

The Applications and Limitations of Using Remote Sensing Platforms to Detect Harvest Activity

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Abstract

Multispectral remote sensing applications that detect changes in vegetative reflectance in the near infrared are used to identify forest cover change in forests across the globe. Remote sensing platforms are used to identify changes in vegetative density often using the NDVI (Normalized Difference Vegetative Index) or other similar methods based a change of vegetative reflectance over time. Changes in forest cover may represent any number of disturbance events, fire, hurricane damage, human harvest behavior, and land use change. This paper aims to develop an accuracy assessment of using remote sensing products that identify indiscriminate changes in vegetative density to identify human harvest activity across multiple geophysical regions and forest cover types in the Southeastern United States.

Introduction

Multi-spectral remote sensing data have been used for years to model forest cover extent and change. Advances in technology and methodology have led to improved predictions of annual forest cover gain, loss, and extent. These advances have been useful for monitoring changes in the global forest resource, particularly in developing countries and rapidly developing areas in developed countries. In order to better understand the predictions generated by these models, this paper aims to generate an accuracy assessment of a publicly available remote sensing forest loss dataset generated by GlobalForestWatch.org. Attempts have been made to use these remote sensing tools to identify the harvest history and activity of a region that is intensively managed for timber production, and experiencing rapid development. Previous harvest magnitudes and spatial/temporal location of past and present harvests provide valuable indicators of future resource availability for standing carbon, available timber and pulp, as well as other aesthetic factors.

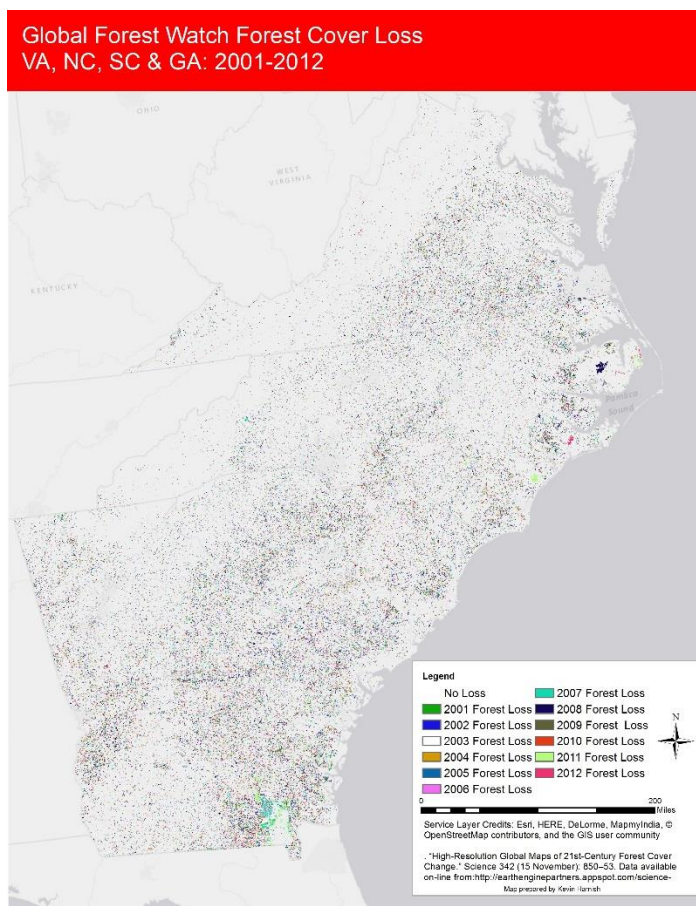
This paper aims to quantify the accuracy with which the GFW predicted tree cover loss map identifies harvested forest areas in the Southeastern United States. The Global Forest Watch Tree Cover Loss (TCL) map aims to predict areas at a 30 meter pixel resolution where stand replacing disturbances of any kind occurred. ‘Tree cover loss’ does not strictly indicate deforestation, or categorize the disturbance as a human harvest or natural disturbance. In many cases, the loss signal indicates a natural disturbance, such as a wildfire or hurricane altering the vegetative density of the forest. Furthermore, the “loss” may represent a harvest of trees, which will regenerate as a forest in the following year. Harvests vary greatly in density, with clearcut harvests removing nearly 100% of standing vegetation, and thinning and retention harvests removing from 75% to less than 5% of standing vegetation. This paper examines the accuracy with which an undifferentiated predicted loss map may be used to identify areas of human harvest activity.

The Southeastern United States is an area that has experienced increased development, and high levels of forest management over the past two decades. (Wear et. al, 2012) The forest resource in the Southeastern United States is monitored as part of the Forest Inventory and Analysis (FIA) program, administered by the United States Forest Service. The intensive management, development pressure, excellent reference dataset, and diverse geophysical regions make the Southeastern United States an ideal location for an assessment of the accuracy with which the Global Forest Watch Loss dataset may be used to separate human harvest activity from natural disturbances, and land use changes.

Study Area

The states of Virginia, North Carolina, South Carolina, and Georgia will be included in an analysis of the large scale general accuracy analysis in this study. These states are all generally composed of 3 Level 1 geophysical regions, Coastal Plain, Piedmont, and Mountains. The ecoregions were identified using the US Forest Service 'ECOMAP' (Butry, 2000). (Figure 10) These three geophysical regions have different population densities, forest management intensity, timber markets, vegetative productivity, and climate. Consequently, this paper will examine the differences in harvest activity among these three regions. These states were chosen because of their diverse geophysical regions, intensive forest management, diverse development patterns, and FIA measurement frequency. The predicted areas of forest "loss" in the study area is depicted in figure (1) below.

Figure 1



In order to test the temporal accuracy of the predicted tree cover loss map, temporally explicit reference data is required. As FIA plots are measured on at a wider interval than GFWL tree cover loss map predicts, the temporal analysis is conducted at the individual property level. Hofmann forest, owned and managed by NC State College of Natural Resources Endowment was selected. Hofmann forest is a 79,243 acre intensively managed pine plantation located on the coastal plain of North Carolina.

Data Used

Three data sets were used in this study, the Tree Cover Loss (TCL) data set (2001-2012) was used as the predictive map. Forest Inventory and Analysis (FIA) plots served as one reference data set, a GIS shapefile of the extent of forest stands within Hofmann Forest and the associated silviculture records related to these stands were used

as a separate reference data set.

The Global Forest Watch "Tree Cover Loss" (TCL), (Hansen et al., 2013) dataset was developed by analyzing Landsat images taken during the growing season from 2000-2012. The images were taken during the growing season so that "leaf on" conditions were consistently captured. Over 600,000 images taken from Landsat 7 satellite were used in this study.

(Hansen et. al., 2013) used a supervised learning algorithm to identify changes in vegetative density (Normalized Difference Vegetation Index) (NDVI) at the per 30 meter pixel level. “The learning algorithm was trained on high spatial resolution data such as Quikbird imagery, existing percent tree cover layers from Landsat data, and global MODIS percent tree cover”. Using the vegetative density of the forest cover recorded in the year 2000 as a baseline, (Hansen et. al., 2013) define per 30 meter pixel gross forest “loss” as a reduction in vegetative density resulting in a stand-replacing disturbance.

FIA Reference Data Set

The Forest Inventory and Analysis program (FIA) monitors approximately 350,000 permanent “plots” across the United States at a density of approximated 1 plot per 6,000 acres. To be classified as a forest, the area the plot is located on must be at least 1 acre in size, 10% stocked with trees, and at least 120 feet wide. Areas that do not meet the stocking requirement but remain in forest use, such as a recently clearcut area, are still classified as forestland use. (Bechold, 2005). Non-Forest plots that have any chance of being forested are visited by forestry technician to monitor if the plot has reverted back to a forest.

Plots are revisited by a forest technician depending upon the sampling panel a given state uses, typically every 5 to 7 years. When visiting a forested FIA plot, the technician establishes 4 fixed (24 foot radius) subplots. The location of the FIA plot serves as the first subplot location, and the remaining 3 subplots are located 120 feet from the first subplot at azimuths of 0, 120 and 240 degrees. The area measured within the 4 subplots totals 1/6 of an acre. Trees within these plots 5 inches diameter breast height and larger are measured, stocking conditions are recorded, forest use, forest cover type, harvest activity, and other relevant attributes are recorded. (Bechold, 2005)

Plot condition assessments are made at each plot visit. If multiple qualitative conditions were observed within the plot location, such as a disturbance that impact one section of the plot area, but not another, multiple condition plots are reported, along with the corresponding proportion of impacted area. If only one condition is observed at the plot, only one condition plot is reported. In order achieve the best one to one relationship between the reference dataset (the FIA plot location) and the predictive map (GFWL), only FIA plots where a single condition represented the plot area were included in the study. Figure 4 identifies the all FIA plot locations used in this paper.

