Title: Remote sensing of forest insect disturbances: current state and future directions

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Abstract: Insect disturbance are important agents of change in forest ecosystems around the globe, yet their spatial and temporal distribution and dynamics are not well understood. Remote sensing has gained much attention in mapping and understanding insect outbreak dynamics. Consequently, we here review the current literature on the remote sensing of insect disturbances. We suggest to group studies into three insect types: bark beetles, broadleaved defoliators, and coniferous defoliator. By so doing, we systematically compare the sensors and methods used for mapping insect disturbances within and across insect types. Results suggest that there are substantial differences between methods used for mapping bark beetles and defoliators, and between methods used for mapping broadleaved and coniferous defoliators. Following from this, we highlight approaches that are particularly suited for each insect type. Finally, we conclude by highlighting future research directions for remote sensing of insect disturbances. In particular, we suggest to: 1) Separate insect disturbances from other agents; 2) Extend the spatial and temporal domain of analysis; 3) Make use of dense time series; 4) Operationalize near-real time monitoring of insect disturbances; 5) Identify insect disturbances in the context of coupled human-natural systems; and 6) Improve reference data for assessing insect disturbances. Since the remote sensing of insect disturbances has gained much interest beyond the remote sensing community recently, the future developments identified here will help integrating remote sensing products into operational forest management. Furthermore, an improved spatiotemporal quantification of insect disturbances will support an inclusion of these processes in regional to global ecosystem model.

Keywords: Insect disturbance; Biotic disturbance; Bark beetle; Defoliation; Forest health; Insect outbreak

1. Introduction

Disturbances by insects are natural processes in forest ecosystems and an integral driver of their dynamics, helping to maintain healthy and heterogeneous forests that can provide important ecosystem services (Raffa et al. 2009). However, many forest ecosystems have experienced an increase in the rate, magnitude and frequency of insect disturbances, with recent disturbance activity considerably exceeding levels known from 20th century experience (Millar and Stephenson 2015). This raised concerns regarding the impact of insect disturbances on biogeochemical cycles (Edburg et al. 2012), especially the carbon cycle (Kurz et al. 2008; Seidl et al. 2014), biodiversity (Beudert et al. 2015; Müller et al. 2008), and the economic value of forests (Dale et al. 2001). Despite the importance of forest insects for tree mortality globally, there is a lack of consistent data sets tracking insect disturbances systematically through space and time (Kautz et al. 2016). This data gap substantially hampers the development of process-based models for making informed prediction of potential future changes under global climate change, and thus the development of adequate management strategies (Kautz et al. 2016; Seidl et al. 2011).

Forest insects can be broadly grouped into xylophagous (e.g. bark beetles) and folivorous insects (e.g. defoliators). There exist also smaller groups of mucivores insect (fluid-feeders), though we do not focus on those here as they are less important in most forest ecosystems. Many bark beetle species of importance in the context of forest disturbance regimes reproduce in the phloem tissue of live and dead trees and – through introduction of associated fungal pathogens – disrupt the translocation of water and nutrients within the tree. A successful infestation of bark beetles can thus be mortal for trees (Raffa and Berryman 1983). Defoliating insects feed on the needles or leaves of trees, essentially impacting the trees capacity to perform photosynthesis. This can lead to growth reduction, deformation, and – in conjunction with secondary pressures such as simultaneous bark beetle attacks or drought – tree mortality (Cooke et al. 2007). However, after the collapse of defoliator populations

trees usually resprout in the following year, or – in the case of some broadleaved tree species – even in the same year.

Insect disturbances act at varying spatial and temporal scales that all need to be considered to develop a holistic understanding of their dynamics, and subsequently predict their future changes (Raffa et al. 2008). While much research has utilized laboratory and field data to understand the drivers of host colonization by insects and their reproductive success, those small-scale drivers are often not sufficient for predicting the landscape- to regional-scale infestation patterns observed in recent outbreaks (Seidl et al. 2015; Senf et al. 2017; Simard et al. 2012). Hence, besides tree- and stand-scale factors, it is also important to understand how insect populations interact with their surrounding landscape, as well as with regional-scale climate. Tackling those larger-scale processes requires data that a) are spatially explicit, b) cover large geographic extents, c) deliver a temporal resolution that fits the life-cycle of the insect of interest, and d) allows for assessing long time series to capture the long-term natural fluctuations that are inherent to insect dynamics. While dendroecology and long-term ecological monitoring allow for an extensive historical view on insect disturbances over relatively large geographic extents (Swetnam and Lynch 1993), they do not offer the spatially explicit perspective needed for understanding the patterns and interactions of insect outbreaks at the landscape scale. Furthermore, the finest temporal resolution that can be consistently obtained from dendroecological investigations is often only in the range of decades, and an attribution to specific disturbance agents remains challenging (e.g., Janda et al. 2016). Remote sensing largely fulfills all the above-mentioned criteria and serves as a powerful approach to study insect outbreaks across large areas at high spatial and temporal resolution (McDowell et al. 2015; Trumbore et al. 2015).

The biological differences between bark beetles, defoliators of coniferous trees, and defoliators of broadleaved trees explained above suggest that there are specific advantages and disadvantages of applying particular remote sensing methods for mapping their

occurrence and infestation severity. However, even though there exist reviews from a regional perspective (Hall et al. 2016), focussing on specific insect types (Rullan-Silva et al. 2013; Wulder et al. 2006a), or general forest health decline (Lausch et al. 2016), we yet lack a systematic, comprehensive, and global assessment of the methods best suited for the remote sensing of varying forest insect agents. A systematic review of the methods applied, and a better understanding of their underlying biological and ecological processes, will help to improve future studies that aim at mapping and estimating insect disturbances. Consequently, we systematically reviewed the approaches employed in the remote sensing of forest insect disturbances, specifically addressing the following three questions:

1) What are the insect types, species, and biomes that have been studied using remote sensing?

2) What are the methods best suited for mapping disturbances from bark beetles, defoliators of coniferous trees, and defoliators of broadleaved trees?

3) What are the challenges for current remote sensing approaches, and how can they be overcome in the future?

We first present a systematic literature review to answer research questions 1 and 2.

Subsequently, using a more qualitative approach, we synthesize the results of the systematic review to address research question 3.

