8 Remote Sensing of Forest Damage by Diseases and Insects

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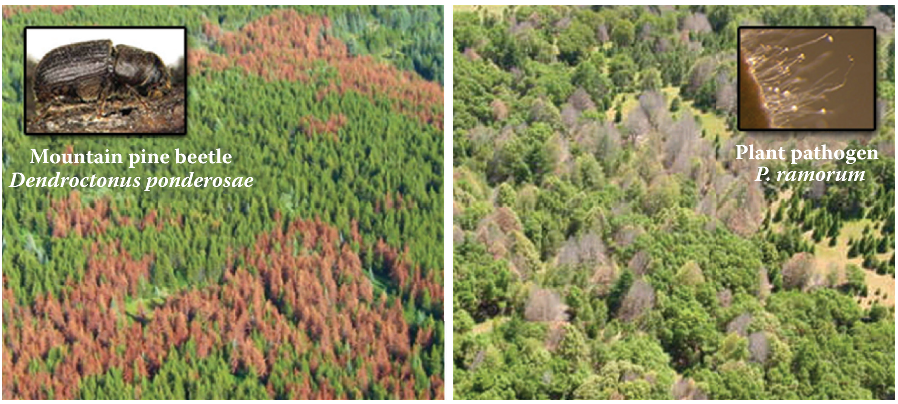
CONTENTS

8.1 INTRODUCTION

Forests are an integral part of natural ecosystems, providing numerous ecological, economic, social, and cultural services (Boyd et al. 2013; Chen et al. 2015a). For example, they store approximately 45% of terrestrial carbon (C) and remain as a large net C sink by capturing one-quarter of the anthropogenic carbon dioxide (CO_2) each year (Bonan 2008; Pan et al. 2011). However, environmental change (e.g., severe drought) and global trade have increased forest vulnerability to a range of natural disturbances, including diseases and insects (Asner 2013; Boyd et al. 2013; Wang et al. 2008; Wingfield et al. 2015). Forest diseases are caused by pathogens that are infectious and transmissible, such as bacteria, fungi, viruses, and helminths. Insects attack different parts of the tree, with defoliators feeding on leaves or needles, and bark/wood borers boring into the bark/wood. While some pathogen and insect species are native to local ecosystems, many of the recent disturbances arise from the nonindigenous species that may pose more pernicious and unpredictable threats to forest health (Boyd et al. 2013). Over the past few decades, the frequency and intensity of disease- and insect-caused forest disturbances have dramatically increased, leading to extensive tree mortality in key forest biomes worldwide. Examples include the sudden oak death epidemic in western United States, outbreaks of mountain pine beetle in Canada's boreal forest, bronze bug damage in plantation forests in South Africa, and the spread of bark beetles in central Europe and Scandinavia (Fassnacht et al. 2014; Meentemeyer et al. 2015; Oumar and Mutanga 2014; Wulder et al. 2009). Figure 8.1 illustrates two typical symptoms of forest damage attributed to the outbreaks of mountain pine beetles and the infectious disease sudden oak death, respectively.

Sustainable forest management is essential to mitigating the destructive impacts of diseases or insects on forest ecosystems. This is especially true when major disturbance events have the potential to reduce the dominant native species, causing a permanent change in forest structure. One prerequisite for effective management is to understand the spatial distribution and severity of forest damage. Consequently, mitigation efforts can be performed to limit the population and the spread of pathogens or insects on infected or susceptible host trees. Although conventional field mensuration remains the most accurate way to quantify stages of infestation, it becomes time-consuming and costly when pathogen or insect populations reach epidemic levels. Remote sensing provides a timely and accurate approach to scale up field measurements and characterize spatially explicit information about the Earth's surface at landscape to regional scales. Recent developments in spaceborne and airborne sensors have further



(a) (b)

FIGURE 8.1 Landscape-scale forest mortality caused by (a) mountain pine beetle and (b) sudden oak death. The infected trees show distinct symptoms of (a) red needles and (b) brown-to-gray leaf lesions, respectively. (Courtesy of (a) Ministry of Forests, Lands and Natural Resource Operations, http://www2.gov.bc.ca/gov/content/governments/organizational-structure/ministries-organizations/ministries/forest-and-natural-resource-operations, and (b) California Oak Mortality Task Force.)

