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Review

Automated attribution of forest disturbance types from remote sensing data: A synthesis

Amanda T. Stahl [a,*], Robert Andrus [a], Jeffrey A. Hicke [b], Andrew T. Hudak [c], Benjamin C. Bright [c], Arjan J.H. Meddens [a]

[a] *School of the Environment, Washington State University, Pullman, WA 99164, United States of America*
[b] *Department of Earth and Spatial Sciences, University of Idaho, Moscow, ID 83844, United States of America*
[c] *Rocky Mountain Research Station, USDA Forest Service, Moscow, ID 83843, United States of America*

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ABSTRACT

Remote sensing is widely used to detect forest disturbances (e.g., wildfires, harvest, or outbreaks of pathogens or insects) over spatiotemporal scales that are infeasible to capture with field surveys. To understand forest ecosystem dynamics and the ecological role of human and natural disturbances, researchers and managers would like to characterize spatiotemporal patterns of several types of disturbance. Recent advances include the development and testing of algorithms to automatically detect and attribute an array of disturbance types across large forest landscapes from remotely sensed imagery. We reviewed the scientific literature for automated disturbance type attribution in forest ecosystems to synthesize current knowledge and inform future work. We created metrics that characterize study contexts, methods, and outcomes to evaluate 34 studies that automated the attribution of several (two or more) forest disturbance types. Reported accuracies of ~80% for up to eight disturbance types at local (500 km^2) to continental (6.5 × 10^6 km^2) spatial extents reaffirm the potential for attributing forest disturbances from remote sensing data at scales relevant to ecological research and forest management. Generally, greater accuracies were reported for attributing disturbance types that affect most of a pixel and exhibit spectral signatures distinct from other disturbances or the prior (undisturbed) condition. Accuracy of attributing disturbance type tends to be notably lower for disturbances with smaller spatial extents or resulting in subtle spectral changes, such as small patches of tree mortality covering <40% of a pixel or areas of tree damage without evident mortality (e.g., defoliator outbreaks). Nearly all (33 of 34) studies used Landsat image time series to attribute disturbance types because the Landsat archive is freely accessible, spans several decades (allowing longer-term change analyses), is calibrated to facilitate change analyses, and has multiple spectral bands that aid algorithms. In our synthesis, most studies focused on specific disturbance types of interest within a particular study area, rather than a comprehensive list of types that would make the algorithm more generally applicable at broader spatial extents. We recommend several future research areas to improve the thematic resolution, accuracy, and potentially the transferability of attribution algorithms. Further development and testing of algorithms will continue to reveal the most effective approaches for attributing disturbance types that have been more difficult to detect with available spectral data to date, such as insect damage or low severity wildfire, and to evaluate model sensitivity as well as accuracy. The lessons that collectively emerge from automated forest disturbance attribution studies have the potential to guide future research and management applications.

1. Introduction

Ecological disturbances are an integral component of forest ecosystem dynamics (Allen et al., 2010, 2015; McDowell et al., 2020; Senf and Seidl, 2021). Disturbances are defined as relatively discrete events that reduce plant biomass or productivity (Grime, 1979) and lead to changes in the structure and dynamics of ecological communities (Pickett and White, 1985). The timing and distribution of disturbances affect the provisioning of forest ecosystem services (Thom and Seidl, 2016), including carbon storage (Bonan, 2008) and hydrologic services

* Corresponding author.
E-mail address: atstahl@wsu.edu (A.T. Stahl).

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related to water supply and quality (Maxwell and St Clair, 2019; Stevens et al., 2020). Disturbance events may last hours (e.g., wildfire) to multiple years (e.g., insect outbreaks, urban expansion), and the extent varies from several square meters (e.g., individual tree mortality) to 100 s of km^2 (e.g., insect outbreaks, volcanic eruptions; Turner, 2010). Climate change is rapidly altering the spatiotemporal dynamics of many types of disturbance (Raffa et al., 2008; Seidl et al., 2017), increasing the urgency of identifying and tracking disturbances and their impacts (Spittlehouse and Stewart, 2003). Methods to accurately assess the spatial and temporal patterns of disturbances in forest ecosystems at local to continental scales are essential for informing forest policy and management decisions and forecasting shifts in forest ecosystem structure and function (Cohen et al., 2016; Hansen et al., 2013; Hislop et al., 2019; Schroeder et al., 2017).

The increase in freely available satellite imagery, improvements in computing power, and the development of machine learning algorithms have spurred a growing number of studies aiming to improve the process of detecting ecological disturbances (Zhu et al., 2020). Continuously acquired satellite image datasets offer a spatial and temporal record that is extensive and consistent over the past several decades (e.g., Landsat TM, ETM+, OLI: 1984 to present) for detecting and monitoring disturbances in forest ecosystems (Kennedy et al., 2014; Meddens and Hicke, 2014; Trumbore et al., 2015). In these approaches, forest disturbances, such as timber harvest or insect damage, are detected from changes in spectral signatures (i.e., change detection; Cohen et al., 2010) at the resolution of the sensor (e.g., 30 m × 30 m pixels for Landsat; e.g., Huang et al., 2010; Senf et al., 2017). Remote sensing tools are widely implemented by land managers to monitor changes in vegetation structure (e.g., Monitoring Trends in Burn Severity, http://www.mtbs.gov).

Several articles have reviewed and synthesized current knowledge for identifying a particular subset of forest disturbances (i.e., disturbance attribution) with remote sensing. For example, Senf et al. (2017) reviewed the literature on remote sensing to detect forest insect disturbances; others focused on a specific type of insect (e.g., Bright et al., 2020; Rullan-Silva et al., 2013) or on insect damage within a particular region (e.g., Hall et al., 2016). Disturbances caused by individual abiotic agents (e.g., hurricanes, tornadoes, volcanic eruptions), biotic agents (e.g., insects or diseases), or land use and management (timber harvest, roads) have successfully been identified at the stand scale. We approximate the stand scale as the area of one pixel in the study's source imagery; 900 m^2 for Landsat or 1 km^2 for MODIS. Accuracies are relatively high for various types of disturbance (e.g., ~90% for wildfire (Ahmed et al., 2017, Nguyen et al., 2018); >90% for wildfire and harvest (Cohen et al., 2010); and ~ 90% for bark beetle-affected forests (Meddens et al., 2013)). Previous studies have found that accuracy generally increases with the severity of tree mortality within a pixel (Meddens et al., 2013). Widespread and spatially clustered (severe) tree mortality caused by insects, pathogens, or stand-replacing disturbance types (e.g., moderate-to-high severity wildfires or clear-cut harvesting) that causes measurable change at the spectral and spatial resolution of the data source are more accurately detected and attributed. In contrast, isolated pockets of tree mortality that cover <40–50% of a pixel (Meddens et al., 2013) or defoliating insects that cause lower levels of tree damage (i.e., diffuse disturbances) only result in subtle changes in spectral reflectance. Consequently, diffuse disturbances are much more challenging to detect and attribute with current methods and commonly used data sources (Furniss et al., 2020; Meddens and Hicke, 2014; Rodman et al., 2021; Senf et al., 2017).

Methods are needed not only for detecting and attributing individual disturbance types, but also for automating the classification of disturbances into different types (i.e., *automated disturbance attribution*; Fig. 1), such that the classification can be objectively applied over large areas that may contain several disturbance types. Within a given study area or management unit, ecosystem dynamics often involve more than one type of disturbance. Each type of disturbance (e.g., wildfire versus defoliator outbreaks) plays a unique role in forest ecosystem dynamics, and an initial disturbance may affect the dynamics of subsequent disturbances and the accuracy of attribution (Furniss et al., 2020; Kane et al., 2017; McCarley et al., 2017; Meddens et al., 2015; Rodman et al., 2021). In the last several years remote sensing studies have increasingly focused on systematic disturbance identification across large forested

