# USING OBJECT-ORIENTED CLASSIFICATION TO MAP FOREST COMMUNITY TYPES

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## ABSTRACT

The ability to spatially quantify changes in the landscape is one of the most powerful uses of remote sensing. The recent release of all of the Landsat imagery has opened up doors to many entities not previously able to afford this type of data. A strength of Landsat is its temporal resolution, so a useful application of the imagery is to create land cover maps through time to quantify land cover change. Recent advances in object-based image analysis (OBIA) have also improved classification techniques for developing land cover maps. However, when creating land cover maps with specific land cover types, such as forest types, the collection of reference data becomes extremely important. When using an OBIA technique, collecting ground data to classify polygons for use as reference data may not be straight forward, since polygons generally contain a variable number and types of pixels. In previous studies, one sample location within a reference unit was often used to assess cover type for a reference unit, however this study shows that one sample may not be enough to accurately classify a polygon reference unit. This study evaluates how many prism sample locations are needed within a forested reference unit to accurately classify that reference unit using dominant tree species. In general, anywhere from 7 to 13 points were necessary, depending on the characteristics of the polygon being identified.

**KEYWORDS:** object-based image analysis, polygon sampling, reference unit collection, prism sampling, forest cover types

## INTRODUCTION

Land cover change has become one of the most important factors in assessing global change of ecological systems (Vitousek, 1994; Xiuwan, 2002). Changes in land cover can not only indicate changes in water quality and nutrient cycling, but also in biodiversity in general (Foody, 2002). Since there is the need for timely and accurate creation of land cover maps, remote sensing has become intrinsic to the process of detecting land cover change. Images captured using remote sensing are one of the preferred ways to create land cover maps because the data can easily be used to make consistent, and spatially continuous, land cover maps (Foody, 2002). Generally speaking, there are three techniques that are used to create land cover maps from remotely sense data: (1) visual interpretation, (2) pixel-based approaches, and (3) object-based approaches.

Visual interpretation is the traditional approach to creating land cover maps and relies upon the expertise of the photo-interpreter to delineate different land cover types. This technique is very time consuming and can be very dependent on the skill of the photo-interpreter creating the map, however, it is still used since humans can often grasp the complexity of the landscape better than any automated classification algorithm (Desclée et al., 2006). However, both pixel-based and object-based approaches are often chosen in favor of visual interpretation, since the two methods are more often objective and repeatable. Object-based image analysis techniques are relatively new in the age of image interpretation. The most traditional automated approaches classify images pixel by pixel since it only relies upon the spectral reflectance of individual pixels and is far less computationally intense than the object-based approach (Congalton & Green, 2009). The object-based approach analyzes individual pixels in the context of its surrounding pixels and groups pixels with similar properties into polygons through segmentation. The polygons then can be given land cover labels using not only the reflectance values of the individual pixels but also the characteristics of the polygon, such as shape or texture (Desclée et al., 2006; Congalton & Green, 2009). Because of the added power of knowing the context of the pixels, the object-based approach has been preferred in more recent years as computational power becomes less restrictive (Warner et al., 1998).

In any of the approaches to creating a land cover map from remotely sensed data, training and accuracy samples must be acquired. Training sites are used to create a classification scheme to classify the image and accuracy sites are used to test how well the classification was performed (Congalton & Green, 2009). For many remote sensing images, reference data (both training and accuracy samples) are collected either through a single ground visit to the site or through photo-interpretation of the site (Foody, 2002; Congalton & Green, 2009). These methods can be very effective for classification systems with very broad labels (i.e. urban vs. forest) or in areas that aren't very variable (i.e. parking lots). However, as classifications become more complicated, ground visits to the study area become incredibly important since many variations in land cover types may not be seen during photo-interpretation (Congalton & Green, 2009).

In the pixel-based approach, a small group of pixels (a 3x3 cluster) is generally used as a reference site. When the pixels are relatively small, a single sample unit taken on the ground may be sufficient to capture all of the variability and label that group of pixels accurately enough to use it as a reference site. However, if the pixels of the image are large, or an object-based approach is used, a single sample unit will often not be sufficient to capture the variability within each reference site. When using the object-based approach, the entire polygon is used as a reference site and a single sample within that polygon may not be sufficient to give that polygon an accurate land cover label. With inaccurate reference data, it becomes increasingly more difficult to design and implement a classification scheme and the accuracy of the resulting land cover map may be quite low (Foody, 2002). In these cases, it is often imperative to determine how many sample units are needed to correctly classify a reference site.

