ABSTRACT

Title of Dissertation: SPATIAL AND TEMPORAL DYNAMICS OF DISTURBANCE WITHIN AND BETWEEN FOREST REGIONS OF THE U.S.

Katelyn Anne Dolan, Doctor of Philosophy, 2015

Dissertation directed by: Professor. George C. Hurtt, Geographical Sciences

Forest disturbances play a critical role in shaping forest structure and influencing the ecosystem services that forests provide. However, the rates, patterns and consequences of disturbance remain largely uncertain. How do disturbance rates vary within and between regions and how vulnerable are forests to changes in disturbance? This research takes a tiered approach to quantifying the spatial and temporal patterns and impacts of disturbance within and between diverse forested landscapes of the contiguous U.S. First an intraregional characterization of the patterns and process of disturbance, as captured by over a quarter century of Landsat imagery was performed over the highly forested northeastern state, New Hampshire U.S. Next an inter-regional comparison of disturbance rates, trends and size distributions were conducted across three regions representing diverse forested landscapes in the U.S. with different dominant disturbance regimes. Finally, a framework was developed to assess the vulnerability of forested ecosystems to disturbance and how vulnerability

may change in the future. Results showed that disturbance is not homogenous but varies both spatially and temporally within and between regions. Further ecosystem vulnerability to disturbance varies strongly across the U.S., with western forests generally exhibiting greater sensitivity and vulnerability to disturbance under current climates. Under a potential climate scenario, the majority of U.S. forest area was estimated to increase in resiliency to disturbance, which may buffer some of the impact of intensified forest disturbance. The challenge and opportunities going forward is to continue to quantify and integrate the complex rates, patterns and processes of disturbance into ecosystem models and field study designs that link impact assessment of changes to ecosystem function and services.

SPATIAL AND TEMPORAL DYNAMICS OF DISTURBANCE WITHIN AND BETWEEN FOREST REGIONS OF THE U.S.

by

Katelyn Anne Dolan

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
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Dedication

For my Norni, Sarah Antonette Famiglietti (1920-2010)

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Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Motivation & Background

Forested ecosystems provide critical ecosystem services including but not limited to carbon storage, biodiversity habitat, water quality and flow regulation, recreational uses and land atmosphere exchanges of energy and water, that have local to global significance (Lorimer et al., 2003; Drummond and Loveland 2010; In Young et al., 2012). Forests are currently estimated to cover approximately 30% of the global land surface, store more carbon then is found in the atmosphere (FAO, 2010). Forest disturbances, defined by Pickett and White (1985) as relatively discrete events that alter stand structure, resource availability and or physical environment, play a critical role in shaping most forests and the ecosystem services they provide. Quantification of disturbance rates, patterns, severity and mechanism is crucial to improve forest management, monitoring and initialization and parameterization of terrestrial ecosystem models that are working toward understanding forest function and dynamics now and into the future.

Disturbance can vary in intensity, size, mechanism and frequency across different forest types and geographic regions. While some disturbances cause large-scale tree mortality (landslide, severe hurricane or fire) others cause damage that affect community structure and organization (hemlock wooly adelgid, ground fires) (Dale et al., 2001). It has been estimated that between 0.4 and 0.7 million km^2 of forest globally are impacted by disturbance greater than 0.1 ha every year (Frolking et al., 2009). Disturbances can be separated between anthropogenic and natural causes, however, the definitional boundaries between the two classifications can be difficult to delineate due to a spectrum of influence and feedbacks (Dale et al., 2001; Pan et al., 2011; Masek et al., 2011). In the U.S., pests and disease may annually affect the largest area of forestland, however damage severity varies greatly. For example, 23 million acres of forestland were mapped to have some level of mortality reported in 2006 by the USDA Forest Health Technology Enterprise Team (FHTEM), but more than three quarters of the disturbed areas were classified as only having light mortality. In the U.S., timber harvesting affected on average 10 million acres annually during the last half of the 20th century, however, approximately 60% is through partial harvest (Masek et al., 2011; Smith et al. 2004). Zeng et al. (2009) estimated that over the period of 1851-2000 tropical cyclones impact approximately 97 million trees each year over the entire United States, while Pu et al. (2007) estimated an average of 5,500 km^2/ year of forest area burned in the U.S. from 1989-2000. However there is no consistent map of past disturbances events and their causes at global or continental scales (McDowell et al., 2015; Schleeweis et al., 2013).

Forest disturbance rates and impact have shifted throughout history in space and time (Drummond and Loveland 2010). In the conterminous U.S. over the last 300 years there was a dramatic decline and subsequent gain of forest area linked tightly to clearing of forests for agriculture and fuel followed by land abandonment as the nation developed and agriculture moved to more productive lands (Mather 1992, Hurtt et al., 2002; Drummond and Loveland 2010; In Young et al., 2012). In the last few decades reforestation has slowed or been reversed in most areas. Recently studies have highlighted novel disturbance regimes resulting from pollution, invasive pests and climate change (Dietze & Moorcroft, 2011; Raffa et al., 2008; Seymour, et al., 2002). Dale et al., (2001) makes a convincing argument that climate change can alter the frequency and duration of fire, drought, insect/pathogen outbreaks, landslides, wind and/ or ice storms, and that we must consider this in our predictions of forest function and structure into the future.

Forested ecosystems constitute a large stock of carbon within the terrestrial biosphere, and forest disturbance and recovery are critical mechanisms for transferring carbon between the land surface and the atmosphere (Hurtt et al., 2002; Masek et al., 2008; Oliver and Larson 1996). In the second half of the 20th century, the U.S. forests were calculated to be a carbon sink due to the suppression of forest fires and reforestation on abandoned farmland (Houghton, 1999; Hurtt et al., 2002). Despite a growing awareness of the importance of disturbance in shaping terrestrial ecosystems, the role of forest disturbance within the terrestrial carbon cycle still remains uncertain. A growing body of research in the last decade have placed more emphasis on this question (Hurtt et al., 2002; Kasischke et al., 2013; Williams et al., 2012), yet many regional to global carbon ecosystem models do not account for disturbance factors such as pests and hurricanes (McNulty, 2002). As the potential of a carbon market grows, valuation of forestland may change which could result in shifts in current forest management (Drummond & Loveland, 2010). Many different management strategies can be undertaken such as fire suppression, shifts in rotation periods, and/or reforestation that can lead to large impacts on ecosystem services such as increases or decreases in forest biodiversity, carbon storage and other ecosystem services (Drummond & Loveland, 2010; Hurtt et al., 2002; Le Page et al., 2013; Lorimer &

White, 2003; Yeo & Huang, 2013). Further forest owners, investors and policy makers have shown interest in historical natural disturbance regimes to both inform management as well as a way of understanding the potential impact to their 'investments' (Long, 2009; Seymour et al., 2002). Despite growing interest, much uncertainty remains on the quantification of past and present disturbance regimes and their future predictability.

Satellite and airborne remote sensing technologies are being used to measure and monitor regional to global land cover and vegetation properties that can be linked to field studies and models to improve understanding of important biogeophysical processes (McDowell et al., 2015; Wulder et al., 2012). The long history of optical remote sensing combined with emerging active remote sensing technologies, such as lidar are providing powerful tools to study forest structure, composition, disturbance and recovery (Asner et al., 2013; Dolan et al., 2009). In particular the Landsat series of satellites have provided information on land cover and land ecosystem dynamics by collecting imagery of the earth surface since 1972 (Cohen & Goward, 2004; Wulder et al., 2012). However, previous to a policy change 2008 that lead to open access of the Landsat archive, prohibited costs and data access limited the temporal scope and spatial scales for which Landsat Imagery was used in earth system science. The change in policy coupled with technical advances in computing capabilities has opened opportunities to monitor and investigate long term changes in forest properties over large areas (Hansen et al., 2013; Huang et al., 2010; Kennedy et al., 2008).

The development and advancement of terrestrial biosphere models have allowed the assessment of complex dynamics in global ecosystems over spatial and temporal scales that would be challenging to achieve through observation and or field experimentation alone (Becknell et al., 2015; Bonan, 2008; Bond, Woodward, & Midgley, 2004; Hurtt et al., 1998). Predictive processed based modeling studies that simulate extreme events over larger areas have improved scientific understanding of global carbon and ecosystem dynamics (Bonan et al., 1992; Bond et al., 2004; Moorcroft et al., 2001; Shukla, et al., 1990). However, despite growing awareness of the influence of disturbance on forest structure, function and role in transferring carbon between land surface and atmosphere, the current capabilities for robustly simulating disturbance events and their impacts in many terrestrial biosphere models is still limited in large part due to a lack of consistent, robust data sets on historical disturbance and future disturbance projections (Huntzinger et al., 2013). More consistent data sets on historical and current disturbance can be used directly terrestrial ecosystem models and or aid in the development of prognostic sub-models of disturbance.

1.2 Research Overview

Given the important role disturbance plays in shaping forest structure, function and dynamics coupled with remaining uncertainty in the rates, patterns and consequences of disturbance this research focuses on the following questions: How do disturbance rates vary within and between regions, and how vulnerable are forests to changes in disturbance rates now and in the future?

This research takes a tiered approach to quantifying the spatial and temporal patterns and impacts of disturbance within and between diverse forested landscapes of the contiguous United States. First, in Chapter 2, an intraregional characterization of the patterns and process of disturbance, as captured by over a quarter century of Landsat imagery was performed over the highly forested state of New Hampshire, U.S. In Chapter 3, an inter-regional comparison of disturbance rates, trends and size distributions were conducted across three regions of the contiguous U.S. representing diverse forested landscapes with different dominant disturbance regimes. Finally, in Chapter 4, a framework was developed and used to assess forest ecosystems vulnerability to altered rates of disturbance. Finally in Chapter 5, the main findings, limitations and areas of future research are addressed.

Chapter 2. Intraregional Patterns of Forest Disturbance Rates, Trends and Severity as Captured by a Quarter Century of Landsat Imagery in New Hampshire, USA

2.1 Abstract

Disturbances are one of the dominant processes that shape ecosystem composition, structure, and function. Since forests provide critical local to global provisioning (timber), regulating (climate), and supporting (habitat creation) services, the characterization of disturbance regimes (rates, patterns, processes) is critical to understanding the capabilities of forests to provide these services. Advances in remote sensing technologies are enhancing our ability to capture and now monitor forest properties over large spatial domains. This research examines the forest disturbance and recovery regimes of Northern New England Forests across the state of New Hampshire, USA using over 25 years of annual Landsat remote sensing images and an automated change detection algorithm. Specifically we were interested in the question 'How do intraregional patterns of disturbance vary spatially, temporally, and mechanistically across one the most forested state in the U.S.'. Specific results showed an average rate of disturbance of 0.6% a year. However, this average rate did not appear to be representative of the entire study period as a significant temporal trend in annual area disturbed between 1985-2010 was detected. Strong intraregional patterns of disturbance were found within the states with disturbance recorded to be 4 times higher on private lands than public lands. Further

average rates, and trends varied significantly between counties. Results suggest that management is one of the driving factors affecting forest disturbance in the state, but show that large natural disturbances such as the 1998 ice storm can have significant impacts on statewide rates. While different disturbance events were shown to have different remote sensing characteristics, continued work is needed to classify mechanism of disturbances. The implications of these findings are that the region cannot be well characterized with single average rate spatially, temporally, or in terms of severity. Ongoing monitoring and advances in modeling will be needed to continue to quantify this variation and assess its implications for carbon and other applications.

2.2 Introduction

Forested ecosystems provide critical ecosystem services with local to global significance. These services range from wildlife habitat, biogeochemical processes that control water filtration, carbon transfer and storage, and nutrient cycling, to soil stabilization, water storage, economically important forest product and recreational opportunities (Kasischke et al., 2013; Lorimer & White, 2003). Forest disturbances ranging from multi tree canopy openings to entire forest removal strongly influence forest structure, function and thus the ecosystem services they provide. Quantifying disturbance location, extent, severity and the fate of disturbed biomass has been noted as a way to improve regional to global carbon budget estimates and lead to better initialization, parameterization and /or testing of forest carbon cycle and ecosystem models (Frolking et al., 2009; Hurtt et al., 2002). Further, at regional scales many wildlife and forest managers have shown interest in managing forests more similar to their historic disturbance regimes, yet there is debate on how well we can quantify these past regimes and the of impact changing management may have implications to both economics and biodiversity in the region (Lorimer & White, 2003; Rogers, 1996; Seymour et al., 2002). The spatial and temporal distribution of disturbance is more important than knowing average disturbance rates when determining forest dynamics (Worrall et al., 2005). However, considering the relatively short duration of disturbance events coupled with their relatively infrequent occurrence as compared to forest growth, it has been historically difficult to adequately make these characterizations of forest disturbance regimes at high resolution over large spatial areas (Rogers, 1996).

In the last half-century major advances in active and passive remote sensing technologies, as well as increased data processing and storage capabilities, have brought us into an era of unprecedented forest data and research. These technologies have been instrumental in expanding the characterization and assessment of global vegetation properties but adequately assessing dynamics in these systems remain a challenge. With the agreement to make the Landsat data archive free to the public in 2010, paving the way for mapping forest change at high spatial and temporal resolution from landscape to continental scales (Hansen et al., 2013; Hansen & Loveland, 2012; Masek et al., 2013; Woodcock et al., 2008).

The Vegetation Change Tracker (VCT) is a highly automated change detection algorithm that can detect annual to biannual forest change using time series stacks of Landsat (LTSS) imagery (Huang et al., 2009b). The VCT is making it possible to quickly map forest disturbance at high spatial resolution over large areas of the world's forests. Forest properties such as forest age, which can be inferred from disturbance maps created by forest change algorithms like the VCT, has been shown to be a useful a surrogate variable for analyses of disturbance on forest carbon (Dolan et al., 2009; Goward et al., 2008; Masek et al., 2008; Pan et al., 2011; Williams et al., 2012).

Given the increased awareness of disturbance as a critical process in shaping ecosystem properties and the emerging opportunities to characterize disturbance, this research examines the question: 'How do intraregional patterns of disturbance vary spatially, temporally mechanistically across one the most forested state in the U.S.?' To address this question, disturbance statistics were calculated over the state of New Hampshire, U.S. using over a quarter century of annual Landsat remote sensing images run through an automated change detection algorithm. Specific Objectives were (i) determine annual area of forest canopy disturbed over the study period (ii) test for spatio-temporal variability of disturbance rates across the state (iii) examine the severity and when possible attribution of forest disturbance.

2.3 Data and Methodology

2.3.1 Site description

New Hampshire was chosen as the study region and is located in the northeastern U.S. (Figure 2-1). There are two major Eco-regions the Northern Hardwoods, covering the majority of the state cover the entire western portion of the state and extend north and east. The second Eco-region the Northeastern Coastal Zone covers the southeastern third of the state. Over two thirds of the state's forests are dominated by Northern Hardwoods (maple/beach/birch), followed by pine dominated forests (white/red/Jack pine) at ~15%. Spruce/Fir dominate forests are found in higher elevations while oak/hickory dominated forests are mostly distributed in the southern portion of the state (Ruefenacht et al., 2008). Elevation across the state ranges from sea level to 1,917m.

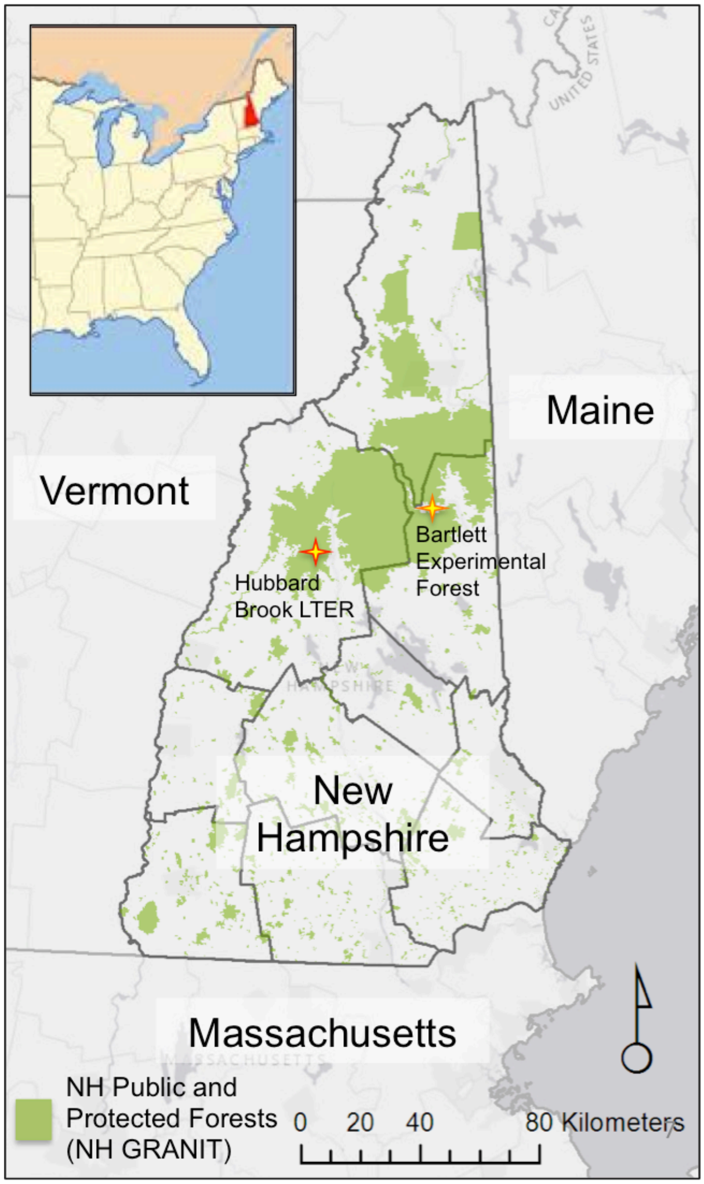


Figure 2-1: Location of the study region, New Hampshire, U.S. overlaid with NH public and protected forests and two long term experimental forests.

Forests in New Hampshire have changed dramatically since European settlement. Forest coverage was estimated to be less than 50% in the mid 1800s due to extensive farming, grazing and logging practices of the time (Foster and Aber 2004). But forest cover has increased significantly across the state after extensive pasture and agricultural abandonment, and the state is now described as the most forested state in the U.S., expressed as a percentage of tree coverage over the state (Nowak & Greenfield, 2012). Logging is still a major part of the state's economy and is most active in Coos County in the northern portion of the state. At the same time, population growth in New Hampshire, mainly derived from the expansion of the Boston metropolitan area, increased from just below 1 million in 1985 to over 1.3 million in 2000 and is placing new pressure on forested lands. Major disturbances in the region include a diversity of harvest practices, land use conversion, insects, disease, wind and ice damage (DeGraaf & Yamasaki, 2001; Foster and Aber, 2004; Rhoads et al., 2002). Natural disturbance events such as the Hurricane of 1938 have been shown to cause significant alteration in forest structure and loss in above ground live biomass over large swaths of the state (Foster and Aber, 2004). Fires are currently relatively rare across the state impacting between 100 – 500 acres annually between 2002 and 2010, but evidence suggest that they were much higher pre European settlement, although these fires were most strongly linked to anthropogenic activities altering landscapes (Foster and Aber 2004; NH Statewide Forest Resource Assessment, 2010). Currently, timber harvesting, and permanent conversion have been considered the major drivers of forest change in the state.

The state is approximately 70% privately owned with the remaining land split relatively equally between National Forest, Industry and other public lands (NH Statewide Forest Resource Assessment, 2010). The White Mountain National Forest covers 16% of the state and contains 5 wilderness areas where development and human management are banned. Bartlett Experimental Forest and Hubbard Brook

Long Term Ecological Research (LTER) site are two long-term research sites situated in the White Mountain National Forest. These sites have played critical roles in advancing the study of forested ecosystems over the last century, and are of particular interest to the development of studies looking at forest response to disturbances (Bormann and Likens, 1979; Dahlgren and Discoll, 1994; Leak 1996; Thomas et al., 2008; Campbell et al., 2008).

2.3.2 The Vegetation Change Tracker (VCT)

Over 120 Landsat 5 & 7 scenes across four Landsat Path/Rows (P13/R30, P12/R30, P12/R29, P13/R29) acquired between June and August from 1984-2010 were selected and run through the highly automated Vegetation Change Tracker (VCT) (Huang et al., 2010; Huang et al., 2009b) (Figure 2-4). Scene selection and VCT processing followed the same criteria laid out in Huang et al. (2009b). However, if a cloud free scene could not be collected in a given year then a composite of images were used to create a cloud free scene for a given year. The minimum spatial mapping unit (mmu) in this study was 0.09 ha. We report disturbance at annual resolution, but the temporal minimum mapping unit is 2 years, meaning disturbances to canopy that did not persist for two time steps were not flagged as disturbed by VCT. Outputted VCT layers used in this study included: Year of First and Last Disturbance, Annual Disturbance Maps and Annual Disturbance Magnitude maps (Figure 2-2).

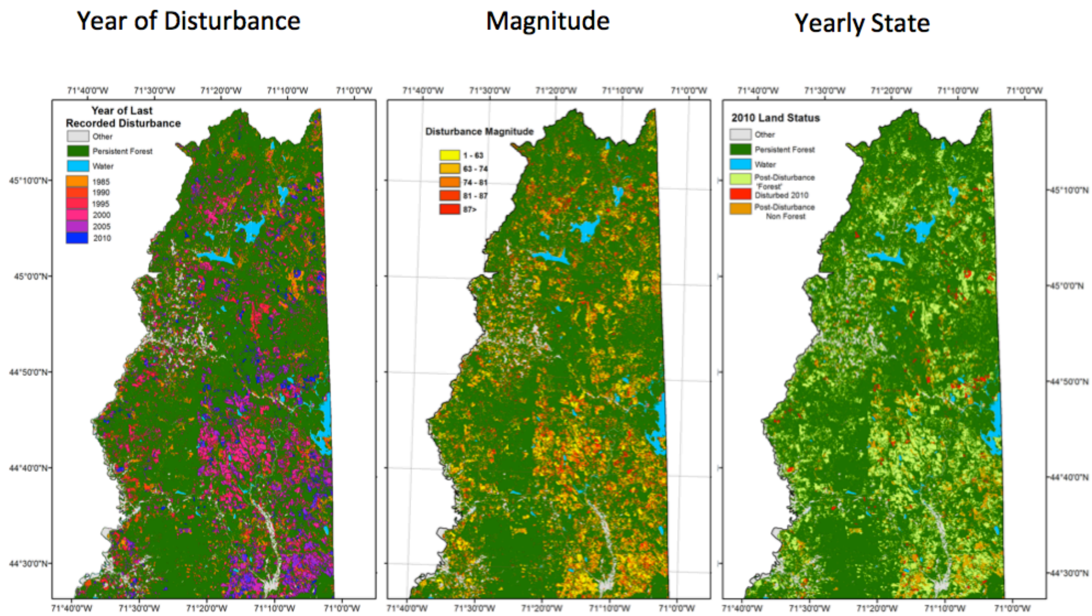


Figure 2-2: Examples of VCT mapped outputs over the northern portion of New Hampshire

Annual disturbance maps classify Landsat pixels into 6 categories: Persisting Non-forest, Persistent Forest, Water, Regenerating Disturbed Forest, Disturbed in mapped year, and Post-Disturbed Non-Forest while Year of First and Last Disturbance maintain the first three categories but then indicate year of disturbance in one layer. It is important to note that year of recorded disturbance (i.e. 1998) represents a range of time in which the disturbance was first detected (i.e. May 1997 – September 1998), since we use leaf on images in the northern hemisphere, disturbances occurring in the later half of the year will be recorded as disturbed in the following calendar year (Figure 2-3).