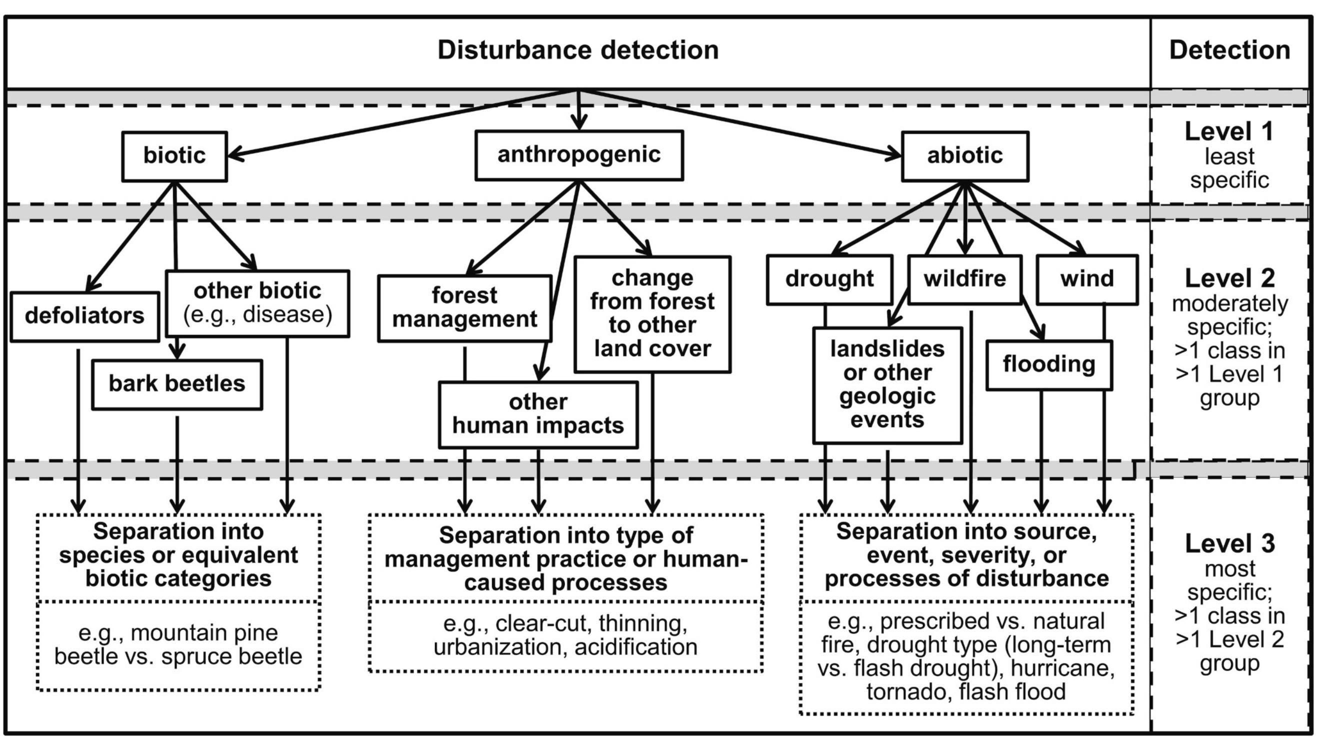

Fig. 1. Levels of thematic resolution within studies that automated disturbance attribution. Solid boxes indicate classes that have successfully been attributed with remote sensing methods, while dotted boxes are at the frontiers of current research.

areas (>10,000 km^2) to fill gaps in coverage of field data, aerial surveys, or other ad hoc data sources (e.g., Ahmed et al., 2017; Schleeweis et al., 2020; Vogeler et al., 2020). For example, aerial surveys of forest damage are primarily implemented only in areas under active agency management (e.g., they may exclude wilderness areas), and the timing of data collection events may leave data gaps (e.g., during the recent COVID-19 pandemic when aerial surveys of forest insect damage in the US were reduced). Algorithms that automate disturbance attribution typically utilize spatiotemporal patterns of spectral change, sometimes incorporating ancillary information such as forest inventory or historical disturbance data (e.g., White et al., 2014) or models of species distribution (e.g., He et al., 2019). Input datasets can be utilized in various ways, depending upon the number of attribution types and their effect on forest canopy changes. For example, topographic, landcover, and species distribution maps may help constrain possible forest types (e.g., in the context of specific coupled insect-host disturbance events) and subsequent analysis could employ spectral data to infer likely damage agents.

Our objective was to synthesize the existing literature on automated forest disturbance attribution from remotely sensed data to guide future research and management applications. We restricted our literature review to scientific studies with algorithms that automate the process of attributing at least two types of forest disturbance. Thus, we intentionally exclude the vast body of published studies that detect disturbed areas but do not attribute disturbance types (see Senf et al. (2017) for a review of detection studies). We organized and analyzed the relevant articles to address the following questions:

- What steps were used to attribute areas of detected change to a disturbance type?
- In what ecological, geographic, and spatiotemporal contexts were attribution algorithms applied?
- What were the spectral or ancillary data sources used in attribution, and what characteristics (e.g., spectral indices) were used as predictors?
- How were attribution classes of one or more disturbance types defined?
- What were the similarities and differences in attribution algorithms among studies?
- How accurate were attribution algorithms, what factors influenced accuracy, and how were models evaluated?

We discuss knowledge gaps and recommend future directions that will improve automated disturbance attribution. With this information, researchers and managers will be better positioned to develop and apply automated disturbance attribution for forest management and monitoring, as well as advance understanding of disturbance dynamics and ecosystem functions such as carbon and water cycling.

2. Methods

2.1. Inclusion criteria

Our purpose was to review studies that automatically attributed two or more forest disturbance types using a variety of methods, datasets, and contexts. We began by searching Web of Science for peer-reviewed scientific literature that included the terms: ("remote sensing" and "forest disturbance") and ("type" or "agent") and ("attribution" or "classification" or "identification") and ("cover change" or "harvest" or "tree mortality"). We then added articles with keywords including "forest disturbance mapping", "pest management", "forest mortality", "windfall or windthrow", or "insect outbreak" that were cited in one of the original articles, or that we otherwise encountered during our literature review. We included scientific publications published as of April 2022. We omitted studies that did not meet the criteria for inclusion, i.e., studies that detected only one type of disturbance, did not use remote sensing data for attribution, or did not use automated attribution algorithms.

2.2. Metrics comparing attribution approaches

We summarized key characteristics of each article to identify metrics that would effectively compare approaches to automated forest disturbance type attribution. For each study, we recorded information to summarize the study context and findings; sources and characteristics of data used in the attribution algorithm; class definition, detection, and attribution methods; and accuracy evaluation (Table 1; for details, see Tables A1, A2). We identified and reported the similarities and differences among studies, including whether disturbed areas were detected prior to or simultaneously with attribution, study extent, temporal extent of time series, whether disturbance types were attributed to patches or individual pixels, spectral or patch (spatial) characteristics and types of ancillary data sets, number of disturbance types, type of classifier, evaluation methods, and accuracy. To compare the thematic resolution of disturbance attribution classes in different studies, we created a conceptual diagram of the thematic resolution of attribution as described in Section 2.2.1.

To record the spatial setting, we identified the country in which the study was conducted and grouped studies by areal extent into local, regional, and continental categories. Areas <75,000 km^2 were categorized as local, 75,000-1,400,000 km^2 regional, and > 1,400,000 km^2 as continental in extent (following natural breakpoints that emerged during tabulation). We grouped data sources (for attribution or evaluation) into remote sensing (e.g., Landsat time series) or ancillary (e.g., forest inventory) data categories. We compiled overall accuracies of attribution and accuracies reported by disturbance type.

We categorized disturbance attribution classes into eight disturbance categories (Table 2), including harvest; land-use change; wildfire; context-specific change (i.e., unique disturbance types occurring locally and not encountered in other reviewed studies; see, for example, Table 2); biotic disturbances or other stress, referring to degradation of the forest canopy due to insect damage, disease, or unspecified stress (which can include abiotic or anthropogenic drivers such as drought or acidification); infrastructure; weather; and hydrologic processes. Accuracies of attribution for these disturbance categories were extracted from each study (where present).

Table 1
Information tabulated from the reviewed articles; see Tables A1 and A2 for study entries.

Category	Contextual characteristics
Study context and findings	Objective of study Spatial setting: location, extent Timeframe: years of imagery included Ecosystem type: forest type, dominant species Main findings: lessons learned in attribution
Sources and characteristics of data used in attribution step of algorithm	Data sources: spectral, ancillary, patch/shape characteristics Use of Landsat time series versus other imagery Spectral characteristics: bands, indices, or spectrally derived metrics
Detection and attribution methods	Attribution classes defined: type, number, thematic resolution Attribution algorithm: description of steps, type of classifier
Accuracy evaluation	Overall accuracy (%) Evaluation data type Disturbance timing: if used in attribution, whether evaluated

Table 2
Disturbance categories with example attribution classes from the reviewed articles.

