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North Carolina's forest disturbance and timber production assessed using time series Landsat observations

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Wood products provide a relatively long-term carbon storage mechanism. Due to lack of consistent datasets on these products, however, it is difficult to determine their carbon contents. The main purpose of this study was to quantify forest disturbance and timber product output (TPO) using time series Landsat observations for North Carolina. The results revealed that North Carolina had an average forest disturbance rate of 178,000 ha per year from 1985 to 2010. The derived disturbance products were found to be highly correlated with TPO survey data, explaining up to 87% of the total variance of county level industrial roundwood production. State level TPO estimates derived using the Landsat-based disturbance products tracked those derived from ground-based survey data closely. The TPO modeling approach developed in this study complements the ground-based TPO surveys conducted by the US Forest Service. It allows derivation of TPO estimates for the years that did not have TPO survey data, and may be applicable in other regions or countries where at least some ground-based survey data on timber production are available for model development and dense time series Landsat observations exist for developing annual forest disturbance products.

Keywords: timber products output; remote sensing; vegetation change tracker

1. Introduction

Timber is a major forestry product with important economic values, providing raw materials for furniture, paper, construction materials, and many other wood products. These wood products, whether in use or in landfill, can store carbon for years, decades, or longer (Skog and Nicholson 1998; Smith et al. 2006). In North America, harvested wood products are estimated to provide the third largest carbon sink, next to forest and woody encroachment (CCSP 2007), providing 10% of the total forest sector net carbon stock change in the USA (Woodbury, Smith, and Heath 2007). In order to account for this carbon pool, many carbon and ecosystem models require or provide explicit estimates of carbon fluxes associated with harvested wood products (e.g. Chen et al. 2013; Houghton 2005). Therefore, quantifying harvested wood products is important for improved understanding of carbon dynamics, and hence relevant to digital earth for carbon and climate change studies.

In the USA, reports on timber product output (TPO) are produced by the Forest Service Forest Inventory and Analysis (FIA) program through surveying wood processing mills (Woodbury, Smith, and Heath 2007). With details on the amount and type of timber

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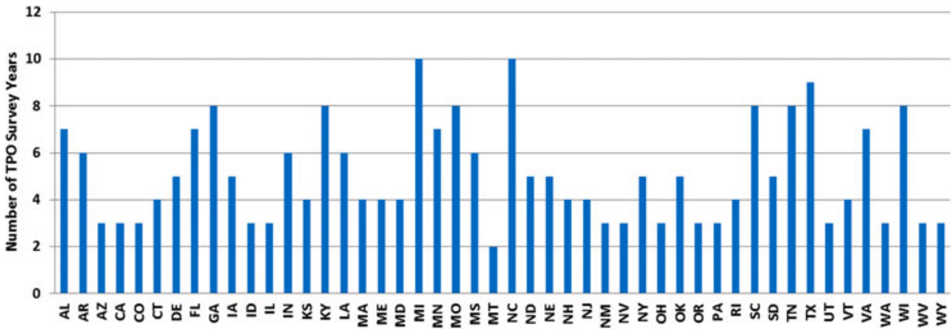

Figure 1. Number of years for which ground-based TPO survey data exist in the conterminous USA (updated as of June 2013).

harvested at county or state levels (Johnson 2001), these reports have been used to calculate carbon stored in wood products (Smith et al. 2006). The availability of historical TPO data, however, is highly inconsistent among different states, making it difficult to derive consistent and accurate estimates of carbon stocks and fluxes at regional to national scales (Birdsey 2004; Zhu et al. 2010). When this study was conducted, some states had up to 10 surveys, but others had far less (Figure 1).

With the ability to image the Earth's land surface repeatedly, satellite remote sensing provides spatially and temporally more consistent observations than allowed by using ground survey methods, and therefore may provide an opportunity for deriving more consistent estimates of harvested wood products. Satellite data have been used to estimate timber volume and other forest attributes in many studies (e.g. Trotter, Dymond, and Goulding 1997; Makela and Pekkarinen 2001). Recently, a number of algorithms have been developed for producing time series data products on forest disturbances using satellite data (e.g. Hilker et al. 2009; Zhu, Woodcock, and Olofsson 2013; Huang, Goward et al. 2010; Kennedy, Yang, and Cohen 2010). In the southeastern USA, most disturbances mapped using satellite data are due to timber harvest and logging (Thomas et al. 2011). We hypothesized that in this region, timber harvest volume should be correlated with Landsat-based disturbance estimates. The main purpose of this study was to test this hypothesis through a case study conducted in North Carolina, a major timber production state in southeastern USA. Specifically, we used time series Landsat data and the vegetation change tracker (VCT) algorithm (Huang, Goward et al. 2010) to map forest disturbances annually for the state of North Carolina. Relationships between these products and TPO survey data were then evaluated for each year that had TPO survey data, based on which an overall regression model was developed and used to produce an annual TPO record for all years that had VCT disturbance products.

2. Materials and methods

2.1. Study area

North Carolina is located in the southeastern USA. With 100 counties and a total area of 139,390 km^2, the state extends from the Atlantic coast in the east to the Great Smoky Mountains in the west. It is divided into four ecoregions, including the Blue Ridge Mountains in the west, the Piedmont Plateau in the middle, and Southeast Plains and Middle Atlantic Coastal Plain in the east (Figure 2). The state is 60% forested, with 98%

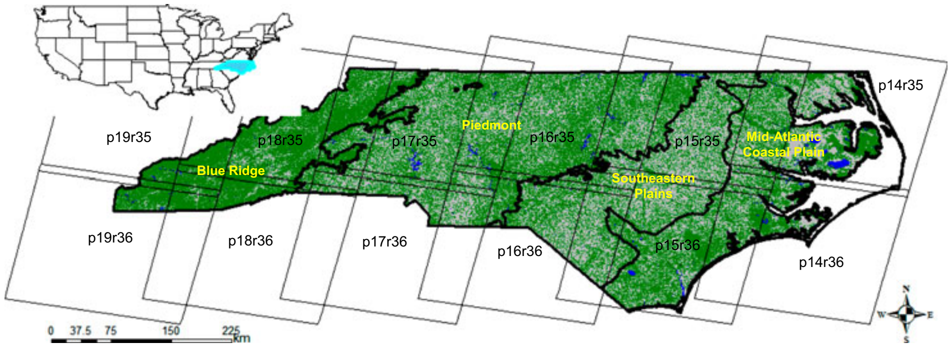

Figure 2. Location of the study area, with the North Carolina state map showing its four ecoregions and the distribution of forest cover in 2010 (green, gray, and blue are forest, non-forest, and water, respectively). The quadrangles are the WRS2 path/row tiles needed to cover North Carolina, with the path and row numbers shown as ‘pxxryy.’

of the forest land being classified as timberland (i.e. capable of growing 1.4 m^3 of wood per ha per year) (Bardon et al. 2010). Seventy-eight percent of the state’s forests are owned by Non-Industrial Private Forest (NIPF) owners, 8% by industrial forest companies, and 14% by the public. Most forests owned by NIPF and industrial forest companies are planted for timber harvest although damages from hurricane, insect outbreak, snow/ice, fire, and other natural disturbances are also common. Loblolly pine (*Pinus taeda*) and shortleaf pine (*Pinus echinata*) are among the major species used in plantation forests, which typically have roughly the same age at individual stand level. Many of the natural forests, however, have mixed ages and are often dominated by deciduous or mixed species groups.