2. Systematic literature review

2.1 Database search

For obtaining an initial sample of the relevant literature we searched the *ISI Web of Science* database (<http://www.webofknowledge.com/>) with general search terms focussing on the mapping of forest insect disturbances by remote sensing, using the following search string: TS = (bark beetle* OR defoliator* OR insect* OR pest*) AND TS = (forest* OR tree*) AND TS

= (remote sensing OR remotely sensed OR mapping OR satellite* OR earth observation*)¹.

This initial search led to a total of n=868 studies. We screened the titles and abstracts of those studies to exclude studies obviously unrelated to our review (e.g., medical studies, studies using remote sensing for guiding field work, simulation studies), which decreased the total number of studies to 149. For those studies, we downloaded the full text for further screening. We subsequently analyzed each study by the following criteria set for the inclusion in our review:

- A specific insect agent must be defined. Studies mapping general forest decline or change due to multiple agents were not considered.
- A map was produced or could easily be produced with the methods described in the paper. Experimental studies limited to a few selected pixels or simulation studies were excluded.
- Studies mapping infestations in plantations or orchards were not considered.
- Approaches must be (semi-) automatic. Studies applying manual digitalisation of remote sensing data or manual mapping from aircrafts (aerial surveys or sketch maps) were not considered.

After applying these criteria, a total of 59 studies were selected for inclusion in the analysis. However, we noted that 16 studies that were initially not included in our sample were frequently cited in other studies considered in our review. After checking them against the above described criteria, we also added those studies to our literature base, yielding a final number of n=75 studies to be included in the systematic review.

2.2 Information extraction and analysis

For each study in the sample, we extracted the same set of attributes for analysis (Table 1). In particular, we noted the insect type (i.e., bark beetle, defoliator coniferous, defoliator

¹ TS = Topic search, including title, abstract, and author keywords. Asterisks (*) are wildcards for any type and number or character.

broadleaved), the insect species, if the species was native to the ecosystem studied, and its primary host species. Furthermore, we recorded the response variable and how reference data was collected, as well as the location of the study area. To characterize the sensor used in each study, we recorded the sensor name, the spatial, temporal, and spectral properties of the sensor, as well as the sensor. Finally, we noted the classification/regression model used for mapping/estimating infestation, if a fitting technique was applied (for temporal smoothing, etc.), if auxiliary data was used in the model, as well as the measure of accuracy/model performance and the level of accuracy/model performance obtained. For a detailed description of the attributes see Table 1.

[Table 1 approximately here]

After extracting the information for each study included in our analysis, we first mapped and visualized the spatial and temporal distribution of studies and insect types. Moreover, we extracted the biome the study site was located in using the biome classification by Olson et al. (2001). We created statistical summaries of all sensor attributes and methods applied to study insect disturbances, grouped by the four insect types. Finally, we investigated the distributions of accuracies achieved when mapping/estimating disturbances. While many different measures are used in the literature for estimating accuracy/model performance, we here focused on overall accuracy as measure of map accuracy and the coefficient of determination (R^2 or pseudo- R^2) as measure of model performance.

2.3. Results of the systematic review

2.3.1 Insect types and biomes

In total, there were 27 insect species studied using remote sensing, of which five were non-native (Table 2). Most studies were located in North America and Europe, whereby the European studies clustered either in the boreal biome or in selected sites in mountainous environments (Fig. 1; Table 3). There was only one study located in South America, Australia, and Africa, respectively; and only few studies were located in Asia. Bark beetles

and broadleaved defoliators were mostly studied in temperate forest ecosystems, while coniferous defoliators were mostly studied in the boreal forests (Table 3). Very few studies (7%) were located in the subtropical region and no study was located in the tropics. From a historic perspective, remote sensing was mostly used from 2003 onwards for mapping insect disturbances, with a substantial increase in recent years (Fig. 2). While early studies nearly exclusively mapped defoliating insects, the recent increase in remote sensing-based studies of forest insect disturbances was largely related to studies mapping the bark beetle *Dendroctonus ponderosae* in North America.

[Figure 1 approximately here]

[Figure 2 approximately here]

[Table 2 approximately here]

[Table 3 approximately here]

2.3.2 Sensors and methods

While a variety of sensors were used to study forest insect disturbances (Table 4), Landsat was by far the most widely applied data source for mapping insect disturbances. A total of 13% of the studies used coarse resolution data (thereof 75% MODIS), 57% of the studies used medium resolution data (thereof 83% Landsat), 15% of the studies used high resolution data (most frequent: HyMap, QuickBird, RadpidEye, and WorldView-2), and another 15% of the studies used very high resolution data (including Lidar, which accounted for 7% of the total number of studies). Coarse resolution data (i.e., MODIS) was mainly used for mapping the effect of defoliators, and only a single study applied it for mapping bark beetle disturbances (Fig. 3A). Medium resolution data was used equally across all insect types, while high resolution data was particularly used for mapping the effects of bark beetles (Fig. 3A).

[Figure 3 approximately here]

Differences between insect types were also evident in the spectral properties of sensors. The majority of studies mapping defoliation of broadleaved and coniferous trees used a single

spectral index (82% and 50%, respectively). The most frequently used spectral index for mapping broadleaved defoliation was the Normalized Difference Vegetation Index (NDVI; 43%), while a variety of indices was used for mapping coniferous defoliation (NDVI, Normalized Burn Ratio [NBR], Moisture Stress Index [MSI], Leave Area Index [LAI]). For mapping bark beetle disturbances, studies mostly relied on multi-spectral data (47%), though 29% of the studies also used single spectral indices. The most frequently used spectral index for mapping the effects of bark beetles was the difference in the Tasseled Cap Wetness component (Enhanced Wetness Difference Index [EWDI]), followed by the NBR and Disturbance Index (DI). Only 12% of the studies mapping bark beetle disturbances used Lidar data, and another 10% used hyperspectral imagery. Interestingly, hyperspectral data was neither used in the context of broadleaved nor coniferous defoliators, and Lidar was only used in one study on coniferous defoliators.

In terms of temporal resolution our analysis showed that very dense time series (i.e., more than one image per year) were mainly used for mapping defoliation, especially of broadleaved trees (Fig. 3). Multi-date information was used throughout for all insect types with few studies mapping bark beetle disturbances and coniferous defoliation from dense (i.e., annual) time series. Single-date data was used in more than 50% of the studies mapping the effect of bark beetles, though was less commonly used for mapping defoliation. Time series fitting techniques were either used with very dense MODIS time series data (i.e., TIMESAT; Joensson and Eklundh (2004)) or annual Landsat time series (i.e., LandTrendr; Kennedy et al. (2010)). Only one study used a fusion approach (Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model; Zhu et al. (2010)), combining very dense and multi-date time series.