Methods

Current data limitations necessitate analyzing clearcuts and variable density removals together in the predicted loss dataset. The GFWL data indiscriminately detects hurricane damage, fire, ice damage, insect damage, and other disturbances. These occurrences will certainly impact the accuracy with which the GFWL data identifies harvests. The magnitude of the false positives, or pixels that predict a “loss”, but are determined to be incorrect by the reference data set will be analyzed in the accuracy assessment.

The Forest Inventory and Analysis reference dataset includes quantitative and qualitative descriptions of forest changes. As such, it is possible to examine the magnitude of the impact of various non-harvest activities on an undifferentiated loss prediction product. This study filters the reference dataset in four distinct ways. 1. Any disturbance recorded at the plot location,

insect damage, fire, harvest activity ect.. (referred to as “Delta” for simplicity), 2: Thinning or clearcut harvest observed referred to as “Thin or CC”, 3: Cutting of any kind, Timber Stand Improvement, Thinning, Clearcut, Salvage Harvest ect.. referred to as FIA_harvest and, 4. Clearcut harvest recorded at plot, referred to as Clearcut. This analysis performs separate accuracy assessments of the undifferentiated loss prediction product using multiple reference dataset categories. The reference categories range from an extremely broad categorization of disturbance captured by the reference category “Delta” to an extremely narrow categorization of disturbance captured by the reference categories “Clearcut” or “Thin”. Separate statistics were calculated for each accuracy assessment, and were compared to examine the impact of changing the reference dataset.

Accuracy Assessment

This accuracy assessment follows Olofsson’s guidelines for establishing a spatial assessment unit, selecting a sampling design, selecting a reference dataset, calculating accuracy statistics, and estimating area change outlined in “Good Practices For Estimating Area and Assessing Accuracy of Land Change” (Olofsson, 2014). The spatial assessment unit used was the individual “Tree Cover Loss” 30 meter pixel, classified as loss, no loss. Reference data for the assessment were taken from data recorded at the FIA plot locations. The FIA plot center was the minimum mapping unit of the reference data. An FIA plot samples trees within approximately 1 acre of forest, which translates to nearly a 3 x 3 group of 30 meter pixels in the GFWL map. It is essential that the spatial resolution of the reference dataset be finer than the resolution of the tested map. As the entire FIA plot is nearly 3 times the size of a single pixel in the predicted map, only FIA plots that had a single predicted condition were used in the sample. This insured that the conditions associated with the plot visit were representative of the conditions at plot center, allowing for the use of plot center as the minimum mapping unit in the reference dataset. The reference dataset indicates the type of harvest activity recorded at the plot center. FIA plots that indicated the particular form of human harvest activity (Clearcut, Thin or Clearcut, Delta, or FIA_Harvest) above were labeled as “harvested forest”. Plots that indicated no harvest activity were labeled “undisturbed forest”.



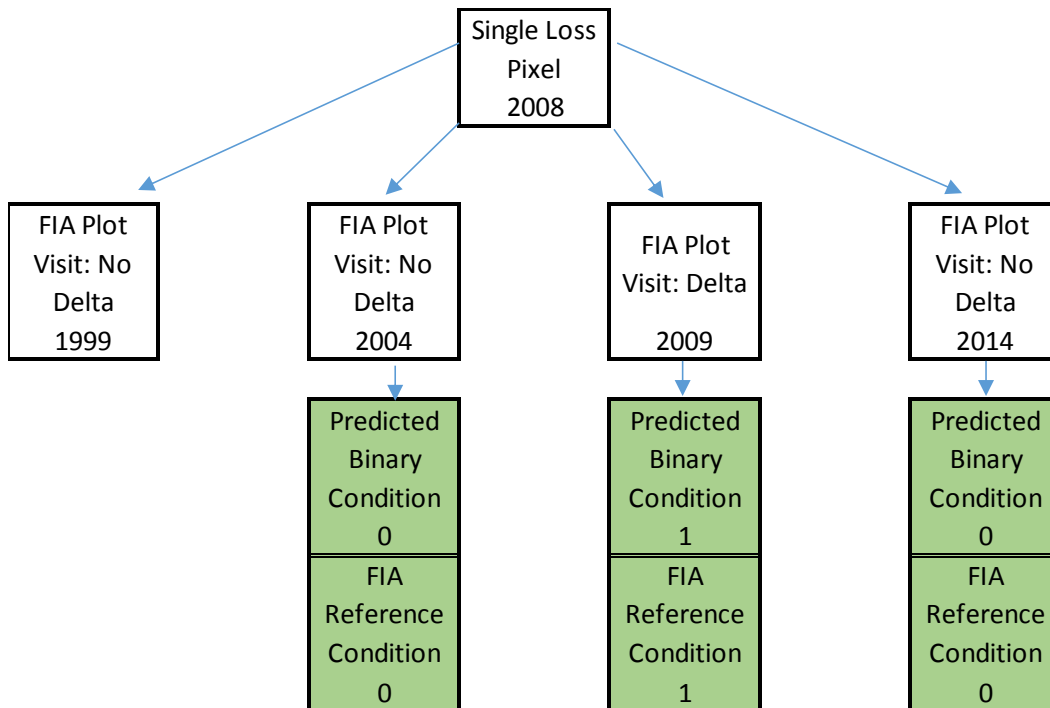
The defining agreement for the accuracy assessment of the TCL layer was defined as follows. If a TCL pixel was classified as loss and the reference label of the FIA plot within it was classified as one of the given reference classifications, the TCL pixel was assessed to be correct. If the FIA plot within the TCL pixel was labeled as “non-forest” or “undisturbed forest” and the TCL pixel was classified as no loss, the TCL pixel was assessed to be correct. If an FIA plot was labeled as “non-forest”, “undisturbed forest”, or “no-harvest natural disturbance” and fell within a TCL pixel that was classified as loss, the pixel was assessed to be incorrect. If an

FIA plot fell within a TCL pixel that was classified as no loss, and the FIA plot was labeled “harvested forest” the TCL pixel was assessed to be incorrect.

Binary Assessment

Forest Inventory and Analysis plots are measured on an annual basis, each plot is revisited on 5-7 year interval, and the Global Forest Watch Loss Data is reported on an annual basis. As the FIA data serves as the reference dataset, it is necessary to aggregate the reference data set in such a way that it correspond to the predicted value on the map. It is essential that the year of the plot visits correspond to the timing of the predicted tree cover loss. A spatial intersection of a single loss pixel and an FIA field plot yield records from multiple plot visits over time. The records from only one plot visit may be used to define the agreement between the FIA plot (reference data) and the loss pixel.

For example, a spatial intersection between the TCL pixel that indicates a loss took place in 2008 and FIA plot location yields records from visits to the FIA plot that took place in 1999, 2004, 2009, and 2014. As the 1999 intersection predates the satellite record (2001), this plot visit is not included in the sample. Only the records from the visit to the plot that follows the predicted loss will be considered in the test of agreement between the predicted loss pixel and the reference dataset. In this example, the agreement between the pixel that predicts a loss took place in 2008 will be tested against the records from the FIA plot visit that took place in 2009.



The 2004 and 2014 plot visits will still be included in the sample, but the pixel they are associated with will be categorized as no predicted loss. This will allow for a test of agreement between years when the predicted map indicated that no loss took place, and records gathered at the FIA plot location in the visits preceding the predicted loss year, or following the plot visit that was selected to test the agreement between the year loss was predicted to have taken place.

The binary approach codes predicted loss as a 1, and no loss as a 0. Reference plots where the selected disturbance classification took place are coded with a 1, and where that disturbance was absent a 0. An error matrix is developed using the sample counts of true negative (no delta reference, no loss GFW predicted), false positive (no delta reference, loss GFW predicted), true positive (delta reference, loss GFW predicted), false negative (delta reference, no loss GFW predicted). This error matrix is displayed in figure 2.

