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Forest disturbance and recovery: A general review in the context of spaceborne remote sensing of impacts on aboveground biomass and canopy structure

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[1] Abrupt forest disturbances generating gaps >0.001 km^2 impact roughly 0.4–0.7 million km^2 a^{-1}. Fire, windstorms, logging, and shifting cultivation are dominant disturbances; minor contributors are land conversion, flooding, landslides, and avalanches. All can have substantial impacts on canopy biomass and structure. Quantifying disturbance location, extent, severity, and the fate of disturbed biomass will improve carbon budget estimates and lead to better initialization, parameterization, and/or testing of forest carbon cycle models. Spaceborne remote sensing maps large-scale forest disturbance occurrence, location, and extent, particularly with moderate- and fine-scale resolution passive optical/near-infrared (NIR) instruments. High-resolution remote sensing (e.g., ~1 m passive optical/NIR, or small footprint lidar) can map crown geometry and gaps, but has rarely been systematically applied to study small-scale disturbance and natural mortality gap dynamics over large regions. Reducing uncertainty in disturbance and recovery impacts on global forest carbon balance requires quantification of (1) predisturbance forest biomass; (2) disturbance impact on standing biomass and its fate; and (3) rate of biomass accumulation during recovery. Active remote sensing data (e.g., lidar, radar) are more directly indicative of canopy biomass and many structural properties than passive instrument data; a new generation of instruments designed to generate global coverage/sampling of canopy biomass and structure can improve our ability to quantify the carbon balance of Earth's forests. Generating a high-quality quantitative assessment of disturbance impacts on canopy biomass and structure with spaceborne remote sensing requires comprehensive, well designed, and well coordinated field programs collecting high-quality ground-based data and linkages to dynamical models that can use this information.

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1. Introduction

[2] Atmospheric CO_2 concentrations continue to increase [*Forster et al.*, 2007], and evidence of contemporary climate change is accumulating [*Trenberth et al.*, 2007]. Significant effort is being devoted to better quantifying the carbon balance of terrestrial ecosystems [*Grace*, 2004], and to develop and improve Earth system models capable of incorporating the role of ecosystems, including forests and forest dynamics, in the Earth's coupled climate-carbon system [e.g., *Friedlingstein et al.*, 2006; *Bala et al.*, 2007]. Substantial uncertainties in the global carbon budget are attributed to net carbon fluxes from land use and an unidentified terrestrial carbon sink, both about 1.6 Pg C a^{-1} [*Forster et al.*, 2007]. Forest disturbance and recovery play an important role in both regional and global carbon budgets, and in forest ecosystem processes.

[3] A recent report on near-term priorities for Earth science applications from space by the National Research Council recommended a suite of satellite missions, including a mission 'to observe the extent of changes in ecosystem structure and biomass' [*National Research Council* (*NRC*), 2007]. The report noted that the horizontal and vertical

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structure of vegetation is a key feature influencing ecosystem carbon storage, surface energy balance, and species habitats. Forests warrant particular focus because the vertical structure of forest canopies is more complex and variable than other ecosystems (grasslands, arid lands, tundra, agricultural lands). Forest vertical canopy structure plays a central role in forest ecology, productivity, and biodiversity [*Lowman and Rinker*, 2004]. Vertical canopy structure can vary with stand age to a greater degree than for nonforested ecosystems, and also varies with soil properties, nutrient and water availability, and small-scale variability in climate patterns. The horizontal structure of a forested landscape encompasses the spatial heterogeneity in species, gap, and canopy height distributions.

[4] The *NRC* [2007] report also stated, 'Quantifying changes in the size of the [vegetation biomass] pool, its horizontal distribution, and its vertical structure resulting from natural and human-induced perturbations, such as deforestation and fire, and the recovery processes is critical for measuring ecosystem change.' If forests were static ecosystems, mapping relevant forest properties would be relatively straightforward, and monitoring would be unnecessary. However, forest disturbance and recovery ensures that the species composition, age, biomass, and biogeochemical properties of forests are not static, and land cover change and biome migration (e.g., woody encroachment or desertification) ensures that the location and extent of forest cover is also dynamic.

[5] The carbon balance of a forest ecosystem is fundamentally linked to its cycle of disturbance and recovery. Major disturbances entail either a rapid release of biomass carbon (e.g., combustion [*Körner*, 2003]) or a large transfer of biomass from living and potentially growing vegetation to dead material that either decomposes over a period of years (e.g., coarse woody debris [*Harmon et al.*, 1986; *Chambers et al.*, 2000; *Palace et al.*, 2007]) or is removed from the forest (e.g., wood products [*Winjum et al.*, 1998]). Forests recovering from disturbance are generally strong carbon sources immediately following the disturbance (from combustion or decomposition of abundant dead wood) shifting to carbon sinks due to regrowing vegetation for many decades thereafter [*Chambers et al.*, 2004; *Law et al.*, 2004; *Keller et al.*, 2004a]. Averaged over large area and decades, the carbon losses from disturbances and the carbon gains from recovery may be approximately equal [e.g., *Körner*, 2003], unless changes in the rate, severity, or extent of disturbance or in the rate of recovery or regrowth cause a change in the equilibrium carbon stock of a region's forests. Disturbance/recovery changes may play an important role in the net terrestrial sink term of the global C budget. Earth system models will simulate the dynamics of ecosystem carbon cycling as it interacts with the climate system, with both forcings and feedbacks. Initialization and/or evaluation of carbon models require regional- to global-scale data sets of both forest extent and forest properties related to the coupled climate-carbon system. Fundamental forest properties (e.g., stand biomass, stand age distribution, life form (evergreen or deciduous or mixed), canopy height, foliar biomass and leaf area, and potential productivity) can be measured both directly on the ground by forest inventories or, generally indirectly, by spaceborne satellite remote sensing.

[6] Forest disturbance can be abrupt (e.g., hurricanes) or chronic (e.g., acid rain); stand-replacing (e.g., clear-cut logging) or not (e.g., selective logging); complete (e.g., landslides) or incomplete (e.g., insect defoliation); natural (e.g., tornados) or anthropogenic (e.g., land conversion); widespread (e.g., fire) or geographically restricted (e.g., avalanches); temporary (e.g., blowdowns) or permanent (deforestation and land use conversion).

[7] Disturbance is a major agent in determining the heterogeneity of forest ecosystems across a broad range of scales in space and time. Methods for projecting carbon storage change in forests and for assessing plant and animal habitat all contain assumptions about the physical structure of forests. Characterizing a forest requires quantification of more than a single feature. For example, a complex multi-species, multilayered forest can be very different in many of its dynamic functions than a mono-species, mono-layered forest with an equivalent leaf area index (LAI). Additional canopy structure information (e.g., canopy height and its variance, gap sizes and frequencies, and aboveground biomass) will provide a more complete picture of the state of the forest than just LAI. In a world with conspicuous environmental change, quantifying the structural aspects of forests across large areas is a key factor in both qualitative and quantitative descriptions of the state of forests.

[8] Much spaceborne remote sensing is based on measuring the reflectance of incoming solar radiation. For these so-called passive instruments reflected solar radiation is broadly classed as visible (0.4–0.7 μm), near-infrared or NIR (0.7–1.2 μm), and short-wave infrared or SWIR (1.2–2.0 μm); active instruments beam radiation down and measure the reflectance of that radiation. Spaceborne passive optical/NIR remote sensing has been an important tool for mapping the extent and location of large-scale, stand replacing forest disturbances such as deforestation and land conversion [e.g., *Skole and Tucker*, 1993; *Achard et al.*, 2002; *Hansen et al.*, 2008], logging [e.g., *Asner et al.*, 2005; *Souza et al.*, 2005; *Masek et al.*, 2008], fires [e.g., *Kasischke and Turetsky*, 2006; *Roy et al.*, 2008], and wind storms [e.g., *Nelson et al.*, 1994; *Chambers et al.*, 2007b]. There remain several key hurdles to accurate continental to global assessments of forest areas and forest disturbance: (1) cloud interference at all spatial scales, particularly in humid tropical and temperate forests [e.g., *Asner*, 2001; *Simon et al.*, 2004; *Cardoso et al.*, 2005; *Zhao et al.*, 2005; *Sano et al.*, 2007]; (2) definitional problems and changing assessments of forest areas [e.g., *Grainger*, 2008; *Houghton and Goetz*, 2008]; (3) for fine scale assessments (e.g., Landsat), the challenge of developing robust algorithms that generalize across a region [e.g., *Woodcock et al.*, 2001; *Foody et al.*, 2003]; and (4) the difficulty of detecting smaller-scale disturbances that, in aggregate, are of global significance [e.g., *Asner et al.*, 2002a, 2002b].

[9] High-resolution (e.g., <5 m) passive optical/NIR remote sensing data (e.g., Ikonos, QuickBird) provides a much more detailed view of forest canopies [e.g., *Palace et al.*, 2008a], but with only limited and targeted coverage [e.g., *Hurtt et al.*, 2003]. With these new instruments there has been work on remote sensing of the growth, mortality and reproduction of individual trees [*Clark et al.*, 2004a, 2004b; *Wulder et al.*, 2008; *Kellner*, 2008], as well as estimation of stand-level characteristics such as basal area,

frequency of canopy gaps and land use history [*Asner et al.*, 2002a, 2002b; *Palace et al.*, 2008a; *Kellner et al.*, 2009; *Wulder et al.*, 2008; *Malhi and Román-Cuesta*, 2008].

[10] A more complete assessment of the impact on the coupled climate-carbon system of forest changes through disturbance and conversion or recovery requires more than just information on the location and extent of these changes. How many trees were killed? How many were damaged? How much necromass (standing dead and coarse woody debris) was generated? For an earlier disturbance, what is the current state of forest recovery in terms of biomass, or LAI, or stand height? Specific quantitative, geospatial information on changes in forest biomass and canopy structure will be more useful to carbon budget studies and Earth system modeling than inferences of these changes from maps of the location of disturbance and general forest biome statistical data. Lidar (light detection and ranging [*Lefsky et al.*, 2005]), SAR (synthetic aperture radar [*Saatchi and Moghaddam*, 2000; *Saatchi et al.*, 2007a]), and interferometric SAR (InSAR [*Treuhaft et al.*, 2004]) all offer the potential to complement the ongoing spaceborne remote sensing work on forest disturbance mapping by providing a more detailed assessment of predisturbance and postdisturbance forest biomass and canopy structure.

[11] The state of a forest landscape with respect to the collection of mosaic patches that comprise it is essential to understanding the long-term dynamics of that landscape. Forest in recovery from large disturbances will have a narrow age distribution, while mature forests long-recovered from a similar disturbance will have a broader age distribution across a set of distributed samples or the entire forest mosaic. These patterns of recovery versus equilibrium may not be well quantified by the variation in the features of forests that are easily monitored with conventional spaceborne remote sensing systems. The variation and higher moments of landscape variability in leaf area, biomass, height, etc., are necessary to reveal these essential forest features. One can detect some of the variability with passive remote sensing instruments (particularly at higher resolutions or using multiangle "looks" at the vegetation) but the suite of forest structure variables (and the richness of potential interpretation) is greater with the addition of active remote sensing (radar and lidar sensors).

[12] In this paper, we review major types of large-scale and small-scale forest disturbances in terms of scale, frequency, and impact on forest structure and aboveground biomass, and the capabilities of existing spaceborne remote sensing instruments to map disturbance location, extent, timing, and impacts. Our examination of existing remote sensing studies allows us to assess advantages, benefits, and limitations of such research, and to make suggestions about the development and synthesis of new studies and satellite platforms necessary to the understanding of the role of forest disturbance and recovery on forest carbon cycle dynamics on both regional and global scales.

2. Definitions

[13] Our focus is the measurement of changes in forest aboveground biomass distribution detectable by remote sensing at different spatial scales (branch to landscape to biome). Although the terms forest, biomass, canopy, disturbance, and recovery are common in forest ecology and carbon cycle science literature, specific scientific definitions vary based on the scale of study and the ecological concept being examined.

[14] Biomass is the dry weight of living or dead organisms; in forests most of the biomass is found in plants. Vegetation biomass, or the mass of plant and plant-derived organic matter, can be disaggregated into several categories [*Clark et al.*, 2001a, 2001b]. In forests, aboveground living biomass consists primarily of the wood of canopy trees, but also includes vine, epiphyte, canopy leaf, understory, and groundcover biomass, and would exclude all aboveground dead material (standing dead, coarse woody debris, litter and duff) [*Keller et al.*, 2001]. Necromass is defined as dead vegetation biomass that has not been incorporated into soil organic matter, and is sometimes included in biomass estimates. Necromass can be partitioned into a fine component, including fallen leaves and small twigs/branches, and a coarse component, including standing dead and coarse woody debris [*Harmon et al.*, 1995]. Estimates of necromass and comparison with live biomass can aid in the understanding of spatial and temporal patterns of disturbance [e.g., *Rice et al.*, 2004; *Palace et al.*, 2008b]. We focus on aboveground biomass (live and dead), as belowground biomass is not observable from space.

[15] *Spies* [1998] discussed four key components of forest structure: live-tree size distribution, vertical foliage distribution, horizontal pattern, and coarse woody debris. Live-tree size distribution includes tree height distributions, tree diameter (e.g., diameter at breast height or DBH) distributions, stem density (number per unit area), and age distributions. Vertical foliage distribution can include information on LAI, canopy vertical distribution profile, canopy architecture (leaf size, shape, orientation and clumping index, and life form: deciduous or evergreen), canopy roughness, and understory and groundcover biomass, height, life form, spatial pattern. Coarse woody debris includes information on standing and fallen dead: diameter, height, mass, and decay state [e.g., *Keller et al.*, 2004a, 2004b; *Palace et al.*, 2007]. Horizontal pattern includes information on the forest canopy as an element of the landscape structure: stand/patch and gap size and shape distributions, and edge density and habitat connectivity.