Studies mapping disturbance occurrence and severity were nearly equally distributed in the literature (55% and 46%, respectively), with only minor differences between insect types. For studies mapping bark beetle infestation severity, the most frequently used measures were

percent mortality, percent dead stems, and percent basal area mortality. For coniferous defoliators, severity was mostly measured in categories (i.e., three to five levels of defoliation intensity), while for broadleaved forests defoliation severity was mostly measured as percent canopy loss.

As for calibration and validation data, most of the studies utilized field data (55%), followed by interpretation of very high resolution remote sensing data (28%). Interestingly, VHR data interpretation was more often used in the case of bark beetles than for mapping defoliators. The remaining studies either used aerial overview survey (AOS) maps (8%), medium resolution image or time series interpretation (6%), helicopter surveys (4%), or Lidar (2%) as reference data.

The majority of studies mapping disturbance occurrence used classification models such as random forest (20%), maximum likelihood (14%), or (logistic) regression (12%). However, one quarter (25%) of the studies mapping disturbance occurrence relied on a simple rule-based approach (Table 5). Studies estimating the severity of infestation most frequently used statistical regression models (37%), followed by random forest regression (19%), and rule based approaches that classify a continuous measure into severity classes (12%).

Mapping accuracies did not show any substantial differences between the three insect types, with overall accuracies ranging from 60 to >90% (Fig. 4a). For estimating disturbance severity, however, higher modeling performance was found for defoliators than for bark beetles (Fig. 4b).

[Figure 4 approximately here]

3. Current approaches in the remote sensing of forest insect disturbances

3.1 Bark beetles

Landsat is currently the most prominent sensor for mapping bark beetle disturbances, suggesting that spatial resolution is a key feature for mapping bark beetle infestation. Indeed, the high number of studies employing sub-pixel approaches (i.e., mapping infestation

severity) and using high and very-high resolution data for analyzing bark beetle disturbances further support this conclusion. Landsat also delivers continuous observations over several years, which in turn allows to monitor outbreaks of bark beetles, which often last several years (Meigs et al. 2015b).

From a spectral perspective, our results show that spectral information from the short-wave infrared range of the electromagnetic spectrum is of particular importance for detecting bark beetle infestations, likely due to the sensitivity of this spectral region to changes in needle water content. Changes in the needle water content allow for an accurate detection of trees turning red (red-attack stage) and grey (grey-attack stage) in the wake of an infestation (Skakun et al. 2003; Wulder et al. 2006a).

Studies increasingly rely on multi-date time series of medium resolution data to capture changes in the spectral signal associated with changes in the needle water content (Goodwin et al. 2008; Meddens et al. 2013). With high and very-high spatial resolution data, however, the analysis of single-date images is still the norm (e.g., Hicke and Logan 2009; Pontius et al. 2008). Following the opening of the USGS Landsat Archive in 2008 (Wulder et al. 2012), the use of dense (i.e., annual) time series became more prominent (e.g., Meddens and Hicke 2014; Meigs et al. 2011). Using dense time series of Landsat data allows for an annual analysis of bark beetle disturbances, which delivers detailed information on the spatial and temporal patterns of outbreaks (Meigs et al. 2015b). Very dense time series (i.e., intra-annual) are rarely used for mapping bark beetle infestations, suggesting that the intra-annual variation in the spectral signal is less important in this context, and does not counterbalance the loss of spatial information that comes with current high frequency, coarse resolution sensors (i.e., MODIS or AVHRR).

Finally, we found that field plots and image interpretation (i.e., airborne very-high resolution data) were the primary sources of reference data for mapping bark beetle disturbances. While studies utilizing field data mostly measured mortality as percent basal

area killed or number of trees killed (e.g., Bright et al. 2014; Meigs et al. 2015b), very-high resolution data interpretation was mostly used for estimating a sub-pixel fraction of mortality (i.e., percent of Landsat pixel infested; e.g., Meddens and Hicke (2014)). Moreover, there were differences between studies mapping infestation in early stages (red-attack) and later stages (grey-attack). Some studies even aimed at mapping very early infestation stages (green-attack) with the aim of providing decision support for risk management actions (Fassnacht et al. 2012).

3.2 Coniferous defoliators

The majority of studies mapping disturbances of coniferous trees by defoliators used medium resolution data, with Landsat and SPOT being the most prominent sensors (e.g., Franklin et al. 2008; Olsson et al. 2012; Sangüesa-Barreda et al. 2014). While older works employed supervised classification of single-date multi-spectral data (e.g., Franklin et al. 1995; Luther et al. 1997), more recent studies almost exclusively relied on comparing one vegetation index between two or more dates in time to track vegetation changes caused by defoliation (Meigs et al. 2011; Meigs et al. 2015b; Olsson et al. 2012; Sangüesa-Barreda et al. 2014; Senf et al. 2015). A wide variety of vegetation indices was used that all made use of the near-infrared and shortwave-infrared bands. Changes in those bands can detect chlorosis and structural changes in the canopy caused by insect defoliation, but the relationship between coniferous insect defoliation and the corresponding spectral responses is poorer understood than for bark beetles (Senf et al. 2015).

Coniferous defoliation was often associated with decrease in one or several spectral indices that lasted over several years, highlighting that coniferous defoliation is a gradual process (Vogelmann et al. 2009). Indeed, there is evidence that disturbances by coniferous defoliators are on average longer in duration than disturbances by bark beetles, with the latter resulting in tree mortality within a few years (Meigs et al. 2011; Wulder et al. 2006a). Nonetheless, also very dense time series information – i.e., intra-annual variation in the

spectral signal – were used to map coniferous defoliators, although with mixed results (Eklundh et al. 2009; Olsson et al. 2016a). While defoliation was indeed visible in the intra-annual changes of vegetation index time series, the spatial resolution of the underlying time series data (MODIS) limits the applicability in heterogeneous landscapes. Nonetheless, dense time series information could enhance the detectability of defoliation by delivering spectral information from peak feeding periods within the year, where differences between infested and un-infested forests are largest (Fraser and Latifovic 2005).