Figure 2

| | Reference No Delta | Reference Delta |
|-------------------|--|--|
| Predicted No Loss | # of sample Counts (True Negative) | # of sample Counts (False Negative) |
| Predicted Loss | # of Sample Counts (False Positive) | # of sample Counts (True Positive) |

An accuracy assessment should not be performed using sample counts alone. “The cell entries of the population error matrix and parameters derived from it must be estimated from a sample. Suppose the sample based estimator of p_{ij} is denoted as \hat{p}_{ij} . One \hat{p}_{ij} is available for each element of the error matrix, parameters can be estimated by substituting \hat{p}_{ij} for p_{ij} in the formulas for the parameters. Accordingly, the error matrix should be reported in terms of these estimated area proportions, \hat{p}_{ij} , and not in terms of sample counts, n_{ij} . The specific formula for estimating p_{ij} depends on the sampling design used. For equal probability sampling designs, (e.g. simple random sampling and systematic sampling) and for stratified random sampling in which the strata correspond to map classes” (Olofsson, 2013) (eq. 4).

$$\text{Estimated Proportion Area } \hat{p}_{ij} = W_i n_{ij} / n_i$$

These estimated proportion of areas may be used to estimate overall accuracy, producer’s accuracy, and user’s accuracy. Overall accuracy is calculated by adding together the proportion of correctly classified pixels. Following Olofsson et al. 2014 (eq. 1 & eq. 5) Overall accuracy is calculated by identifying the total number of correctly classified pixels in the sample, and dividing the by the total number of pixels in the sample. Where q is the number of classes (No Harvest, Harvest), (i) is the individual class. (Olofsson, 2014) (eq. 1).

$$\text{Overall Accuracy} = \sum_j^q p_{jj}$$

$$\text{Overall } \widehat{Acc} \text{ Variance} = \sum_{i=1}^q W_i^2 \times \widehat{User's Acc}_i (1 - \widehat{User's Acc}_i) / (n_i - 1)$$

Producer’s accuracy and user’s accuracy must be analyzed at the individual classification level. Producer’s accuracy identifies the accuracy with which the producer of the map correctly identified the condition on the ground. The user’s accuracy indicates the percent of pixels that are identified in the mapping product as a given category, and are actually in the category on the ground. These two assessments must be considered together in order to properly assess the accuracy of a land classification. (Congalton, 1999)

Producer’s accuracy is calculated using estimated proportion of area by taking the number of pixels that were correctly classified in the category, over the proportion of pixels that

were actually in that category in the sample of the reference dataset. Producer's accuracy standard error may be calculated by taking the square root of the variance. (Olofsson, 2014) (eq. 3 & eq. 7). User's accuracy is calculated by taking the proportion of correctly classified pixels in the category, and dividing it by the proportion of pixels that the mapping product classifies within that category of the sample. User's accuracy standard error may be calculated by taking the square root of the variance (Olofsson, 2014) (eq. 2 & eq. 6).

$$\text{Producer's Accuracy}_j = p_{jj}/p_j$$

Producer's Accuracy Variance

$$= \frac{1}{\widehat{N}_j^2} \left[\frac{N_j^2 (1 - \widehat{Prod Acc}_j)^2}{n_j - 1} + \widehat{Prod Acc}_j^2 \sum_{i \text{ not } j}^q N_i^2 \frac{n_{ij}}{n_i} \left(1 - \frac{n_{ij}}{n_i} \right) / (n_i - 1) \right]$$

$$\text{User's Accuracy}_i = p_{ii}/p_i$$

$$\text{User's Accuracy Variance} = \widehat{User's Acc}_i (1 - \widehat{User's Acc}_i) / (n_i - 1)$$

FIA Slice Sensitivity Results

The frequency with which FIA plots were visited was shown to have a significant impact on the applicability of the FIA plots as a reference dataset for this study. As the TCL dataset only identifies pixels within the 2001-2012 window, it is essential that a plot not only be visited within this window but also; either visited later than or equal to the year 2008, or have a prior visit to the plot occur after 2001. If a harvest event predates the analysis window of 2001, and no FIA plots were established at the location before, or the plot had not been visited prior to 2001, the next plot visit will likely record a harvest that took place before the analysis window start date of 2001. This would result in a (false) false positive, as the reference data indicates that a harvest occurred during the analysis horizon, but it actually didn't. See figure (3).

Figure 3

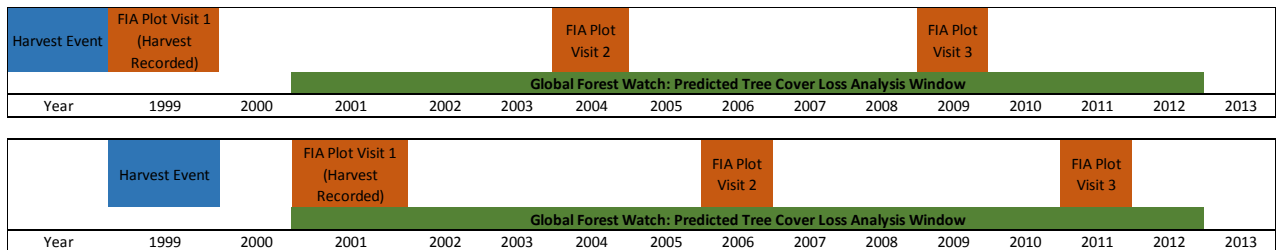
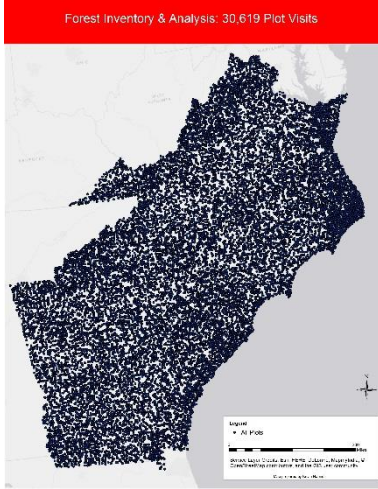
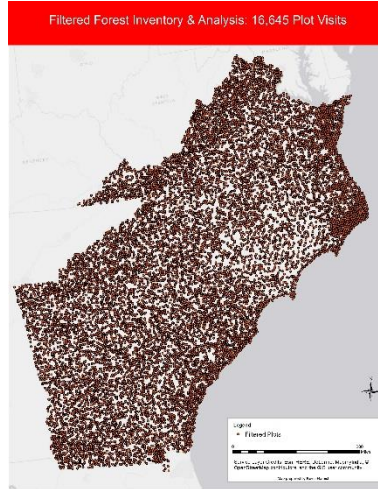


Figure 4**Figure 5**

FIA reference plot visits were removed from the sample if they had no visits prior to the year 2001, unless the plot was visited later than 2008. (Figure 5) Filtering the reference data set helps to provide fewer instances of error related to the infrequency of temporal data collection in the reference data set. Including all plots increases that likelihood that a plot visit records activity that took place outside of the analysis horizon and has the potential to dramatically increase the error of the reference dataset.

Estimating Area

The error matrix results allow for an estimate of the area that is harvested, and area that is not harvested as well as the associated confidence intervals. Following Olofsson et al, for “an estimated error matrix with P_{ij} in terms of proportion area, a direct estimator of the proportion of area of class k is” (Olofsson, 2014, eq 8 & eq. 9) The standard error is estimated by taking the square root of the variance of the estimated proportion of class k. A 95% confidence interval of the estimated area is estimated by taking the area of class k and multiplying it times 1.96 times the standard error of the estimated proportion of area class k.

$$\widehat{Proportion\ Class}_k = \sum_{i=1}^q \widehat{Proportion\ Class}_{ik}$$

$$Variance\ Prop\ \widehat{Class}_k = \sum_i \frac{W_i \widehat{Proportion\ Class}_{ik} - \widehat{Proportion\ Class}_k^2}{n_i - 1}$$

Results

In order to establish the applicability of an undifferentiated loss predictive product (TCL), to detect a specific harvest category, it is first necessary to establish the accuracy with which the TCL product detects any disturbance, ie comparing an undifferentiated loss prediction, with an undifferentiated loss reference data set. The following binary accuracy assessment uses “Delta” reference plots to identify the accuracy with which the predicted map identifies any disturbance recorded at plots. 30,619 FIA plots were included in the sample. An error matrix was developed compiling the counts of true negative 26,239 (no delta reference, no delta GFW predicted), false positive 238 (no delta reference, delta GFW predicted), true positive 811 (delta reference, delta GFW predicted), false negative 3,331 (delta reference, no delta GFW predicted). This error matrix is displayed in figure 6.