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advanced our ability to collect Earth observation data across multiple spatial, temporal, and spectral scales, making remote sensing feasible to monitor forest disturbances (e.g., variations in forest biophysical and biochemical parameters) in response to the disease and insect outbreaks of varying stages of invasion. Such rapid and accurate delineation of large-area forest damage allows decision makers to take prompt and informed actions, supporting the sustainable management of forests.

The main objective of this chapter is to provide a brief survey of remote sensing assessment of forest damage by diseases and insects. Emphasis is directly laid on mapping forest disturbances with satellite and airborne Earth observation data. The following sections are organized to (i) summarize the recent trends of applying remote sensing to detect forest disease and insect outbreaks, (ii) investigate remote sensing characteristics and its qualifications for studying the topic, (iii) provide a brief review of remote sensing algorithms, and (iv) discuss several remaining challenges that face researchers and decision makers in sustainable forest management.

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8.2 TRENDS OF REMOTELY DETECTING FOREST DISEASE AND INSECT OUTBREAKS

While the idea of applying remote sensing to detect disease- and insect-induced forest damage was considered as early as the 1970s and 1980s (e.g., Heller and Bega 1973; Nelson 1983; Rock et al. 1986), only recently (since the late 1990s) did the topic receive considerable attention for managing emerging outbreak (Table 8.1). Two reasons possibly explain slow adoption. First, a growing number of studies showed that the frequency and intensity of forest disease and insect attacks significantly increased over the past two decades as a result of climate change and globalization (see a brief review by Boyd et al. [2013]). There was a growing need to understand the mechanisms (e.g., spatial patterns) of the landscape-scale disease and insect progression informing effective mitigation strategies. Second, the collected Earth observation data have increased immensely during the same time period. The large volumes of data sets with relatively cheap acquisition costs, for example, the opening of more than four decades of Landsat archive (Woodcock et al. 2008), made it easier to systematically analyze the impact of certain diseases or insects in specific areas of interest. Ironically, one of the recent challenges facing many researchers is how to better handle such *big data*.

Geographically, research hotspots were primarily located in North America (e.g., Canada and the United States) and Europe (e.g., Germany, Norway, Spain, Sweden, and the United Kingdom), with several other studies conducted in Australia, China, and South Africa. Please note that the case studies cited in Table 8.1 were collected by searching Elsevier's ScienceDirect database with the following formula: *remote sensing* AND *forest* AND (*disease* OR *insect*). We also respectively substituted *pathogen* for *disease*, and *pest* for *insect* in the search. The results were further refined by removing the studies that did not contain a significant remote sensing component or did not target specific disease or insect types.

Compared to forest diseases, insects appeared to be more intensively studied using remote sensing (Table 8.1). This reflects the fact of high tree mortality induced by insects as well as their globally widespread occurrence. For example, among the

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TABLE 8.1
Types of Diseases and Insects, and the Corresponding Regions, Countries, and Case Studies

Region	Type of Disease or Insect	Country	Case Study
Europe	Autumnal moth (*Epirrita autumnata*)	Sweden	Babst et al. 2010
	Bark beetle *Ips grandicollis*	Germany	Fassnacht et al. 2014
	Bark beetle *Ips typographus* L.	Germany	Kautz 2014
	Beech leaf-miner weevil (*Rhynchaenus fagi*)	Spain	Rullán-Silva et al. 2015
	Fungal spore *Ganoderma* sp.	United Kingdom	Sadyś et al. 2014
	Insect *Physokermes inopinatus*	Sweden	Olsson et al. 2012
	Pine processionary moth (*Thaumetopoea pityocampa*)	Spain	Sangüesa-Barreda et al. 2014
	Pine sawfly (*Neodiprion sertifer* (Geoffrey))	Norway	Solberg et al. 2006
North America	Black-headed budworm (*Acleris gloverana* (Walsingham))	Canada	Luther et al. 1997
	Blister rust fungus (*Cronartium ribicola*)	United States	Hatala et al. 2010
	Eastern hemlock looper (*Lambdina fiscellaria*)	Canada	Fraser and Latifovic 2005
	Eastern spruce budworm (*Choristoneura fumiferana*)	United States	Wolter et al. 2009
	Emerald ash borer (*Agrilus planipennis* Fairmaire)	United States	Pontius et al. 2008
	Gypsy moth (*Lymantria dispar* L.)	United States	de Beurs and Townsend 2008; Townsend et al. 2012; Thayn 2013
	Hemlock woolly adelgid (*Adelges tsugae* Annand)	United States	Siderhurst et al. 2010
	Jack pine budworm (*Choristoneura pinus pinus* (Free.))	Canada, United States	Leckie et al. 2005; Radeloff et al. 1999
	Mountain pine beetle (*Dendroctonus ponderosae* Hopkins)	Canada, United States	Assal et al. 2014; Bright et al. 2012; Cheng et al. 2010; Coops et al. 2009; Goodwin et al. 2008; Hatala et al. 2010; Meddens et al. 2011; Meigs et al. 2011, 2015; Raffa et al. 2013; Skakun et al. 2002; Walter and Platt 2013; Wulder et al. 2008, 2009
	Spruce budworm (*Choristoneura fumiferana*)	Canada, United States	Wolter et al. 2008