A feature that was outstanding for mapping coniferous defoliation was the frequent use of severity categories (i.e., trace, low, medium, strong defoliation) instead of a measurable unit of insect impact (as with bark beetles and broadleaved defoliators). A reason for this might be the fact that measuring long-term (i.e., over several years) needle loss caused by defoliation is challenging and cost-intensive (Långström and Hellqvist 2004), in particular compared to assessing deadwood (as with bark-beetles) or loss in foliage within one year (as with most broadleaved defoliators).

3.3 Broadleaved defoliators

Medium and coarse spatial resolution sensors were most frequently used for mapping broadleaved defoliation, and many studies employed intra-annual time series analysis for analyzing these data sets (Olsson et al. 2016b; Townsend et al. 2012). This suggests that for mapping the impact of broadleaved defoliators the intra-annual variation in the spectral signal is of particular importance. Several studies show that a denser time series improves the detectability of broadleaved defoliators, because most broadleaved trees are able to resprout in the same year of the disturbance (De Beurs and Townsend 2008; Gartner et al. 2016; Spruce et al. 2011). Denser time series thus result in a higher chance of obtaining a cloud free observation during the short period of maximum defoliation. In the context of broadleaved defoliators, higher temporal resolution thus seems to compensate for coarser spatial resolution of the applied sensors. However, there were also studies using Landsat intra-annual spectral

variability (Townsend et al. 2012) or fused products of varying sensors (Gartner et al. 2016) to overcome spatial limitations of coarser spatial resolution data.

We found that most studies using very dense time series for mapping broadleaved defoliation only used a single spectral index instead of multi-spectral data. This finding might suggest that the use of very dense time series hampers the use of multi-spectral information with current algorithms. Interestingly, most studies mapping broadleaved defoliation used near-infrared based indices, which clearly contrasts with studies mapping bark beetle infestation and coniferous defoliation. This finding suggests that changes in leaf area are more important for detecting broadleaved defoliation than changes in water content and changes in the overall canopy structure. Consequently, reference data for measuring broadleaved defoliation severity mostly included field data that measured the loss in leaf area (e.g., Hall et al. 2003; Rullan-Silva et al. 2015; Townsend et al. 2012).

4. Challenges and ways forward

4.1 Separate insect disturbances from other agents

Forest insects are often not the only disturbance agent present in a forest ecosystem. In order to map insect disturbances and estimate their severity it is thus necessary to discriminate between insect and other disturbance agents, a step that is largely neglected in the current literature. Most studies assessed here either simply assumed that all spectral anomalies found in their analysis related to one particular insect agent (e.g., based on local knowledge of the authors), or they used existing masks (i.e., harvest masks, forest type masks) to exclude areas unlikely to be affected by the insect in focus. While those approaches are common in remote sensing studies, they result in an overestimation of the true mapping accuracy, since the accuracies reported in the studies often apply only to a subpopulation of the map (e.g., all coniferous forest pixels). Several studies thus explicitly separated insect disturbances from other agents such as fire or harvest, which often have a substantially different spectral behaviour (e.g., Goodwin et al. 2008; Meigs et al. 2015b; Senf et al. 2015). However, insect

disturbances are often triggered by other disturbances – bark-beetle outbreaks following blowdown (Seidl and Rammer 2016) or defoliation following drought (Senf et al. 2016) – which can make a clear distinction between different disturbance agents challenging. In particular, clusters of small-scale disturbances might result in pixels spectrally mixed between both disturbance agents (i.e., bark beetle at the edge of blowdowns), or one disturbance might transition into another disturbance, leading to a single decrease in spectral signals (i.e., drought triggering subsequent defoliation). Hence, a potential improvement of current approaches would be to improve the discriminatory power between insect disturbances and unrelated other disturbance agents (i.e., fire, harvest, flood, avalanches), while simultaneously acknowledging that insect disturbances often interact with each other and might thus not be separable from other disturbances (i.e., blowdown, drought).

Separating insect disturbances from other disturbances is challenging, though there has been substantial improvement in recent years (Hermosilla et al. 2015; Kennedy et al. 2015). Specifically, the use of spectral-temporal information has emerged as particularly important for separating varying disturbance agents in general and insect agents in particular. Spectral characteristics include the magnitude of change (i.e., the absolute or relative change in a vegetation index or spectral band) and the spectral signature of change (i.e., how changes manifest in a multi-spectral feature space). Spectral characteristics can be derived from single- and multi-date approaches, as well as from dense and very dense time series. Temporal characteristics, however, which describe the duration of an event, can solely be quantified from dense, that is annual or intra-annual, time series. Duration was found important in a variety of studies separating insect disturbances from other disturbance agents (Kennedy et al. 2012; Meigs et al. 2015a). Finally, there is recent evidence that spatial characteristics, that is the size and shape of disturbances patches, might deliver important information for separating disturbance agents (Hermosilla et al. 2015).

A fourth information stream that yet has seldom been utilized for discriminating insect disturbances from other disturbance agents is information on the intra-annual timing of a disturbance. The intra-annual timing – i.e., information of when a disturbance occurred within a year – might contain important information on the underlying agent of change. For example, blowdown from cyclonal storm systems mostly occurs in winter in Europe’s forests, while bark beetle infestation reaches its maximum in spring and summer. Such approaches will become more feasible with an increasing available of temporally dense medium resolution image time series (Zhu et al. 2012). They could further be facilitated by using fused products between, e.g., Landsat and MODIS (Hilker et al. 2011).

4.2 Extend the spatial and temporal domain of analysis

Many studies analyzed here were limited to single watersheds, protected areas, or other geographically distinct landscape units. Only very few studies mapped insect disturbances over larger geographic gradients, covering several climatic and or biogeographic regions (e.g., Meigs et al. 2015b; Senf et al. 2015). Such large-scale assessments are, however, crucial for a better understanding of the impacts of forest disturbances at landscape and regional scales (Hicke et al. 2012; Kautz et al. 2016). Thus, while localized case studies often result in very detailed maps of insect infestation that are useful for forest management (e.g., Lausch et al. 2013; Olsson et al. 2012), large scale mapping approaches could yield important scientific insights (Kautz et al. 2016; Trumbore et al. 2015). Remote sensing has proven to be operational for mapping harvest and fire disturbances over very large geographic extents (Hermosilla et al. 2016) and computational resources are now available to conduct landscape to regional scale assessments of forest insect disturbances. Currently, a limiting factor is the transferability of approaches developed for specific case studies and/or specific agents to a wider geographic extent. Improving the generalizability and transferability of existing approaches will thus help in conducting regional to global assessments of forest insect disturbances.