Figure 6

| | REFERENCE NO DELTA | REFERENCE DELTA | row total | W(i) | GFW MAPPED PIXELS |
|-------------------|--------------------|-----------------|-----------|-------|-------------------|
| PREDICTED NO LOSS | 26,239 | 3,331 | 29,570 | 0.899 | 524,288,504 |
| PREDICTED LOSS | 238 | 811 | 1,049 | 0.101 | 58,610,136 |
| column total | 26,477 | 4,142 | 30,619 | 1.000 | 582,898,640 |

An accuracy assessment should not be based on sample counts alone, but by an error matrix that is expressed in terms of estimated area proportions. The estimated proportion error matrix is displayed in figure 7. A total 582,898,640 pixels were mapped, 58,610,136 pixels were classified in the TCL map as loss, 524,288,504 pixels were classified no loss. The proportion of pixels that were classified as loss within the time frame was 10.05%, and the proportion of pixels classified as no loss as 89.95%.

Figure 7

| | REFERENCE NO DELTA | REFERENCE DELTA | row total | GFW MAPPED PIXELS |
|-------------------|--------------------|-----------------|-----------|-------------------|
| PREDICTED NO LOSS | 0.798 | 0.101 | 0.899 | 524,288,504 |
| PREDICTED LOSS | 0.023 | 0.078 | 0.101 | 58,610,136 |
| column total | 0.821 | 0.179 | 1.000 | 582,898,640 |

The Overall Accuracy of the GFWL product is calculated as:

$$\text{Overall Accuracy} = 0.798 + 0.078 = .876$$

This indicates that 87.6% of the mapped pixels in the sample were classified correctly. This initially suggests that the TCL product is performing fairly well. It is crucial to look at the individual classifications in this case, as the no loss area represents a considerably larger portion of the mapped area, and this inflates the estimated overall accuracy.

In order to capture the proportion a classification represents within the map product, estimated proportions of a given classification may be used to calculate producer's accuracy as well, and is calculated as follows. The estimated true positive proportion of a given classification is divided by the total proportion of the classification that were actually that classification in the sample. The producer's accuracy of no delta pixels is calculated as:

$$\text{No Delta Producer's Accuracy} = 0.798 / 0.821 = 0.972$$

$$\text{Delta Producer's Accuracy} = 0.078 / 0.179 = 0.436$$

In this case, 97.2% of the no delta areas were correctly identified in the GFWL map product, but only 43.6% of the delta areas on the ground were correctly identified in the GFWL map product.

In order to capture the proportion a classification represents within the map product, estimated proportions of a given classification may be used to calculate user's accuracy as well, and is calculated as follows. The estimated true positive proportion of a given classification is divided by the total proportion of the classification that was predicted to be in that classification in the map. The user's accuracy of no delta pixels is calculated as:

$$\text{No Delta User's Accuracy} = 0.798 / 0.899 = 0.887$$

$$\text{Delta User's Accuracy} = 0.078 / 0.101 = 0.773$$

In this case, 88.7% of the no delta areas identified in the GFWL map product are actually no delta areas on the ground, and only 77.3% of the delta areas predicted by the GFWL map were actually delta areas on the ground. As nearly 10% of the sample was identified as a Delta on the ground but missed by the TCL product (false negative), it make sense that the producer's accuracy of delta be extremely low. As the FIA reference data records "delta" records at a considerably finer resolution than the 30% density threshold that the GFWL data uses, it is not surprising that the false negative rate is very high. Many disturbances such as a distributed insect spot, minimal ice damage, timber stand improvement, fire ect.. that a forester on the ground will record will not be picked up by the TCL product. Crucially, the false positive rate is very low when including all "Delta" in the FIA reference data. This indicates that although the TCL product doesn't pick up everything that the FIA plot records, it very rarely indicates a disturbance when the FIA plot indicates no disturbance was actually on the ground. In order to take a look at how well the TCL product identifies harvests, clearcut harvests were used in the reference data.

Clearcut harvests remove all or nearly all of forest cover from the harvested area. This dramatic change in vegetative density makes clearcut harvests the most likely harvests to be detected by the remote sensing platform. Sample counts, estimated proportion of area, overall accuracy, producer's accuracy, and user's accuracy summarized below for using clearcut harvests as the reference dataset. (figure 8).

Figure 8

| | REFERENCE NO CLEARCUT | REFERENCE CLEARCUT | row total | W(i) | GFW MAPPED PIXELS |
|-------------------|-----------------------|---------------------|-----------|-------------------|-------------------|
| PREDICTED NO LOSS | 29,062 | 508 | 29,570 | 0.899 | 524,288,504 |
| PREDICTED LOSS | 511 | 538 | 1,049 | 0.101 | 58,610,136 |
| column total | 29,573 | 1,046 | 30,619 | 1.000 | 582,898,640 |
| | REFERENCE NO DELTA | REFERENCE DELTA | row total | GFW MAPPED PIXELS | |
| PREDICTED NO LOSS | 0.884 | 0.015 | 0.899 | 524,288,504 | |
| PREDICTED LOSS | 0.049 | 0.052 | 0.101 | 58,610,136 | |
| column total | 0.933 | 0.067 | 1.000 | 582,898,640 | |
| | USER'S ACCURACY | PRODUCER'S ACCURACY | | | |
| NO CLEARCUT | 0.983 | 0.948 | | | |
| CLEARCUT | 0.513 | 0.769 | | | |

Note that the user's and producer's accuracy for no clearcut remains high, but that the user's accuracy and producer's accuracy flip from using "Delta" as the reference source and using "Clearcut" as the reference source. Unsurprisingly, the number of false positives increases from 238 using the "Delta" reference to 511 using the less inclusive "Clearcut" reference. The false negative count falls dramatically from 3,331 using delta as the reference data, to 508 using clearcut as the reference data. It is surprising that the TCL predictive map misses roughly the

same number of clearcut harvests (508) on the ground as it identifies correctly (538). This surprising finding called to a close examination of the FIA reference data set.

The sample size of plot visits that took place between 2001 and 2012, without filtering out visits that were not preceded by another visit is 30,619 plot visits. When filtering the results so that only visits that either occurred later than 2007, or had a prior visit that took place later than the year 2000, there were 16,645 visits. The sample size reduction is significant, but the reduced noise in the data is substantial. Figures 9 and 10 display the sample count confusion matrix results, and proportional confusion matrix results, respectively.

Figure 9

| | REFERENCE NO CLEARCUT | REFERENCE CLEARCUT | row total | W(i) | GFW MAPPED PIXELS |
|-------------------|-----------------------|--------------------|-----------|-------|-------------------|
| PREDICTED NO LOSS | 15,924 | 87 | 16,011 | 0.899 | 524,288,504 |
| PREDICTED LOSS | 315 | 319 | 634 | 0.101 | 58,610,136 |
| column total | 16,239 | 406 | 16,645 | 1.000 | 582,898,640 |

Using the larger, unfiltered sample, the false negative sample count of clearcuts was 508. By contrast, the false negative rate using the filtered sample size and the same harvest criteria was 87. Proportionally speaking, the rate of predicted loss to true loss pixels in the unfiltered sample was shown to be 1.5%, by contrast the false negative percentage of the total predicted pixels only represented 0.5% of the filtered sample.

