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Deep Learning for Satellite-Based Forest Disturbance Monitoring: Recent Advances and Challenges

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ABSTRACT

Climate change and land use pressures are intensifying forest disturbances in many world regions, as reflected in the increasing frequency and severity of wildfires, widespread drought-induced tree mortality, and extensive forest degradation. Hence, spatially explicit and timely information on disturbances is essential for safeguarding the ecological integrity and societal value of both managed and natural forest ecosystems. Satellite-based remote sensing has long been central to forest monitoring, and recent advances in deep learning (DL) are further enhancing the extraction of information from remotely sensed data, thereby improving the accuracy and scalability in detecting, mapping, and attributing disturbance events. Such applications range from mapping logging activities and delineating burned areas to the complex task of classifying disturbances into different agents such as pests, fire, and logging. Despite this progress, DL-based approaches also face significant challenges, including the demand for large annotated training datasets and limited generalization, which might hinder their integration into operational monitoring frameworks. Addressing these barriers will require interdisciplinary collaboration that bridges algorithmic innovation with domain knowledge. This review synthesizes recent advances in DL-based forest disturbance research, situates them within the broader landscape of traditional remote sensing methods, and highlights emerging innovations with the potential to overcome current limitations. We conclude with perspectives on key research priorities for advancing the role of DL in global forest disturbance monitoring.

1 | Introduction

Forests are dynamic systems shaped by natural disturbances such as wildfires, storms, and insect outbreaks, which play a crucial role in maintaining biodiversity, promoting ecosystem renewal, and driving landscape heterogeneity (Seidl et al. 2017). However, disturbance regimes are changing at a pace unmatched in the instrumental and historical record, driven by both anthropogenic climate change and, increasingly, by land management (Altman et al. 2024; Seidl et al. 2017; Turner and Seidl 2023). This threatens not only forest ecosystem functioning, but also the essential services forests provide—including carbon sequestration, local and global climate regulation, maintenance of the hydrological cycle, and biodiversity conservation (Thom and Seidl 2016). Understanding and monitoring the causes, extent, and frequency of forest disturbances is therefore crucial for assessing their current and potential future impacts. Improved disturbance information can guide conservation efforts, enable timely interventions (e.g., through deforestation alerts), and facilitate reporting for global commitments such as the Reduce Emissions from Deforestation and forest Degradation (REDD+) framework, thereby informing evidence-based strategies to sustain and enhance forest resilience (Kacic et al. 2023; Dixon et al. 2023; Schleeweis et al. 2020).

The application of remote sensing to forest monitoring has already provided substantial information on global trends in the frequency, size, and severity of forest disturbances (Senf and Seidl 2020; Wulder et al. 2019). However, several data and methodological challenges persist that constrain its usefulness at regional and global scales (Altman et al. 2024). Using satellite imagery to detect disturbances is not a trivial task, especially in the case of low-severity and very small size tree cover changes, as the data usually contain a mix of information on phenological variations, 'real' disturbances and noise, which can be hard to distinguish (Du et al. 2023; Ouaknine et al. 2025). Disturbance detection is further influenced by sensor characteristics, particularly spatial and temporal resolution (Hirschmugl et al. 2017). Spatial resolution determines the minimum detectable disturbance size and the ability to resolve fine-scale spatial patterns, whereas temporal resolution might influence the detectability of gradual events, or those followed by quick canopy recovery (Reiche et al. 2021). Moreover, some forest disturbances might be concealed by the forest canopy (e.g., understory fires, selective logging) and are therefore not directly visible to optical sensors, or they manifest as subtle canopy changes that fall below detection thresholds due to spatial or temporal resolution limits (Mitchell et al. 2017). Beyond these resolution-related constraints, traditional detection algorithms are becoming increasingly inadequate given both the volume and higher resolution of satellite data now available, and the increasing complexity of contemporary forest disturbances and degradation (Hirschmugl et al. 2017). Methods such as the LandTrendr (Kennedy et al. 2010) are widely used for detecting disturbances, but they typically detect only the largest event in a time series rather than multiple events, often rely on a single vegetation index (Qiu et al. 2023), and are difficult to generalize across different ecosystems without recalibration of parameters (Wu, Huang, et al. 2025). These limitations highlight the need for more flexible and powerful approaches capable of learning directly from data, integrating multiple sources of information, and adapting to diverse disturbance regimes.

Deep learning (DL), a sub-class of machine learning (ML), has become an invaluable tool in the field of remote sensing (Ball et al. 2017). The recent rapid adoption of DL methods in this field has been made possible due to improvements in computing hardware (e.g., high-performance GPUs), cloud computing, and the increased availability of (preprocessed) open data, which together enable the analysis of large amounts of long-term Earth imagery (Kattenborn et al. 2021). While DL cannot overcome constraints imposed by sensor resolution, it offers several advantages over traditional methods, particularly regarding better use of the spatial and temporal information available in satellite datasets (Reichstein et al. 2019). A key advantage lies in its ability to automatically learn meaningful features directly from raw data and to build hierarchical feature representations that increase in complexity with deeper network layers, rather than relying on manually engineered features (Li et al. 2018). In addition, they can incorporate spatial context beyond per-pixel analysis through architectures such as Convolutional Neural Networks (CNNs) and simultaneously capture spatial and temporal dynamics using models like transformers and ConvLSTMs. Their applications in forest disturbance span a broad spectrum of tasks, including classification, segmentation and object detection (Zhang et al. 2016). They have been demonstrated to not only effectively detect disturbances (Kong et al. 2018), but also classify forest disturbance agents (Du et al. 2023) and map ecological responses such as standing deadwood (Schiefer et al. 2023). Nevertheless, there is a significant gap between the forefront of DL research and its practical use in forest applications. Adapting these techniques to forest monitoring requires not only extensive research, but also a concerted, interdisciplinary effort between remote sensing, forestry and ML researchers.

Given the diversity of processes encompassed by the term "forest disturbance monitoring", we clarify our conceptual scope in Figure 1. In this review, forest disturbance refers to discrete or progressive events that disrupt the structure, composition, or functioning of forest ecosystems, thereby altering environmental conditions and resource availability (FAO 2004). Figure 1 distinguishes between disturbance agents, their ecological responses, and long-term forest trajectories following disturbance. Natural disturbance agents include biotic drivers (e.g., insect infestations, diseases, and animal damage) and abiotic drivers (e.g., wildfire, windthrow, and drought), whereas anthropogenic disturbances include activities such as legal and illegal logging and other forest management practices. Disturbance agents rarely act in isolation; most events arise from interacting drivers that can amplify overall impacts (Rogers 1996). Some disturbances occur abruptly, while others unfold gradually, for example through multi-year tree mortality caused by water stress, insects, or pathogens (Perbet et al. 2024). These agents trigger ecological responses such as canopy damage or loss, defoliation, and tree mortality, ranging from localized, non-stand-replacing events to landscape-scale tree cover loss (Dalagnol et al. 2023). Satellite observations primarily detect these structural or physiological responses as changes in canopy condition or spectral signals. Over longer time scales, these responses may lead to different forest trajectories. Importantly, forest disturbance does not necessarily imply ecological loss or permanent land-cover change, as forests can recover following disturbance events. When impacts persist but the land remains classified as forest, the process is referred to as forest degradation, defined as a sustained reduction in structural attributes, biomass, canopy cover, or ecological function. In contrast, deforestation denotes a semi-permanent or permanent conversion of forest to non-forest land use. The definitions illustrated in Figure 1 are applied consistently throughout this review.

By examining the recent literature on DL-based forest monitoring, this study aims to identify current research gaps and future trends in both methods and datasets becoming available to inform the development of more effective tools for monitoring forest ecosystems under changing disturbance regimes. This work builds upon previous reviews that looked at the use of DL in remote sensing (Zhu et al. 2017), and CNNs for vegetation remote sensing (Kattenborn et al. 2021), by both providing a deeper focus on disturbance-related applications, and by incorporating emerging DL architectures that show strong potential for advancing this field. Unlike systematic reviews, this work adopts a perspective-driven approach that synthesizes recent progress in forest disturbance research while drawing on DL studies to identify algorithms with potential for disturbance monitoring. We focused on satellite imagery with high to moderate spatial and temporal resolution