2.2. TPO survey data

In the USA, TPO data are collected through the US Forest Service FIA program using ground-based survey methods. To determine the origin, harvest date, volume, species, and use of harvested roundwood products, FIA canvasses all primary wood-using mills, harvest sites, residential users, and commercial producers that harvest and sell wood products (Woodbury, Smith, and Heath 2007; Johnson 2001). The TPO program strives to achieve 100% response from all primary wood-using mills for each TPO survey conducted for a state (Johnson 2001). The collected data are used to generate TPO reports that provide county level estimates of harvested wood products. These reports are the only and most valuable ground-based data source on harvested wood products in the USA (Figure 1). Like many other datasets collected using survey-based methods, however, the TPO reports are not immune from human errors. However, there is no published assessment on the nature and magnitude of potential errors in these reports.

When this study was conducted, TPO reports for North Carolina were available for 10 survey years, including 1992, 1994, 1995, 1997, 1999, 2001, 2003, 2005, 2007, and 2009. The reports for 1992 and 1994 were available in printed format only (Johnson 1994; Johnson and Brown 1996). For the other 8 years, TPO data were available both in printed format and in the FIA TPO database available at the FIA website (http://www.fia.fs.fed.us/tools-data/). These TPO datasets provided county level estimates of industrial roundwood (including hardwood sawlog, hardwood pulpwood, softwood sawlog, and softwood pulpwood), fuelwood and other wood products such as chips, post, poles, and pilings. Data for industrial roundwood were provided in all 10 survey years, but no information on fuelwood and other wood products was available in 1992 and 1994. Since industrial roundwood accounted for about 95% of the total roundwood production and 85% of the total wood production in North Carolina (Howell and Brown 2004), only this wood type was considered in this study. All references to TPO data in the remaining sections of this paper only included the total industrial roundwood production.

2.3. Forest disturbance mapping

Forest disturbances were mapped using Landsat time series stacks (LTSS) and the VCT algorithm. An LTSS is a stack of Landsat images assembled for a World Reference System (WRS) path/row tile to provide clear view observations at a regular time step. An annual LTSS typically consists of one image per year for the years that have at least one cloud free or near cloud free (<5% cloud cover) image acquired during the summer leaf-on season. If no such image is available in a particular year, multiple partly cloudy images acquired during the summer leaf-on season of that year are used to produce a composite using a best observation method. Here, best observation is defined based on criteria designed to enhance forest disturbance mapping. Specifically, if no more than 1 clear view observation is available in a year at a given pixel location, the pixel with the maximum Normalized Difference Vegetation Index value is selected. If more than 1 clear view observation is available, the clear view observation that has the highest brightness temperature is selected. Here, clear view observations are those that are not contaminated by cloud or shadow and do not have other data quality problems. Pixels contaminated by cloud and shadow were identified using an automated cloud masking algorithm developed by Huang et al. (2010).

For the 12 path/row tiles needed to cover North Carolina (Figure 2), a total of 656 Thematic Mapper and Enhanced Thematic Mapper Plus images acquired between 1985 and 2010 were used to assemble the LTSS (Table 1). These images were downloaded from the US Geological Survey (USGS) at the 30-m resolution. They were first converted

Table 1. Number of Landsat images used in this study to map forest disturbance over the study area.

WRS path/row tile (pxxryy)	Number of images used
p14r35	47
p14r36	44
p15r35	53
p15r36	50
p16r35	54
p16r36	43
p17r35	60
p17r36	36
p18r35	57
p18r36	66
p19r35	80
p19r36	66
Total	656

top-of-atmosphere reflectance and then to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) atmospheric correction algorithm (Masek et al. 2006). In general, LEDAPS-based Landsat surface reflectance products are highly comparable with Moderate-resolution Imaging Spectroradiometer reflectance data (Feng et al. 2012, 2013). Geometrically, no additional correction was performed on these images, because they had already been orthorectified by the USGS to achieve subpixel geolocation accuracy. A detailed description of the procedures for assembling LTSS has been provided in a previous study (Huang, Goward, Masek et al. 2009).

The LTSS were analyzed using the VCT algorithm. This algorithm consists of two major steps (Huang, Goward et al. 2010). First, it automatically identifies forest samples in each Landsat image and uses those pixels to estimate the mean and standard deviation of the reflectance value of forest pixels, which are then used to calculate an integrated forest *z*-score (IFZ) index for each pixel:

$$\mathrm{IFZ} = \sqrt{\frac{1}{3}\sum_{\mathrm{band}3,5,7}\left(\frac{b_i - \bar{b}_i}{\mathrm{SD}_i}\right)^2},$$

where b_i is the spectral value of a pixel in band i, and $\bar{b}_i$ and SD_i the mean and standard deviation of the previously identified forest samples in that band. IFZ is a non-negative, inverse indicator of forest likelihood. The closer to 0 this value, the more likely a pixel being a forest pixel. The higher this value, the more likely a pixel being a non-forest pixel. Thus, a forest pixel typically maintains low IFZ values when undisturbed. When a disturbance occurs, that pixel loses part or all of its forest cover, often resulting in a sharp increase in the IFZ value. The IFZ then decreases gradually if trees grow back after that disturbance event. In the second step, VCT tracks the change of the IFZ to detect forest disturbance and calculates an IFZ-based disturbance magnitude for each detected disturbance (Figure 3). With annual Landsat observations, this algorithm can detect most disturbance types, including clearing due to harvest, logging, urban sprawl, as well as severe damages due to fire, storm and insect outbreak. Detailed descriptions of the

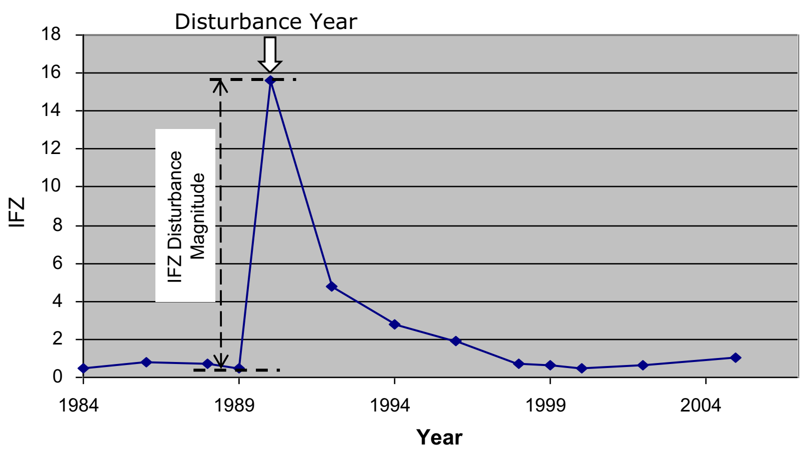

Figure 3. VCT tracks the temporal profile of the IFZ to detect forest disturbance. For each detected disturbance, it identifies the disturbance year and calculates an IFZ disturbance magnitude.

VCT algorithm and its products have been provided in previous publications (Huang et al. 2011; Huang, Goward et al. 2010; Huang, Goward, Schleeweis et al. 2009).