(*Continued*)

TABLE 8.1 (CONTINUED)
Types of Diseases and Insects, and the Corresponding Regions, Countries, and Case Studies

Region	Type of Disease or Insect	Country	Case Study
	Sudden oak death (*Phytophthora ramorum*)	United States	Kelly and Meentemeyer 2002; Lamsal et al. 2011; Liu et al. 2006, 2007; Meentemeyer et al. 2008; Pu et al. 2008
	Western spruce budworm (*Choristoneura freemani*)	United States	Meigs et al. 2011, 2015
Others	Aphid (*Essigella californica*)	Australia	Goodwin et al. 2005
	Bark beetle (*Ips grandicollis*)	Australia	Verbesselt et al. 2009
	Fungal pathogen (*Sphaeropsis sapinea*)	Australia	Goodwin et al. 2005
	Insect (*Thaumastocoris peregrinus*)	South Africa	Oumar and Mutanga 2014; Oumar et al. 2013
	Mopane worm (*Gonimbrasia belina*)	South Africa	Adelabu et al. 2014
	Pine caterpillar (*Dendrolimus superans* Butler, Dendrolimus: Lasiocampidae, Lepidoptera)	China	Huang et al. 2010

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United States' 20 major diseases and insects that caused 6.4 million acres of tree mortality in 2011, 60% were insects; mountain pine beetle (*Dendroctonus ponderosae* Hopkins) alone killed 3.8 million acres of trees (USDA Forest Service 2012). Several other insects, such as bark beetle *Ips grandicollis*, gypsy moth (*Lymantria dispar* L.), and jack pine budworm (*Choristoneura pinus pinus* [Free.]), have also been well studied across forest biomes (Table 8.1). In contrast, remote detection of the disease impacts on forest ecosystems was less studied. One exception is sudden oak death caused by the invasive plant pathogen *Phytophthora ramorum* (Rizzo et al. 2005), which received considerable attention as a result of rapid transmission and widespread mortality of oak and tanoak trees in coastal forests of California and Oregon (Table 8.1).

8.3 REMOTE SENSING CHARACTERISTICS AND QUALIFICATIONS

The premise of utilizing remote sensing to detect disease- or insect-infested forests is that the damaged trees show distinct symptoms capable of being observed remotely. Depending on the type or stage of damage, the symptoms may indicate the decline in chlorophyll/water quantity in foliage, leaf discoloration, defoliation, or treefall gaps. For effective monitoring, Earth observation data acquired from satellite or airborne sensors are expected to capture the differences in the reflected radiation from damaged versus healthy trees. In this section, we base our discussion on the previous research efforts to demonstrate the qualifications of remote sensing for monitoring forest disturbances attributed to diseases and insects.