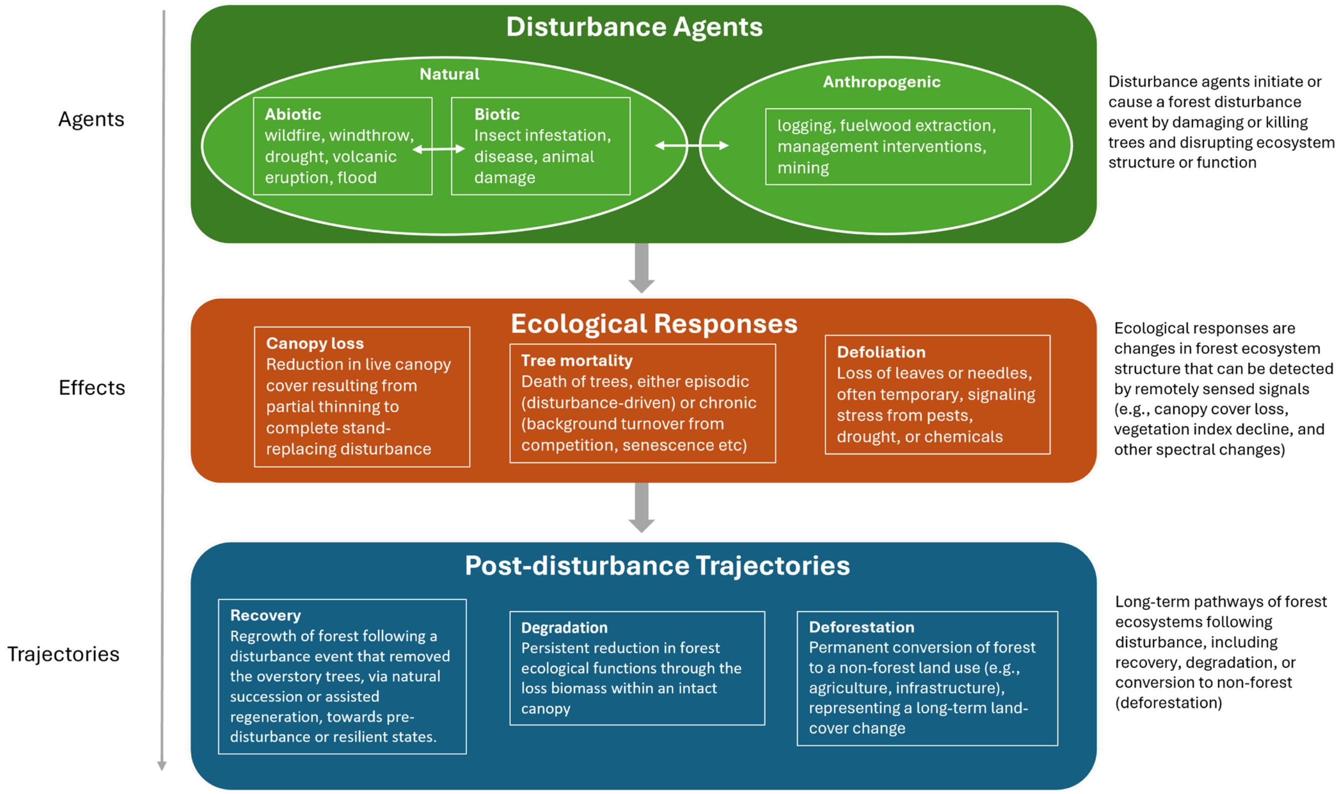

FIGURE 1 | Key terms used in forest disturbance monitoring, illustrating the progression from disturbance agents to ecological responses, and long-term forest trajectories.

(~3–30 m, monthly to annual observations) because data at this scale is widely available from operational satellite missions and well suited for large-scale forest monitoring. This resolution range balances spatial detail with broad areal coverage, offering up to global extent, relatively consistent data acquisition, and long-term openly accessible archives that enable retrospective analyses, despite occasional observational gaps (e.g., due to cloud cover) (Md Jelas et al. 2024). To ensure reproducibility and broad applicability, we prioritized studies using free and open datasets. In exceptional cases, studies that did not fully meet these criteria were included due to their high relevance to the topic.

2 | Traditional Satellite-Based Forest Disturbance Monitoring

Satellite-based Earth Observation enables standardized, large-scale, and high-temporal-resolution monitoring of forest dynamics (Hislop et al. 2020), providing a powerful alternative to time-specific, plot-based forest data collection (Nesha et al. 2021; Sebald et al. 2021). A major milestone in satellite-based forest monitoring came in 2008, when the United States Geological Survey (USGS) made the entire Landsat archive freely available. This global, 30-m imagery enabled for the first time the systematic detection of long-term trends in deforestation, as well as the integration into operational forest monitoring systems, such as the Global Forest Change (GFC) (Hansen et al. 2013; Senf and Seidl 2020). Capabilities were expanded further with the European Space Agency (ESA)'s Copernicus program, particularly with the launch of the Sentinel-2 satellite mission in 2015. Sentinel-2 offers 13 spectral bands ranging from 10 to 60 m spatial resolution, and 2–5 days revisit cycles depending on the latitude, allowing more detailed characterization of vegetation status and change (Senf 2022; Drusch et al. 2012). Sentinel-2 has enabled the detection of smaller scale disturbances, such as the tracking of selective logging activities, previously undetectable in coarser Landsat imagery (Slagter et al. 2023; Grabska et al. 2020).

Beyond passive sensors, radar technology has become especially relevant for regions with frequent cloud cover, such as the tropics, because it operates independently of sunlight and can penetrate clouds. ESA's Sentinel-1 Synthetic Aperture Radar (SAR), for instance, with < 10-m resolution, supports near-real time disturbance alerts in the Congo Basin (Reiche et al. 2021) and monthly forest harvest mapping (Zhao et al. 2022). Concurrently, LiDAR technology uses laser pulses to penetrate canopies and enables detailed measurements of canopy height, gap size, vegetation density and three-dimensional maps of forest structure (Senf 2022). LiDAR has been applied to monitoring disturbances from hurricanes and fires, and biomass change, as well as mapping biodiversity and habitat distribution (Senf 2022; St. Peter et al. 2021; Kattenborn et al. 2021). Although high acquisition costs have historically limited coverage, LiDAR is becoming more accessible through missions such as NASA's Global Ecosystem Dynamics Investigation (GEDI). GEDI is installed on the International Space Station (ISS) which has an equatorial orbit that ranges from approximately 51.6 degrees north and south in latitude. While its temporal and spatial coverage is limited, integrating GEDI with imagery from Landsat

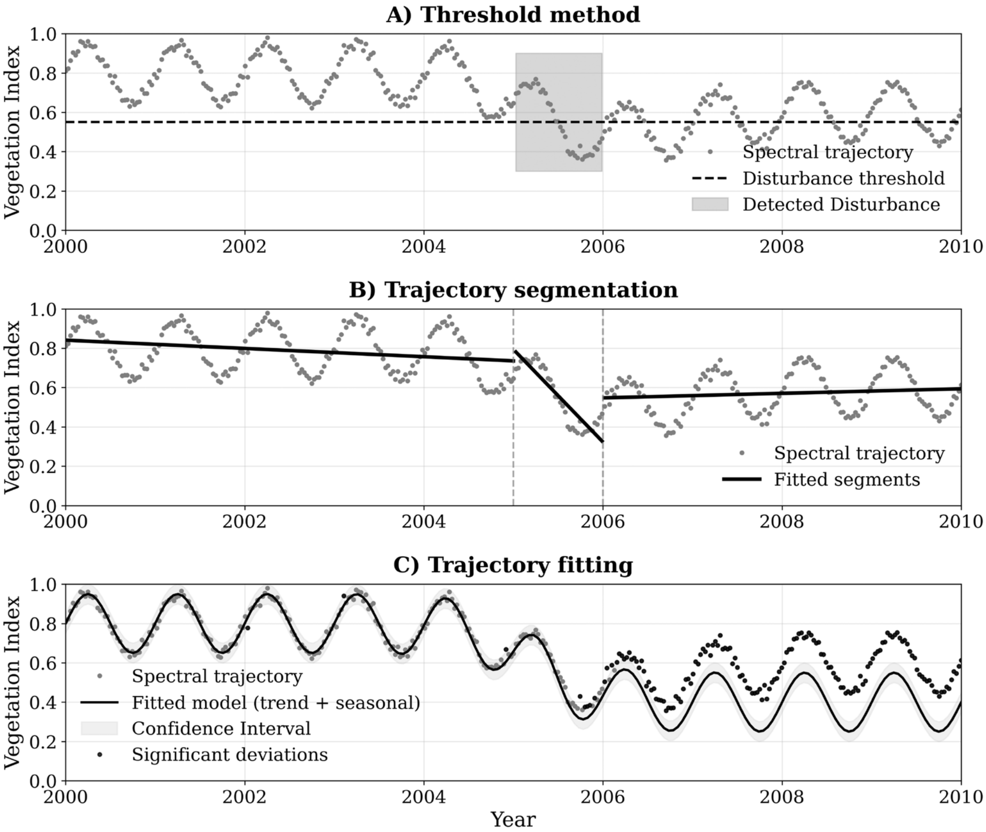

FIGURE 2 | Overview of spectral-based change detection algorithms. (A) Threshold method: disturbance detected when vegetation index drops below predefined threshold. (B) Trajectory segmentation: piecewise linear or polynomial segmentation function identifies breakpoints. (C) Trajectory fitting: statistical deviations from fitted model indicate disturbances.

or Sentinel-2 enables wall-to-wall forest structure mapping (Potapov et al. 2021; Lang et al. 2023; Burns et al. 2024). Furthermore, recent and upcoming satellite missions are expanding opportunities for biomass and canopy structure monitoring, such as ESA's Biomass Earth Explorer mission, launched in 2025, which is expected to further improve global biomass estimation by using SAR to measure tree height and volume. Together, these sensor technologies provide complementary perspectives on forest change and structure.

