Preliminary Analysis of Forest Stand Disturbances in Coastal Georgia (USA) Using Landsat Time Series Stacked Imagery

Shingo Obata\textsuperscript{1*}, Chris J. Cieszewski\textsuperscript{1}, Pete Bettinger\textsuperscript{1}, Roger C. Lowe III\textsuperscript{1}, Sergio Bernardes\textsuperscript{2}

Abstract: A determination of forest characteristics across broad areas is of great concern to the forest industry in the southern United States, as timber supply decisions can be based on opportunities, or lack of thereof, across all wood procurement areas. This is important in areas such as the southern United States, where the land ownership distribution is highly fragmented and where no general comprehensive source of forest data exists other than the low-intensity USDA Forest Service FIA surveys. In an effort to describe forest characteristics along the lower Coastal Plain of the State of Georgia (USA), we utilized a time series of Landsat data and an algorithm that assesses an integrated forest Z score. The methodology was used to create disturbance maps for over 30 years that represent the year of disturbance for specific locations. The overall accuracy was 52\% when all years were considered, and approximately 70\% from 1991 forward. Preliminary findings showed moderate levels of accuracy when determining ages for current forests, most of which are even-aged nature stands. Further modifications to the process were necessary to adapt to the unique conditions of study region. The modeling process also prompted several areas for future refinement, including improvement of the temporal resolution of the analysis by using all the available Landsat imagery and detection of the regeneration that normally occurs several years after disturbances.

Keywords: forest planning, forest resource management, land cover change analysis, mathematical modeling, remote sensing

1. Introduction

Acquisition of information regarding the state of natural resource availability and their characteristics can be one of the most expensive components of forest management (Bettinger et al. 2017). Satellite technology can provide a cost-effective source of spatial information and can facilitate processes that allow one to estimate various natural resource characteristics needed for the planning and management of forests, sustainability analysis (Cieszewski et al. 2004; Liu and Cieszewski 2009) and biomass supply assessment (Cieszewski et al. 2011). Of the many satellites currently in operation, those belonging to the Landsat series are frequently used for terrestrial resource assessments / monitoring due to the long life of the program (first launched in 1972) do not change the characteristics of the platform: orbit, sensors, temporal resolution, consistent footprint, and moderate spatial resolution (Roy et al. 2014). Along with the growing power and availability of computing and software technology, the evolving body of scientific research is continuously revealing growing potential to estimate more detailed forest information using satellite imagery. This progression in applied science has evolved beyond static analyses of single satellite images to spatiotemporal analyses of series (stacks) of images captured at different points in time. Time series analysis of remotely-sensed data can help identify forest disturbance, which is one critically important process in an assessment of the current state of forest resources across broad landscapes. Dating disturbance events by using remote sensing can facilitate the determination of forest age and of current stage of forest development. In this paper, the term “disturbance” is used to refer to abrupt loss of forest cover in an area. This includes any types of the causes that lead the change. Disturbance is caused by two types of events. The first one is natural disturbance such as forest fire and windthrow. The other is anthropogenic disturbance including major harvesting that clears all the foreststand and minor harvesting that leaves majority of the forest cover.

With temporal trajectory-based image analysis (change detection), changes in land use can be detected with a help of an algorithm that assesses a time series of satellite images to locate changes in the spectral signatures of arbitrary locations within a landscape (Brooks et al. 2014). The Vegetation Change Tracker (VCT), for example, uses an integrated forest score (IFZ) as a metric to
distinguish forested areas from others areas at the resolution of a single pixel (Huang et al. 2009). Application of these types of algorithms enables the development of a map, which specifies the years of stand disturbances. LandTrendr is another example algorithm for automatic detection of changes in land use (Kennedy et al. 2010). Other models (e.g., Vogelmann et al. 2012; Jin et al. 2013) share common characteristics: stacking annual images captured during a specific season of the year, using one or more indices for detection of changes, and comparing results with adjacent years to verify the changes. The novelty of this kind of research is of great relevance to forest management. For example, Brooks et al. (2014) used statistical process control tools to detect not only major disturbances (final harvests) but also minor disturbances, such as thinnings. And Zhu et al. (2015) developed an algorithm to remove seasonal effects from the analysis of satellite imagery. Further, the North American Carbon Program created North American Forest Dynamics (NAFD) products which are a spatially explicit disturbance detection maps for conterminous United States between 1986 and 2010. NAFD product is comprised of 25 annual and two-time integrated forest disturbance map that shows the specific year of disturbance with 30-meter spatial resolution (Goward et al. 2015).