When using an object-based approach to create land cover maps, forest stands are often delineated and dominant tree species are used as the classification labels. However, forest stands can be quite variable in comparison to other land cover types. Therefore, more ground sample units are usually necessary to create accurate reference samples of these forested sites (Squires & Wistendahl, 1975; Held & Wistendahl, 1978). When sampling, efforts are usually limited by time and money, so ways of reducing/speeding up sampling, while still attaining accurate results, is always preferred. One recommended way of quickly sampling forests for composition is through prism sampling (i.e. horizontal point sampling or Bitterlich sampling). Prism sampling is a quick and efficient method of sampling trees using a variable radius plot, with the probability of sampling a tree proportional to its size (Mitchell et al., 1995; Thompson, 2002; Husch et al., 2003). Prism sampling does not require any plot set-up and only trees that are big enough, or close enough, are entered into the sample for any one particular site. A prism with a given basal area factor (BAF) is used to determine whether trees are considered "in" or "out" of the sample from the middle of the sample plot. Different BAFs are chosen based on some knowledge about the density and size of the trees in the forest stand that is going to be sampled (Mitchell et al., 1995; Husch et al., 2003). However, the number of prism samples necessary to classify a polygon created from an object-based image classification approach is still under debate.

Previous prism sampling studies have suggested upwards of 7 prism samples are necessary to classify a forest stand using dominant tree species, depending on the size of the stand (Held & Wistendahl, 1978; Mitchell et al., 1995; Husch et al., 2003). The current guidelines are as follows (Husch et al., 2003):

| Area of Stand (ac) | Number of Prism Samples Required |
|---|---|
| <10 | 10 |
| 11-40 | 1 per acre |
| 41-80 | 20 + 0.5(area in acres) |
| 81-200 | 40 + 0.25(area in acres) |
| >200 | Use equation (1) |

If the area is greater than 200 acres, the following equation is used:

$$n = \frac{t^2(\mathrm{CV}^2)}{E^2} \tag{1}$$

where $n$ = the number of required prism samples
$t$ = Student's $t$-value
CV = coefficient of variation (in percent) of the stand
$E$ = allowable error of the estimate (in percent)

However, most remote sensing studies use far less than 10 prism samples in a single forested reference site, since most studies collect hundreds of different forested reference sites (Foody, 2002; Congalton & Green, 2009). If over 100 different forest reference sites must be visited, 10 prism samples per site may not be feasible given the amount of time and money it takes. Therefore, this research aims to determine whether the 10 prism sample minimum is necessary in all forested polygons created through the segmentation of a Landsat 5TM image.

## STUDY SITE AND PRISM DATA

The study was carried out in four different areas of the Coastal Watershed of New Hampshire (Figure 1). The Coastal Watershed is approximately 61% forested and is dominated by Hemlock-Hardwood-Pine stands. The watershed contains some of the most valuable habitat in the state according to The Nature Conservancy (TNC), but it is also one of the regions with the highest population growth rates in the state and is identified by TNC as a 'crisis ecoregion' where habitat is at high risk of suffering irreversible losses. Therefore, monitoring land cover change in this region is extremely important. However, for an accurate representation of how different forest types are changing in this region, accurate reference data must be collected for the different forest types.

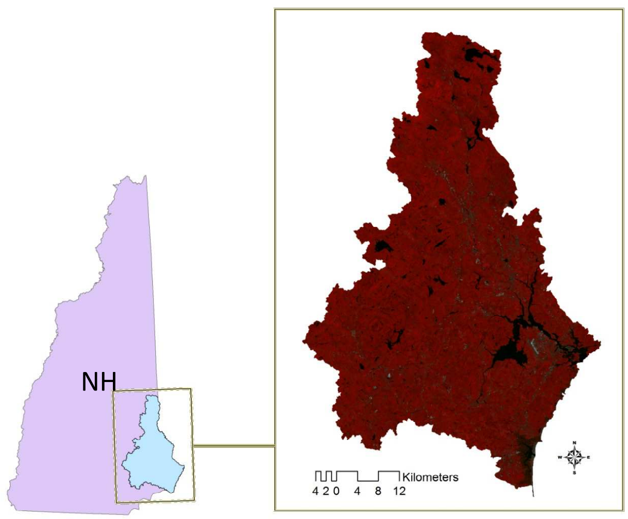


**Figure 1.** The location of the Coastal Watershed in New Hampshire. The image pictured is a Landsat 5TM false color composite of the watershed.