Disturbance category	Example attribution classes
Harvest	Clearcut (Jarron et al., 2017)
	Selective logging (Nguyen et al., 2018)
Land-use change (interpreted)	Urbanization (Kennedy et al., 2015)
	Change from forest to agricultural (Murillo-Sandoval et al., 2018)
Wildfire	High or low severity (Schleeweis et al., 2020)
Context-specific change	Rubber plantations (Shimizu et al., 2019)
	Clearing for goat pasture followed by regrowth with continued goat grazing (Helmer et al., 2010)
	Glacial retreat and expansion (Pastick et al., 2019)
Biotic or other stress	Mountain pine beetle (Senf et al., 2015)
	Spruce budworm (Ahmed et al., 2017)
	Stress (Huo et al., 2019)
Infrastructure	Roads (White et al., 2014)
	Well sites (White et al., 2014)
Weather	Windthrow (Vogeler et al., 2020)
	Hurricane (Mascorro et al., 2016)
Hydrologic	Flooding (Pouliot and Latifovic, 2016)
	Dam construction (Shimizu et al., 2017)

2.2.1. Attribution class comparison

To compare attribution classes across studies, we developed a conceptual framework for assessing the thematic resolution in attribution class definitions (Fig. 1). This was an important step in our analysis because each study defined attribution classes differently, presumably because these definitions were based on a priori knowledge and relevance to the study system and objectives. For example, Hermosilla et al. (2015) attributed wildfire, harvest, road, and non-stand-replacing changes whereas Kennedy et al. (2015) attributed urbanization, intensified urbanization, forest management, riparian change, and other natural causes of change. To analyze the variability in attribution class definitions, we assigned each study a level of thematic resolution (hereafter "Level" 1–3). In this scheme, Level 1 algorithms provided the coarsest level of attribution with a maximum of one class in each of these broader groups: biotic (e.g., insect damage or disease), anthropogenic (e.g., timber harvest or land-use change), or abiotic (e.g., wildfire, windthrow, or flooding). Level 2 algorithms represented a finer level of detail involving more than one class within each of the three (biotic, anthropogenic, or abiotic) groups. Level 3 represents the finest thematic resolution, in which an algorithm distinguishes several specific agents, practices, impacts, or events. We conceptualized Level 3 as needed information for forest management based on the resolution of insect and disease attribution by skilled human observers in airplanes conducting aerial detection surveys for operational use by the US Forest Service (Potter and Conkling, 2020). To refine our description of thematic resolution, we introduced a Level 1+ to characterize studies that identified some classes at Level 1 and other classes at Level 2. Finally, note that the level to which a study was assigned represents its thematic resolution in separating disturbance types (i.e., this does not mean that the study attributed all disturbance types listed in that level in Fig. 1).

3. Results

We found and reviewed 34 papers that met our criteria — automated attribution of at least two disturbance types with remotely sensed imagery. All studies followed the same general methodological steps for attribution, but details varied at each step (Fig. 2). For example, nine studies used only imagery to generate predictors of disturbance type (e.g., Hermosilla et al., 2015), whereas 25 used ancillary data sources in addition to remote sensing data for predictors (e.g., Schroeder et al.,

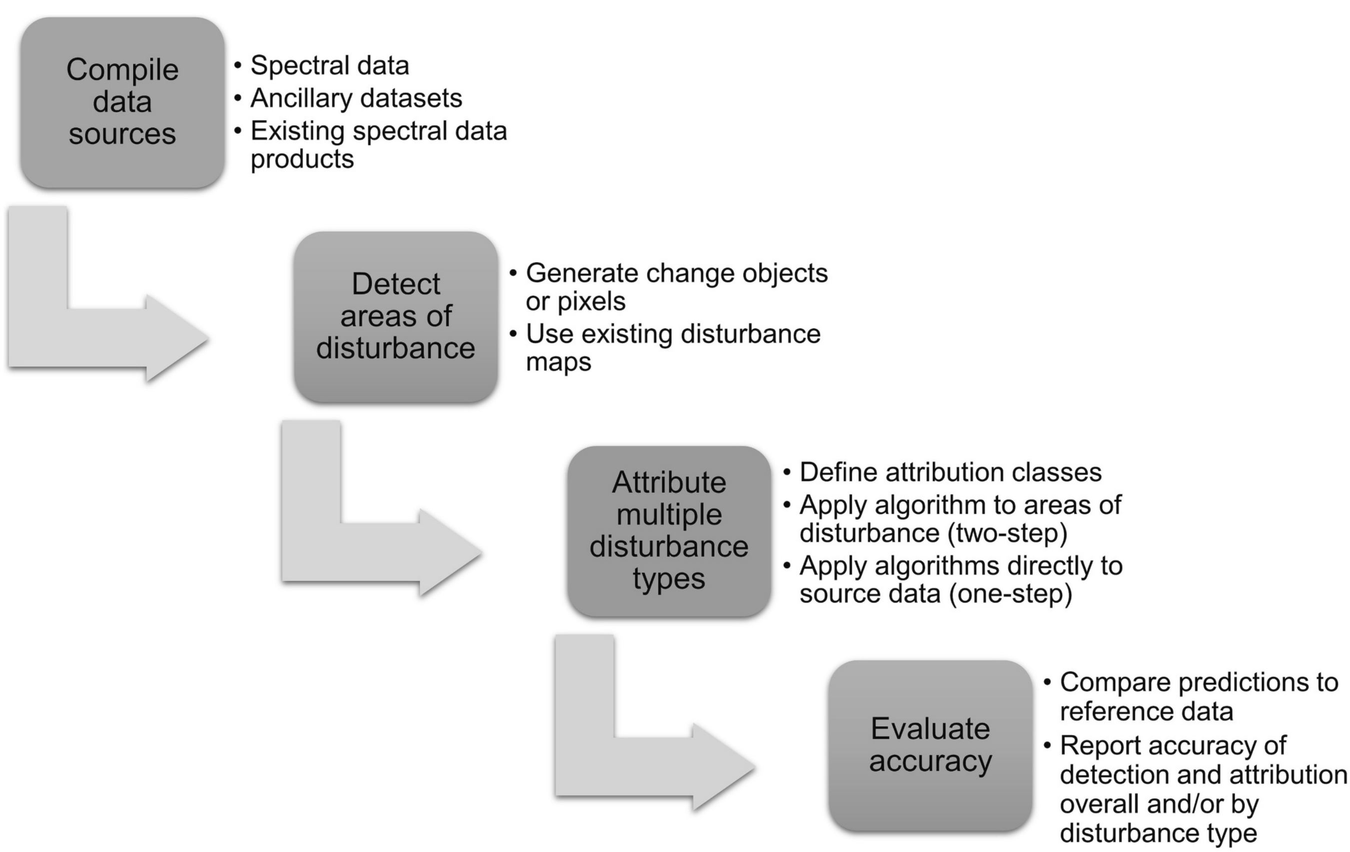

Fig. 2. Generalized flow chart showing the sequence of steps in disturbance attribution studies reviewed here. At each step, studies included at least one of the bulleted items listed. Two-step algorithms first detected any areas of disturbance (independent of type) and then attributed the disturbance types, whereas one-step algorithms detected and attributed disturbance types in one step.

2017). Studies varied in spatiotemporal context, the data sources and characteristics used in attribution, details of classification algorithms, and accuracy evaluation (Table A1).

3.1. Steps in disturbance type attribution

Two general approaches to attribution were applied in the reviewed studies. The most common was a two-step approach in which areas of disturbance were detected (or existing disturbance maps were assembled) and subsequently disturbances were separated by attribution class (e.g., wildfire, bark beetles, harvest). Most studies (29 of 34) used two-step attribution methods (Fig. 3a). Five of the studies used one-step attribution methods, in which attribution classes were separated using spectral signatures without first detecting disturbed versus undisturbed areas. Three of the one-step attribution studies also tested two-step algorithms. Shimizu et al. (2017, 2019) compared the accuracies of models generated from one-step and two-step attribution methods and found the outputs from the two approaches to be comparable (e.g., Shimizu et al., 2017 reported 90.9% accuracy for a two-step and 92.4% accuracy for a one-step model). Schroeder et al. (2017) used a two-step algorithm for attribution and found the accuracy to be no greater than that of a one-step model.

3.2. Study context

Study areas were located on multiple continents, with the majority (22 of 34) in Canada or the US, two in Myanmar, two in Mexico, two spanning countries in Europe, and one each in Australia, Austria, Germany, Columbia, and The Bahamas. One study compared an attribution algorithm between study areas in European Russia and Minnesota, USA (Baumann et al., 2014). The areal extent of the analyses ranged from ~500 km^2 to 6.5 × 10^6 km^2. Most studies (23 of 34) focused on disturbances over local areal extents (i.e., <75,000 km^2, Fig. 3b). Eleven studies applied algorithms to regional or national extents. Study areas included a variety of ecological settings and climatic conditions including conifer and broadleaf forests and temperate, tropical, Arctic, and boreal forests.