Translating these satellite data into useful information or biophysical quantities requires several preprocessing steps, including radiometric, geometric and atmospheric corrections, which aim to remove sensor- and atmosphere-related noise, ensure spatial consistency, and retain only reliable surface reflectance observations (Shah et al. 2025). Following preprocessing, spectral enhancement steps such as the calculation of vegetation indices (VIs), including the Normalized Difference Vegetation Index (NDVI), the Enhanced Vegetation Index (EVI) and the Normalized Burned Ratio (NBR), have long served as a cornerstone for information retrieval. These indices are computed using specific spectral bands that better highlight vegetation health and condition (Senf 2022). By analyzing temporal series of VIs, algorithms can detect anomalies from long-term patterns, revealing shifts that might indicate disturbances (Pasquarella et al. 2017). A variety of algorithms have been developed for time-series change detection based on spectral-temporal properties. They can be broadly categorized into three main groups: threshold methods (Figure 2A), trajectory segmentation methods (Figure 2B), and time-series decomposition or trajectory fitting methods (Figure 2C).

Threshold-based methods, such as the Vegetation Change Tracker (VCT), use a user-defined threshold to separate real changes from other spectral variations caused by factors like geometric misregistration, seasonality, or changes in illumination (Kennedy et al. 2007). These methods are effective for detecting sudden, pixel-level disturbances, but they often struggle to capture gradual changes and can be difficult to apply consistently across ecosystems, since suitable thresholds vary with species composition and local conditions (Huang et al. 2009; Hilker et al. 2009). Trajectory segmentation methods address some of these limitations by dividing a time series into segments that represent periods of stability or change. They fit simple linear or polynomial models to VI data, identifying change when the slope or residuals shift sharply between segments. A widely used approach is the LandTrendr (Landsat-based Detection of Trends in Disturbance and Recovery) (Kennedy et al. 2010), which pinpoints both the timing and magnitude of forest disturbance and recovery. Time-series decomposition methods, such as BFAST (Breaks for Additive Season and Trend), take a different approach by separating long-term trends, seasonal patterns, and noise within a signal (Verbesselt et al. 2012). When new observations deviate significantly from this modeled baseline, a change is flagged. Related statistical models include CCDC

(Zhu and Woodcock 2014), COLD (Zhu et al. 2020), and SCCD (Ye et al. 2021), which fit continuous or harmonic functions to long-term satellite data. The choice of algorithm usually depends on the type of disturbance. Threshold-based methods are limited to capturing abrupt events, whereas segmentation and decomposition methods enable superior detection of more gradual or subtle changes (Schleeweis et al. 2020). While these spectral-based approaches are relatively simple and require little reference data, they have a number of limitations. They typically rely on a single VI, making them sensitive to sensor differences, atmospheric effects, and seasonal variation. In addition, their need for frequent, cloud-free imagery restricts their use in areas or periods with limited data availability (Parra and Simard 2023).

Moreover, classification-based algorithms, including classical ML models such as RFs and support vector machines (SVMs), are increasingly used. These methods can combine information from multiple sensors, spectral bands, and auxiliary data, allowing them to capture more complex disturbance patterns under varying environmental conditions, since these become part of the predictors. They also enable the detection of multiple disturbance events per pixel, in contrast to many spectral-based methods that typically detect only the largest event (Viana-Soto and Senf 2025).

3 | Deep Learning for Forest Disturbance Monitoring

DL has become a cornerstone in many scientific fields, owing to its capacity to approximate highly complex, non-linear functions; its end-to-end learning paradigm that obviates the need for handcrafted features; its modular architecture, which enables model customization for specific tasks; and its ability to generate compact internal representations (embeddings) that can be transferred across tasks or fine-tuned for domain-specific applications (Molnar 2022). These methods offer particular value in Earth System Science, where processes are governed by complex spatial and temporal dependencies (Reichstein et al. 2019). Vegetation succession, disturbance, and recovery unfold across scales in space and time (Foster et al. 1998), requiring models that can represent both short- and long-range dependencies. Advanced DL architectures are specifically designed to capture such relationships, allowing them to learn correlations across space (e.g., neighboring pixels using CNNs or vision transformers (Dosovitskiy et al. 2020)) and time (e.g., sequences in time series with Long Short-term Memory (LSTM) (Hochreiter and Schmidhuber 1997) or transformers (Vaswani et al. 2017)) directly from data.

In this review, we highlight advances in spatiotemporal DL models that integrate two-dimensional spatial maps with temporal sequences, enabling modeling of dynamic forest change processes. We also examine and discuss emerging AI paradigms—including representation learning through embeddings, foundation models, and generative AI, which might help advance the field by improving model generalization, scalability, or—following a data-centric view—simply the quality and quantity of training data. Embeddings can capture transferable representations of spectral–temporal patterns; foundation models offer pretrained architectures that can be fine-tuned for forest applications under a smaller data volume; and generative AI can synthesize or augment scarce training data.

3.1 | Spatiotemporal Models

Recurrent neural networks (RNNs), particularly LSTMs, have been widely used to model long-range temporal dependencies in environmental time series (Natel et al. 2022; Kong et al. 2018; Schiefer et al. 2023) and have proven their reliability over time. However, the emergence of transformers, with their parallelizable self-attention mechanism and superior handling of long-term dependencies—avoiding the vanishing gradient issues that can affect LSTMs—is rapidly surpassing LSTM-based approaches in performance (Beck et al. 2024). In parallel, convolutional architectures (LeCun and Bengio 1998) have also shown comparable or superior performance in sequential tasks (Bai et al. 2018), while simultaneously being able to exploit spatial patterns. Although a range of LSTM architectures is being constantly developed to overcome their typical limitations, such as ConvLSTM (Shi et al. 2015), xLSTM (Beck et al. 2024), and Vision-LSTM (Alkin et al. 2024), it is expected that models that are inherently more suitable for spatiotemporal analysis will become more important in forest disturbance research in the coming years.

CNNs have demonstrated exceptional effectiveness in semantic segmentation tasks, learning to distinguish between different classes and objects using extensive training data (Boulila et al. 2024). They employ convolutional kernels to exploit spatial and temporal structure (e.g., in the case of 3D CNNs). These kernels operate over small neighborhoods—inspired by receptive fields in vision—allowing the network to learn multi-pixel patterns instead of independent weights for each feature (LeCun and Bengio 1998; Szegedy et al. 2016). The combination of many kernels in the depth dimension of a layer and the stacking of many such convolutional layers in a CNN architecture expands the receptive field and yields a hierarchy of features, from simple edges and textures in early layers to complex spatial arrangements in deeper ones (Szegedy et al. 2015; He et al. 2016; Kattenborn et al. 2021). This capacity to capture local-to-global patterns holds particular promise for detecting subtle forest changes and attributing disturbances by incorporating contextual information that can help classification. Among CNN-based architectures, the U-Net (Ronneberger et al. 2015) has become particularly prominent in forest monitoring. Its encoder–decoder structure combines a contracting path that extracts context with an expansive path that restores resolution, aided by skip connections that preserve fine details. U-Nets have been applied to track tropical forest cover change with high accuracy (Zhao et al. 2022; Dalagnol et al. 2023) and monitoring reforestation in degraded landscapes (Andresini et al. 2024).

Vision transformer architectures (Vaswani et al. 2017; Dosovitskiy et al. 2020) also represent a major advance in modeling spatiotemporal data (Du et al. 2023). Earlier RNN-based methods were limited by sequential information flow and vanishing gradients, which constrained their ability to capture long-range dependencies and hindered parallelization. While LSTMs and GRUs mitigated some of these issues through gating mechanisms and memory cells, they remain inherently sequential and are still susceptible to vanishing gradient problems due to the sequential nature of their computations. Transformer architectures, in contrast, allow for efficient parallelization by employing attention mechanisms. The self-attention mechanism computes dependencies in an input sequence, being able to integrate information across an entire image (Boulila et al. 2024), regardless of position, and it helps the model to learn context and long-range dependencies by weighting the importance of each element within the input sequence. Early applications of transformer architectures in forest disturbance research demonstrate clear promise and mark a broader shift toward models that can capture complex spatiotemporal dependencies. Collectively, recent studies show that self-attention models can outperform traditional change-detection methods (Du et al. 2023) and convolutional approaches (Kaselimi et al. 2023), particularly for subtle or underrepresented disturbance classes (Schiller et al. 2024; Du et al. 2023). While most transformer-based applications to date in forest monitoring have relied only on self-attention, cross-attention mechanisms also hold potential for multimodal data fusion—linking features across complementary data sources such as Sentinel-1 SAR and Sentinel-2 imagery to improve cloud-shadow handling and disturbance detection (Nagrani et al. 2021). Cross-attention mechanisms can capture how elements in a source sequence relate to elements in a target sequence.