The objective of this research was to describe the current age class distribution of forests in the lower Coastal Plain of the State of Georgia, an area where forests are managed mainly through even-aged methods, and where forests are intermixed with other land uses. In this paper we present the comprehensive explanation of the work that was briefly summarized in Obata (2018). A long (33 year) time series of Landsat imagery was used to determine the date of the most recent major forest disturbance (final harvest). The forested and agricultural settings in this region include a complex interspersed of croplands (e.g., onions), pasture, conifer plantations, deciduous bottom-lands, cypress (Taxodium) forests, and mixed species stands of trees that are managed by public agencies, private landowners, and the U.S. military. This landscape heterogeneity, along with the variety of land management objectives that follow, present both challenge and opportunity to those who seek to describe the current state of forests. While previous research has illustrated sophisticated algorithms for estimating disturbance years, most do not utilize Landsat 8 OLI imagery, which started acquiring images in 2013. Landsat 8 OLI shares common characteristics with Landsat 5 TM in most aspects, yet there is a difference in band centers, where wavelengths located at the center of the each band in Landsat 8 are different than those of Landsat 5. This difference may result in inconsistencies of the disturbance / regeneration map derived from the imagery. Therefore, it is a challenge to the current research to develop an up-to-date disturbance map for our Coastal Plain study site by combining multiple years of Landsat 5 TM and Landsat 8 OLI satellite imagery.

2. Methodology

2.1. Study area

Our study area consists of seven counties along the Atlantic Ocean coastline in the lower Coastal Plain of the State of Georgia, USA (Figure 1), representing approximately 900,000 hectares. In this area, loblolly pine (Pinus taeda) and slash pine (Pinus elliottii) are the dominant coniferous trees species that are planted, and many areas are managed by the forest product industry. We selected these counties for three reasons. First reason is that this area has been directly influenced by an intensive forest management program that was initiated in the 1980s on lands that were managed by corporations, companies, and investment management organizations. With the financial support of the U.S. Department of Agriculture (USDA) Conservation Reserve Program (CRP), private landowners have also been able to obtain funds for a portion of the forest management costs (Georgia Forestry Commission 2018), which gave them an incentive to increase the intensity of forest management on their lands, and even shift some of their land uses from agriculture to forestry. In these ways, intensive forest management has been used to reduce the rotation ages of even-aged forests in this region. Second, the study area includes mostly rural areas. The largest cities (Savannah, Georgia and Jacksonville, Florida) are on the north and south ends of the study area, respectively. Third, the topography in this area is very consistent, with relatively gentle slopes, compared to the Piedmont or mountainous areas of the southern United States (and further inland in Georgia).
2.2. Training data

We used the Landsat 5 TM and Landsat 8 OLI imagery to develop the training data set for the classification process as described below. The development was subject to two conditions: (i) the imagery needed to be captured during the heart of the growing season, which we assumed to be from the beginning of June to the end of August; and (ii) the imagery needed to be captured between 1984 and 2016. Imagery from 2012 was lacking because neither Landsat 5 nor Landsat 8 was in operation during this year. Landsat 7 data could have been used for 2012, however, due to the failure of the scan line corrector, Landsat 7 data suffer from significant data gaps (Chen et al. 2011).

The images were downloaded via EarthExplorer (U.S. Geological Survey 2017); for each year a single image with the least cloud cover was selected to represent it. We used the C function of the mask (CFMask) band to remove the effect of clouds (presence and shadows). For pixels representing water, we applied criteria to mask a pixel when its normalized difference vegetation index (NDVI) was less than 0.5 and when the surface reflectance value from the near infrared band was less than 0.15. After performing these processes, we visually inspected the quality of the resulting imagery, and decided to exclude the 1993 scene, as the processes failed to eliminate thin, cirrus clouds correctly.