3.3. Data sources

All studies except one used Landsat time series (30-m resolution); the exception was a study that instead used (250-m) MODIS-derived land cover data (Mascorro et al., 2016) (Table A1). The number of years of Landsat data included ranged from two to 45; most commonly 21–30 years of data were included (Fig. 3c). Most (29 of 34) studies used spectral indices as predictors. The spectral indices most commonly used in time series algorithms were Tasseled Cap (TC) Brightness, Wetness, and Greenness and the Normalized Burn Ratio (NBR) (Fig. 3d). NDVI was also included in nine algorithms, often in a derivative form or in combination with other indices or individual bands. Spectral bands were less commonly used as predictors than spectral indices; when used, they were typically in the NIR wavelengths (3 of 34 studies) or in combination with other bands (7 of 34 studies). Patches derived from spectral data were used to generate patch-level characteristics (e.g., patch size and form from the R package *landscapemetrics*; Sebald et al., 2021) and included in the attribution algorithms of eight studies. Fine-resolution imagery (e.g., GeoEye or aerial photography, commonly accessed via Google Earth; see Table A1) was also used to generate training data in twelve studies. Most (25 of 34) studies incorporated ancillary data as predictor variables for the attribution algorithm. Existing forest inventory or disturbance data sets were the most common ancillary data source (19 of 34), followed by topographic metrics (8 of 34) (Fig. 3e).

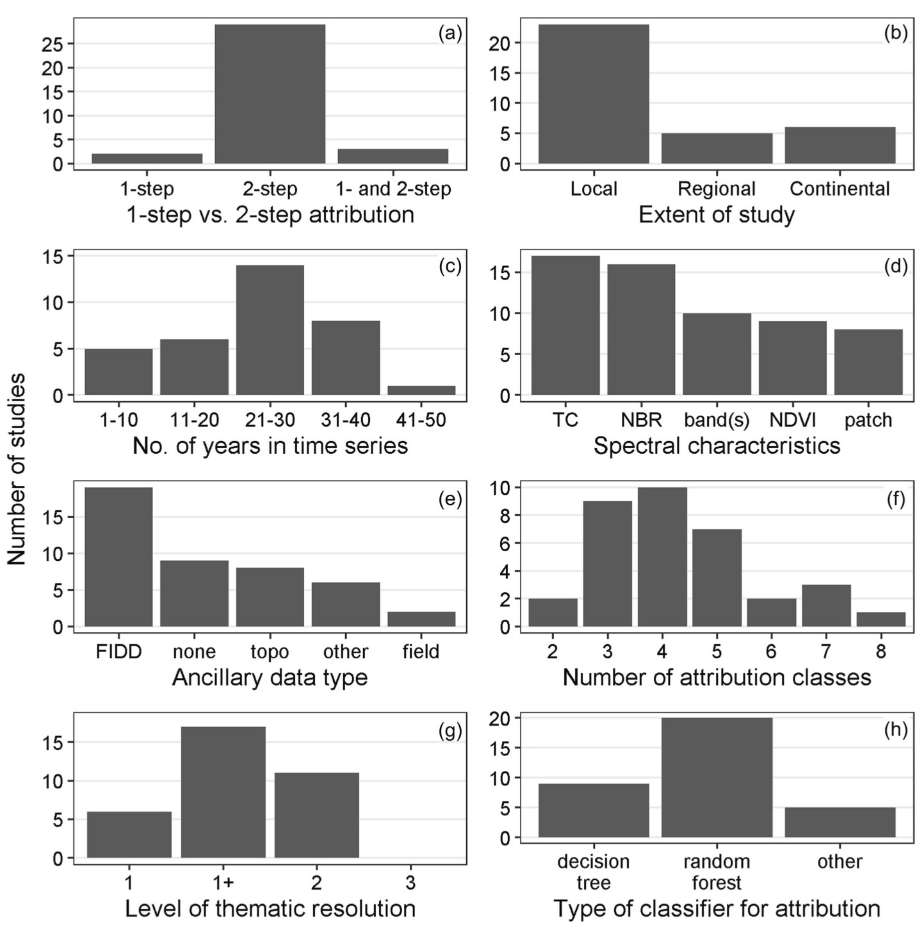

Fig. 3. Number of reviewed studies organized by (a) change detection as a separate step from attribution (two-step) or directly from spectral (+/− ancillary) data (one-step), (b) areal extent of analysis, (c) number of years spanned by time series of spectral imagery, (d) spectral characteristics used in the attribution algorithm, (e) ancillary data types used in the attribution algorithm, (f) number of attribution classes, (g) level of thematic resolution (see Fig. 1), (h) type of classifier used to separate attribution classes. Local — <75,000 km2, Regional — 75,000-1,400,000 km2, Continental — >1,400,000 km2, TC — Tasseled Cap indices, NBR — Normalized Burn Ratio, NDVI — Normalized Difference Vegetation Index, band(s) — one or more spectral bands, patch — patch-level characteristics derived from spectral data, topo – topographic data (e.g., elevation and aspect), FIDD — forest inventory or disturbance (e.g., fire perimeters or burn severity) data set.

Several studies used novel ancillary data sources. For instance, Sebald et al. (2021) incorporated calculated measures of local spatial autocorrelation to represent landscape context as a predictor and found that this increased attribution accuracy by up to 26%.

3.4. Attribution algorithms

The number of attribution classes within each study ranged from two to eight, with the majority identifying three to five classes (Fig. 3f). The most commonly attributed disturbance categories were harvest (typically clearcut areas), wildfire, biotic or other stress, context-specific change, land-use change, and weather (Table 3). The thematic resolution of attribution class definitions within a given disturbance category varied among studies (Table A1). For example, of the studies that attributed change in cover from forest to other types, some attributed different types of land-use conversion individually (e.g., Helmer et al., 2010; Murillo-Sandoval et al., 2018; Kennedy et al., 2015) whereas others combined all land use change from forest to other uses in a single attribution class (Schroeder et al., 2017; Vogeler et al., 2020). About 50% of the studies (17 of 34) distinguished attribution classes to thematic resolution Level 1+ (e.g., separating wildfire from timber harvest and land use conversion) and 32% (11 of 34) distinguished classes to thematic resolution Level 2 (e.g., separating tree mortality from insect outbreaks into functional groups) (Fig. 3g). We did not find any studies with algorithms that met criteria for Level 3, which would require at least two specific attribution classes in at least two of the broader groups (biotic, anthropogenic, or abiotic; Fig. 1). The majority of studies (20 of 34) used a random forest classifier (Breiman, 2001) for attribution; many of the others used various decision tree classifiers (Fig. 3h).

3.5. Accuracy evaluation

Of the 34 studies reviewed, 30 reported overall accuracy values (%) for the attribution algorithms, which enabled us to coarsely compare accuracies among studies. The four that did not report overall accuracy typically reported confidence values or cited other studies using similar methods that had been previously evaluated. Of the 30 studies that reported overall accuracy, 27 studies reported attribution accuracies for individual disturbance categories that enabled us to compare values among studies (Table 3, A2) One study reported attribution accuracy for specific land-use changes (Kennedy et al., 2015) that did not overlap with the disturbance categories in the other 27 studies; thus we excluded it from the comparison of accuracy by disturbance category (Fig. 4c). Accuracy was evaluated with on-screen interpretation of imagery, in some cases supplemented by ancillary data sets (e.g., forest inventory or disturbance data) (Fig. 4a). All 30 studies that reported overall attribution accuracy included on-screen interpretation in model evaluation. Seven relied solely on on-screen interpretation of imagery for evaluation data. Most incorporated more than one type of evaluation data; ~80% of the studies (24 of 30) combined ancillary data sets with on-screen interpretation to evaluate attribution accuracy. Field data were collected for evaluation in ~17% of studies (5 of 30), all of which were local in extent (<75,000 km^2). Forest inventory data sets or other existing data sets related to forest disturbance were used for evaluation in ~70% of studies (21 of 30).

Overall accuracies for disturbance type attribution (in the 30 studies that reported percent accuracy) ranged from 67% to 97%; nearly all (28 of 30) reported accuracies >70% (Fig. 4b). The same range of accuracies occurred for each evaluation approach; we did not find any clear relationships between accuracy and evaluation methods, reference data types, or spatial resolution of imagery used in evaluation (Fig. 4, Tables A1, A2). Studies that used fine-resolution imagery to generate training data ranged in attribution accuracy from 80% to 97%, similar to accuracy values reported from studies that used Landsat imagery alone (67% to 97%) to generate predictor variables. The study that used coarse-resolution MODIS imagery did not report overall percent accuracy.