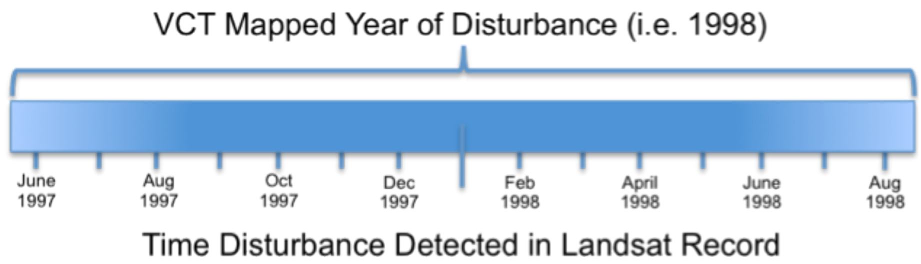


Figure 2-3: Comparison between recorded year of VCT and actual time period disturbance could have occurred

Annual disturbance magnitude maps include three different disturbance metrics; Change in Forest Index (FI), Normalized Difference Vegetation Index (NDVI), and Normalized Burn Ratio Index (NBR) at 30m resolution for both the first and last year of disturbance (Huang et al. 2009). All VCT output for the state were projected to a common spatial reference: 1984_UTM_Zone_19N and mosaicked in ArcGIS 10 software to create seamless disturbance records for the state (Figure 2-4).

2.3.3 Auxiliary Datasets for Disturbance Characterization

In this study, spatially explicit logging records from 1984-1993 created by New Hampshire GRANIT, aerial disturbance polygons from 2000-2010 provided by the Department of Resource and Economic Development (DRED) and imagery within Google Earth were compared to VCT disturbance maps both qualitatively and quantitatively to the accuracy and range of disturbances captured by the VCT across the state. From the NH GRANIT database the NH county boundaries and the NH public lands shapefiles were also downloaded and used for this analysis. County population statistics were obtained from the U.S. census. In addition, spatial grids were created in ArcGIS from 0.25 – 2-degree resolution over the state to explore representation of rates at scales comparable to resolutions to global ecosystem and coupled climate models.

The New Hampshire Timber Clear Cut Inventory produced by NH GRANIT was produced to identify areas cleared to meet forest management objectives (wildlife and timber liquidation). We compared the mapping of disturbed areas of VCT to the disturbance polygons as one means of an accuracy assessment. To create the dataset, clear cuts were identified in Landsat Thematic Mapper (TM) and SPOT panchromatic satellite imagery and were validated and visited by foresters across the state. To be identified as a clearcut, the patch had to be at least 3 acres in size and have a residual basal area per acre of less than 20 ft. The clearcuts were separated into clear cuts identified as with Landsat and SPOT imagery as being cleared before 1990, but no more than 10 to 15 years previous and cuts that occurred between 1990 and 1993 which were detected from SPOT imagery alone. This study used clear cuts records for time period 1990-1993 to extract the magnitude indices of VCT, with the assumption that these areas had high confidence of full biomass clearing. We then compared the distributions of magnitude indices measured in the clear cut regions to the distribution of magnitudes mapped for all disturbance over the state to produce maps of disturbance severity with varying degrees of full clearing confidence.

Digitized Aerial Surveys of forest damage for 2000-2010 (no surveys existed for 2002-3) were provided directly by the NH DRED, Division of Forest and Lands – Forest Health division. Maps were created using the Forest Service Aerial Survey

Standards that include attributes of cause, extent and severity. Additionally, shapefiles of a digitized map of the 1998 Ice storm damage, which provided two levels of severity, was also obtained from NH DRED.

Using ArcGIS and JMP statistical software zonal statistics on disturbance rates and severity were extracted and quantified over the entire state of NH, and broken down by course resolution grids, ownership and county boundaries as well as auxiliary disturbance survey records.

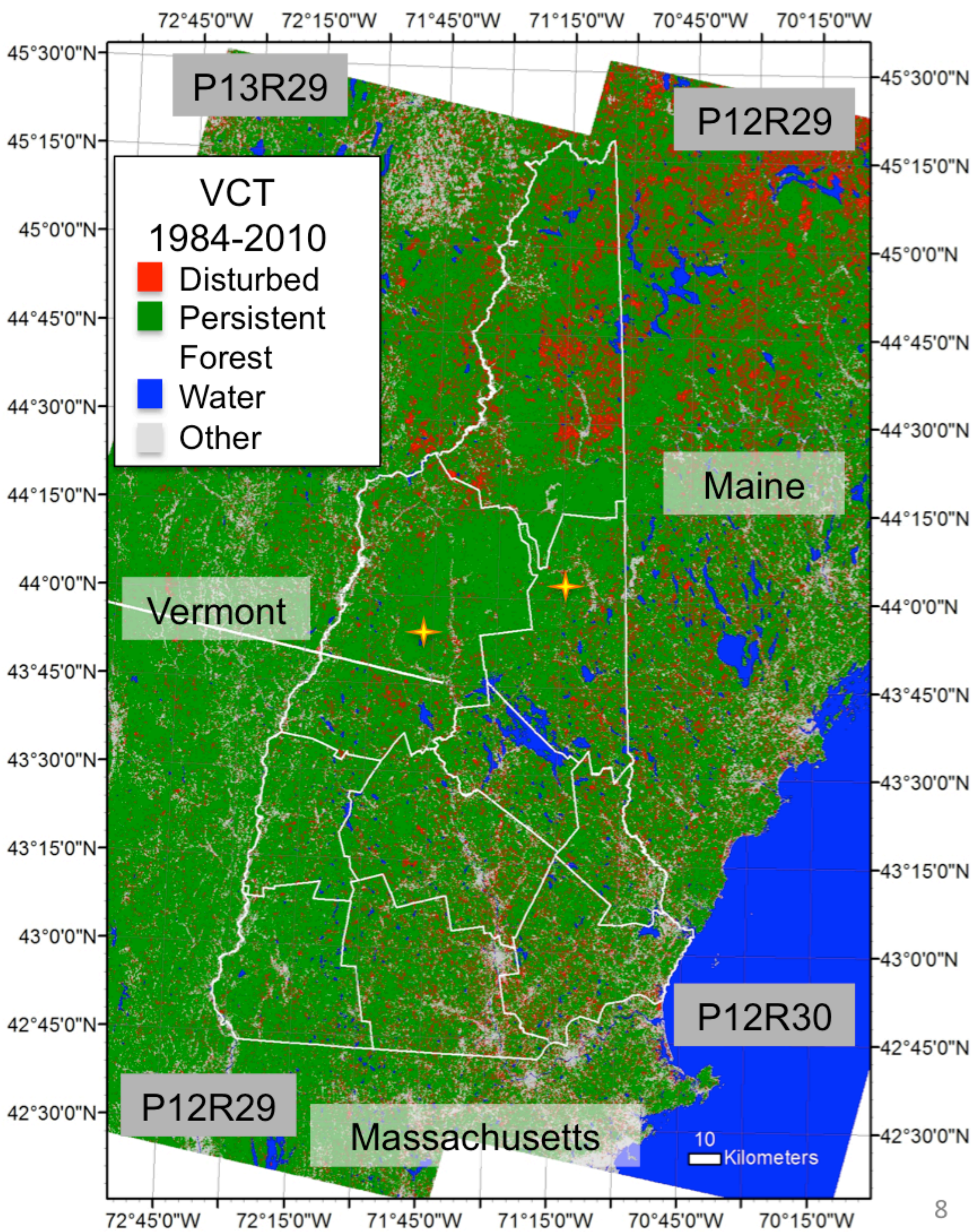


Figure 2-4: VCT mapped disturbance over NH study region.

2.4 Results

2.4.1 Statewide Results

VCT mapped the land area of NH as 2,402,074ha, of which ~90% (2,164,494ha) was defined as being forest for all or some portion of the study VCT record (1984-2010). Note, our definition of forest differs from U.S. forest service, as we did not impose the 1-acre minimum mapping unit to be considered forest in our study. Between 1985 and 2010 over 305,000 Ha or 15.1% of the state forest area was recorded as being disturbed. An average annual disturbance rate at 0.65% (SE +/- 0.07, 1SD 0.17) was measured over the state with just over 15% of the states mapped forestland having more then one forest disturbance event recorded during the study period. Annual rates ranged from a low of 0.37% in 1988 to a high of 1.05% percent of forest area disturbed in 1998. Statewide, forest area disturbed annually showed a statistically significant (alpha = 0.05) increase between 1985 and 2010, with an average annual increase of 367 ha per year or 0.0169% forest area per year (95% CI = +/-0.006%, $r^2 = 0.54$, $p < 0.0001$) equivalent to a doubling of the disturbance rate over the study period (Figure 2-5).

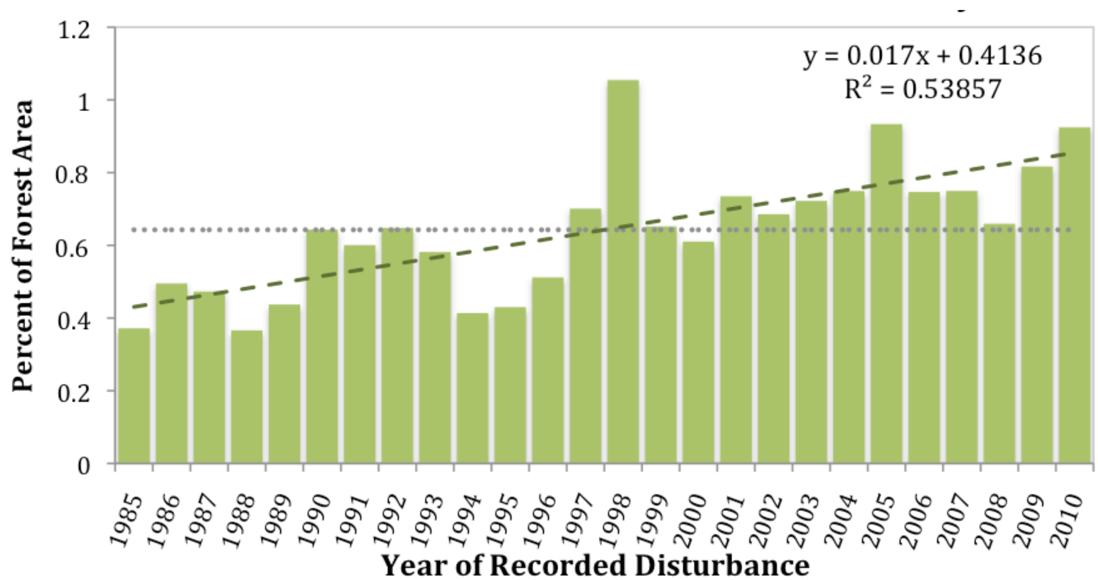


Figure 2-5: Annual percent of forest area mapped as disturbed between 1985-2010 with mean and trend.

2.4.2 Characterization of Intraregional Variability in Rates and Trends

Are these trends and rates representative of the state? What factors are driving variability? The average rate of disturbance across the state hid substantial spatial variability. When disturbance were aggregated to quarter degree scale, total disturbed forest area ranged from 3.4% in the center of the state to 33% in the northern Coos County, differences in total disturbance could be more than 6 times higher between neighboring areas (3.4 – 25.3%) (Figure 2-6).

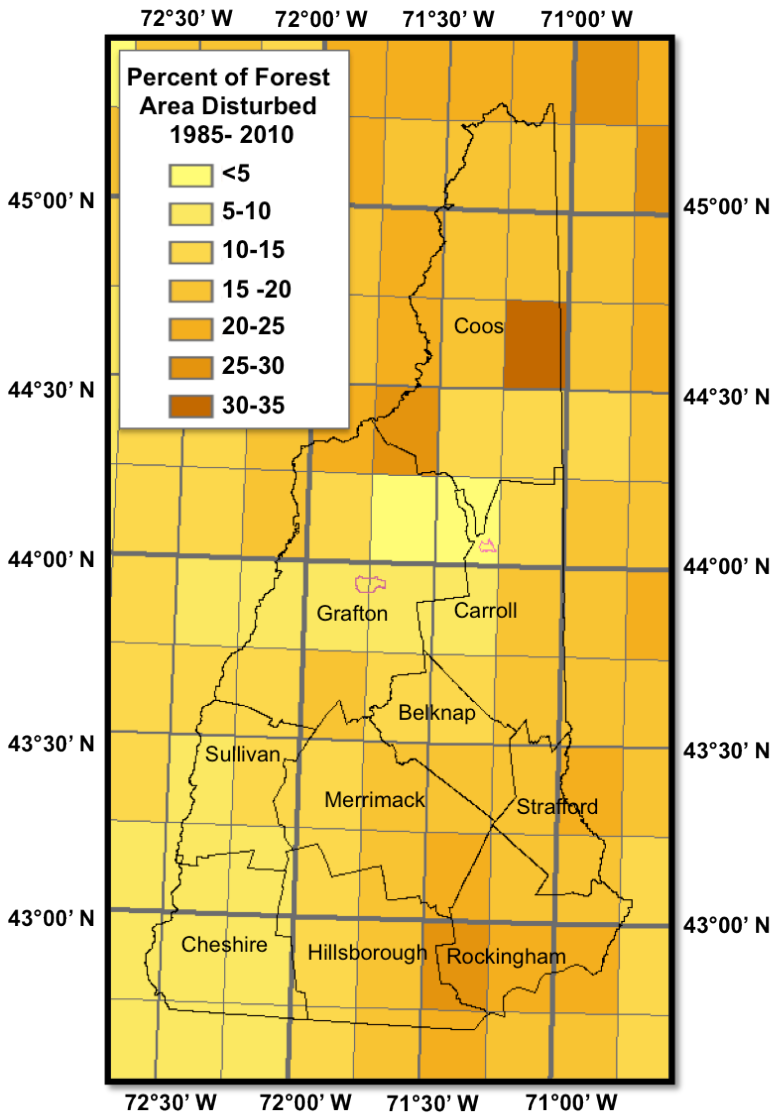


Figure 2-6: Percent forest area disturbed between 1985-2010, mapped at quarter degree resolution, show strong variations in disturbance rates across the state. Counties are provided for spatial reference.

Results showed large differences in the total amount and annual percent of forest disturbed between counties across the state (Figure 2-7, Figure 2-8). Coos County, the northern most county in the state, showed both the highest rates of forest disturbance and total forest area disturbed, while also containing the lowest population density. Grafton County had a similar total forest cover as Coos County but had disproportionately low rates of forest disturbance. In general, the southeastern counties had a higher percent of mapped disturbance not recovering within the VCT record, with Rockingham County showing the highest percentage of forests not recovering within ten years of the disturbance. Counties also on average higher inter-annual variation then that mapped at the state level and 7 of the 10 counties displayed a significant temporal trend (Figure 2-8).

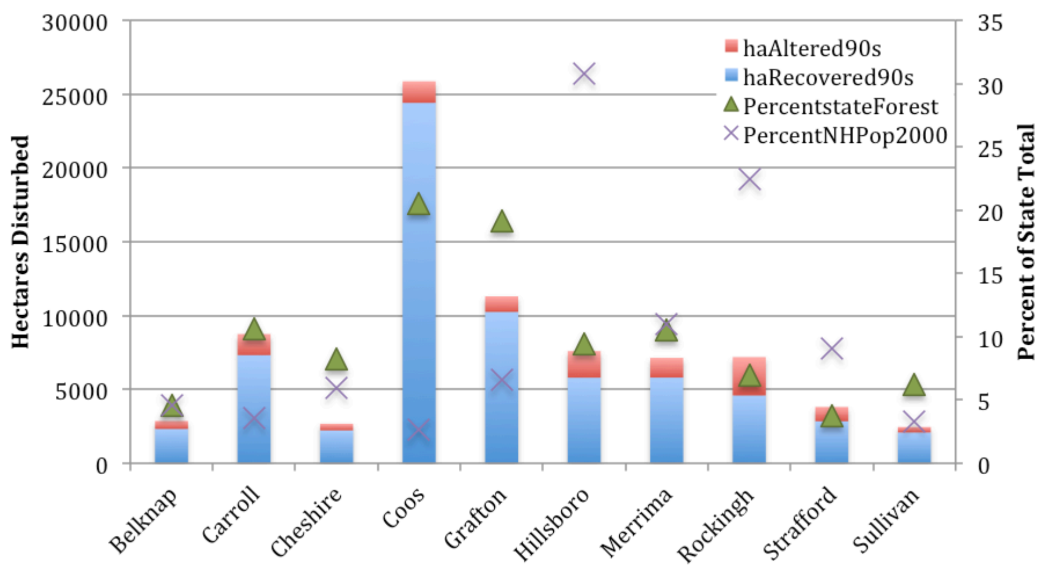


Figure 2-7: Comparison of disturbed forest area (ha) between 1990-1999, with fraction of disturbed area showing recovery in blue and no recovery in red. Percent of NH forest area occurring in county and county population in each county are shown for comparison. *Note disturbed lands with more than one recorded disturbance are excluded from this analysis.

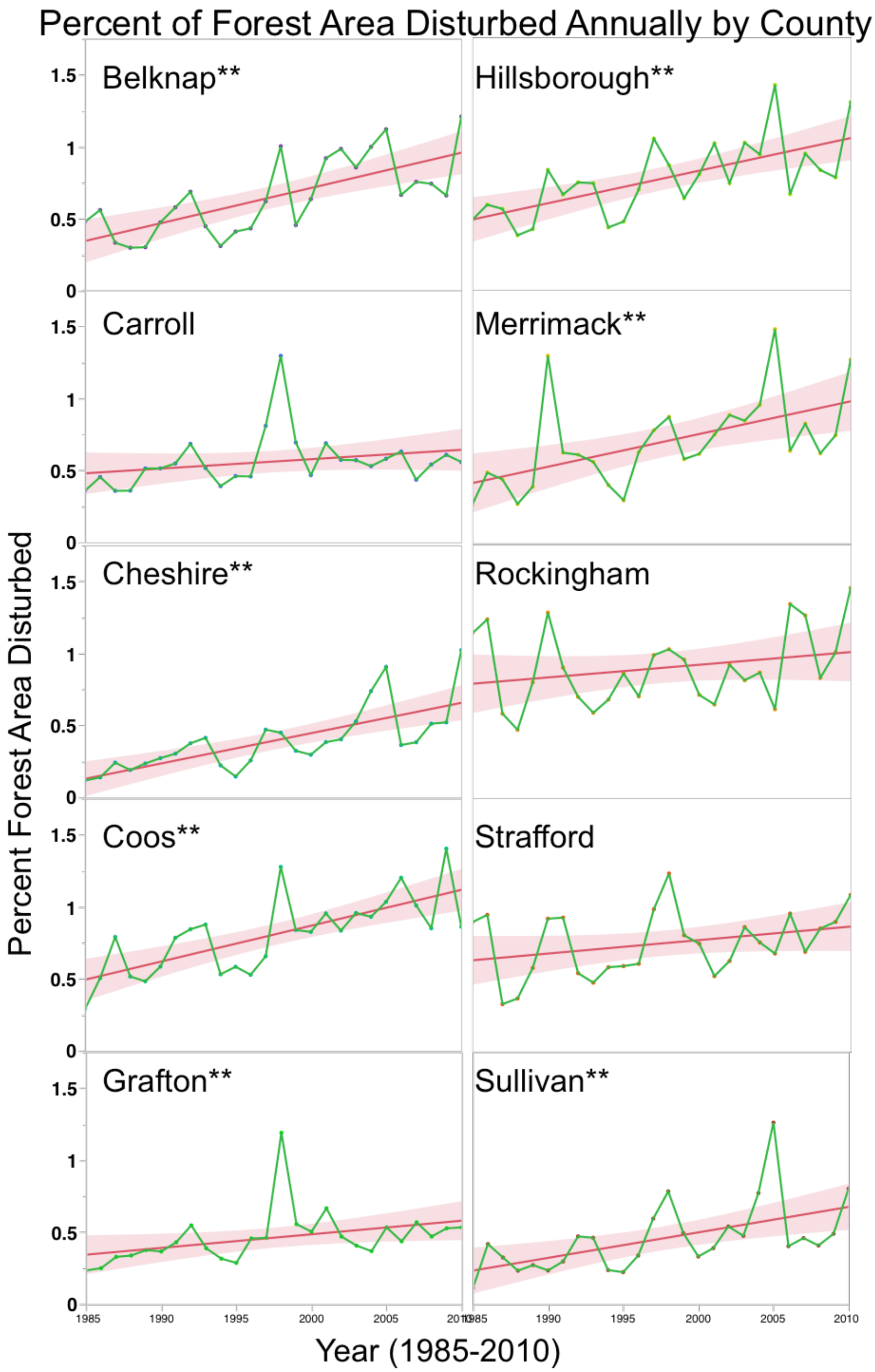


Figure 2-8: The annual percent area disturbed for 10 counties in NH between 1985-2010. Red line shows the estimated trend over the study period, with shaded area representing the uncertainty in trend at 95% confidence interval. **Denotes counties with a significant ($p < 0.05$) temporal trend in disturbance rate.

Disturbance was recorded to be on average 4 times higher on private lands vs. public lands (Figure 2-9). Further there was no evidence of an increasing trend in disturbed area over time within public lands, declines in area disturbed after 1993 may the result of a 1993 change in forestry policy in the White Mountain National forest and or may also reflect the increase in conservation lands during the study period.