2.3. Reference data

To verify the accuracy of the created forest age map, we used as reference images from Google Earth, Landsat 5 TM and Landsat 8 OLI imagery. Google Earth was the primary source of reference data for the accuracy assessment for more recent years, as the frequency and quality of high-resolution imagery is greater in the last 15 years than before that. We used Landsat imagery for verification of disturbances for earlier years in our time frame (2000 and before). Annual mosaics of Landsat imagery were created using Google Earth Engine in an effort to acquire cloud-free representations of the landscape. To create annual mosaics, imagery selected to conduct classification were not used so that training data and reference data are not mixed each other. These mosaics were used to verify whether disturbances had occurred during the accuracy assessment process (described below).

2.4. Forest disturbance detection method

The algorithm we developed computed the Integrated Forest Z-score (IFZ value) to detect major forest disturbances. The IFZ value is a common index (Huang et al. 2010) for this purpose and can be interpreted as the normalized distance between a pixel value of multi-spectral satellite imagery...
and the value of a previously identified, reference forest pixel. When a small IFZ value is produced for a given year, this suggests an area of relatively stable mature forest. Large IFZ values, on the other hand, indicate areas where major disturbances have recently occurred. The IFZ value is computed using the mean and standard deviation of identified forest regions within the satellite imagery. An identified forest region is a group of pixels which were manually selected to represent forest areas. Calculation of the IFZ value for each pixel within an image begins with the calculations of stand Z-score ($FZ_{jik}$) for each pixel $j$ in each band $i$ for each year $k$.

\[ FZ_{jik} = \frac{b_{jik} - \bar{b}_i}{SD_{ik}} \quad \forall i, j, k \]

where:
- $b_{jik}$ = surface reflectance value of pixel $j$ in band $i$ during year $k$
- $\bar{b}_i$ = the mean surface reflectance of forest regions of training areas in band $i$ during year $k$
- $SD_{ik}$ = the standard deviation of surface reflectance for forest regions of training areas in band $i$ during year $k$

Each $FZ_{jik}$ is then integrated into a single scalar value for each pixel $j$ during each year $k$, $IFZ_{ik}$, using the following formula:

\[ IFZ_{jk} = \sqrt{\sum_{i=1}^{NB}(FZ_{jik})^2} \quad \forall j, k \]

Where: $NB$ = the number of bands used

Three bands (red, shortwave infrared-1, and shortwave infrared-2) were used to determine the IFZ value. The actual band numbers used in this computation were bands 3, 5 and 7 (Landsat 5) and bands 4, 6 and 7 (Landsat 8). In calculating the mean and standard deviation values for forest regions, 15 training areas were selected to represent coniferous forests and another 15 training areas were selected to represent broadleaf forests. The area of each individual training region was about 100 ha.

2.5. Image classification

The classification algorithm was created to detect the most recent disturbance year of forests in our study area. The algorithm computed the IFZ value for each pixel and each year of the time series. The resulting series of IFZ images was then used to compute the difference in IFZ values between two consecutive images along the series. This allowed a determination of whether a pixel should be categorized as either disturbed or undisturbed. A large difference in IFZ values between consecutive scenes in the series indicated the occurrence of a major disturbance. Non-disturbance related features are represented by minor variations in IFZ values. The chronological order of the application of the algorithm was from the most distant year (1984) to the most current year (2016). For each pixel in year $k$, when all the following conditions were met, the pixel was updated in year $k + 1$ as having been disturbed.

(a) In year $k$, the IFZ value is lower than $x$.
(b) The difference in IFZ values between year $k$ and $k + 1$ is greater than $x$.
(c) Through year $k + 1$ to $k + y$, the IFZ value is larger than $x$.