Attribution accuracy varied widely among disturbance categories (Fig. 4c; (27 of 34 studies reported accuracies by attribution class such that we could compare among studies)). Most disturbance categories had studies that reported accuracies of ≥90%, with the exception of weather, although median accuracy varied by category. Higher accuracies (median > 75%) occurred for wildfire, harvest, and hydrologic disturbance categories. Lower accuracies occurred for infrastructure, biotic or other stress, and land cover change categories. Most categories had studies with accuracies <65%; the biotic/stress and wildfire disturbance categories had studies with accuracies <50% (Fig. 4; Schleeweis et al. (2020) reported ~30–40% accuracy for low severity wildfire). Accuracies of studies ranged within each disturbance category; notably, there was large variability in reported accuracy values in the biotic disturbance category (22.8% to >90%).

Although 27 of 34 reviewed articles (79%) used timing (year) of onset in their disturbance detection or attribution steps, only 10 of 27 studies (37%) specifically evaluated accuracy in detecting the onset year of disturbance with independent data sets (Table 3). When reported, the year of disturbance initiation (±1 year) was identified correctly with ~75–90% accuracy. Related studies have demonstrated the difficulty of detecting the timing of initiation of insect outbreaks with Landsat resolution (e.g., Rodman et al., 2021, found 27% accuracy for spruce beetle (*Dendroctonus rufipennis*) outbreaks ±1 year). Methods for evaluating the accuracy of disturbance timing have been developed and demonstrated (e.g., see Schroeder et al., 2017) but do not appear to be widely implemented as a common practice in disturbance attribution.

4. Discussion

Our literature review and categorization of automated forest disturbance attribution studies enabled us to characterize the variability in attribution class definitions and thematic resolution (referred to herein as Levels), approaches to algorithm development, and evaluation methods. The reviewed studies indicated that remote sensing data and methods exist for attributing several types of forest disturbance with high accuracy (>90%) at ecologically and management relevant scales. In the following sections, we discuss the current state and future directions for automated attribution of forest disturbance.

4.1. Steps in disturbance type attribution

Most (29 of 34) studies involved two-step attribution (Fig. 2). However, the three studies that compared one- versus two-step attribution methods found no substantial difference in attribution accuracy between the two; if anything, the one-step attribution methods yielded higher accuracies (Shimizu et al., 2017, 2019; Schroeder et al., 2017). The authors suggested that one-step attribution should be pursued as a potential option for generating more efficient and equally accurate algorithms. When existing disturbance data sets (e.g., fire perimeters) or detection algorithms (e.g., the Vegetation Change Tracker) are suitable for a given study context, two-step approaches (i.e., using existing disturbance maps for attribution) may continue to be the most common choice without compromising efficiency. However, in the absence of readily available disturbance data, one-step attribution methods may be worth testing to determine their potential value in streamlining algorithms to inform forest management.

4.2. Study context

We found that the extent and selection of study area boundaries were tightly linked to the number and definitions of attribution classes. The attribution classes were almost all predefined by the researchers with a priori knowledge of the list of potential disturbance types within a study area. Most studies took place in the continental United States and Canadian ecosystems, and focused on coniferous, broadleaf, and mixed

Table 3
Attribution classes in the reviewed articles, summarized by disturbance category (in decreasing frequency of use from left to right, decreasing number of classes from top to bottom; see Tables A1, A2 for additional details). Y—yes; N—no; accuracy reported by class—accuracy was reported by disturbance types (in addition to reports of overall attribution accuracy); timing of onset/accuracy reported—algorithm included temporal signatures to separate disturbance types, accuracy of detecting disturbance timing was reported.

Citation	harvest	wildfire	biotic or other stress	context-specific change	land use change	weather	infra-structure	hydro-logic	no. of classes	accuracy reported by class	timing of onset/ accuracy reported
Pastick et al., 2019		1	1	2	3			1	*8*	N	Y/N
Shimizu et al., 2019	1			2	2		1	1	*7*	Y	N/N
Ahmed et al., 2017	1	1	2	1			1	1	*7*	Y	Y/N
Shimizu et al., 2017	1			2	2		1	1	*7*	Y	Y/N
Vogeler et al., 2020	1	1		1	1	1		1	*6*	Y	Y/N
Harris et al., 2016	1	1	2		1	1			*6*	N	Y/N
Schleeweis et al., 2020	1	1	1		1	1			*5*	Y	Y/N
Nguyen et al., 2018	2	2		1					*5*	Y	Y/Y
Schroeder et al., 2017	1	1	1		1	1			*5*	Y	Y/Y
Mascorro et al., 2016	1	1			2	1			*5*	N	Y/N
Pouliot and Latifovic, 2016	1	1	1	1				1	*5*	Y	Y/N
Kennedy et al., 2015				4	1				*5*	Y	Y/N
Helmer et al., 2010					5				*5*	Y	Y/Y
Coops et al., 2020	1	1		1			1		*4*	N	Y/Y
Oeser et al., 2017	2		1			1			*4*	Y	Y/Y
Havašová et al., 2017	1	1	1			1			*4*	Y	Y/N
Moisen et al., 2016	1	1	1		1				*4*	Y	Y/N
Hermosilla et al., 2016	1	1		1			1		*4*	Y	Y/Y
Hermosilla et al., 2015	1	1		1			1		*4*	Y	Y/Y
Senf et al., 2015	1	1	2						*4*	Y	Y/N
White et al., 2014	1	1					2		*4*	N	Y/N
Neigh et al., 2014b	1	1	1	1					*4*	Y	N/N
Hilker et al., 2011	1	1					2		*4*	Y	N/N
Zhang et al., 2022	1	1	1						*3*	Y	Y/N
Sebald et al., 2021	1		1			1			*3*	Y	Y/N
Senf and Seidl, 2021		1				1			*3*	Y	Y/Y
Huo et al., 2019	1	1	1						*3*	Y	Y/N
Murillo-Sandoval et al., 2018				1	2				*3*	Y	Y/N
Jarron et al., 2017	3								*3*	Y	Y/Y
Mascorro et al., 2015		1		1		1			*3*	N	N/N
Zhao et al., 2015	1	1	1						*3*	Y	N/N
Neigh et al., 2014a	1		1	1					*3*	Y	N/N
Chen et al., 2021	1	1							*2*	Y	Y/Y
Baumann et al., 2014	1					1			*2*	Y	N/N
Number of studies	28	24	16	15	12	11	8	6		28	27/10
(%)	82%	71%	47%	44%	35%	32%	24%	18%		82%	79%/37%