8.3.1 Spectral Characteristics

The spectral values in a forest image scene are often biased to representing the upper layer traits of tree canopies. While the top-down manner of photographing vegetation lacks the ability to characterize the entire tree, it is possible to link the status of canopy to forest health because diseases or insects substantially affect a tree's ability to photosynthesize and store moisture in foliage. One consequence is the noticeable change in foliage color (i.e., discoloration). For example, needles on pine trees turn red in the red-attack stage by mountain pine beetle (Wulder et al. 2006). Oak trees visually appear brown and freeze-dried as a result of sudden oak death (Kelly and Meentemeyer 2002). Remote sensors with the capacity to record the visible portion of the electromagnetic spectrum (wavelengths from approximately 400 to 700 nm) are able to detect these symptoms, which appear similarly in the human visual system. However, disease- and insect-mediated forest mortality is a gradual process. Some early-stage symptoms cannot be easily observed; for instance, unhealthy trees with reduced chlorophylls may only appear to be slightly brighter than the healthy trees in the visible spectral range owing to reduced absorbance of the blue and red wavelengths by foliage (Knipling 1970). Sensors with the capacity to further detect the near-infrared spectrum (wavelengths from approximately 700 to 1300 nm) are probably more sensitive to such physiological stress. Similarly, the amount of energy reflected in the short-wave infrared range (wavelengths from approximately 1300 to 2500 nm) is correlated with vegetation moisture (Laurent et al. 2005). Today's remote sensing technologies are already capable of recording the radiation reflected in those spectral ranges. To further advance the performance of remote detection, researchers utilized a variety of spectral indices (i.e., combinations of spectral bands) and have repetitively confirmed their effectiveness in monitoring forest damage subject to disease and insect attacks (see case studies in Table 8.1). Examples of the indices include normalized difference vegetation index (NDVI; Tucker 1979), enhanced vegetation index (Liu and Huete 1995), disturbance index (DI; Healey et al. 2005), normalized difference moisture index (NDMI; Jin and Sader 2005), normalized difference infrared index (Jackson et al. 2004), and enhanced wetness difference index (EWDI; Skakun et al. 2003).

While multispectral imagery has proven its potential to assess the status of damaging diseases and insects, previous studies discovered that the subtle spectral discrepancies between healthy and damaged trees (e.g., during the previsual green mortality stage) can be better detected by fine-spectral resolution data, that is, dozens to hundreds of narrow and contiguous spectral bands acquired through hyperspectral imaging (Coops et al. 2003; Hatala et al. 2010). On the basis of this technology, researchers have further developed narrowband vegetation indices, some of which were freshly designed (e.g., transformed chlorophyll absorption reflectance index; Haboudane et al. 2002), while the others were simple modifications of the traditional vegetation indices by means of substituting narrowband for broadband reflectance (e.g., red edge NDVI; Gitelson and Merzlyak 1994). Although not as common as the

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broadband indices yet, narrowband indices have shown the potential to explain the physiological changes in the forests suffering damage from insects (Fassnacht et al. 2014; Oumar et al. 2013).

8.3.2 Spatial Characteristics

Recent development in remote sensing allows us to perceive spatial details on the Earth's surface at varying scales, for example, 1 km/500 m/250 m MODIS, 30 m/15 m Landsat, 10 m/5 m SPOT-5, 4 m/1 m IKONOS, 1.2 m/0.3 m Worldview-3, and centimeter-level aerial photos. This offers forest practitioners a range of choices for balancing the accuracy of detecting disease or insect occurrence and data acquisition cost. Typically, coarse to moderate-resolution imagery has been traditionally applied to measure forest structural change at the landscape scale. For example, de Beurs and Townsend (2008) applied MODIS data with a 250-m spatial resolution to monitor more than 16,000 km^2 of insect defoliation of hardwood forests by gypsy moth. Fraser and Latifovic (2005) showed that 1-km-resolution SPOT VEGETATION data were sufficient for mapping a 350,000-km^2 area of coniferous forest mortality in Quebec, Canada, caused by the eastern hemlock looper. A higher-severity disturbance event may lead to a more satisfactory detection result, because the infected tree patches tend to be larger on average.

However, challenges arise if the majority of the damaged trees are within small, discrete patches. High–spatial resolution satellite and airborne imagery are more suitable for fine-scale detection and have proven to be feasible in previous studies (e.g., Adelabu et al. 2014; Cheng et al. 2010; Kautz 2014; Meddens et al. 2011; Wulder et al. 2008). It should be noted that a unique consideration of processing such type of data sets is the recent paradigm shift from pixel-based to object-based image analysis, that is, geographic object-based image analysis (GEOBIA; Blaschke et al. 2014). Because a high-resolution pixel often covers a portion of a tree or a small tree cluster, the corresponding pixel value may contain a high spectral variation as a result of the complex forest 3D structure and sun–tree–sensor geometry (Chen et al. 2011). Compared to the traditional pixel-based modeling, GEOBIA extracts image objects (groups of pixels) to represent meaningful geographic objects, for the purpose of reducing spectral noises and increasing mapping accuracies.