The reviewed studies indicate a trend toward spatiotemporal models that are more flexible and data-efficient like transformers than classical ML methods or purely statistical models. Yet, challenges remain regarding transferability of these models to global scales (see Section 4.3). It is also worth mentioning that approaches that merge the strengths of different DL architectures are a common practice in the field of ML, for example, by integrating convolutional elements in transformer models to enhance the overall effectiveness of vision transformers (Wu et al. 2021; Zhang and Zhang 2023) and other methodological advances to address computational costs and optimization of DL models. Benchmark datasets for wildfire modeling have enabled systematic comparisons of DL models of varying complexity, with results suggesting that simpler architectures are often sufficient to capture fire disturbance patterns (e.g., comparing LSTMs and ConvLSTMS, or vanilla transformers to more advanced transformer architectures) (Kondylatos et al. 2022; Di Giuseppe et al. 2025; Becker et al. 2026). This could be related to data quality issues, in which increasing modeling complexity does not necessarily lead to performance improvements (Di Giuseppe et al. 2025). However, going beyond off-the-shelf DL models, and following up close DL innovations is essential to bring the forest disturbance research up to date with state-of-the-art AI solutions, and ultimately leading to new breakthroughs.

3.2 | Strategies for Machine Learning With Limited Labeled Data

Supervised DL methods typically require large labeled datasets. These methods develop predictive models by training on datasets in which each sample is associated with a known ground-truth value or label. While they have achieved impressive success across many applications, acquiring such large labeled datasets, particularly for forest disturbances, remains challenging due to the high cost and labor-intensive nature of data annotation (Wang, Albrecht, et al. 2022). To overcome data limitation issues, recent research has increasingly focused on weakly supervised learning paradigms, which leverage unlabeled or partially labeled data to enhance model performance. These approaches include self-supervised, semi-supervised, few-shot, and zero-shot learning methods (Zhou 2018; Gui et al. 2024) (Figure 3), offering practical solutions for forest monitoring tasks where labeled data are limited.

Self-supervised learning (SSL) and semi-supervised learning for example, leverage large amounts of unlabeled data to improve representation learning. In SSL (Figure 3A), models are pretrained on unlabeled data using pretext tasks that generate pseudo-labels automatically, before being fine-tuned on labeled datasets (Gui et al. 2024). Several SSL approaches can be employed, including generative, contrastive, and predictive methods (Ziv and LeCun 2024). Generative methods learn to reconstruct input data, contrastive methods learn to maximize the similarity between semantically identical inputs (positive pairs), while minimizing the similarity between different inputs (negative pairs), and predictive methods learn to predict self-generated labels (Wang, Albrecht, et al. 2022). The best technique to be used as well as the definition of the pretext task requires expert knowledge. After pretraining using a pretext task on large unlabeled satellite imagery, the learned representations can be fine-tuned with limited labeled data for downstream tasks such as disturbance detection and mapping (Kuzu et al. 2024). Semi-supervised approaches (Figure 3B) refer to the combination of a small amount of labeled data and a large amount of unlabeled data to train models, using techniques such as generative modeling, low-density separation, or graph-based propagation (Olivier et al. 2006). In forest monitoring, these strategies have been applied to tasks such as deforestation classification using active learning (Dallaqua et al. 2018) and forest fire segmentation from unmanned aerial vehicles (UAV) imagery, where SSL with data augmentation improved performance relative to classic methods despite limited labels (Wang, Fan, et al. 2022). A hybrid graph-based SSL method combined with an expert system have also achieved high accuracy in vegetation mapping from Sentinel-2 in comparison to a supervised approach (Layegh et al. 2022), and more recently, Chen et al. (2025) proposed a semi-supervised boundary segmentation network (BS-GAN) to reduce dependency on labeled data, achieving superior accuracy and generalization capabilities compared to existing segmentation networks for remote sensing imagery, which could help address the common scarcity of labeled data in disturbance mapping tasks.

Weakly supervised semantic segmentation (WSSS) (Figure 3D) relaxes the requirement for pixel-wise segmentation mask labels by exploiting coarser annotations such as image-level classification labels (e.g., only indicate presence/absence of an object class, not its location) (Jonnarth and Felsberg 2022). This is particularly relevant for forest disturbance models, as ground observations at plot scale (e.g., National Forest Inventory point-based) usually cannot be perfectly aligned with satellite imagery, and image-level labels could be used to train segmentation models without pixel-level annotation. These approaches reduce annotation cost by using algorithms

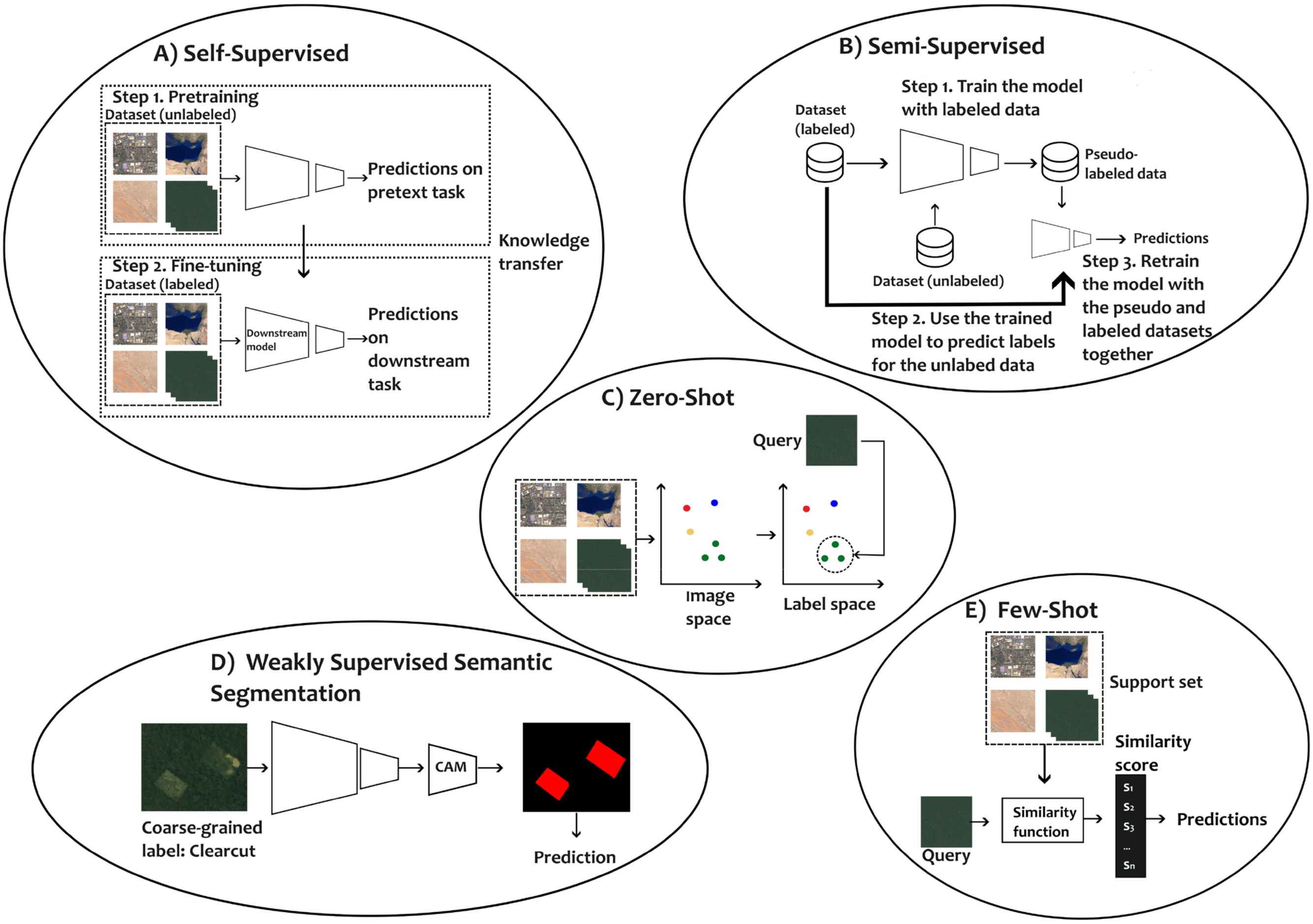

FIGURE 3 | Overview of weakly supervised learning approaches, including (A) self-supervised, (B) semi-supervised, (C) zero-shot, (D) weakly supervised semantic segmentation, and (E) few-shot learning.

such as Class Activation Maps (CAMs) (Zhou et al. 2016), attention mechanisms, and multi-instance learning, to infer fine segmentation details from coarse signals. For instance, CAMs can reflect the most discriminative location of an image, serving as pseudo-labels that guide the training of a subsequent segmentation network (Lai et al. 2021). Several studies demonstrate that WSSS can be a cost-effective alternative for large-scale surveys where detailed (semantic) labeling is impractical or unavailable (Illarionova et al. 2021; Moraes et al. 2025; Wang et al. 2020). Moreover, even when accurate labels are available, weak supervised learning can act as a form of regularization, helping to prevent the model from overfitting.