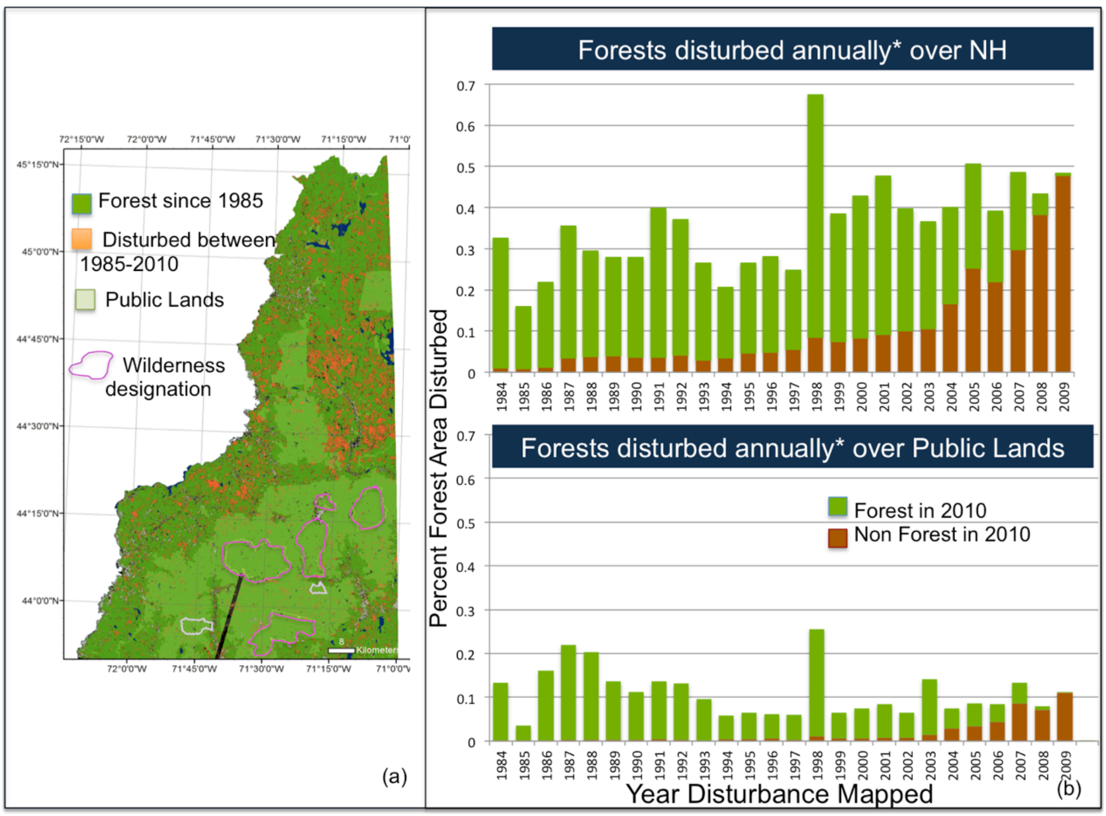


Figure 2-9: Disturbance mapped on private vs. public and protected lands (a) VCT mapped disturbance overlaid by public lands show decrease in disturbed area (b) comparison of annual disturbance rates over the state (top) vs. public lands (bottom). *Note lands having more than one recorded disturbance are omitted.

2.4.3 Towards Disturbance Mechanisms and Severity

VCT showed good agreement with the CC record with 70% of SPOT polygon areas (1990-1993) mapped as being disturbed within the same year by VCT (Figure 2-10). Some of the miss match may be explained by misregistration between the two layers and residual forest area within the clear-cut boundaries. We extracted magnitude metrics from VCT maps that fell within the Clear Cut polygons. Assuming the clear cuts on average give us high confidence of clearing we used the quartile information on the distribution of magnitude as a means of confidence of clearing (Figure 2-10 b-c). Using this metric of certainty we mapped magnitudes over the state and found that ~50% of the mapped disturbance have medium to high confidence that full clearing took place, where as 50% of the state fell within to the lowest severity bracket extracted from the clear cuts. Another possible way to assess severity from the VCT record is measuring the time to spectral recovery (S- Figure 2-14).

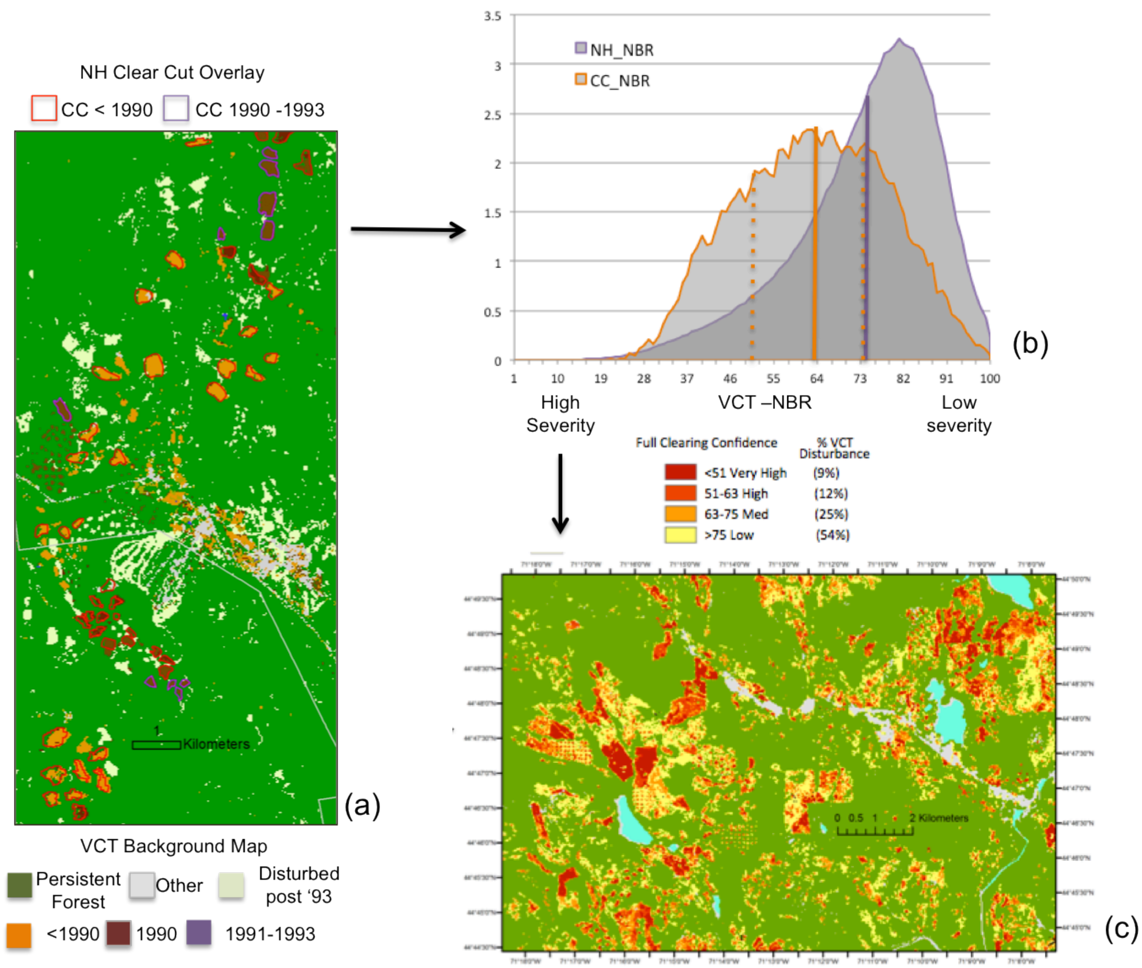


Figure 2-10: Comparison of VCT mapped disturbance and magnitude in comparison to NH Clear Cut data. (a) VCT mapped year of disturbance overlaid by NH GRANIT Clear Cut observation near Bretton Woods Ski area in NH. (b) Comparison of distribution of 1 metric of disturbance magnitude, NBR, as recorded within clear-cut sites (CC_NBR) and over the entire state (NH_NBR). The mean magnitude for each distribution is shown in solid lines. (c) Using the distribution of recorded magnitude within cleared areas VCT records were categorized over the state into confidence of full canopy clearing.

Mapped disturbance rates were anomalously high in 1998 over state forests, with the anomaly more distinct over public lands and within western and northern counties. In January of 1998 an unusually long, severe and extensive ice storm was recorded that extended from the northwestern New York and Quebec through central and southern Maine. After the ice storm special aerial surveys of damage were conducted by the NH Division of Forests and Lands (DRED) and the USDA Forest Service. The digitized polygon layers of aerial sketch maps delineating forests displaying high and moderate damage after the January 1998 ice storm covered 10% of all of the states forest (Figure 2-11). VCT mapped rates of forest disturbance were compared within areas mapped by DRED as having High or Medium damage and were further compared to the reaming state forestlands. Both the Medium and High damage areas showed lower than average annual rates of disturbance before the January 1998 ice storm then the surrounding forests. During the year of the ice storm event, 1998, VCT recorded annual rates of disturbance significantly higher in areas within mapped damage then either any of the years before or after. Both areas mapped with High severity and Medium severity also showed significantly higher rates of disturbance then those areas not mapped in 1998. VCT recorded rates of disturbance in 1998 was highest in areas mapped as having High damage (Figure 2-12). Disturbances within these areas accounted for 23% of the entire mapped disturbance across the state in 1998. A study by Shortle et al. (2014) looked at tree survival 5-15 years post the ice storm revealed that paper birch tree mortality increased from 1-5% for those trees that lost less than one half of their crown in the ice storm and from 5 to 24% for those trees who lost more than half. These finding may in part explain the higher and more variable rates of disturbance within ice storm zones post the event.

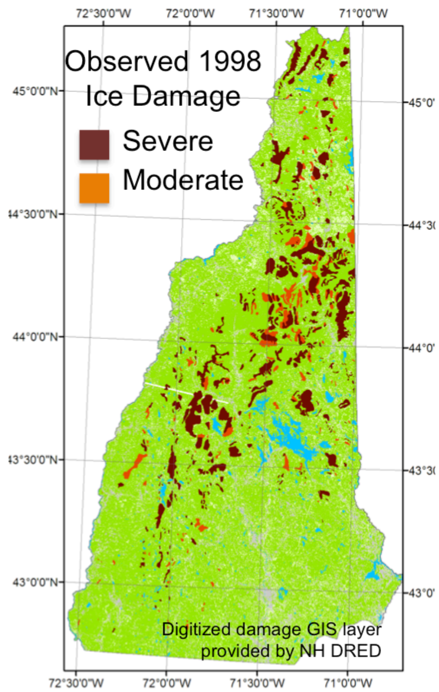


Figure 2-11: Forest areas mapped by NH DRED aerial team as having severe and or moderate damage from the January 1998 ice storm.

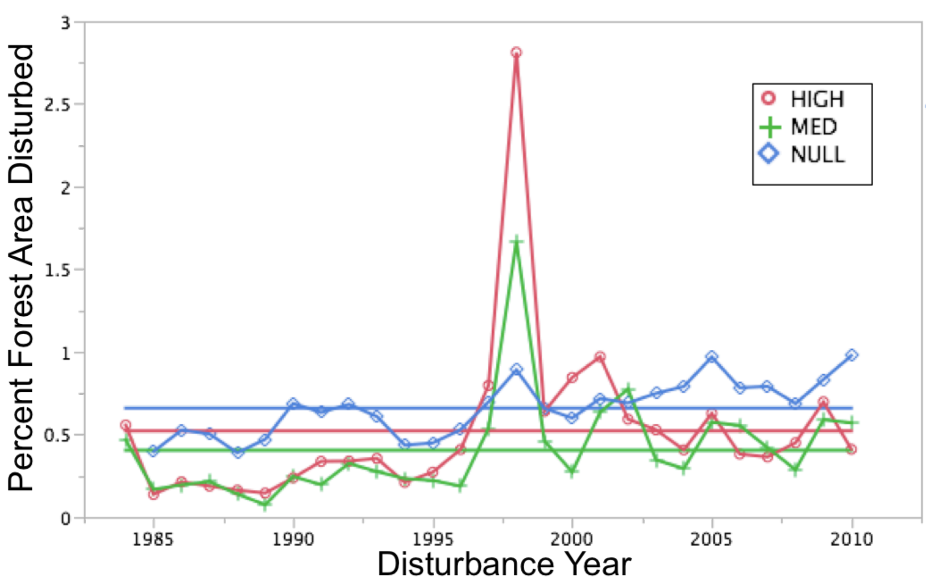


Figure 2-12: Annual disturbance rates measured within areas mapped by NH DRED as having High (Red) or Medium (Green) canopy damage resulting from the 1998 ice storm. Rates for all other state forest area are shown in blue.

A clear linear disturbance event was visibly evident as a spatial anomaly in VCT state maps of disturbance. Strong evidence links the cause of damage to a tornado that hit the state on July 24th 2008. The tornado was tracked for over 50 miles in southeastern NH, making it the longest recoded tornado in New England history. Comparing VCT mapped disturbance to the aerial polygons, the generality at which DRED damage surveys are conducted over the state is evident, with clear tracks outside the sketched boundaries of disturbance (Figure 2-13). When comparing the VCT annual mapped disturbance both within the DRED mapped zones, VCT recorded disturbance in 2008 was 10 times higher than average within DRED mapped tornado damage zone (Figure 2-13). Mapped disturbance was still significantly higher than the average rate 2 years post event, possibly signaling dieback and salvage operations.

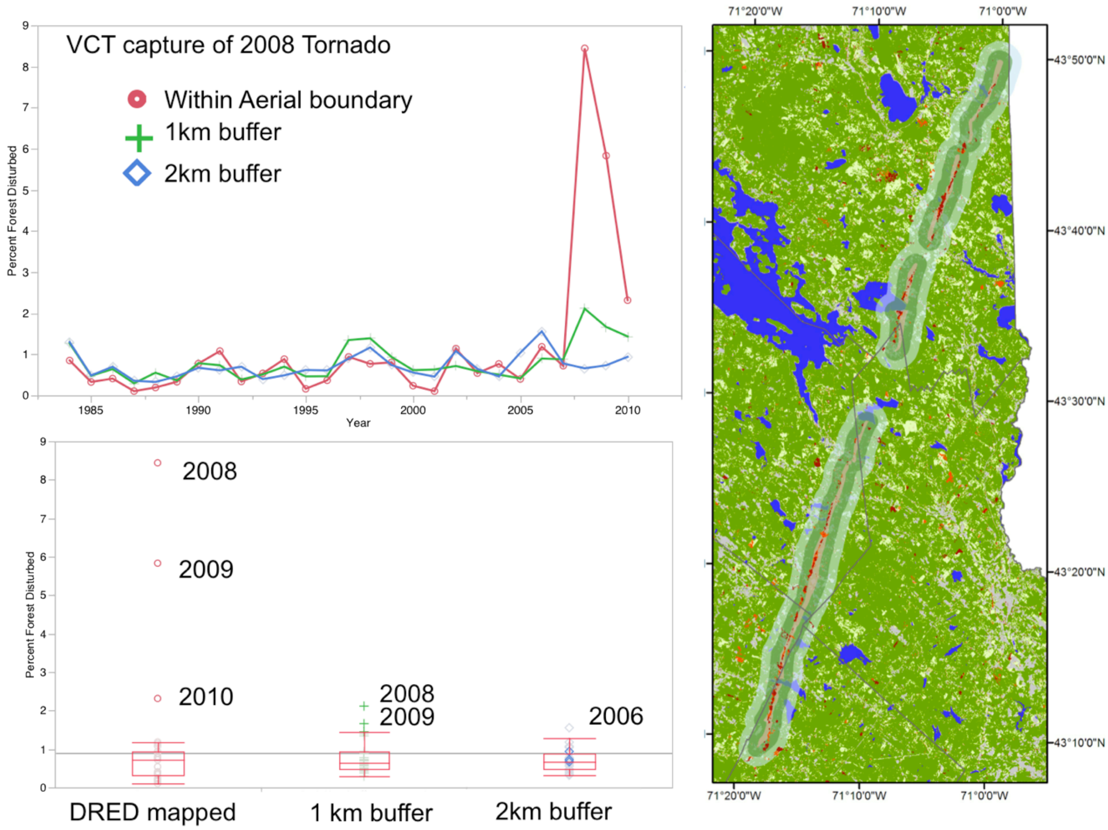


Figure 2-13: Comparison of VCT annual disturbance rates within DRED mapped 2008 tornado damage, and in areas lying within 1km and 2km buffer.

2.5 Discussion

While the state wide an average rate of disturbance was 0.6% a year, results showed strong intraregional patterns of disturbance across the study area as well as a significant temporal trend in annual area disturbed between 1985-2010. Rates across the state when aggregated to quarter degree resolution could differ by a factor of ten, with adjacent areas showing up to a six fold difference. Further average rates, trends and severity varied significantly between geopolitical boundaries with disturbance recorded to be 4 times higher on private lands than public and protected lands.

Disturbance events with different severity were shown to have different remote sensing characteristics. Results suggest that management is one of the driving factors affecting forest disturbance in the state, but that large natural disturbances such as the 1998 ice storm can have significant impacts on statewide and intraregional rates of disturbance. Implications of these findings are that the region cannot be well characterized with single average rate spatially, temporally, or in terms of severity. Ongoing monitoring and advances in modeling will be needed to continue to quantify this variation and assess its implications for carbon and other applications.

It is important to note that previous research on natural disturbances indicate that disturbance most often occur at gap phase, or non stand clearing, over the majority of NH study region (Rogers 1996). Further harvest practices in some areas of the state may be moving away from clear cuts to emulating natural gap phase dynamics (Seymour 2002). VCT may be underestimating these disturbance events (Masek et al. 2013). Results presented in this chapter show the capture of less intensive clearing, and also highlight the ability to capture wind and ice damage; however there may be underestimation in areas of the state where gap-phase dynamics dominate. Further characterization of disturbance size characteristics and across the state may aid in estimating smaller disturbances.

The annually mapped products produced by the VCT produced a novel look at the spatial and temporal distribution of canopy clearing disturbances. Although this study was not able to link attribution to all mapped disturbances, the strong agreement to clear cut records, capture of wind and ice events and observed spatial and temporal trends observed in this study support continued work linking observed data to mechanisms, severity and fate of disturbed forests (Cohen et al., 2010, Masek et al., 2013, Schleeweis et al., 2013). Assessing county and ownership statistics suggest strong anthropogenic influence on the disturbance regime as captured by VCT across the state with strong geopolitical trends, which may be linked to population growth and forest ownership and management. However natural disturbance still play an important role in NH forests. FIA estimates of mortality (not related to harvest or conversion) within forest stands were the highest ever recorded in the state over the 1997- 2007 inventory a period (FIA 2007). Disturbance captured by Landsat imagery also increased during the same period, the increase was particularly evident in areas hit by the 1998 ice storm. The temporally rich and spatially explicit data on disturbance presented in this study can be very useful to carbon monitoring and modeling efforts as well as, monitoring and planning of other ecosystem properties and services such as wildlife habitat (Thomas et al., 2008; Frolking et al., 2009; Greenberg et al., 2011; Becknell et al., 2015).

2.6 Supplementary Material

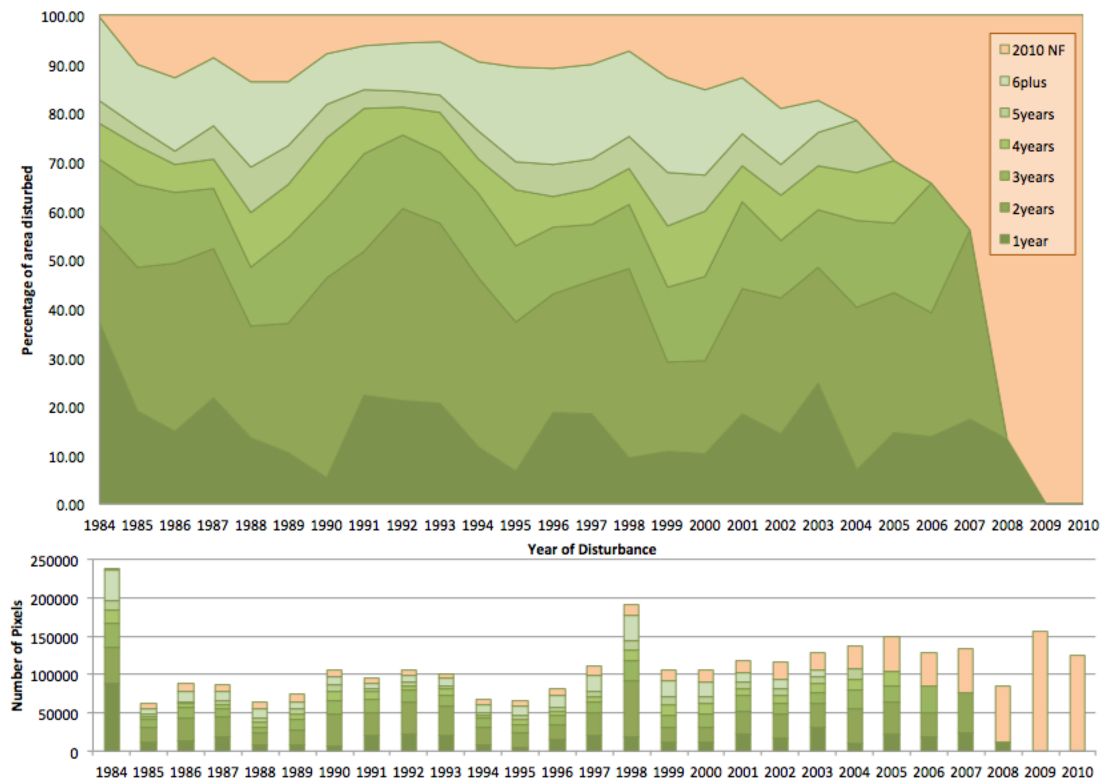


Figure 2-14: Average number of years an area was flagged as disturbed post disturbance year shown as both a percentage of the year total (top panel) and absolute amount (bottom panel). Data is only shown for years that had one disturbance in the study period.

Chapter 3. Spatial and Temporal Patterns of Forest Disturbance Within and Between Three Diverse Regions of the U.S: Rates, Trends and Size Distributions

3.1 Abstract

Disturbances strongly influence forest structure, function and the ecosystem services they provide. However the spatial patterns, rates and processes driving disturbances remain highly uncertain. This research addresses the question: How do the rates, trends and sizes of disturbance vary between regions with different forest types and modes of disturbance? To address this question, a quarter century of annual Landsat imagery was used in the Vegetation Change Tracker (VCT) to obtain annual maps of disturbance over three diverse forested regions in the contiguous United States (CONUS). Results showed significant distinctions in disturbance rates, variability and size distributions across the Northeast (NH), Northwest (OR) and Southeastern (NC) study regions. The Southeastern region, displayed the highest annual rates of disturbance with an average rate of 2% y^{-1}. The Northwestern region's average annual disturbance rate was intermediate at 1.2% y^{-1}, had the largest recorded disturbances, but showed the largest inter-annual variability in proportion of large events. The Northeastern region had the lowest average annual rate at 0.6% y^{-1}, was dominated by the greatest proportion of small disturbances, and had both a significant increase in both the rate and size of disturbance over the period. These results

demonstrate that forest disturbance is a complex and heterogeneous process that varies both between region and through time. Key challenges in the future involve monitoring these events over large areas at high resolution, and subsequently incorporating this heterogeneity into models to estimate impacts on carbon and other important forest properties.