Figure 10

| | REFERENCE NO HARVEST | REFERENCE HARVEST | row total |
|----------------------|----------------------|-------------------|-------------------|
| PREDICTED NO HARVEST | 0.895 | 0.005 | 0.899 |
| PREDICTED HARVEST | 0.050 | 0.051 | 0.101 |
| column total | 0.945 | 0.055 | 1.000 |
| NO HARVEST | USER'S ACCURACY | USER'S SE | USER'S 95% CI |
| | 0.995 | 0.001 | 0.001 |
| HARVEST | USER'S ACCURACY | USER'S SE | USER'S 95% CI |
| | 0.503 | 0.020 | 0.039 |
| NO HARVEST | PRODUCER'S ACCURACY | PRODUCER'S SE | PRODUCER'S 95% CI |
| | 0.947 | 0.002 | 0.004 |
| HARVEST | PRODUCER'S ACCURACY | PRODUCER'S SE | PRODUCER'S 95% CI |
| | 0.912 | 0.009 | 0.018 |
| OVERALL | OVERALL ACCURACY | OVERALL SE | OVERALL 95% CI |
| | 0.945 | 0.002 | 0.004 |

The change in the false positive counts was considerably less dramatic, from 511 to 315. The proportion of false positive to predicted pixels in the unfiltered sample was 49%, and the filtered sample the proportion was 50%. The true positive rate of loss analyzed as clearcut was 538 in the unfiltered dataset, and 319 in the filtered dataset, 51.2% & 50.3% respectively. The true positive rate of no harvest of the unfiltered sample was 29,062 at 98.2%, and unfiltered results were 15,924 at 98.1%. The producer's accuracy changes dramatically from the raw FIA reference data to the

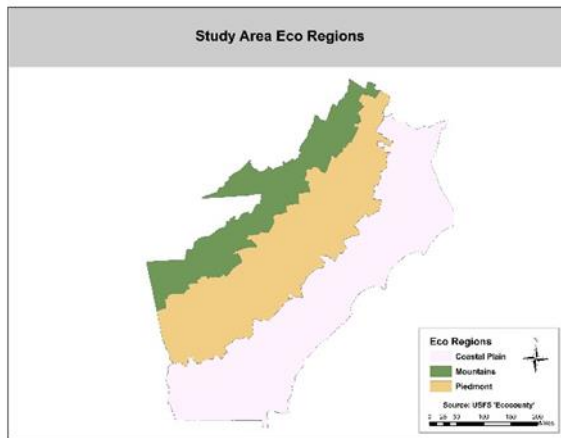
filtered FIA reference data, from 76.9% of clearcuts on the ground properly identified by the map, to an excellent 91.2%. The user's accuracy went from 51.3% in the unfiltered dataset, to 50.3% in the filtered dataset. The user's accuracy remains consistent, as the false positive rate is very similar between the two datasets.

These results indicate that a large number of plot visits recorded harvest activity that had taken place prior to the purview of the remote sensing platform analysis. This had a large impact on the false negative rate of the accuracy assessment, as the reference dataset was not properly applied to the predicted sample. This had virtually no impact on the true positive loss, false positive loss, and true positive no loss, as including harvest activity that may have occurred outside of the analysis horizon would have had no impact on these measures of accuracy. The remainder of the analysis will use the filtered reference dataset.

Regional Comparison

The study area is composed of 3 distinct geophysical regions; Mountains, Piedmont, and Coastal Plain. These geophysical regions each represent a unique combination of terrain, soils, and climate. Variation in soil quality and terrain make some regions more hospitable to residential and commercial development, as well as agricultural use. These geophysical and anthropogenic variables, among others result in generally different forest cover types, forest management intensity, and markets within each geophysical region. Regional accuracy statistics are included in full in the appendix.

Figure 10



A comparison of how well the TCL dataset detects “Delta” of any kind is depicted in Figure (11). It is clear that the Mountain region is estimated to be considerably less disturbed (11.1%) than the Coastal Plain (19.3%) or the Piedmont (16.2%). Consistently, the TCL dataset misses approximately 8% to 9% of “Delta” activity in each region. False positive rates are consistent across regions well, representing with 1% to 2% of the predicted pixels with reference to “Delta” in the regions. The user’s accuracy, overall accuracy, and producer’s accuracy of “No Delta” of all of the regions are very similar.

Figure 11

| Coastal Plain | | | | Piedmont | | | | Mountains | | | |
|---------------------|---------------|-------------------|-------------|---------------------|---------------|-------------------|-------------|---------------------|---------------|-------------------|-------------|
| DELTA | | | | DELTA | | | | DELTA | | | |
| REFERENCE | REFERENCE | row total | | REFERENCE | REFERENCE | row total | | REFERENCE | REFERENCE | row total | |
| NO DELTA | DELTA | | | NO DELTA | DELTA | | | NO DELTA | DELTA | | |
| PREDICTED NO LOSS | 6,219 | 743 | 6,962 | PREDICTED NO LOSS | 4,843 | 493 | 5,336 | PREDICTED NO LOSS | 3,289 | 324 | 3,613 |
| PREDICTED LOSS | 62 | 278 | 340 | PREDICTED LOSS | 67 | 186 | 253 | PREDICTED LOSS | 12 | 29 | 41 |
| Column total | 6,281 | 1,021 | 7,302 | Column total | 5,010 | 679 | 5,689 | Column total | 3,301 | 353 | 3,654 |
| GFW MAPPED PIXELS | 227,968,007 | 31,500,493 | 259,468,498 | GFW MAPPED PIXELS | 186,951,462 | 23,187,206 | 210,138,668 | GFW MAPPED PIXELS | 109,349,035 | 3,922,439 | 113,271,474 |
| WJ) | 0.879 | 0.121 | WJ) | 0.890 | 0.110 | WJ) | 0.965 | 0.035 | WJ) | | |
| REFERENCE | REFERENCE | row total | | REFERENCE | REFERENCE | row total | | REFERENCE | REFERENCE | row total | |
| NO DELTA | DELTA | | | NO DELTA | DELTA | | | NO DELTA | DELTA | | |
| PREDICTED NO LOSS | 0.785 | 0.094 | 0.879 | PREDICTED NO LOSS | 0.809 | 0.081 | 0.890 | PREDICTED NO LOSS | 0.879 | 0.087 | 0.965 |
| PREDICTED LOSS | 0.022 | 0.009 | 0.121 | PREDICTED LOSS | 0.029 | 0.081 | 0.110 | PREDICTED LOSS | 0.010 | 0.024 | 0.035 |
| Column total | 0.807 | 0.103 | 1.000 | Column total | 0.838 | 0.162 | 1.000 | Column total | 0.889 | 0.111 | 1.000 |
| USER'S ACCURACY | USER'S SE | USER'S 95% CI | | USER'S ACCURACY | USER'S SE | USER'S 95% CI | | USER'S ACCURACY | USER'S SE | USER'S 95% CI | |
| NO DELTA | 0.893 | 0.004 | 0.007 | NO DELTA | 0.909 | 0.004 | 0.008 | NO DELTA | 0.910 | 0.005 | 0.009 |
| DELTA | 0.818 | 0.021 | 0.041 | DELTA | 0.735 | 0.028 | 0.054 | DELTA | 0.707 | 0.072 | 0.141 |
| PRODUCER'S ACCURACY | PRODUCER'S SE | PRODUCER'S 95% CI | | PRODUCER'S ACCURACY | PRODUCER'S SE | PRODUCER'S 95% CI | | PRODUCER'S ACCURACY | PRODUCER'S SE | PRODUCER'S 95% CI | |
| NO DELTA | 0.973 | 0.003 | 0.006 | NO DELTA | 0.965 | 0.004 | 0.007 | NO DELTA | 0.989 | 0.003 | 0.005 |
| DELTA | 0.514 | 0.011 | 0.021 | DELTA | 0.501 | 0.014 | 0.028 | DELTA | 0.221 | 0.020 | 0.039 |
| OVERALL ACCURACY | OVERALL SE | OVERALL 95% CI | | OVERALL ACCURACY | OVERALL SE | OVERALL 95% CI | | OVERALL ACCURACY | OVERALL SE | OVERALL 95% CI | |
| OVERALL | 0.884 | 0.004 | 0.008 | OVERALL | 0.890 | 0.005 | 0.009 | OVERALL | 0.903 | 0.005 | 0.010 |

Notably, the producer’s accuracy rate (Figure 12) for detecting “Delta” is considerably lower in the mountains (22.1%), than in the Coastal Plain (51.4%), or the Piedmont (50.1%). This may be a result of a greater proportion of low density disturbance in the Mountains relative to the other two geophysical regions. In likely related observation, the user’s and producer’s accuracy rates detecting “THIN” are higher in the Mountains than the other two regions. These regional differences may derive from a higher prevalence of lower intensity silviculture in the deciduous and mixed forests on the mountains. This hypothesis is strengthened by the fact that the user’s accuracy rate of clearcut harvests in the mountains is considerably lower than in the other two regions. In the mountains, 39% of the predicted loss pixels are clearcut harvests, whereas in the Piedmont and Coastal Plain, 49% and 52.6% of predicted pixels are respectively clearcut harvests.