In order to determine how many prism samples are necessary to accurately classify different forest types in the Coastal Watershed, several locations within the watershed were extensively sampled and analyzed. The properties involved in the study are all owned by the University of New Hampshire (UNH) and managed by the UNH Office of Woodlands & Natural Areas. Three of the sampled locations (College Woods, MacDonald Lot, and Kingman Farm) were all in the southeastern part of the watershed near the UNH campus, while the fourth location (Jones Property) was in the northern part of the watershed. All four of the properties were sampled by the UNH Office of Woodlands & Natural Areas using a prism with a BAF 20. Prism samples were systematically located throughout the property so that there was 1 point for every 2.5 acres. The locations were determined by walking transects through each of the properties and placing a sample every 330ft along each transect. At each location, each tree determined to be "in" using the prism was identified by species and tallied.

## OBJECT-BASED IMAGE SEGMENTATION AND SAMPLE SELECTION

Initially, a cloudless Landsat 5TM image from August 30, 2010 was chosen as the reference image for the study (Figure 2). The image was then clipped to the extent of the Coastal Watershed in New Hampshire and all bands except for the thermal band were corrected for any atmospheric affects using the cosine of the solar zenith angle (COST) method (Chavez, 1996). A normalized difference vegetation index (NDVI) band and the first three tasseled cap bands were calculated and added to the six-banded Landsat image (all but the thermal band). The forested areas of the image were then delineated using the 2001 NH Land Cover Dataset as a reference for the location of forested areas (Justice et al., 2002) (Figure 3). The NH Land Cover Dataset was created using a pixel-based approach, with forest reference data generated by taking three prism samples in each reference pixel. The overall accuracy of the dataset was 82.2% (Justice et al., 2002).

**Figure 2.** Landsat 5TM image from August 30, 2010, the reference image used in segmentation.

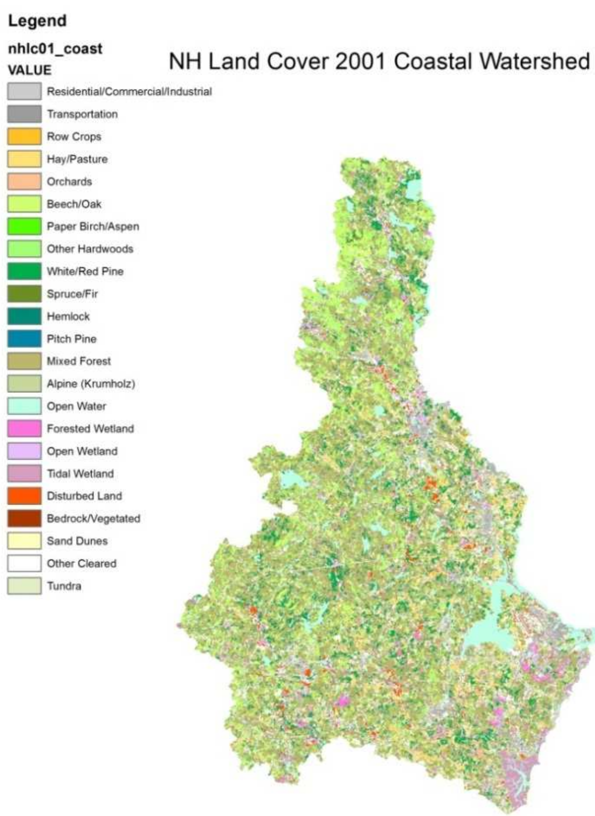


**Figure 3.** The 2001 New Hampshire Land Cover Dataset (Justice et al., 2002).

Despite some minor changes to the watershed from 2001 to 2010 and the inaccuracies of the Land Cover Dataset, the delineation of the forested areas using this dataset allowed for the segmentation of the forested areas on the image only using the reflectance values found within forested areas. Since the inclusion of the non-forested areas would increase the variance of reflectance values to be grouped, the segmentation would not delineate different forest stands as efficiently since it would also need to differentiate forest from non-forest sites. The benefits of first delineating forest from non-forest using the NH Land Cover Dataset far outweigh the possibility of including small areas on non-forest, or missing small areas of forest for this project, especially since all areas of interest are included in the forest delineation.