[16] *Clark* [1990] defined forest disturbance as 'a relatively discrete event causing a change in the physical structure of the environment (vegetation and surface soil).' These disturbances can range from branchfalls to landscape-level blowdowns [*van der Meer and Bongers*, 1996; *Clark and Clark*, 1991], and there is inverse relationship between temporal and spatial patterns [e.g., *Lorimer and Frelich*, 1989; *Fisher et al.*, 2008]. Following *Clark* [1990], we focus in this review on disturbances that are abrupt events that cause changes in forest biomass and structure (Table 1) that are potentially detectable by space-based remote sensing (Table 2). We exclude phenological or regenerative changes in canopy biomass or structure. Regenerative changes and growth will fall under our definition of recovery (below). Seasonal phenological cycles induce relatively predictable and repetitive changes in forest canopy structure. However, significant anomalies in bioclimatic seasonality can have measurable impacts on forest canopies and regional carbon cycles, at least over a growing season,

Table 1. Abrupt Forest Disturbance Types Considered in This Study[a]

Type	Description	Cause[b]	Range of Occurrence[c]	Spatial Scale (km^2)	Recurrence	Trend	Impact
Fire	ground/understory or surface fires do not reach canopy. crown fires ascend to and burn forest canopy.	N and A	global	<1 to >10^4 (F98)	<10–1,000 years (B07; C03a; O96; W95)	boreal: fire area increased and large fire years increased in 1980s/1990s versus 1960s/1970s in N. Am. (K06); increases predicted for boreal Canada with climate change (F05a). temperate: increasing with warming and drying (W06). tropics: anthropogenic fires likely to increase (e.g., C03b).	impact severity highly variable, often heterogeneous, depending on fire intensity, susceptibility of vegetation, rate of spreading (O96).
Wind	hurricane/typhoon/cyclone; tornado; severe storm blowdown or downburst; individual windfall	N	global; lower frequency, severity in boreal forests	hurricane: 10^3–10^5 (F98; D01; O08) tornado: 1 – 10 (F98; O96) blowdown: <0.01 – 10^3 (N94; R07)	hurricane: 15–200 years (M02) tornado: infrequent. blowdown: not well known.	hurricanes: uncertain; variable by ocean basin (see text). tornadoes: uncertain and probably variable (see text). blowdown: extreme weather event frequency expected to increase (M07).	hurricanes: damage gradient from severe (>50% mortality) to light (O96; C07). tornadoes: severe damage in swath; sharp boundaries (F98). blowdown: damage gradient from severe (>50% mortality) to light (O96).
Ice storm	ice coating and accumulation (up to several cm) on canopy elements.	N	restricted to winter	synoptic weather scale; restricted by elevation	~100 years (D01)	trends unknown, but locations likely to shift with warming (D01).	some immediate mortality and felling, mostly crown disturbance/damage (O96).
Landslide	sudden soil slumping; associated with earthquakes, land use.	N and A	restricted to steep slopes	<1 (G79)	~1,000 years (G79)	deforestation and development on sloped terrain may increase likelihood.	all vegetation disturbed, removed from site, buried in landslide debris.
Avalanche	sudden movement of snowpack downhill.	N	restricted to snowy slopes, regular paths (J87)	<1 (J87)	steep/upper slope: 2–5 years. runout zone: 20–100 years, depends on topography (J87).	unknown.	land scoured in upper slope, trees bent/broken at snow surface in runout zone (J87; O96; W04).
Flooding	geomorphic changes in narrow, upper reaches severe, prolonged inundation in lower reaches (generally chronic)	N	restricted to valleys restricted to low-lying land	generally<1 10–10^4 (F98)	50–100 years (F98)	extreme weather event frequency expected to increase (M07).	channel reorganization: vegetation disturbed, removed, exposing bare land in former channel. prolonged inundation: mortality widespread, variable, >50% to minimal; heterogeneity and severity depend on duration, species composition, topographic variability (F98); most dead trees stillstanding.

Table 1. (continued)

Type	Description	Cause[b]	Range of Occurrence[c]	Spatial Scale (km^2)	Recurrence	Trend	Impact
Land conversion	permanent: land remains in nonforest use temporary: land cultivated for a few years, natural or selectively managed regeneration (i.e., nonpermanent agriculture)	A	permanent: global temporary: tropics and subtropics (L85)	permanent: >0.01 temporary: <0.01 (e.g., D88; I07)	permanent: not recurring. temporary: declining time in fallow (recovery) from 10 to 30 years to 5–10 years over mid to late twentieth century (e.g., F91).	rates of expansion of permanent cropland slowed in the 1990s (T01); much of increase in agricultural productivity over past few decades has come from intensification as opposed to extensification (T99; F05b); shifting cultivation can be expected to contract in area as economic use of land outcompetes it.	trees cut, wood and slash removed or burned.
Logging	clear-cut: large swath cut selective: selected trees cut, can have substantial collateral damage (e.g., A02) reduced-impact: selective, but with measures taken to minimize collateral damage (S00)	A	global	clear-cut > 0.01 selective < 0.01 reduced-impact < 0.01	depends on forest regrowth; can be as low as 20 years in SE USA (M08), as high as 100 years in boreal forest (S02).	potential plantation forest expansion in 21st century for biofuel production (e.g., N00; v08).	trees cut, wood and slash left in place, removed or burned.

[a]References: A02, *Asner et al.* [2002a, 2002b]; B07, *Balshi et al.* [2007]; C03a, *Cochrane* [2003]; C03b, *Cardoso et al.* [2003]; C07, *Chambers et al.* [2007a]; D88, *Denevan and Padoch* [1988]; D01, *Dale et al.* [2001]; F91, *Flint and Richards* [1991]; F98, *Foster et al.* [1998]; F05a, *Flannigan et al.* [2004]; F05b, *Foley et al.* [2005]; G79, *Garwood et al.* [1979]; I07, *Ichikawa* [2007]; J87, *Johnson* [1987]; K06, *Kasischke and Turetsky* [2006]; L85, *Lanly* [1985]; M02, *McNulty* [2002]; M07, *Meehl et al.* [2007]; M08, *Masek and Collatz* [2006]; N94, *Nelson et al.* [1994]; N00, *Nakicenovic et al.* [2000]; O96, *Oliver and Larson* [1996]; O08, *Oswalt and Oswalt* [2008]; R07, *Rich et al.* [2007]; S00, *Sist* [2000]; S02, *Seely et al.* [2002]; T99, *Tilman* [1999]; T01, *Tilman et al.* [2001]; v08, *van Minnen et al.* [2008]; W95, *Whelan* [1995]; W04, *Walsh et al.* [2004]; W06, *Westerling et al.* [2006].

[b]N, natural; A, anthropogenic.

[c]Spatial and temporal frequency of occurrence can be highly variable across range.

Table 2. Representative Spaceborne Optical/NIR and Microwave Remote Sensing Instruments Currently Flying, With Potential Application to Measuring Regional- to Global-Scale Disturbance and Recovery

Method	Instrument Type (Example)	Spatial Coverage	Approximate Spatial Resolution (m)	Temporal Repeat	Surface Observations	Potential Disturbance/ Recovery Applications	Problems and Challenges
Passive optical/ NIR/SWIR[a]	high resolution (e.g., Ikonos, QuickBird)	local scale, global sampling	1–4	tasked	surface reflectance; land cover; crown size; gap size distribution	local to regional mapping of small to large gaps; stereo image analysis of canopy height	clouds; stereo imaging cogeolocation.
	fine resolution (e.g., Landsat)	local to global	30	16 days	surface reflectance; vegetation indices; land cover	identifying active fires, fire scars, regional mapping of large gaps, early canopy recovery, disturbance history	clouds
	moderate resolution (e.g., MODIS)	regional to global	250–1,000	~daily	surface reflectance; vegetation indices; land cover	identifying active fires, fire scars, regional to global mapping of large gaps, early canopy recovery	clouds; spatial resolution too coarse for many disturbances
	geostationary (e.g., GOES)	global	4,000	continuous	surface reflectance; brightness temperature	identifying active fires	clouds; spatial resolution too coarse for many disturbances
	Hyperspectral (e.g., Hyperion)	regional scale, global sampling	30	tasked	high spectral resolution surface reflectance; canopy chemistry	species biodiversity; canopy vegetation diversity; recovery trajectory	clouds; large data volumes; instrument is deorbiting
	multiangle (e.g., MISR)	global	1100	2–9 days	surface reflectance and its angular dependence	mapping large gaps; canopy structure and heterogeneity; recovery trajectory	clouds; large data volumes
Active optical/ NIR	spaceborne lidar (e.g., GLAS)	global sampling	70	limited to crossovers	canopy height; vertical profile of canopy biomass	canopy structure (height, vertical distribution); gap frequency statistics; recovery stage (canopy height) and growth	clouds, georeferencing for repeat looks
Active microwave	Synthetic Aperture Radar (SAR) (e.g., ERS 1 and 2; PalSAR)	global	10–100	46 days[b]	backscatter (wavelength and polarization dependent)	aboveground biomass for disturbance and recovery	saturation at high biomass
	interferometric SAR (e.g., PalSAR[c])	global	10–100	46 days[b]	canopy height; aboveground biomass	aboveground biomass; canopy height for disturbance and recovery	limited assessment of utility to date; 'repeat pass' uncertainty
	scatterometer (e.g., Quikscat)	global	5,000–25,000	~daily	soil moisture; foliar biomass and moisture; freeze/thaw state	limited application (maybe drought)	spatial resolution too coarse for many disturbances
Passive microwave	radiometer (e.g., AMSR-E)	global	56,000	daily	brightness temperature; surface moisture	limited application	signal obscured by vegetation, ice, precipitation, steep terrain; spatial resolution too coarse for many disturbances

[a]Optical ~0.4–0.7 μm; NIR (near-infrared) ~0.7–1.2 μm; SWIR (shortwave infrared) ~1.2–2.0 μm.
[b]Orbit repeat frequency, but more frequent looks at higher latitudes.
[c]At this time, SAR interferometry is done with single instrument on repeat orbits ('repeat pass interferometry'); ideally, instrumentation would have either two antenna on a single platform (e.g., the Shuttle Radar Topography Mission or SRTM) or tandem platforms (none flying) [*Krieger et al.*, 2005].

such as a reduced midsummer leaf area index in following a late frost in eastern North America in 2007 [*Gu et al.*, 2008]. We also exclude very gradual changes from our definition of disturbance, changes that generally will be detectable only over decades to centuries (e.g., sea level rise onto a coastal plain, permafrost degradation and land surface subsidence, ice sheet development). We also will not focus on chronic disturbances that have an accumulating impact (e.g., pollution, drought, disease, pests) that eventually can manifest in a change in forest canopy biomass/structure [e.g., *Linzon et al.*, 1973]. The impact of a chronic disturbance (e.g., pollution loading) accumulates over weeks to years, and may not initially be apparent. Many chronic disturbances have their most profound impact indirectly, e.g., drought or pest infestation making a forest more susceptible to fire [*Oliver and Larson*, 1996].

[17] Disturbance cause can be broadly classified into natural and anthropogenic (Table 1). Most natural forest disturbances (e.g., windstorms, droughts) are climate related and disturbance rates may change with climate change [*Dale et al.*, 2001]. Anthropogenic disturbances (e.g., logging) have a different set of drivers (mostly socio-economic) that can also be expected to change over time [e.g., *Nakicenovic et al.*, 2000]. An additional disturbance classification axis relates to range and location: global or restricted either in space or in time (Table 1). Restricted disturbances (e.g., an avalanche) can only occur in suitable locations (e.g., mountains) and/or times (e.g., winter), and do not require continuous global observations for detection.

[18] Near its 100th anniversary, it is appropriate to mention the 1908 Tunguska impact on Siberian forests. The Tunguska meteor or comet exploded about 10 km above the surface with a force estimated to be equivalent to 10–15 Mt TNT [*Shoemaker*, 1983], and trees were felled over an area of about 2000 km^2 [*Longo*, 2007]. Meteor impacts smaller and much larger than the Tunguska have occurred throughout Earth's history, and can be expected to continue, though the frequency of such impacts on forests is not known, and no remote sensing work has been published. For planetary impactors, the relevant satellite instruments should be looking out to space, rather than in toward Earth. Volcanic eruptions can also have a major impact on surrounding forests through explosive blasts, debris and lava flows, toxic chemicals and heat, landslides, and ash and ejecta deposition [e.g., *Foster et al.*, 1998]. We do not consider volcanic eruptions in this analysis because the locations of volcanoes are well known, though the timing of eruptive explosions is not, and so the task for forest disturbance remote sensing, i.e., to map damage posteruption, is relatively well defined.

[19] Forest recovery refers to the reestablishment or redevelopment of forest biomass and canopy structure characteristics after the impact of a particular disturbance. The nature and rate of recovery will depend on the size and severity of the disturbance, the predisturbance state of the site, and the processes of seedling establishment and nutrient cycling, which will be a function of climate, postdisturbance soil nutrient status, and the inherent productivity of the site [e.g., *Doyle*, 1981; *Yarie*, 1983; *Oliver and Larson*, 1996; *Johnstone and Chapin*, 2006a, 2006b]. Following disturbance, forest recovery/regeneration can follow several trajectories. In some cases, such as permanent land use conversion to cropland, there is effectively no recovery of forest biomass and canopy structure. In some other cases, such as plantation forestry, recovery is meant to follow a prescribed trajectory to meet silvicultural and production goals, with management including transplanting seedlings of selected species at prescribed stem densities, nutrient amendments, and pest and weed control [e.g., *Fox et al.*, 2007]. In cases with minimal human influence postdisturbance, small disturbances with minimal soil impact (e.g., natural mortality forest gaps) recover via advance regeneration and the soil seed bank of old-growth species. Large disturbances, or canopy-tree-killing and stand-replacing events, and those that severely impact the soil, such as landslides, intense fires, and anthropogenic forest clearing of large areas, lead to a very different regeneration pathway, usually by a very restricted set of pioneers species with very small seeds or bird dispersal [e.g., *Clark*, 1990]. The timescale of canopy recovery following a particular disturbance depends on both the severity of the disturbance and the canopy structural variable(s) of interest (e.g., LAI < canopy height < biomass).