Few-shot learning (FSL) (Figure 3E) addresses the challenge of training with only a handful of labeled samples per class. It achieves this by leveraging prior knowledge from large amounts of related data, learning generalizable feature representations that can be quickly adapted to new classes from just a few examples. Using the *N*-way *K*-shot framework, a model is trained to classify data across *N* classes (the "*N*-way") using only *K* labeled examples per class (the "*K*-shot"). Models are trained to generalize from a small support set to a larger query set. The key idea is that the model learns to compare new examples with previously seen examples in a learned embedding space or to adapt its parameters quickly through meta-learning, enabling accurate predictions even with very limited labeled data. Metric learning approaches, such as Siamese networks, have been particularly successful in forest applications. A Siamese network learns a distance metric (or similarity function) by processing pairs of inputs through identical subnetworks with shared weights to produce embeddings, then computing a distance between them (Chicco 2021). Training optimizes the network to minimize the distance between embeddings of similar pairs and maximize it for dissimilar pairs, often using contrastive loss functions (Hosseiny et al. 2023). For example, FSL has been applied to detect invasive and native species in the mid-Atlantic rainforest from UAV-based imagery (Gevaert et al. 2025), and image-based plant species identification with small datasets (Figueroa-Mata and Mata-Montero 2020). Similarly, few-shot semantic segmentation has enabled cross-biome generalization, with models trained on tropical forests successfully adapted to temperate forests (Puthumanaillam and Verma 2023).

Zero-shot learning (ZSL) (Figure 3C) takes this one step further by enabling classification of categories for which no labeled examples exist. For example, a model trained to recognize common tree species in a forest could identify a new, previously unseen species based on descriptions of its characteristics, such as leaf morphology and bark texture (Praveena et al. 2024) without ever having been shown labeled examples of that species. This allows the model to generalize to entirely new classes without

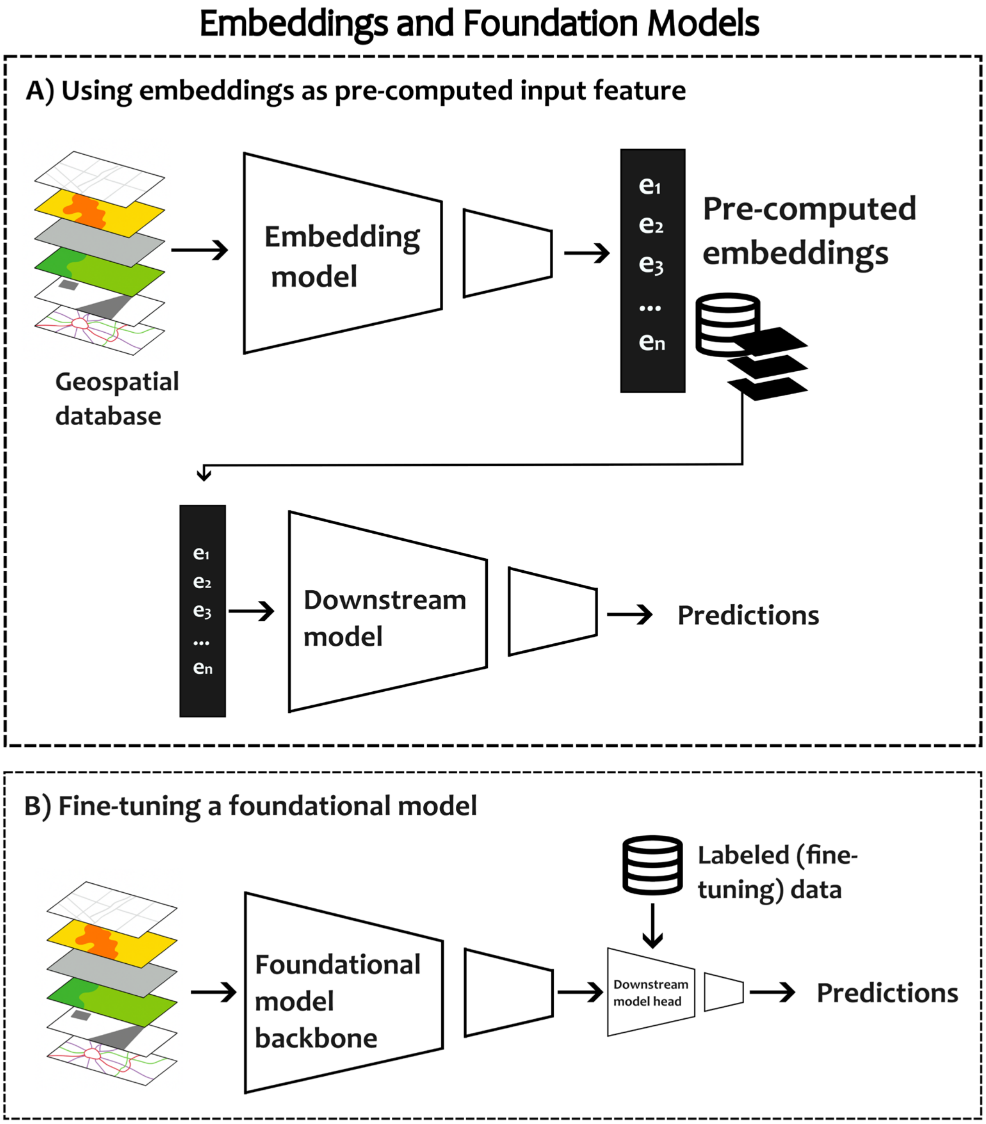

FIGURE 4 | Overview of how (A) embeddings and (B) geospatial foundation models can be used in downstream tasks. Embeddings are the representations produced by a model, that is, vectors of numbers that compress the content of an image into a machine-readable form. These can be used as input features to downstream models. Geospatial foundation models are pretrained models that learn these representations from large-scale Earth observation data and often output embeddings as one of their main products. They can also serve as base models for fine-tuning on downstream tasks.

additional labeled data. ZSL methods transfer semantic knowledge through attribute-based learning or embedding spaces, linking known to unseen classes (Wang et al. 2019).

3.3 | Embedding Models

Embedding models (Figure 4A) can transform raw satellite imagery into compact, structured, and analysis-ready numerical representations. These embeddings encode latent features—underlying spatial and spectral patterns that are not directly observable in the raw data—into dense numerical vectors. Such deep features provide a powerful and flexible foundation for a wide range of downstream ML applications (Liu et al. 2025), including similarity search, change detection, automatic clustering, and classification, often achieving high accuracy with significantly less labeled training data. By extracting task-relevant information in a lower-dimensional and structured form, embeddings have the potential to supplant conventional image composites and manually engineered features such as spectral indices or harmonic models. This representation can enable more accurate differentiation between disturbance classes and improve model generalization.

The efficacy of embedding models for monitoring forest disturbance critically depends on their handling of temporal dynamics. Models that explicitly encode temporal information (e.g., Tollefson (2025)) can be directly used as features to train supervised change detection algorithms. In this case, disturbance events can be identified by quantifying the dissimilarity between embedding vectors of the same location at different times. This approach allows not only for the identification of changes, but also the tracking of disturbance and recovery dynamics. Unsupervised clustering of embeddings, in turn, can assist in attributing specific disturbance types. Moreover, embeddings can summarize patterns related to vegetation structure and other spatial characteristics associated with distinct disturbance processes—for example, linear boundaries indicative of clearcut or circular burn scars typical of wildfires.

Recent years have seen the development of several prominent models, such as Clay (2025), AlphaEarth Foundations (Tollefson 2025), and SatCLIP (Klemmer et al. 2025). These models are typically trained using SSL on vast corpora of satellite imagery and other georeferenced data. A key advantage of embeddings is that they are user-friendly, that is, they can be downloaded just like remote sensing data. AlphaEarth foundations for example, offers global, precomputed embeddings at 10-m resolution for the period 2017–2024, providing an immediately usable data product. This “analysis-ready” characteristic means they circumvent the need for extensive preprocessing of satellite images, such as atmospheric correction and cloud masking, or the precomputation of VIs. Embeddings can also be learned by fusing data from multiple sensors—such as Sentinel-1 C-Band SAR, Sentinel-2 and Landsat multi-spectral observations, and GEDI canopy height metrics—effectively condensing multi-source information into a unified, easy-to-use representation. The recently proposed TESSERA embeddings for example, outperforms state-of-the-art methods across very specific forest monitoring tasks, such as estimating canopy height, mapping above-ground biomass, identifying fire scars and evaluating agroforestry stocking indices (Feng et al. 2025).