| Coastal Plain | | | | Piedmont | | | | Mountains | | | |
|---------------------|---------------|-------------------|-------|---------------------|---------------|-------------------|-------|---------------------|---------------|-------------------|-------|
| THIN | | | | THIN | | | | THIN | | | |
| REFERENCE | REFERENCE | row total | | REFERENCE | REFERENCE | row total | | REFERENCE | REFERENCE | row total | |
| NO HARVEST | HARVEST | | | NO HARVEST | HARVEST | | | NO HARVEST | HARVEST | | |
| PREDICTED NO LOSS | 0.884 | 0.034 | 0.918 | PREDICTED NO LOSS | 0.855 | 0.034 | 0.890 | PREDICTED NO LOSS | 0.956 | 0.010 | 0.965 |
| PREDICTED LOSS | 0.098 | 0.023 | 0.121 | PREDICTED LOSS | 0.088 | 0.023 | 0.110 | PREDICTED LOSS | 0.025 | 0.009 | 0.035 |
| Column total | 0.942 | 0.058 | 1.000 | Column total | 0.943 | 0.057 | 1.000 | Column total | 0.981 | 0.019 | 1.000 |
| USER'S ACCURACY | USER'S SE | USER'S 95% CI | | USER'S ACCURACY | USER'S SE | USER'S 95% CI | | USER'S ACCURACY | USER'S SE | USER'S 95% CI | |
| NO THIN | 0.961 | 0.002 | 0.005 | NO THIN | 0.961 | 0.003 | 0.005 | NO THIN | 0.998 | 0.002 | 0.003 |
| THIN | 0.153 | 0.021 | 0.041 | THIN | 0.206 | 0.029 | 0.056 | THIN | 0.257 | 0.118 | 0.232 |
| PRODUCER'S ACCURACY | PRODUCER'S SE | PRODUCER'S 95% CI | | PRODUCER'S ACCURACY | PRODUCER'S SE | PRODUCER'S 95% CI | | PRODUCER'S ACCURACY | PRODUCER'S SE | PRODUCER'S 95% CI | |
| NO THIN | 0.936 | 0.003 | 0.006 | NO THIN | 0.907 | 0.003 | 0.006 | NO THIN | 0.974 | 0.004 | 0.008 |
| THIN | 0.406 | 0.030 | 0.058 | THIN | 0.398 | 0.037 | 0.073 | THIN | 0.485 | 0.118 | 0.231 |
| OVERALL ACCURACY | OVERALL SE | OVERALL 95% CI | | OVERALL ACCURACY | OVERALL SE | OVERALL 95% CI | | OVERALL ACCURACY | OVERALL SE | OVERALL 95% CI | |
| OVERALL | 0.888 | 0.003 | 0.006 | OVERALL | 0.878 | 0.004 | 0.008 | OVERALL | 0.965 | 0.004 | 0.009 |

Figure 12

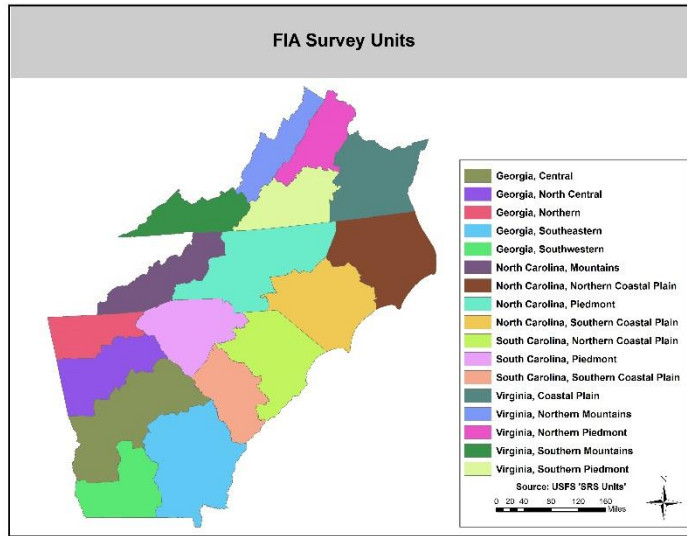
The estimated area that was clearcut harvested in the years 2001-2012, is displayed in figure (13). An average of 556,187 acres are estimated to be clearcut harvested over the entire study area on an annual basis.

Figure 13

| Entire Study Area | | | |
|-------------------|-----------------|-----------------------|--------------------------|
| | ADJ. PROP. AREA | ADJ. PROP. AREA SE | ADJ. PROP. AREA CI |
| No Clearcut | 0.945 | 0.002 | 0.004 |
| Clearcut | 0.055 | 0.002 | 0.004 |
| | ESTIMATED ACRES | 95% LOWER LIMIT ACRES | 95% CI UPPER LIMIT ACRES |
| No Clearcut | 113,627,226 | 113,140,223 | 114,114,229 |
| Clearcut | 6,674,243 | 6,187,240 | 7,161,247 |

The Forest Inventory and Analysis program estimates the average annual harvest. FIA summarizes regional groups of counties into FIA survey units, displayed in figure (14). The following graph (15) compares the estimated

Figure 14

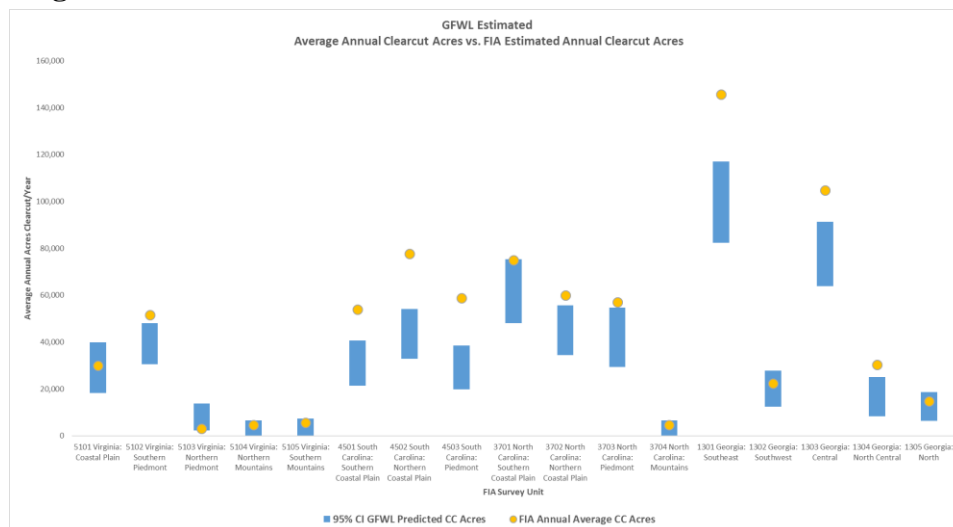


annual clearcut harvest by survey unit in FIA and GFWL. FIA estimated annual harvests were estimated using the FIA Evaluator tool. GFWL estimates were taken from the 95% confidence interval around the estimated area of the classification of harvest generated in the accuracy assessment. This estimate was divided by 12 to achieve an annual average for the 12 year analysis horizon.

The FIA data consistently reports higher estimates of harvested acres. This may be due to the fact that the method used to quantify the estimated average acres harvested on an annual basis used plot data collected

after the analysis horizon, in the years 2013-2015, in addition to earlier years.

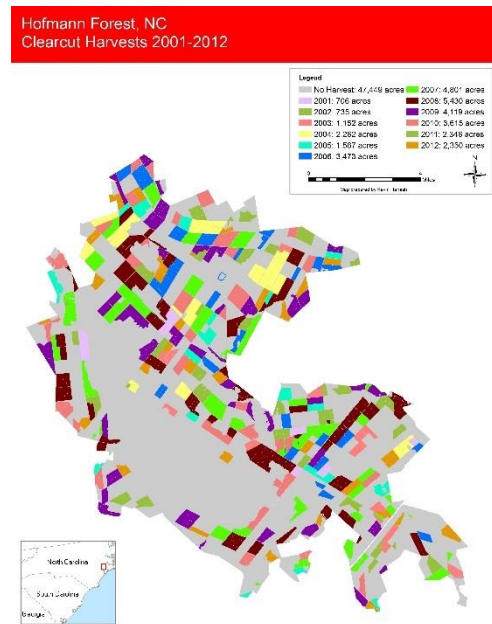
Figure 15



It is noteworthy that the state of Virginia is consistently the closest to the FIA estimate of harvested acres. This may reflect a difference in frequency of data collection, or intensity of management, or other factors.