Here, $x$ is set to 3 for two reasons. First, Huang et al. (2009) used $x = 3$ in their analysis. Second, we confirm through the comparison between IFZ value and satellite imagery that pixels of IFZ $< 3$ are forest. Also, $y$ is set to 3 years in the algorithm since IFZ value of the most of the pixels disturbed was greater than 3 for two more years since the year of disturbance. If any of the conditions noted above are not met, the pixel was considered not disturbed in year $k + 1$. If these three conditions are met in more than one year in the time horizon (1984 to 2016), the pixel was
noted as being last disturbed in the most recent year to 2016. This allowed a determination of the current age of the forest represented by the pixel. As the algorithm requires IFZ value for the year before disturbance, the algorithm began detecting disturbances in 1985. For years 2015 and 2016, \( x \) was assumed to be 2 and 1 years, respectively. Due to the unavailability of the imagery in 1993 and 2012, the algorithm used a slightly different process for years \( k - 3 \) to \( k - 1 \) when \( k = 1993 \) or 2012. For \( k - 3 \), \( x \) was assumed to be to 2 years. For \( k - 2 \), condition (c) was modified:

\[
(c') \text{ In year } k + 1 \text{ and } k + 3, \text{ the IFZ value is larger than 3.}
\]

For \( k - 1 \), conditions (b) and (c) were modified:

\[
(b') \text{ The difference in IFZ values between year } k \text{ and } k + 2 \text{ is greater than 3.}
\]

\[
(c'') \text{ In year } k + 2 \text{ and } k + 3, \text{ the IFZ value is larger than 3.}
\]

For year \( k \) (1993 or 2012), the algorithm does not evaluate each pixel. The algorithm was implemented in the \( R \) programming language.

### 2.6. Accuracy assessment

An accuracy assessment of the classification process was conducted in an attempt to validate the quality of the age class prediction through the forest disturbance maps. One hundred sampling points per year (1984-2016) were randomly selected across the landscape applying a stratified sampling method to generate the points. The total number of sampling points for this purpose was 3,100. For each sampling point, the specific year of the last disturbance was recorded, as evidenced using the reference data noted above. The land use for each point in each year was also visually inspected by using reference data. Two types of classification accuracy were determined, the first using user’s and producer’s accuracy values reflecting exact (to the year) coincidence of the classified maps and the reference data. The second allows a ±1-year deviation from the reference data, as a ±1-year deviation from the reference data was frequently observed due to cloud coverage and other temporal misalignments of implemented practices and the satellite imagery.

### 3. Results

The process employed in this study produced a disturbance map (Figure 2) that illustrates the years of the most recent major disturbances. Our assumption is that these years correlate directly with the initiations of a new stands assuming that forestry will continue to be the designated land use after occurrence of the major disturbance, such as final harvest and that the landowner or land manager will begin preparation of the new forest soon after the disturbance.

A typical final harvest produces a significant change in the IFZ value, and over time, the IFZ value will return to a range of normal values for these forests. Figure 3 illustrates through true color composite (images on the left) and through IFZ value images (to the right) how the landscape would be perceived when a major disturbance occurred in 2001. As time progresses and assuming forestry remains the dominant use of the land area, the imprint of the final harvest gradually diminishes in both true color and IFZ value representations. The change, or difference, that is noted between years 2000 and 2001, if significant enough, would prompt the algorithm to conclude that a major disturbance had occurred. When IFZ values for the land area are plotted over time (Figure 4), the change in IFZ value is more dramatic between 2000 and 2001. The minor variation in IFZ value amongst the earlier years is likely a function of local weather conditions and date of acquisition; therefore, the threshold change in IFZ amongst adjacent years (noted earlier) would have prevented the algorithm from concluding a disturbance had occurred in other years when differences among subsequent years were observed.

The result of the accuracy assessment for the 3,100 reference points suggests that the overall accuracy of the classification process was 52% (Table 1). If a ±1 year of error is allowed, the relaxed overall accuracy rises to 71%. Concerning this accuracy assessment, it is worth noting that imagery from Google Earth generally has a higher spatial resolution than Landsat imagery. The historical image tool in Google Earth automatically provides the imagery which has the highest spatial resolution of all the imagery that Google can serve. Imagery captured after 2005 has higher spatial resolution.
Figure 2. Subset of disturbance map. Dates represent most recent disturbance for the period. The class value of -99 (black color on the map) represents the pixels which are identified by our algorithm as either persistent forest, persistent non-forest between 1984 - 2016.

Figure 3. (a) Time series true color composite of Landsat 5 TM imagery, and (b) time series IFZ value map.