3.4 | Foundation Models

Foundation models (Figure 4B) are large-scale neural networks typically trained on multiple data modalities, such as text, images, and structured data, using SSL. This exposure to diverse datasets enhances their generalization capacity, enabling strong performance on a wide range of downstream tasks that were not seen during training (Li et al. 2023). While computer vision models pretrained on datasets like ImageNet (Deng et al. 2009), such as the Segment Anything Model (SAM) (Kirillov et al. 2023), indicate potential for remote sensing applications (Osco et al. 2023), geospatial foundation models (GFMs) extend this paradigm by leveraging vast, unlabeled remote sensing data, from individual sensors to multi-satellite archives, to learn task-agnostic representations of the Earth's surface (Jakubik et al. 2025). This domain-specific training allows them to capture the unique spectral, spatial, and temporal patterns found in satellite imagery, leading to superior performance in remote sensing tasks. For instance, the Prithvi GFM (Jakubik et al. 2023), trained on harmonized Landsat and Sentinel-2 data, has demonstrated stronger generalization than specialized U-Net models over(fitted) on small datasets for a range of Earth observation tasks (e.g., wildfire scar segmentation, multitemporal crop segmentation etc.). This is a rapidly evolving field, with many new GFMs being developed to address remote sensing challenges more effectively (Smith et al. 2025; Wu, Zhang, et al. 2025; Xiao et al. 2025; Tollefson 2025). The Presto model (Pretrained Remote Sensing Transformer) (Tseng et al. 2023), for example, is trained on data from multiple sensors yet remains lightweight enough for deployment in compute-constrained environments while maintaining high performance. Ishikawa et al. (2025) demonstrated that fine-tuning Presto in a small dataset of tree species outperforms the classic hand-defined harmonic features for classification by a large margin of up to 10%. Similarly, FoMo-Net integrates a wide range of spectral bands and sensors to serve as a flexible backbone for global forest monitoring (Bountos et al. 2025). Fine-tuning such pretrained GFMs on smaller, labeled forest disturbance datasets offers a promising pathway toward developing robust and generalizable models for detecting and characterizing forest change.

3.5 | Generative Artificial Intelligence

Generative models that are able to produce text, images, video, and other data modalities have already been incorporated in several fields (Choi et al. 2017; Ziegler et al. 2022; Dunn et al. 2019), and recently have also been explored for ecology (Rafiq et al. 2025). These models generate new data that preserve the statistical patterns and properties of the underlying training distributions.

In forest monitoring, two applications are especially promising. First, data augmentation can address data scarcity by generating synthetic samples that complement limited real-world datasets (Hennessy et al. 2021). Generative adversarial networks (GANs) and diffusion models can create image-like data to represent rare or underrepresented forest disturbance events. Second, large language models (LLMs), such as GPT-4, can expand access to unstructured forest-relevant information from sources including research papers, news reports, and government bulletins. For example, Castro et al. (2024) demonstrated that GPT-4 can identify relevant documents, extract geographical references, infer coordinates, and return structured outputs from species distribution texts. Similar approaches have been applied to extract disease-report data (Gougherty and Clipp 2024) and to retrieve information on invertebrate pests and their controllers from research abstracts (Scheepens et al. 2024) and other ecological data from written texts (Edwards et al. 2022; Scheepens et al. 2024). Applied to forest monitoring, this capacity could facilitate the acquisition of auxiliary data to enrich ML training, or for instance generating weak labels for satellite images. Moreover, emerging work suggests that generative models could contribute to uncertainty quantification by estimating label confidence or sampling alternative interpretations of ambiguous cases (Shu and Farimani 2024; Price et al. 2025), further improving the robustness of forest monitoring pipelines.

4 | Current Forest Monitoring Challenges and Deep Learning Opportunities

4.1 | Detecting Disturbances of Varying Severity

Forest disturbances span a wide gradient of severity, which largely determines their detectability from satellite observations. Large-scale, stand-replacing disturbances, such as high-severity wildfires, windstorms, and clear-cut harvests, are characterized by the abrupt death and removal of most or all trees within a forest stand (Acil et al. 2025). These events produce strong and often persistent spectral signals, reliably detectable using moderate-resolution satellite imagery (e.g., Landsat at 30 m). Given the strength and persistence of these signals, a range of methods have been successfully applied to their detection. Trajectory-based methods such as LandTrendr (Kennedy et al. 2010) remain widely used, and classification-based approaches (e.g., RFs) offer the added ability to identify multiple disturbance events within a single time series. More recently, DL models applied to Landsat data have been shown to outperform traditional methods (Du et al. 2023; Perbet et al. 2024), enabling not only the mapping of disturbance years but also the attribution of disturbance types.

At the other end of this severity gradient, detecting low-severity disturbances via remote sensing is considerably more challenging. These events remove only a small fraction of trees or cause gradual stress, leaving the canopy largely intact. Examples include selective logging, minor insect or disease outbreaks, low-intensity surface fires, or progressive tree mortality from droughts. Such disturbances produce only subtle spectral signals, often smaller than the pixel size of moderate-resolution satellite sensors, and may be quickly obscured by regrowth (Dalagnol et al. 2023). Persistent cloud cover in tropical regions further complicates monitoring. Although low-severity disturbances are relatively small, they are important because their effects accumulate over time, influencing forest structure, biodiversity, and the balance of carbon sinks and sources. Early detection also helps track ecosystem health and supports timely management actions, such as adaptive measures aimed at maintaining the forest's carbon sink potential (Ferretto et al. 2025).

A large body of research has been conducted in an attempt to map selective logging and other small-scale disturbances (Asner et al. 2010; Matricardi et al. 2007, 2020; Shimabukuro et al. 2014). While conventional approaches that rely on VIs struggle to distinguish disturbance signals from seasonal variability or noise, leading to frequent under-detection (Zhang et al. 2021), recent progress in both data availability and analytical methods is beginning to close this gap. In terms of data, fusing Landsat and Sentinel-2 imagery has been shown to increase the spatial resolution and improve the accuracy of detecting smaller-scale disturbance events (Zhang et al. 2021). Furthermore, combining passive sensors with radar data, such as Sentinel-1 SAR, improves monitoring robustness under cloudy conditions, because radar can penetrate clouds, offering a critical advantage (Reiche et al. 2021; Zhao et al. 2022). Commercial satellites, such as PlanetScope with imagery at 3–5 m resolution imagery, now enable for near-monthly tracking of selective logging before rapid canopy recovery obscures the disturbance event (Reiche et al. 2021). Figure 5, which illustrates logging road expansion followed by selective logging visible as small canopy gaps, highlights both the spatiotemporal patterns that DL models can exploit and the need for high temporal resolution imagery to capture disturbances quickly obscured by vegetation regrowth.

DL pipelines applied to high-resolution Norway's International Climate and Forests Initiative (NICFI) satellite data have successfully mapped both rapid and subtle land cover changes across Brazil at 3–5 m resolution (Wagner et al. 2023). Additionally, U-Net architectures trained on PlanetScope imagery (4.22 m) have proven effective for identifying and attributing specific disturbance drivers, including logging, fire, and road development (Dalagnol et al. 2023). Sentinel-2's 10 m imagery has also been shown to detect illegal logging without the need for manually derived VIs when paired with DL methods (Schiller et al. 2024).

Table 1 synthesizes how disturbance at different severity translate into data and modeling requirements. For high-severity

FIGURE 5 | Monthly PlanetScope imagery (3 m spatial resolution) showing logging road expansion in January, February, March, followed by selective logging in September and October, and rapid canopy closure in November. Circles indicate canopy openings after logging in October, and canopy closure within 1 or 2 months in November. *Source:* Figure from Reiche et al. (2021), https://doi.org/10.1088/1748-9326/abd0a8. Licensed under CC BY 4.0: https://creativecommons.org/licenses/by/4.0/.

TABLE 1 | Summary of forest disturbance detection challenges by severity, their spectral signatures, data resolution requirements, current bottlenecks and data and DL opportunities.

Event characteristics	Typical agents	Spectral and landscape signature	Spatial res.	Temporal res.	Current method bottlenecks	DL opportunities/ architectures	Ancillary data/ data types
Large-scale/ stand-replacing	Windstorm, clear-cut harvest, large fire	– Abrupt canopy removal – Contiguous patches – Strong spectral change	Moderate (e.g., 30 m)	Annual	– Cannot capture recurrent events – Reliance on single vegetation index – Only largest event in time series – No disturbance attribution	– Spatiotemporal models for multi-event and class detection in time series	– SAR for cloudy regions
Small-scale discrete	Selective logging	– Sub-pixel canopy gaps – Short-duration openings – Irregular geometrySubtle spectral change	High (e.g., < 10 m)	Monthly	– Poor sub-pixel sensitivity – Difficult separation from phenology/ noise	– Spatiotemporal models for spatial context and temporal tracking – U-Net for segmentation	– SAR/LiDAR for texture and vegetation structure
Small-scale gradual	Drought, insect infestation, pathogen	– Gradual canopy discoloration – Progressive decline – Patchy patterns	High (e.g., < 10 m)	Monthly	– Difficult separation from phenology/ noise	– Spatiotemporal models (e.g., transformers and ConvLSTMs)	– Climate variables – Soil moisture – Hyperspectral for plant stress

disturbances, increasing model complexity often yields limited additional benefit, as the signal is already strong and well captured by existing methods. By contrast, detecting low-severity disturbances requires both finer spatial resolution and higher temporal sampling to resolve sub-pixel canopy openings and short-lived signals. Moreover, such data improvements alone are insufficient. Fully exploiting these data requires DL models that can capture spatial context and temporal persistence, particularly for disturbances that unfold more gradually over time such as selective logging and from droughts.