3. Forest Disturbance and Recovery Impacts on Biomass and Structure

[20] We divide disturbances (Table 1) into two categories by size: (1) large disturbances that generate gaps $>\sim 0.001$ km^2; and (2) small disturbances that generate small gaps of one to a few mature trees (<0.001 km^2) and/or damage the forest canopy without felling trees. In general, most modes of disturbance in category (1) also generate disturbance appropriate to category (2); e.g., a hurricane can generate large gaps along its path, but peripheral winds are weaker and forest damage will be less, including small gaps and extensive nonlethal damage.

3.1. Large Disturbances

[21] Large forest disturbances that generate gaps larger than 0.001 km^2 or 0.1 ha (often much larger) include permanent and temporary land conversion, logging, fire, severe windstorms, flooding, landslides, and avalanches (Table 1). Land conversion, logging, fire, windstorms, and flooding are unevenly but widely distributed throughout the world's forests. We estimate the total forest area disturbed to be $\sim 4-7 \times 10^5$ km^2 a^{-1}, based on these rough calculations: wood harvest is ~ 1 Pg C a^{-1} [*Hurtt et al.*, 2006], and at a mean global harvestable forest biomass of 50–100 t C ha^{-1} [*Houghton*, 2005], this would require $1-2 \times 10^5$ km^2 a^{-1}; 250 million shifting cultivators clearing one-sixth of a hectare of forest for cultivation every 2–4 years [*Lanly*, 1985] clear $\sim 1-2 \times 10^5$ km^2 a^{-1}; *Tansey et al.* [2004] report $\sim 3 \times 10^6$ km^2 a^{-1} burned, with $\sim 3\%$, or 1×10^5 km^2 a^{-1}, in forest; *Dale et al.* [2001] estimated 0.15×10^5 km^2 a^{-1} of U.S. forests are damaged by wind, so we estimate $\sim 1 \times 10^5$ km^2 a^{-1} globally; global area of flood disturbance is probably less than wind disturbance. *Tilman et al.* [2001] showed crop and pastureland area expanding in the 1990s at $\sim 0.4 \times 10^5$ km^2 a^{-1}, while conversion to built-up land is $\sim 0.1 \times 10^5$ km^2 a^{-1} [*Klein Goldewijk*, 2006]; only a fraction of these land use changes will have cleared forested land. Landslides and avalanches are confined to sloping and, for avalanches, snowy terrain. *Garwood et al.* [1979] estimated that earthquake-generated landslides denude 2–16% of sus-

ceptible areas per century, 1 to 5 times more than erosional landslides. They estimated susceptibility at 38% of Indo-Malayan, 14% of American, and <1% of African tropical forests ($\sim$2 × 10^6 km^2 in total forest area); at 10% per century this is $\sim$2 × 10^3 km^2 a^{-1}. *Dale et al.* [2001] estimated that landslides disturb $\sim$1 × 10^3 km^2 a^{-1} of forest in the U.S. Globally, avalanches probably disturb less area than landslides; together they probably disturb <10^4 km^2 a^{-1} of global forest.

[22] These major disturbances differ substantially in (1) their impact on forest canopy structure and biomass, (2) in the shape of the disturbance impact and the abruptness of its boundaries, (3) in the fate of the forest biomass lost by the canopy, and (4) in the recovery trajectory following disturbance. In permanent land conversion, either for agricultural or residential/industrial use, the forest is cut and the wood and slash are typically removed and/or burned in situ. There is no forest regrowth until subsequent abandonment, although forest cover in residential land use can be substantial. Land conversion disturbance typically has a sharp impact-intensity boundary. Similarly, clear-cut logging removes most woody biomass and transfers it to fuel, pulp and/or lumber pools; woody slash can be harvested for pulp or piled to burn or decompose; belowground biomass is generally left in the ground to decay. Clear-cut logging disturbance typically has a sharp impact-intensity boundary.

[23] Large fires (ignited by lightning or humans) can burn mostly on the ground (with little forest canopy damage), or can climb into and burn the forest canopy. They burn a fraction of the forest woody biomass in hours to days; and can continue to spread and burn for months. Remaining dead wood on site is often standing. Large fires generally have a diffuse and irregularly shaped impact intensity boundary, and impact severity within the burn scar can be very heterogeneous [*Foster et al.*, 1998]. Active fire suppression in the twentieth century has reduced fire disturbance rates and extent of damage in temperate forests of eastern North America [e.g., *Frelich and Lorimer*, 1991].

[24] Severe windstorms include hurricanes (known as typhoons when they develop in the Pacific Ocean and as cyclones when they develop in the Indian Ocean; hurricanes develop in the Atlantic Ocean), tornados, and microburst downdrafts associated with major convective storms. Most biomass that is felled remains on site (woody debris can be $\sim$1 m deep [*McNulty*, 2002]), many trees are injured/broken but not completely felled; many trees are still standing, the soil seed bank is intact and many juvenile trees survive. Wind-caused mortality can cause variable mortality rates among different species and stand ages, and can thus affect overall forest species composition and successional trajectories [*Rich et al.*, 2007]. Severe storm wind damage can be a major cause of disturbance in temperate hardwood forests, with most disturbance events damaging only a small fraction of canopy trees, leading to a very mixed-age canopy; e.g., *Frelich and Lorimer* [1991] estimated that two-thirds of the disturbance events (most were wind, not fire) during 1850–1969 caused <20% gap creation within 0.005 km^2 plots studies in northern Michigan, USA. Hurricanes generally have a diffuse and irregularly shaped impact intensity boundary and heterogeneous impact within the damage region, though with a general gradient correlating to wind intensities [*Foster et al.*, 1998; *Chambers et al.*, 2007b; *Chapman et al.*, 2008]. Poststorm salvage logging can collect and remove $\sim$10% of the felled and damaged trees [*McNulty*, 2002]. Tornadoes generally have a sharp impact intensity boundary, and a fairly linear impact zone [*Foster et al.*, 1998]. In the neotropical forests of Brazil, blowdowns generate relatively large gaps ($\sim$0.05 to >20 km^2) sometimes characterized by fan-shaped forms, with damage severity diminishing toward the edges [*Nelson et al.*, 1994; F. Del Bom Espirito-Santo, personal communication, 2008].

[25] Landslides generally completely denude the source area, and frequently bury their terminal area, while avalanches can scour the ground near their origin ('start zone') but generally just damage trees at the bottom of the slope ('runout zone') [*Oliver and Larson*, 1996; *Johnson*, 1987]. Avalanche locations are generally determined by mountain slope and aspect, and typically reoccur at the same place every few years (start zone) with damage in the runout zone less frequent as it is dependent on the size of the avalanche. Avalanches reduce seedling densities, but impacts are more severe on larger, older trees, while younger, shorter trees have higher survival rates [*Johnson*, 1987; *Kajimoto et al.*, 2004].

3.1.1. Mapping Large-Scale Forest Disturbance With Remote Sensing

[26] Quantification of forest clearing and conversion rates has been the focus of substantial work for the past few decades [e.g., *Food and Agricultural Organization* (*FAO*), 1996, 2001, 2006; *Grainger*, 2008]. Because forests are widespread, and often vast and not easily accessible, spaceborne remote sensing has played a major role in these efforts, providing large-scale coverage and repeated viewing with the same instrument. Such remote sensing has the potential for automated analyses but requires substantial ground truth data for calibration and interpretation of the data [*Steininger*, 2000]. Moderate resolution sensing (e.g., MODIS at 250 m to 1000 m resolution) is too coarse for reliable detection of much land conversion and logging activity [e.g., *Hansen et al.*, 2008], but has twice-daily repeat viewing and so has many chances for gathering cloud-free data. Fine resolution data (e.g., Landsat at $\sim$30 m) can detect large-scale disturbances, and has been used in the tropics for large-scale regional disturbance mapping assessments for many years [*Skole and Tucker*, 1993; *Achard et al.*, 2002; *Hansen et al.*, 2008]. Methods have improved from manual digitizing of wall-to-wall images of the Brazilian Amazon [*Skole and Tucker*, 1993], to collecting $\sim$100 Landsat samples for the tropical forest biome [*Achard et al.*, 2002], to combining Landsat and MODIS data to generate an automated wall-to-wall assessment of pan-tropical forest clearing [*Hansen et al.*, 2008]. Mean deforestation rates were $\sim$0.4–0.5% a^{-1} in all three of these studies, despite differences in method, domain, and time period. Applied to $\sim$20 million km^2 of tropical forests globally [*FAO*, 2001], this is $\sim$1 × 10^5 km^2 a^{-1}. Regional variability was high, and local/regional rates were as high as 3–6% a^{-1} [*Achard et al.*, 2002] or 4–5% a^{-1} [*Hansen et al.*, 2008]. *Achard et al.* [2002] also quantified reforestation (0.08% a^{-1}) and forest degradation (0.2% a^{-1}), while *Skole and Tucker* [1993] quantified forest fragmentation ($\sim$1% a^{-1}). An assessment combining Landsat and MODIS imagery from the boreal forest estimated 4% reduction from year 2000 forest area over 2001–2005, with the overall majority being

lost to fire, particularly at higher latitudes, while other disturbances (logging, insect damage) dominated in the southern Canadian and European boreal zones [*Potapov et al.*, 2008].

[27] Shifting cultivation, or swidden or nonpermanent agriculture, contributes significantly to forest cover dynamics in many relatively remote regions of the tropics [e.g., *Lanly*, 1985; *Rojstaczer et al.*, 2001; *Hurtt et al.*, 2006; *Olofsson and Hickler*, 2007] but has not been studied with spaceborne remote sensing. Most swidden fields are <0.01 km^2 [e.g., *Denevan and Padoch*, 1988; *Ichikawa*, 2007], are cultivated for a couple of years, and then cultivation stops and forest regrowth occurs, although this regrowth can be managed to favor tree species with food, fiber, or medicinal value [*Denevan and Padoch*, 1988]. There are on the order of 500 million people engaged in nonpermanent agriculture [*Rojstaczer et al.*, 2001], with roughly half clearing forested land and half in grassland/savanna [*Lanly*, 1985]. If basic sustenance requires one-sixth hectare per person [*Lanly*, 1985], with a 2–4 year cultivation period this should result in clearing (and abandonment) of about $1-2 \times 10^5$ km^2 a^{-1}. Although highly uncertain, this is approximately the area estimated for tropical deforestation disturbances above. However, much of the shifting cultivation forest disturbance activity was probably not observed in the analyses of *Hansen et al.* [2008], *Achard et al.* [2002], *Skole and Tucker* [1993], or other similar work, both because the shifting cultivation fields are generally small, scattered, and difficult to detect, and because the 5–10 year return observation interval in these remote sensing studies will miss some of the rapid turnover.

[28] In an analysis of the majority of North American temperate and boreal forests, *Masek et al.* [2008] quantified stand-clearing forest disturbance that occurred in the 1990s, using temporal change detection of wall-to-wall Landsat imagery from c.1990 and c.2000. They validated this at 23 locations using higher frequency Landsat imagery. They measured disturbance rates of up to 2–3% a^{-1} in some regions and a disturbance rate of 0.9% a^{-1} for the conterminous U.S. Most disturbance in Canada's boreal forest was attributed to fire, with an overall disturbance rate of 0.4% a^{-1}, while in southern Canada and the conterminous U.S., most disturbance was attributed to logging, with the highest rates, ~2.5% a^{-1} in the southeastern U.S., but with rates nearly as high in the Pacific Northwest, Maine, and southern Quebec.

[29] Fire scar mapping determines the area burned by detecting changes in surface reflectance. Fire scar mapping has been done with spaceborne optical/NIR remote sensing at the global scale, starting in the 1990s with AVHRR data, and more recently SPOT-Vegetation and MODIS data [*Chuvieco and Kasischke*, 2007; *Roy et al.*, 2008]. At regional to local scales, fire scar mapping has been done with Landsat data, using a variety of detection algorithms [*Chuvieco and Kasischke*, 2007; *Masek et al.*, 2008]. Global fire scar mapping has been done with daytime data from the Along Track Scanning Radiometer (ASTR-2) instrument (e.g., the GLOBSCAR product) using reflectance band and index thresholds [*Simon et al.*, 2004]. This estimates that about 0.31 million km^2 of forest are burned annually, with ~67% in Africa. *Tansey et al.* [2004] report 3.5 million km^2 of burned land (forest and nonforest) in 2000, based on 13 months of daily SPOT VGT data (1 km resolution), using a set of regional fire scar detection algorithms; average fire scar size (reported by nation) ranged from ~1 km^2 to ~30 km^2 [*Tansey et al.*, 2004].

[30] Active fire mapping detects fire radiant energy [e.g., *Ichoku et al.*, 2008]. The MODIS active fire product detected 3.22×10^5 km^2 of forest fires and 7.07×10^5 km^2 of woody savanna fires for July 2001 to June 2002 [*Roy et al.*, 2008]. Boreal fires burned ~0.7×10^5 km^2 a^{-1} during 1950–2000 [*Balshi et al.*, 2007], though the burned area varied significantly from year to year [*Stocks et al.*, 2002]. In Canada, large fires (>2 km^2) are <5% of the total number of fires, but account for more than 95% of total burned area in Canada [*Stocks et al.*, 2002]; in Alaska large fires account for ~99% of total area burned [*Kasischke and Turetsky*, 2006]. Fires in tropical rain forests are generally associated with land use and forest edges, and fire return intervals correlate with distance from deforested area [*Cochrane*, 2003]. Cloud cover can significantly compromise fire detection in the tropics [e.g., *Cardoso et al.*, 2003, 2005].