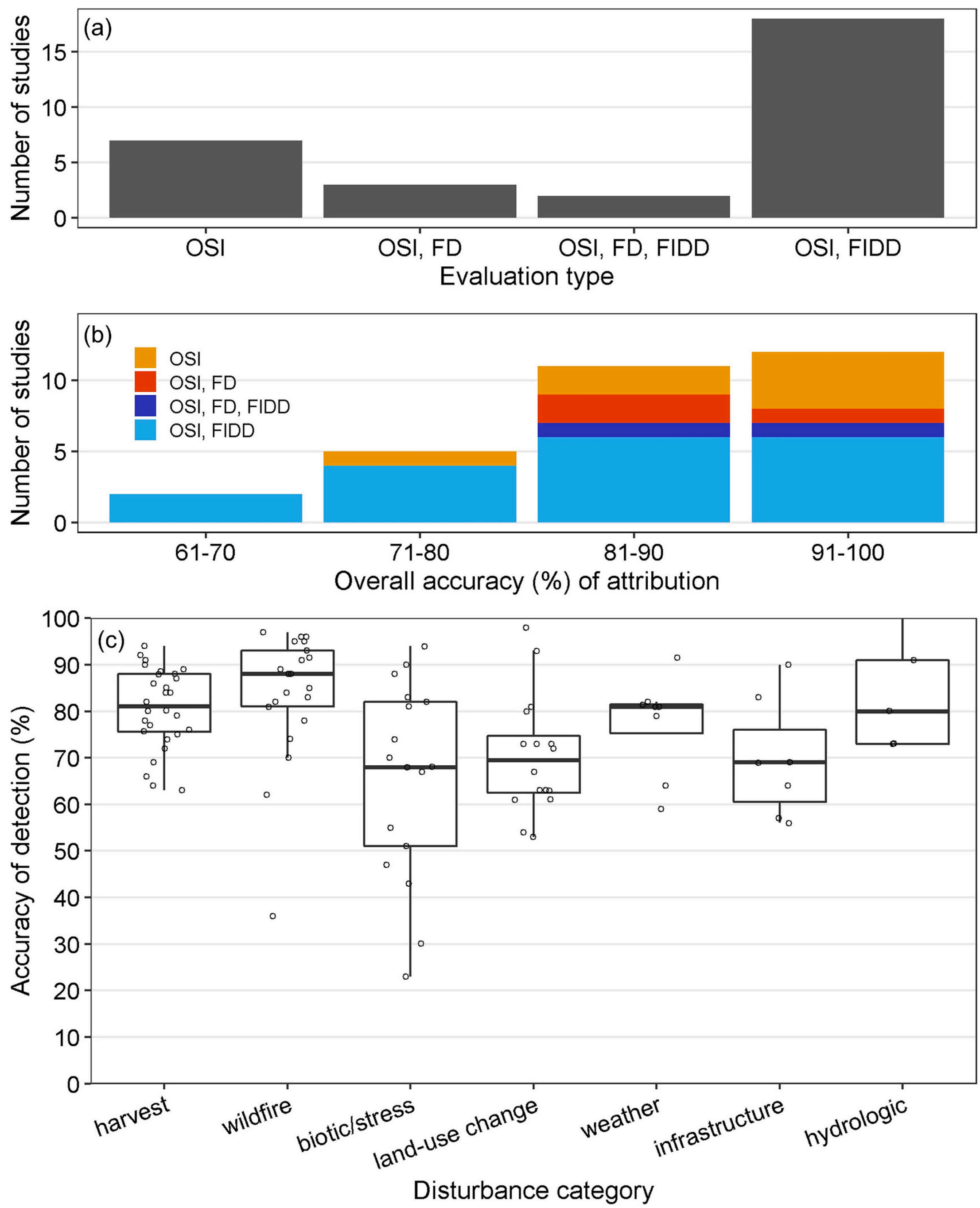

Fig. 4. (a) Data sources used to evaluate attribution accuracy, (b) overall accuracy of disturbance type attribution, (c) Attribution accuracy for disturbance categories. OSI — manual on-screen interpretation of imagery; FD — field data; FIDD — forest inventory or disturbance data set (e.g., Forest Inventory and Analysis program of the U.S. Forest Service or fire perimeters).

forests. Only three studies were conducted in tropical forests (Mascorro et al., 2015, 2016; Helmer et al., 2010) and two were in the same study area (Yucatan Peninsula), potentially due to the complexity of studying forest disturbances in tropical regions (e.g., cloud cover or difficult access).

Most studies to date were "local" in scope (23 of 34, 68%) and such areal extents (<75,000 km^2) may be more conducive to identifying more specific attribution classes than regional or continental extents (>75,000 km^2). For instance, insect damage agents are typically combined within a single attribution class labeled as insect agent, tree stress, or non-stand-replacing disturbance in continental-extent studies (e.g., Hermosilla et al., 2016; Huo et al., 2019; Zhang et al., 2022). Using current methods, insect-host tree species associations may simply be too spectrally similar to allow for accurate attribution of species-level insect damage agents, particularly at regional to continental extents for which multiple insect-host associations may occur. Within local areas with less spectral variability, insect-host associations may be more straightforward to separate with remotely sensed imagery and ad hoc knowledge of the study area. Moreover, a smaller study area is more likely to be covered completely by existing ancillary data sets (e.g., forest inventory data) and may be more feasible for collecting sufficient field data for ground-truthing (e.g., Ahmed et al., 2017). Even so, insect damage studies at local extents found attribution accuracies ranging as low as ~23% (Sebald et al., 2021; the low accuracy may be due to bark beetle outbreaks being labeled as harvest) to as high as ~88% (Oeser et al., 2017; the higher accuracy may be due to the inclusion of topography-related metrics because bark beetle outbreaks occurred at higher elevations than harvest).

Whether "local" or "regional" attribution algorithms can be adapted to other study systems or broader areas is uncertain. One study tested an attribution algorithm in both a temperate forest in European Russia and a boreal forest in Minnesota, USA and found similar accuracies (>75%; Baumann et al., 2014). Another study attempted to transfer attribution methods (developed in the Midwestern part of the United States) to a different ecosystem in the Pacific Northwest and found lower accuracies for fire and insect disturbances (Neigh et al., 2014b). The reduced accuracy was attributed to less dense temporal coverage in aerial photos used to train models and the availability of ancillary data sets that might limit transferability or extent at which the attribution algorithm was applied (Neigh et al., 2014b). More reliance on mechanistic understanding of the timing, spectral, and spatial characteristics of various disturbance types as well as improved evaluation data might yield better models that are transferable (adaptable) to other regions.

4.3. Data sources

4.3.1. Remote sensing data

Landsat imagery was most commonly used for attribution, as expected due to its global availability and unmatched length. The Landsat image archive has facilitated considerable advancement in disturbance detection and attribution algorithms, and most algorithms use Landsat image time series analyses. Although algorithms used a variety of indices and spectral data, the Tasseled Cap indices and the Normalized Burn Ratio were most commonly used for attribution in the studies we reviewed, illustrating the effectiveness of the Landsat shortwave infrared band for detecting change in forest cover from disturbances (e.g., Meddens et al., 2013; Kennedy et al., 2010).

Types of disturbance that were less easily separated using Landsat time series include those that cause less severe damage to tree canopies (e.g., low severity wildfire; Schleeweis et al., 2020) or are more diffuse (e.g., bark beetle caused-tree mortality in mixed host/non-host stands; Meddens et al., 2013). However, disturbances that occur over multiple years within a stand, such as outbreaks of bark beetles, can be detected if the image time series spans the timing of onset and damage (Rodman et al., 2021; Ye et al., 2021). In the studies we reviewed, the more gradual or less severe disturbances were often either (a) combined into a single type (such as non-stand-replacing change; e.g., Hermosilla et al., 2015), (b) attributed with lower accuracy than other types (e.g., Ahmed et al., 2017), or (c) excluded from the attribution algorithm altogether (e.g., Mascorro et al., 2015) (Table A1, A2). Studies using Landsat imagery typically found that disturbance types causing concentrated patches of mortality larger than ~360 m^2 (i.e., loss of canopy cover >40% of a Landsat pixel) were most conducive to high-accuracy attribution, which is consistent with the findings of previous disturbance detection studies (e.g., Rodman et al., 2021; Meddens et al., 2013). New algorithms using image time series that include Sentinel (e.g., Lastovicka et al., 2020) or PlanetScope (Francini et al., 2020) data at finer spatial or temporal resolutions may be necessary to detect these subtle disturbances (e.g., Cardille et al., 2022); see section 4.4.3 for more information.

4.3.2. Ancillary data

Most (25 of 34) studies used ancillary data sources for attribution, but reporting on the predictive power of different data sources ranged widely. In general, studies that evaluated the predictive power of ancillary data, either to constrain the applied algorithms or as explanatory variables, reported improvements in attribution algorithms. In particular, incorporating existing forest inventory or disturbance data sets showed potential for increasing attribution accuracy and refining error reporting for biotic disturbances. For example, Senf et al. (2015) incorporated monotypic versus mixed host tree stands from a vegetation resource inventory database and found attribution errors of up to 45% in mixed stands (whereas overall accuracy in pure stands was ~88%). The 18 other studies that included inventory or disturbance data sets did not specifically report their effects on attribution accuracy. In some studies, ancillary data yielded the most important predictors (e.g., topographic data or timing of storm events in Oeser et al., 2017; Kennedy et al., 2015; landscape context in Sebald et al., 2021). In other studies, tests of predictor performance indicated that ancillary data did not substantially improve attribution (e.g., elevation data in a study by Schroeder et al., 2017). Climatic data (from weather prediction and drought monitoring data sources) were included in predictor variables in one study (Harris et al., 2016), but the relative importance of climatic predictors for disturbance type attribution was not reported.

Although ancillary data might improve the accuracy of attribution, the inclusion of such data may have disadvantages as well. First, attribution models that include ancillary data could lead to reduced generalizability or simply erroneous predictions when extrapolating models to other regions. For instance, elevation in one area may improve attribute accuracy by capturing the idiosyncrasies of that area, such as land management practices or climate that vary in locally specific ways across the elevation gradient. Second, inclusion in attribution mapping studies of some ancillary data that are drivers of disturbances may limit the capability of subsequent studies that seek to use the mapping to study causes of disturbance. That is, a driver (e.g., climate) cannot be used to both map a disturbance and explain its cause.