Once all forested areas were delineated, the segmentation of the forested areas of the image was completed using ERDAS Imagine software with a minimum segment size of 9 pixels (ERDAS, Inc.) (Figure 4). All segments were then given a label from the 2001 NH Land Cover Dataset using majority rule, so that the label given from the new prism data can be compared to the old label given by the 2001 NH Land Cover Dataset (Figure 5). The four extensively sampled properties were then located on the new segment data to determine which segments contained enough samples to be used in this analysis. Polygons were chosen for analysis if they contained 10 or more sample sites, since the current recommendation for minimum prism samples within a forest stand is 10 (Figure 6). These criteria meant that a total of seven polygons were sampled enough to be used to test whether the minimum prism sample needed to classify a polygon created through an object-based image analysis was more or less than 10. Three of these polygons are located in College Woods, two are located in Kingman Farm, and the last two are located in the MacDonald Lot and the Jones Property. Of the seven polygons, five are labeled as Mixed Forest in the 2001 NH Land Cover Dataset, one is labeled as Pine Forest, and the last is labeled as Other Hardwood Forest.

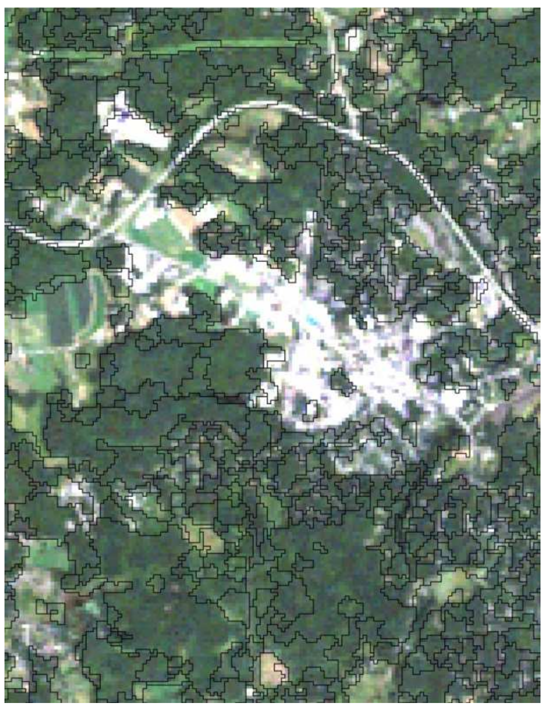

**Figure 4.** Example of forested segments (in black) produced near the UNH campus, Durham, NH.

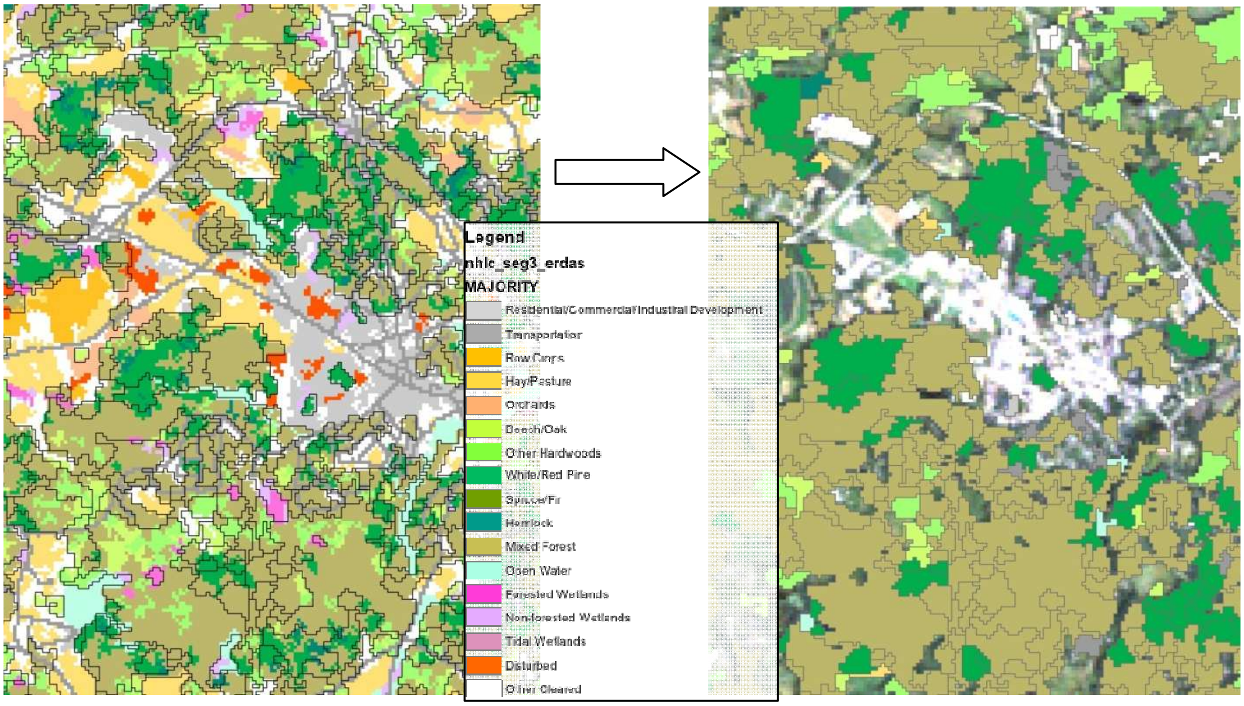