[31] Soil moisture in fire scars is often different from adjacent unburned forests, and this signal has been detected with a number of active microwave C band SAR sensors: ERS-1 in Alaska [*French et al.*, 1996; *Bourgeau-Chavez et al.*, 2007], ERS-2 in Borneo [*Siegert and Ruecker*, 2000], RADARSAT-1 in Spain [*Gimeno and San-Miguel-Ayanz*, 2004], and Envisat Advanced SAR in Siberia [*Huang and Siegert*, 2006]. In Alaska, fire scars soils were detectable because they were wetter, probably due to decreases in evapotranspiration rates and melting of the permafrost, while in Borneo, fire scar soils were drier in the dry season, likely due to increased solar loading and soil evaporation. No continental- to global-scale analyses have been done.

[32] Major hurricanes/typhoons/cyclones can have a large impact on forest biomass and structure. The forest area impacted by a single storm can be larger than 10^4 km^2 [*Dale et al.*, 2001]; severity of damage will vary substantially across this region, correlating with wind intensities and forest susceptibility, e.g., forest height and species composition [*Foster et al.*, 1998; *Chambers et al.*, 2007b]; up to 10–100 Tg C in woody biomass can be transferred from live to dead pools [*McNulty*, 2002; *Chambers et al.*, 2007b], though timber salvage can recover ~10% of downed woody biomass [*McNulty*, 2002]. The large deadwood pool generated by a hurricane can increase fire risk for several years [*McNulty*, 2002]. If it does not burn and is not salvaged, this necromass will slowly decompose, enhancing total ecosystem respiration for years. Despite reduced productivity and damaged trees, there is no evidence of increased insect or disease damage following a hurricane [*McNulty*, 2002].

[33] Tornado damage is generally much more restricted, with a narrow band of severe damage, typically <1 km wide and <~10 km long [*Foster et al.*, 1998; *Oliver and Larson*, 1996]. Blowdowns are caused by strong microburst winds that can accompany large convective storms [*Fujita*, 1985] and have been mapped in the mature forests of the Amazon basin, using Landsat imagery, by manual classification with a minimum area threshold of 0.3 km^2 by *Nelson et al.* [1994], and with automated classification and manual checking with a minimum area threshold of 0.05 km^2 by F. Del Bom Espirito-Santo (personal communication, 2008).

Blowdowns were discriminated from other gaps by remoteness from anthropogenic activity. The largest blowdown observed by *Nelson et al.* [1994] was ~33 km^2, and the largest observed by F. Del Bom Espirito-Santo (personal communication, 2008) was ~22 km^2. In both studies most blowdown areas were less than a few km^2, and in each study the largest fractional disturbed area due to blowdowns was 0.3% of a Landsat-scene. Tree mortality is not 100% within an area defined by a blowdown, and it can be difficult to define a boundary. Recurrence intervals are likely quite long (order of 10^4 years). It should be noted that important intensity and size issues remain unresolved. These events may be too clustered to be adequately sampled on forest inventory plots [*Fisher et al.*, 2008], yet many blowdowns are too small to be easily detected in most existing remote sensing studies.

[34] Individual landslide and avalanche disturbances are generally small, and have not had comprehensive large-scale studies of size and distribution. Mapping has been done on a smaller scale, mostly for determining hazard zones [e.g., *Tralli et al.*, 2005]; for example, *Nichol and Wong* [2005] found that postclassification change detection with SPOT images in the Hong Kong metropolitan area could detect about 70% of the landslides identified in Ikonos imagery; omission errors were mostly due to small landslide size, while commission errors were generally due to human-induced terrain disturbance or building (e.g., roads). Avalanches are more restricted (steep and snowy slopes), and have been mapped locally with Ikonos [*Walsh et al.*, 2004].

3.1.2. Beyond Mapping Extent and Location of Large-Scale Disturbances

[35] Much of the work described above entails mapping the location and size of large-scale disturbances, and relevant techniques and instruments (e.g., Table 2) continue to improve, though the small size of many of the ‘large-scale’ disturbances continues to present a challenge for global mapping. However, as the role of land use and land cover change becomes increasingly important to our understanding of the Earth’s coupled climate-carbon system, it is important to also go beyond mapping large-scale disturbances to characterizing large-scale disturbances. This characterization can address several questions; we consider four: (1) How much biomass was disturbed, and what was its fate: burned, removed and used for fuel or fiber, remaining as standing dead or coarse and fine woody debris? (2) How has forest structure changed? (3) Has the land been degraded such that forest recovery will not rapidly establish a forest equivalent to the one that was disturbed? (4) When did the disturbance happen? There are several spaceborne remote sensing instruments (flying and planned) that can be applied to these questions (Table 2).

[36] For carbon cycle studies a key question is not what area of land has been disturbed but how much aboveground biomass (or carbon) has been disturbed [*Houghton and Goetz*, 2008]. For some large-scale disturbances, all aboveground biomass has been disturbed. This still requires a quantification of predisturbance forest biomass, which is currently based on limited ground-based sampling; these sampling sites may not always be representative of the forests that are disturbed. For other large-scale disturbances (windstorms and fire) not all trees are killed and felled, so measuring the biomass disturbed will depend on both predisturbance and postdisturbance quantification with sufficient accuracy to get a meaningful difference.

[37] Moderate and fine-scale passive optical/NIR remote sensing such as MODIS and Landsat, the workhorse tools for large-scale disturbance mapping, cannot fully address these questions. Aside from clouds and shadows, these instruments are most sensitive to aggregate canopy foliage and soil within their footprint, and so they are very sensitive to the regrowth of canopy leaf area, which generally occurs during the initial years of recovery [*Asner et al.*, 2004b]. *Woodcock et al.* [2001] noted that in efforts to generalize fine resolution optical/NIR remote sensing detection algorithms across space (i.e., regional- to global-scale analyses) and time (i.e., change detection) there will be tradeoffs between the level of detail of surface properties monitored and the generalizability of the algorithms. Forest cover change detection (i.e., the mapping discussed above) is achievable for large regions, but forest canopy structure and biomass discrimination may not be. For example, tropical forest biomass correlates with Landsat spectral bands and vegetation indices, with correlation coefficients (r) of 0.7–0.8 across biomass ranges of 30–600 Mg ha^{-1} (estimated from DBH allometries), however statistical relationships between biomass and vegetation indices developed in a single Landsat scene generally do not transfer well to other scenes [e.g., *Foody et al.*, 2003]. Lack of transferability can be attributed to uncertainties in field data, offsets in timing of remote sensing acquisition and field observations, and impacts of atmospheric variability and Sun-sensor geometry on remote sensing reflectance [*Foody et al.*, 2003].

[38] *Puhr and Donoghue* [2000] found strong correlations between Landsat TM SWIR reflectances and canopy height and basal area (both of which correlate with biomass) in temperate coniferous forests in Scotland, which they attributed to the contribution of understory vegetation to the total SWIR reflectance, which will decline as stand height and basal area increase. *Baccini et al.* [2004] looked at the relationship between MODIS reflectances and ground-based measurements of temperate forest/woodland biomass (from timber volume data); they found that MODIS SWIR reflectance was strongly correlated with biomass for low reflectance values (<0.2), which they attributed to the changing nature of the forest canopy from young, short, relatively uniform canopy to an older, mixed, more heterogeneous canopy with more gaps and shadows. More work would be needed to determine if SWIR data analysis can be developed into a more robust and broadly applicable relationship.

[39] Important additional information can come from active microwave instruments. At appropriate wavelengths, microwave radiation interacts with woody biomass, so the backscatter from active microwave instruments (particularly L and C band), which depends on the size, mass and dielectric properties of the scattering surface, can provide direct, remotely sensed observations that can be related to forest aboveground biomass [*Waring et al.*, 1995; *Saatchi and Moghaddam*, 2000; *Saatchi et al.*, 2007a, 2007b] (S. S. Saatchi et al., Radar measurements of vegetation structure, submitted to *Journal of Geophysical Research*, 2009). Microwave remote sensing has the additional benefit of

being relatively insensitive to clouds, and so can acquire much more frequent observations of wet tropical and temperate forests. SAR instruments have an observation swath, and data will accumulate to complete global coverage. However, radar does not measure biomass directly (as a scale would), but instead relates the power of the backscattered microwave radiation to biomass through regression equations [e.g., *Saatchi et al.*, 2007a]. Therefore, accurate global biomass retrievals will depend on substantial, high-quality ground-based biomass or allometry data, accurate at the spatial scale of the sensor footprint, from forest biomes around the world (see section 3.3).

[40] *Drezet and Quegan* [2007] used coherence in tandem ERS-1 and ERS-2 C band active microwave data to map age and productivity of forests in Britain. Coherence between the two instrument backscatter signals, collected 24 h apart, was related to stable landscape elements (e.g., soil, woody biomass), while the signals from unstable elements (e.g., foliage, twigs) would have random phase differences. Signal coherence and backscatter power were related to canopy depth and forest biomass, which was correlated with tree age and productivity, based on ground data from a number of sites, which also provided uncertainty estimates. *Saatchi et al.* [2007b] used airborne SAR fully polarimetric L and P band SAR backscatter data to estimate both crown and stem live biomass in evergreen needleleaf forests in Yellowstone National Park, USA. They correlated HH, HV, and VV polarization backscatter with field measured biomass data. L band data had higher sensitivity for low biomass stands (<20 Mg ha^{-1}), while P band data (lower frequency, longer wavelength) had higher sensitivity over a larger biomass range, up to about 200 Mg ha^{-1}. These results point to limitations for radar remote sensing of biomass for high-biomass forests; depending on wavelength, radar detection of biomass appears to saturate at 50–200 Mg ha^{-1} [e.g., *Waring et al.*, 1995]; wet tropical and temperate forest biomass can exceed these limits, and the biomass of many mature temperate forests is near or above the high end of this range. For example, in mapping forest biomass in the Amazon basin using data from multiple sensors and climate data, *Saatchi et al.* [2007a, 2007b] found the L band SAR was useful, with other data, for mapping lower biomass stands (<150 Mg ha^{-1}), but not for higher biomass stands.

[41] By definition, large-scale disturbances change forest canopy structure, ranging from stand-clearing events to less severe or spatially heterogeneous impacts. If there is sufficient damage, this should be detectable by microwave sensors as a reduction in biomass, but the nature of that damage will be difficult to determine (e.g., were some-to-many trees felled or were most-to-all trees damaged?). High-resolution passive optical/NIR instruments can be used to map gap distributions in a disturbed forest (see section 3.2.1). Lidar instruments direct a pulse of laser light down from the instrument, and measure the precise time of the return of the reflected light. These lidar return waveforms can be used to measure the height and vertical distribution of the forest canopy [*Lefsky et al.*, 2002, 2005] (R. Dubayah et al., Lidar measurements of vegetation structure, submitted to *Journal of Geophysical Research*, 2009). With adequate ground data to calibrate/interpret the lidar return waveforms, or with predisturbance and postdisturbance observations and accurate geolocation, changes in canopy structure can be observed [*Kellner et al.*, 2009]. In addition, forest aboveground biomass can be estimated from allometric relationships with canopy height [e.g., *Lefsky et al.*, 2002], though how appropriate these allometric relationships are postdisturbance will need to be carefully evaluated. Again, accurate postdisturbance forest structure retrievals will depend on substantial, high-quality ground-based structural data from disturbed forest biomes around the world. The pulse nature and small footprint size of lidar instruments means that they are not designed to generate full global coverage, but rather to develop a high-density sample of the landscape (Dubayah et al., submitted manuscript, 2009). Lidar, like passive optical/NIR, cannot generate reliable data under cloudy conditions.

[42] Interferometric synthetic aperture radar (InSAR) combines the reflected signal power (phase and amplitude) from two backscattered microwave pulses separated by a distance (baseline) to determine 3-D geometry of the reflecting surface (e.g., forest canopy height) [*Treuhaft et al.*, 2004]. At this time spaceborne SAR interferometry is done with single instrument on repeat orbits (‘repeat pass interferometry’); ideally, instrumentation would have either two antenna on a single platform (e.g., the Shuttle Radar Topography Mission or SRTM) or tandem platforms (none flying) [*Krieger et al.*, 2005]. *Treuhaft et al.* [2004] outline three methods for data fusion of InSAR with optical data for improved retrieval of canopy structural characteristics: with hyperspectral data to determine leaf area density, with multiangular optical data, or with lidar data for improved accuracy of regional InSAR canopy height estimates.

[43] Disturbance severity will determine what fraction of live aboveground biomass is killed, and the degree to which juvenile trees and the seed bank are disturbed. Fire severity impacts forest canopy combustion and carbon emissions [e.g., *Kasischke et al.*, 2005], and postfire recovery [e.g., *Johnstone and Chapin*, 2006a], and detection ‘remains a challenge’ [*Chuvieco and Kasischke*, 2007]. In an assessment of a number of remote sensing indices, *Epting et al.* [2005] found that the Normalized Burn Ratio (NBR), the ratio of difference to sum of near-infrared and midinfrared reflectances from Landsat data, ranked in the top three correlations for all four burns in both a postburn assessment and for three of four burns in preburn and postburn change assessments. For forested land, the correlation between NBR and ground data was $r > 0.75$. *Miller and Thode* [2007] found that a threshold relative change in NBR had good success at detecting severe fires across a range for prefire forest stand densities. *Roy et al.* [2006] assessed the reliability of NBR as an index of fire severity for Landsat ETM+ data from southern Africa and 500-m MODIS data for Russia, Australia, and South America at pixels where 1-km MODIS active fires were detected. On the basis of a metric for burn signal optimality related to changes in near-infrared and midinfrared reflectances relative to the NBR index, they found that the NBR was far from optimal in most cases. They concluded that ‘[an] improved severity index should incorporate improved knowledge of how fires of different severity displace the position of prefire vegetation in multispectral space.’