VCT disturbance products have been evaluated over many sites in the USA (Thomas et al. 2011; Huang, Goward, Schleeweis et al. 2009; Huang et al. 2011). To determine the quality of the disturbance products derived through this study, we examined them thoroughly through visual assessment, and derived accuracy estimates over the WRS2 path 16/row 35 tile, which covered a large portion of central North Carolina (Figure 2). The reference data used in the accuracy assessment was developed following the procedure described by Thomas et al. (2011). Specifically, a stratified random sampling method was used to select over 900 reference samples across the entire tile. Each sample, a 30-m pixel, was interpreted to derive reference disturbance information through visual examination of pre- and post-disturbance Landsat observations as well as available GoogleEarth high-resolution images. The derived reference data were used to construct a confusion matrix and to calculate the overall as well as class specific user's and producer's accuracies following standard accuracy assessment methods (Congalton 1991). Inclusion probabilities of the selected samples were tracked and used to assign appropriate weights to those samples according to Stehman et al. (2003).

The disturbance products generated for each WRS tile were merged to create statewide mosaics. These mosaics were then overlaid on county polygons to calculate each county's forest disturbance area for each year between 1985 and 2010.

2.4. TPO modeling and prediction

The timber output of an area is determined by many factors, including the total area harvested, the amount of timber available for harvest (i.e. pre-harvest timber density), as well as harvest intensity. The VCT disturbance products derived through this study provided information on the area, timing (year of disturbance), and spectral measures of the intensity of each disturbance event (Figure 3). But no statewide datasets on pre-harvest timber density and disturbance agent were available to this study. Since most forest disturbances in this region were due to timber harvest and logging (Thomas et al. 2011), use of VCT disturbance products alone may allow reasonable modeling of timber output. In this study, ordinary least square (OLS) regression methods were used to model the relationships between TPO and VCT disturbance products.

One issue in linking TPO data to the VCT disturbance products was that the date range of the TPO data collected in a survey year did not match the date range of the disturbances mapped for that year (Figure 4). Specifically, the data provided in each TPO report was collected during a calendar year, i.e. between 1 January and 31 December, but the disturbances mapped by VCT for a year could occur at any time between the acquisition dates of that year's Landsat image and the previous year's Landsat image used by VCT. The disturbance map for a TPO survey year (referred to as TPO year hereafter) included disturbances that occurred in the second half of the immediately previous year (after the acquisition date of the Landsat image used in that year), while disturbances that occurred during the second half of a TPO survey year (after the acquisition date of the Landsat image used in that year) were mostly included in the next year's disturbance map (referred to as post-TPO year hereafter).

Under certain circumstances, part of the timber harvested in a TPO survey year might be also associated with disturbances mapped in the year before the TPO survey year (referred to as pre-TPO year hereafter). As will be discussed in Section 3.1 and Table 3,

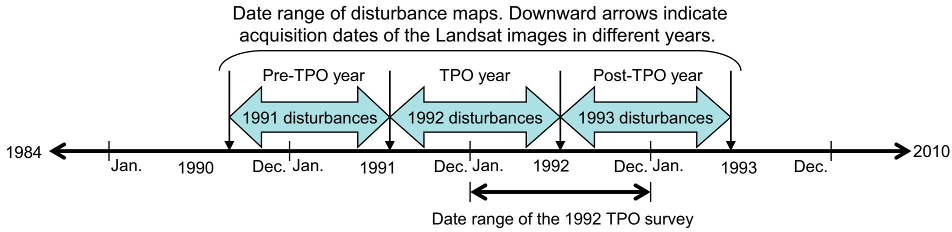

Figure 4. Schematic chart showing the date range mismatch between the 1992 TPO survey and forest disturbances mapped for 1992. The 1992 TPO report provided data collected between 1 January and 31 December, but the disturbances mapped for 1992 could occur at any time between the 1991 and 1992 Landsat images used by the VCT. Therefore, the 1992 disturbance map included disturbances occurred in 1991 after the acquisition of the 1991 image. Similarly, harvests that occurred in 1992 after the acquisition of the 1992 image were included in the 1993 disturbance map. Such date range mismatches existed between TPO survey data and VCT disturbance maps in all other TPO survey years. Notice the acquisition dates of the Landsat images used in the LTSS were determined by image availability, and were in general different in different years (Huang et al., 2009).

for example, significant portions of the disturbances in 1991, 1993, and 2007 were mapped by VCT as disturbances in the years before the actual disturbance years. Timber harvested through salvage logging, a common practice employed to reduce timber revenues loss due to severe damages from storms or other natural disturbances (Lindenmayer, Burton, and Franklin 2008), might also be associated with disturbances occurred in a previous year when salvage logging after a disturbance event was delayed until the next calendar year. In order to evaluate the impact of such temporal mismatches between TPO data and VCT disturbance products, for each TPO survey year we examined the relationships between TPO roundwood production and (1) disturbances mapped in the TPO year as a single predictor, (2) disturbances mapped in the TPO year and the post-TPO year as two separate predictors, and (3) disturbances mapped in the TPO year as well as the post- and pre-TPO years as three separate predictors.

To evaluate the usefulness of disturbance magnitude information for TPO modeling, we calculated two sets of disturbance areas. In the first set, disturbance area was calculated by adding up that year's disturbance pixels without considering disturbance magnitude. In the second set, the disturbance pixels were divided into four groups according to their disturbance magnitude values. The first group had IFZ disturbance magnitude values of less than 3, the second group between 3 and 6, the third group between 6 and 9, and fourth group greater than 9. These threshold values were derived partly based on our knowledge of approximate relationships between disturbance magnitude and harvest intensity and partly on an analysis of the histograms of the disturbance magnitude of the disturbance pixels. Most pixels in the first group likely were partial disturbances and those in the fourth group stand clearing disturbances. Pixels in groups two and three could have either partial or complete canopy removal. The disturbance areas of the four groups were used as four separate predictor variables in the regression analyses below.

With 3-year combinations to consider and two ways to calculate disturbance area, six groups of predictor variables were derived for TPO modeling (Table 2). Each group was used to establish a regression model between TPO and VCT disturbance products for

Table 2. Groups of predictor variables used in the TPO OLS regression analyses.

Group name	No. of variables	Disturbance data used	Disturbance magnitude
One year, no magnitude	1	TPO year only	Not considered
Two years, no magnitude	2	TPO year + post-TPO year	Not considered
Three years, no magnitude	3	TPO year + pre-TPO year + post-TPO year	Not considered
One year, with magnitude	4	TPO year only	Considered
Two years, with magnitude	8	TPO + post-TPO year	Considered
Three years, with magnitude	12	TPO year + pre-TPO year + post-TPO year	Considered

each TPO survey year. These models were evaluated using the adjusted R^2 and the second-order corrected Akaike Information Criterion (AICc):

$$\text{Adjusted } R^2 = R^2 - (1 - R^2)\frac{p}{n-p-1},$$

$$\text{AIC}_c = \text{AIC} + \frac{2p(p+1)}{n-p-1},$$

where n and p were the number of observations and predictor variables, and R^2 and AIC were calculated following standard textbooks (e.g. Tabachnick and Fidell 2013). In general, a better model should have a higher adjusted R^2 and a lower AICc value. The variable group that yielded the highest adjusted R^2 and lowest AICc for the individual TPO survey years was selected in developing a final, multi-year model for predicting TPO for all VCT disturbance years.