**Figure 5.** The 2001 NH Land Cover Dataset is pictured on the left with the segments (in black) overlain. On the right, the segments are pictured with their labels given by assigning the 2001 NH Land Cover Dataset class that appears most often within that segment.

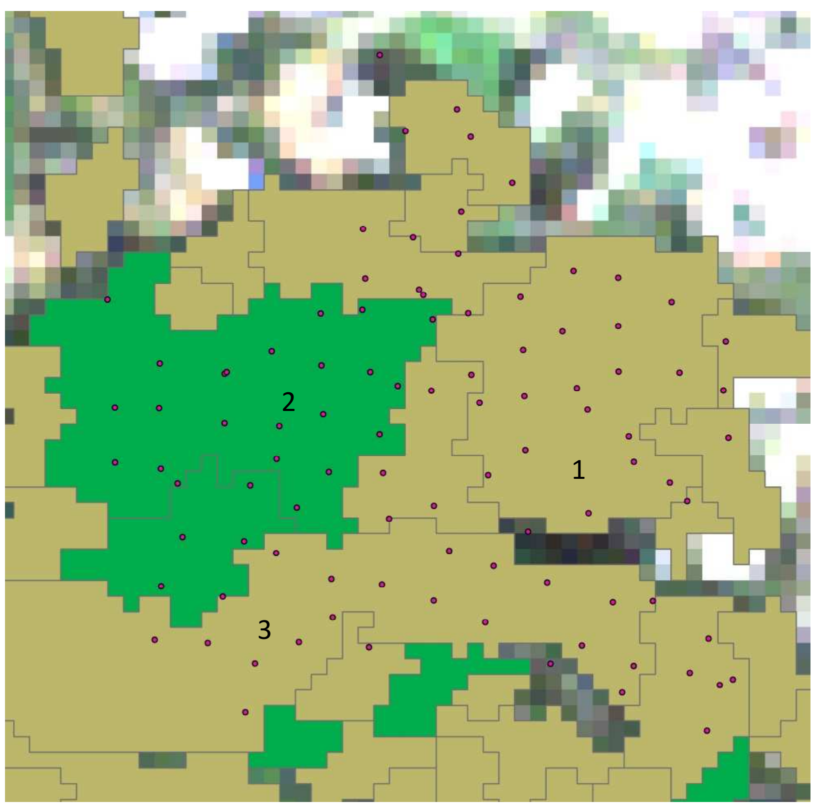


**Figure 6.** Prism locations for College Woods on top of the labeled polygons. The numbers 1, 2, and 3, indicate the only three polygons that contained enough sample sites to be analyzed.

## BOOTSTRAP CALCULATIONS

Each of the seven properties analyzed in this study contain a different number of prism samples ranging from 10 to 43. Each of the prism samples also contain a different number of total trees and for the purposes of this study, each prism sample is treated as an independent sample, even though it may be similar to the prism samples taken in the same polygon. Since each prism sample is considered an independent sample, the amount of each tree species at each point was normalized by the total number of trees sampled at that point. Therefore, the percent of each species recorded at a prism sample location is analyzed rather than the tree count of each species. A data table of the percent of each species of the total tree count at each point was created for each polygon. For each polygon, a bootstrap estimate of the mean percent of each species within the polygon was generated in the R statistical software package, along with the standard error of the mean using different numbers of prism samples (See Appendix). For example, a mean percent of each present species was generated in the first College Woods polygon using only 2 prism samples, and then again with 3 prism samples, etc.