8.3.3 Temporal Characteristics

The size of Earth observation data archives is growing at an unprecedented pace. With rich time series data, it becomes feasible to extract the trajectories of disease and insect progression over a long term (e.g., Meigs et al. 2011; Vogelmann et al. 2009; Walter and Platt 2013). Because most of the infected trees do not die instantly, many forest disease or insect studies tend to apply annual or biannual imagery to characterize the spatiotemporal patterns of forest change. To mitigate the impact of seasonal variation, multidate images are preferably collected in the same months or the same seasons. Of the variety of date archives, Landsat time series have been the most widely used (see case studies in Table 8.1). This is possibly attributed to the features of four decades of data storage with minimized

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temporal gaps, free data access, and global coverage (Woodcock et al. 2008). However, as we are entering the remote sensing big data era, we expect to see an increasing application of diverse data archives for long-term forest health monitoring in the near future.

8.4 A REVIEW OF REMOTE SENSING ALGORITHMS

To date, a variety of remote sensing algorithms have been developed to measure forest damage caused by diseases and insects. The main principle is to extract the differences in spectral reflectance between healthy and infected trees, as well as among the infected trees during varying stages of decline. Here, we provide a brief review of those algorithms and categorize them into five groups: thresholding, classification, change detection, statistical regression, and the others, with details described below.

8.4.1 Thresholding

Compared to healthy trees, damaged trees have distinct symptoms, such as reduced moisture, discolored foliage, and defoliated canopy. A thresholding method defines one or multiple thresholds to extract the pixels representing damaged trees from the entire forest image scene. While the operation appears simple, the success of applying thresholding largely depends on the effective description of forest symptoms and the accurate definition of threshold(s).

Describing the symptoms of forest damage has been primarily relying on image spectral indices. Some of those indices were specifically designed to assess forest disturbances. For example, Coops et al. (2006) created a red–green index, the ratio of QuickBird red to green wavelengths, to extract the red-attack damage (i.e., foliage color turning red from green) in the mountain pine beetle–infested coniferous forests. Their results confirmed the potential of using a simple threshold to red–green index values for separating the infected from the healthy trees. For many other studies, however, thresholding methods often directly employed or modified the existing indices that had not been intentionally developed for monitoring infestation. For example, multiple thresholds were applied to Landsat NDMI for extracting beetle-infested trees and forest regrowth after disturbance events (Coops et al. 2010; Goodwin et al. 2008). Similarly, Coops et al. (2009) calculated DI using 1-km-resolution MODIS images covering a part of the terrestrial land base of Canada. They found that those DI pixel values larger than ±1 standard deviation of the long-term mean were consistent with the areas flagged as infested using aerial survey. To further improve the thresholding performance, Skakun et al. (2003) created an EWDI through combing three different dates of wetness bands (derived from the Landsat TM tasseled cap transformation). Likewise, Olsson et al. (2012) modified the classic NDVI index by substituting the green band for the red band in the equation. The new index GNDVI was found to outperform NDVI, and negative GNDVI values indicated damage. Overall, the thresholding methods are simple to implement, with thresholds typically defined with assistance of field survey and manual photo interpretation. One major limitation for

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thresholding is that it is only suitable to identify major stages of forest disturbances, for example, extracting heavily damaged trees from healthy ones.

8.4.2 Classification

Land-cover classification using imagery to differentiate between land-cover types was developed almost immediately after the advent of remote sensing. The suitability of using image classification to measure forest damage is based on the fact that the distinct symptoms of infected forests make them appear as *new* land-cover types. It also seems to be consistent and convenient to apply one classification framework to extract not only the damaged/healthy forests but also the other land-cover types coexisting with forests, for example, grasses, shrubs, built-ups, and water.

