Dynamics of national forests assessed using the Landsat record: Case studies in eastern United States

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The national forests (NFs) in the United States are protected areas managed for multiple purposes, and therefore are subject to both natural and anthropogenic disturbances. Monitoring forest changes arising from such disturbances and the post-disturbance recovery processes is essential for assessing the conditions of the NFs and the effectiveness of management approaches. In this study, we used time series stacks of Landsat images (LTSS) to evaluate the dynamics of seven NFs in eastern United States, including the De Soto NF, the Talladega NF, the Francis Marion NF, and the Uwharrie NF in southeastern U.S., and the Chequamegon NF, the Hiawatha NF, and the Superior NF in northern U.S. Each LTSS consisted of 12–14 Landsat images acquired for the same location, spanning from 1984 to 2006 with a nominal interval of one image every 2 years. Each LTSS was analyzed using a vegetation change tracker (VCT) algorithm to map forest disturbance. Accuracy assessments of the derived disturbance maps revealed that they had overall accuracy values of about 80%, with most of the disturbance classes having user’s accuracies ranging from 70% to 95%. The producer’s accuracies were generally lower, with the majority being in the range between 50% and 70%. While this may suggest that the disturbance maps could slightly underestimate disturbances, a more detailed assessment of the omission errors revealed that the majority of the disagreements were due to minor disturbances like thinning or storm damages that were identified by the image analysts but were not captured by the VCT algorithm.

The derived disturbance year maps revealed that while each of the seven NFs consisted of 90% or more forest land, significant portions of the forests were disturbed since 1984. Mapped disturbances accounted for about 30%–45% of total land area in the four NFs in southeastern U.S. and about 10%–20% in the three NFs in northern U.S. The disturbance rates were generally higher in the buffer zones surrounding each NF, and varied considerably over time. The time series approach employed in this study represents a new approach for monitoring forest resources using the Landsat or similar satellite data records. The disturbance products derived using this approach were spatially explicit and contained much more temporal details than conventional bi-temporal change products, and likely will be found more useful by many users including ecologists and resources managers. The high disturbance rates found in the southeastern U.S. suggest that this region may have a more significant role in modulating the atmospheric carbon budget than currently recognized.

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1. Introduction

The national forests (NFs) in the United States were created for the purposes of improving and protecting land, securing favorable waterfows, and providing a continuous supply of timber. These are protected areas managed for multiple purposes, including outdoor recreation, range, timber, watershed, and wildlife and fish (USDA, 2007), and therefore are subject to disturbances arising from various management activities as well as natural events such as fire, storm, and insect and disease damages. Continuous monitoring of forest changes arising from such disturbances and the post-disturbance recovery processes is essential for assessing the conditions of the NFs and the effectiveness of management approaches, and for developing sound management strategies that will allow the NFs to provide a sustainable supply of goods and services.

In this paper we present a study of forest dynamics within and around seven NFs in eastern U.S., including four in southeastern U.S.
and three in northern U.S. This study was derived from a larger project — North American Forest Dynamics (NAFD) funded by the North American Carbon Program (NACP) as part of an effort to balance the carbon budget for the North America. One of the many goals of this project was to evaluate forest disturbance and regrowth history for the conterminous U.S. using the Landsat record dating back to 1972. This goal was achieved by analyzing forest changes using time series stacks of Landsat images for locations selected across the country using a probability based sampling design (Kennedy et al., 2006). The NFs evaluated in this study intersected with the sample locations used in the NAFD project (see Section 2.1).

The Landsat record is a unique data source for monitoring NFs. Each Landsat image has a relatively large footprint (approximately 180 km x 180 km), and yet the fine spatial resolutions can provide the spatial details necessary for characterizing many of the changes arising from natural or anthropogenic disturbances (Townshend & Justice, 1988). In addition, with images available as early as 1972, this record makes it possible to analyze changes over the last 30+ years. Numerous studies have been conducted to analyze forest change using Landsat images. Comprehensive reviews of different change detection techniques using satellite imagery have been provided in a number of publications (e.g. Singh, 1989; Coppin et al., 2004; Lu et al., 2004). Many studies were concerned with changes between two dates evaluated using bi-temporal change detection algorithms (e.g. Malila, 1980; Nelson, 1983; Genc & Smith, 2003), while bi-temporal and multi-temporal change detection techniques have also been used to analyze changes between multiple dates (e.g. Cohen et al., 1998; Miller et al., 1998; Franklin et al., 2002; Yang & Lo, 2002; Healey et al., 2005). Use of multiple image acquisitions in change analysis over a relatively long period (e.g., a decade or longer) is necessary not only for understanding the temporal variability of changes but also for capturing transient changes, especially in regions where trees grow rapidly. For example, we have noticed that in the southeastern U.S., the spectral signal of a forest harvest may degrade quickly due to rapid regrowth, and can become spectrally indiscernible in just a few years. Significant portions of such changes likely will not be captured if change analysis is performed using sparse image acquisitions (Lunetta et al., 2004; Masek et al., 2008).