[44] Damage from wind disturbance can vary from tree mortality approaching 100% over large tracts of forest from

the most powerful hurricanes and downbursts [*Nelson et al.*, 1994; *Chambers et al.*, 2007b], to a subtle increase in tree mortality rates beyond background rates [*Lugo and Scatena*, 1996]. Since background mortality rates for most forested ecosystems fall within the range of 1–2% stems a^{-1}, even an additional 1% mortality from a disturbance event corresponds to a 50–100% increase in the average mortality rate over that interval. *Chambers et al.* [2004] found that a shift in average tree mortality rate from ~1% to 2% resulted in a greater than 50% loss in of aboveground live tree biomass for a Central Amazon forest study. Forest inventory plots provide valuable information on background mortality rates; however, due to the clustered nature of most episodic disturbances, forest inventory plots may not be adequate to capture regional shifts in disturbance regimes [*Fisher et al.*, 2008].

[45] Remote sensing enables the sampling of events over a much broader range of disturbance intensity, and field studies directed using remote sensing analysis are needed to better understand impacts at a regional scale. *Nelson et al.* [1994], for example, demonstrated use of Landsat imagery to identify blowdown patches across the Amazon basin, but it remains unclear how tree mortality varies across the entire area impacted by the blowdown. *Chambers et al.* [2007b] utilized Landsat imagery to stratify a forested area hit by Hurricane Katrina into disturbance intensity classes, and then used this map to carry out stratified random sampling of tree mortality and damage in the field. Results showed a strong relationship between forest impacts and Landsat image analysis of change in the fraction of nonphotosynthetic vegetation. This close coupling of field studies and remote sensing analysis enabled initial estimates of mortality and severe structural damage of 320 million trees from Hurricane Katrina, with a 100 Tg C flux from live to dead biomass pools. These methods build on those developed to quantify selective logging in tropical forests [*Asner et al.*, 2005; *Souza et al.*, 2005], and will enable improved quantitative links between spectral changes observed from remote sensing platforms, and ecological changes in the field.

[46] *King et al.* [2005] assessed forest canopy damage from the major northeastern North America ice storm of January 1998, locally with field assessment of canopy damage and airborne color infrared photography (0.6 m resolution) collected the following summer, and regionally with prestorm and poststorm, midsummer Landsat data. They could not adequately map canopy damage with Landsat data, but had best results from a neural network classification of canopy damage into three classes (0–25% crown loss; 26–50% crown loss; and >50% crown loss) with 50–100% accuracies. In field assessments done 2 and 5 years after the storm, *King et al.* [2005] reported a tendency for strong foliage production initially, with subsequent decline or mortality at younger than normal tree ages, indicating that initial poststorm damage assessments would not represent the full impact. *Olthof et al.* [2004] also used a neural network classifier, and mapped deciduous forest canopy damage caused by this ice storm into three damage classes. They analyzed ~10,000 km^2 of eastern Ontario, with accuracies of 50–85% for 10 field plots not in the training data set.

[47] *D'Aoust et al.* [2004] evaluated the impact of a 1970–1987 spruce budworm outbreak in southern boreal Quebec, quantifying canopy openness from preoutbreak and postoutbreak aerial photos for five ~50 ha forest stands of different composition. Visual estimation of canopy percent openness in 500 m^2 grid cells was done on 1:15 000 aerial photos with an 8x magnifying lens. Before the outbreak, all four stands had ~20% openness. In four stands (hardwood, mixed, and conifer) ~50% of the cells had minimal changes in openness. Overall, the two mixed and two conifer stands showed a significant increase in openness, while the hardwood stand did not. Heavily impacted cells tended to cluster into patches of ~5–10 ha size.

[48] The spaceborne Multiangle Imaging SpectroRadiometer (MISR) instrument acquires solar reflectance data nearly simultaneously from nine viewing angles; analysis of the multiangle data can be used to determine subpixel surface heterogeneity [e.g., *Widlowski et al.*, 2001; *Gobron et al.*, 2002], but only a limited number of studies have been conducted, so it is not yet known if this could be a useful tool for mapping disturbance severity. *Lobell et al.* [2001] found that airborne hyperspectral SWIR reflectances could be used in an automated analysis system to map coniferous forest canopy cover in Oregon, with potential application to land use change analysis.

[49] The exact timing of logging and land conversion is not crucial to land use and carbon cycle studies; for annual budgeting, specifying the year is sufficient, though even that is not always well known. However, changes in land surface biophysical properties (e.g., albedo and roughness) are important for regional and global climate models, and these impacts will vary seasonally. Perhaps more importantly, if disturbances are detected from analysis of change in a time series of images (e.g., Landsat), the time series used must have frequent enough cloud-free sampling to detect logging and land conversion. Ideally, observation frequency should be annual or better, and seasonally synchronized as, for example, there can be classification complications when comparing early and late dry season images [*Hagen*, 2006]. Similar constraints will apply for large blowdowns in tropical forests. Large, severe windstorms like hurricanes are monitored in real time as natural hazards, so their timing is known.

[50] Of all the disturbances considered, fires have the most rapid emissions of a number of important atmospheric gases (e.g., CO_2, CO, CH_4) and large fires have generated a detectable signal in the global atmospheric flask-sampling network [e.g., *Dlugokencky et al.*, 2001; *Kasischke and Bruhwiler*, 2002; *Kasischke et al.*, 2005]. The atmosphere's 750 Gt CO_2-C is spread fairly uniformly over the Earth's 550×10^6 km^2 surface, giving a column equivalent concentration of about 1500 t C km^{-2} or 15 t C ha^{-1}. Mature forest aboveground biomass C ranges from 20 to 250 t C ha^{-1} [*Olson et al.*, 1985]. A major forest fire will therefore cause a rapid and substantial perturbation on column CO_2 in the vicinity of the fire and should be readily detectable from spaceborne instruments like the recently launched Greenhouse Gases Observing Satellite (GOSAT [*Kuze et al.*, 2006]) and the proposed Active Sensing of CO_2 Over Days, Nights, and Seasons instrument (ASCENDS [*NRC*, 2007]). Thus fire detection and emissions quantification will provide an important data set for interpreting observations from current and next generation atmospheric composition remote sensing instruments measuring CO_2 and other constituents

(AIRS [*Xiong et al.*, 2008]; SCHIAMACHY [*Frankenberg et al.*, 2005]; and GOSAT). As atmospheric data accumulates and our understanding of the immediate impacts of fire on atmospheric composition improves, these atmospheric composition observations may also contribute to mapping the location and intensity of fires. In a manner similar to how fires are detected as visible light sources in nocturnal satellite imagery when data are collected over a long enough period to different stable lights (e.g., cities) from dynamics lights (mostly fires) [*Elvidge*, 2001], these instruments could map stationary, relatively stable or predictably seasonal, greenhouse gas sources (e.g., cities, major industrial sites, rice paddies); then strong but temporary sources would indicate something else (e.g., fire).

[51] Global-scale active fire detection is currently done with passive infrared remote sensing instruments such as ASTR 1-km data every 3 days [e.g., *Arino et al.*, 2005], MODIS 1-km data twice daily [e.g., *Giglio et al.*, 2006], and GOES 4 km data every 30 min [e.g., *Schroeder et al.*, 2008a]. Fire intensity (or fire radiative power) can also be estimated from thermal band brightness [e.g., *Wooster et al.*, 2003] and has been correlated with biomass burned [e.g., *Roberts et al.*, 2005]. Major uncertainties in fire detection are related to short-lived anthropogenic fires (often restricted to daytime [e.g., *Cardoso et al.*, 2005; *Ichoku et al.*, 2008]) and omission of fires obscured by clouds [e.g., *Roy et al.*, 2008]. *Schroeder et al.* [2008a] evaluated MODIS and GOES active fire detection products against higher spatial resolution (30 m) ASTER and Landsat ETM+ data. They found that omission errors (no fire detected by GOES or MODIS when colocated ASTER or Landsat pixels showed active fires) were common for small fires, dropping below 50% when ~2–4% of the 30-m pixels within the larger MODIS and GOES pixels had fires, and below 20% when ~6% of the 30-m pixels within the larger MODIS and GOES pixels had fires. Many omission errors were associated with linear savanna fires, not forest fires. *Schroeder et al.* [2008b] estimated that ~11% of omission errors in Amazonia were obscured by clouds. *Schroeder et al.* [2008a] also found that commission errors (i.e., fire detection by MODIS or GOES when no Aster or Landsat pixels had active fires) were also common (~15% false positives), and mostly associated with areas of recent burning (scars visible, which could lead to repeat detection for up to a month), or smoldering (smoke visible). Initial analysis with a change detection algorithm reduced false positives.

[52] The fact that three major tropical forest disturbance studies [*Skole and Tucker*, 1993; *Achard et al.*, 2002; *Hansen et al.*, 2008] all arrive at generally similar conclusions about the rate of deforestation is encouraging. However, although their methods are somewhat different, the instruments and data types (i.e., ~30-m passive optical/NIR reflectances) are basically the same, and are common to many analyses of tropical forest disturbance [e.g., *Grainger*, 2008]. Note that *Grainger* [2008], analyzing the FAO Forest Resource Assessments, also shows fairly uniform rates of decline in tropical forest area in the 1980s and 1990s. Although passive optical/NIR instruments continue to improve, and data analysis methods improve as well, the information is still coming from sunlight reflected from complex forest canopies, passing through a variable atmosphere, and so will always have inherent limitations. Developing a comprehensive ground-based data set of forest cover change at continental scale for validating this kind of remote sensing analysis is prohibitively difficult and expensive. How else can these results be independently evaluated? Annual global-coverage mapping with SAR could provide a completely independent remote sensing data set that should be able to detect large-scale disturbance, not only quantifying biomass changes for carbon cycle studies, but also providing an independent estimate of location and extent with comparable spatial resolution. A spaceborne lidar instrument with high-frequency sampling will not provide global coverage, but could provide annual global forest height sampling. To the extent that the lidar instrument is designed to have frequent track crossovers in forested biomes, it could provide a second, completely independent data set that samples large-scale disturbance location and extent. The synthesis of several independent data sets will provide a more comprehensive view of forest disturbance and vegetation dynamics than can come from any individual data set. Coherence and correlation in these completely independent, spatially distributed time series data sets will substantially increase the confidence with which interpretations can be made. Analysis of data from multiple sensors (data fusion) can also extract more detailed biomass/structure information [e.g., *Saatchi et al.*, 2007a] (S. J. Goetz et al., Synergistic use of spaceborne LiDAR and optical imagery for assessing forest disturbance: An Alaska case study, submitted to *Journal of Geophysical Research*, 2009) or foster a more efficient analysis of large-scale data sets [e.g., *Hansen et al.*, 2008].

3.1.3. Regrowth and Recovery in Large Gaps

[53] A first step to recovery analysis is detecting disturbance and determining forest age since disturbance. Several research groups have assembled 'data cubes', such as a set of ~10–20 annual Landsat scenes, and these can be classified and overlain to detect forest disturbance [e.g., *Goward et al.*, 2008]. *Lucas et al.* [2002a] assembled 11 scenes for the tropic forest north of Manaus, Brazil, from Landsat MSS, SPOT HRV and Landsat TM data for 1973–1991; the largest time interval between successive scenes was four years. Scenes were classified as mature forest, regenerating forest and nonforest, and overlays of these maps was used to approximate time of land use. Limited sampling due to clouds and smoke/haze meant that land use during some intervals had to be inferred. In addition, misclassifications in any one image could be incorrectly interpreted as change (or no change) from the previous or subsequent image.

[54] Most assessments of forest recovery/regrowth with remote sensing have used the chronosequence approach, a standard methodology in forest ecology [*Foster and Tilman*, 2000], taking care to minimize differences in predisturbance forest properties and disturbance impact severity. Data are analyzed from a collection of sites at various known ages since disturbance, and site differences are attributed to the trajectory of recovery [e.g., *Nilson and Peterson*, 1994]. For example, *Lucas et al.* [2002a] worked at sixteen 0.1 ha field sites near Manaus, measuring DBH for all trees with DBH > 3 cm; each tree was identified to genus or species, a sample of tree heights was collected, and canopy gap fraction was estimated from hemispherical photos. They found for young regenerating forests (<20 years) that stand age and species

dominance (*Cecropia* or *Vismia* species dominance) correlated with reflectance in NIR and MIR bands, and that species dominance in early succession was correlated with the duration and intensity of nonforest land use before reforestation. *Lucas et al.* [2002b] found that MODIS NIR (band 2) and MIR (band 6) data could be used for similar discrimination, though with substantial uncertainty.

[55] Early work on monitoring postfire spatial and temporal variability in soil moisture status with microwave remote sensing shows promise in work done in boreal Alaska (e.g., C band SAR [*Bourgeau-Chavez et al.*, 2007]). At these sites, soil moisture was related to levels of tree recruitment into the burn scar [*Kasischke et al.*, 2007], indicating that microwave remote sensing may be useful in quantifying and monitoring an important environmental variable related to forest recovery post fire, at least in the boreal region.

[56] Up to now, only a few remote sensing studies have followed the trajectory of forest recovery/regrowth at a particular disturbance site. Reestablishment of a forest canopy in a large gap can take decades, and during this time several important structural properties recover at different rates. Monitoring this with remote sensing requires long-term data sets with stable instrumentation and well established algorithms. For example, *Schroeder et al.* [2007] used annual Landsat TM and ETM+ scenes covering 18 years following forest clearing in western Oregon. They first mapped three clear-cut harvests from the Landsat images, then classified the time series of images into percent tree cover, and then were able to classify recovery after clear-cutting into four rate classes, from 'little-to-no' to 'fast'. These classes were correlated with a number of environmental explanatory variables (e.g., potential radiation, elevation, July maximum temperature) with 'fair agreement' (k statistic).