Of the variety of classification algorithms, the classic supervised maximum likelihood classifier (MLC) demonstrated continued success in forest disease and insect monitoring. For example, MLC was effectively applied to Landsat imagery for differentiating mountain pine beetle–induced red attacks from non-red attacks (Walter and Platt 2013). MLC and Landsat imagery were also used to extract gypsy moth–caused defoliation from the nondefoliated trees (Thayn 2013). In addition, previous studies suggested that the application of MLC to classify high–spatial resolution imagery has the potential to detect forest damage of multiple stages. For example, Leckie et al. (2005) was able to estimate jack pine budworm–induced four classes of discoloration (nil–trace, light, moderate, and severe) through the application of MLC and 2.5-m-resolution aerial imagery acquired from the multispectral electro-optical imaging sensor. Meddens et al. (2011) and Bright et al. (2012) independently used aerial photography and MLC to classify beetle-caused tree mortality into green, red (dead trees with red needles), and gray (dead trees without needles) tree classes with the same overall accuracy of 87%. When integrated with hyperspectral imagery, MLC was found to be a viable solution to estimate forest stress during the early previsual stage of a sudden oak death outbreak (Pu et al. 2008).

Novel machine learning methods, as a complement to classic classifiers, have been introduced to the domain of remote sensing classification since the 1990s. Support vector machines (SVMs) are a successful example, which have proven to be feasible to detect three levels of insect defoliation ranging from nonimpacted undefoliated plants to partly defoliated plants and finally refoliating plants after severe defoliation in an African savanna (Adelabu et al. 2014). When applied to classify hyperspectral imagery acquired from HyMap, SVMs were found to have notable high overall accuracies mapping bark beetle–caused tree mortality, with the best result reaching as high as 97% accuracy (Fassnacht et al. 2014). Random forests (RFs) act as another popular machine learning method in classification. In a case study of mapping insect defoliation levels with RapidEye 5-m-resolution imagery, Adelabu et al. (2014) compared RFs and SVMs, and found comparable results. It should be noted that one outstanding feature of RF is that it can rank all the input variables based on their importance (Breiman 2001), which facilitates result analysis by identifying the most crucial spectral bands or indices in disease and insect mapping.

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A subpixel classification scheme is needed if the spatial resolution of image pixels is too coarse to detect small, fragmented disturbances in a patchy distribution. To do so, spectral mixture analysis (SMA) provides a viable means, which is typically based on the assumption that the spectral value of each pixel is a linear combination of the reflectance from surface materials (endmembers) weighted by their factions. For example, Radeloff et al. (1999) performed SMA on Landsat TM imagery to classify jack pine budworm defoliation levels in a mixed forest stand and found a strong negative correlation between SMA-derived green needle fraction and field-measured budworm population ($r = -0.94$). With SMA and 0.5-m-resolution multispectral imagery, Goodwin et al. (2005) quantified the fractional abundance of three endmembers: sunlit canopy, shadow, and soil. Their results suggested a possibility of using the sunlit canopy image fraction to describe crown/leader color in the forests affected by damaging agents. When it comes to classifying hyperspectral imagery, the high spectral noises in data often challenge the performance of classifiers. To address the issue when using HyMap imagery, Hatala et al. (2010) employed the mixture-tuned matched-filter algorithm, an improved SMA through maximizing the target response and minimizing background spectral signatures, to classify whitebark pine stress and mortality.

8.4.3 Statistical Regression

Statistical regression analysis allows practitioners to estimate not only the discrete stages of forest disturbances (e.g., damaged vs. healthy) but also continuous defoliation or tree mortality levels from none to 100%. Compared to most classification methods, regression has the capacity to demonstrate the significance of the selected explanatory variables derived from remote sensing imagery. Such information can inform sustainable forest management, for example, predicting forest vulnerability in response to disease or insect attacks.

Logistic regression has been shown as a simple solution for identifying forest status of being damaged or not. For example, this model was applied to estimate an outbreak of black-headed budworm in Western Newfoundland, Canada, with a proven success to distinguish susceptible trees from those that were not (Luther et al. 1997). However, such analysis may not be sufficient for developing effective mitigation strategies. Researchers have expressed higher interests in understanding the detailed (i.e., continuous) tree damage levels. To do so, classic multiple linear regression was widely used to link remote sensing–derived metrics (e.g., spectral bands, spectral indices, and topographic variables) with field-measured damage indicators, such as defoliation intensity (de Beurs and Townsend 2008; Pontius et al. 2008), basal area (Siderhurst et al. 2010), leaf area index (Solberg et al. 2006), foliar nitrogen and plant growth vigor (McNeil et al. 2007), concentration of total chlorophyll (Cheng et al. 2010), and leaf water content (Cheng et al. 2010). Their studies also indicated the suitability of applying multiple regression to analyze a wide range of remote sensing data types (e.g., MODIS, Landsat, lidar, and the hyperspectral).