In this study, time series stacks of Landsat (LTSS) images with a nominal temporal interval of 2 years were used to analyze forest changes within and around the selected NFs. Each LTSS consisted of more than ten images spanning from about 1984 to 2006. Use of existing change detection methods to analyze the LTSS was determined extremely inefficient because most of those methods could handle only 2 or 3 images at a time and typically required intensive human inputs. To improve the efficiency of forest change analysis using LTSS, we have developed a highly automated change detection algorithm called vegetation change tracker (VCT), which can be used to analyze all images of a LTSS at the same time. The major goal of this study is to use the VCT algorithm to evaluate the dynamics of the seven selected NFs in eastern U.S. for the period between 1984 and 2006. In the following sections we first describe the study areas,
preprocessing of the Landsat images, the change mapping method, and validation approaches. The derived results are then presented, followed by discussions and conclusions.

2. Data and methods

2.1. Study areas

Seven NFs in eastern United States were selected for this study, including three in north central U.S. and four in southeastern U.S. (Fig. 1). These NFs were selected to represent different forest ecosystems and disturbance regimes along the latitudinal gradient in eastern U.S. to the degree allowed by available satellite data. Most of the selected NFs extended beyond the nominal frame of one Landsat image as defined by the tiling system of the World Reference System (WRS). Due to data budget constraints, however, images were acquired for only one WRS tile for each NF. Only the portion of each NF that intersected with the selected WRS tile was considered in this study. Boundaries of the selected NFs were based on the Federal Owned Land data set of the ESRI Data and Maps product that accompanied the ARCGIS software. Table 1 lists the selected NFs, the WRS tiles where LTSS were assembled, and the area and percentage of each NF within the corresponding WRS tile. Through the remaining sections of this paper, all characterizations of the seven NFs were based on the portion that intersected with the corresponding WRS tiles as shown in Fig. 1 and Table 1.

2.2. Landsat imagery

For each selected WRS tile, we acquired a time series stack of Landsat (LTSS) images with a nominal interval of one image every 2 years for the period between roughly 1984 and 2006. This biennial image interval was necessary in order to minimize possible omission errors in detecting disturbances. We have noticed that in the southeastern U.S. and other areas where trees grow rapidly, even a stand clearing harvest can be replaced by thick young forests in just a few years, which are often spectrally similar to undisturbed forests. As a result, a harvest event may not be spectrally detectable if no image is acquired immediately after the event.

The LTSS consisted of mostly Thematic Mapper (TM) images. From 1999 to 2003, we considered both TM and Enhanced Thematic Mapper Plus (ETM+) images and selected the least cloudy one for a particular target year. To avoid processing complications arising from dealing with data gaps caused by the Scan Line Corrector (SLC) failure that occurred in May 2003, no ETM+ images acquired after that date were used in this study. All selected images were acquired during the growing season, which was defined to be between mid-June and mid-September for mid- and high latitude regions but was relaxed to include May and October in southeastern U.S. Images acquired during or near the leaf-off season were not considered, because due to spectral confusions between leaf-off deciduous forests and disturbed forest land, leaf-off images were generally not suitable for land cover change analysis. Table 2 lists the acquisition dates of all images selected for the seven WRS tiles. Notice we did not make distinction between TM and ETM+ images in the list because the two types of images had very similar spatial and spectral characteristics and there was essentially no difference between them in terms of the preprocessing and change mapping algorithms described below.

2.3. High level image preprocessing

The raw images we received from the data vendor were geometrically and radiometrically corrected by the data vendor using standard systematic correction methods (Landsat Project Science Office, 2000). These images typically contained considerable geometric errors because no ground control points were used in the standard correction and the correction did not deal with terrain effects. In this study, these images were further corrected using high level correction algorithms to reduce the geometric and radiometric
errors. For radiometric correction, the images were re-calibrated using recently updated calibration coefficients to improve absolute calibration accuracy of the Landsat 5 TM images. This step was not necessary for the Landsat 7 images because the initial calibration of those images by the data vendor was deemed accurate. The images were then converted to top-of-atmospheric (TOA) reflectance according to Markham and Barker (1986) and the Landsat 7 Science Data User’s Handbook (Landsat Project Science Office, 2000). To further reduce atmospheric effect, the images were corrected using an atmospheric correction algorithm adapted from the MODIS 6S radiative transfer approach (Vermote et al., 2002). Validation of the derived Landsat surface reflectance using simultaneously acquired MODIS daily reflectance products revealed that the discrepancies between the two products were generally within the uncertainty of the MODIS products themselves — the greater of 0.5% absolute reflectance or 5% of the retrieved reflectance value (Masek et al., 2006).

Geometrically, the images were corrected through the following two steps:

- Precise identification of satellite obit as represented by the nadir view of a target image using an orthorectified base image and tie-points: For each WRS tile, we used the orthorectified GeoCover image (Tucker et al., 2004) acquired in the 1990s as the base image. Tie-points between a target image and the base image were identified automatically using a correlation algorithm (Kennedy & Cohen, 2003).
- Orthorectification according to the viewing geometry of the satellite and a digital elevation model (Schowengerdt, 1997): For the digital elevation model we used the elevation data set produced through the Shuttle Radar Topography Mission (SRTM) program (Rabus et al., 2003), which had better spatial resolutions and should be more accurate than the elevation data sets used to create the GeoCover images (Tucker et al., 2004).