Remote sensing offers a consistent insight over several decades into forest disturbances, and can thus shed light on outbreaks that would otherwise be poorly documented (Assal et al. 2014). Landsat data was most often used for historic assessments of insect disturbances (± 30 years of data). However, only few studies have made use of the full potential by integrating Landsat MSS to date (Assal et al. 2014; Pflugmacher et al. 2012). Integrating Landsat MSS, and thus extending the time series to 40+ years, might substantially improve our understanding of insect disturbance dynamics. In particular, a longer time series of spectral observations would allow to cover several outbreak cycles and thus increase our ability to test hypothesis on underlying drivers (Senf et al. 2016).

4.3 Make use of dense time series

Our systematic review revealed that for mapping defoliators – in particular broadleaved defoliators – a high intra-annual data availability is advantageous for reliably estimating infestation occurrence and severity. However, we also found that this requirement is currently only fulfilled by coarse-resolution sensors, such as MODIS, that have important drawbacks resulting from their spatial resolution (e.g., in the highly heterogeneous landscapes of Central Europe). Consequently, mapping defoliation might be significantly improved by increasing intra-annual data availability for medium- and high-spatial resolution sensors. An important development in this regard is the recent launch of Sentinel-2, which has a 10- to 20-meter spatial resolution and a ten-day revisit time (five days when combining Sentinel-2a/b). Different resolution sensors can also be combined into one data stream to further increase data availability (Wulder et al. 2015). However, those approaches limit analyses to recent years, where dense time series of varying sensors are available, and thus preclude the historic perspective offered by, e.g., the Landsat sensor family.

Furthermore, based on our synthesis of the literature the timing of image acquisition within the year can substantially influence the detectability of defoliation. This finding likely also applies to bark beetle disturbances, which are best detected by using observations from

late summer that allow for detecting most of the spring infestations and still steer clear of the regular needle loss that happens in fall. Hence, utilizing the timing of image acquisition in the context of the respective insect agent and vegetation phenology would further enhance the detectability and attribution of insect infestations. This might be particularly important for ephemeral disturbances and ecosystems with very high recovery rates. Insights on optimal dates for image acquisition can, for instance, be gained from utilizing models of insect populations. For example, De Beurs and Townsend (2008) utilized the BioSIM model (Régnière and Saint-Amant 2014) to model annual population development of gypsy moth and thus to identify the optimal day of image acquisition. Similarly, phenological information can be utilized to identify the optimal image acquisition date in terms of maximum greenness (Frantz et al. 2017), which might increase the separability of infested and uninfested forests (Fraser and Latifovic 2005).

4.4 Operationalize near-real time monitoring of insect disturbances

Satellite images allow for the (near) real-time detection of forest disturbances (Verbesselt et al. 2012). Remote sensing thus can be used as early-warning tool for upcoming large scale insect infestations, since regional outbreaks often emerge from localized epicenters (Seidl et al. 2015; Senf et al. 2017; Simard et al. 2012). However, to date only few studies exist that utilize remote sensing for (near) real-time monitoring of insect disturbances (Olsson et al. 2016b); as well as there are only few operational applications (e.g. <https://forwarn.forestthreats.org/>). Reasons might be the often complex processing steps involved in pre-processing remote sensing data (i.e., radiometric- geometric, and atmospheric corrections; cloud masking), missing ground-truth data, and the often low data availability with medium spatial resolution sensors (Wulder et al. 2009). This also explains why current studies detecting insect infestations in near real-time make exclusive use of MODIS, which is available as a ready-to-use product already shortly after acquisition. Nevertheless, with the recent increase in ready-to-use medium spatial resolution satellite products (i.e., the Landsat

surface reflectance higher-level data products), the potential to combine several medium-resolution sensors into one data stream (Wulder et al. 2015), and the increase in cloud-based processing environments that have many standard disturbance detection algorithms already implemented (e.g., Google Earth Engine), it is likely that the use of medium spatial resolution remote sensing for (near) real-time monitoring of forest insect disturbances will increase significantly in the future. Also, Unmanned Aerial Vehicles (UAVs) might significantly improve rapid assessments of insect disturbances, yet there are only few studies testing the potential of UAVs for insect disturbance mapping (Nasi et al. 2015).

Moreover, remote sensing has been used to assess the susceptibility of forests to insect infestation, which in turn can guide management action to prevent or contain the eruption of large-scale outbreaks. Approaches included the use of hyper-spectral imagery to detect changes in chlorophyll absorption as indicator of tree vigor (Lausch et al. 2013), and using Landsat time series to assess the stress-level of forest stands as an indicator of their susceptibility to bark beetle attacks (Hais et al. 2016). The former approach might be substantially enhanced by the recent development of space-born hyper-spectral instruments such as the Environmental Mapping and Analysis Program (EnMAP) mission (Foerster et al. 2016).

4.5 Identify insect disturbances in coupled human-natural systems

Forests in many parts of the world are coupled human and natural systems, i.e. their dynamics is an emerging property of an integrated and interactive set of social and ecological drivers (Liu et al. 2007). Frequently, forests prone to insect infestation are under active forest management, resulting in human disturbances (i.e., sanitation and/or salvage harvest) superimposing the insect disturbance signal. Hence, it is likely that the spectral properties of insect disturbances in managed forests resemble the spectral properties of harvest or selective logging. As a consequence, studies mapping disturbances in managed forests might often underestimate the true rate of insect disturbance. Overcoming this issue is challenging since it

requires separating between scheduled harvests and salvage/sanitation harvests, which might require incorporating auxiliary data that is not always available (i.e., aerial overview surveys; Schroeder et al. (2012)). Nevertheless, the increased use of dense and very dense time series will support detecting multiple disturbances such as salvage logging following an insect disturbance, and separating between different harvest types (Jarron et al. 2016).