Recent sensor development has increased image spectral resolution and extended the coverage of data spectral range. However, this poses a challenge to regression modeling, that is, high dimensionality and collinearity of remotely sensed explanatory variables. To address this issue, Verbesselt et al. (2009) applied the least absolute shrinkage and selection operator (LASSO) to model bark beetle–induced tree mortality in *Pinus radiata* plantations. Compared to the standard data fitting method of least squares, LASSO is an alternative regularized version to minimizing the residual sum of squares "under a constraint on the sum of the absolute values of regression coefficient estimates" (Verbesselt et al. 2009). Another solution is partial least squares regression (also known as projection to latent structures), which finds new hyperplanes for minimizing the variance between impendent and dependent variables (Geladi and Kowalski 1986). Researchers have confirmed its effectiveness of mitigating the variable multicollinearity effects in studying insect-caused forest damage (Oumar and Mutanga 2014; Oumar et al. 2013; Wolter et al. 2008).

The aforementioned regression models are considered as fixed effects, that is, treating all the variables as nonrandom. However, Rullán-Silva et al. (2015) argued that a mixed-effects model, containing both fixed and random effects, is more appropriate for estimating the percentage of defoliation caused by beech leaf-miner weevil. The addition of random effects to a fixed-effects model was found to better account for the variability possibly introduced by environmental uncertainties (Rullán-Silva et al. 2015). While the mixed-effects models are relatively new to the field of remote sensing, we note that their merits have been increasingly recognized in forest ecology (Bolker et al. 2009).

8.4.4 Change Detection

Change detection employs multitemporal imagery (i.e., time series data) to measure the spatial patterns of forest disturbances through time. In contrast with using single-date imagery to identify damaged trees, this approach analyzes shifts in spectral reflectance across multiple dates. Accordingly, extra considerations are required to deal with spectral variation through time that arises from both forest disturbances and differences in atmospheric conditions and the sun–view–tree geometries (Chen et al. 2011; Song et al. 2001).

Previous efforts showed two ways of conducting change detection. First, the spectral discrepancies between multidate images are calculated through differencing the same spectral bands or indices from the base year (before disturbance) and the disturbance year(s). This is followed by applying thresholding, statistical regression, or classification to extract the pixels containing higher spectral variation (indicating damaged trees) than the others (e.g., de Beurs and Townsend 2008; Townsend et al. 2012; Wulder et al. 2008). Second, change detection focuses on measuring forest damage directly through all the spectral bands or indices. For example, Babst et al. (2010) applied principal component analysis to transfer multidate NDVI images (derived from Landsat time series) into new principal components. They discovered that the second principal component contained crucial information representing the change of NDVI, which was correlated with the level of defoliation caused by autumnal moth. Additionally, because the spectral discrepancies among the Landsat time series include both real and noisy false changes, Kennedy et al. (2010) developed a LandTrendr temporal segmentation algorithm to capture only the salient features of the trajectory (representing real changes) using a multilevel model fitting strategy. This algorithm was employed by Meigs et al. (2011) to successfully characterize the impacts of bark beetle on tree mortality.

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8.4.5 Additional Approaches

In addition to the aforementioned mainstream methods, several other algorithms have been developed for unique considerations in disease and insect monitoring. For example, the occurrence of tree dieback is associated with specific forest environmental factors (e.g., distance from hosts to target trees; Kelly and Meentemeyer 2002). Liu et al. (2006) modeled such ecological compatibility with Markov random field, which was used to refine the results from a noncontextual SVM classification.

To deal with nontraditional data types, such as lidar for characterizing forest 3D structure (Chen and Hay 2011; Lim et al. 2003), Zhang (2008) applied mathematical morphology to process lidar point clouds for identifying small gaps in mangrove forests owing to natural disturbances, including the outbreaks of insects. Bright et al. (2012) employed lidar to estimate forest aboveground carbon. When integrated with the beetle-caused tree mortality map from an MLC classification, the carbon storage map was able to clearly reveal the impact of insect severity on forest carbon loss.

8.5 CHALLENGES AND OPPORTUNITIES

Advancements in remote sensing data acquisition and analysis have remarkably improved the feasibility of assessing landscape-scale forest disturbances induced by diseases or insects. However, challenges remain. In this section, we identify some of those challenges and suggest potential solutions.