4.2 | Attributing Forest Disturbances

Attributing disturbances in forest monitoring involves identifying and assigning causal agents to observed changes in ecosystems. These agents may be natural, such as wind-throws, wildfires, or pathogen outbreaks, or anthropogenic, such as timber harvests. Understanding why disturbances occur and what their effects are is crucial for supporting targeted management responses and policy development that target the resilience of forests and their sustained ecosystem services.

There are, however, several attribution challenges. In Table 2, we summarize these open challenges, highlighting current bottlenecks in data and methods, and describe how DL and emerging AI approaches can help address them.

4.2.1 | Separation of Disturbance Agents

Different disturbance agents can produce highly similar spectral and landscape signatures in satellite imagery, making attribution inherently difficult. Automated approaches relying on a single spectral index tend to produce higher omission and commission errors. To address this, studies have explored integrating temporal, landscape, and topographic features into classification models (Li et al. 2022), alongside incorporating multiple spectral bands and indices to improve disturbance attribution. Additional auxiliary variables, such as tree species occurrence, may further enhance the classification of disturbance agents (Schroeder et al. 2017). Nevertheless, fine-scale attribution of small-scale disturbances such as wind, stress classes, and bark beetle damage remains difficult (Sebald et al. 2021; Schroeder et al. 2017).

TABLE 2 | Summary of key challenges in forest disturbance attribution from remote sensing, including current methodological bottlenecks and emerging deep learning opportunities.

Challenge	Description	Current data and method bottlenecks	Data strategies and DL opportunities
Separation of disturbance agents	– Similar spectral/structural signatures across agents – Difficult attribution from imagery alone	– Heavy reliance on spectral indices – Limited discrimination of agents with similar spectral/landscape signatures – Limited radar/hyperspectral integration	– Multi-modal DL fusion (optical, SAR, LiDAR, hyperspectral) – Attention-based models – Spatial–temporal models – Embeddings – Integration of ancillary environmental data
Standardization in disturbance agent classification schemes	– Inconsistent schemes across studies/regions – Limited comparability between datasets	– No harmonized taxonomy – Incompatible label schemes – Varying spatial resolutions – Lack of global reference datasets	– Domain adaptation/transfer learning – Weakly supervised learning – Ontology matching/label harmonization
Resource-intensive labeling	– Field surveys required for training/validation – High collection cost and effort	– Expensive manual interpretation – Spatial bias toward accessible areas – Rare agents underrepresented – Spatial/temporal mismatch in field data	– Active learning for sample prioritization – Self-supervised learning – Synthetic data generation – Citizen science/pseudo-labeling
Compound and novel disturbance types	– Single-agent assumptions often invalid	– Single dominant-agent labeling and modeling – Poor representation of interacting drivers – Limited disturbance history in ground truth	– Temporal models – Multi-label classification – Causal inference frameworks

A promising direction is the combination of high-resolution imagery with spatiotemporal DL models that enable fine-scale attribution by capturing spatial cues that might help distinguish between different disturbance types. Figure 6 illustrates spatial patterns in imagery that these models can exploit. For instance, patterns such as the presence of trails, log decks, and gaps are usually associated with degradation by logging (Figure 6A) and provide contextual cues that U-Net architectures can use to differentiate logging from other disturbance types (Dalagnol et al. 2023). Similarly, the construction of roads in the middle of forests, followed by forest gaps, might indicate logging activities because these roads are used for timber transport. Conversely, burned rings point to disturbance by fire (Figure 6C), with different reflectances indicating different times of the disturbance.

More broadly, spatial configuration offers valuable information for attribution. Harvesting events are often characterized by regular geometric shapes associated with commodity-driven

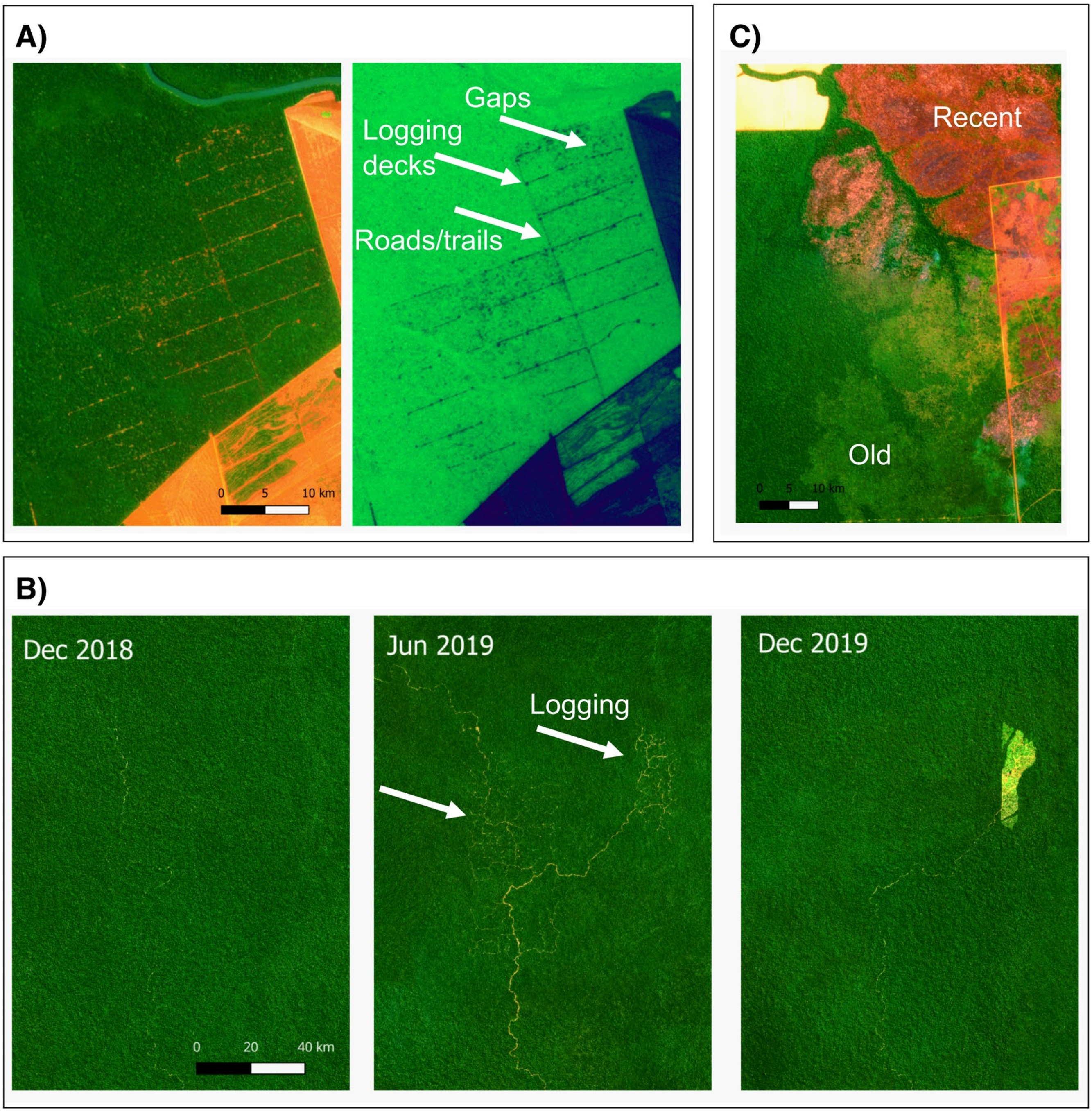

FIGURE 6 | Spatial cues in remote sensing imagery that support spatiotemporal deep learning models for forest disturbance segmentation and attribution. The figure illustrates key spatial patterns associated with: (A) degradation from logging (e.g., trails, log decks, canopy gaps), (B) logging-road expansion followed by selective logging, this panel also illustrates phenomena variability, in which the same disturbance type can manifest with markedly different spatial signatures in different regions—from the regular geometric patterns in A (Mato Grosso, Brazil) to the diffuse patches of selective logging visible in the June 2019 image (Acre, Brazil), and (C) fire impacts at different stages of regeneration, including characteristic burn rings. *Source:* Planet NICFI imagery with 4.77 m resolution.

deforestation or managed forestry operations. In contrast, natural disturbances tend to produce irregularly shaped patches, such as those resulting from wind throws or insect outbreaks. These spatial characteristics can be modeled using spatiotemporal DL, which can also track gradual canopy loss from insect or drought stress (Gnilke and Sanders 2022). However, it is important to note that region-specific practices can complicate attribution. In the Brazilian Amazon, trails with tree-fall gaps and nearby logging decks serve as recognizable spatial cues (Dalagnol et al. 2023), however, these patterns may not transfer to other tropical regions as shown in Figure 6A,B. Distinguishing legal from illegal harvesting is another challenge. Sometimes, attribution is based on the presence of sharp, structured boundaries, which are assumed to indicate legal clear-cuts. However, low-impact or selective logging, though legal, can be misclassified as either natural disturbances or illegal logging because of the similar spatial patterns (Dalagnol et al. 2023).