Figure 4. Annual IFZ values of the pixel on which disturbance occurred in 2001.
spatial resolution than that of Landsat 5 TM imagery, which is 27.5 meters. Thus, Google Earth allows one to detect the subtle changes in forest character that may not be detectable with Landsat 5 and 8 imagery.

We created a box-and-whisker plot for major disturbances (Figure 5) that illustrates the magnitude of the difference between our predicted year of disturbance and the reference data. This analysis illustrates large differences between subclasses (individual years); annual user’s accuracy ranges between 40% and 90%. User’s accuracy in the early 1980s is low because pixels disturbed after 2005 may have been misclassified to subclasses of 1980s for reasons such as cloud cover (missing the disturbance) or other anomalies. User’s accuracy is better than overall accuracy in the 1990s and 2000s. In 2014, the user’s accuracy is lower perhaps due to the combined effect of cloud cover and the lack of imagery in 2012. Nonetheless, from 1991 forward the accuracy of the classification process has been approximately 70%. The process to place a forest initiation date on even-aged forests that are 25 years old (a typical even-aged rotation age) or lower in the lower Coastal Plain of the southeastern United States seems plausible.

![Figure 5. Box-and-whisker plot for major disturbances. For each year, the thick horizontal bars represent median, the rectangles are 25 to 75 percentile range and dashed vertical lines cover maximum and minimum values.](image)

We also estimated the area of major forest disturbance in each year between 1984 and 2016 (Figure 6). The disturbed area for each year ranged from 1,118 ha to 27,989 ha. Mean annual disturbance over the period is 10,238 ha. In four of these years, many pixels were detected as having been disturbed. The size of the disturbed area in these years is more than mean over time plus one standard deviation over time. Fluctuations in regional and global markets (and economies) may explain some of this variation. Furthermore, since the study area was a sub-set of the markets for several major wood demand centers, it seems plausible that harvest activity could have shifted into and out of the area from one year to the next. Interestingly, the area of disturbance has an increasing trend over time, and about 32% of the land area within our area of interest is disturbed at least once in the last 32 years. Previous reports regarding the forest cover status of the southern United States have suggested that commercial, reserved, deferred, and unproductive forest areas accounted for about 45.7% of the landscape in 2012 (Oswalt et al. 2014). Given the long history of forest management in the southern United States (U.S. Department of Agriculture 1988), activity on 32% of the forests over 32 years does not seem unreasonable.
Table 1. Error matrix of accuracy assessment.

| Reference | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2013 | 2014 | 2015 | 2016 | RT | UA | RUA |
|-----------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|-----|-----|-----|
| Projection | -99  | 68   | 2    | 1    | 1    | 1    | 2    | 1    | 1    | 1    | 2    | 1    | 1    | 2    | 1    | 1    | 2    | 1    | 1    | 2    | 1    | 1    | 2    | 100  | 88% | 88% |
| 1985      | 25   | 39   | 9    | 4    |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      | 100  | 89% | 89% |
| 1986      | 18   | 12   | 32   | 9    |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      | 100  | 83% | 83% |
| 1987      | 8    | 12   | 50   | 4    | 1    | 1    | 1    | 1    | 1    | 3    | 6    | 4    | 2    | 100  | 78% | 78% |
| 1988      | 21   | 1    | 42   | 3    |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      | 100  | 70% | 70% |
| 1989      | 12   | 31   | 36   | 2    | 1    |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      | 100  | 66% | 66% |
| 1990      | 24   | 2    | 31   | 5    | 3    | 1    | 1    | 1    | 1    | 1    | 3    | 3    | 2    | 100  | 51% | 51% |
| 1991      | 5    | 27   | 44   | 3    | 1    | 1    | 1    | 1    | 1    | 1    | 1    | 1    | 1    | 100  | 51% | 51% |
| 1992      | 14   |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 1993      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 1994      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 1995      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 1996      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 1997      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 1998      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 1999      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2000      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2001      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2002      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2003      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2004      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2005      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2006      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2007      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2008      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2009      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2010      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2011      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2012      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2013      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2014      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2015      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2016      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |

CT: Column total, PA: Producer's accuracy, RPA: Relaxed Producer's accuracy.
4. Discussion