3.2 Introduction

Forest disturbance strongly influence forest structure, function and the ecosystem services they provide (Drummond & Loveland, 2010; Lorimer & White, 2003; Oliver & Larson, 1996). Ecologists have thus been interested in the question of the how disturbance spatially manifests itself across forested landscapes and regions for many years (Asner et al., 2013; Franklin & Forman, 1987; Frolking et al., 2009; Turner et al., 2001) With increasing population, competing land uses, and climate changes altering natural disturbance rates and regimes, it is ever more pressing to have spatially explicit monitoring systems of forest change over long time periods with high temporal frequency (Dale et al., 2001; Goward et al., 2008).

In the last half-century, major advances in active and passive remote sensing technologies, as well as increased data processing and storage capabilities, have allowed for the collection, storage and analysis of global vegetation properties and dynamics (McDowell et al., 2015; Wulder et al., 2012). These technologies are instrumental in documenting the spatial patterns of forest disturbance. Space-borne optical remote sensing has been used to map large-scale forest disturbance occurrence, location, and extent over the last 30 plus years (Mukai et al., 1987; Morton et al. 2006; Chambers et al. 2007; Masek et al. 2008; Roy et al. 2008; Hilker et al., 2009). Within the last decade, the agreement to make the Landsat data archive free to the public has made it feasible to map forest change at high spatial resolutions from landscape to continental scales, with sub decadal to annual temporal resolution (Hansen & Loveland, 2012; Huang et al., 2010; Jeffrey G. Masek et al., 2013; Woodcock et al., 2008). Additional metrics such as forest age, which has been shown to be a useful surrogate variable for analyses of disturbance on forest carbon, can be inferred from these products and are advancing our understanding of disturbance on the terrestrial carbon cycle (Dolan et al., 2009; Goward et al., 2008; Masek et al., 2008; Pan et al., 2011; Williams et al., 2012).

Quantifying the rates, trends and size distribution, of disturbances is important for accurate monitoring of forest carbon dynamics, as well management and planning for carbon sequestration, wildlife and forest products (Chambers et al., 2013; Fisher, et al., 2008; Franklin & Forman, 1987; Frolking et al., 2009; Greenberg et al., 2011; North & Keeton, 2008; Seymour et al., 2002). It has been well documented that gap-size distribution in forests can generally be characterized by more small-sized gaps than large-sized gaps (Yamamoto 2000; Nelson 1994; Kellner et al., 2009; Chambers et al., 2013; Asner et al., 2013b). The shape and steepness of this relationship may have important implications on growth dynamics, habitat suitability, and the ability of various sampling procedures to capture landscape-scale, carbon balance estimates. Fisher et al. (2008) demonstrated, using models, how the ability to accurately estimate net carbon balance from field sampling is strongly affected by the granularity of disturbance across the landscape. When a forested region is dominated by small and frequent disturbances randomly distributed across its landscape (i.e., a well mixed heterogeneous landscape), even small and infrequent sample plots can represent domain behavior. However, in landscapes with a greater dominance of rare and large disturbance events, observations from plots tend to under sample regional mortality from disturbance and thus show significant bias in their estimates towards growth. Thus, current remote sensing technologies may help to better quantify regional disturbance regimes spatial and temporal dynamics, helping to inform both plot placements for short term forest assessments or in the appropriate scaling of sparse long term plot measurements of growth and mortality (Fisher et al., 2008; Rogers, 1996). Kellner and Asner (2009) quantified forest gap size frequencies of over 400,000 canopy gaps across five diverse tropical rain forest landscapes using lidar remote sensing and found that scaling relationships were qualitatively similar despite differences in prevailing modes of disturbance. Similar results were found in the lowland Peruvian Amazon (Asner et al., 2013b). Chambers et al. 2013 studied forest gap size distributions caused by wind events in central Amazon and noted the difficulty in capturing intermediate sized disturbance events using either small field plots or coarse resolution satellite data.

Turning to North America, the contiguous U.S. has one of the most robust ground based forest monitoring programs globally, managed under the Forest Inventory and Analysis (FIA) program. However, it has been noted that FIA historically has not been well structured to capture relatively rare disturbance events (Schleeweis et al., 2013). Further, national inventories based estimates of disturbance area come from a suite of databases for harvest, fire and insect which may not always be consistent (Masek et al., 2013; Schleeweis et al., 2013). Therefore, gathering spatially and temporally consistent high-resolution data on disturbance rates, sizes and spatial organization can give us new insights into disturbance regimes throughout the CONUS.

Given the importance of disturbance in shaping the structure and function of forest ecosystems, the various climate and anthropogenic pressures altering regional disturbance, and the technological advancements in mapping disturbance, this research aimed to address the following question: How do the near present rates and patterns of disturbance vary between regions with different dominant forest types and disturbance regimes? To address this question a quarter century of Landsat data were analyzed over three district-forested regions within the U.S.

3.3 Methods

3.3.1 Study Site Descriptions

To conduct this research, a quarter century of Landsat data was analyzed over three district-forested regions within the U.S. The three geographically distinct regions were chosen to represent a range of forest types, climate, topography, and dominate disturbance mechanisms (Figure 3-1).

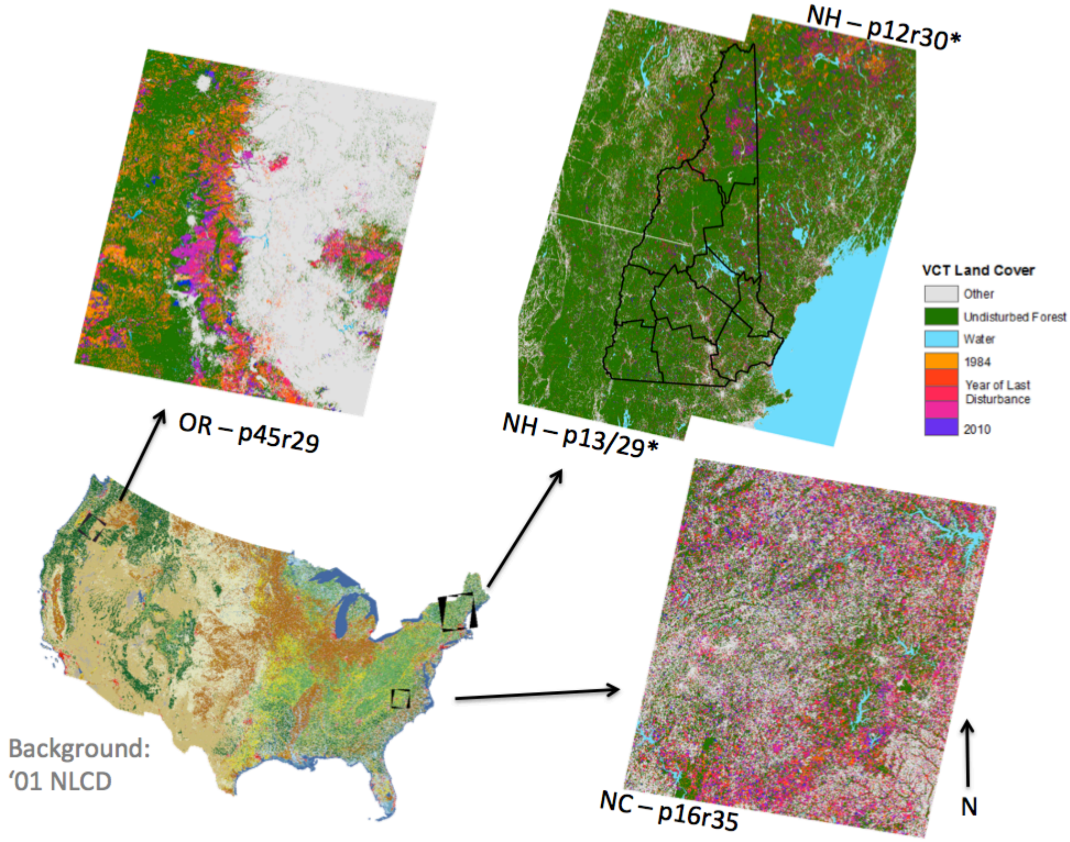


Figure 3-1: Location of the three study sites representing diverse biophysical regions in the U.S. with different dominant mechanisms of disturbance. VCT mapped land cover and year of last disturbance shown for each region.

New Hampshire (NH): According to the U.S. Forest Service, as of 2008, New Hampshire is the most forested state in the U.S., expressed as a percentage of land cover (Nowak & Greenfield, 2012). Over two thirds of the state's forests fall under the Northern Hardwoods (Maple/Beach/Birch), followed by Pine (White/Red/Jack pine) at approximately fifteen percent Spruce/Fir are prominent in higher elevations, while Oak/Hickory forests are mostly distributed in the southern portion of the state (Ruefenacht et al., 2008). Major disturbances in the region include a diversity of harvest practices, land use conversion, insects, disease, wind and ice damage (DeGraaf & Yamasaki, 2001; Rhoads et al., 2002). Fire is a much smaller portion of the disturbance portfolio with between 40-400 hectares burned annually since 1990 (NH Statewide Forest Resource Assessment, 2010). The state is approximately 70% privately owned with the remaining land split relatively equally between National Forest, industry and other public lands (NH Statewide Forest Resource Assessment, 2010). Elevation across the state ranges from sea level to 1,917m. Four Landsat Path/Row tiles (P12/R29, P12/R29, P13/R29, P13/R30) were selected to cover the state.

Central North Carolina/ Southern Virginia (NC): A majority of this study region falls within the Piedmont Plateau geologic region covered by Landsat scene P16/R35. Oak/hickory was the most dominant forest type, covering over 60% of the forest area. A quarter of the region was characterized as loblolly/shortleaf pine, and 10% as an oak/pine mix (Ruefenacht et al., 2008). Urbanization and harvest have been noted as the current dominant mechanisms of forest disturbance in the region (Huang et al., 2015; Thomas et al., 2011), though more infrequent hurricanes and windstorms can cause catastrophic damage, such as Hurricane Fran in 1996 (Xi, 2008). Approximately 80% of all forestland in North Carolina is privately owned with a much higher percentage in the Piedmont region (Brown and New, 2013). Elevation within the study region ranges from sea level to 610 meters.

Central Oregon (OR): The study region covered by P45/R29 is a mix of temperate evergreen forests in the west, dry grass and shrubs in the central and eastern regions (Thomas et al., 2011). Douglas-fir, followed by ponderosa pine, were the most abundant forest types (40% and 25% respectively), while approximately 18% of mapped forest types in this study area were pinyon/juniper (Ruefenacht et al., 2008). Due to their sparseness, most of the pinyon/juniper forestlands were not included in VCT forest classification. More than 12% of the forested landscape was classified as fir/spruce/mountain hemlock. Fire, harvest and fuel treatments have been listed as the dominant mechanics of forest disturbance in the region (Thomas et al., 2011). More than 85% of the forested land in the study region was under federal ownership (ESRI USA Federal Lands). Elevation within the study scene ranged from ~145- 3425 meters above sea level.

3.3.2 Vegetation Change Tracker

To quantify disturbance in these three different regions, annual cloud free Landsat 5 & 7 scenes were acquired between the months of June and August for the period of 1984-2010. If a cloud-free scene could not be collected in a given year, then a composite of images were used to create a cloud free scene for a given year. In total approximately 200 Landsat scenes were collected and processed through the Vegetation Change Tracker (VCT) following the criteria laid out in Huang et al. (2009a). This study utilized Annual Disturbance Maps created by VCT, which classify Landsat pixels into 6 categories: Persistent Non-forest, Persistent Forest, Water, Regenerating Disturbed Forest, Disturbed in mapped year, and Post-Disturbed Non-Forest. It is important to note that year of recorded disturbance (i.e. 1998) represents a range of time in which the disturbance was first detected (i.e. May 1997 – September 1998). Since leaf on images were used, disturbances occurring in the later half of the year will be recorded as disturbed in the following calendar year.

Disturbance is reported at annual resolution in this study but the temporal minimum mapping unit is 2 years, meaning disturbance to canopy that do not persist for two time steps will not be flagged as disturbed by VCT. The minimum spatial mapping unit (mmu) in this study was kept to the resolution of 0.09 ha (900 m^2), equivalent to a single 30m resolution Landsat pixel.

The VCT disturbance products have been assessed in multiple studies over a variety of landscapes in the continuous U.S. (Huang et al., 2009a; Huang, et al., 2009b; Li et al., 2009; Huang et al., 2010; Huang et al., 2015;). The ability of VCT to characterize disturbance in the North Carolina and Oregon study regions were in part validated through the North American Carbon Programs North American Forest Dynamics Phase I and Phase II actives (Masek et al., 2013; Thomas et al., 2011) and a detailed accuracy assessment for North Carolina scene can be found in Huang et al., 2015.

This study did not distinguish between disturbance mechanisms rather all disturbance events large enough to be detected by the VCT were grouped together (see Huang 2009 for an analysis of VCT detection). Further, permanent conversion of lands were not separated, thus, the definition of disturbance used in this study focuses on forest 'turn-over' and resembles usage of *gross forest cover loss* (Hansen et al., 2010; Masek et al., 2013).

3.3.3 Rates, Trends and Disturbance Size

Descriptive statistics, including percent of scene categorized as persistent forest or disturbed forest, were calculated for each region using GIS software. JMP statistical software was used to quantify variance in annual rates within regions, test for temporal trends within regions. The all pairs Tukey-Kramer test was used to test if rates between regions were significantly different. The distribution of disturbance patch sizes in each region was also quantified annually. The raster to polygon tool in Arc10.1 was used to create annual disturbance polygon layers from annual VCT disturbance raster layers. Unique disturbance polygons were defined as a single pixel or group of pixels that shared an edge (excluding corners). For example, a VCT-mapped disturbed pixel that shared no edges with any other disturbed pixel in the same year would be considered a unique disturbance patch and would have a recorded disturbed area of 900 m^2. Though it is recognized that any given disturbed pixel could represent a range of live biomass loss (Chambers et al., 2013) it was beyond the scope of this study to distinguish between partial and full clearing in the reporting of disturbance patch areas.

Based on previous studies (Asner et al., 2013; Chambers et al., 2013; Fisher et al., 2008; Kellner & Asner, 2009) a power law probability distribution (eq 1.1) was used to describe disturbance patch sizes frequencies across each study regions. The number of patches (N) of a given areal size (x) is assumed to vary as:

$$N_x = Ax^{-\alpha}$$

where α is the scaling exponent and A is an overall scale or normalization constant (Fisher et al., 2008). Assuming an equal amount of total area in a region has been disturbed, a larger alpha would show the majority of disturbed area coming from a larger number of very small events. As alpha decreases, a greater proportion of disturbed area would come from larger, more infrequent, events. The tendency for disturbance patch sizes to fit a power law probability distribution was assessed following three approaches: (1) least square fit to raw image data (LS-lin); (2) least square fit to normalized logarithmic binned data (LS-bin); and (3) maximum likelihood estimation (MLE).

Least squares estimator (LSE) approaches have been criticized in recent years for their inability to accurately estimate the parameters of power-law distributions. Nonetheless, LSE approaches represent historic and widespread methodologies used in the field of ecology and thus their parameters were calculated and reported in this study (Clauset et al., 2009; Milojević, 2010b; Stumpf & Porter, 2012; White et al., 2008). Annual disturbed area and patch records were imported into JMP Pro 10 statistical software. To calculate the relationship between frequencies of gaps by their size within a region annually, the study used disturbance 'patch size area' as the independent variable (X axis) and the number of events occurring of a given size as the dependent variable (Y axis). In the first approach, a linear regression was fit to the log transformed X and Y values, with the slope of the fit line giving an estimate of the scaling exponent, α. The scaling exponent, α, was calculated annually, in 5-year intervals and over the 25-year study period. Other than the binning inherent to the resolution of the Landsat data (1 pixel = 900m^2), there was no additional binning performed within the analysis.

The second approach, normalized logarithmic binning, retrieves information and trends that are not visible in noisy power-law tails. This approach produces more stable and accurate estimates of parameters than linear binning (Milojević, 2010a; White et al., 2008). The study used the partial logarithmic binning procedures outlined in Milojevic 2010, binning patch sizes (N pixels) bins of 0.1 decades[1]. By normalizing the number of observations in each bin the study converted counts into densities (number of observations per unit x). Parameters were then estimated following the same procedures described in the previous section.

The third approach was to use the framework laid out by Clauset et al. (2009) for discerning and quantifying power-law behavior in empirical data by combining maximum-likelihood (MLE) fitting methods with goodness of fit tests based on the Kologorov-Smirnov (ks) statistic and likelihood ratios. The Python Power-Law package, created to analyze heavy- tailed distributions by Alstott et al. (2013), was used to analyze disturbance patch frequencies annually, as well as over the 25-year study period. Candidate distributions (lognormal, and exponential) were also compared using log likelihood ratios to identify which distributions fit the data better. Based on the methodologies laid out in Alstott et al. (2013) an x-min of 4 pixels or (3600 m^2) was found to provide the best fit over the largest range of years and regions.

[1] An interval where x changes by a factor of 10 is called a decade.

3.4 Results

3.4.1 Regional Overview

Although the NH study area (2,402,074ha) was smaller than the NC and OR sites (2,901,839 ha and 2,941,998 ha respectively), it contained the greatest amount of forest area at 2,164,494 ha (~90% forested) (Table 3-1). Just over half of the OR study region was forested at 1,520,610 ha, while NC fell in the middle of the range with 1,971,725 ha (~68% of study area) . Between 1985 and 2010, the NC study region had the highest percent of forest area disturbed with just under 50% of all the forest land experiencing a disturbance sometime in the VCT record, followed by OR and NH at 36 and 15 percent respectively (Table 3-1).

Table 3-1: Regional Study Site Characteristics

Summary Statistic	OR	NH	NC
Total Study Area (Ha)	2,941,998	2,402,074	2,901,839
Total Forest Area[A] (Ha)	1,520,610	2,164,556	1,971,725
Total Disturbed Area[B] (Ha) 1984-2010	549,026	326,597	926,353
Total Disturbed Area (Ha) 1986-2010	351,924	296,435	804,998
Percent of forest landscape disturbed 84_10	36.1	15.1	47
25yr Average annual disturbance (1986-2010)	17,107	14,147	39,385
Average Annual disturbance rate 86_10 (Upper and lower CI)	**1.13** (0.96 - 1.29)	**0.65** (0.58 - 0.72)	**2.00** (1.75 - 2.25)

[A] Total Forest Area = All land area classified as forest for any portion of time within imagery acquisition (1984-2010)

[B] Total Disturbed Area is a sum of all land area disturbed during the study period; areas recording multiple disturbances are only recorded once

[C] Average annual disturbance- is an average of the annual disturbed area (multiple disturbances are included in average)

[D] 1984 is eliminated from most statistics because it may be recording previous years disturbances, it also includes non-forest areas that may become reforested in future years.

3.4.2 Regional Rates and Variability

NC had both the highest average annual rate of forest disturbance at 2.00% (+/- 0.25) and the highest inter-annual variability with annual rates ranging from 0.73 to 3.52% (SD 0.60). OR followed at 1.13% (+/- 0.16) range 0.47-1.98% (SD 0.40). NH had the lowest average annual disturbance rate at 0.65% (+/- 0.07), annual rates ranged from 0.37 to 1.05 (SD 0.17) (Figure 3-2). The average annual disturbance rate between

1986 and 2010 were significantly different among all three regions (alpha 0.05) (Figure 3-3). Comparing regional coefficients of variation (CV) is a useful measure of dispersion of annual estimates from the average annual rate measured in each region. Despite the fact that NC region showed the largest range in annual rates of forest disturbance, the OR region showed the largest amount of variability in its annual estimates of disturbance relative to its mean rate (OR - CV = 35.5, NC - CV = 30.2). New Hampshire showed the lowest variation in annual rates relative to the 25-year mean (CV = 26).

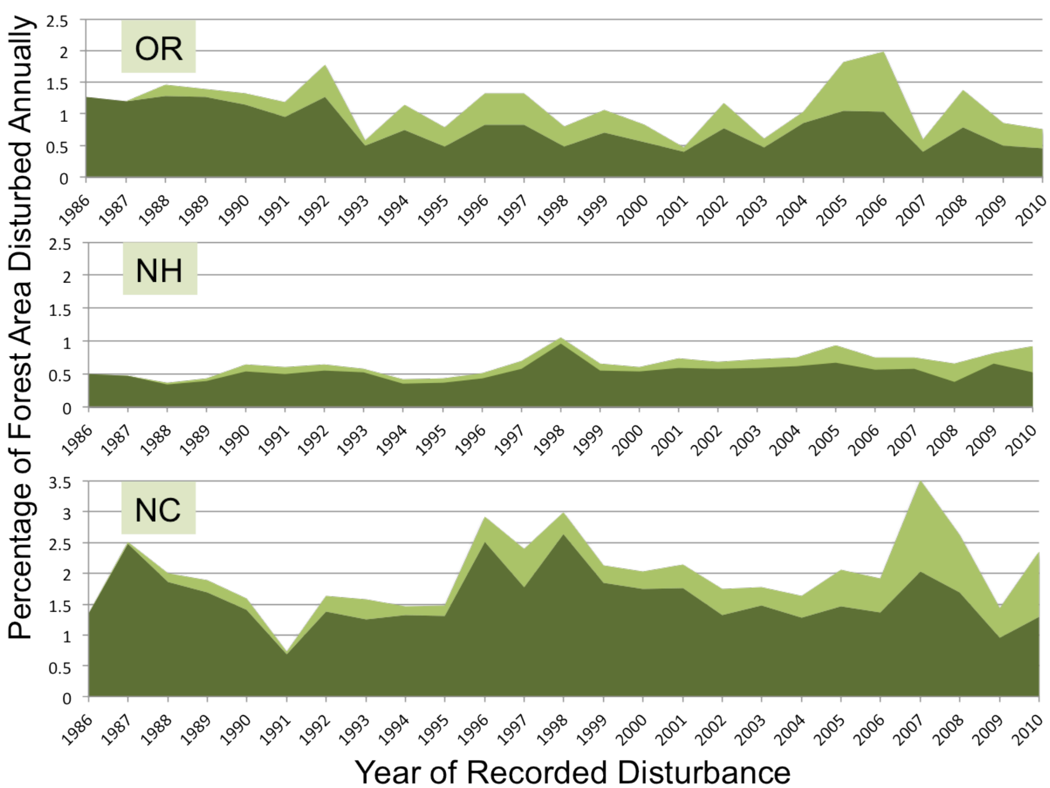


Figure 3-2: Regional Rates of forest disturbance between 1986-2010. Light green areas represent the percentage of annual disturbed forestland that has previously been mapped as disturbed within the study period.