4.4. Attribution algorithms

4.4.1. Thematic resolution of attribution classes

To complement other data sources (e.g., burn severity spatial data) that inform forest management, remote sensing methods would ideally provide the capability to distinguish among damage from different insect species (e.g., among bark beetle-host associations), specific management practices or human impacts (e.g., thinning versus acidification), and separate sources, events, processes, or spatiotemporal patterns (e.g., stress versus a particular storm event or whether a "clearcut" should be attributed to natural disturbance versus logging/harvest) — in the context of the present study, Levels 2 and 3 (Fig. 1). In this review, we found that 32% of studies attributed classes at Level 2 and 0% at Level 3. Data from ground-based or aerial surveys — in which expert observers identify areas of disturbance and attribute them to damage agents such as insect or disease — can capture this level of detail (Coleman et al., 2018) but may be limited in spatial or temporal coverage. Furthermore, funding for survey coverage needs to be balanced with other higher priority needs such as wildfire management. Funding for forest management is limited, despite renewed worldwide recognition of the importance of sustainable forest management for global health and resilience in the wake of the COVID-19 pandemic (UN/DESA (United Nations Department of Economic and Social Affairs), 2020). This leaves a gap that could be filled with remote sensing detection and attribution algorithms if results are at a level of detail sufficient to inform science and management. Even if species-level identification of insect damage areas is not possible, the ability to separate insect agents at a coarser level (e.g., separating defoliators from bark beetles, thinning practices from insect-caused mortality, or salvage logging after natural disturbances from the felling of standing killed trees) over larger areas would be useful for management purposes.

4.4.2. Classifiers used for disturbance attribution

Random forest and decision tree classifiers were most commonly used in forest disturbance attribution algorithms. We note that the studies that used random forest and decision tree algorithms generally included a suite of predictor variables to optimize classification results. Even though random forest classification has proven to be a successful and powerful method for separating disturbance types, random forest classifiers alone do not provide a mechanistic understanding of the spectral characteristics of the individual disturbance classes. We recommend that future research efforts rigorously investigate and report relationships between predictor variables and attribution classes, regardless of the classification method used. For instance, Schroeder et al. (2017) used a random forest classifier and a rule-based model, then reported the relative importance of the predictor variables. It is possible that boosted decision tree classifiers may be beneficial for refining algorithms to perform better at continental scales (Brown et al., 2020). Further research into the unique characteristics of the spectral response of the attribution classes will enable classification and detecting across larger regions and image types.

4.4.3. Spatial and temporal characteristics of attribution algorithms

Disturbance attribution shares the limitations and caveats of disturbance detection. Detection is limited by spectral, spatial, temporal resolution and separability as discussed by Kennedy et al. (2015). Inclusion of spectral information from fine-spatial-resolution remote sensing data (e.g., WorldView, GeoEye, aerial photography) or high-temporal-resolution data (e.g., Sentinel and PlanetScope; Francini et al., 2020) can improve the timing and detection; and thus attribution of more subtle disturbance types (e.g., defoliator damage) or one disturbance type superimposed on another (e.g., post-fire salvage logging or post-fire beetle damage), although there can be drawbacks associated with cost, computational processing time and power, or data storage. New and emerging satellite data sources (e.g., the Sentinel Mission under the Copernicus Program of the European Space Agency) are producing finer resolution imagery with shorter return intervals. For example, Sentinel-2 imagery has finer spatial (10 m) and temporal resolution (return interval ~ 5 days) than Landsat (30 m and ~ 7–16 day return interval), and thus Sentinel-2 may be more conducive to near real-time and/or early detection of diffuse disturbances than Landsat. For instance, Abdullah et al. (2019) found spectral vegetation indices derived from Sentinel-2 imagery were more successful than Landsat-8 at detecting bark beetle green attack in Germany. Harmonized Landsat-Sentinel (HLS) time series (Claverie et al., 2018) may combine the benefits of Landsat's historical record with the finer spatial resolution of Sentinel imagery (with global coverage since 2016). Alternatively, a nested approach (e.g., see Cardille et al., 2022) might be most effective for capturing diffuse mortality detection and attribution across larger spatial extents. For example, finer spatiotemporal patterns of disturbance could be detected from finer-resolution imagery and then fed into a multitemporal, multispectral, multi-sensor (e.g., HLS) algorithm that operates on the 30 m resolution data achieved by both sensors (e.g., Campbell et al., 2020; Meddens et al., 2013).

4.5. Accuracy evaluation

If accurate attribution of several specific disturbance types was unrealistic to achieve with current data sources, we might expect to see lower accuracy values in studies with a larger number of classes, more specific classes, or larger extents. However, we observed no clear patterns between accuracy and number of classes, level of thematic resolution, or analysis extent (Tables A1, A2). This suggests that either there are not yet enough articles on this topic to detect such patterns, or that other factors, such as evaluation data and methods, disturbance type, severity, extent, spatial distribution of tree species, or study context (including availability of ancillary data sets) influenced model accuracy. The diversity of disturbance type definitions may have also confounded our ability to compare accuracies across studies. Given the small number of studies on automated disturbance type attribution and that each study identified a different array of disturbance types, we cannot yet specify further which disturbance types were most difficult to separate. Although there is much room for improvement, 13 of the 34 previous studies demonstrated automated attribution of five or more disturbance types at various levels of thematic resolution (Table 3).

Evaluation data and methods differed among studies, which reflects differences in publicly available datasets and the need for commonly accepted practices for reporting disturbance attribution accuracy. Generally, attribution accuracy evaluation methods rely heavily on on-screen interpretation of imagery, typically using high-resolution satellite and aerial imagery (<3 m, e.g., the US National Agriculture Imagery Program). Surprisingly, field data were rarely collected for the purpose of verifying disturbance type and model evaluation (5 of 34 studies). The limited use of field data may be due to circumstances in which field data are unavailable, field protocols yielded data sets that are difficult to relate to available remotely sensed data (e.g., spatial scale mismatch), or the impracticality of collecting new field data (e.g., to adequately represent large areas with varying ecological characteristics and management systems). Ground-truthing with field data is valuable in that it is not influenced by the biases of aerial image interpretation. However, where previous studies have established that classifications using fine-resolution imagery were highly accurate compared with field data, on-screen interpretation can be an accurate and reliable source of evaluation data (e.g., see Copass et al., 2019). For instance, severe disturbance types with distinct spectral signatures (e.g., high-severity wildfire) may be reliably evaluated via image interpretation, while disturbance types that contribute to stress may be more likely to require ground-based data to evaluate attribution accuracy (e.g., either insect damage or drought can cause trees to appear red in imagery). Many (27) of the 34 reviewed studies used timing of disturbance in some form in the detection or attribution algorithms, but only 37% (10 of 27) explicitly evaluated the accuracy of timing detection (Table 3). If disturbance timing continues to be incorporated in attribution algorithms, we suggest that accuracy reporting should routinely include reports of accuracy in detecting the timing when feasible.

Each type of evaluation data involves potential sources of error; for instance, there is human error associated with visual surveys (whether ground-based or aerial). We noted that on-screen image interpretation yielded higher overall accuracy results than other methods (field observations, forest inventory or disturbance data sets). Biases inherent in remotely sensed image analysis and interpretation (regardless of the spatial resolution) used in on-screen image interpretation may slightly inflate accuracy assessments relative to other evaluation methods. Regardless of the evaluation methods, the same good practices for assessing accuracy (e.g., see Olofsson et al., 2014) should be applied. Such practices may include addressing or leveraging possible interpretation errors (e.g., using interpreter confidence as a predictor of disturbance type; Kennedy et al., 2015; Rodman et al., 2021), ground-truthing, systematic approaches for collecting reference data (e.g., Hislop et al., 2021), and standards for accuracy reporting (e.g., presenting accuracy for each attribution class and for disturbance timing when relevant).

4.6. Future work

4.6.1. Algorithm design and evaluation

Additional algorithm development and testing is needed to determine whether all disturbances in a location can be accurately separated with the detail, timing, and extent that would be most relevant for understanding and managing forest ecosystems. What are the best (or good) practices for automated disturbance attribution? How might algorithms be improved, e.g., by streamlining methods, applying deep learning techniques, or incorporating other data sets or models? We recommend future work that develops and tests how accuracy of attribution varies with spatial scale as well as temporal and thematic resolution and pixel- versus patch-based approaches. Available field data, whether collected at the specific project (landscape) level or regionally at systematic monitoring plots (e.g., the Forest Inventory and Analysis Program within the US Department of Agriculture Forest Service), could be better utilized to optimize detection thresholds and accuracy evaluation at operational scales. Models that supplement remotely sensed data, such as bark beetle phenological models or species distribution models (e.g., to predict the probability of disease infection, He et al., 2019), could improve attribution algorithms, but only if they are highly accurate and suitable for the study context. Studies are needed to evaluate the advantages and disadvantages of different attribution methodologies (Fig. 2, Table A1) to determine which approaches merit use to inform forest management under different circumstances.