3. Results

3.1. Forest disturbances in North Carolina

3.1.1. Accuracy of the disturbance products

In general, the VCT disturbance products derived in this study had accuracies similar to or better than those reported in previous studies (Huang, Goward, Schleeweis et al. 2009; Thomas et al. 2011; Huang et al. 2011). Visual examination of these products across the state revealed that most of the mapped disturbance patches had spatial–temporal patterns characteristic of different disturbance processes. For example, linear or other forms of ‘well-defined’ boundaries were mostly associated with timber harvest and logging (Figure 5C). Disturbances that appeared to be caused by fire or hurricane damages could be linked to known disturbance events (Figure 5B and 5D). Roads and other urban features were apparent for disturbances driven by urban sprawl (Figure 5A).

Over the WRS path 16/row 35 tile, the VCT products had an overall accuracy of 88.6%. Many disturbance year classes had user’s and producer’s accuracies of over 80% (Table 3). Accuracies below 70% were mostly due to misclassifications between adjacent

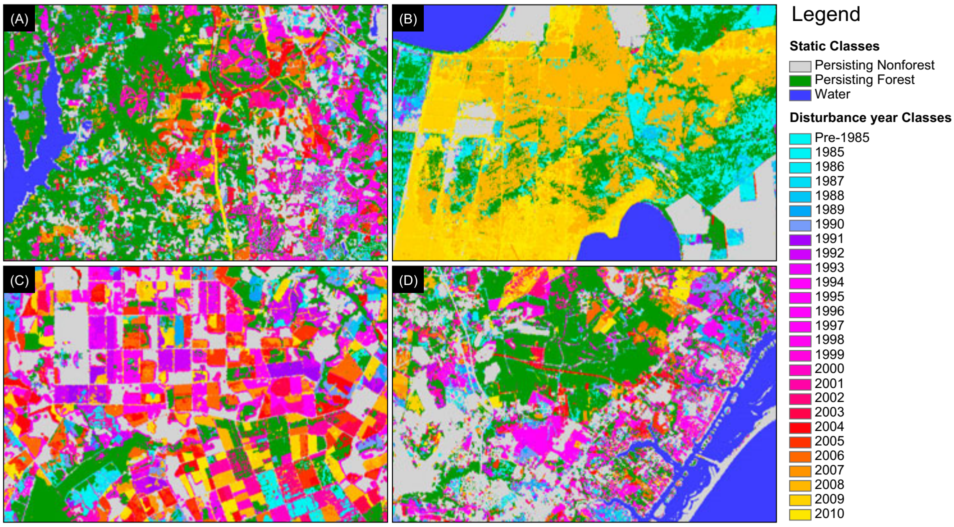

Figure 5. Example disturbance types that could be associated with known disturbance events or be verified through visual assessment, including (A) urban sprawl characterized by roads and other urban features (western Raleigh near the Jordan Lake), (B) lightning induced fire (Pocosin Lakes National Wildlife Refuge, burned from 1 June 2008 to 9 January 2009), (C) industrial logging that often had linear patch boundaries, and (D) Hurricane Fran (1996) damages near suburban Wilmington, NC. Each image represents a ground area of 19.2 km by 14.4 km.

years. For example, nearly half of the 1.40% 1993 disturbances in the reference data were assigned to 1992, slightly less than one-third of the 2.81% 2007 disturbances to 2006, and about a quarter of the 1.36% 1991 disturbances to 1990 (Table 3). These lower accuracies were associated with 3 years that had the highest cloud cover over this path/row – 12.3%, 17.1%, and 7.0% in the 1991, 1992, and 2006 images, respectively. A visual examination of the Landsat images revealed that many of the disturbed pixels in those years had cloud cover in the images acquired before the disturbance years. In such cases, VCT tended to identify the pre-disturbance cloudy year as the disturbance year, because cloudy pixels typically had IFZ values much higher than those of pre-disturbance. In general, the compositing algorithm was effective in reducing cloud cover – from 51.8% and 29.3% in the input images to 17.1% in the composited image for 1992, and from 12.5% and 49.3% to 7.0% for 2006. Unfortunately, further reduction was not possible due to lack of clear view observations over the cloudy areas in those composites.

3.1.2. Forest disturbance rates

The VCT products revealed that from 1985 to 2010, an average of 178,000 ha forests in North Carolina were disturbed each year, which added up to 4.62 M ha during the 26-year period, or 55.6% of the state's total forest area. Major disturbance events mapped by the VCT included harvest/logging, hurricane, urban growth, fire, and other forms of disturbances that resulted in substantial forest canopy loss (Figure 5). Most of the counties with high disturbance rates were in eastern North Carolina (i.e. Mid-Atlantic Coastal Plain and Southeastern Plain). The cumulative disturbance rate, which was calculated as the ratio of the 26-year total disturbance area over the total forest area in a

Table 3. Accuracy table of the VCT disturbance products for the WRS path 16/row 35 tile (overall accuracy = 88.6%).

	Reference																											
VCT	Non-forest	Forest	PSD	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Grand Total	*User's acc.*
Nonforest	**26.77**	0.78	0.26	0.26	0.52					0.26				0.26			0.26											29.36	91.2
Forest	0.25	**26.85**		0.10	0.06	0.05	0.07			0.04	0.05					0.08					0.24				0.09			27.86	96.4
PSD	0.61	0.56	**5.01**	0.09									0.04			0.08			0.10	0.06	0.06			0.09	0.09			6.77	74.0
1985			0.33	**1.11**																							0.05	1.48	74.7
1986				0.05	**1.57**	0.18	0.06																	0.09				1.94	80.6
1987		0.05	0.14			**1.04**	0.05																					1.28	81.4
1988		0.07			0.07		**0.68**	0.03																				0.85	80.2
1989		0.21					0.09	**0.91**	0.03																			1.24	73.4
1990			0.05						**0.82**	0.36																		1.23	66.7
1991	0.09	0.04								**0.66**																		0.78	84.0
1992											**0.97**	0.64	0.09														0.06	1.75	55.1
1993		0.04										**0.75**	0.08											0.09				0.95	79.1
1994		0.05								0.04			**1.18**															1.27	93.0
1995														**1.13**	0.06													1.19	95.0
1996		0.05													**1.68**	0.15	0.08						0.07					2.02	83.1
1997		0.15											0.08			**1.60**	0.23											2.07	77.7
1998																0.06	**1.59**											1.65	96.2
1999		0.31																**1.55**	0.05									1.91	81.0
2000		0.05																	**1.17**	0.15								1.37	85.0
2001													0.06							**1.62**								1.68	96.4
2002		0.06																			**1.19**							1.25	95.2
2003																						**1.32**	0.06					1.38	95.7
2004		0.07																					**1.13**	0.13				1.32	85.0
2005																								**1.89**				1.89	100.0
2006		0.09		0.09																					**0.94**	0.85		1.96	47.8
2007																										**1.96**		1.96	100.0
2008																											**1.59**	1.59	100.0
Grand total	27.71	29.41	5.79	1.68	2.21	1.27	0.94	0.94	0.86	1.36	1.01	1.40	1.52	1.39	1.74	1.97	2.15	1.55	1.32	1.84	1.49	1.32	1.25	2.28	1.11	2.81	1.70	100	
Producer's	97.0	91.3	86.6	65.9	70.8	81.8	72.0	96.4	96.0	48.4	95.2	53.9	77.8	81.3	96.6	81.4	73.7	100.0	88.3	88.3	80.0	100.0	89.9	82.9	84.6	69.7	93.8		

Note: User's and producer's accuracies are in percentage (%), with some of the lowest accuracies highlighted in gray. Values in other cells are percentages of the total area of the entire tile with the proportion of corrected pixels for each class highlighted in bold face. PSD refers to pre-1985 disturbance. Each four-digit number refers to the disturbance year.