[57] Recovery of canopy structural properties can depend on disturbance severity. For example, *Diaz-Delgado et al.* [2003] evaluated prefire and postfire Landsat TM NDVI at a 27 km^2 fire in Spain, which was mapped into 7 fire-severity classes based on field measurements. They found that NDVI decline due to fire was positively correlated with field fire severity class, but that NDVI recovery post fire (up to 1165 days) was not correlated with fire severity until they also accounted for spatial variability in species composition, precipitation, and topography.

[58] Recovery of canopy photosynthetic capacity is important for site primary productivity and carbon balance, canopy albedo, evapotranspiration, interception of precipitation, and the surface energy balance. Photosynthetic capacity can recover relatively quickly, as early successional species and even nonwoody groundcover vegetation occupy the disturbed area and establish a leaf area index sufficient to capture most incoming solar radiation; *Asner et al.* [2004a] noted that gaps generated by conventional logging in the eastern Amzaon had closed, often with 'low-stature secondary species,' within 0.5–3.5 years. This can be quantified with passive optical/NIR sensors; examples of this include tracking vegetation greenness indices [e.g., *Diaz-Delgado et al.*, 2003] or tree density [*Schroeder et al.*, 2007]. However, rapid recovery of photosynthetic vegetation, particularly in tropical forests, makes it difficult to detect disturbances more than a few years old [*Grainger*, 2008]. *Masek et al.* [2008] note that for North American forests, detection rate for disturbances 5–6 years old is only half that for new disturbances. Hyperspectral instruments measure canopy reflectance in a large number of narrow spectral bands, and image spectroscopy with these instruments can be used to characterize canopy chemistry [e.g., *Wessman et al.*, 1988] and forest species composition [e.g., *Martin et al.*, 1998]. Since early successional species generally have higher foliar nitrogen content than late successional species, this provides a potential for either independently characterizing relative stand age or for monitoring forest successional pathways with spaceborne hyperspectral remote sensing, though much work needs to be done. One complication is that foliar nutrient status will also reflect soil/site nutrient status [*Ollinger et al.*, 2002], which is relatively independent of stand successional development.

[59] Recovery of canopy height is an important measure of forest regrowth, as it can be used as a proxy for recovery for forest age and canopy biomass through allometric relationships developed in field studies. In principle, lidar data should be able to measure this. *Woodget et al.* [2007] collected airborne lidar data, gridded to 5 × 5 m pixels, over a spruce plantation forest in northern England in 2003 and 2006. They found strong correlations between lidar-derived height and ground data, but weak and negative correlations between lidar-derived growth and ground data. The presented three possible reasons for this: geolocation discrepancies between the two data sets, such that spatial variability was confused with growth, (2) uncertainty in the ground-based measurements of growth, and (3) differences in lidar instrument/observation configuration between the two data sets (scan angle, flight altitude, and lidar pulse density). The first two of these are very relevant for similar studies with satellite data. To date, there are no spaceborne lidar data time series over a timescale relevant for forest recovery to evaluate lidar's ability to quantify forest height recovery postdisturbance. However, K. Dolan et al. (Regional forest growth rates measured by combining ICESAT GLAS and Landsat data, submitted to *Journal of Geophysical Research*, 2009) detected correlations between lidar-derived stand height and time since disturbance for several forest stands in the eastern U.S. *Yu et al.* [2006] used airborne lidar (40 cm beam size) to measure tree growth of boreal trees from data collected 5 years apart. Their analysis required tree-matching algorithm to detect growth in individual trees, and also tree harvest [*Yu et al.*, 2004]. *Kellner et al.* [2009] looked at two discrete-return airborne lidar overflights of old-growth tropical rain forest. Canopy gaps detected by lidar were well correlated with ground data. At 5 × 5 m scale, 39% of patches showed heights changes of $\geq$5 m. In contrast, at the landscape scale mean height was very similar for each overflight.

[60] Recovery of canopy/stand biomass is important for the carbon balance, the recovery of forest economic value, and for a range of ecosystem services. In principle, radar data should be able to measure this. To date, there are no radar data time series over a timescale relevant for forest recovery to evaluate radar's ability to quantify forest biomass recovery postdisturbance. *Lucas et al.* [2006a] combined Landsat-derived measure of foliage cover, using TM and ETM+ dry-season images, with airborne SAR fully polarimetric C, L, and P band (HH, VV, and HV) backscat-

ter data to map woody regrowth on former agricultural land in southeastern Queensland, Australia. C band backscatter increased with Landsat-derived foliar cover for all forest types, and both quickly rise to values similar to neighboring remnant forests, and therefore were not considered useful for mapping regrowing forests. On the other hand, longer wavelength L and P band backscatter from young regrowing forests was similar to nonforest backscatter. By combining the data sets, regrowing forests were mapped as having high C band backscatter or foliar cover and low L or P band backscatter. *Lucas et al.* [2006b] found that the airborne SAR backscatter was nonlinearly related to aboveground biomass, as estimated by field data and low-flying Lidar (footprint diameter $\sim$ 0.15 m). C band SAR saturated in these dry, sparse forests at aboveground biomass values of $\sim$50 Mg ha^{-1}, while L band HV polarization saturated at $\sim$80 Mg ha^{-1}. Maximum aboveground biomass in these forests was 165 Mg ha^{-1}, and the median value (n = 4500) was 82 Mg ha^{-1}.

[61] Finally, recovery of canopy heterogeneity or rugosity is important for providing a range of habitats for plants and animals. In early stages of recovery after a major disturbance, a forest stand can have a relatively uniform canopy height, which becomes more heterogeneous, and rougher, as the forest ages and natural mortality introduces variation [*Oliver and Larson*, 1996]. These small disturbances are discussed in the next section. In addition, as a forest stand develops and matures after a disturbance, it can go through a series of changes in species composition from dominance by early to late-successional species. The changes in species composition may be detectable by hyperspectral sensing [e.g., *Asner and Vitousek*, 2005]. Accurate assessment of forest recovery dynamics across the range of tropical, temperate, and boreal forest biomes will depend on substantial, high-quality ground-based data.

3.2. Small-Scale Disturbances

[62] Canopy gaps are holes in the forest canopy due to the death of one to a few trees; as a small-scale event, they occur much more frequently than the larger disturbances discussed in section 3.1 [e.g., *Denslow*, 1980, 1987; *Fisher et al.*, 2008; *Marthers et al.*, 2009]. The spatial patterning and distribution of gaps are of ecological significance because they drive the gap-phase regeneration of the canopy, influencing stand structure and biomass, tree regeneration dynamics and species diversity and distribution [*Schemske and Brokaw*, 1981; *Denslow*, 1987; *Vitousek and Denslow*, 1986]. Gaps increase light levels in the understory, release nutrients, and create structural habitat for some species of flora, fauna, and fungi [*Schemske and Brokaw*, 1981; *Denslow*, 1987; *Vitousek and Denslow*, 1986]. Gap dynamics can be a driving force of carbon dynamics in forested ecosystems [e.g., *Shugart*, 1998]. There is no single definition of what constitutes a gap [*Marthers et al.*, 2009]; crown characteristics estimated using remotely sensed data can differ from those estimated from field data [*Broadbent et al.*, 2008].

[63] There are numerous causes for tree mortality, and different modes of tree death generate different forest structural changes and canopy gaps [*Orians*, 1982]. Often a disturbance event will generate both large and small gaps as well as nonlethal disturbance. In addition, the death of individual trees and their subsequent fall can generate small gaps and canopy damage without an event detectable by many types of remote sensing. The multiple processes involved with individual tree mortality and crown disturbance often act in conjunction with one another or are multicausal. Quantitative study of these mechanisms of small-scale disturbances in forests is logistically demanding, and is often based on repeat censusing of forest inventory plots.

[64] Trees lose branches and portions of their canopy through a number of processes that do not lead to whole tree mortality. These process include self-abscission (due to leaf loss, low light levels and drought [*Addicott*, 1978; *Rood et al.*, 2000]), mechanical failure (due to epiphytic loading, wind storms, lightning [*Prance and Lovejoy*, 1985; *Whitmore*, 1978; *Nelson et al.*, 1994]), interaction between crowns (resulting in "crown shyness") [*Putz et al.*, 1984], animal activity resulting in limb breakage or rot of branches [*Perry*, 1978], as well as death of adjacent trees (resulting in secondary hits from falling trees, death of understory trees [*Keller et al.*, 2004a, 2004b, 2004c]), and lianas pulling down adjacent canopies and limbs [*Gillman and Ogden*, 2005; *van der Heijden et al.*, 2008]. In addition, many of the causes of small-scale disturbance have a low intensity but can be prevalent across the landscape, affecting not just biomass, but also forest productivity and nutrient dynamics.

[65] Disturbances smaller than individual trees also influence understory light levels, release nutrients, alter photosynthetic material, and increase tree seedling mortality [*Brokaw*, 1987; *Martinez-Ramos et al.*, 1988, 1989; *Clark and Clark*, 1991] similar to gaps generated from the death of individual trees. Branchfall, limbfall and nonlethal crown disturbances impact aboveground biomass stocks [*Clark et al.*, 2001a; *Chave et al.*, 2001], contribute to necromass production [*Clark et al.*, 2001a; *Chambers et al.*, 2001; *Palace et al.*, 2007], alter crown shape and dimension [*Young and Hubbell*, 1991], dictate tree architecture [*Addicott*, 1978], increase understory light levels through small canopy gaps [*Schemske and Brokaw*, 1981; *Denslow*, 1987; *Vitousek and Denslow*, 1986], increase nutrient availability [*Vitousek and Sanford*, 1986; *Vitousek and Denslow*, 1986], and often kill or injure adjacent trees and saplings [*Gillman and Ogden*, 2005; *Lang and Knight*, 1983; *Aide*, 1987; *Clark and Clark*, 1991; *van der Meer and Bongers*, 1996; *Scariot*, 2000]. The temporal frequency of branchfall when examined on the individual tree level ranges from annual to decadal timescales. At the landscape level branchfall impacts can vary annually, seasonally, or at a longer temporal scale through succession [*Palace et al.*, 2008b; *Eaton and Lawrence*, 2006].

[66] An inability to quantify small-scale disturbances hinders understanding of carbon dynamics and the patch-mosaic across the landscape. Forest productivity measurements do not necessarily account for branch fall and other sublethal stem damage [*Clark et al.*, 2001a; *Chambers et al.*, 2001]. Limbfall and sublethal disturbance accounts for a fundamental difference between field-measured necromass production and the estimation of necromass production based solely on mortality rates [*Palace et al.*, 2008b]. *Kira* [1978] estimated annual branchfall to be 0.5% of the total biomass of a tropical forest in Southeast Asia, while in neotropical forests, field-based estimates of branchfall and

crown damage range from 0.5 to 3.4 Mg ha^{-1} a^{-1} [*Chambers et al.*, 2001; *Chave et al.*, 2003; *Palace et al.*, 2008b]. Field plots can provide only a limited amount of data, due to the size and heterogeneity of major forest landscapes and the stochastic nature of many disturbance events. Remote sensing of small-scale disturbance may be the only effective and economical way to quantify forest biomass and three-dimensional structure over the landscape. Improved data sets on small-scale gap dynamics will help to parameterize and test forest carbon cycle models [e.g., *Prince and Steininger*, 1999; *Kellner et al.*, 2009]. Use of remote sensing can also aid in designing field experiments [e.g., *Clark and Clark*, 2000].

3.2.1. Remote Sensing of Small Canopy Gaps

[67] Canopy dynamics and gap generation associated with small-scale disturbances are substantially smaller in scale than moderate resolution spaceborne sensors (e.g., MODIS at 250 m or MISR at 1000 m resolution). Spectral unmixing of moderate resolution reflectance data [e.g., *Hagen et al.*, 2002; *Braswell et al.*, 2003] is not likely to detect individual events that impact <1% of the pixel area, but has been used for deforestation 'hot spot' detection to focus fine-resolution Landsat analysis [*Hansen et al.*, 2008]; a similar approach may work for relatively low-intensity disturbances that are prevalent over a large area.

[68] The largest of these small disturbances is on the scale of fine-resolution remote sensing, but detection with these sensors is difficult. Using Landsat data from a region with selective logging, *Asner et al.* [2005] found that all but the largest disturbance elements (log decks) were not resolvable unless the gap fraction was >50%, and that the observable features rapidly became indistinct due to vegetation recolonization or forest regrowth within 0.5 to a few years. *Asner et al.* [2004a, 2004b, 2005] used intensive field data collection to develop a Monte Carlo unmixing model that was successful in estimating small-scale disturbance from selective logging. *Hansen et al.* [2008] used a linear spectral mixing model with Landsat TM data to quantify vegetation, soil, and shade contributions to reflectance; these are then segmented, classified, and manually checked to estimate deforestation rates in the tropics. In a remote sensing study of reduced-impact selective logging in the central Amazon Basin, *Read* [2003] found that only major logging features could be detected with Landsat images collected within one year of logging activity, while roads and some but not all logging gaps could be detected with high-resolution Ikonos imagery. *Read* [2003] found that spatial analyses (texture analysis, spatial autocorrelation) were more effective than spectral analyses for detecting small gaps.