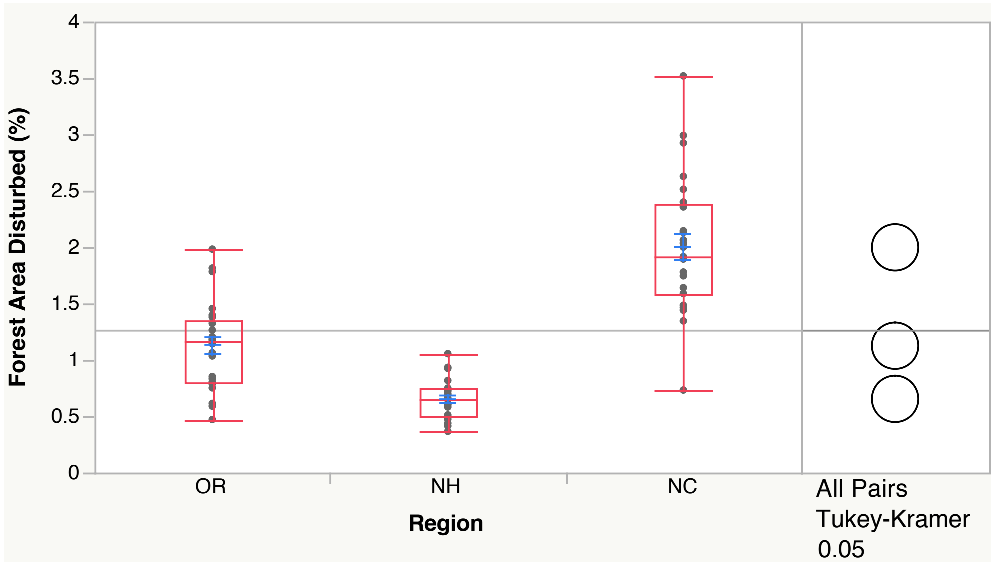


Figure 3-3: Comparison of mean annual disturbance rates (1986-2010) between the three study regions. Quantile box plots are shown in red, and 25 year mean with error shown in blue. Black circles on the right show Tukey HSD comparison of means.

The study regions differed in disturbance trend over time. Only the Northeastern study region, NH, had a statistically significant (alpha =0.05) increasing trend in area disturbed between 1986 and 2010 with an average annual increase of 355 ha or +0.0164% yr^{-1} (CI +/- 0.007%, $R^2 = 0.49$, p-value <0.001). No statistically significant temporal trend was detected in either NC or OR. NC averaged an annual increase in disturbed area of 530 ha or + 0.27% yr^{-1} (CI +/- 0.033%, $R^2 = 0.11$, p-value 0.107). OR showed an average annual decrease of - 0.011% yr^{-1} (CI +/-0.057%, R^2 0.04, p-value 0.315).

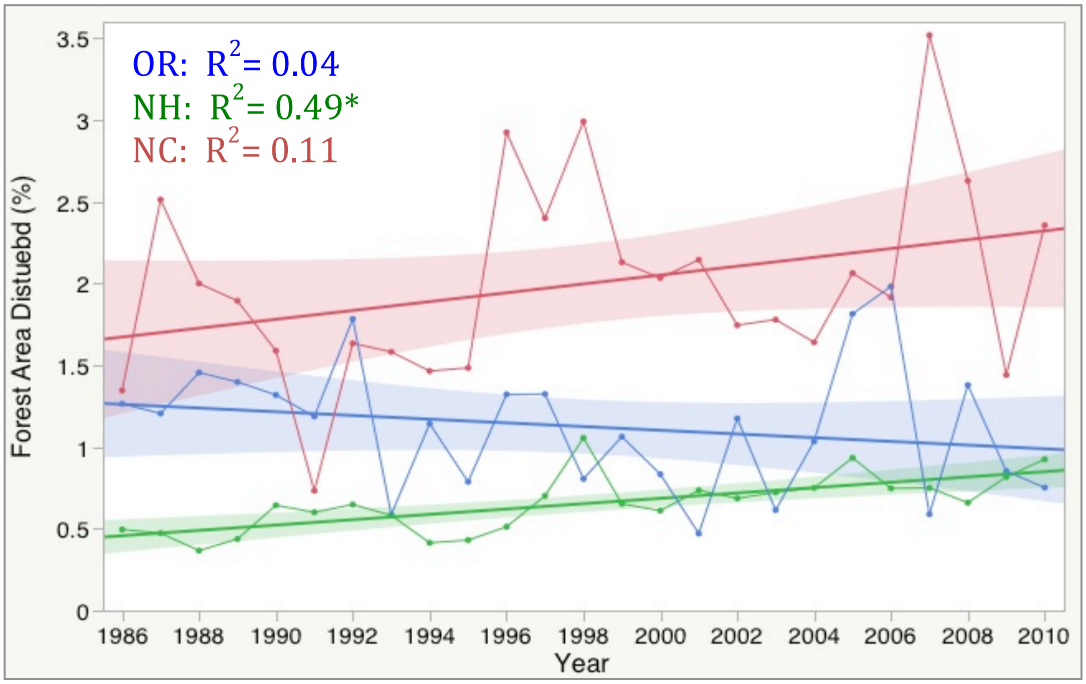


Figure 3-4: Linear regression fit to annual percent forest area disturbed over 25 years. Shaded area around trend line shows confidence of fit (alpha 0.05). * NH was the only region to show a significant increase in disturbed area over the study period (p <0.001). The shaded region shows the confidence range of the estimated trend.

3.4.3 Disturbance Size Distributions

In total, over 5 million unique disturbance patches were recorded in the three regions between 1986-2010. Just over half of the recorded events were in NC, while NH and OR recorded 1.2 and 1.3 million disturbed patches respectively. The mean annual disturbance patch size was significantly smaller in NH (0.29 ha +/- 0.04 SD) than in OR (0.38 ha +/- 0.14 SD) or in NC (0.43 ha +/- 0.15SD) (Figure 3-5). The NH region was the only region that showed a significant positive temporal trend in gap size with an average increase of 0.004 ha yr^{-1} ($R^2 = 0.41$, CI = +/- 0.002, $p < 0.001$).

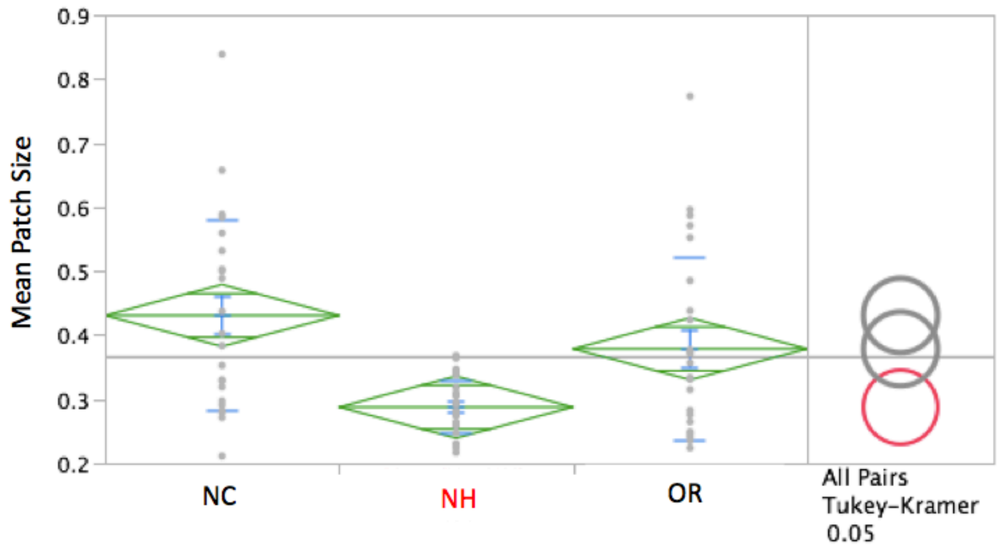


Figure 3-5: Comparison of regional annual distribution and average mean disturbance patch size. Blue markers represent the standard deviation, the annual disturbance rates, and the standard error of the mean. The gray line represents the group mean. Green triangles show regional 25-year mean with confidence intervals assuming the variances are equal across the regions while the left-hand panel tests differences in means.

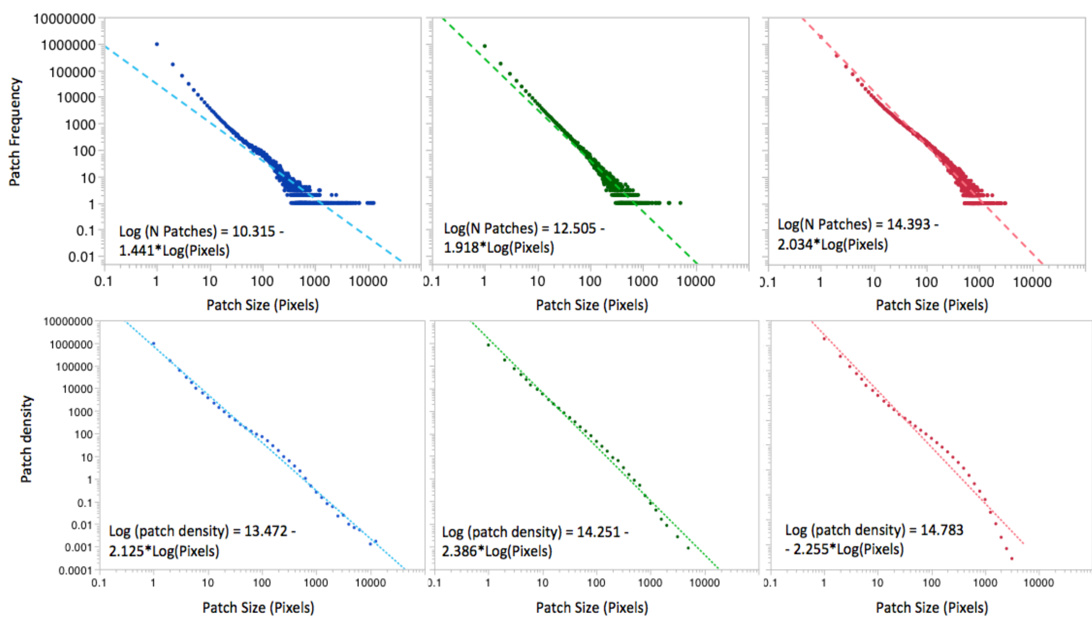


Figure 3-6: Regional comparisons of disturbance patch frequencies over the 25-year study period. Where top panel shows the frequencies of all recorded event sizes, the bottom panel displays distributions under logarithmic binning following Milojevic 2010. Blue- OR Green- NH Red- NC

Looking at the frequency of patches occurring across the range of patch sizes, all three regions annually exhibited an approximately linear relationship on a log-log plot over at least two orders of magnitude in both the x and y axis (
Figure 3-9). Therefore, the power law probability function was considered a good candidate to describe disturbance patch size distribution in each region. Using un-binned least squares regression (LS-lin), the average annual alpha of disturbance ranged from 1.17 (+/-0.12 SD) in OR, 1.43 (+/-0.06 SD) in NC and 1.53 (+/-0.11 SD) in NH (Figure 3-7). The average fitted alpha parameters calculated across the 25 year period using the Normalized Binning approach (LS-bin) were steeper, ranging from 2.01 (+/-0.08 SD) in OR, 2.05 (+/-0.05 SD) in NC and 2.22 (+/-0.08 SD) in NH.

When patch frequencies were compiled to create a 25-year distribution of patch sizes (Figure 3-6), both LSE approaches predicted steeper alpha parameters than those predicted for individual years, the difference was minimal in the LS-bin approach (Table 3-2). Finally, using the MLE method with an x min of 3600m2 (4pixels) the average annual calculated alphas ranged from 2.14 (+/-0.20 SD) in OR, 2.04 (+/-0.21 SD) in NC, and 2.32 (+/-0.12 SD) in NH. Across all three methodologies the average fitted alpha parameters for NH were significantly steeper than NC or OR. Though OR showed significantly lower alpha values when calculated using ordinary un-binned LSE, differences between the means were not significant in NC and OR using the more advanced methodologies (Figure 3-7). Further, the method of calculation created large variation in the fitted parameters, which highlighted the need to understand the mechanisms driving the distributions and the differences in the distributions causing alterations in the slope before extrapolating out any of the results. The power law fit the patch-size distribution better than either logarithmic or exponential distributions in all three regions.

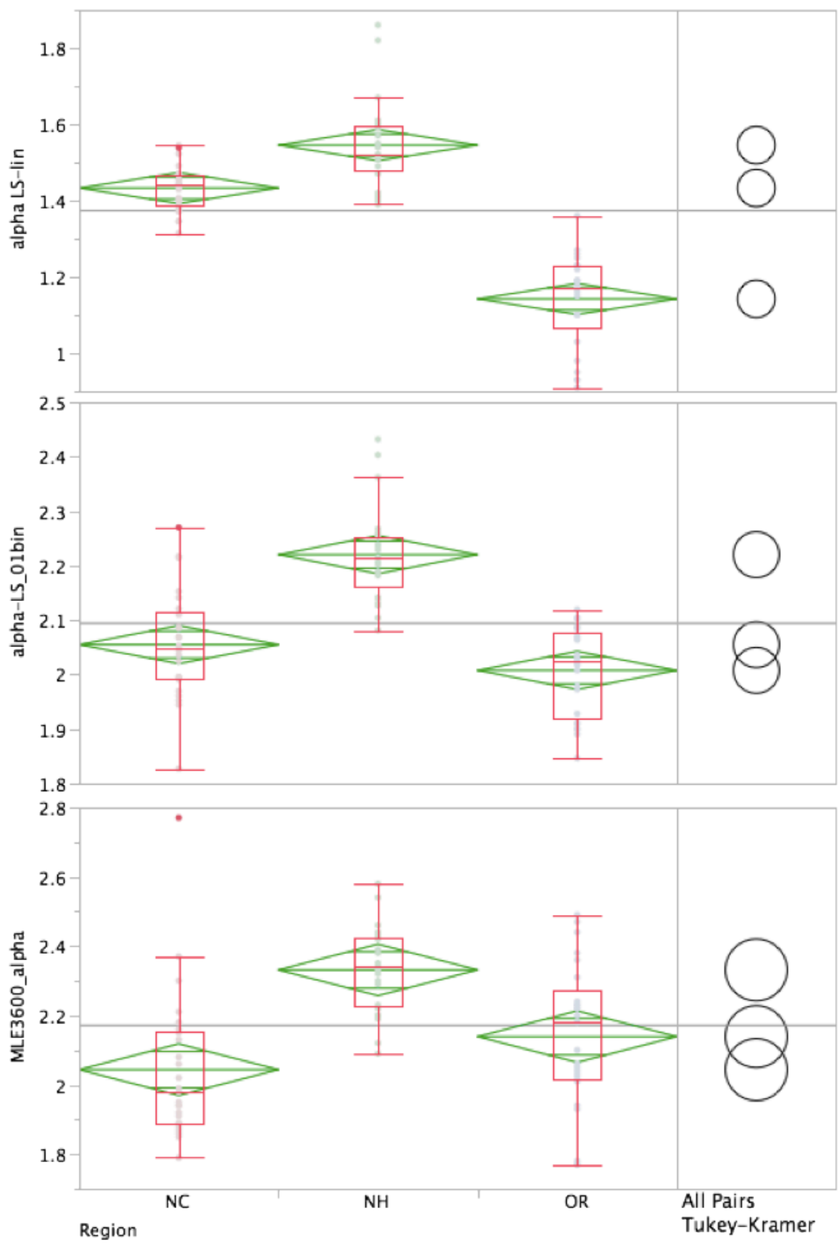


Figure 3-7: Comparison of regional variations in estimated gap-size distribution alpha parameter as calculated by the three methodologies

Disturbance patches less than 0.2 hectares (1-2 pixels), accounted for between 23% (NC) and 30% (NH) of each regions disturbed area, while the percentage ranged as low as 10% and high as 40% depending on the region and year (Figure 3-8). The NH site was dominated by smaller disturbances, with ~50% of all forest area disturbed coming from disturbances less than 1ha in size and 80% below 10ha. In contrast, approximately half of NC total disturbance area could be attributed to disturbance within the size range of 10-100ha. While, nearly 100% of the disturbed area in the two eastern sites came from disturbances smaller than 100 ha, approximately 10% of annual disturbed area in OR was caused from disturbances larger than 100 ha. OR showed the largest annual variability in proportion of area disturbed attributed to large disturbances.

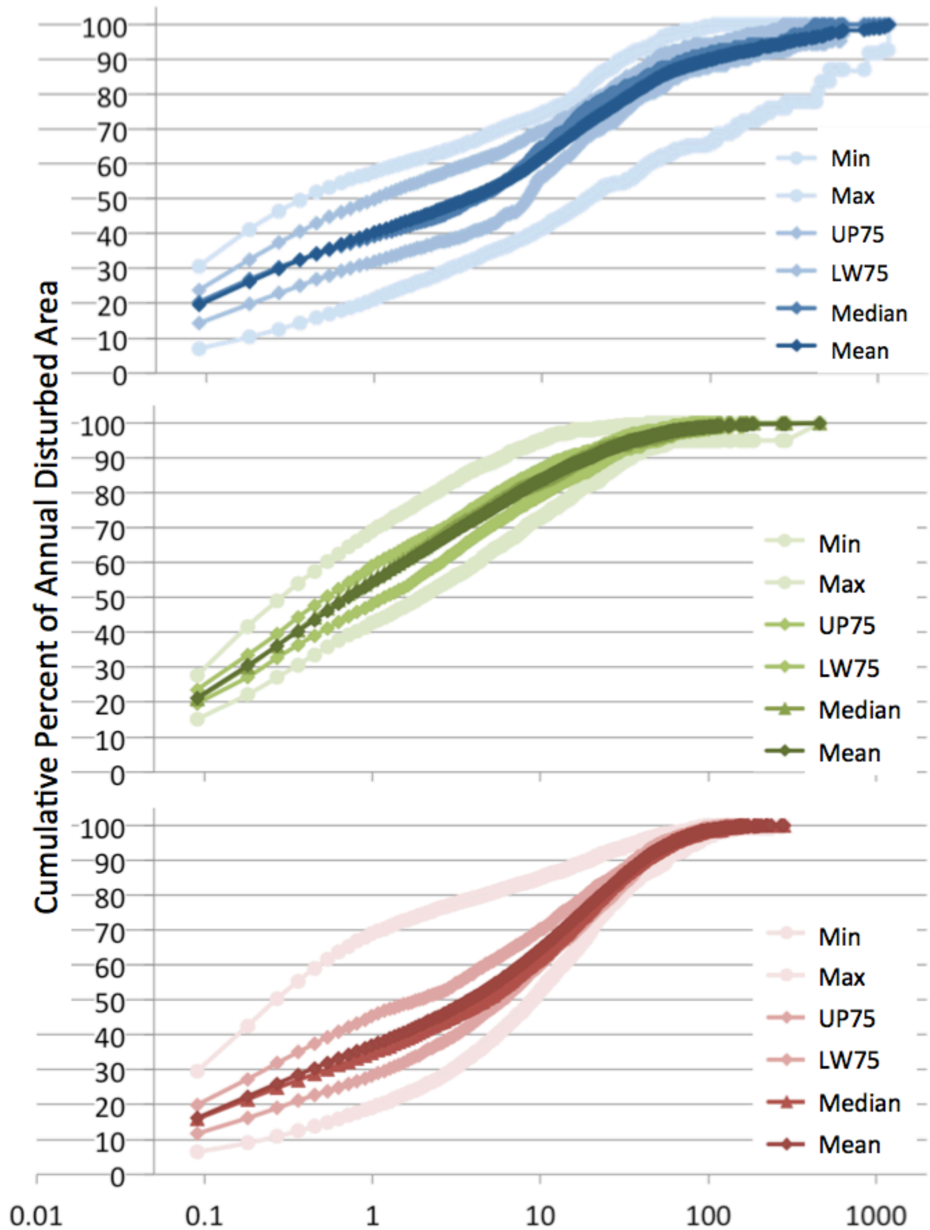


Figure 3-8: Cumulative percent of annual disturbance area for three study regions Blue- OR, Green-NH, Red –NC. Annual variably within regions is represented by quartile boundaries.

3.5 Discussion

The quantification of disturbance location, extent and severity has been noted as a way to improve carbon budget estimates and lead to better initialization, parameterization and/ or testing of forest carbon cycle models (Hurtt et al., 2002; Frolking et al., 2009; Masek et al., 2013). Further, these same metrics have been proven advantageous to the monitoring and modeling of other critical ecosystem services, such as wildlife and water resource management (Franklin 1987; Brawn et al. 2001; Greenberg et al., 2011). This study utilized remote sensing data, coupled with geographic information systems, to compare spatial and temporal distributions of disturbance between three distinct regions in the contiguous United States. Results indicate important differences in disturbance rates, trends, and size distribution between study regions. The Southeastern site, NC, had the highest average annual rate of disturbance at just over ~2% forest area disturbed, followed by Northwest, OR, (~1%) and Northeast, NH, (~0.5%). While the Southeastern site had the largest range in annual disturbance rates, the Northwestern site showed the largest inter-annual variation in disturbance as compared to its 25-year average rate.

New Hampshire was the only region that showed a significant trend in disturbance rate over time, with disturbed area nearly doubling over the 25-year study period. This trend suggests an increase in natural or anthropogenic disturbance in the state. Continued research is needed on disturbance severity and mechanism classification, which may help us detect trends associated with specific biophysical or anthropogenic agents (Schleeweis et al., 2013). For example, looking at the New

Hampshire time series, 1998 stood out as an anomalous year. This year also coincides with one of the most intense ice storms on record in the latter half of the 20th century for northern New England, which caused extensive statewide forest damage and subsequent salvage logging (Rhoads et al., 2002). Similarly disturbance peaks in the North Carolina piedmont region that occurred between 1996 and1998 may be the result of damage and post-storm salvage logging after Hurricane Fran (Xi 2008). The Oregon study region shows a slight "U" shaped distribution, with disturbance rates dropping after ~1993 followed by some of the highest recorded disturbances rates recorded in the last decade. The observed drop in disturbed area post-1993 may reflect a change in forest logging do to policies under the Northwest Forest Plan., Rate spikes within the last decade may reflect increases in natural disturbance, such as pest outbreak and fire (Cohen et al., 2010; Kennedy et al., 2010). The NC study region showed the largest inter-annual rates in our study. Located at the northern boundary of U.S. southeastern planted pine range the large variations between years could be explained by volatility in harvest rates, although existing scales of national geospatial harvest data make attribution difficult (Schleeweis et al., 2013).