4.6 Improve reference data for assessing insect disturbances

During our systematic review, we found that field data was the major source of reference data for calibrating and validating insect disturbance models. Field data is the ‘gold standard’ in modeling, since it represents exact measurements that depict the true condition on the ground (ground-truthing). However, field data is also costly to acquire, which limits its use over large geographic extents. Some studies therefore made use of existing inventory data that monitor relevant measurements (i.e., changes in basal area deadwood) over time (Meigs et al. 2015b). However, forest inventory data are not consistently available across countries (Gschwantner et al. 2016; Levers et al. 2014; Neumann et al. 2016) and are often difficult to combine with remote sensing data due to mismatch in plot size and spatial resolution of remote sensing sensors. To better integrate existing field and inventory data with remote sensing approaches we suggest two improvements: First, we urge that all researcher publicly archive their field data upon publication (e.g., in archives such as Dryad or Figshare) explicitly include spatial metadata to enable a linkage with remote sensing information. Second, researchers and managers planning new inventories or field campaigns could include considerations of remote sensing in their campaign designs to accrue added value from fusing terrestrial and earth observation data sources in the future.

While field data was overall the most important source of calibration and validation data, the interpretation of very-high spatial resolution imagery was especially important as reference data for mapping bark beetle disturbances. Bark beetle disturbances can be easily delineated in very-high resolution imagery, which makes it an important data source for forest

management (Meddens et al. 2011). Very-high resolution imagery also allows for creating reference data over large geographic extents at relatively low costs (Olofsson et al. 2014). Finally, it also can help scaling field data to medium spatial resolution remote sensing data (Wulder et al. 2004). An increased availability and accessibility of very-high spatial resolution imagery can thus significantly improve the creation of high-quality reference data sets for calibrating remote sensing models of insect disturbances. The often large databases of many governmental agencies hold great potential in this regard (e.g., <https://eros.usgs.gov/aerial-photography> for the US or <http://www.nrcan.gc.ca/earth-sciences/geomatics/satellite-imagery-air-photos/9265> for Canada). However, the data must be made accessible to researchers at low costs.

A relatively new method for acquiring reference data is the use of Landsat spectral trajectories, that is the interpretation of disturbance occurrence and agents using dense Landsat time series and corresponding image chips (see Cohen et al. (2010) for further information). Interpreting Landsat spectral trajectories and image chips though trained interpreters allows for an assessment of forest disturbances at the plot level over very large geographic extents, and was used successfully in various recent studies as tool for obtaining calibration and validation data (Hermosilla et al. 2015; Kennedy et al. 2012; Meigs et al. 2015b; Potapov et al. 2015; Senf et al. 2015). However, while high-severity disturbances such as harvest and fire can be easily identified in spectral trajectories, it is much more challenging to detect the subtle disturbances caused by many insects. The quality of reference data thus varies with disturbance severity and with the density of observations (Cohen et al. 2010).

5. Conclusion

We here presented a systematic review of the literature on the remote sensing of insect disturbances. We found that specific methods and sensors are particular useful for specific types of insect agents – that is bark beetles, defoliators of broadleaved trees, and defoliators of coniferous trees. While our review documents a significant increase in studies mapping insect

disturbances in recent years, we also identified several challenges with current approach. To overcome those challenges, we suggest six areas of improvement:

1. Separate insect disturbances from other agents;
2. Extend the spatial and temporal domain of analysis;
3. Make use of dense time series;
4. Operationalize near-real time monitoring of insect disturbances;
5. Identify insect disturbances in the context of coupled human-natural systems; and
6. Improve reference data for assessing insect disturbances;

Addressing these issues in future studies can help integrating remote sensing-based maps into operational forest management and improving regional to global ecosystem models.

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Table 1: Information extracted from the literature.

Attribute	Possible values	Description
Insect type	BB, DC, DB, Other	Insect type: bark beetle (BB), coniferous defoliator (DC), broadleaved defoliator (DB), fluid feeders, etc. (others)
Insect species	-	Binomial name of the insect species. If more than one species within one genus were mentioned, we only recorded the genus.
Native	Yes, No	Whether the insect species is native to the forest ecosystem studied.
Host species	-	Binomial name of the host species. If more than one species within one genus were mentioned, we only recorded the genus. If more than one host species of varying genera were studied, we only noted the major host.
Response type	Occurrence, Severity	Whether the study mapped solely the occurrence of an infestation or also its severity. If severity was mapped, its unit/ measure was also specified.
Reference data	-	How reference data used for model calibration and validation was collected (i.e., source and method)
Latitude/longitude	-	Location of the study area. If no location was given in the paper, we either used Google Maps to determine the approximate location, or we used the Landsat WRS2 reference system to identify the center location of the Landsat footprint used in the analysis.
Sensor	-	Sensor used. If no sensor was specified the field was left empty.
Platform	Satellite, Air, UAV	The platform of the sensor, that is satellite-borne, air-borne, or un-manned aerial vehicle (UAV)
Spatial properties	CR, MR, HR, VHR	The resolution of the sensors used: coarse resolution: >100m; medium resolution: 10-100m; high resolution: 1-10m; very high resolution: <1m.
Temporal properties	SD, MD, D, VD	The temporal resolution of the data stream: SD = single date; MD = multi date (more than one image but less than annual coverage); D = Dense (annual coverage); VD = Very dense (intra-annual coverage).
Spectral properties	VI, Multi, Hyper, Lidar, SAR	The spectral properties used in the analysis: VI (a single vegetation index or band was used; the index name was noted), Multi (multi-spectral bands or multiple spectral indices were used), Hyper (hyper-spectral bands or multiple narrow-band indices were used), Lidar (Light detection and ranging), and SAR (Synthetic Aperture Radar).

Temporal fitting	-	The algorithm that was used for fitting/smoothing the spectral signal over time. If no such algorithm was used the field was left empty.
Model	-	The model that was used for detecting infestations, and applied to create maps.
Auxiliary	Yes, No	Was auxiliary data (e.g., climate information) used in addition to remote sensing data?
Accuracy measure	-	The measure of accuracy reported in the study. If more than one measure was given, we always preferred overall accuracy over producer's/user's accuracies, and the coefficient of determination (R^2 or pseudo- R^2) over the root mean square error, respectively. If several methods/scenarios were compared, we always extracted the overall highest accuracy achieved.
Accuracy	-	Level of accuracy, according to accuracy measure described above.