Temporal Assessment: Hofmann Forest

Figure 16



Hofmann forest is composed of 79,243 acre property. 54,352 acres of the property is intensively managed loblolly pine plantation, the remainder of the property is covered in pocosion, natural mixed pine hardwood stands, roads, and ditches. In order to perform a temporal assessment of the accuracy with which the remote sensing platforms identify harvest activity at Hofmann Forest, clearcut harvests will be analyzed. As many stands are thinned on a 4 to 5 year interval, multiple density changes may occur within the within the 12 year analysis horizon. The high frequency of disturbance at Hofmann Forest makes developing an accurate reference dataset that includes thinning very difficult.

Virtually all of the stands that are clearcut harvest have been thinned multiple times prior to clearcut harvest. For the clearcut analysis, the year of the clearcut is used for the harvest year within the clearcut Hofmann reference data set. The Hofmann forest harvest records are excellent, but even so, they often do not identify the exact year a harvest occurs. Harvest contracts typically span a one to two year period in the Southeastern United States. This allows buyers to access the timber even if a given season has poor weather. A harvest may begin in 2002, but end in 2003. The reference data set could indicate that either 2002 or 2003 was the harvest year. This fact should be taken into account when considering the accuracy statistics associated with an annual temporal assessment.

The Global Forest Watch Loss (GFWL) data set is comprised of a 30 meter raster grid, the forest stand extent often did not line up with the shape of the predictive square GFW grid. In order avoid overlap, forest stand shapefiles were dissolved in ARC GIS according to common harvest year. The extent of the recorded clearcut harvest activity on Hofmann Forest is displayed in figure 16. Using the “Create Random Points” tool in Arc GIS, 1,000 random points were generated within the Hofmann Forest boundary. These 1,000 random points were intersected with the GFW TCL grid, and an accuracy assessment was performed. A confusion matrix representing the sample counts of harvest activity is displayed below in figure (17)

Figure 17

| | | Hofmann Reference Data Indicating Clearcut Harvest | | | | | | | | | | | | | |
|------------------------------------|---------|--|------|------|------|------|------|------|------|------|------|------|------|------|--------------|
| | | No Clearcut | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | Column Total |
| Predicted Global Forest Watch Loss | No Loss | 497 | 1 | 0 | 2 | 3 | 1 | 1 | 1 | 0 | 1 | 3 | 1 | 7 | 518 |
| | 2001 | 11 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 |
| | 2002 | 2 | 1 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5 |
| | 2003 | 3 | 0 | 2 | 5 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 11 |
| | 2004 | 5 | 0 | 0 | 7 | 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 |
| | 2005 | 1 | 1 | 0 | 0 | 16 | 15 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 34 |
| | 2006 | 3 | 0 | 0 | 0 | 1 | 3 | 19 | 0 | 0 | 0 | 0 | 0 | 1 | 27 |
| | 2007 | 11 | 0 | 0 | 0 | 0 | 0 | 8 | 43 | 0 | 0 | 0 | 0 | 0 | 62 |
| | 2008 | 16 | 0 | 0 | 0 | 0 | 0 | 0 | 26 | 48 | 1 | 0 | 0 | 0 | 91 |
| | 2009 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 32 | 1 | 2 | 0 | 73 |
| | 2010 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 12 | 37 | 1 | 0 | 59 |
| | 2011 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 11 | 0 | 30 |
| | 2012 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 9 | 21 | 42 |
| Adjusted Total | | 581 | 13 | 4 | 14 | 35 | 19 | 29 | 70 | 78 | 46 | 58 | 24 | 29 | 1000 |

Figure 18 displays a confusion matrix representing the estimated proportion area.

Figure 18

| | | Hofmann Reference Data Indicating Clearcut Harvest | | | | | | | | | | | | | Column Total |
|------------------------------------|---------|--|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|--------------|
| | | No Clearcut | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | |
| Predicted Global Forest Watch Loss | No Loss | 0.521 | 0.001 | 0.000 | 0.002 | 0.003 | 0.001 | 0.001 | 0.001 | 0.000 | 0.001 | 0.003 | 0.001 | 0.007 | 0.543 |
| | 2001 | 0.010 | 0.009 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.018 |
| | 2002 | 0.003 | 0.002 | 0.003 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.008 |
| | 2003 | 0.005 | 0.000 | 0.003 | 0.008 | 0.000 | 0.000 | 0.000 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 | 0.017 |
| | 2004 | 0.005 | 0.000 | 0.000 | 0.007 | 0.014 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.026 |
| | 2005 | 0.001 | 0.001 | 0.000 | 0.000 | 0.016 | 0.015 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.033 |
| | 2006 | 0.003 | 0.000 | 0.000 | 0.000 | 0.001 | 0.003 | 0.019 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.027 |
| | 2007 | 0.011 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.008 | 0.043 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.062 |
| | 2008 | 0.013 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.021 | 0.040 | 0.001 | 0.000 | 0.000 | 0.000 | 0.075 |
| | 2009 | 0.009 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.024 | 0.028 | 0.001 | 0.002 | 0.000 | 0.063 |
| | 2010 | 0.008 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.012 | 0.037 | 0.001 | 0.000 | 0.058 |
| | 2011 | 0.004 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.015 | 0.011 | 0.000 | 0.000 | 0.030 |
| | 2012 | 0.009 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.002 | 0.008 | 0.019 | 0.039 |
| Adjusted Total | | 0.601 | 0.012 | 0.006 | 0.017 | 0.034 | 0.019 | 0.029 | 0.066 | 0.066 | 0.041 | 0.057 | 0.023 | 0.028 | 1.000 |

Figures (19, 20)

| Overall Accuracy | Overall Accuracy SE | 95% CI Overall Accuracy |
|------------------|---------------------|-------------------------|
| 0.766 | 0.011 | 0.022 |

| YEAR | User's Accuracy | User's Accuracy SE | 95% CI User's Accuracy | Producer's Accuracy | Producer's Accuracy SE | 95% CI Producer's Accuracy |
|--------------|-----------------|--------------------|------------------------|---------------------|------------------------|----------------------------|
| No Harvest | 0.959 | 0.009 | 0.017 | 0.866 | 0.012 | 0.023 |
| 2001 Harvest | 0.476 | 0.112 | 0.219 | 0.705 | 0.133 | 0.260 |
| 2002 Harvest | 0.400 | 0.245 | 0.480 | 0.506 | 0.227 | 0.445 |
| 2003 Harvest | 0.455 | 0.157 | 0.309 | 0.469 | 0.115 | 0.225 |
| 2004 Harvest | 0.556 | 0.097 | 0.191 | 0.421 | 0.061 | 0.120 |
| 2005 Harvest | 0.441 | 0.086 | 0.169 | 0.783 | 0.089 | 0.175 |
| 2006 Harvest | 0.704 | 0.090 | 0.176 | 0.657 | 0.074 | 0.145 |
| 2007 Harvest | 0.694 | 0.059 | 0.116 | 0.658 | 0.042 | 0.082 |
| 2008 Harvest | 0.527 | 0.053 | 0.103 | 0.596 | 0.044 | 0.086 |
| 2009 Harvest | 0.438 | 0.058 | 0.115 | 0.668 | 0.062 | 0.121 |
| 2010 Harvest | 0.627 | 0.063 | 0.124 | 0.637 | 0.047 | 0.092 |
| 2011 Harvest | 0.367 | 0.089 | 0.175 | 0.476 | 0.089 | 0.174 |
| 2012 Harvest | 0.500 | 0.078 | 0.153 | 0.698 | 0.081 | 0.159 |