[69] High resolution optical/NIR image data, with a resolution of $\sim$1 m, is well suited for detecting gaps as small as an individual tree fall, because individual crowns of trees are discernible in the image data and can be linked to ground measurements [*Asner et al.*, 2002a, 2002b; *Clark et al.*, 2004a, 2004b]. Since 2000, there have been an increasing number of high-resolution satellite platforms that provide commercially available image data (e.g., Ikonos, QuickBird, OrbView3, and WorldView). Resolution of these satellites varies but is generally $\leq$1 m and most provide slightly coarser multispectral image data as well. Computation speed and increased data storage have alleviated constraints on the analysis of forest structure using high-resolution image data, but data availability and cost are still issues.

[70] There are numerous methods that allow for forest structure variables to be estimated from high-resolution satellite image data, including both manual interpretation and automated methods [e.g., *Chambers et al.*, 2007a]. Manual methods tend to be time consuming, nonreplicable, and prone to human error [*Asner et al.*, 2002a, 2002b]. *Dawkins* [1963] conducted one of the first canopy and remote sensing studies in the tropics to look at canopy dimensions, by measuring crowns manually in an aerial photograph and then measuring with a new photograph after trees were removed and large white crosses were placed on stumps. More recently *Asner et al.* [2002a, 2002b] manually delineated a large area for tree crowns and compared landscape averages with an extensive stratified sampling of field data. They developed allometric equations providing association of crown width, height, depth, and DBH. *Asner et al.* [2002a, 2002b] also included estimates of understory and crown level trees in the allometric equations, providing the means to compare with optical remotely sensed data which can only estimate forest structure that is visually apparent at the top of the canopy. *Read et al.* [2003] analyzed selective logging with high resolution image data using manual interpretation.

[71] The majority of recently published work in the interpretation of forest structure from high-resolution image data use automated methods. Currently, high-resolution image data automated analysis of forest structure can be grouped into two categories, texture or landscape level estimates and crown delineation methods. Methods to extract forest structure information at the stand level include semivariance, gappiness (lacunarity) and fractal dimension, and threshold, Fourier, entropy and wavelet analysis techniques [*Shugart et al.*, 2001; *Malhi and Román-Cuesta*, 2008; *Popescu et al.*, 2003; *Hudak and Wessman*, 1998]. *Shugart et al.* [2001] used semivariograms calculated from high-resolution remote sensing data to distinguish forest types and successional types. *Read* [2003] examined natural forest and selectively logged forests and was able to use automated methods such as texture and fractal dimension to differentiate the two forest types. *Malhi and Román-Cuesta* [2008] used lacunarity estimates, fractal dimension and an index of translational homogeneity for specific box sizes to estimate the spatial distribution of structural properties of forest canopies.

[72] Crown delineation algorithms and methods use a variety of automated methods: local maxima and minima identification, image segmentation, template matching, valley finding, space-scale theory, Fourier and wavelet filtering, and 3D modeling [*Morales et al.*, 2008; *Popescu and Zhao*, 2008; *Palace et al.*, 2008a, 2008b; *Wulder et al.*, 2000; *Pouliot et al.*, 2002; *Leckie et al.*, 2003a, 2003b; *Quackenbush et al.*, 2000; *Gougeon*, 1995; *Gong et al.*, 2002; *Weinacker et al.*, 2002; *Brandtberg and Walter*, 1998]. Careful crown delineation can also map gaps (spaces between crowns), and in repeat observations with good georeferencing, identify trees that have fallen [*Clark et al.*, 2004a, 2004b]. The crown detection algorithm developed by *Palace et al.* [2008a] simultaneously estimates crown widths, crown dimensions and area, stems frequencies, and locations. Use of allometric equations allow for

trunk diameter distributions to be calculated. Little comprehensive work on canopy biomass partitioning has been conducted in tropical forests, but *Broadbent et al.* [2008] examined a Bolivian forest canopy in three dimensions and estimated aspects of the canopy that would be visible to remotely sensed data. *Broadbent et al.* [2008] also applied the algorithm from *Palace et al.* [2008a] to compare field data with remotely sensed estimates of canopy structure.

[73] Stereoscopic imaging with high-resolution imagery can provide detailed information about canopy geometry. *Brown et al.* [2005] processed airborne stereo video imagery (pixel size 0.1 m) collected over a pine-savannah ecosystem in Belize to map individual trees and shrubs, identify them to plant type, measure height and crown area, and create a virtual 3-D forest. They could then estimate stand biomass from field-based allometry data. There is the potential for stereoscopic imaging with high-resolution spaceborne sensors such as Ikonos and QuickBird [e.g., *Li*, 1998], and there has been at least one recent application to forest height and structure analysis. *St-Onge et al.* [2008] used stereo Ikonos images and airborne lidar data to generate surface elevation models, and converted these to forest height and forest biomass maps for a mixed boreal forest in Canada. They used ground-based measures of tree height to assess their forest height maps, and ground-based measures of DBH and allometric equations to develop forest height-biomass relationships. In their analysis, remotely sensed estimates of biomass saturated at around 300 Mg ha^{-1}, but tree heights were still increasing, so they felt this saturation might be a function of limited ground data from high biomass stands. A single Ikonos stereo-pair covers about 100 km^2, and could be used to interpolate between airborne lidar data observations if allometric equations are applicable across the image. Airborne lidar data are being collected in many regions of the world [e.g., *Stoker et al.*, 2006], and this methodology should have widespread applicability for relatively local-scale analyses. A similar analysis has not been done with spaceborne lidar data.

[74] High-resolution image data do have potential problems and limitations. One problem relates to data availability, as the sensors are tasked to collect images, and not designed for global coverage. Data can be sparse or non-existent in many areas of the world. Requesting and tasking for a new image is quite expensive compared to larger spatial-scale satellite data, but archived image data are available for a fraction of the cost of a new image. A second problem relates to image geolocation for image intercomparison, less problematic for two high-resolution images with highly distinctive points for georeferencing than for stereo image analysis of high-resolution forest images or comparing a high-resolution with a lower-resolution image. High-resolution imagery is also very sensitive to Sun angle, sensor image angle, crown shadows, and terrain influences [*Asner and Warner*, 2003]. It is necessary to link high-resolution data with field-measured data in order to interpret the high-resolution imagery in terms of forest structural information; this requires precise geolocation of both image and field sample sites, yet GPS points are difficult to collect under a dense canopy, particularly in the tropics [*Clark et al.*, 2004b]. Field-based locations of crown edges often are approximations and can difficult to align with remotely sensed satellite imagery [*Asner et al.*, 2002a; *Clark et al.*, 2004b; *Broadbent et al.*, 2008]. Finally, if the field plots are not directly designed for remote sensing evaluation, the field data may not include all aspects of forest structure that might be detectable from remote sensing, or the remote sensing imagery may span several field sites that have used different methods for sampling.

[75] Lidar and microwave imagery are sensitive to properties of the forest below the top of the canopy. Forest canopy structure can be measured by airborne laser range-finding methods [*Tanaka and Hattori*, 2004]. Digitizing waveform lidar has been used to estimate canopy structure and biomass in tropical forests [*Drake et al.*, 2002a, 2002b; *Hurtt et al.*, 2004]. Discrete return small-footprint lidar has been successfully used over tropical rain forest landscapes to generate digital terrain models, estimate tree heights [*Clark et al.*, 2004], measure and map canopy treefall gaps, and assess canopy height changes over time [*Kellner et al.*, 2009]. Near-surface altimetry has been used to examine stand development and complexity [*Parker and Russ*, 2004]. High resolution SAR has been used in tropical forests to estimate crown projections [*Varekamp and Hoekman*, 2001]. JERS-1 was used successfully examine vegetation spatial and temporal variability [*Salas et al.*, 2002] and biomass [*Santos et al.*, 2002]. Spatial patterns have also been estimated by combining microwave data and modeling [*Sun and Ranson*, 1998; *Varekamp and Hoekman*, 2001].

3.2.2. Remote Sensing Detection of Small Disturbances

[76] There are very few studies that have examined small-scale disturbance using high-resolution image data from satellites. Studies involving aerial photography exist, but most use manual interpretation that do not allow for replication of analysis or the application of an algorithm to a new data set. A few studies have highlighted the use of high-resolution image data to examine small-scale forest disturbance at the individual tree level [*Clark et al.*, 2004a, 2004b; *Walsh et al.*, 2004; *Wulder et al.*, 2008]. *Clark et al.* [2004a] used manual comparison of two successive images to quantify mortality of emergent trees in a tropical forest. Mortality rates estimated from satellite data were essentially identical to independent data from ground plots. *Wulder et al.* [2008] looked a vegetation change due to canopy loss or change using multiple high-resolution satellite image data combined with an automated crown delineation algorithm. *Walsh et al.* [2004] could discriminate avalanche source, track, and runout zones from each other and from the surrounding forests in Montana with Ikonos multispectral data (4 m resolution). Even with the use of high-resolution optical data (Ikonos and QuickBird), crown shadow proves problematic in crown delineation [*Clark et al.*, 2004a; *Palace et al.*, 2008a], and it is difficult to estimate crown damage or loss, even for large emergent trees. Larger scale lidar and radar might prove more useful in estimating small-scale disturbances through estimates of the change of plot level biomass.

[77] The combination of multiple remote sensing sensors or platforms is useful in addressing limitations of some sensors [e.g., *Ranson et al.*, 2003]. High spatial resolution instruments provide detailed textural information, but have the drawbacks of small area coverage; they can sample a region, but not map a region. Moderate spatial resolution sensors have daily or near-daily repeat intervals, but contain

less detailed spectral and spatial information on the landscape level. The combination of remotely sensed data from multiple sensors at multiple spatial and temporal scales is highly advantageous in estimating forest structure and structural change [*Asner et al.*, 2008]. Beyond spatial and temporal scales, different types of sensors (e.g., passive and active, optical/NIR and microwave; see Table 2) provide information about different aspects of a forest canopy, and combining data from two different sensors can improve information retrieval. *Brown et al.* [2005] combined a high-resolution profiling laser with very high-resolution (0.1 m) video imagery in an airborne instrument to generate a three dimensional reconstruction of the canopy of a pine-savanna ecosystem in Belize. Combining this with ground-based allometry data, they mapped aboveground carbon density for ~70 plots (<1 ha). *Anderson et al.* [2008] showed that combining airborne hyperspectral and lidar data improved estimates of temperate mixed forest aboveground biomass and basal area compared to either instrument alone.

3.3. Importance of Field Studies

[78] The importance of fieldwork must be stressed because ground-based measurements are the only means to understand and evaluate remotely sensed estimates of forest biomass and structure and attempt to quantify uncertainty and errors of such estimates. A limiting feature in a remote sensing analysis of forest disturbance is often the lack of adequate field-derived biometric data collected at the plot level [e.g., *Keller et al.*, 2001; *Palace et al.*, 2008a, 2008b]. Future work to ensure proper interpretation of remote sensing studies requires standardized field data collection, collected over larger areas and in plots that take into consideration forest disturbance dynamics and what temporal and spatial disturbances can or will be captured on such plots. In addition, long-term field studies, designed with consideration of the temporal and spatial aspects of the disturbance type to be examined, are crucial for quantifying disturbance recurrence intervals.

[79] Biomass estimates have been made using the derived relationship between crown height, crown width, wood density, DBH or diameter above buttresses, or some combination of these variables, and the biomass of individual trees [*Brown et al.*, 1995; *Chambers et al.*, 2001; *Araujo et al.*, 1999; *Ketterings et al.*, 2001]. *Chave et al.* [2004] state that allometric equations account for the largest source of error in biomass estimates. In temperate and boreal forests, tree species have been well studied and allometric equations are well developed. In the tropics, with its very high diversity of species, there have been many fewer allometric studies done [e.g., *Araujo et al.*, 1999; *Brown et al.*, 1995; *Chambers et al.*, 2001; *Carvalho et al.*, 1998]. Advancement and development of allometric equations, specifically in tropical regions of the world, would be useful for remote sensing analysis of small-scale disturbances and for better estimates of regional biomass stocks. We note that this work is underway at several large-scale field survey networks in the tropics, such as the Smithsonian Center for Tropical Forest Science field plots [*Losos and Leigh*, 2004], and the Amazon Forest Inventory Network (RAINFOR) [*Malhi et al.*, 2002], but that this network is insufficient to adequately characterize global tropical forests.

[80] It is also important to note that while some field data is directly measured, such as basal area, DBH, stem density, species richness, and wood density, most field data on biomass are modeled from allometric relationships between biomass and variables like DBH and estimated wood density. Allometrically derived biomass estimates are likely to be correct in a relative sense from site to site as long as the same allometric equations are used (within one life zone but not across life zones), but there is no way of knowing how accurate they are in absolute terms without direct measures of biomass, i.e., cutting and weighing the forest [e.g., *Fearnside et al.*, 1993], which is not a common practice.

3.4. Changes in Rates of Disturbance and Recovery

[81] *Fisher et al.* [2008] used a simple stochastic model of gap generation and recovery to model the expectation value of stand biomass, B, and change in stand biomass, dB/dt, as a function of the relationship between gap size and gap recurrence interval. With a constant growth rate G, and constant disturbance probability, m, the expectation value of the stand biomass, i.e., the mean stand biomass over a uniform region that is much larger than disturbance areas, behaves as $B(t) = (G \div m)(1 - e^{-mt})$, and $B(t)$ asymptotically approaches an equilibrium value, B^* ($= G \div m$). This model is a major simplification of reality (at a minimum, it ignores all spatial heterogeneity and temporal variability), but it has straightforward and important implications. A change in the growth rate, G, or disturbance rate, m, will give the system a new equilibrium value, and the timescale for the system to approach that new equilibrium is on the order of m^{-1}. If a typical forest disturbance or turnover rate is 2% a^{-1}, then the timescale of the system response to a change in growth or disturbance rate is 50–250 years. Thus, if there has been a change in forest growth rates or disturbance rates in the recent past, forests could be a net sink (or source) of carbon for ~100–200 years, with diminishing strength over that time. Since it is very likely that neither natural nor anthropogenic disturbance rates have been constant over the past century, this is probably playing a role in the net land carbon balance. This highlights the importance of quantifying forest biomass, forest growth rates, and forest disturbance rates (size and recurrence interval).