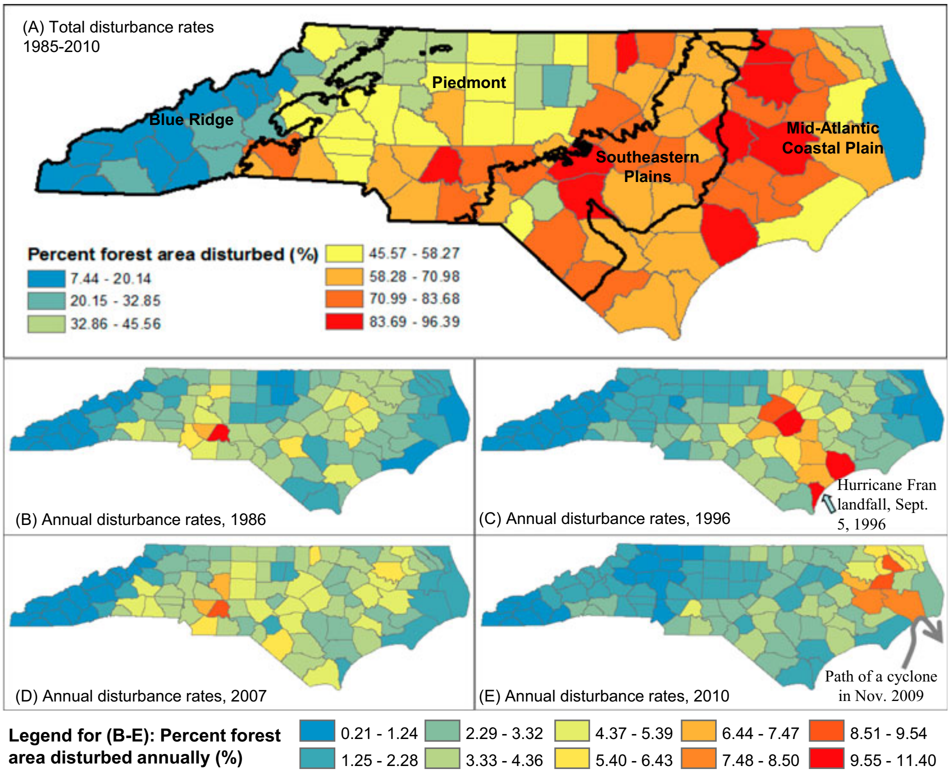

Figure 6. Cumulative county level disturbance rates from 1985 to 2010 (A) and annual rates in the 4 years that had the highest statewide disturbance rates (B–E). Most counties with very high cumulative disturbance rates were in the Mid-Atlantic Coast Plain and the Southeastern Plains ecoregions. The high annual disturbance rates in several counties in 1996 (C) and 2009 (E) appeared to be related to hurricane or extratropical cyclone damages. But the 1986 and 2007 disturbance maps had no spatial patterns that could be linked to hurricane damages.

county, reached 96% in several counties (Figure 6A). This is possible even though the percentage of 'undisturbed' forests in those counties were more than 4%, because many forested areas in this region had more than one disturbance during the 26-year period. Counties with very low disturbance rates were mostly in western North Carolina where the Smoky Mountain National Park and several National Forests are located. Geographically located between the Blue Ridge region and the Southeastern Plain, the Piedmont region also had disturbance rates in between the two regions to its east and west.

The total disturbed forest area over the entire state varied substantially from year to year, with two major peaks in 1996 and 2007 and two smaller peaks in 1986 and 2010 (Figure 7). The 1996 peak appeared to be related to two major hurricanes that made their landfall near Wilmington, North Carolina (Hurricanes Bertha and Fran on 12 July 1996 and 6 September 1996, respectively). Most of the counties that had very high disturbances rates were located along the path of Hurricane Fran (Figure 6C). In 2010, the counties with the highest disturbance rates were clustered in northeastern North Carolina, which likely were related to damages from an extratropical cyclone that was formed following Hurricane Ida and hit that region in November 2009 [(Figure 6E), see

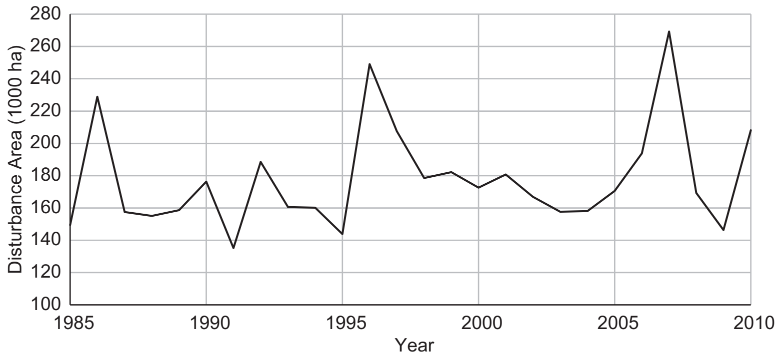

Figure 7. Temporal variability of annual forest disturbance area in North Carolina.

http://www.wpc.ncep.noaa.gov/tropical/rain/ida2009.html for more information on this extratropical cyclone]. Counties with high disturbance rates in 1986 and 2007 were scattered across much of the state (Figure 7B and 7D). The coastal counties that were often affected by tropical storms did not stand out as having high disturbance rates. While this might indicate that the high disturbance rates in those 2 years likely were not related to coastal storms, hurricane damages likely contributed substantially to the disturbances mapped by VCT in many other years, as North Carolina was often affected by multiple hurricanes or other tropical storms each year. For example, the state was hit by three hurricanes in 1999 that caused record-breaking flooding and severe damages (e.g. see http://www.nc-climate.ncsu.edu/climate/hurricanes/affecting.php for a list of hurricanes that affected North Carolina) although the disturbance rate in 1999 was not as high as the 4 years discussed above.

3.2. TPO–disturbance relationships

In general, the TPO survey data had good relationships with the VCT disturbance products. Although in any given year, the date ranges of the TPO survey data and VCT disturbance products only had an overlap of approximately 6 months (Figure 3), the adjusted R^2 of linear regressions between same-year TPO data and disturbance area exceeded 0.5 in 7 of the 10 TPO survey years (Figure 8A). The low adjusted R^2 values in 1997 and 1999 likely were related to multiple hurricanes in 1996 and 1999 (see Section 3.1.2) that resulted in severe damages (and likely delayed salvage logging, see Section 2.4) that complicated the TPO–disturbance relationship. In 2007, the low adjusted R^2 value was probably due to a large misclassification error in that year's disturbance product (see Section 3.1.1). Including the post-TPO year's disturbance area in the regression analyses resulted in significant increases in the adjusted R^2 and decreases in the AICc values for 1994, 1997, 1999, 2007, and 2009. When disturbances mapped in the pre-TPO years were also considered, further increases in the adjusted R^2 and decreases in AICc were observed in 1992, 1995, 1997, 2001, and 2007 (Figure 8A and 8C).