Comprehensive visual assessments of the orthorectified images revealed that image-to-image registration errors among the images were generally within one TM pixel.

2.4. Forest change mapping

The LTSS produced through the above high level preprocessing procedures were used to map forest disturbances using a method called vegetation change tracker (VCT). This method differs from most existing land cover change detection methods in that it automatically detects and tracks changes by analyzing all images of a LTSS at the same time, which allows it to take advantage of the rich temporal information of the LTSS in characterizing forest, non-forest, and disturbance. It is very efficient. For each LTSS, it took less than 4 h for the current version of this algorithm to produce the disturbance products described in Section 3.1, which, based on our experiences in forest cover change analysis using bi-temporal change detection techniques, could take an experienced image analyst at least ten days or much longer. Another algorithm capable of analyzing image stacks similar to the LTSS as a whole was a trajectory-based change detection algorithm developed by Kennedy et al. (2007). No comparison has been made between that method and the VCT algorithm yet. Here we provide a brief description of the VCT algorithm. Detailed description of all components of this algorithm is beyond the scope of this paper and will be reported in a separate paper.

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4 The GeoCover 1990 data set has a nominal acquisition year of 1990. Due to data availability and cloud contamination, the actual acquisition year for each WRS tile can be different.

5 Both the SRTM and GeoCover data sets were obtained from the Global Land Cover Facility at http://www.landcover.org/index.shtml.
The VCT algorithm consists of two major steps. During the first step, each image of a LTSS is analyzed independently to create a mask and to calculate an integrated forest z-score index (IFZ). This step is called single image masking and normalization. Once this step is complete for all images of a LTSS, the derived forest index images are stacked to form an IFZ time series for each pixel, which is then analyzed to detect and track forest changes.

2.4.1. Single image masking and normalization

The major goal of this step is to use the spectral signature of known forest pixels within each image to normalize that image. Suppose the mean and standard deviation of the band i spectral values of known forest pixels within an image are \( \overline{b_i} \) and \( SD_i \), respectively, then for any pixel \( b_{io} \) in that image, a forest z-score (IFZ) value for that band can be calculated as follows:

\[
IFZ_i = \frac{b_{io} - \overline{b_i}}{SD_i}
\]

For multi-spectral satellite images, the IFZ value of each pixel is defined by integrating \( IFZ \) over the spectral bands as follows:

\[
IFZ = \left( \frac{1}{NB} \sum_{i=1}^{NB} (IFZ_i)^2 \right)^{\frac{1}{2}}
\]

where NB is the number of bands used. For Landsat TM and ETM+ images, bands 3, 5, and 7 are used to calculate the IFZ. Bands 1 and 2 are not used because they are highly correlated with band 3. The near infrared band (band 4) is excluded because, while forest canopy typically has high reflectance values in this band, non-forest surfaces can have high or low reflectance values in this band depending on the non-forest cover type. As a result, forest disturbances do not necessarily lead to spectral changes in a particular direction in this band, and spectral changes in this band do not necessarily indicate real disturbances.

Notice that if the spectral signature of forest pixels has a normal distribution, \( IFZ_i \) can be directly related to the probability of a pixel being a forest pixel using the Standardized Normal Distribution Table (SDST) published in statistical textbooks (e.g., Davis, 1986). As the root sum square of \( IFZ_i \), IFZ can be interpreted similarly. While the forest pixels within a Landsat image may not have a rigorous normal distribution in all bands, an approximate probability interpretation of \( IFZ_i \) and \( IFZ \) makes it possible to use probability based threshold values later on during time series analysis that might be applicable to images acquired in different dates over different places. An intuitive interpretation of \( IFZ \) is that it is an inverse measure of the likelihood of a pixel being a forest pixel. Pixels having low IFZ values near 0 are close to the spectral center of forest samples and therefore have high probability of being forest pixels, while those having high IFZ values are likely non-forest pixels.

For each satellite image, confident forest samples are delineated using a dark object approach (Huang et al., 2008). This approach is based on a well known observation that, due to substantial shadows cast within tree canopy, forest is generally darker than most other vegetated surfaces in the visible and shortwave infrared bands (Colwell, 1974; Goward et al., 1994; Huemmrich & Goward, 1997). In a histogram created using a local image window consisting of substantial forest pixels, those forest pixels are located towards the lower end of the histogram and often form a peak called forest peak. Automatic delineation of forest pixels is achieved by locating the forest peak and then thresholding the local image window using threshold values defined by the forest peak. A detailed description of this dark object approach for delineating confident forest pixels has been provided by Huang et al. (2008).

Although every effort was made to select cloud free images in assembling the LTSS, due to data availability constraints some images contained small portions of cloud cover. To minimize the risk of clouds over forest being mapped as disturbances, a cloud and shadow masking algorithm was applied to each image to mask out clouds and shadow. This algorithm uses the forest samples delineated using the above described method as reference and makes use of spectral, thermal, spatial, and elevation information. Detailed description of the cloud algorithm will be reported separately along with the VCT algorithm.