[82] Increased forest growth rates have been cited in numerous studies as a potential mechanism for the carbon sink needed to balance the global carbon budget (so-called 'missing sink'): mechanisms include CO_2 and N fertilization, climate variability and change [e.g., *Norby et al.*, 2005; *Magnani et al.*, 2007]. If this growth-related carbon sink is spread diffusely across numerous biomes, it will be very difficult to detect with field-based sampling or spaceborne remote sensing, as the signal will be small against a large background 'noise' due to interannual variability in weather [e.g., *Ciais et al.*, 2005], spatial heterogeneity, and, for remote sensing, subpixel disturbances that affect pixel biomass but are not identifiable as disturbances.

[83] Another mechanism for enhanced terrestrial C sequestration is a change in disturbance rates. Through the twentieth century, the largest such changes likely have been anthropogenic, including fire suppression in North America, Europe, and China [e.g., *Hurtt et al.*, 2002; *Lu et al.*, 2006; *Girod et al.*, 2007; *Fellows and Goulden*, 2008]; land conversion to agriculture (cropland area increased by

6.8 million km^2 from 1900 to 2000 [*Klein Goldewijk*, 2006]); reforestation of former agricultural lands [e.g., *Albani et al.*, 2006]; and increasing wood harvest (global wood harvest in 2000 was ~1.3 Pg C a^{-1}, up threefold from ~0.4 Pg C a^{-1} in 1900 [*Hurtt et al.*, 2006]). With continuing increases in human population over the next several decades [*Lutz et al.*, 2001], direct anthropogenic disturbance rates are likely to increase, although future scenarios are highly uncertain [e.g., *Morgan et al.*, 1999]. The IMAGE 2.1 model predicted an increase in agricultural area of >5 million km^2 in Africa and >3 million km^2 in Asia between 1990 and 2050, or ~0.1 million km^2 a^{-1}, much of it from conversion of forested land [*Leemans et al.*, 1998; *DeFries et al.*, 2002]. This rate is similar to rates of tropical deforestation observed over the past few decades, as discussed above. Future projections for wood harvest demand have increases of as much as 400% (IMAGE Model, A1B scenario [*IMAGE-Team*, 2001]). The Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) [*Nakicenovic et al.*, 2000] projected from 1 to 10 million km^2 of land devoted to energy biomass production globally in 2100, depending on scenario and model; a significant fraction of this will likely be plantation forestry [*Stengers et al.*, 2006]. Future scenarios developed more recently [*Clarke et al.*, 2007] do not report land areas for bio-energy production, but project that increased use of bio-energy to meet stringent greenhouse gas stabilization levels could lead to substantial conversion of previously unmanaged lands to biomass production. Scenario analysis by *van Minnen et al.* [2008] projects that there will be ~5–10 million km^2 of carbon plantations by 2100. Shifting cultivation operates in remote and marginal land areas, which are being squeezed as mechanized agricultural expands its domain. This, coupled with population growth, is leading to shorter fallow periods and a more frequent recurrence of disturbance [*Flint and Richards*, 1991; *Borggaard et al.*, 2003; *Styger et al.*, 2007; *de Neergaard et al.*, 2008], though likely within an ever-shrinking domain.

[84] Climate change is also expected to change the rates of many types of forest disturbance [e.g., *Dale et al.*, 2001]. *Kasischke and Turetsky* [2006] documented an increase in burned area and in the frequency of large fires (>2 km^2) in the North American boreal forest between the 1960s and the 1990s. *Gillett et al.* [2004] attributed the observed increase in Canadian forest fires 1960–2000 to warming during the dry season. *Flannigan et al.* [2004] predict a climate change driven increase in annual burned area in Canada of 70% to 120% over the next century, based on 3xCO_2 climate change scenarios of two GCMs. Their estimates do not explicitly take into account several factors that will impact fire occurrence and severity, including changes in vegetation, ignitions, fire season length, and human fire management. As noted above, fires in tropical forests are closely related to land use and climate (dryness), and fire frequency can be expected to change as those factors change. *Allan and Soden* [2008] suggest that precipitation extremes (droughts and heavy rains) are likely to increase with climate warming, which may enhance flooding and drought disturbance rates. Flooding frequencies will also be sensitive to changes in land use and water management. There is still a great deal of uncertainty as to climate change impacts on hurricane frequency and severity [*Saunders and Lea*, 2008; *Emanuel et al.*, 2008; *Vecchi et al.*, 2008], and future tornado frequency and intensity is also very uncertain [*Raddatz*, 2003; *Diffenbaugh et al.*, 2008]. In general, the frequency of extreme weather events such as flooding and drought are expected to increase with climate change [*Meehl et al.*, 2007].

4. Summary and Conclusions

[85] Abrupt, large-scale forest disturbance generating gaps larger than 0.001 km^2 occurs on about 0.4–0.7 million km^2 of forest each year; this is a rough estimate: at this time we do not have good, comprehensive, global information on forest disturbance and recovery rates. Much of this total comes from fire, windstorms, logging, and temporary agriculture (shifting cultivation), with smaller amounts due to land conversion, flooding, landslides, and avalanches. All of these disturbances have substantial impacts on aboveground canopy biomass and structure, and are important to quantify (location, extent, severity, fate of disturbed biomass) to improve regional and global carbon budget estimates and to better initialize, parameterize, and/or test ecosystem-carbon cycle models. Chronic, disturbances, such as insect and pest damage, drought, and pollution loading, typically operate at lower intensity and manifest more slowly, sometimes by making a forest more susceptible to an abrupt disturbance. Small-scale disturbances generate small gaps, fell individual trees, or cause sublethal damage to forest canopies. Causes include selective and reduced impact logging, fire, wind, avalanches, and natural mortality. Forest disturbance due to natural and anthropogenic causes plays an important role in determining the structure of forest canopies, the spatial heterogeneity of the forested landscape, and the rate of carbon exchange between the forest and the atmosphere. Changing rates of forest disturbance and/or recovery can have a large impact on the global net carbon budget. Different forest biomes will have different spatial and temporal disturbance dynamics and this needs to be addressed in designing both field studies and remote sensing instruments.

[86] Both passive and active spaceborne remote sensing detect electromagnetic radiation scattered up from the land surface to the detector (passive microwave and thermal infrared detect direct surface emissions) and can be used to characterize the land-surface based on the intensity, spectral distribution, timing, and/or polarization of this reflected radiation. This makes them quite suitable for mapping disturbance, as surface scattering is directly related to a number of canopy properties that change with disturbance (e.g., soil, shadow, and nonphotosynthetic vegetation fractions; heterogeneity of an image; spectral brightness changes by band or vegetation indices; and seasonal variability in reflectances). Much work has been done with spaceborne remote sensing to map the regional and global occurrence, location, and extent of large-scale forest disturbance, particularly with passive optical/NIR instruments of moderate-scale resolution (e.g., MODIS) and fine-scale resolution (e.g., Landsat). These instruments provide large area coverage with frequent repeat views need for detecting disturbance, but are hampered by clouds and smoke. Some large-scale disturbances are too small or spatially heterogeneous for reliable mapping with moderate scale instruments, but most can be mapped with fine-scale instruments, and

new methods combine the two scales of observation to identify hot spots of disturbance (with moderate-scale imaging), and then better quantify the extent of disturbance (with stratified sampling of fine-scale imaging) [e.g., *Hansen et al.*, 2008]. Also, as the remote sensing data record with relatively stable instrumentation extends into several decades, regional estimates of rates of disturbance [e.g., *Achard et al.*, 2002; *Masek et al.*, 2008; *Hansen et al.*, 2008] and recovery [*Schroeder et al.*, 2007] from image time series analyses are becoming more feasible.

[87] There are still a number of challenges for spaceborne mapping of forest disturbance. In areas of highly dynamic land use, accurate assessment of disturbance and recovery requires frequent looks, ideally at least annually, and preferably at the same phenological time of year. This is difficult for optical/NIR instruments (passive and active) in cloudy regions of the world. Methods are not well developed for quantifying degree of disturbance for large-area disturbances that are very heterogeneous in impact intensity (e.g., peripheral disturbance in hurricanes, and patchy disturbance in large fires or major thunder storms, which are the dominant modes of natural disturbance for many temperate and boreal forests). Related to this, there are no well established methods for regional- to global-scale mapping of disturbances that are <0.01 km^2 (in tropical forests this would include several major disturbance mechanisms: shifting cultivation, selective and reduced-impact logging, and severe storm microbursts). Of course, there are also numerous challenges for ground-based mapping of forest disturbance at regional to global scales; access to remote forests and adequate field sampling for statistical reliability (number and size of field sites) are two major obstacles.

[88] To reduce uncertainty in the impact of disturbance and recovery on the carbon balance of global forests requires quantification of (1) forest biomass prior to disturbance; (2) the impact of disturbance on the standing biomass and the fate of the disturbed carbon: burned, removed, left to decompose; and (3) the impact of disturbance on forest structure/composition and the rate of biomass accumulation during the recovery from disturbance. However, no spaceborne remote sensing instruments directly measure canopy biomass or most forest structural properties. This means that the characterization of forest biomass or canopy structure from spaceborne remote sensing is completely dependent on being relatable to high-quality, comprehensive, temporally coherent, and spatially extensive and representative ground-based measurements. Any program that strives to generate a high-quality quantitative assessment of forest canopy biomass and structure with spaceborne remote sensing must include a well designed and well coordinated field program to collect high-quality ground-based forest structure data, including variables related to biomass, since biomass is rarely measured directly in the field. There is a major research need for improved allometric equations relating forest biomass to variables more readily measureable on the ground (e.g., DBH) and from space (e.g., height), particularly in the tropics.

[89] There are a range of methods and spaceborne instruments with the ability or potential to (indirectly) assess forest biomass and structure. In all cases, these methods are less well developed and less widely applied than spaceborne disturbance mapping. Some work has been done with passive solar reflectance instruments at local or small regional scales, looking at SWIR bands or multiangle imaging, which are more sensitive to canopy heterogeneity than the more common MODIS and Landsat optical/NIR analyses, and using hyperspectral analyses of canopy chemistry, which can vary along a recovery trajectory. More work has been done with active remote sensing instruments (lidar in the visible/NIR and SAR in the microwave), which are generally more directly sensitive to forest canopy biomass (microwave) and canopy height and vertical biomass distribution (lidar and InSAR) than are passive solar reflectance instruments, though not without their own shortcomings (e.g., clouds/smoke interference for lidar, biomass saturation for radar). These have mostly been local-scale studies, using airborne and spaceborne instruments, to develop and test methods for wider application, but there have recently been some continental-scale analyses with spaceborne SAR. Most of the remote sensing work on forest biomass and structure analysis has not focused on disturbance impacts, but just on canopy characterization (an exception is fire severity work). A new generation of active instruments designed to generate global coverage/sampling of forest canopy biomass and structure will improve our ability to quantify the carbon balance of the Earth's forests [*Houghton and Goetz*, 2008], and to initialize and/or evaluate ecosystem and Earth system models that simulate forest carbon cycling. It should also, over a multiple-year record, provide data for assessing the capabilities of remote sensing for detecting and quantifying disturbance and recovery impacts on forest biomass and structure.

[90] As the surface characteristics to be quantified with spaceborne remote sensing become more complex (e.g., not just occurrence, but canopy structure impacts of disturbance) they typically become less directly related to any single surface reflectance characteristic. There has been limited work to date on large-scale (regional to global) multisensor data fusion studies, but methods are being developed and tested in an ever-growing collection of studies that have shown the benefits of the synthesis of data from multiple remote sensing instruments that observe different characteristics of the landscape (mass, horizontal texture, height and vertical distribution, foliar chemistry, temporal dynamics). Synthesis of multiple instruments provides a more complete description of a forested landscape, and also, through consistencies or inconsistencies between the data sets, can enhance or diminish confidence in the interpretation of the data.

[91] Small-scale disturbance and forest canopy gap dynamics associated with natural mortality cannot be easily observed with moderate- or fine-resolution spaceborne remote sensing. High-resolution remote sensing (e.g., $\sim$1 m resolution for passive optical/NIR, small footprint lidar) can map crown geometry and gaps, but has not yet been applied over large regions in a systematic study. There is the potential, however, to use high-resolution remote sensing to assemble a very large data set on tree mortality and small gap dynamics, sampling much more of the Earth's forested area than can be easily or affordably sampled by ground-based field studies.

[92] The temporal and spatial scales of disturbance/recovery span large ranges, and dictate which satellites can be useful

for studying the various processes. All satellite instruments come with their own limitations for observing forest disturbance and recovery; spatial resolution, spatial coverage, and temporal repeat frequency are generally not a perfect match to the scales of disturbance and recovery. One goal of terrestrial remote sensing science is to analyze existing data from airborne and spaceborne instruments to plan future instruments and missions to better address outstanding scientific questions related to forest disturbance and recovery across as many scales as possible. The field of spaceborne remote sensing of forest canopy biomass and structure is developing rapidly, as the collection of papers in this special issue attests. As this field continues to develop, and as new instruments are planned, built, and launched, our capacity to detect forest disturbance and recovery from space will improve, as will our ability to quantify those impacts if extensive and coordinated ground measurement programs are an integral part of the research effort. While passive optical/NIR instruments with frequent global coverage will continue to provide essential data layers, active optical/NIR and microwave instruments (e.g., lidar, SAR, and InSAR) are needed to provide additional information about biomass and canopy structure that cannot be derived from passive optical/NIR instruments. Together, spaceborne and ground-based efforts will provide essential data for reducing uncertainties in the terrestrial carbon budget, and for improving our ability to model the terrestrial carbon cycle.

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