As this is a preliminary assessment of a process for determining an age classification of lower Coastal Plain forests in the southeastern United States, some processing challenges were encountered. Many testing areas of land that were actually disturbed around 2010 were not classified to an age class of this vintage. Instead, they are misclassified to the earlier age class (mainly before 1980). Individual visual observation of these age classes using Google Earth and Landsat imagery reveal that our algorithm failed to reliably detect the disturbances around 2010. This might be because we did not use imagery from 2012 and the forest vegetation (as described by the IFZ value) recovered rather quickly. Additionally, given the lack of imagery in 2012, and depending on the relationship between the time of activity and the time of data capture via the satellite, some disturbances from 2012 were likely attributed to 2013. Since the magnitude of the difference in pre- and post-disturbance IFZ values is greatest when the time interval is only one year, we conclude that more frequent (i.e., semi-annual) temporal assessments may be necessary to best ascribe an establishment age to an even-aged forest in the landscape we are studying.

The presence of cloud cover and its differences between adjacent years of imagery can also cause problems in comparing annual IFZ values (and thus determining whether a major disturbance has occurred). Although we selected the imagery with the least cloud coverage for each year, some imagery still contained more than 20% cloud cover. Some of these clouded areas that were masked from the analysis contained forests, and thus it is possible that high cloud cover ratio affects the ratio of forest in our area of interest. Along these lines, another possible factor affecting the accuracy of the classification involves thin, cirrus clouds. Some thin clouds were not recognized and masked by the CFMask process and the resulting IFZ values were likely affected in these areas.

The lower Coastal Plain of the southeastern United States provides the climate and substrate for vegetation to establish and grow very quickly. The dormant season (generally December to March) is short and herbaceous and small woody vegetation can grow quickly in spring. Therefore, beyond the environmental and technical challenges noted above, more consideration likely needs to be directed to the impact of the form of forest management on the IFZ value that is computed. As an example, assume that the Landsat imagery for an area was captured in June 2009. Later, in July 2009 a final harvest may have been applied to this area. The next Landsat imagery may have been captured in June 2010. During the intervening 11 months, the forest landowner may have had the site prepared the area (chopped, burned, piled, or raked the debris and perhaps bedded the ground) or applied a chemical treatment to control the vegetation that would compete for resources with planted trees. Depending on the timing of these activities, the land area may have been given an IFZ value that would prompt the system to conclude a disturbance had occurred. However, had the land area recovered quickly with pioneering vegetation, or had the landowner delayed (or avoided) site preparation and chemical vegetation control treatments, it is plausible that the difference in IFZ value between two subsequent satellite images may not have been dramatic enough for the process to conclude that a major disturbance had occurred. This would also lead us to conclude that more
frequent (i.e., semi-annual) temporal assessments may be necessary to best ascribe an establishment age to an even-aged forest in the landscape we are studying.

4. Conclusions

The algorithm presented here, which is similar to the Vegetation Change Tracker and other methods for automatic detection of changes in land use, was developed to help understand the age class distribution of current forests in the lower Coastal Plain of the State of Georgia (USA). The algorithm relied on three bands (visible and infrared regions) within Landsat data and a long time series of growing season images to determine when major forest disturbance events occurred. It was moderately successful in determining the years of disturbances and current age classes of forests in this region, given that many of them are managed as even-aged stands. The development and its testing met some technological challenges. The lack of suitable imagery for two years required modifications to the mathematical assessment of the integrated forest Z score (IFZ value), and the presence of cloud cover, ubiquitous to the area during the growing season, may have led to some classification errors. More specifically, cloud cover, when masked from the analysis, could have required examining non-adjacent years for evidence of disturbance, which may have added to classification error.

Acknowledgement

This graduate research is funded by Japan Student Service Organization. This work was also supported by the U.S. Department of Agriculture, National Institute of Food and Agriculture, McIntire-Stennis project 1012166, administered by the University of Georgia. We thank our colleagues from the University of Georgia Warnell School of Forestry and Natural Resources who provided valuable advice and expertise that greatly assisted the research.

References

Bettinger, P., Boston, K., Siry, J.P., Grebner, D.L. (2017) Forest Management and Planning, 2nd edition. Academic Press, New York.