2.4.2. Tracking forest change using the IFZ

Because IFZ measures the likelihood of a pixel being a forest pixel, its change over time can be used to track forest changes. For pixels masked as cloud or shadow in the single image masking and normalization step (see Section 2.4.1), their IFZ values were calculated through linear interpolation using good observations (i.e., not contaminated by cloud or shadow) that were acquired in the years immediately before and after the concerned acquisition year. Fig. 2 shows the typical temporal profiles of the IFZ for major forest cover change processes. For a persisting forest pixel that did not experience disturbance during the entire observing period of a LTSS, the IFZ value stays low and is stable throughout the monitoring period (Fig. 2(A)). The occurrence of a major disturbance will result in a sharp increase in the IFZ value in the image acquired immediately after the disturbance (Fig. 2(B)). The acquisition year of that image is defined by the VCT algorithm as the disturbance year for that disturbance, although the actual disturbance year can be that year or any year between that year and the available previous image acquisition. A less dramatic change will result in a moderate increase in the IFZ value (Fig. 2(C)). For recovery from a disturbance that occurred before the acquisition of the first image in the LTSS or conversion from non-forest to forest, the IFZ will start with high values but will go down gradually as the trees grow (Fig. 2(D)). Finally, the IFZ is generally all time high for persisting non-forest land. For cropland the IFZ may also fluctuate greatly as surface conditions change from one year to another due to harvesting and crop rotation (Fig. 2(E)).

The very distinctive IFZ temporal profiles for different forest cover change processes allow identification of those change processes using the following simple rules:

- Pixels having low IFZ values throughout the entire observing period are classified as persisting forest;
- Pixels having low IFZ values for at least two consecutive observations but not for the entire observing period are classified as disturbed forest pixels. The disturbance year is determined as the acquisition year when the IFZ value increases sharply from a low level (Fig. 2(B));
- Pixels having high IFZ values or having undulating IFZ values throughout the entire observing period are classified as persisting non-forest.

It should be noted that while only the IFZ is used here to track forest changes, the band specific IFZ values could be used to determine change types such as logging or fire. These issues are still being investigated and the results will be reported separately.

2.4.3. Disturbance products produced by the VCT algorithm

The VCT algorithm calculates two attributes for each detected disturbance — disturbance year and disturbance magnitude (Fig. 2(B)). As discussed earlier, the disturbance year for a detected disturbance is defined by the acquisition year of the image in the concerned LTSS that is acquired immediately after the occurrence of that disturbance. When the disturbance year is the first acquisition year of a LTSS, this disturbance is called pre-observation disturbance (Fig. 2(D)). This disturbance category not only includes pixels that were disturbed before the first image acquisition, but also includes conversion of previously non-forest land to forest. For a detected disturbance, its disturbance magnitude is calculated as the difference between the
IFZ value at the disturbance year and the mean IFZ value of forest observations within the concerned LTSS (indicated by the length of the double arrow shown in Fig. 2(B)). In the disturbance year map, pixels that remained water, forest, and non-forest are defined as persisting water, persisting non-forest, and persisting forest respectively, and an arbitrarily defined fill value is assigned to those pixels in the disturbance magnitude map. We hypothesize that the disturbance magnitude can serve as an indicator of whether a disturbance is a major or minor disturbance, where minor disturbances refer to partial removal of woody biomass caused by selective logging or storm damage, while major disturbances include stand clearing events such as clear cuts or stand replacement fires. Measurements of biomass change for known disturbances based on field work or high resolution images will be needed in order to test this hypothesis.

It should be noted that because trees grow rapidly in southeastern U.S., some forests can be harvested or disturbed more than once during the entire observing period. In a single layer disturbance year map, however, only a single disturbance can be recorded, although the VCT algorithm tracks all detected disturbances. In this study, the disturbance year maps recorded the first disturbance when multiple disturbances were detected for a pixel, and the validation and analysis described below were based on the first disturbance only.

2.5. Validation of the disturbance products

Validation of land cover products derived using satellite observations typically relied on independent reference data collected through ground based field work, visual interpretation of high resolution images, or both (Congalton, 1991; Stehman & Czaplewski, 1998). For the disturbance products derived in this study, however, such a validation approach has many practical difficulties. In order to validate the disturbance year product, for example, one would have to conduct field work or acquire high resolution images in each of the acquisition years of a LTSS. This would be impossible even with unlimited available resources, because 1) most of the required high resolution images do not exist, and 2) due to the natural growth of vegetation, one cannot reliably determine the ground conditions immediately before and after the occurrence of a disturbance through a field trip conducted at the time of disturbance.

Fig. 3. Visual validation of three mapped disturbances using pre- and post-disturbance Landsat images. The disturbance year map was selected from a 17.1 km by 11.4 km area from the Uwharrie NF. The size of the Landsat images as shown was 2.85 km by 2.85 km, which was zoomed in twice as compared with the disturbance year map.
mapping, which could be many years after the occurrence of that disturbance. To avoid these problems, we designed a hybrid approach to validate the disturbance year maps.

