deviations less than the mean elevation for each population, while global occupancy includes all land above the minimum elevation at which spruce-fir forest is found at 1155m (3800ft).

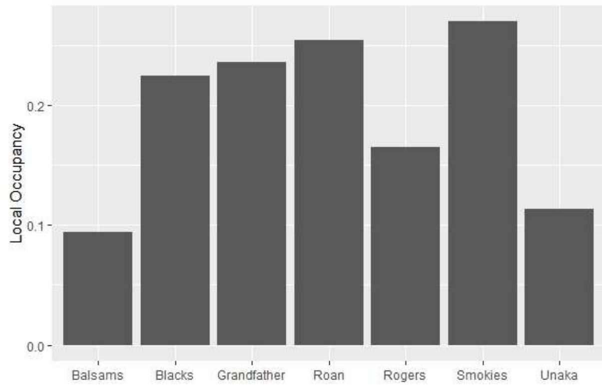

Figure 7. Local population occupancy

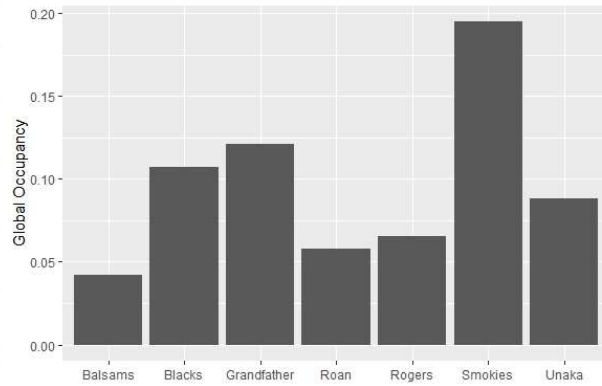

Figure 8. Global population occupancy

4. Discussion

Raster classifications results, caveats, and considerations

Here a validated and comprehensive raster classification of Southern Appalachian spruce-fir forests was produced with an accuracy of 89.7% combined user's and producer's accuracy. This paper provides a workflow, considerations, and caveats of working with spruce-fir forest, and a baseline from which to work from in the future. As a tool this classification can serve to improve our understanding of spruce-fir forests, informing research and conservation efforts with validated and comprehensive coverage statistics and population level variability.

Several caveats must be considered when working with spruce-fir forest. Training and validation sample data is ideally a random representative sample. However, because this is difficult to achieve, samples must instead be acquired manually. The patchy nature of spruce-fir forest makes random point sampling nearly impossible; if conducted the majority of points would need to be manually discarded due to partial or no coverage. Additionally, manual ground truthing is infeasible for several reasons. Access and time limitations make a truly random ground truthed data set with large sample sizes impossible. Additionally, positional agreement between a ground plot and a $30m^2$ satellite pixel is tenuous, as is confirming consistent spruce-fir coverage within that plot.

Additionally, there is large variability in stand densities corresponding to the many sub-habitats found with the spruce-fir ecosystem. Ideally these different stand densities would be fairly represented in both training and validation data. However, no evaluation of stand densities was used here and fair representation cannot be ensured. Use of a fuzzy validation scheme to account for this variability would provide a better understanding of classification accuracy of different stand densities and sub-habitats. This would require ground thruthed plots or a system to measure stand density from very high-resolution satellite imagery.

Sample size is an important factor for statistical validity. Here a maximum sample size was utilized, limited by the availability of spruce-fir presence plots. As standard practices utilize somewhere between 50 and 500 validation points (Congalton, 2019) we felt reasonably confident with our sample sizes. Despite this, figures 2 and 3 demonstrate high variability of proportion of misclassifications even in a 10,000-pixel sample size. This could significantly and incorrectly skew accuracy results. Overall a more statistically robust, quantitative approach to sample size optimization should be undertaken for future studies.

Sources of misclassifications

Several sources of misclassifications became apparent and should be carefully considered. Exposed rhododendron (not covered by canopy), and planted and natural evergreen stands appear to be the primary natural sources of misclassifications. These areas are however somewhat limited to low elevations and regions known not to contain spruce-fir forests. Additionally, lakes, roofs, and asphalt are frequent sources of misclassifications. Northwestern North Carolina was most affected by misclassifications, possibly due to the large number of housing developments at high elevations, Christmas tree farms, and planted evergreen stands. More southerly regions are less affected due to less high-elevation development. Despite this, lands in the direct vicinity of most spruce-fir stands remain unaltered and less affected by misclassifications, thus careful manual editing can remove most problematic regions.