Use of disturbance areas divided into four groups based on the IFZ disturbance magnitude in the regression analyses resulted in substantial improvements in TPO modeling as compared to the regressions derived without considering disturbance magnitude. Improvements of 0.1 or more in the adjusted R^2 were achieved in five, six, and eight of the ten TPO survey years when disturbances mapped in the TPO year, TPO

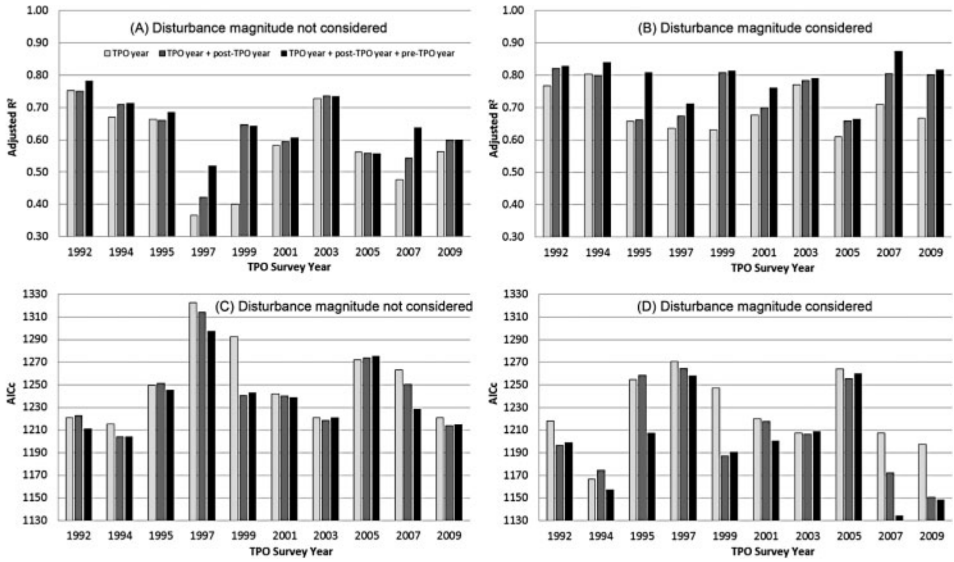

Figure 8. Adjusted R^2 (A and B) and AICc values (C and D) of TPO regression models derived using disturbance area calculated by counting VCT disturbance pixels without (A and C) and with (B and D) considering the IFZ disturbance magnitude. In general, the adjusted R^2 increased while AICc decreased when disturbance pixels were stratified using the IFZ disturbance magnitude, and when disturbances mapped in post-TPO and pre-TPO years were included in addition to those mapped in the TPO survey year (TPO year) in the regression analyses.

year + post-TPO year, and TPO year + post-TPO year + pre-TPO year, respectively, were used in the regression analyses (Figure 8A and 8B). Four of the ten TPO survey years had regressions with improvements in the adjusted R^2 of 0.2 or more, including 1997, 1999, 2007, and 2009. Increases in the adjusted R^2 values were less than 0.1 in 1992 and 2003. But those improvements were accompanied by decreases in AICc (Figure 8C and 8D), indicating that use of the IFZ disturbance magnitude to stratify the disturbance pixels also improved TPO modeling in these years.

It should be noted that while in general the relationships between TPO and VCT disturbance products were strengthened substantially by considering the IFZ disturbance magnitude and by including pre- and post-TPO year disturbances, for each TPO survey year not all variables considered were necessary. Many variables had slope values not statistically different from 0 (Tables 4 and 5). There were substantial among-year differences as to which variables had non-zero slopes, and most variables had different slope values in different years, suggesting that there likely were other important year and/or county specific factors that affected the TPO–disturbance relationships but were not considered in this study. As discussed earlier, such factors included disturbance type and pre-disturbance timber density.

3.3. Multi-year TPO estimates

The above regression analyses based on individual year TPO data revealed that the 3 years, with magnitude variable group (see Table 2 for definitions of different variable groups) allowed better modeling of TPO than any of the other variable groups. Therefore,

Table 4. Regression coefficients for the TPO models derived by using VCT disturbance area but not the IFZ disturbance magnitude.

	TPO year only		***TPO year + post-TPO year***			***TPO year + post-TPO year + pre-TPO year***			
Year	Intercept	Slope	Intercept	Slope_TPO	Slope_post-TPO	Intercept	Slope_pre-TPO	Slope_TPO	Slope_post-TPO
1992	18.8^^	119.2**	25.0^^	123.8**	–9.3	4.0^^	74.8**	95.8**	–19.4^^
1994	27.4^^	125.3**	18.5^^	62.1**	76.6**	26.4^^	71.3**	–21.9^^	85.3**
1995	41.2^	159.2**	41.6*	156.2**	1.6^^	28.8^^	88.3**	67.2**	2.7^^
1997	138.0**	68.1**	80.6**	28.0^	78.8**	90.3**	–53.5*	68.5**	72.4**
1999	39.5^^	110.9**	31.6^^	–22.6^	145.5**	31.6^^	–22.5^^	–0.2^^	145.6**
2001	42.9*	109.2**	36.4^	69.1**	47.3^	32.0^^	40.1^^	48.1^	31.6^^
2003	19.4^^	141.9**	13.6^^	113.1**	32.4*	12.7^^	111.1**	3.3^^	31.4^
2005	31.1^^	121.4**	27.3^^	108.5**	13.4^	25.7^^	89.5**	18.8^^	15.6^^
2007	37.8^^	68.4**	22.8^^	35.2**	61.6**	10.0^^	2.3^^	73.2**	37.7*
2009	35.1*	101.6**	20.1^^	57.3**	38.4**	14.7^^	47.2*	13.9^^	36.7**

Note: The units for the intercept and slope values are thousand m^3 and m^3/ha, respectively.**$p < 0.01$; *$p < 0.05$; ^$p > 0.05$; ^^$p > 0.10$.

Table 5. Regression coefficients for the TPO models derived by considering both disturbance area and magnitude.

		Slope											
		Pre-TPO year				TPO year				Post-TPO year			
Year	Intercept	magn1	magn2	magn3	magn4	magn1	magn2	magn3	magn4	magn1	magn2	magn3	magn4
						TPO Year Only							
1992	29.0**					310.6**	−142.2*	527.6**	14.6*				
1994	42.7**					230.5*	−207.4**	730.3**	12.8*				
1995	46.1**					42.4^^	93.5**	326.7**	134.7**				
1997	111.6**					398.5*	−396.6**	359.6**	309.3**				
1999	70.1**					140.2^	−401.4**	1204.6**	−102.1**				
2001	52.7**					215.2^	−356.8**	1058.2**	−20.1*				
2003	41.6**					218.5*	−272.2**	719.2**	96.7**				
2005	82.9**					293.7^^	−294.0**	384.9**	192.1**				
2007	74.8**					176.6^	−226.7**	544.8**	112.8**				
2009	38.5**					213.1**	−64.7**	393.3**	105.3**				
						TPO year + post-TPO year							
1992	55.9**					198.9*	−27.8^^	392.4**	−44.5^^	417.6**	−413.1**	336.7*	95.8^^
1994	41.9**					244.8*	−213.1**	722.2**	45.2^^	−8.0^^	19.1^^	26.9^^	−49.5^^
1995	45.4*					128.8^^	135.3^^	126.7^^	94.3^^	−19.8^^	−70.6^^	377.2*	−66.0^^
1997	100.1**					452.1*	−358.6**	201.4^^	237.6**	−112.6^^	−151.3^^	644.4**	−82.3^^
1999	96.0**					−10.8^^	−89.4^^	504.5**	−190.8**	360.0**	−592.2**	1020.3**	71.7^^
2001	42.0*					134.2^^	−221.5^	745.5**	−60.1^^	214.7^^	−218.5**	344.6^^	61.7^^
2003	31.4^^					120.2^^	−126.0^^	409.9*	188.9**	−2.4^^	−44.6^^	307.0*	−133.1*
2005	77.6**					238.9^^	−224.0^	88.4^^	108.6^^	84.9^^	−207.0^	672.5**	−57.3^^