In the hybrid validation approach, we determined the disturbance year through visual inspection of all Landsat images of each LTSS. For most major disturbances the disturbance year determined this way should be reliable because 1) most forests are spectrally distinctive in Landsat images and can be easily separated from non-forest by experienced image analysts, 2) major disturbances often yield spectral change signals in the Landsat images that are significant enough to recognize, and 3) visual interpretation is one of the most reliable approaches for analyzing satellite images because of the ability of human eyes to combine spectral, spatial (including texture and contextual information), and temporal information in image analysis. Fig. 3 shows a disturbance year map for an area within the Uwharrie NF and the Landsat images acquired before and after the occurrence of major disturbances. The three disturbances can be reliably identified as pre-observation disturbance, persistent forest, and the Landsat images acquired before and after the occurrence of disturbances. The three disturbances can be reliably identified as pre-observation disturbance, persistent forest, and the Landsat images acquired before and after the occurrence of disturbances.

Due to the extensive effort required by this hybrid approach, it was used to validate the disturbance year products for one site in southeastern U.S. (WRS path 21/row 37) and one site in northern U.S. (WRS path 27/row 27). For each of the two WRS tiles, a stratified random sampling approach was used to select validation points. Specifically, the disturbance year map was used to define the strata where each class was a stratum. The number of points selected from each stratum was proportionate to its areal proportion within the concerned image tile. For rare classes where the number of points calculated this way was too low, it was increased to allow reliable calculation of class specific accuracy values. Points located along polygon edges as determined through visual inspection were moved such that they were at least 2 pixels away from any edge to avoid the difficulty in determining the reference label for such points arising from residual misregistration errors among the Landsat images. For each point, the surface conditions determined at the 1-m resolution for that particular date can be used as a reference by an image analyst in interpreting all Landsat acquisitions for that particular location.

The overall accuracy was 79.7%. Per class agreements are in bold face. Class code is defined as follows: 1 — pre-observation disturbance, 15–36 — disturbance year by adding 1970 to the code (e.g. 17 indicates a 1987 disturbance).

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<td>0.648</td>
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<td>0.487</td>
<td>0.560</td>
<td>0.776</td>
<td>0.773</td>
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<td>0.649</td>
<td>0.819</td>
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<td></td>
<td>0.797</td>
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</table>

The overall accuracy is 79.7%. Per class agreements are in bold face. Class code is defined as follows: 1 — persisting non-forest, 2 — persisting forest, 14 — pre-observation disturbance, 15–36 — disturbance year by adding 1970 to the code (e.g. 17 indicates a 1987 disturbance).
edge pixels only accounted for small portions of the total pixels within each LTSS, the potential biases in the derived accuracy estimates due to not including the edges in the accuracy assessment should be small. It is also worth noting that the residual misregistration errors among the Landsat images should not necessarily lead to the forest edges being more likely to be mapped as disturbances. Such edges could be mapped.

Fig. 4. Disturbance year maps for a 17.5 km by 10 km area selected within each of the seven NFs (A: De Soto, B: Talladega, C: Francis Marion, D: Uwharrie, E: Superior, F: Chequamegon, G: Hiawatha).
as disturbances only in the unlikely event when the misregistration errors had a temporal trend such that they caused the IZ profile for a persisting forest (Fig. 2(A)) to look like that for a disturbance (Fig. 2(B–D)).

For the remaining five sites concerned in this study (Table 1), the disturbance year maps were visually checked using the approach shown in Fig. 3. During the visual checking we picked a few windows from each disturbance map on an ad hoc basis and visually inspected those windows to evaluate whether each map contained substantially more errors, or it had a similar level of accuracy as the two maps that were assessed using the above described hybrid approach. The disturbance magnitude products were not validated in this study because neither the visual validation approach nor the hybrid approach could provide definitive validation information. As discussed earlier, measurements of biomass change for known disturbances based on field work or high resolution images will be needed for validating these products.

3. Results

3.1. The disturbance year products

Each of the seven LTSS listed in Table 1 was analyzed using the VCT algorithm to produce disturbance products. The disturbance year maps for two of the seven sites were validated using the hybrid approach described in Section 2.5. The derived confusion matrices for the two sites are given in Tables 3 and 4 respectively. The overall, user’s, and producer’s accuracies were calculated according to Stehman and Czaplewski (1998) and Stehman et al. (2003). At the per-pixel level, the overall accuracy was 79.7% for path 21/row 37 and 78.7% for path 27/row 27. Both sites had relatively high user’s accuracy values for the disturbance classes. While the lowest user’s accuracies were just over 50%, the majority of the disturbance classes had user’s accuracies of over 80% in path 21/row 37 and over 70% in path 27/row 27. The average user’s and producer’s accuracies were 80.6% and 68.8% for path 21/row 37 and 78.7% and 67.1% for path 27/row 27, respectively.