The bootstrap estimate of the mean of each species is calculated by first averaging the percent of each species from $N$ number of prism samples randomly selected with replacement from the total possible number of prism sample points within the polygon. The mean is calculated using:

$$\hat{D}^{*m} = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{2}$$

where $\hat{D}^{*m}$ = the estimate of the mean percent of each species
$N$ = the number of prism samples used to estimate the mean
$y_i$ = the percent of the total tree count of one species

The calculation of the mean is then repeated 200 times using the same $N$ value. The average of the 200 means is then calculated and used as the basis for comparison when calculating the standard error of the mean. The overall mean is calculated using:

$$\hat{D}_b = \frac{1}{M}\sum_{m=1}^{M} \hat{D}^{*m} \tag{3}$$

where $\hat{D}_b$ = the estimate of the mean of the means generated in equation (2)
$M$ = the number of times the means in equation (2) were generated ($M$=200)

The standard error of the mean (SEM) was calculated using:

$$SEM = sqrt\left(\frac{1}{M-1}\sum_{m=1}^{M}\left(\hat{D}^{*m} - \hat{D}_b\right)^2\right) \tag{4}$$

The SEM is used to determine how variable a prediction of the dominant tree species might be using $N$ prism samples. In this study, as suggested by other studies, it is assumed that a SEM of less than 10% for the top three species is enough to make a reasonable classification of the polygon (Squiers & Wistendahl, 1976).

## RESULTS

Each of the seven polygons was analyzed using the bootstrap estimator to determine how many prism samples are necessary to achieve a SEM of 10% or less for the three most dominant tree species. The polygon with the largest number of prism samples, the Kingman Farm Polygon #2 with 43 prism samples, is a polygon labeled as Mixed Forest in the 2001 NH Land Cover Dataset. The three most dominant species are determined by taking the mean percent of the total tree count for each species, as determined by the bootstrap estimator, for $N$ = the total number of prism samples in the polygon, or for this polygon, $N$=43. Since this polygon contained the largest number of prism samples, it has the least variable estimate of the mean percent each tree species is of the total tree count. The three dominant tree species in this area were Red Oak (22% ± 4%), Eastern Hemlock (17% ± 4%), and Red Maple (16% ± 4%) (Figure 7). As seen in Figures 7 and 8, as $N$ increases, the SEM decreases, but the decrease in SEM is only drastic for the first few increases in $N$, and the decrease in SEM becomes less and less for each increase in $N$.