Brooks, E.B., Wynne, R.H., Thomas, V.A., Blinn, C.E., Coulston, J.W. (2014) On-the-fly massively multitemporal change detection using statistical quality control charts and Landsat data, IEEE T, Geosci. Remote. 52: 3316-3332.

Cieszewski, C.J., Zasada, M., Borders, B.E., Lowe, R.C., Zawadzki, J., Clutter M.L., Daniels R.F. (2004) Spatially explicit sustainability analysis of long-term fiber supply in Georgia, USA, Forest Ecol. Manag. 187(2-3): 349-359.

Cieszewski, C.J., Liu, S., Lowe, R.C., Zasada M. (2011) Spatially explicit biomass supply sustainability analysis for bioenergy mill siting in Georgia, USA, The Open Forest Sci. J. 4: 2-14.

Chen, J., Zhu, X., Vogelmann, J.E., Gao, F., Jin, S. (2011) A simple and effective method for filling gaps in Landsat ETM+ SLC-off images, Remote Sens. Environ. 115: 1053-1064.

Georgia Forestry Commission (2018) Conservation Reserve Program (CRP), <http://www.gfc.state.ga.us/forest-management/private-forest-management/landowner-programs/other-landowner-programs/> (Accessed 12 February 2018).

Goward, S.N., Huang, C., Zhao, F., Schleeweis, K., Rishmawi, K., Lindsey, M., Dungan, J.L., Michelis, A. (2015) NACP NAFD project: Forest disturbance history from Landsat, 1986-2010, ORNL DAAC, Oak Ridge, TN.

Huang, C., Goward, S.N., Schleeweis, K., Thomas, N., Masek, J.G., Zhu, Z. (2009) Dynamics of national forests assessed using the Landsat record: Case studies in eastern United States, Remote Sens. Environ. 113: 1430-1442.
Huang, C., Goward, S.N., Masek, J.G., Thomas, N., Zhu, Z., Vogelmann, J.E. (2010) An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks, *Remote Sens. Environ.* 114: 183–198.

Jin, S., Yang, L., Danielson, P., Homer, C., Fry, J., Xian, G. (2013) A comprehensive change detection method for updating the National Land Cover Database to circa 2011, *Remote Sens. Environ.* 132: 159–175.

Kennedy, R.E., Yang, Z., Cohen, W.B. (2010) Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr – Temporal segmentation algorithms, *Remote Sens. Environ.* 114: 2897–2910.

Liu, S., Cieszewski, C. (2009) Impacts of management intensity and harvesting practices on long-term forest resource sustainability in Georgia, *Math. Comput. Forestry Nat.-Res. Sci.* 1(2): 52–66.

Obata, S. (2018) Estimation of forest stand disturbance through implementation of vegetation change tracker algorithm using Landsat time series stacked imagery in coastal Georgia, *Math. Comput. Forestry Nat.-Res. Sci.* 10(1): 32.

Oswalt, S.N., Smith, W.B., Miles, P.D., Pugh, S.A. (2014) *Forest resources of the United States, 2012: A technical document supporting the Forest Service update of the 2010 RPA Assessment*, USDA Forest Service, Washington, D.C. General Technical Report WO-91.

Roy, D.P., Wulder, M.A., Loveland, T.R., Woodcock, C.E., Allen, R.G., Anderson, M.C., ..., Scambos, T.A. (2014) Landsat-8: Science and product vision for terrestrial global change research, *Remote Sens. Environ.* 145: 154–172.

U.S. Department of Agriculture (1988) *The South’s Fourth Forest: Alternatives for the Future*, USDA Forest Service, Washington, D.C. Forest Resource Report No. 24.

U.S. Geological Survey (2017) EarthExplorer, <https://earthexplorer.usgs.gov/> (Accessed 21 June 2017).

Vogelmann, J.E., Xian, G., Homer, C., Tolk, B. (2012) Monitoring gradual ecosystem change using Landsat time series analyses: Case studies in selected forest and rangeland ecosystems, *Remote Sens. Environ.* 122: 92–105.

Zhu, Z., Woodcock, C.E., Holden, C., Yang, Z. (2015) Generating synthetic Landsat images based on all available Landsat data: Predicting Landsat surface reflectance at any given time, *Remote Sens. Environ.* 162: 67–83.