8.5.1 Early Warning of Forest Damage

Forests that are infected by diseases or insects do not die instantly. The detection of early stage forest damage offers forest managers an opportunity to perform efficient disease and insect control. During this stage, the infected trees may only show a slight decline in chlorophyll levels and leaf water content. Previous efforts have confirmed the potential of applying hyperspectral remote sensing to assist with early detection of tree stress (e.g., Fassnacht et al. 2014; Pu et al. 2008). However, most of the sensors were mounted on airborne platforms (e.g., CASI, HyMap, and AVIRIS), making data acquisition an expensive process. To date, only a few satellite sensors (e.g., EO-1 Hyperion) are operational, although their application has been restrained because of limited spatial coverage and high spectral noises. To address the challenge, developing Landsat-like hyperspectral sensors is a promising solution. For example, NASA's hyperspectral infrared imager (HyspIRI) mission will mount two instruments on a satellite in low Earth orbit. Once launched, HyspIRI will deliver global coverage hyperspectral imagery at the 10-nm spectral resolution from the visible, short-wave infrared range to the thermal infrared range (NASA 2015). Another potential solution is to assemble a small, inexpensive hyperspectral unmanned aircraft system (UAS; see a recent review by Pajares [2015]). While such a system still has small spatial coverage, its highly operational flexibility combined with a proper sampling strategy makes early warning feasible. One limitation, however, is the obligation to meet UAS regulations and policies that may vary considerably from region to region.

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8.5.2 Consistent Monitoring of Long-Term, Historical Forest Damage

While several remote sensing programs (e.g., AVHRR, Landsat, or SPOT) have been operational for three to four decades, many new types of sensors appeared only recently, such as those featuring high spatial resolution, hyperspectral resolution, and the ability to characterize forest 3D structure. These new sensors do have a higher capacity to detect forest stress and mortality; however, their data archives often have limited temporal and spatial coverage. This poses a challenge for consistently monitoring the long-term, historical impacts of diseases and insects on forests. One dilemma facing many researchers is that the study area was only partially covered by the data acquired from high-performance sensors for limited periods. Choosing the data that have full coverage (e.g., Landsat) can be one solution, while combining data from multiple sensors can be another solution (e.g., using Landsat data to fill in the gaps that lack hyperspectral imagery). In the latter case, the developed algorithms should have the capacity to accommodate varying types of remote sensing data across spatial, spectral, and temporal scales, so that all the results can be compared using consistent criteria.

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8.5.3 Differentiating among Compound Disturbances

Forests are a natural ecosystem. The disturbances affecting the same forested regions may come from a range of sources. Besides insect and disease, other natural disasters (e.g., wildfire and wind) or anthropogenic activities (e.g., logging) can lead to compound disturbances. It is also possible that one disturbance regime (e.g., wildfire) may influence forest responses to another disturbance (e.g., disease), resulting in interacting disturbances (Turner 2010). Recent remote sensing studies have been limited on the topic of differentiating between disease-/insect-caused forest damage and other types of damage. One major challenge is that single sensors are typically not suitable to complete this task. For example, in a study of estimating burn severity in a forest that had experienced pre-fire disease outbreaks, Chen et al. (2015b) found similar spectral reflectance in burned and diseased trees using Landsat imagery. Therefore, a likely solution is the development of a multisensor approach, taking advantage of the strengths from individual sensors, for example, Landsat time series for temporal analysis of disease and insect progression, hyperspectral imaging for tracking the early signs of forest damage, and lidar for assessing the change in forest vertical profiles. Data integration maximizes practitioners' ability to estimate changes in forest biophysical and biochemical parameters, augmenting accurate assessments of forest damage.

8.6 CONCLUSION

Global forest ecosystems face high frequencies of landscape-level disturbances resulting from disease and insect epidemics. Over the past decades, remote sensing tools have improved detection of forest disturbances in a timely and cost-effective manner. As sensor technologies advance, richer Earth observation data with higher spatial, spectral, and temporal resolutions are expected to offer better choices to assess varying stages of disease/insect invasion in a range of forest biomes.

Accordingly, algorithms for modeling spectra–disturbance relationships will need to be continually refined or redeveloped to take advantage of new data and novel landscape changes caused by nonnative, invasive pathogens and insects.

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