Previous studies have noted higher omission errors for forest thinning events, which may have implications for detecting disturbances, such as selective logging and single tree harvest. Omission errors may likewise affect the detection of certain natural disturbance events, such as pest outbreak or winds storms that cause partial mortality (Masek et al., 2011; Thomas et al., 2011). Many previous studies also implement a minimum mapping unit for report disturbance events using Landsat imagery to increase user accuracy (Masek et al., 2013; Schleeweis et al., 2013). This study uses the entire record of disturbances without a minimum mapping unit and found that 23-30% of recorded disturbances in each region occurred in patches less than 0.2 hectares (or 2 pixels). Depending on the year and region, the percentage of recorded disturbance below 0.2 ha could be as high as 40%. Majority filtering was shown to reduce per-scene disturbed area by ~20% over 50 Landsat scenes throughout the United States (Masek et al., 2013). Future research merging high density lidar or plot-based records of disturbance directly to VCT metrics of severity may help to quantify smaller and non-stand clearing disturbance events, which can then be integrated into improved calculations of regional disturbance rates (Asner et al., 2013; Chambers et al., 2013; 2007).

This study also analyzed the size distribution of disturbance events. Historically, canopy gap distributions have been measured over small spatial scales or on small repeat plots (Yamamoto, 2000). Recent studies utilizing advanced remote sensing techniques have shown that tropical forests from Hawaii, Costa Rica and the lowlands of Amazonia have strong similarity in canopy gap-size frequency distributions despite differences in topography, climate and disturbance histories (Asner et al., 2013; Kellner & Asner, 2009). The ability to quantify frequency and size distributions of canopy gaps caused by disturbance can help with the parameterization of development of disturbance models, with the planning of field campaigns, and the ability to extrapolate disturbance rates taken from smaller, temporal or spatial scale, studies (Fisher et al., 2008). Fitting a power law distribution to disturbance patch size data can reveal regional trends, further the regional and temporal deviations from the estimated distribution be of equal importance, and may provide indicators of driving processes in a region (Milojević, 2010). Using three different methodologies to fit regional disturbance size frequency distributions New Hampshire consistently had significantly steeper slopes suggesting a more heterogeneous well mixed forest. The OR and NC regions displayed slopes consistently shallower then NH, suggesting a higher dominance of lager disturbances patches on their landscape. The regions represented in this study have varied natural and anthropogenic disturbance such as logging, fire and land use change that may have fundamentally different signatures. Looking closer at North Carolina and Oregon's patch size frequency distributions, deviations from the power law fit may suggest multiple patterns occurring from different disturbance mechanisms (i.e. logging vs. conversion vs. fire). In particular NC exhibits both a higher proportion of large mid-sized events and steeper drop of in the density of the largest events then would be expected from its power distribution, possibility suggesting an exponential cut off, which may be an result of existing forest fragmentation, or forest management (Franklin, 1995; Milojevic, 2010). In future analysis these statistics could be broken down by eco-regions and management zones and ideally disturbance mechanism which will further aid in mapping the geography of forest disturbance regimes (Asner, 2013).

Finally, ecosystem models from regional to global scales have advanced over recent years to incorporate disturbance, as the importance of disturbance in shaping regional ecosystem structure and function has been realized (Turner 1993; Moorcroft et al., 2001; Hurtt et al., 2002; Moorcroft et al., 2006; Fisk et al., 2013). Many models have relied on single average rates of disturbance and have been shown to be very sensitive to this parameter. This study builds upon previous research showing regionally variability in disturbance rates and results and if expanded spatially could be used as inputs to terrestrial ecosystem models. If coupled with additional information on mechanistic drivers, the patterns observed, could be useful in the development of sub models of forest disturbance for terrestrial ecosystem models (Fisk et al., 2013). With increasing population, competing land uses, and changes in climate altering natural disturbance rates and regimes, it is ever more pressing to have spatially and temporally explicit monitoring systems of forest change over long time periods. This study grouped all disturbance events large enough to be detected by the VCT without attributing mechanism cause. Although such exclusivity limits the study's perspective, the broad patterns offer noteworthy findings that could provide the catalyst for a more global analysis in the future. Breaking disturbance down to mechanism and fate of biomass loss is a critical next step. Work is continuing based on the severity of disturbance to look at sub pixel gaps and intensity of clearing. Results have implications on various sampling regimes ability to adequately capture disturbance across the regions and thus implications on estimates of forest carbon storage and flux (Asner, 2013; Fisher et al., 2008). Results of disturbance rates and patch-size distributions also have direct relevance to many wildlife studies and habitat suitability models (Guisan & Zimmermann, 2000; MacArthur & MacArthur, 1961).

3.6 Supplementary Material

Table 3-2: Annual Summary of Rates and Disturbance Patch Characteristics

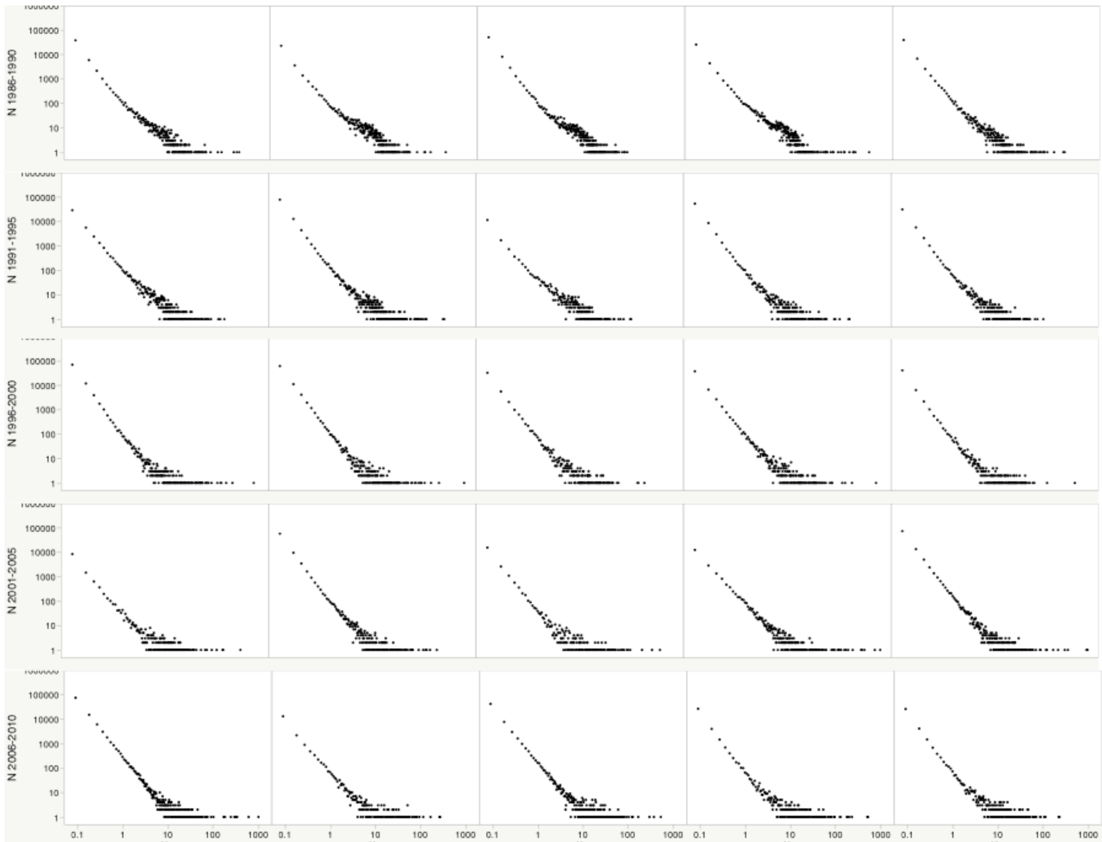
Year	Region	N Patches	Disturbed area (ha)	% Forest Disturbed	OLS alpha	OLS Bin alpha	MLE alpha 3600	sigma 3600	Ks 3600
1986	**OR**	50972	19219	1.26	**1.23**	**2.04**	**1.77**	0.0116	0.0755
1987	**OR**	32084	18317	1.20	**1.25**	**1.97**	**1.93**	0.0123	0.0653
1988	**OR**	66843	22121	1.45	**1.36**	**2.02**	**1.77**	0.0111	0.0651
1989	**OR**	36213	21248	1.40	**1.18**	**1.98**	**2.04**	0.0134	0.0448
1990	**OR**	54092	20041	1.32	**1.23**	**2.07**	**2.03**	0.0134	0.0438
1991	**OR**	42552	18043	1.19	**1.26**	**2.07**	**2.22**	0.0141	0.0401
1992	**OR**	102476	27106	1.78	**1.19**	**2.03**	**1.78**	0.0163	0.0566
1993	**OR**	16139	8910	0.59	**1.17**	**1.90**	**2.22**	0.0172	0.0391
1994	**OR**	69705	17368	1.14	**1.22**	**2.06**	**2.18**	0.0192	0.0446
1995	**OR**	42424	11962	0.79	**1.27**	**2.09**	**2.49**	0.0197	0.0346
1996	**OR**	89869	20098	1.32	**1.1**	**2.08**	**2.47**	0.0180	0.0308
1997	**OR**	82000	20121	1.32	**1.19**	**2.10**	**2.24**	0.0199	0.0361
1998	**OR**	43535	12240	0.80	**1.17**	**2.02**	**2.23**	0.0173	0.0349
1999	**OR**	51327	16160	1.06	**1.16**	**2.01**	**2.31**	0.0216	0.0329
2000	**OR**	52659	12665	0.83	**1.17**	**2.03**	**1.94**	0.0235	0.0462
2001	**OR**	12010	7154	0.47	**0.91**	**1.85**	**2.36**	0.0180	0.0353
2002	**OR**	75952	17850	1.17	**1.23**	**2.10**	**2.10**	0.0230	0.0440
2003	**OR**	21293	9328	0.61	**0.93**	**1.90**	**2.01**	0.0163	0.0241
2004	**OR**	20350	15725	1.03	**0.95**	**1.91**	**2.38**	0.0148	0.0280
2005	**OR**	100089	27581	1.81	**1.15**	**2.09**	**2.44**	0.0136	0.0273
2006	**OR**	106697	30137	1.98	**1.19**	**2.12**	**2.02**	0.0210	0.0290
2007	**OR**	18460	8954	0.59	**0.98**	**1.89**	**2.23**	0.0154	0.0281
2008	**OR**	58807	20960	1.38	**1.1**	**2.02**	**2.06**	0.0202	0.0453
2009	**OR**	34637	12955	0.85	**0.93**	**1.91**	**2.05**	0.0200	0.0443
2010	**OR**	34236	11426	0.75	**1.03**	**1.93**	**2.20**	0.0186	0.0342
25yr _Avg	**OR**	52617	17108	1.13	**1.14**	**2.01**	**2.14**	0.0172	0.0412
25 yr all	**OR**	1315421	427688		**1.44**	**2.13**	**2.13**		

Year	Region	N Patches	Disturbed area (ha)	% Forest Disturbed	OLS alpha	OLS Bin alpha	MLE alpha 3600	sigma 3600	Ks 3600
1986	**NH**	49474	10714	0.49	**1.82**	**2.40**	**2.54**	0.021	0.043
1987	**NH**	44438	10236	0.47	**1.86**	**2.43**	**2.46**	0.020	0.045
1988	**NH**	35328	7923	0.37	**1.67**	**2.36**	**2.58**	0.025	0.030
1989	**NH**	38419	9461	0.44	**1.51**	**2.20**	**2.35**	0.021	0.042
1990	**NH**	52858	13925	0.64	**1.59**	**2.25**	**2.34**	0.017	0.041
1991	**NH**	47588	12997	0.60	**1.55**	**2.21**	**2.32**	0.017	0.036
1992	**NH**	54540	14023	0.65	**1.54**	**2.22**	**2.38**	0.017	0.038
1993	**NH**	45039	12589	0.58	**1.60**	**2.26**	**2.35**	0.017	0.038
1994	**NH**	34209	8951	0.41	**1.51**	**2.27**	**2.44**	0.022	0.038
1995	**NH**	36121	9307	0.43	**1.57**	**2.19**	**2.44**	0.022	0.039
1996	**NH**	37511	11076	0.51	**1.52**	**2.18**	**2.29**	0.018	0.037
1997	**NH**	55445	15171	0.70	**1.60**	**2.24**	**2.33**	0.016	0.038
1998	**NH**	62056	22827	1.05	**1.52**	**2.21**	**2.20**	0.012	0.035
1999	**NH**	48372	14113	0.65	**1.59**	**2.19**	**2.34**	0.016	0.032
2000	**NH**	36310	13208	0.61	**1.42**	**2.13**	**2.19**	0.016	0.037
2001	**NH**	51415	15907	0.73	**1.41**	**2.14**	**2.23**	0.015	0.036
2002	**NH**	42815	14839	0.69	**1.47**	**2.13**	**2.22**	0.015	0.032
2003	**NH**	50875	15634	0.72	**1.61**	**2.25**	**2.33**	0.015	0.033
2004	**NH**	57603	16218	0.75	**1.49**	**2.23**	**2.42**	0.016	0.029
2005	**NH**	69474	20205	0.93	**1.54**	**2.24**	**2.39**	0.014	0.032
2006	**NH**	52990	16162	0.75	**1.41**	**2.14**	**2.30**	0.015	0.034
2007	**NH**	48086	16223	0.75	**1.52**	**2.21**	**2.20**	0.014	0.038
2008	**NH**	44862	14267	0.66	**1.39**	**2.10**	**2.12**	0.015	0.033
2009	**NH**	51645	17681	0.82	**1.40**	**2.08**	**2.09**	0.014	0.035
2010	**NH**	80958	20010	0.92	**1.52**	**2.24**	**2.43**	0.015	0.033
25yr Avg	**NH**	49123	14290	0.66	**1.53**	**2.22**	**2.33**	**0.02**	**0.04**
25 yr all	**NH**	1178957	342951		**1.92**	**2.39**	**2.31**		

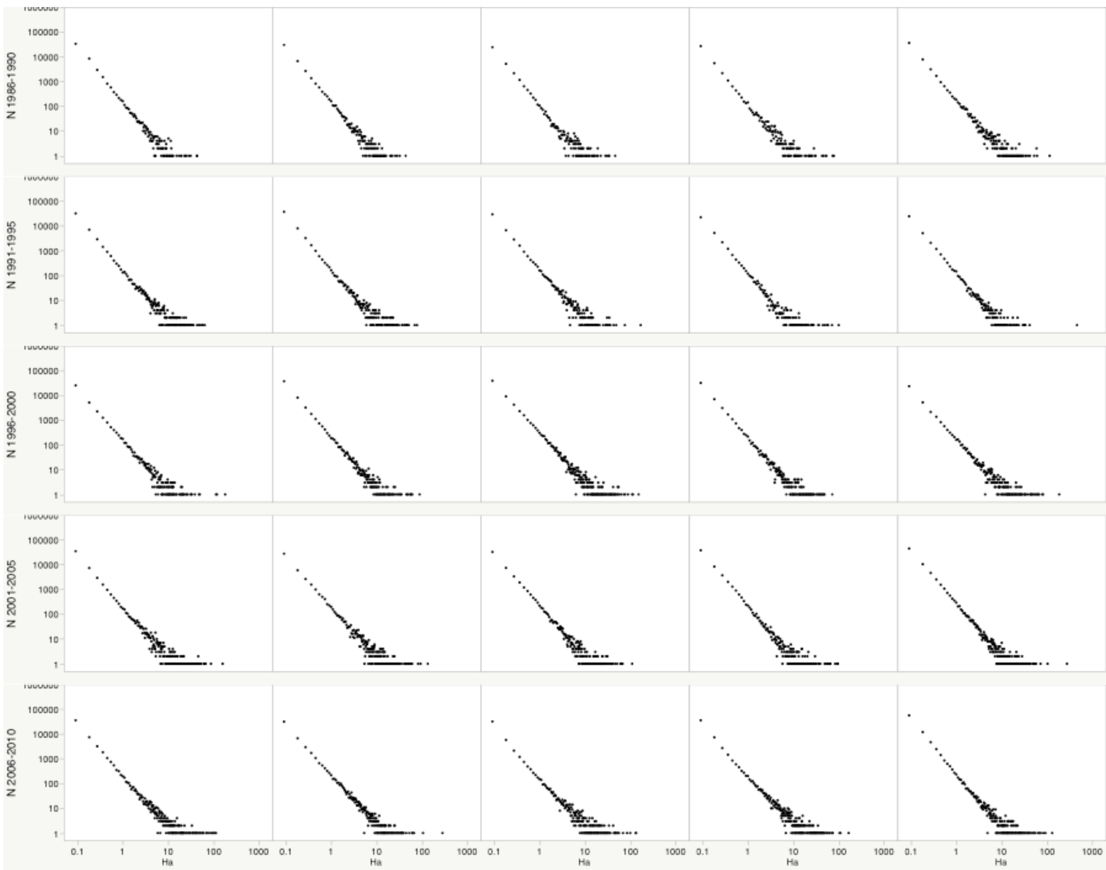
Year	Region	N Patches	Disturbed area (ha)	% Forest Disturbed	OLS alpha	OLS Bin alpha	MLE alpha 3600	sigma 3600	Ks 3600
1986	**NH**	49474	10714	0.49	**1.82**	**2.40**	**2.54**	0.021	0.043
1987	**NH**	44438	10236	0.47	**1.86**	**2.43**	**2.46**	0.020	0.045
1988	**NH**	35328	7923	0.37	**1.67**	**2.36**	**2.58**	0.025	0.030
1989	**NH**	38419	9461	0.44	**1.51**	**2.20**	**2.35**	0.021	0.042
1990	**NH**	52858	13925	0.64	**1.59**	**2.25**	**2.34**	0.017	0.041
1991	**NH**	47588	12997	0.60	**1.55**	**2.21**	**2.32**	0.017	0.036
1992	**NH**	54540	14023	0.65	**1.54**	**2.22**	**2.38**	0.017	0.038
1993	**NH**	45039	12589	0.58	**1.60**	**2.26**	**2.35**	0.017	0.038
1994	**NH**	34209	8951	0.41	**1.51**	**2.27**	**2.44**	0.022	0.038
1995	**NH**	36121	9307	0.43	**1.57**	**2.19**	**2.44**	0.022	0.039
1996	**NH**	37511	11076	0.51	**1.52**	**2.18**	**2.29**	0.018	0.037
1997	**NH**	55445	15171	0.70	**1.60**	**2.24**	**2.33**	0.016	0.038
1998	**NH**	62056	22827	1.05	**1.52**	**2.21**	**2.20**	0.012	0.035
1999	**NH**	48372	14113	0.65	**1.59**	**2.19**	**2.34**	0.016	0.032
2000	**NH**	36310	13208	0.61	**1.42**	**2.13**	**2.19**	0.016	0.037
2001	**NH**	51415	15907	0.73	**1.41**	**2.14**	**2.23**	0.015	0.036
2002	**NH**	42815	14839	0.69	**1.47**	**2.13**	**2.22**	0.015	0.032
2003	**NH**	50875	15634	0.72	**1.61**	**2.25**	**2.33**	0.015	0.033
2004	**NH**	57603	16218	0.75	**1.49**	**2.23**	**2.42**	0.016	0.029
2005	**NH**	69474	20205	0.93	**1.54**	**2.24**	**2.39**	0.014	0.032
2006	**NH**	52990	16162	0.75	**1.41**	**2.14**	**2.30**	0.015	0.034
2007	**NH**	48086	16223	0.75	**1.52**	**2.21**	**2.20**	0.014	0.038
2008	**NH**	44862	14267	0.66	**1.39**	**2.10**	**2.12**	0.015	0.033
2009	**NH**	51645	17681	0.82	**1.40**	**2.08**	**2.09**	0.014	0.035
2010	**NH**	80958	20010	0.92	**1.52**	**2.24**	**2.43**	0.015	0.033
25yr Avg	**NH**	49123	14290	0.66	**1.53**	**2.22**	**2.33**	**0.02**	**0.04**
Fit 25 yr all	**NH**	1178957	342951		**1.92**	**2.39**	**2.31**		

Figure 3-9: Annual disturbance size frequency distribution

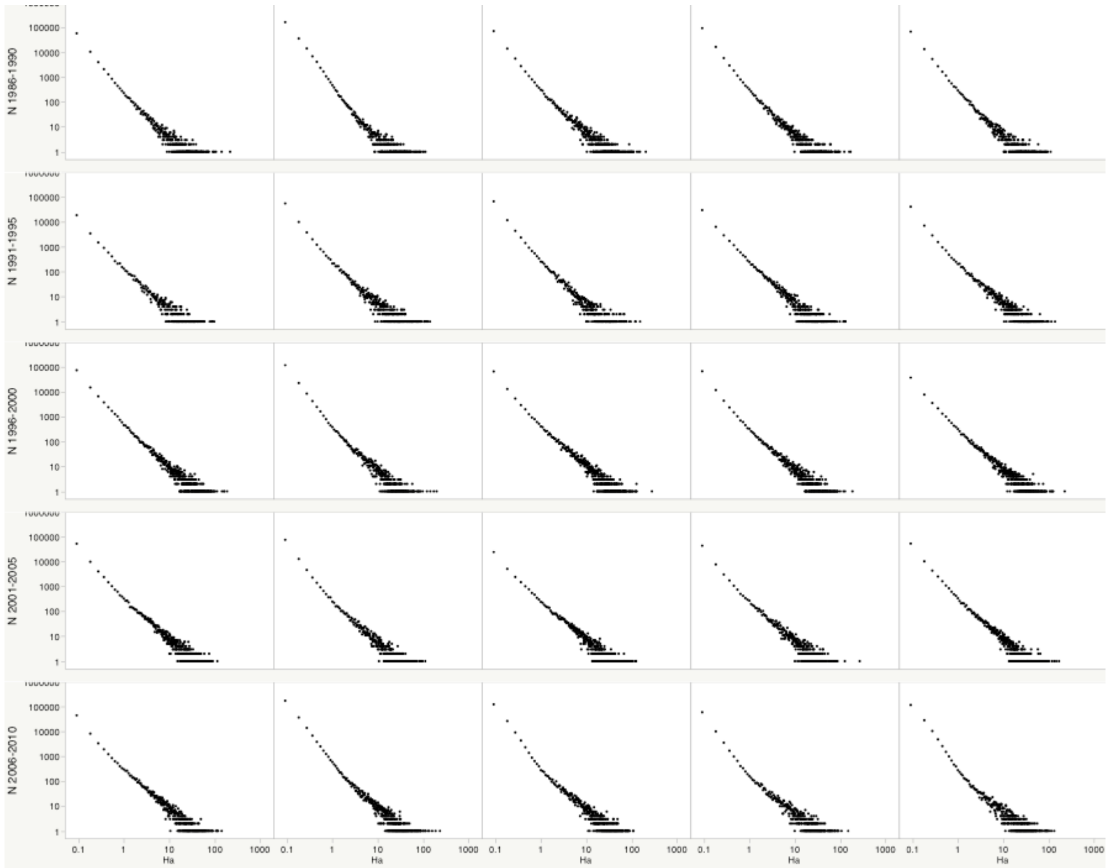
OR



NH



NC



N 1986-1990
N 1991-1995
N 1996-2000
N 2001-2005
N 2006-2010
100000
10000
1000
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10
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Chapter 4. Disturbance Distance: A Framework for Quantifying the Vulnerability of Forest to Disturbance Under Current and Future Conditions

4.1 Abstract

Recent studies highlight the potential intensification and novel creation of forest disturbance regimes under global climate change and anthropogenic activity. Addressing the question of 'how vulnerable forested ecosystems are to disturbance now and in the future?' is of high importance. This study developed a framework to assess forest vulnerability to disturbance in order to address that question. Critical threshold rates of disturbance, rates for which forest ecosystems could no longer be sustained (λ*), were estimated across the coterminous U.S. by simulating vegetation dynamics under a range of disturbance scenarios using an advanced mechanistic ecosystem model (ED). Observed rates of forest disturbance for 50 study sites, measured as part of the North American Forest Disturbance (NAFD) program, were compared to each site's estimated threshold rate to determine the rate increase in average annual disturbance that may lead to an ecosystem shift to non-forest conditions, which has been termed a regions Disturbance Distance (λD). Results showed that current average rates of disturbance were at or below λ* in 95% of sample sites. In general western forests had much smaller disturbance distances,

suggesting higher vulnerability to change, while eastern sites showed larger disturbance distances, indicating they may be more resilient to increased disturbance rates. To assess the vulnerability of these sites to disturbance in the context of potential future changes, simulations of vegetation sensitivity to disturbance were also run with future climate conditions. While the majority of sites were predicated to increase their resilience to disturbance (λ^*), several sites, inducing southwestern California became more vulnerable. Further research is needed to determine the balance between predicted increases in disturbance distance and future altered and novel disturbance regimes. The simplicity of this study provides a framework for assessing landscapes vulnerability to altered disturbance, which can be used to map hotspots that may benefit from further impact, vulnerability and adaption (IAV) studies.