The confusion matrices reveal distinctive patterns of errors by the VCT algorithm. In both sites the VCT algorithm missed significant amount of changes and labeled them as persisting forest instead. The WRS path 21/row 37 site had 67 such samples whereas the WRS path 27/row 27 site had 64. The majority of those changes (52 of 67 for WRS path 21/row 37 and 44 of 64 for WRS path 27/row 27), however, were identified as minor changes by the analysts. The path 21/row 37 site also had a group of errors located below the diagonal of the confusion matrix (Table 3), indicating that many early-year disturbances in the reference data were mapped as disturbances in later years by the VCT algorithm. A re-examination of the 77 points that had this problem revealed that 49 of them had a minor disturbance in an early year followed by a major disturbance in a later year, which was detected correctly by the VCT algorithm. In other words, despite the errors below the diagonal of Table 3, the majority of the changes mapped by the VCT algorithm were disturbances that did occur in the mapped disturbance year. These two groups of errors revealed that the current VCT algorithm may miss significant portions of minor changes. On the other hand, the fact that the majority of the omission errors were attributed to pixels that experienced minor changes suggests that omission errors for major changes should be low, and therefore biases in change rates calculated using the VCT derived maps should be small for those major changes. Due to lack of ground information or high resolution data collected immediately after the occurrence of each disturbance, here the distinction between major and minor disturbances was determined by visually checking the post-disturbance Landsat images. After a minor disturbance, the post-disturbance pixels looked brighter and less green than the pre-disturbance pixels; but they still looked like forest pixels. For a major disturbance caused by clear cut or other stand replacing events, however, the post-disturbance pixels did not look like forests any more.

Another group of error found in both sites included small number of samples where the disturbance year only differed by one observation between the VCT and the reference data. Such errors were likely due to inconsistencies between the VCT algorithm and the analysts in determining the disturbance year for situations where selective logging occurred immediately before stand clearing harvests. The WRS path 27/row 27 site also had a group of 44 samples that were labeled as persisting non-forest by the analysts but were mapped as persisting forest or as disturbances by the VCT algorithm (Table 4). Based on the Landsat images and high resolution images obtained from the TerraServer (see Section 2.5) and Google Maps (http://maps.google.com/maps), most of those pixels were wetland pixels, which often looked dark and green and were difficult to separate from forest pixels. Use of a land cover map like the National Landsat Cover Dataset (NLCD) (Vogelmann et al., 2001; Homer et al., 2004) should reduce much of this type of confusions.

Visual validation of the disturbance year maps for the remaining five sites listed in Table 1 using the approach shown in Fig. 3 revealed that those disturbance maps should have similar accuracy values as those for the two sites discussed above. An example disturbance year map for each of the seven NFs is shown in Fig. 4. While most of the disturbances had shapes or linear edges that were indicative of the human origin of those disturbances, evidence of natural disturbance were also visible in these maps. For example, the sequence of 2003 disturbance patches in the Chequamegon NF (lower part of Fig. 4(F)) likely represented the path of a tornado touchdown.

3.2. Dynamics of the NFs

The disturbance year products allowed evaluation of the land cover dynamics of the seven NFs. For each NF, land cover composition and forest disturbance rates were derived from the disturbance year map. While those maps have both commission and omission errors, most of the errors were associated with minor disturbances (see Section 3.1). For major disturbances, the calculated change rates should be relatively reliable. For comparison, we also calculated disturbance rates for three buffer zones defined by distance of 0–5 km, 5–10 km, and 10–15 km from the boundary of each NF. As with the NFs, only the portion of a buffer zone that intersected with the corresponding WRS tile was considered in this study. In addition, because the management practices for wilderness areas and national parks most likely are different from those employed by private land owners, any wilderness areas or national parks that intersected with the buffer zones were excluded from the buffer zone analysis.

3.2.1. Land cover and disturbance characteristics

Table 5 summarizes the percentage of water, non-forest land and forest land within the seven NFs. The percentages of water and non-forest were directly calculated according to the persisting water and persisting non-forest classes in the disturbance year products, respectively. Forest land included both persisting and disturbed forest lands. Here disturbed forest refers to pixels that were mapped as

<table>
<thead>
<tr>
<th>NF name</th>
<th>Water (%)</th>
<th>Non-forest (%)</th>
<th>Forest (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>De Soto</td>
<td>0.1</td>
<td>8.9</td>
<td>91.0</td>
</tr>
<tr>
<td>Talladega</td>
<td>0.1</td>
<td>4.5</td>
<td>95.4</td>
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<tr>
<td>Francis Marion</td>
<td>0.6</td>
<td>6.5</td>
<td>92.9</td>
</tr>
<tr>
<td>Uwharrie</td>
<td>1.0</td>
<td>8.9</td>
<td>90.0</td>
</tr>
<tr>
<td>Chequamegon</td>
<td>1.5</td>
<td>5.2</td>
<td>93.3</td>
</tr>
<tr>
<td>Hiawatha</td>
<td>2.4</td>
<td>5.5</td>
<td>92.1</td>
</tr>
<tr>
<td>Superior</td>
<td>5.2</td>
<td>3.8</td>
<td>91.0</td>
</tr>
</tbody>
</table>

Table 5: Percentage (%) of land cover types within the seven NFs evaluated using the LTSS.
disturbed at any time during the observing period of the correspond-

ing LTSS. Based on this definition, all seven NFs considered in this

study were highly forested, consisting of at least 90% forest land

(Table 5). The four NFs in southeastern U.S. (i.e., De Soto, Talladega,

Francis Marion, and Uwharrie) had no more than 1% water, while the

other three NFs in northern U.S. consisted of considerably more water.