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Insect species	Host tree species	Type	Native	#	Source
<i>Acleris variana</i>	<i>Abies balsamea</i>	DC	√	1	Luther et al. (1997)
<i>Adelges tsugae</i>	<i>Tsuga spp.</i> , <i>Tsuga canadensis</i>	Other	–	5	Kantola et al. (2016), Jones et al. (2015), Hanavan et al. (2015), Royle and Lathrop (2002), Royle and Lathrop (1997)
<i>Agrilus planipennis</i>	<i>Fraxius spp.</i>	BB	–	2	Murfitt et al. (2016), Pontius et al. (2008)
<i>Apocheima cinerarius</i>	<i>Populus euphratica</i>	DB	√	1	Gartner et al. (2016)
<i>Choristoneura occidentalis</i>	<i>Pseudotsuga menziesii</i>	DC	√	4	Senf et al. (2015), Meigs et al. (2015b), Meigs et al. (2011), Franklin et al. (1995)
<i>Choristoneura conflictana</i>	<i>Populus tremuloides</i>	DB	√	1	Hall et al. (2003)
<i>Choristoneura fumiferana</i>	<i>Picea spp.</i>	DC	√	2	Franklin et al. (2008), Leckie and Ostaff (1988)
<i>Choristoneura pinus pinus</i>	<i>Pinus banksiana</i>	DC	√	1	Radeloff et al. (1999)
<i>Dendroctonus frontalis</i>	<i>Pinus spp.</i>	BB	√	1	Cook et al. (2007)
<i>Dendroctonus ponderosae</i>	<i>Pinus contorta</i> , <i>Pinus spp.</i> , <i>Pinus albicaulis</i>	BB	√	17	Long and Lawrence (2016), Senf et al. (2015), Meigs et al. (2015b), Assal et al. (2014), Walter and Platt (2013), Meddens et al. (2013), Meigs et al. (2011), Meddens et al. (2011), Hicke and Logan (2009), Wulder et al. (2008), Goodwin et al. (2008), White et al. (2007), Wulder et al. (2006b), Coops et al. (2006), Wulder et al. (2005), Skakun et al. (2003), Franklin et al. (2003)
<i>Dendroctonus pseudotsugae</i>	<i>Pseudotsuga menziesii</i>	BB	√	1	Lawrence and Labus (2003)
<i>Dendroctonus rufipennis</i>	<i>Picea spp.</i> , <i>Picea Engelmannii</i>	BB	√	2	Hart and Veblen (2015), DeRose et al. (2011)
<i>Dendrolimus superas</i>	<i>Pinus sibirica</i>	DC	√	2	Liang et al. (2014), Bright et al. (2014), Bright et al. (2013)
<i>Diprion pini</i>	<i>Pinus sylvestris</i>	DC	√	1	Kharuk et al. (2007), Kharuk et al. (2004)

<i>Epirrita autumnata</i>	<i>Betula pubescens</i>	DB	√	3	Vastaranta et al. (2013)
<i>Gonimbrasia belina</i>	<i>Colophospermum mopane</i>	DB	√	1	Olsson et al. (2016b), Olsson et al. (2016a), Babst et al. (2010)
<i>Ips grandicollis</i>	<i>Pinus radiata</i>	BB	√	1	Adelabu et al. (2014)
<i>Ips typographus</i>	<i>Picea abies</i>	BB	√	10	Verbesselt et al. (2009)
<i>Lambdina fuscicollis</i>	<i>Abies balsamea</i>	DC	√	2	Nasi et al. (2015), Havasova et al. (2015), Nielsen et al. (2014), Latifi et al. (2014b), Latifi et al. (2014a), Immitzer and Atzberger (2014), Fassnacht et al. (2014), Ortiz et al. (2013), Lausch et al. (2013), Fassnacht et al. (2012)
<i>Lymantria dispar</i>	<i>Quercus spp.</i> , among others	DB	–	5	Fraser and Latifovic (2005), Fraser et al. (2005)
<i>Neodiprion sertifer</i>	<i>Pinus sylvestris</i>	DC	√	5	Thayn (2013), Townsend et al. (2012), Spruce et al. (2011), De Beurs and Townsend (2008), Muchoney and Haack (1994)
<i>Operophtera brumata</i>	<i>Betula pubescens</i>	DB	√	1	Olsson et al. (2016a), Gilichinsky et al. (2013), Solberg (2010), Eklundh et al. (2009), Solberg et al. (2006)
<i>Ormiscodes amphimone</i>	<i>Nothofagus</i>	DB	√	1	Jepsen et al. (2009)
<i>Physokermes inopinatus</i>	<i>Picea abies</i>	DC	–	1	Paritsis et al. (2011)
<i>Rhynchaenus fagi</i>	<i>Fagus sylvatica</i>	DB	√	1	Olsson et al. (2012)
<i>Taeniothrips inconsequens</i>	<i>Acer saccharum</i>	DB	–	1	Rullan-Silva et al. (2015)
<i>Thaumetopoea pityocampa</i>	<i>Pinus spp.</i>	DC	√	1	Vogelmann and Rock (1989)
<i>Tortrix viridana</i>	<i>Quercus spp.</i>	DB	√	1	Sangüesa-Barreda et al. (2014), Gooshbor et al. (2016)

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Table 3: Distribution of studies across biomes.

Biome	Number of studies				
	BB	DB	DC	Others	Total
Boreal Forests/Taiga	1	-	11	-	12
Deserts & Xeric Shrublands	1	2	1	-	4
Flooded Grasslands & Savannas	-	-	-	-	-
Mangroves	-	-	-	-	-
Mediterranean Forests, Woodlands & Scrub	-	-	1	-	1
Montane Grasslands & Shrublands	-	-	-	-	-
Temperate Broadleaved & Mixed Forests	1-	8	2	3	23
Temperate Conifer Forests	20	-	3	-	23
Temperate Grasslands, Savannas & Shrublands	4	1	1	2	8
Tropical & Subtropical Coniferous Forests	-	-	-	-	-
Tropical & Subtropical Dry Broadleaved Forests	-	-	-	-	-
Tropical & Subtropical Grasslands, Savannas & Shrublands	-	-	-	-	-
Tropical & Subtropical Moist Broadleaved Forests	-	-	-	-	-
Tundra	-	4	-	-	4
Total	36	15	19	5	75

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Table 4: Sensors used to study forest insect disturbances