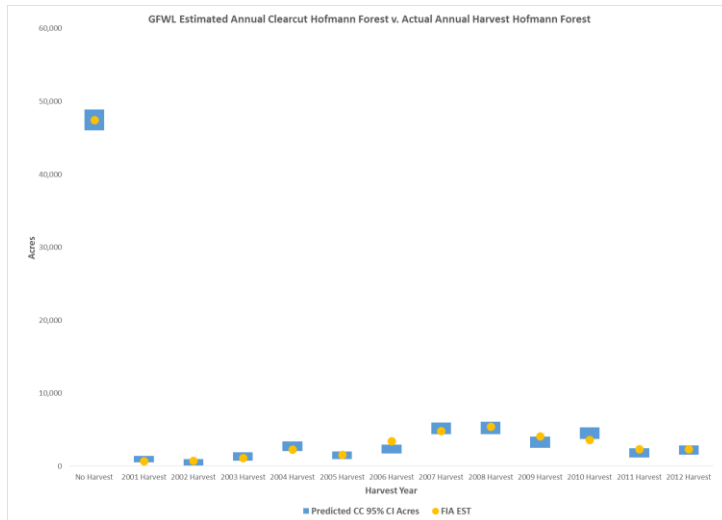
An overall accuracy of 76.6% indicates the predicted map is not doing a very good job of identifying the harvest year. The areas that were not harvested were identified with acute accuracy. The

temporal sensitivity of the remote sensing platform appears to be quite low. User's accuracy ranges from .367 (2011) to .704 (2006), while producer's accuracy ranges from 0.421 (2004) to .705 (2001). The reference dataset may not precisely identify the year each portion of a polygon his harvested. In the Southeastern United States, timber harvests often span multiple calendar

years due to weather related delays. A harvest may have been classified in the reference dataset as completed in 2008, but half of the harvest area may have been completed in 2007. Significant false negative counts immediately preceding and following the true positive harvest year indicate multi-calendar year harvests may influence the accuracy statistics. Thinning activity at Hofmann Forest is likely a cause of a majority number of the relatively few false positive sample points.

The predicted area of harvest was considerably more accurate. This is likely a function of a large data set relative to the sampled area, and the fact the the majority of the forest is actively managed for timber production.

Figure 21 and 22



| Harvest Year | Lower Limit 95% CI GFWL Harvest Acres | Upper Limit 95% CI GFWL Harvest Acres | Actual Clearcut Harvest Acres |
|--------------|---------------------------------------|---------------------------------------|-------------------------------|
| No Harvest | 46,013 | 48,878 | 47,449 |
| 2001 Harvest | 513 | 1,430 | 706 |
| 2002 Harvest | 55 | 946 | 735 |
| 2003 Harvest | 727 | 1,908 | 1,152 |
| 2004 Harvest | 2,036 | 3,392 | 2,262 |
| 2005 Harvest | 945 | 2,030 | 1,567 |
| 2006 Harvest | 1,714 | 2,923 | 3,473 |
| 2007 Harvest | 4,378 | 5,998 | 4,801 |
| 2008 Harvest | 4,354 | 6,105 | 5,430 |
| 2009 Harvest | 2,494 | 4,036 | 4,119 |
| 2010 Harvest | 3,719 | 5,329 | 3,615 |
| 2011 Harvest | 1,180 | 2,449 | 2,346 |
| 2012 Harvest | 1,532 | 2,835 | 2,350 |

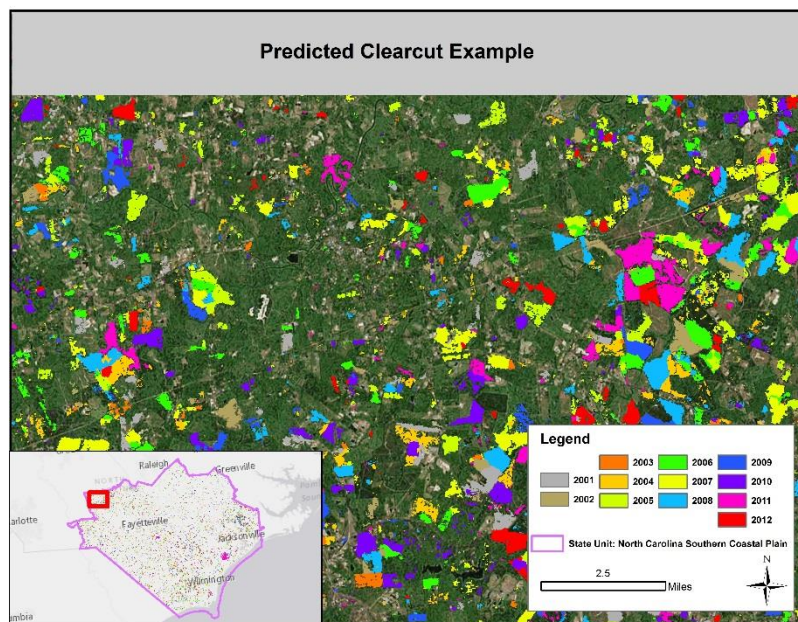
Actual harvest results were generally within the 95% confidence interval of the predicted harvested area, as displayed in figures (21 and 22).

Discussion

The available reference data was of high quality, but was not generated with an eye towards an accuracy assessment of this kind. It is possible that a reference data set built specifically for this purpose would yield different statistical results. Currently FIA estimates of harvest activity are not spatially explicit below the county level, and are average annual estimates over the remeasurement period. Remote sensing platforms are well positioned to provide supplemental information to the current FIA database. Predictive maps generated by remote sensing products such as the Global Forest Watch Tree Cover Loss dataset provide estimates at a fine spatial resolution, and are temporally accurate at nearly an annual level.

Coupling a remote sensing product with the current FIA plot design has real potential to improve the precision of FIA estimates. For example, a forest density change prediction map could be intersected with the FIA plot information, and the FIA field technician could indicate if the predicted delta occurred, and what kind of delta it was. If the delta occurred, the FIA plot would now have a very good indication of which year the delta occurred. If it didn't the predictive error would be recorded.

Figure 23



Currently the predictive tree cover loss maps strengths are correctly identifying the temporal location of a disturbance, and rarely identifying areas as disturbed that were not in fact disturbed. This indicates that the area identified by the predictive mapping product may then be subjected to proportional and probabilistic estimates of how much change of a particular sort took place within the predicted area.

The map in figure 23 depicts FIA Survey Unit 371, North Carolina Coastal Plain.

According to the user's accuracy statistics derived from this area using "Clearcut" as the reference dataset, 69.7% of the pixels identified as loss in this map are actually clearcuts on the ground, and 99.03% of the areas depicted as no loss (no color) are actually no loss on the ground. The accuracy assessment does not provide any insight with respect to which of the pixels were correctly identified. Furthermore, this accuracy assessment does not distinguish between silvicultural clearcut harvests that will regenerate as forests, and a land use change from forest to non-forest. Nevertheless, this remains an extremely useful spatially explicit indicator of where harvest activity is located. Furthermore, the temporal assessment at Hofmann Forest indicates that the TCL layer does a fairly good job of indicating the harvest year, within a range of one or

two years. Developing a temporally specific forest regeneration layer would also be extremely useful. By coupling a temporally explicit “gain” layer with a current temporally explicit loss layer, researchers could begin to attempt to track land use changes, historically and in near real time.

Works Cited

Bechtold, W. A., & Patterson, P. L. (2005). The enhanced forest inventory and analysis program-national sampling design and estimation procedures. *Southern Research Station General Technical Report, SRS--80*, 26.

Butry, David (2000). 'ecocnty', vector digital data, Salt Lake City, UT, USDA Forest Service, <<http://www.srs.fs.usda.gov/sustain/data/>>

Congalton, Russell G., and Kass Green. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Boca Raton: Lewis Publications, 1999. Print.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. 2013. "High-Resolution Global Maps of 21st-Century Forest Cover Change." *Science* 342 (15 November): 850–53. Data available on-line from:<http://earthenginepartners.appspot.com/science-2013-global-forest>.

Olofsson, Pontus, Giles M. Foody, Martin Herold, Stephen V. Stehman, Curtis E. Woodcock, and Michael A. Wulder. "Good Practices for Estimating Area and Assessing Accuracy of Land Change." *Remote Sensing of Environment* 148 (2014): 42-57. Web.

Ortman, Antonia, (2014). Accuracy-assessment.error_matrix_analysis: R package version 1.14.4.

David, Wear N., and Greis G. John. "USDA Forest Service Southern Research Station." *Southern Forest Futures Project*. USFS, Oct. 2012. Web. 07 Aug. 2016.