Fig. 5 shows the amount of persisting and disturbed forest land for

each NF and its three buffer zones calculated as the proportion of total

land area in the NF or each buffer zone. It reveals that for each of the

seven NFs,

- The percentage of forest land within the NF was higher than that in

  its surrounding buffer zones. In particular, three of the NFs,

  including the Francis Marion NF, the Uwharrie NF, and the

  Chequamegon NF, had substantially lower percentage of forest

  land in at least one of the three buffer zones than within the NFs.

- The percentage of persisting forest land within the NF was higher

  than those in the buffer zones, while the percentage of disturbed

  forest land within the NF was lower than those in the buffer zones.

Among the NFs, the percentage of disturbed forest land for the four

NFs located in southeastern U.S., including the De Soto NF, the

Talladega NF, the Francis Marion NF, and the Uwharrie NF, were

substantially higher (ranged from near 30% to about 45% of total land

area) than those for the three NFs located in northern U.S. (about 10%–

20% of total land area). This was also true in the three buffer zones

except for the Superior NF where the percentage of disturbed forest

land in the buffer zones reached near 30%.

3.2.2. Temporal dynamics of forest disturbance

The temporal details provided by the Landsat images in the LTSS

allowed an in-depth analysis of the temporal variability of forest

disturbance. With the changes mapped at quasi-biennial temporal

steps, annual disturbance rate was calculated as follows. First, for the

acquisition year of each image in a LTSS, a disturbance rate was

calculated as the ratio of the pixels disturbed in that year over the total

number of forest pixels. This ratio was then divided by the number of

years between that image acquisition and the immediately previous

acquisition included in that LTSS to calculate annual disturbance rate.

Fig. 6 shows the variation of annual forest disturbance rate as a

function of year within the NFs and the three buffer zones

surrounding each of them. Because it was not possible to know

when the disturbances in the pre-observation disturbance category

occurred, the annual disturbance rate for this category was not

calculated and therefore was excluded from Fig. 6.

Fig. 6 shows that for each NF, the disturbance rate varied

considerably from year to year, both within the NF and in the three

surrounding buffer zones. It also shows that except for the Uwharrie

NF, the disturbance rate within the NFs were lower than those in their

surrounding buffer zones during most of the years represented by the

LTSS, although there were short periods when the NFs experienced

about the same or higher levels of disturbance rates than their buffer

zones. The difference in disturbance rate between the Uwharrie NF

and the buffer zones varied from year to year, but over the entire

observing period the NF and the buffer zones had about the same level

of disturbance rates. The shapes or linear edges of the disturbed areas

suggest that most of the disturbances were due to logging, harvesting,

or other management activities for both within and surrounding the

NF (see Figs. 3 and 4(D)).

Fig. 6 also shows that several NFs and/or their buffer zones

experienced substantially higher disturbance rates in some years than

in other years. The Francis Marion NF and its buffer zones had
Disturbance rates of about 8%–10% in 1989 and about 4%–6% in 1990 whereas the rates in other years were mostly below 3%. The most likely cause of the 1989 disturbances was blow-down by Hurricane Hugo, which passed that area on September 21, 1989 and devastated much of the forests in this area. Brown & Schroeder (1999) found that Hurricane Hugo resulted in a distinct pattern of mortality in this region. Salvaging of trees felled by the hurricane may have also contributed to some of the 1989 disturbances, but should be responsible for most of the 1990 disturbances (Marsinko et al., 1993). Higher disturbance rates were mapped in 1988 and 1990 than in other years in the buffer zones of the Talladega NF. The Chequamegon NF had substantially higher disturbance rates in its buffer zones in 1987 and 1988 than in the other years. The Forest Service field office at each individual NF likely has the local knowledge of disturbance events that can be used to help understand such dramatic variations of the disturbance rates over time.

Fig. 6. Temporal variation of the annual forest disturbance rate (y axis, calculated as the percentage of forest land disturbed in each year) within each of the seven NFs and three buffer zones defined by distance of 0–5 km, 5–10 km, and 10–15 km from the boundary of each NF.
4. Summaries and conclusions

Monitoring the dynamics of national forests (NFs) is essential for assessing their conditions and for developing effective management strategies that will allow the NFs to provide a sustainable supply of goods and services. Use of conventional bi-temporal change detection methods applied to sparse image acquisitions (e.g. 10 years apart) can miss significant portions of changes (e.g. Lunetta et al., 2004; Masek et al., 2008). This is because that due to vigorous post-disturbance regeneration, the spectral signal of disturbances that occurred soon after the first image acquisition could disappear by the second image acquisition. In this study we employed a time series approach for monitoring the NFs using time series stacks of Landsat images (LTSS), each of which consisted of images acquired from 1984 to 2006 with a nominal interval of 2 years. The assembled image stacks were analyzed using an automated change mapping algorithm called vegetation change tracker (VCT).