Sensor	Insect Type	n	Source
AVHRR	DC	1	Kharuk et al. (2004)
AVIRIS	Other	1	Hanavan et al. (2015)
Daedalus 1260 MSS	DC	1	Leckie and Ostaff (1988)
HyMap	BB	3	Fassnacht et al. (2014), Lausch et al. (2013), Fassnacht et al. (2012)
Hyperion	BB	1	White et al. (2007)
Intergraph Digital Mapping Camera	Other	1	Kantola et al. (2016)
Landsat MSS, TM, ETM+, and OLI	BB, DB, DC, Other	38	Long and Lawrence (2016), Gooshbor et al. (2016), Gaertner et al. (2016), Senf et al. (2016), Rullan-Silva et al. (2015), Meigs et al. (2015), Jones et al. (2015), Havasova et al. (2015), Hart and Veblen (2015), Sangüesa-Barreda et al. (2014), Liang et al. (2014), Latifi et al. (2014b), Latifi et al. (2014a), Bright et al. (2014), Assal et al. (2014), Walter and Platt (2013), Thayn (2013), Meddens et al. (2013), Townsend et al. (2012), Paritsis et al. (2011), Meigs et al. (2011), DeRose et al. (2011), Babst et al. (2010), Goodwin et al. (2008), Franklin et al. (2008), Cook et al. (2007), Wulder et al. (2006b), Coops et al. (2006), Wulder et al. (2005), Skakunet al. (2003), Hall et al. (2003), Franklin et al. (2003), Royle and Lathrop (2002), Radeloff et al. (1999), Royle and Lathrop (1997), Luther et al. (1997), Franklin et al. (1995), Vogelmann and Rock (1989)
Leica ALS-50 Phase II	DC, BB	3	Vastaranta et al. (2013), Bright et al. (2013)
MODIS	DB, DC, BB	8	Olsson et al. (2016a), Olsson et al. (2016b), Spruce et al. (2011), Verbesselt et al. (2009), Jepsen et al. (2009), Eklundhet al. (2009), De Beurs and Townsend (2008), Kharuk et al. (2007)
Optech ALTM Gemini & Optech 3100 AE	DC, BB	4	Solberg (2010), Solberg et al. (2006), Bright et al. (2013)
Probe-1	BB	1	Lawrence and Labus (2003)
Quickbird	BB	2	Hicke and Logan (2009), Wulder et al. (2008)
RapidEye	DB, BB	2	Adelabu et al. (2014), Oritz et al. (2013)
SpectTIR	BB	1	Pontius et al. (2008)
SPOT	BB, DC, DB	8	Latifi et al. (2014), Latifi et al. (2014), Gilichinsky et al. (2013), Olsson et al. (2012), Franklin et al. (2008), Fraser and Latifovic (2005), Fraser et al. (2005), Muchoney and Haack 1994
TerraX	BB	1	Oritz et al. (2013)
Vexcel	BB	1	Meddens et al. (2011)
Ultracam-D			

WorldView-2	BB	2	Murfitt et al. (2016), Immitzer und Atzberger (2014)
Zeiss RMK	BB	1	Nielsen et al. (2014)
TOP 30			

Table 5: Models used to map forest insect disturbances.

Model type	Model name	Insect type	n	Response type	Source
Parametric	Discriminant function analysis	DC, BB, Other	3	Occurrence, Severity	Gilichinsky et al. (2013), Skakun et al. (2003), Royle and Lathrop (2002)
	Maximum likelihood	BB, DB, DC	9	Severity, Occurrence	Liang et al. (2014), Walter and Platt (2013), Thayn (2013), Meddens et al. (2013), Paritsis et al. (2011), Meddens et al. (2011), Hicke et al. (2009), Franklin et al. (2003), Leckie and Ostaff (1988)
	Regression	BB, DB, Other, DC	20	Severity, Occurrence	Murfitt et al. (2016), Rullan-Silva et al. (2015), Hanavan et al. (2015), Assal et al. (2014), Townsend et al. (2012), Meigs et al. (2011), Verbesselt et al. (2009), Pontius et al. (2008), Franklin et al. (2008), De Beurs and Townsend (2008), White et al. (2007), Cook et al. (2007), Wulder et al. (2006b), Solberg et al. (2006), Coops et al. (2006), Fraser and Latifovic (2005), Fraser et al. (2005), Hall et al. (2003), Royle and Lathrop (1997), Luther et al. (1997)
	Spectral mixture analysis	DC	1	Severity	Radeloff et al. (1999)
	Classification (other)	DC, BB	3	Occurrence	Kharuk et al. (2007), Kharuk et al. (2004), Nielsen et al. (2014)
	k-nearest neighbors	BB	1	Occurrence	Nasi et al. (2015)
	Rule-based	DB, DC, BB	18	Occurrence, Severity	Olsson et al. (2016), Olsson et al. (2016b), Gaertner et al. (2016), Meigs et al. (2015b), Havasova et al. (2015), Sangüesa-Barreda et al. (2014), Meddens et al. (2013), Olsson et al. (2012), DeRose et al. (2011), Solberg (2010), Babst et al. (2010), Jepsen et al. (2009), Eklundh et al. (2009), Wulder et al. (2008), Goodwin et al. (2008), Wulder et al. (2005), Muchoney and Haack (1994), Vogelmann and Rock (1989)
	Isodata	DB, DC	2	Occurrence, Severity	Spruce et al. (2011), Franklin et al. (1995)
	Decision trees	BB	3	Severity, Occurrence	Liang et al. (2014), Lausch et al. (2013), Lawrence and Labus (2003)
	Random	BB,	9	Severity,	Long and Lawrence (2016), Senf et al.
Non-parametric (machine learning)					

forests	DC, DB		Occurrence	(2015), Latifi et al. (2014b), Latifi et al. (2014a), Immitzer und Atzberger (2014), Bright et al. (2014), Adelabu et al. (2014), Vastaranta et al. (2013), Bright et al. (2013)
Support vector machines	Other, BB	4	Occurrence, Severity	Kantola et al. (2016), Hart and Veblen (2015), Fassnacht et al. (2014), Fassnacht et al. (2012)
Maximum entropy	Other, BB	2	Occurrence	Jones et al. (2015), Oritz et al. (2013)

Figure 1: Spatial distribution of studies and insect types according to our sample. (double column width)

Figure 2: Temporal distribution of studies on the remote sensing of insect disturbances by insect types. Insect types include bark beetles (BB), broadleaved defoliators (DB), coniferous defoliators (DC), and others. (single column width)

Figure 3: Percent of studies using specific temporal, spectral, and spatial properties. The summary statistics are stratified by insect type. Insect types include bark beetles (BB), broadleaved defoliators (DB), coniferous defoliators (DC), and others. (double column width)

Figure 4: Overall accuracy (A) and coefficient of determination (B) achieved when mapping forest insect disturbance occurrence/severity. (1.5 column width)