Table 5. (*Continued*)

		Slope											
		Pre-TPO year				TPO year				Post-TPO year			
Year	Intercept	magn1	magn2	magn3	magn4	magn1	magn2	magn3	magn4	magn1	magn2	magn3	magn4
2007	71.9**					29.8^^	−163.6**	588.9**	−66.8^^	131.7*	−114.8^	−16.7^^	310.5**
2009	36.1**					148.9*	−75.2^	250.4*	−35.4^^	−148.8^^	−35.2^^	392.6**	87.5*
						TPO year + post-TPO year + pre-TPO year							
1992	41.0*	118.2^^	6.9^^	143.6^^	72.2^^	123.9^^	−31.5^^	329.5*	−99.0^^	246.3^	−298.5**	196.4^^	117.8^
1994	54.8**	289.0**	−279.3**	196.1^^	153.6**	158.3^^	−107.3^^	497.0**	−0.4^^	27.3^^	59.0^^	27.3^^	−96.2*
1995	63.0**	354.3*	−332.8**	940.1**	132.0^	−58.7^^	78.1^^	−183.0^^	20.8^^	53.2^^	−69.0^^	169.5^^	−138.5*
1997	102.1**	−69.4^^	90.7^^	354.2*	−94.8^^	359.3^	−355.1**	79.0^^	178.4*	18.1^^	−146.2^^	351.7^^	2.9^^
1999	97.2**	41.7^^	−142.2^^	350.5^	14.2^^	−2.0^^	−22.9^^	399.4*	−243.5**	313.2*	−595.0**	937.9**	71.6^^
2001	65.8**	208.2^^	−277.5*	797.4**	−151.2^	56.8^^	−175.0^^	380.2^	87.9^^	233.5^	−272.1*	383.0^	−11.2^^
2003	41.0*	228.3^	−81.2^^	−177.2^^	59.6^^	49.9^^	−103.7^^	478.8**	140.7*	−14.2^^	−33.6^^	275.4^	−79.1^^
2005	70.3**	−184.3^^	168.7^^	107.4^^	−154.9^	155.6^^	−172.7^^	8.7^^	139.6^	122.7^^	−203.0^^	529.9*	30.8^^
2007	57.5**	100.8^	−192.5*	586.4**	−1.3^^	24.8^^	−98.6^	220.9*	−34.1^^	35.3^^	4.0^^	−277.1*	233.0**
2009	37.4*	92.2^^	−64.2^^	−55.7^^	175.6**	118.7^^	−91.8^	370.6**	−114.9*	−690.8^^	19.6^^	295.6*	50.5^^

Note: The variables magn1, magn2, magn3, and magn4 refer to the four groups of disturbance areas calculated based on the IFZ disturbance magnitude (see Section 2.4). The units for the intercept and slope values are thousand m^3 and m^3/ha, respectively.
**$p < 0.01$; *$p < 0.05$; ^$p > 0.05$; ^^$p > 0.10$.

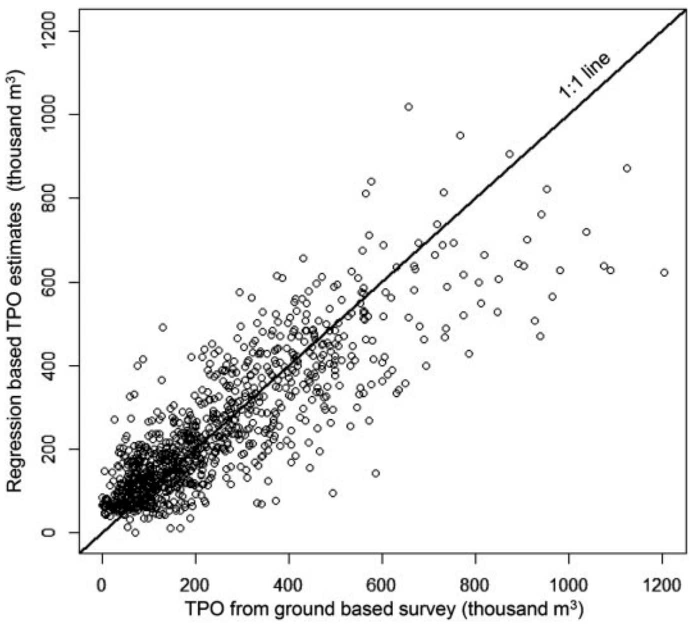

Figure 9. Comparison of county level TPO values predicted using the overall regression model to ground-based survey data for all 10 TPO survey years.

this variable group was used to develop an overall model using TPO data from all 10 survey years. The adjusted R^2 of this model indicated that it explained 71% of the combined spatial and temporal variability of TPO survey data collected across the state over the 10 survey years. In general, county level TPO estimates derived using this model were distributed along the 1:1 line when compared with actual values, with slight underestimation in the higher end and overestimation in the lower end (Figure 9).

Applying the overall model to all VCT disturbance years resulted in an annual TPO record for North Carolina (Figure 10). In general, this record tracked state level TPO estimates calculated from ground-based survey data, with relative errors of less than 7% in 9 of the 10 survey years. The only year where the modeled and survey-based TPO estimates differed by more than 10% was 2005. The larger error in this year might be partially due a misclassification error by VCT. As discussed in Section 3.1.1, over one-third (0.85% out of 2.81%) of the 2007 disturbances in the path 16/row 35 tile were misclassified as 2006 disturbances. As a result, the 2006 disturbance rate was inflated by over 70% (from 1.11% to 1.96%). Since 2006 was a post-TPO year for estimating 2005 TPO, this inflated disturbance rate likely contributed to the over prediction in 2005.

The TPO record derived using the VCT disturbance products and the overall regression model revealed that North Carolina had an average TPO of 23.2 million m^3 per year from 1986 to 2009, or a total TPO of 557.6 million m^3 over the 24-year period. This record had an increasing trend during the first decade, with TPO values growing from 17.0 million m^3 in 1986 to 29.5 million m^3 in 1996. The TPO values then decreased in the next half decade. While the predicted and actual TPO disagreed by 14% in 2005, both decreased sharply after 2006, to below 20 million m^3 by 2009.