4.2 Introduction

Forested ecosystems provide critical ecological services of local to global significance including but not limited to timber production, carbon sequestration, wildlife habitats, nutrient and water cycling, and recreation. Disturbance is a critical force influencing forest structure and function and thus the ecosystem services they provide (Frolking et al., 2009; Hurtt, 2002; Lorimer & White, 2003; Oliver & Larson, 1996). Studies have shown disturbance rates have fluctuated in the past causing shifts in species distribution and ecosystem structure (Eisenhart & Veblen, 2000; Foster, 2006; Long et al., 1998). Climate change can alter the frequency and duration of fire, drought, insect/pathogen outbreaks, landslides, wind and ice storms, and thus is important to consider this in predictions of forest function and structure into the future (Dale et al., 2001). Many studies highlight the potential for novel and dramatic alterations in disturbance regimes in the future on a scale that has not occurred in historic records (Allen et al., 2010; Dale et al., 2001; Drummond & Loveland, 2010; Kurz et al., 2008; Seymour, 2005; Trumbore et al., 2015; van Doorn et al., 2011; Zeng et al., 2009). Which leads to the question: How much disturbance can forestlands handle before they face critical alterations in structure and function and how might their sensitivity change under altered climate and atmospheric conditions?

Though looking at past events and creating small studies in the field have been and continue to be vital to our understanding of changing disturbance impacts to our forests, it is impractical to perform studies in the field of altered disturbance regimes at regional to continental scales (Rogers, 1996). Thus predictive processed based modeling studies that can simulate extreme events over larger areas are critical to advancing our understanding of global ecosystem system dynamics (Bonan et al., 1992; Bond et al., 2004; Shukla et al., 1990). Examples of these studies include Bond et al. (2004), which examined a world without fire and identified fire-dependent ecosystems globally. Shukla et al. (1990) explored the impacts of Amazonian deforestation on regional to global hydraulic cycle and climate and Bonan et al. (1992) which explored boreal vegetation impact on global climate.

Obtaining estimates of historic and current disturbance rates has proven difficult due to the stochastic nature of many disturbance events and the varying spatial and temporal scales at which disturbance occur (Rogers 1996; McDowell et al., 2015). Advances have been made with the creation of a suite of global earth observing satellite data, which help to provide spatially continuous and consistent measurements of global vegetation and change, coupled with the release of the global Landsat archive in 2010, and major advances in computing and storage are dramatically changing the our ability to perform global forest monitoring (Wulder et al., 2012). Though no globally consistent map of past disturbance events and causes exist yet (McDowell et al., 2015), new data sets are becoming available that allow rich temporal and spatial analysis of forest disturbance and change over large regions (Hanson et al., 2013 and Masek et al., 2013) .

Given the critical roles disturbance plays in shaping forest structure, function and dynamics, coupled with large uncertainties in how ecosystem may respond to altered rates of disturbance this study developed a framework (Figure 4-1) to assess ecosystem vulnerability to disturbance. Specifically the framework is used in this study to address the following questions: (1) What is the maximum rate of disturbance for which forest systems can be maintained across the U.S? (2) How close are forest currently to a fundamental shift in ecosystem structure? And (3) How will forest ecosystem sensitivity to disturbance change under future changes to climate and CO_2?

4.3 Methods

A framework was developed to assess forest ecosystem vulnerability/resiliency to altered disturbance rates (Figure 4-1), from here on termed Disturbance Distance (λD). Where the *Critical Threshold Rate of disturbance (*λ*) is defined as the average annual rate of disturbance at which a site no longer supports the presence of forested stands. *Disturbance Rate* (λ) is defined as the sites actual rate of disturbance, or the annual fraction of live biomass killed from factors (i.e. fire, windthrow, pests, and logging) other then competition for resources (light and water). By estimating the above variables a sites *Disturbance Distance* (λD*),* or the amount of additional disturbance that would lead to fundamental change in forest structure, can be determine by subtracting the critical disturbance rate of a site from the current or actual disturbance rate (λ- λ*). Positive numbers are representative of a site's buffer and negative numbers suggest current disturbance rates are above levels that will support forest conditions if these rates persist. Sites with negative or small disturbance distances are identified as forest vulnerability hotspots.

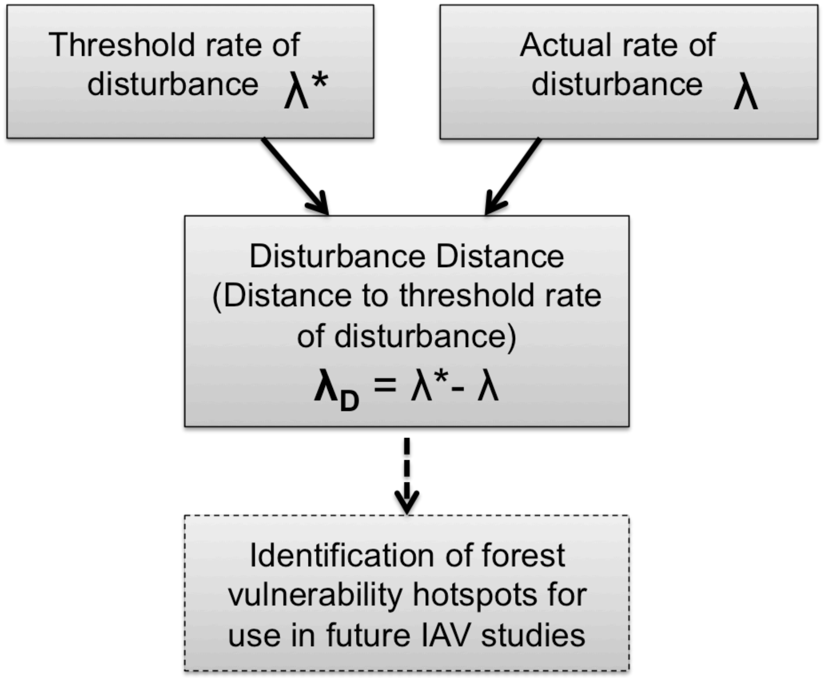

Figure 4-1: Framework for determining ecosystems vulnerability to disturbance

4.3.1 Estimating Critical Threshold Rates of Disturbance (λ^*)

This study used the Ecosystem Demography (ED) model to characterize the sensitivity of potential vegetation to changes in rates of disturbance across the continental United States and determine site level threshold rates of disturbance (λ^*) which lead to fundamental alterations in vegetation structure (i.e. the transition from forest to non-forest). The ED model is a mechanistic model of forest ecosystem dynamics with sub-models of growth, mortality, water, phenology, biodiversity, disturbance, hydrology, and soil biogeochemistry. Due to advanced scaling methods individual-based forest dynamics can be efficiently implemented over regional to global scales due to (Hurtt et al., 1998; Moorcroft et al., 2001). Disturbance within ED is defined as mortality caused by factors other then resource limitation (light and water). ED has been used to study a range of disturbance mechanisms including fire, land-use and tropical cyclones (Fisk et al., 2013; Hurtt, et al., 2002; Moorcroft et al., 2001). For the purpose of this study, disturbance is not broken down by mechanism and the disturbance rate (λ) is the annual fraction of live biomass killed. By simulating potential vegetation dynamics across the U.S. under various levels of disturbance, the critical disturbance rate, or threshold rate (λ^*), at each site under which forest conditions ceased to exist was estimated. In the results presented here the threshold rate (λ^*) was defined as the lowest simulated average rate of disturbance at which a site no longer supports the presence of forested stands. Where the definition of forest is based on forest productivity, under which sites must maintain 2kg/m of above ground biomass (Hurtt et al., 2002).

A series of model simulations were performed to estimate ecosystem response to disturbance over the contiguous U.S. (CONUS) at half-degree spatial resolution. Each run differed in the rate of disturbance simulated on the landscape ranging from 0.15% a year to 24% a year (Table 4-1). Each scenario was simulated for 500 years to stabilize above ground conditions. Critical disturbance rates, λ^*, for each site were recorded as the highest rate of disturbance under which forest conditions persisted.

This experimental design was run under a representative climatology of the 21st century. Climate data from 1901-2010 from the Multi-Scale Synthesis and Terrestrial Model Inter-comparison Project (MsTMIP) as part of the North American Carbon Program (NACP), was used to construct this representative climatology (Wei et al., 2014). The same model design was repeated with future climate data obtained from the North American Climate Change Assessment program (NACCAP) representative of an IPCC A2 scenario for the time period 2065-2070 (Mearns et al., 2009). Detailed information on the Ecosystem Demography model and parameterization has been published in previous studies (Hurtt et al., 2002; Moorcroft et al., 2001).

4.3.2 Estimating Actual Disturbance Rates (λ)

Remote sensing derived estimates of disturbance rates over 50 U.S. samples sites, representative of major forest types, were obtained using North American Forest Dynamics (NAFD) project products (Goward et al., 2008; Jeffrey G. Masek et al., 2013). These disturbance estimates were created by running annual Landsat scenes through the Vegetation Canopy Tracker (VCT) automated algorithm (Huang et al., 2010). Description of the VCT algorithm, and creation of the scene-level NAFD disturbance products as well as accuracy and limitations of data products can be found in previously published papers (Huang et al., 2010; Huang et al., 2009b; Thomas et al., 2011). Annual disturbance rate data, for the 50 sites from 1986-2011 were obtained directly from authors (Huang et al. pers. comm.). Summary statistics on the regional rates were calculated (i.e. distribution, standard deviation and average rate of disturbance). But from hereon observed λ refers to the mean annual rate over the entire site from 1986-2011 unless otherwise stated. Tests for temporal trends within each sample site were conducted using linear regression analysis. Sites that exhibited significant increases or decreases in the average annual rate of disturbance over the ~25 year study were flagged.

4.3.3 Disturbance Distance (λD)

To estimate how far current forest ecosystems may be from no longer supporting forested conditions, measured average annual rates of disturbance (**λ**) within all 50 NAFD study regions can be determine to the average estimated threshold rates of disturbance (**λ***) over the same forested regions. The difference between the threshold rate (**λ***) and the measured disturbance rate (**λ**) was recorded as the sites Disturbance Distance (**λ**D) or the additional average annual fraction of biomass removal that would lead to non-forest conditions.

4.4 Results

Over 110 scenarios of disturbance under past and future climate were run through the ecosystem demography model to produce maps of forest ecosystem disturbance threshold rates. Under current climate conditions, if annual rates were maintained at ~10% a year over the CONUS U.S., less than 0.1% of the area was estimated to support forest conditions, under the altered climate and $C0_2$ scenario ~10% of the U.S. could maintain a forested condition (Figure 4-2c). Not surprisingly, areas of most dense forests are the most resilient (Figure 4-2a). Ecosystem sensitivity to disturbance changed under altered climate conditions, with the majority of the U.S. estimated to increase tolerance to disturbance, though some areas such as the central and southwestern U.S. showed increased sensitivity to disturbance rates (Figure 4-2b,d).

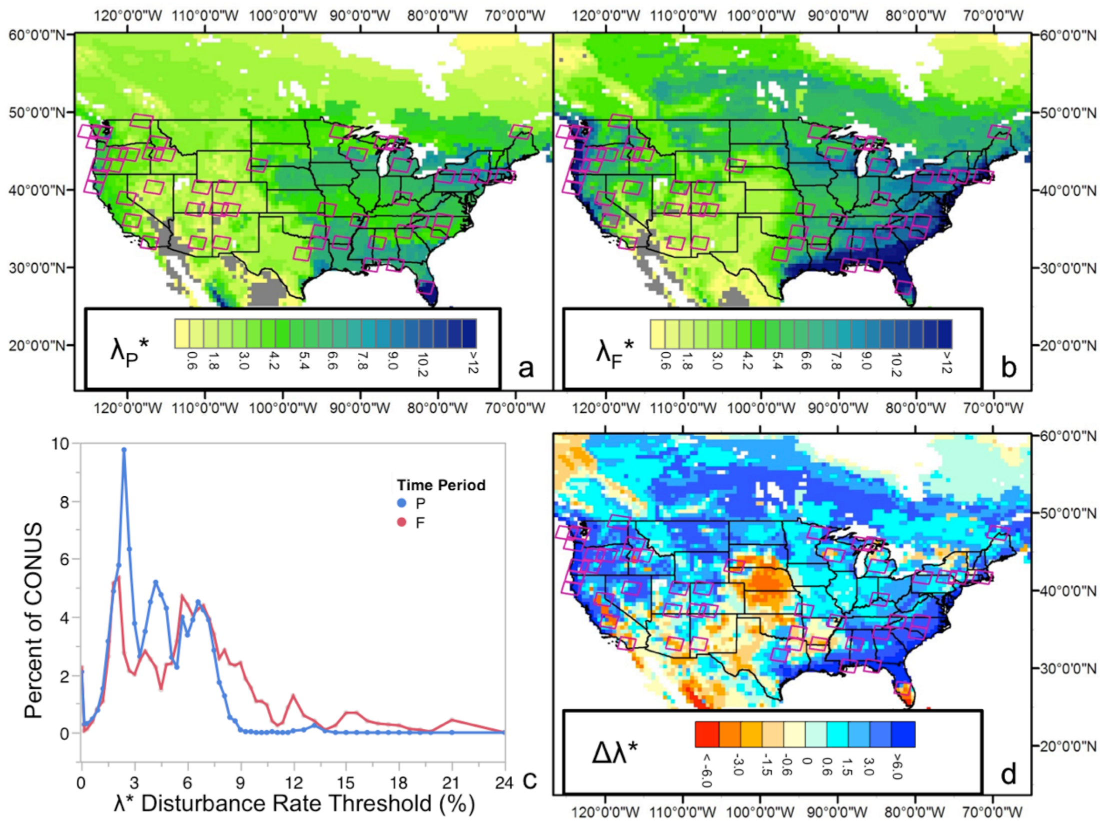

Figure 4-2: Examination of spatial distribution maximum rate of disturbance λ* for which forests can persist under present climate conditions (a) and a high change scenario of future climate (b). Land that was unable to support forest growth under any disturbance scenarios is shaded in gray. Comparison of fraction of contiguous U.S. corresponding to the various critical disturbance rates (c) Areas of increased resiliency (cool tones) and vulnerability (warm tones) are highlighted by examining the change λ* between future and current climates (d). Purple squares represent location of the NAFD sample /Landsat time series stacks (LTSS) used in proceeding analyses.

Measured disturbance rates (**λ_P**) over 50 sample forested landscapes ranged from average annual rates of ~0.4% to ~3.8% with an average annual rate of ~1.2%. Over the same 50 sample regions threshold rates of disturbance (**λ^***) ranged from ~1.5% to just under 12% under 20th century climate conditions (Figure 4-3 a). In general measured rates of disturbance (**λ_P**) within western forest ecosystems (west of 100 W) were much closer to their disturbance rate threshold (**λ^*_P**) with nearly half the western sites estimated to transition to non-forest if an additional 2% of forest area was disturbed annually (Figure 4-3b) while only one forested site in the east had a disturbance distance (λD) below 2% (Figure 4-3 b, c).

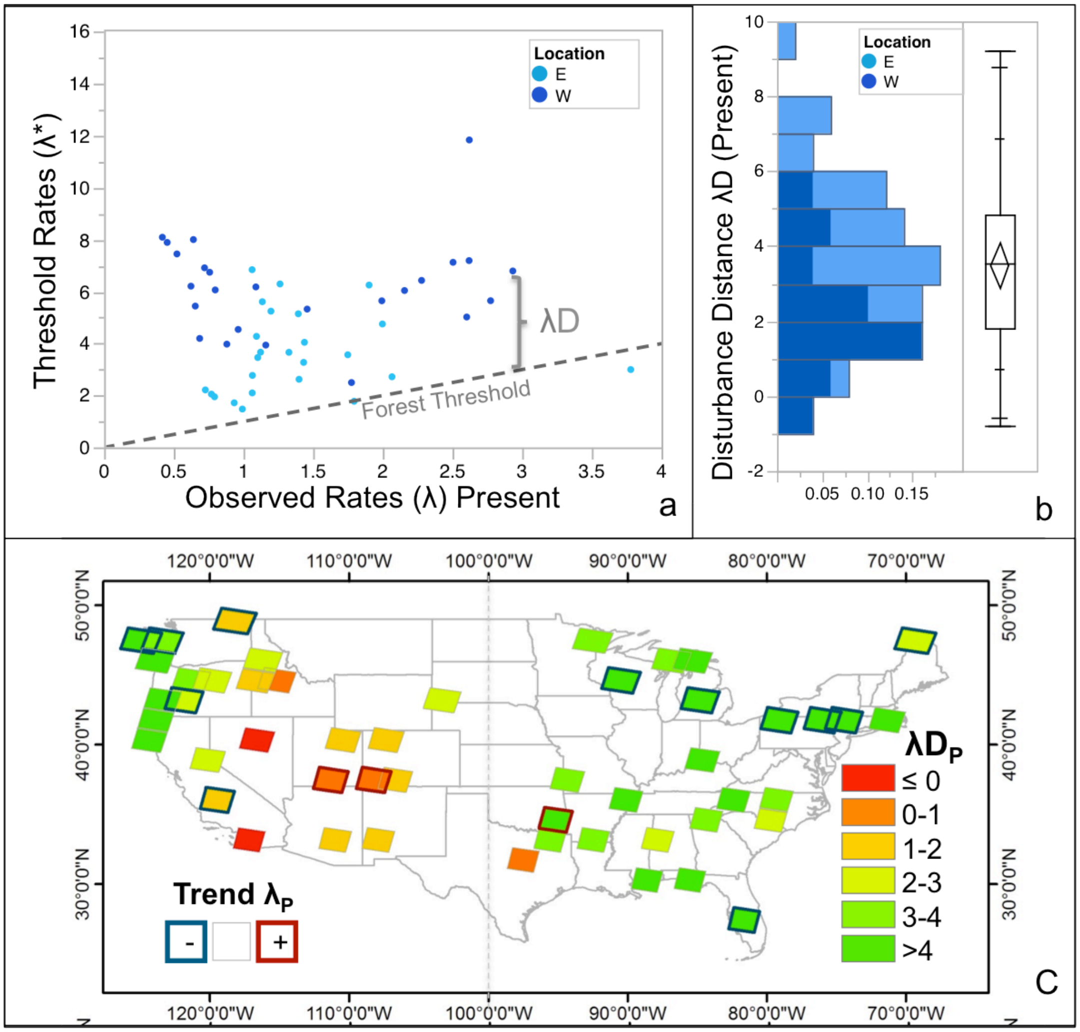

Figure 4-3: Panel (a) compares threshold rates to measured rates of disturbance within 50 sample forest regions. Panel (b) shows the distribution of sites disturbance distance, the amount of variability to altered disturbance highlighting differences between eastern and western sites. Panel (c) show spatial distribution of estimated Disturbance Distance and highlights forests within Landsat scenes that showed significant increasing (red) and decreasing (blue) trends of disturbance over the ~25 year study period (p < 0.1).

Regional disturbance distances (λD), calculated under the altered climate scenario, grew over the majority of sites, suggesting an overall decrease in vulnerability to disturbance rates under future climate and CO_2 (Figure 4-4). However three eastern and four western sites, or 15% of all sites, showed increased vulnerability under future climate conditions as expressed as a decrease in λD (Figure 4-4 b, c). The southern California site stands out as an extreme hot spot as its λD was already negative under current conditions, and is predicted to move into an increased deficit under the altered climate scenario (Figure 4-4 d). The northwestern forests stood out as an area where forest showed the largest resiliency under a potential A2 climate scenario.