Inclusion of new pattern recognition methods could greatly enhance the detection of disturbance agents by picking up the unique imprint they leave on the landscape, spatially (Kislov et al., 2021) or temporally (Chen et al., 2021). For instance, road construction and clear cuts due to harvest might be easily detected by their spatial shape (Abdi et al., 2022). Recent studies show that natural disturbances can be separated by their spatial complexity or surroundings (landscape context) as well as their spectral characteristics (e.g, Senf and Seidl, 2021; Sebald et al., 2021). Patterns of spatio-temporal autocorrelation may be characteristics of certain types of disturbance and severity; with additional research, these patterns of autocorrelation could contribute to improving attribution. Pattern recognition overall shows potential to advance automated attribution methods using currently available data sources.

Two or more disturbances in the same location, such as drought and bark beetle outbreaks (e.g., Meddens et al., 2015), windthrow and subsequent bark beetle outbreaks (e.g., Göthlin et al., 2000), or fire and subsequent salvage logging harvest (e.g., Thompson et al., 2007) need additional consideration of the temporal sequence of disturbances within an attribution framework. For example, drought is a contributor to tree stress and causes mortality, but drought also affects host tree susceptibility to mortality from insect attack and fire. In settings with such linked disturbances, ancillary disturbance datasets or models (e.g., of drought-related mortality; Senf et al., 2020) or incorporation of landscape context (e.g., Sebald et al., 2021; Senf and Seidl, 2021) may help to separate sequential or overlapping disturbance events.

We suggest that wider adoption of common practices among researchers could help facilitate the future development of disturbance attribution algorithms for a variety of forested settings and extents. For example, many studies used the machine-learning random forest classifier, in some instances without sharing sufficient detail from the model (e.g., explaining which predictors were most important and why) to inform researchers in the development of statistical spatial models for other locations. We recommend reporting the relative importance of predictor variables for application and future development of attribution algorithms.

Another recommendation is the development of an attribution classification scheme (expanding upon Fig. 2), similar to the classification of damage causal agents in US aerial surveys but tailored to a remote sensing data attribution approach (e.g., see our attribution level framework, Fig. 1). This would lead to coalescence of attribution classes, more readily comparable predictor variables among studies, and improved utility for natural resource management, because the disturbance types are more clearly and consistently defined. The combination of spatially overlapping disturbances and associated forest ecosystem dynamics may be unique to a given setting; in that case, attribution algorithms may only apply within the setting for which they were developed. Regardless, we suggest that an attribution classification scheme could improve comparisons between attribution algorithms across the same area or region, likely leading to important insights (e.g., see Cohen et al., 2017) and potentially a better understanding of what an acceptable level of accuracy is for research and land management applications.

4.6.2. *Model sensitivity to study context*

Most studies developed and tested one or more attribution algorithms for a particular ecosystem or region. Ecological patterns that hold true in any setting should in theory enable some generalization of algorithms for application in different regions. For instance, beetle-killed pine trees turn red in most settings. The lack of regional-scale automated attribution studies at finer levels of detail (i.e., Levels 2–3, Fig. 1, specifying more than one subdivision of biotic, abiotic and/or anthropogenic disturbance) may reflect current challenges with respect to resolution of imagery and model training and evaluation across heterogeneous landscapes (Cohen et al., 2017). Despite evidence that detection of tree mortality due to bark beetles can be effective with existing finer-resolution spectral data (e.g., Hicke and Logan, 2009; Bright et al., 2020), such data sources are currently too costly and data-intensive to be used operationally in attribution algorithms at larger spatial extents (e.g., National Forests in the US, which span >100,000 km^2). Thus, in addition to ecological characteristics, the availability of suitable reference data is a key consideration for the transferability of attribution algorithms to different locations.

5. Conclusion

Remote sensing is widely used to detect forest disturbances over spatiotemporal scales that are difficult to capture from ground-based or aerial survey data alone. To understand forest ecosystem dynamics and the ecological role of disturbances, researchers and managers need to characterize spatiotemporal patterns for several types of disturbance. To date, we identified 34 scientific studies that have investigated uses of remote sensing to automatically attribute detected forest change to several disturbance types. We found that automated disturbance type attribution from remotely sensed data showed potential for addressing forest management goals and challenges. The reviewed studies presented algorithms that attribute disturbance types with a wide range in accuracy. Improvements to automated disturbance type attribution include increasing the level of detail, moving toward more consistent disturbance type classes that apply to the spatial extents of forest management, refining evaluation and reporting practices, refinement of the timing and detection of diffuse or spatially overlapping disturbances, and application across large areas. Future work should incorporate additional data sources (e.g., more extensive ground surveys, high temporal and spatial resolution data, ancillary datasets) and technological advances (e.g., new image sources, deep learning with pattern recognition, and cloud computing capabilities) to further resolve the spectral, spatial, and temporal characteristics of each disturbance type and potentially combinations of disturbance types, thereby improving attribution accuracy and utility for forest managers and ecological researchers.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Automated disturbance attribution of remote sensing data has not yet reached its full potential (in precision or accuracy) and improvements are needed to inform decision-making for forest managers and advance understanding of disturbance dynamics. As discussed above, we did not find any disturbance attribution studies that achieved the level of thematic resolution needed to fulfill legislative mandates, (e.g., the US National Forest Management Act of 1976 (16 U.S.C. 1600)) or to better inform management in countries with no current program for mapping forest disturbances (e.g., see the SilvaCarbon program, https://www.silvacarbon.org/). To determine whether it is possible to achieve finer levels of attribution, more research is needed to characterize and exploit differences in spectral and spatial signatures of various disturbance types. A mechanistic understanding of the timing, pattern, and specific spectral characteristics of different disturbance types (in particular the difference in biotic disturbances or other stress) for use in automated attribution is missing. This knowledge would help clarify the opportunities and limitations for remote-sensing-based disturbance attribution. For example, awareness of the limitations of remote sensing methods with freely available imagery would indicate where and when it would be beneficial to incorporate more ground or ad hoc aerial surveys or to acquire higher-resolution satellite imagery (e.g., see Bright et al., 2020). To inform future algorithm development, attribution studies should continue to discuss the factors considered in data selection, such as the accuracy, relevance, and spatiotemporal coverage of source data sets.

Timing, duration, and recovery pattern can be key factors for distinguishing disturbance types. Some disturbance agents can be separated by known temporal patterns (e.g., from disturbance databases that document windthrow events, insect outbreaks, or wildfires, or management databases that document actions such as salvage logging; e.g., Havašová et al., 2017; Baumann et al., 2014, Senf and Seidl, 2021). The ability to recognize temporal patterns is limited by the time span of image archives or the temporal density of available imagery or ancillary data sets. Using multiple time series algorithms in sequence may improve change monitoring from existing imagery (e.g., Landsat; Bullock et al., 2020). Increased temporal resolution from dense stacks of Landsat data enhance detection of subtle changes in forest cover and improve within-year estimates of disturbance timing (Ye et al., 2021). Other medium-resolution satellite imagery with high repeat times within a year (e.g., Sentinel) that allow for improved cloud removal, early season detection, and monitoring disturbance progression over a growing season may also prove useful in detecting and attributing disturbances. Studies with finer temporal resolution are increasingly enabled with cloud computing and image analysis platforms (e.g., Google Earth Engine, Microsoft Azure, or Amazon Web Services), which streamline processes using freely accessible data sets such as the complete Landsat/Sentinel archive (i.e., the HLS dataset). The addition of Sentinel data (including Sentinel-1 radar data) to attribution algorithms may help foster additional advances in research and monitoring of forest disturbance and recovery (e.g., Lastovicka et al., 2020), potentially providing greater sensitivity for earlier detection of tree stress.

The capability to accurately extract disturbance information with remote sensing algorithms in near-real time to inform forest management has been explored (e.g., see Olsson et al., 2016) but has not yet been well assessed. Earlier detection, ideally in near-real-time (e.g., within days to weeks of an insect outbreak) could enable managers to more effectively respond to disturbances (Hargrove et al., 2009). Use of dense, intra-annual time series and cloud computing, as described above, will facilitate development of such products that are accessible to a broader audience (e.g., Stahl et al., 2021). Big data analysis techniques that are streamlined with cloud computing and enhanced with deep learning capabilities (e.g., Kislov et al., 2021) could lead to expanded opportunities for automatic attribution across large areas. Once algorithms have been developed, they can be applied to create updated disturbance type maps for managers as new data become available.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2022.113416.

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