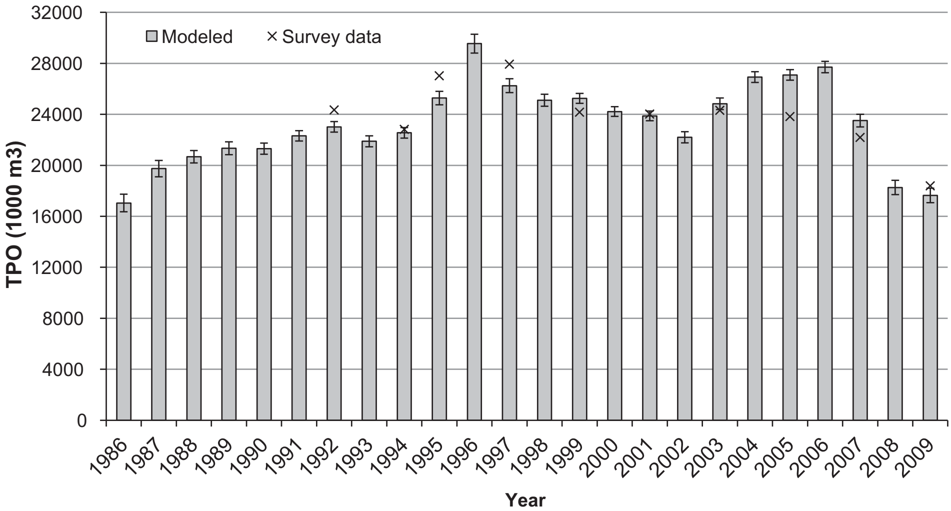

Figure 10. State level TPO estimates derived based on VCT disturbance products as compared to ground survey data, with error bars indicating the 95% confidence interval of those estimates.

4. Discussions

Wood products are a significant carbon sink by storing carbon for years, decades, or longer. The TPO data collected by the US Forest Service using ground survey methods provide a basis for quantifying carbon dynamics in wood products (e.g. Chen et al. 2013; Turner et al. 1995; Houghton and Hackler 2000). The availability of such survey data, however, is highly inconsistent across the USA (Figure 1), making it difficult to derive spatially and temporally consistent estimates of carbon stored in harvested wood products. The method developed in this study may provide an alternative approach for deriving spatially and temporally more consistent TPO estimates using satellite-based disturbance products. While we have demonstrated that in North Carolina, VCT disturbance products were highly correlated with TPO survey data, and the TPO estimates derived based on VCT disturbance products tracked the survey data closely, the modeling approach developed through this study may be improved in several ways.

First, use of disturbance agent information to separate harvest/logging from other disturbance types should help. Unless followed by salvage logging, damages from fire, storm, insect outbreak, and other natural disturbances typically do not contribute to timber production, and therefore should not be included in TPO modeling. The feasibility to separate different disturbance types using Landsat data has been demonstrated in several studies (e.g. Schroeder et al. 2011; Zhao, Huang, and Zhu accepted).

Second, annual biomass or tree cover datasets are needed. Such datasets can provide information on pre-harvest timber density, and can be used to calculate disturbance magnitudes that are based on physical quantities (e.g. biomass or tree cover removal) and therefore may be better linked to harvest intensity than the IFZ-based disturbance magnitude used in this study.

Third, relationships between TPO and VCT disturbance products likely will be improved if they are better matched temporally. As shown in Figure 4, on average the date range of the TPO survey data in any given year had a 6-month offset from that of the

VCT disturbance data. While we were able to reduce the impact of such temporal mismatches in this study by considering disturbances mapped in the pre- and post-TPO years, a better solution to this problem would be to map disturbances at sub-annual intervals (e.g. monthly), which would then allow calculation of disturbance areas for each time period the TPO survey data were collected. The feasibility to map forest disturbances at sub-annual intervals has been explored using existing satellite data (e.g. Zhu, Woodcock, and Olofsson 2013; Xin et al. 2013; Hilker et al. 2009). A combination of newly available (e.g. Landsat 8) and forthcoming satellite datasets (e.g. Sentinel-2) will greatly improve the availability of Landsat-class data for disturbance mapping with sub-annual details (Wulder et al. 2012).

Further, both the VCT disturbance products and the TPO survey methods have room to improve. As discussed in Section 3.3, overestimation of TPO in 2005 by the developed approach was likely due to misclassification of 2007 disturbances to 2006. Reducing such errors should improve disturbance area estimation, and hence TPO modeling. This may be achieved by improving the accuracy of the VCT algorithm, or by using other algorithms capable of producing dense time series disturbance products (e.g. Hilker et al. 2009; Zhu, Woodcock, and Olofsson 2013; Kennedy, Yang, and Cohen 2010) if those algorithms can produce more accurate results. However, since the lowest accuracies in the VCT disturbance products appeared to be related to excessive cloud cover (see Section 3.1.1), more substantive improvements likely will depend on the ability to acquire clear view observations annually or more frequently in all land areas. This, however, cannot be achieved with a single-satellite system provided by the current Landsat program. A virtual constellation of existing (e.g. Landsat 8) and/or forthcoming satellites (e.g. Sentinel-2) will improve the chance to acquire cloud-free observations in many cloudy regions (Wulder et al. 2012).

While the TPO survey data were treated as ‘truth’ in this study, they were collected using survey-based methods, which were susceptible to human errors, especially in determining the origin, harvest date, and use of the harvested wood products. Such errors likely contributed to some of the differences between the modeled and survey-based TPO estimates reported in this study, which likely will be reduced should more accurate TPO survey data become available.

5. Conclusions

A new approach has been developed for establishing annual records of TPO using time series Landsat observations and limited available TPO survey data. This approach builds on the VCT algorithm designed to produce annual forest disturbance products. It first exploits the relationships between available TPO survey data and VCT disturbance products and then uses the established relationships to derive TPO estimates for all years that have VCT disturbance products. This approach was used to quantify North Carolina’s forest disturbance and timber production in this study.

The results revealed that North Carolina had an average forest disturbance rate of 178,000 ha per year from 1985 to 2010. Over the 26-year period, a total of 4.62 M ha, or 55.6% of the state’s total forest land, were disturbed. The disturbance area mapped in each TPO survey year was found to be highly correlated with the TPO survey data collected in that year. Further improvements to the TPO–disturbance area relationships were achieved by including disturbance data from the pre- and post-TPO years and by stratifying the disturbance area using the IFZ disturbance magnitude. Up to 87% of the total variance of county level industrial roundwood production was explained by the regression models developed for individual TPO survey years. A multi-year model developed using all 10 available TPO surveys explained 71% of the combined spatial and temporal variability of the TPO data. At the state level, TPO estimates derived from this model tracked those derived from ground-based survey data, with relative errors of less than 7% in 9 of the 10 TPO survey years. Predictions from this model revealed that from 1986 to 2009, North Carolina had an average TPO of 23.2 million m^3 per year, or a total TPO of 557.6 million m^3 over the 24-year period.

The modeling approach developed in this study complements the ground-based TPO surveys conducted by the US Forest Service. While the specific regressions developed likely cannot be used outside North Carolina, the modeling approach can be used to establish timber production records for any region where only limited ground-based timber survey data exist but available Landsat acquisitions allow reconstruction of forest disturbance history at annual or sub-annual time steps. Assuming TPO–disturbance relationships are relatively scale invariant, this modeling approach may also allow derivation of TPO records at sub-county levels. Forest disturbance maps have already been developed for many areas of the USA (Masek et al. 2013; Li et al. 2009a, 2009b), and maps for the conterminous USA are being developed through the ongoing North American Forest Dynamics project (Goward et al. 2008). With these products, the developed modeling approach may be used to produce an annual, multi-decade TPO record for the USA.

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