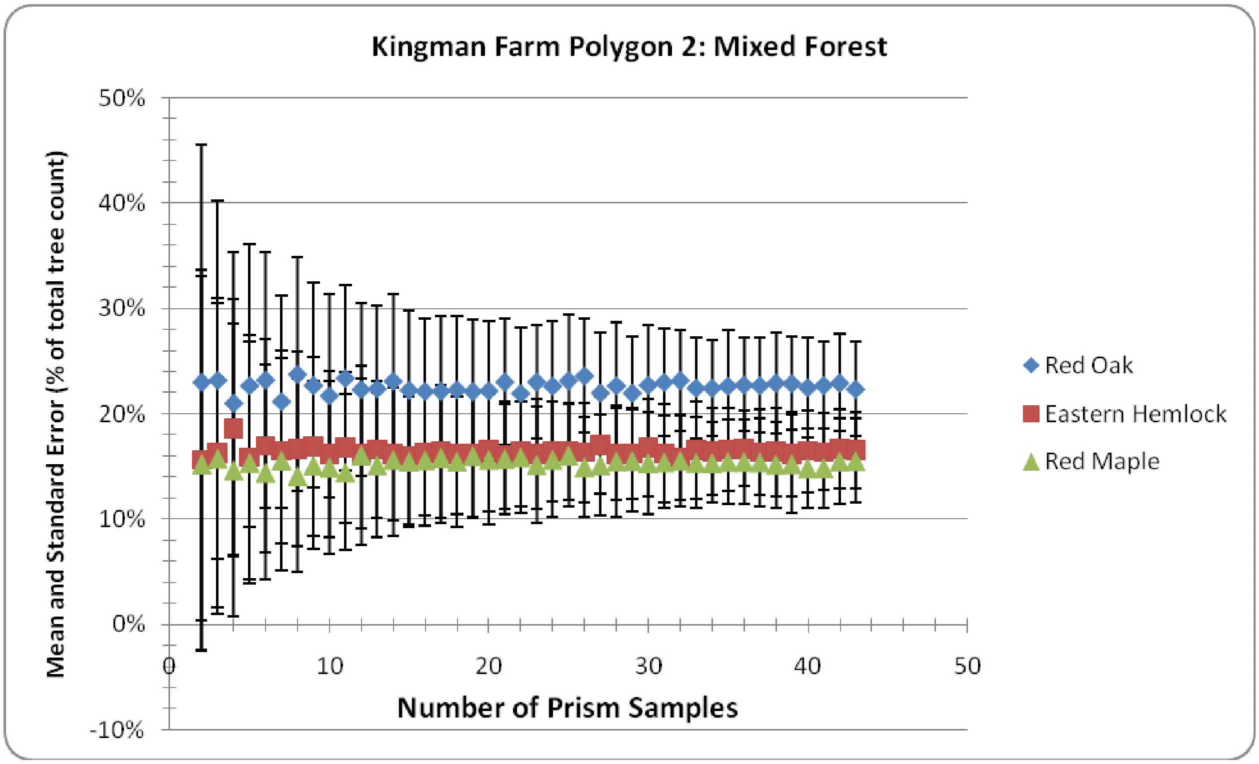


**Figure 7.** The mean percent of the total tree count for each of the dominant tree species for each *N* are shown represented as points and SEM is represented by the whiskers around those points.

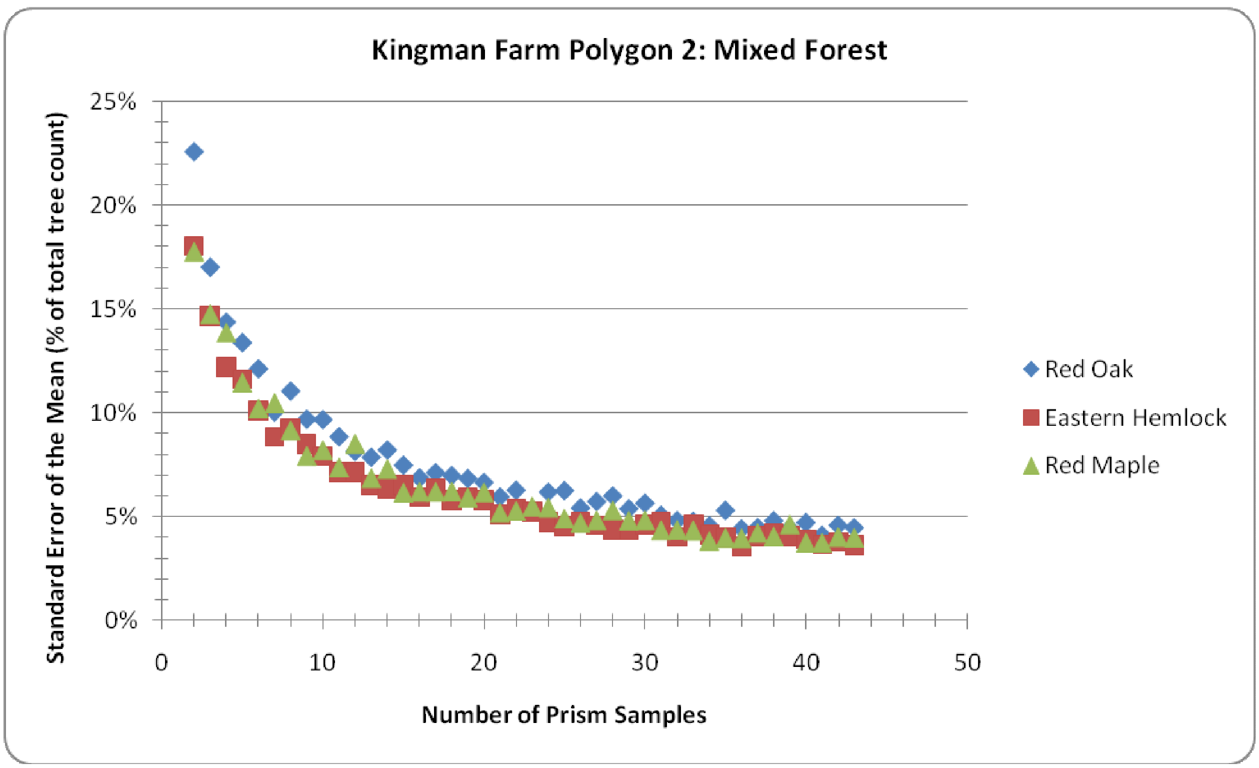


**Figure 8.** The SEM for each of the dominant species as compared to *N*.

When sampling, it is often very expensive to take numerous sample points, therefore, the slight increase in confidence in the estimate of the mean of the dominant tree species through taking one more prism sample, is not cost effective. Therefore, for this study the assumption was made that once all of the dominant tree species could be estimated with a SEM of less than 10%, the increased number of prism samples to reduce the SEM further was not worth the cost of taking more points (Squiers & Wistendahl, 1976). Given this assumption, the seven different polygons had relatively similar results for the number *N* necessary when compared within the same forest types (Table 2). However, the different forest types required different numbers of prism samples. The forest types were assigned using the 2001 NH Land Cover Assessment.