The viewing and illumination angles of the LandSat images create additional misclassifications on steep shaded northerly slopes. This issue could confound results of Figure 6, however the northwesterly preference of spruce-fir forest is observable anecdotally from high resolution satellite imagery. Topographic corrections were not conducted here but are shown to improve vegetation classifications and should be included in future work (Fang, et al, 2020).

The biggest challenge for spruce-fir classification and validation is the very dissected and patchy nature of the forest, which confounds sample gathering but also means Spruce fir forest has a large amount of edge. The resampling method utilized for LandSat 8, cubic convolution, incorporates surrounding values, meaning a forest patch a single or few pixels in size will likely not be classified correctly. Some errors could also occur at edges of larger patches for the same reason. Future work should seek to quantify this edge effect on misclassification.

Population variability and parameters

Population level analysis of spruce-fir forest demonstrates that all populations are not made the same. The Great Smoky Mountains represents a vast majority of area, and our most isolated populations, such as Roan, Grandfather, and Mount Rogers represent a very small proportion of total area. This reinforces the vulnerability of these small, isolated populations and the species within. Despite this disproportionate distribution, these small, isolated populations likely represent a significant share of genetic diversity of spruce and fir and endemic, or imperiled species within (Hedin et al, 2015; Arbogast et al, 2005; Capblancq, 2020).

Spruce-fir forest is believed to remain significantly reduced from pre-colonial coverage (White, 1984) and occupancy parameters (Figures 7 & 8) demonstrate this. The Balsams in particular stand out, not having recovered from logging and wildfires a century ago. If we consider local occupancy, or the occupancy within the elevational window currently occupied by a population, some populations appear to have potential for recovery to the occupancy observed in the Smokies. If, however, we consider the known elevational range in which significant areas of spruce-fir forest occur (>1155m), or global occupancy, all populations are significantly lower than the Smokies. Thus, if we assume all populations experience the same environmental conditions as the Smokies, these populations may have potential for significant recovery to current Smokies coverage levels.

One enduring mystery of spruce-fir forests is the variability of minimum elevation from peak to peak shown in Figure 5. This results in the differences in occupancies observed in Figure 7 and 8. Many potential explanations for this exist, including unique environmental conditions experienced by each population like prevailing winds, soil, rainfall, cloud cover, and temperature. Figure 6 shows the strong preference of spruce-fir for northwesterly slopes, reinforcing the sensitivity of these forests to small scale variations in these conditions. Cogbill and White (Cogbill & White, 1991) suggest a latitudinal effect, however it is doubtful this has any meaningful impact in the Southern Appalachians because the Smokies, the lowest population, is one of the most southernly, and Grandfather populations occur at a much lower elevation than Roan when they occur at similar latitudes. Other explanations also exist, such as the presence of a large seed source upslope maintaining a sink population downslope. Local adaptation and elevational adaptation of Red-Spruce and Fraser fir may also determine elevational limits (Butnor et al, 2019; Capblancq, 2020).

Conclusions and future directions

With the limitations of the data and methods utilized here no distinction is made, or likely could be made, between sub-habitats within the spruce-fir ecozone. This includes distinguishing Red Spruce from Fraser Fir. Fraser fir is generally found at higher elevations than Red-Spruce (Cogbill and White, 1991) and thus has a much smaller range and is more vulnerable to climate change and pests. Remote sensing may only be able to provide a general and indirect idea of where these Fraser-Fir populations stand. As an endemic species to Southern Appalachian spruce-fir forests, it is imperative that the health of Fraser Fir populations be monitored. The addition of Lidar and very high resolution satellite data (i.e. WorldView) to classifications may provide the information needed to distinguish stand types, species, and improve overall accuracy. This may be applicable to identification of sub-habitats and further quantification of their coverage. This effort would require significant resources for on-the-ground evaluations of sub-habitat and stand composition.

Spruce-fir forest has the potential to be severely impacted by global climate change, pests, and pollution in the future. As high elevation habitats around the world are being forced even higher, their coverage becomes exponentially smaller (Koo, 2015). As such, it is imperative that we utilize and optimize every tool available to aid conservation and research. In this study, methodologies and considerations for successfully producing remotely sensed classifications of spruce-fir forests were outlined. Future work will undoubtably improve and build on the methods used here, especially as new data and techniques become available. This study only began to explore some of the many uses of these classifications to discover population level parameters there is undoubtably much more to learn about our fascinating and enigmatic Southern Appalachian spruce-fir forests.

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