This time series approach was used to map forest disturbance history for four NFs in southeastern U.S. and three in north central U.S., including the De Soto NF in Mississippi, Talladega NF in Alabama, Francis Marion NF in South Carolina, Uwharrie NF in North Carolina, Chequamegon NF in Wisconsin, Hiawatha NF in Michigan, and the Superior NF in Minnesota. Due to data budget constraints LTSS was assembled for only one WRS tile for each NF although most of the selected NFs spanned more than one WRS tile. Therefore, the conclusions reached through this study regarding the selected NFs and their buffer zones only apply to the portion where they intersected with the assembled LTSS. For each LTSS, the VCT algorithm produced a disturbance year map and calculated a change magnitude for each mapped disturbance. While the change magnitude can be roughly considered as an indicator as to whether a disturbance was a major (e.g., clear cut or stand replacement fire) or minor one (e.g., thinning, storm damage, or low to moderate intensity fire), its linkage to biomass removal or other physical measurements regarding that disturbance has yet to be established.

The disturbance year maps for two of the seven LTSS, including WRS path 21/row 37 and path 27/row 27, were validated using a design based accuracy assessment method. Without spatial or temporal aggregation, the overall accuracy at the per-pixel level was 79.7% for path 21/row 37 and 75.7% for path 27/row 27, and many of the disturbance classes had user's accuracies of over 70% or higher. While the producer's accuracy values for many disturbance classes were lower, most of the changes not captured by the VCT algorithm were minor disturbances. For the path 27/row 27 site (northern Minnesota), there were also considerable wetlands that were mapped as persisting or disturbed forest. This problem could be reduced by using existing land cover data sets such as the NLCD (Vogelmann et al., 2001; Homer et al., 2004). Visual assessment of the disturbance year maps for the other sites suggested that those maps should have similar accuracy levels as the maps for the two sites where accuracy assessment was performed.

According to the VCT derived disturbance year maps, each of the seven NFs consisted of 90% or more forest land, where forest land included both persisting and disturbed forests. During the 1984–2006 observing period, about 30%–45% of the land pixels in the four NFs in southeastern U.S. and 10%–20% of those in the three NFs in northern U.S. were disturbed at least once. For each NF, the three buffer zones defined at 0–5 km, 5–10 km, and 10–15 km from the boundary of that NF generally had lower percentage of forest land than within the NF, and the proportions of disturbed forest in the buffer zones were considerably higher than within the NF. Temporally, the annual disturbance rates varied considerably both within the boundary and in the three buffer zones of each NF. Except for the Uwharrie NF, where no obvious trend was found as to whether the NF experienced higher or lower disturbance rates than its buffer zones, the disturbance rates within the other NFs were generally lower than in their buffer zones during most of the years of the observing period of each LTSS.

The derived disturbance maps reveal that several NFs and/or their buffer zones experienced substantially higher disturbance rates in certain years than in other years. While we were able to link the extremely high disturbance rates in the Francis Marion NF and its buffer zones in 1989 and 1990 to Hurricane Hugo, which passed that area on September 21, 1989, understanding of the dramatic temporal variations of disturbance rates in other areas requires local knowledge of disturbance events at each individual NF.

The time series approach employed in this study represents a new approach for monitoring national forests and other public or private forest lands. This approach allows reconstruction of disturbance history over the last two decades by taking advantage of the temporal depth of the Landsat archive, and can be used to provide continuous monitoring as new satellite images are acquired. Now that the U.S. Geological Survey has announced plans for no cost access to its Landsat image archive6, and the Landsat images needed for assembling the required LTSS should exist for most places in the U.S. (Goward et al., 2006), this time series approach can be used to monitor protected areas across the U.S., as well as in other countries where the Landsat images needed for developing LTSS exist. Because the FZ and IFZ used by the VCT algorithm are calculated in a self-normalization nature, the VCT algorithm can be adapted for use with other Landsat class satellite imagery, and for integrated use of images from different instruments for areas where images from a single instrument are inadequate for developing LTSS. As with several other issues with the VCT algorithm, this issue will be further investigated and the results will be reported separately.

Because the disturbance products derived using this time series approach are spatially explicit and contain substantially more temporal details than conventional bi-temporal change products, they likely will be found highly valuable for many applications requiring data with adequate spatial and temporal details. For areas where post-disturbance recovery occurred, the disturbance year map can be used to calculate the age of regrowing forests, although the timing as to when regrowth started can vary from one disturbed forest stand to another. More research is needed to determine whether post-disturbance regrowth occurred for a given disturbance, and if it did occur, when it started. This will allow more accurate calculation of the age of a forest stand growing back from a previous disturbance. For carbon modeling studies, use of the derived disturbance products likely will yield substantially reduced uncertainties than using conventional bi-temporal change products or products derived using sparser satellite observations. In fact, if the high disturbance rates calculated for the four NFs and their buffer zones in the southeastern U.S. are indicative of the overall disturbance rates for the whole region, the magnitude of carbon flux arising from the mapped disturbances and the post-disturbance regrowth, and the role of forest disturbance and regrowth in this region in modulating the atmospheric carbon budget need to be reassessed.

Acknowledgements

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6 In January 2008 USGS announced to the USGS/NASA Landsat Science Team that they have plans to make Landsat level 1T data held in the EROS archive freely available through FTP download over the next few years (~2008–2010).
27. Three anonymous reviewers provided many constructive comments for improving the original manuscript.

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