**Table 2.** The number of prism samples necessary to attain a SEM of less than 10% for each of the dominant tree species is listed for each property in the last column (*N*). The forest type, as assigned from the 2001 NH Land Cover Dataset, is given, as well as the total number of prism samples collected within that polygon (Total *N*). The dominant tree species are the three most prevalent tree species within the polygon as determined by the bootstrap estimator with *N* = Total *N*. Only one polygon, Kingman Farm Polygon #1, did not have enough prism samples for the SEM of all of the dominant tree species to reach 10% or less.

| **Location** | **Forest Type** | **Total *N*** | **Dominant Tree Species** | ***N* (SEM<10%)** |
|---|---|---|---|---|
| College Woods Polygon #1 | Mixed Forest | 19 | 1. Eastern Hemlock (40% ± 5%)<br>2. White Pine (18% ± 5%)<br>3. Red Oak (17% ± 5%) | 7 |
| College Woods Polygon #2 | White/Red Pine | 23 | 1. White Pine (58% ± 7%)<br>2. Red Oak (14% ± 5%)<br>3. Eastern Hemlock (8% ± 3%) | 13 |
| College Woods Polygon #3 | Mixed Forest | 20 | 1. White Pine (38% ± 6%)<br>2. Red Oak (26% ± 6%)<br>3. Eastern Hemlock (11% ± 3%) | 8 |
| MacDonald Lot | Mixed Forest | 15 | 1. White Pine (31% ± 6%)<br>2. Red Oak (20% ± 5%)<br>3. Red Maple (18% ± 7%) | 7 |
| Kingman Farm Polygon #1 | Mixed Forest | 10 | 1. Red Oak (23% ± 12%)<br>2. White Pine (22% ± 7%)<br>3. Eastern Hemlock (21% ± 10%) | N/A |
| Kingman Farm Polygon #2 | Mixed Forest | 43 | 1. Red Oak (22% ± 4%)<br>2. Eastern Hemlock (17% ± 4%)<br>3. Red Maple (16% ± 4%) | 7 |
| Jones Property | Other Hardwood Forest | 28 | 1. American Beech (23% ± 5%)<br>2. White Pine (20% ± 6%)<br>3. Sugar Maple (18% ± 5%) | 12 |

## CONCLUSIONS AND FUTURE WORK

Of the three forest types explored, the Mixed Forest category needs the fewest prism samples to accurately estimate the percent of the total tree count accounted for by each of the top three tree species (SEM<10%). Three of the five Mixed Forest polygons require only 7 prism samples, while the other two need 8 or more than 10. However, each of the other forest types requires slightly more than 10 prism samples to nail down the top three dominant species within the forested polygons. Surprisingly, none of the polygons require anywhere near the number suggested by Husch et al. (2003). Most of the polygons were over 25 acres, meaning at least 25 points should be needed for each of the polygons, but the largest number of prism samples necessary for this study is 13, far below the predicted minimum.

The number of prism samples required in this study is also not dependent on area, like Husch et al. (2003) predict for forest stands. The largest polygon, Kingman Farm Polygon #2, needs the least number of prism samples. The reduced dependence on area is likely a result of the process used to define polygons in the segmentation process. The larger polygons in a segmentation process are created where there is little variability in the pixels, while smaller polygons are created when contiguous pixels are very variable. The variability in pixels often relates to observable variation in species on the ground, allowing for larger changes in species present at each prism sample location. Therefore, it is likely that the number of prism samples required in each polygon is more a function of the variability within that polygon rather than the size of the polygon.

In the future, the relationship between the variance of the pixels within a polygon and the number of required prism samples should be assessed. The relationship can then be used to plan future reference data collection so that energy is not wasted on collecting points in polygons that do not need 10 or more sites and concentrating efforts in polygons that may need more prism samples to nail down the abundance of different species. When using the reference data collected using prism sampling, it is important to keep how the labels are defined for the land cover map. In some cases, dominant tree species may not be required for a classification, in those instances a SEM of 10% or less for a specific species may not be necessary, in which case fewer prism samples may be satisfactory for classifying a reference sample. Therefore, it is difficult to create a standard by which to choose a minimum number of prism samples necessary to create reference data from a segmented image, without also taking into account the classification scheme being used to create the land cover map.

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