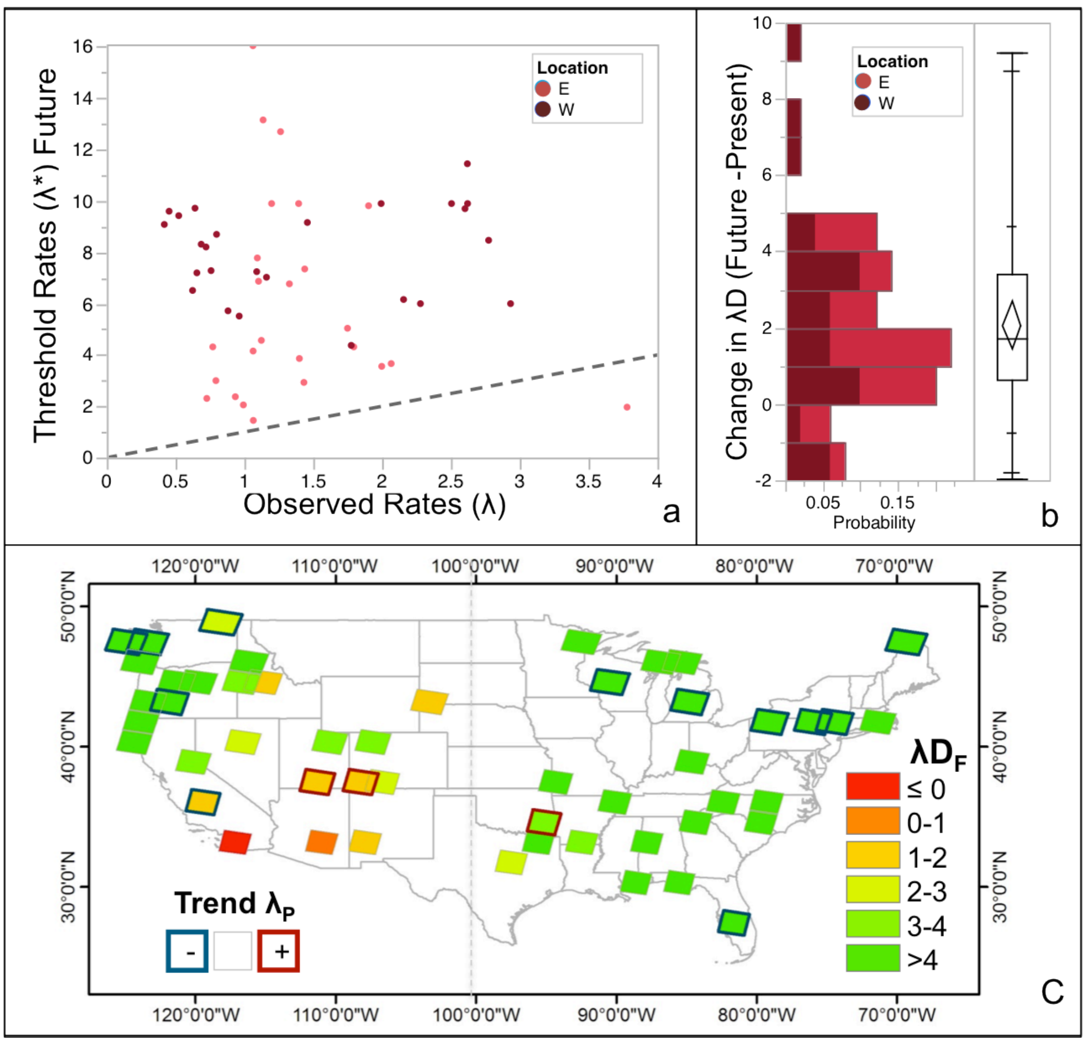

Figure 4-4: Panel (a) compares future threshold rates of disturbance under altered climate to observed rates of disturbance within the 50 sample forest regions. Panel (b) highlights the distribution of changes in ecosystems sensitivity to disturbance in

response to altered climate by looking at the difference in Disturbance Distances estimated in the future period minus those in the past. Panel (c) highlights the spatial variation in ecosystem sensitivity to altered disturbance under climatic conditions. Landsat scenes that showed significant increasing (red boarder) and decreasing (blue boarder) trends of disturbance over the ~25 year study period ($p < 0.1$) are highlighted

Though the current average observed rates were used to calculate future disturbance distance, NACP sites that had significant increases or decreases in disturbance rates were highlighted as possible indication of future direction in which rates might change (Figure 4-4 c). The two western sites showing a increasing trend in disturbance rates under current climate conditions, had disturbance distances less than 1% under current climate signaling them as hot spots. Though these sites showed a small increase in resiliency under future climate if disturbance rates continue to increase an additional 2% results indicate the site could move to non-forest conditions. The one eastern site showing an increase in disturbance in the last quarter century is also predicted to become more vulnerable to disturbance (Figure 4-4 c).

The percent of U.S. forestland land under various disturbance scenarios under present and future climate conditions was estimated under all potential rates of disturbance to address uncertainty in disturbance estimates as well as difficulty in predicating future disturbance rates (Figure 4-5). To address some model uncertainty associated with site heterogeneity variation in estimates within NACP study scenes were used to bound estimates. The temporal and spatial variability within the sample forests across the U.S. varied across sites (Figure 4-6).

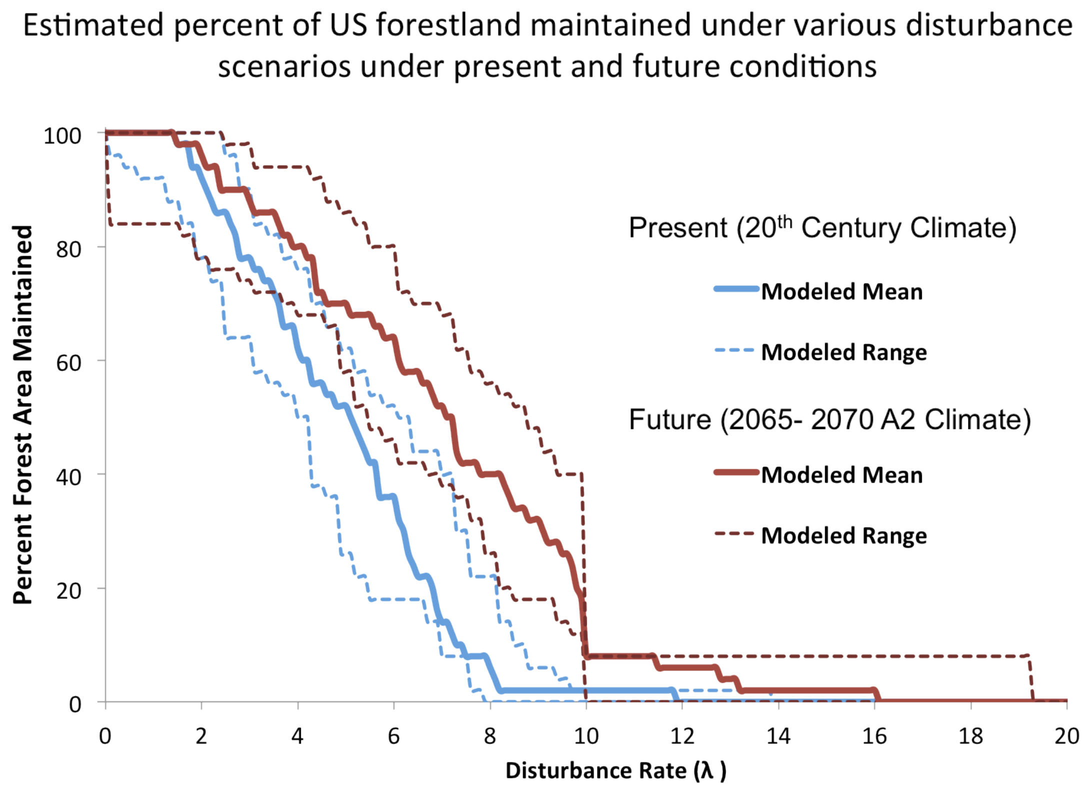

Figure 4-5: Estimated percent of the contiguous U.S. forestland maintained under a suite of annual disturbance rates under current (blue) and future (red) climate conditions. Modeled variation in estimated forest area (dashed lines) accounting for climatic and edaphic heterogeneity within forested regions.

4.5 Discussion

Predicted changes in future climate and anthropogenic forcing from increased population growth and resource demand highlight the importance of improving our ability to monitor and model forest disturbance and ecosystem response.

This study created novel maps showing how much disturbance may be tolerated before forest conditions no longer exist across the diverse climatic and edaphic gradients found within the Continental U.S. Comparing these novel maps to observed rates of forest disturbance, gave indication of how vulnerable or resilient U.S. forests may be to altered rates of disturbance. Under a future climate scenario the majority of U.S. forest are estimated to become more resilient to disturbance. This study represents a simplification of disturbance on the landscape, however we argue it provides an important base line and flexible framework that can be used in future studies which can add complexity, or varied definitions of disturbance and can be scaled up to global or down to regional scales. Further, though our primary aim was to estimate how far current forests may be from transitioning into non forest sates due to changes in disturbance, the maps produced in this study may also highlight areas that have not been historically defined as forest, but may have the capabilities to sustain forests if disturbances such as grazing, fire, and/or wind were suppressed to below critical threshold rates (Bond et al., 2004; Briggs et al., 2005).

Remote sensing data allows observation and characterization of vegetation characteristics, such as disturbance, across large temporal and spatial scales. Estimating current rates of forest disturbance with existing field data and various aerial and remote sensing monitoring schemes is complicated by the diverse spatial and temporal scales at which different disturbance regimes occur (Fisher et al., 2008; Frolking et al., 2009; McDowell et al., 2015). It is thus important to note that previous work show that disturbance products used in this study may underestimate effects of forest thinning events such as some selective harvest and pest outbreak (Masek et al., 2013; Schleeweis et al., 2013) and further may not capture disturbances that occur mostly at the gap scale level (Chambers et al., 2013). Further, there is uncertainty in our estimates of disturbance threshold; one source of uncertainty is that of sub-grid scale heterogeneity in environmental conditions that influence vegetation growth. Because vegetation dynamics are non-linear and rely strongly on environmental conditions, averaging environmental conditions doesn't necessarily give the appropriate average vegetation response (Thomas et al., 2008; Hurtt et al., 2010).

This study highlights the extreme differences in forest vulnerability and resiliency to disturbance across the U.S. The finding that many of the CONUS forests may actually become more resilient to disturbance under altered CO_2 and climate conditions, coincides with previous studies that have shown enhanced productivity stimulated by increases in CO_2 and temperature (Norby et al., 2005), although sustained enhancement of vegetation to CO_2 has been questioned. The forests that have been highlighted as being the most susceptible to critical functional change due to alterations in future disturbance, as well the areas where rates are predicted to increase to levels approaching their thresholds, may warrant more detailed investigation of ecosystem health and how management intervention might be able to ease the transition to new and better adapted forest states, minimizing the losses of ecosystem services (Millar & Stephenson, 2015). These hotspots would also be strong candidates to conduct detailed impact, adaptation and vulnerability studies (IAV).

4.6 Supplementary Material

Table 4-1: Modeled Disturbance Scenarios

Scenario #	Scenario Disturbance Rate	Average Return Interval	Past (P) % CONUS Forest	Future (F) % CONUS Forest	Change in percent area (P - F)
1	**0.15**	666.7	97.13	96.89	-0.24
2	**0.3**	333.3	96.86	96.85	0.00
3	**0.6**	166.7	96.56	96.75	0.19
4	**0.9**	111.1	96.19	96.41	0.22
5	**1.2**	83.3	95.30	95.69	0.39
6	**1.5**	66.7	93.83	94.47	0.64
7	**1.8**	55.6	90.66	91.65	0.99
8	**2.1**	47.6	85.55	86.19	0.63
9	**2.4**	41.7	79.71	80.62	0.90
10	**2.7**	37.0	69.90	77.82	7.92
11	**3**	33.3	63.88	75.59	11.71
13	**3.6**	27.8	57.47	71.13	13.66
15	**4.2**	23.8	49.87	65.97	16.10
17	**4.8**	20.8	40.12	62.31	22.20
19	**5.4**	18.5	33.41	57.71	24.30
21	**6**	16.7	27.16	50.48	23.32
23	**6.6**	15.2	20.16	42.08	21.91
25	**7.2**	13.9	11.55	33.70	22.16
27	**7.8**	12.8	4.51	26.64	22.13
29	**8.4**	11.9	1.54	21.25	19.71
31	**9**	11.1	0.72	16.70	15.99
33	**9.6**	10.4	0.63	12.31	11.68
35	**10.2**	9.8	0.60	9.62	9.02
37	**10.8**	9.3	0.60	7.52	6.92
39	**11.4**	8.8	0.56	6.70	6.14
41	**12**	8.3	0.56	5.50	4.93
42	**12.6**	7.9	0.56	4.29	3.72
44	**13.8**	7.2	0.56	3.16	2.59
46	**15**	6.7	0.41	2.85	2.43
47	**15.6**	6.4	0.06	2.19	2.13
49	**16.8**	6.0	0.00	1.05	1.05
51	**18**	5.6	0.00	0.62	0.62
53	**19.2**	5.2	0.00	0.30	0.30
54	**19.8**	5.1	0.00	0.25	0.25
55	**20.4**	4.9	0.00	0.25	0.25
56	**21**	4.8	0.00	0.22	0.22
57	**24**	4.2	0.00	0.00	0.00

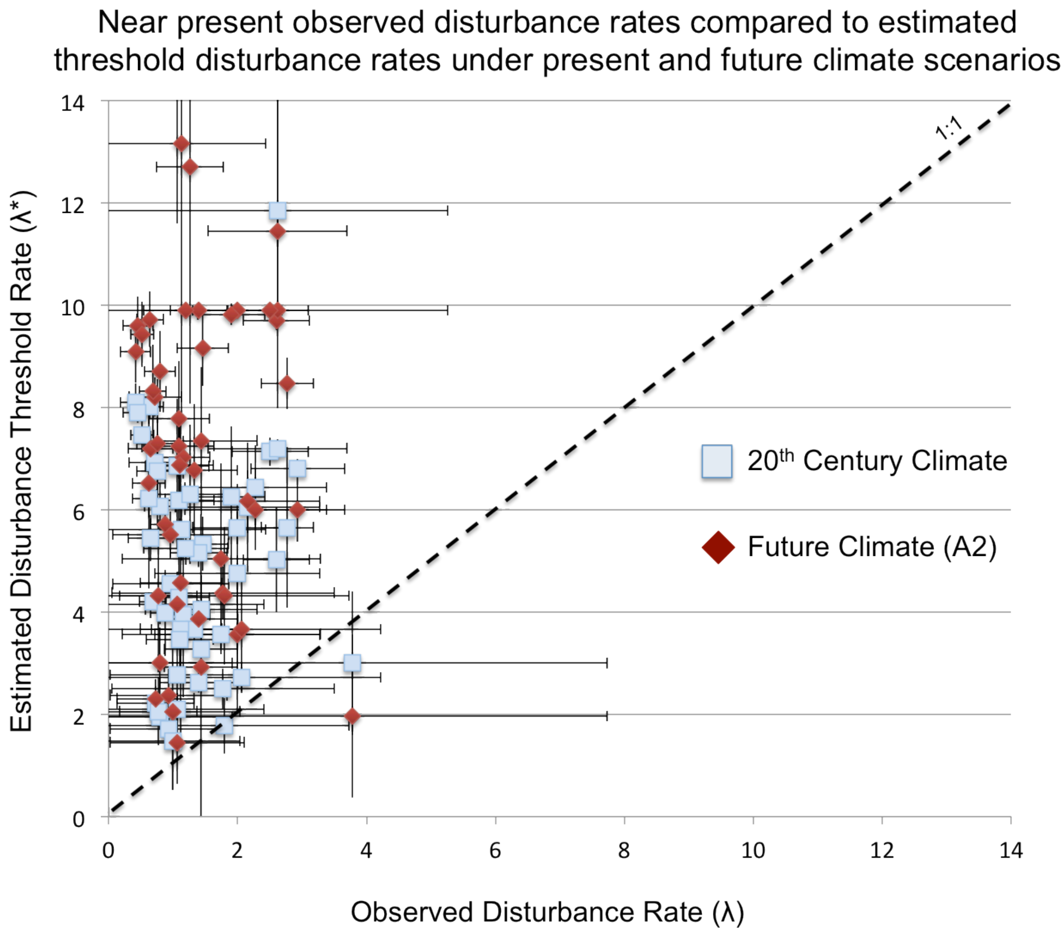

Figure 4-6: Comparison of 50 forested region's observed average annual disturbance rates (λ) to the average predicted regional critical threshold rates (λ*) under present climate conditions (Blue) and future climate predictions (Red). Standard deviation of annual recorded rates (1985-2010) as well as standard deviation of modeled threshold rates within regions are shown as black horizontal and vertical bars respectively.

Chapter 5. Conclusion

This research grew out of a desire to improve the representation of disturbance in terrestrial ecosystem models used to assess regional to global carbon budgets and fluxes. What seemed like a simple task, determine the rates of driving mechanism of disturbance in different regions of the U.S, proved to be extremely complex as historic capabilities to continuously and consistently characterize disturbance was limited. Forest inventories in the U.S. were not historically structured to measure disturbance, and estimates of regional return frequencies of disturbance were often assessed by limited field studies, which limited consistent and seamless estimation. The release of global Landsat archive and development in forest change algorithms appeared as an opportunity to acquire better maps and information on disturbance rates and patterns that could improve the representation of disturbance in forest ecosystem and carbon models, and address the question how do disturbance rates vary within and between regions. As I delved into the literature on the missing carbon sink, potential changes in future disturbance rates driven by climate, and the unprecedented outbreak of mountain pine beetle, whose northern expansion had no historic precedent, the question of how sensitive forests ecosystems are to altered rates of disturbance was developed.

This research took a tiered approach to quantifying the spatial and temporal patterns and impacts of disturbance within and between the diverse landscapes of the contiguous U.S. Chapter 2 started with an in-depth characterization of disturbance within one highly forested region, while Chapter 3 expanded analyses over three geographically distinct regions with different dominant modes of disturbance. Results from Chapters 2 and 3 build on a growing body of knowledge of the spatial patterns and rates of disturbance that may improve the representation of disturbance within prognostic ecosystem models. Finally, Chapter 4, using an advanced ecosystem model and near present observations of disturbances over 50 sample regions, assessed the vulnerability of forests across the contiguous U.S. to altered rates of disturbance and how vulnerability may change under future climate conditions. Below I summarize major finding from each chapter, then discuss priorities for future research.

Chapter 2, focused on characterizing patterns of disturbance over a quarter century for the entire state of NH, as captured by Landsat Imagery. Major results showed disturbance increasing over the state over the study period, a trend that was consistent in 7 out of the 10 counties. Strong interregional patterns of disturbance were observed across the state. Disturbance aggregated to quarter degree resolution, varied by a factor of 10, and within adjacent lands differing by up to a factor of 6. Forest management may be a large influence on spatial variation across the state with private lands being disturbed more than 4 times that of public lands. Inter-regional analysis of NH disturbance rates showed that specific events such as the 1998 ice storm could have strong influence over variations in area-averaged disturbance rates from year to year. Ability to classify disturbance into causal agents, fates and severities over the statewide study was challenged by the availability and consistency of forest survey data. However, continued development of efforts to classify disturbance into causal agents, as well as on the quantitative metrics of severity and fate of disturbed biomass over the state will be important to further understanding the drivers of variability and change as well as regional carbon dynamics and is thus an important area of future research.

In Chapter 3, the rates and size distributions and trends of disturbance were compared between three diverse regions of the contiguous U.S. over 25 years. Results showed significant distinctions in disturbance rates, variability and size distributions across the Northeast, Northwest, and Southeastern study regions. The ability to quantify frequency and size distributions of canopy gaps caused by disturbance can help with the parameterization and development of disturbance models, with the planning of field campaigns, and the ability to estimate disturbance rates and patterns taken from smaller, temporal or spatial scale, studies. In the past, the high cost of obtaining high-resolution field information over large spatial scales has been a restricting factor in expanding the study of gap phase dynamics. Studies in this area have mainly occurred over small scales while the study of stand replacing events occurred over very broad regions at coarse resolutions. This study quantified disturbance sizes annually over a quarter century and identified over 5 million unique disturbance patches over 3 regions. Findings showed disturbance size frequencies follow power law behavior. However, looking at the observed deviations from the power law distributions may provide insight into the disturbance regimes in an area. For example, mid sized-disturbance in the North Carolina study site tended to be higher than expected and large events showed signs of an exponential cutoff. These characteristics may be linked to the highly managed systems in the region, further emphasizing a need to look at the influence of management in future studies. The severity of recorded disturbances was not considered in analyses characterizing disturbance in this study, further, previous studies have shown higher omission error for partial canopy clearing events and low to no detection of single-tree disturbances. To quantify sub pixel mortality and expand the characterization of disturbance to finer resolutions, future research could combine Landsat based maps of disturbance with data from other remote sensing instruments capable of capturing forest structural properties at finer resolutions, such as the LiDAR instrument on NASA Goddard's LiDAR, Hyperspectral, and Thermal Airborne Imager (G-LiHT).

Chapter 4 provided insights into forests vulnerability to altered rates of disturbance now and in the future. Using an advanced ecosystem model to simulate vegetation dynamics under a range of disturbance scenarios, threshold rates of disturbance were determined for which forest ecosystems could not be sustained. Landsat based estimates of forest disturbance by the North American Forest Dynamics (NAFD) project were compared to estimated threshold rates to determine how far current forests in the contiguous U.S. may be from transitioning into non forest states, the difference in rates was termed a sites Disturbance Distance. Results revealed the majority of forested sites across the U.S. trended toward reduced vulnerability to disturbance under a future climate scenario, which may buffer some of the impact of intensified forest disturbance. Strong variations in ecosystem vulnerability to disturbance were observed across the contiguous U.S. Under current climate conditions, western sites generally exhibited greater vulnerability to altered rates than eastern sites, while under a future climate scenario coastal northwestern sites shifted to become some an area of high resiliency. The finding that many the majority of forests may become more resilient to disturbance under altered CO_2 and climate conditions, coincides with previous studies that have shown enhanced productivity stimulated by increases in CO_2 and temperature (Norby et al., 2005). Though the focus of this study was to assess the vulnerability/ resiliency of current forested areas to altered rates of disturbance, the sensitivity analysis run under current and future climate may also provide insights into areas not considered forest but may have the potential to support forest if disturbances such as fire and or grazing were suppressed. Future research could use the flexible framework developed in this study to expand analysis to include more detailed scenarios of disturbance and incorporate more future climate scenarios. Further, the study could be expanded over larger geographic regions as wall-to-wall maps of Landsat mapped disturbance become available (Masek et al. 2013).

Future research priorities include the continued characterization and monitoring of disturbance over space and time as well advances in modeling to assess disturbance impact on forest carbon and other applications. NASA Landsat Satellites have provided critical information on land cover dynamics since 1972, and the continuation of this data is important to assessing future changes in forest dynamics.

While the research presented in this dissertation focused mainly on disturbance, the resultant recovery after disturbance is also very important to understanding carbon dynamics. Combining the spatially and temporally rich disturbance maps from Landsat with information on vertical structure from LiDAR instruments can improve understanding of forest regeneration and impact of disturbance (Dolan et al., 2009). The future Global Ecosystem Dynamics Investigation (GEDI) LiDAR coupled with spatially comprehensive maps of disturbance will be key in expanding estimates of carbon stocks and understanding dynamics in remote regions with limited inventory data.

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