Refining the attribution of forest disturbances will require a dual focus: the development and adoption of high-quality reference datasets, and the application of advanced DL algorithms capable of leveraging both spatial patterns and temporal dynamics. However progress in this field remains constrained by the availability of labeled training data. Large, standardized datasets covering diverse disturbance types are scarce (Schleeweis et al. 2020), and the lack of consistent labeling standards continues to limit comparability across regions (see also Section 5.4). While emerging data-efficient DL paradigms (Section 3.2) can help reduce the dependence on large labeled datasets, they should be understood as complementary tools that improve data efficiency rather than substitutes for sustained efforts to expand and standardize high-quality labeled reference data.

4.2.2 | Standardization in Disturbance Agent Classification Schemes

There is currently no homogenization in how disturbance agents are classified and reported (Hislop et al. 2020). Some datasets apply broad categorical schemes such as “biotic vs. abiotic”, as in the FAO or Montreal Process frameworks (Process 2015), while others distinguish more detailed agents such as fire, harvest, uprooting, and breakage (Senf et al. 2020). These divergent classification systems hinder comparability across studies and regions and often fail to capture compound or novel disturbance types. To address this, domain adaptation and transfer learning can be used to align models trained under different classification schemes, while weakly supervised learning and ontology matching offer pathways to harmonize heterogeneous or partially labeled datasets.

4.2.3 | Limited Labeled Data

Disturbance attribution often relies on ground-based field surveys to both label datasets for ML training and validate models. Acquiring such data is typically resource-intensive and spatially constrained, limiting applicability for large-scale analyses. Field plots are often biased toward accessible areas, rare disturbance agents are underrepresented, and geolocating field observations to pixel-level imagery introduces spatial and temporal mismatches. Active learning can help prioritize high-value sampling locations, while self-supervised learning allows models to leverage large volumes of unlabeled satellite time series. Synthetic data generation, citizen science integration, and pseudo-labeling from existing disturbance maps offer further avenues to reduce dependence on costly field campaigns.

4.2.4 | Interacting and Compound Disturbances

Disturbances increasingly occur as interacting or cascading events, in which agents occur sequentially or concurrently and produce combined effects that cannot be attributed to a single agent (Kleinman et al. 2019). Such interactions involve both amplifying and dampening feedback, resulting in disturbance responses that differ fundamentally from isolated events (Krawchuk et al. 2020). For example, insect-induced changes in fuel structure can either increase or decrease fire burn severity depending on outbreak timing and characteristics (Meigs et al. 2016), and salvage logging may reduce fuel loads and lower fire intensity, though effects vary with management practices (Kleinman et al. 2019). These cascading processes blur the boundaries between conventional disturbance categories, as observed changes often reflect the combined influence of multiple interacting drivers. Traditional classification frameworks, which typically assume a single dominant causal agent, are therefore poorly suited to capturing such dynamics, and training datasets rarely capture disturbance histories or causal chains. Temporal models that track disturbance progression and recovery, multi-label classification for compound events, and the integration of ancillary datasets (e.g., logging permits, road networks) can help address these limitations. Incorporating landscape context and disturbance history into DL frameworks provides models with information on preconditioning factors that shape subsequent disturbance responses. Causal inference approaches offer a complementary pathway by explicitly testing the direction and magnitude of causal relationships and distinguishing direct from indirect effects, they enable more robust inference about underlying drivers even when multiple disturbances co-occur (Schroeder et al. 2017). When combined with spatiotemporal DL, causal models can constrain predictions to ecologically plausible pathways and reduce spurious associations driven by confounding factors.

4.3 | Building Models That Can Generalize Across World Regions

Novel, scalable methods are required to transform the ever-increasing amount of raw satellite data into actionable knowledge for global forest monitoring applications. However, scaling DL approaches from local studies to global forest monitoring remains a major model generalization challenge. This issue is associated with the training data distribution, which typically only covers a specific geographic location, species composition, sensor, and/or spatial scale (Ouaknine et al. 2025). Models trained on limited or biased forest data tend to perform poorly on data that differs from that used during training. This data-centric challenge is compounded by a methodological legacy. Much progress in change detection has historically been built on statistical models, and this legacy continues to shape how domain scientists design and validate DL models, commonly applying models to small regions and using only a small set of data. Under a data-hungry DL modeling paradigm, this hinders achieving maximum potential. For instance, studies have successfully applied DL with high accuracy for deforestation detection in specific contexts, such as the Brazilian Amazon (Bragagnolo et al. 2021) or Germany (Schiller et al. 2024). However, these models are typically validated within a single geographic setting, raising concerns about their broader transferability. A model trained for tropical forests is unlikely to perform well in boreal or temperate contexts without retraining, and generalization even to new areas within the same biome but in a different country is not guaranteed (Schiller et al. 2024). Furthermore, many studies focus narrowly on a single disturbance agent, further limiting broad applicability (Du et al. 2023).

To help overcome these generalization barriers, large-scale and globally representative benchmarks such as the ForTy dataset (Jiang and Neumann 2025) for forest types are emerging as important resources. By providing diverse training data across regions and forest types, these initiatives offer a pathway toward building models that are not only locally accurate but also robust and generalizable for global forest monitoring and a range of targets. The use of additional spatial encoding and context characterizing location-specific features, as well as GFMs fine-tuned to various downstream applications, seems particularly promising routes forward to learn more effectively across wide-ranging Earth observational datasets (see also Section 3.4).

5 | Practical Guidance and Future Outlook

This section provides practitioners with practical advice by summarizing the lessons learned from the reviewed studies and outlining future research directions for advancing DL-based forest monitoring using Earth observations.

5.1 | Training Data Generation and Curation

The effectiveness of DL applications depends critically on high-quality labeled training data, which remains a major bottleneck in forest disturbance applications. A multi-step approach for creating reference data to train and validate models is described in Du et al. (2023). First, an initial land cover mask is used to constrain the sampling domain (e.g., forest vs. non-forest). Within forests, sampling points are then randomly generated, while maintaining a minimum spatial separation between points to reduce spatial autocorrelation. Each sample then undergoes manual interpretation with the aid of high-resolution imagery and spectral time series for that point to classify its historical status, including the timing and causal agent of any change events. In order to create reusable and relevant datasets, it is recommended that attention be paid to selecting appropriate classes. This is necessary to avoid ambiguous or overly broad classes that cannot be reused in further studies. For instance, it is preferable to label "beetle attack" instead of a generic "biotic disturbance" (see also Section 5.4). Digital platforms such as Collect Earth Online (Saah et al. 2019) can be used to streamline the process of data labeling, thereby enhancing the efficacy of annotations. Higher label quality can be attained through expert interpretations, the implementation of confidence levels based on the consensus among annotators, and the exclusion of samples with low confidence from the final training dataset.

In parallel to costly manual interpretation of imagery, two complementary data streams have also emerged as a valuable approach for large-scale geospatial data collection and benchmark dataset creation, (a) citizen science, and (b) unstructured textual data sources. Citizen science is a term used to describe scientific research conducted with active participation from members of the general public, who are often nonprofessional volunteers. Citizen science has been used, for instance, to monitor tropical deforestation, in which volunteers analyze and classify remote sensing images (da Luz et al. 2014), and the labeled data has been further integrated into ML classifiers (Dallaqua et al. 2019). Unstructured textual information constitutes a second emerging source of complementary data. LLMs can facilitate the extraction of relevant disturbance information from scientific publications, news reports, government bulletins, and other text corpora. Such information can be used either to match geographically referenced disturbance descriptions to unlabeled satellite imagery, thereby generating weak labels at the image level, or to augment input features with georeferenced ecological or socioeconomic variables that enrich the training data. Together, these approaches may substantially improve the efficiency of satellite-data annotation and ultimately provide more informative inputs for model development.

To make significant progress in the development of more generalizable models capable of scaling to diverse geographic regions and forest types, it is imperative that researchers adopt open science and FAIR (Findable, Accessible, Interoperable, Reusable) data principles (Wilkinson et al. 2016) when generating and curating training datasets. Making data openly accessible under clear licenses in FAIR repositories will allow the broader scientific community to build upon existing efforts, increase the diversity and volume of training data available, and reduce redundant efforts. It is equally important to develop common standards for data labeling. This will ensure that disturbance types and class definitions are harmonized across studies. The adoption of more homogeneous and hierarchical labeling schemes would facilitate the merging or comparison of datasets at various levels of detail on shared classification levels. This enhancement would significantly improve the interoperability and long-term value of the datasets.

5.2 | DL-Based Forest Monitoring Workflow

A typical workflow for supervised DL in forest disturbance monitoring is presented in Figure 7. The first step is defining the prediction task, such as a binary (e.g., disturbed vs. undisturbed) or multi-class classification (e.g., distinguishing disturbance agents). Satellite image time series are then acquired, typically from multispectral sensors such as Landsat and Sentinel-2, radar systems such as Sentinel-1, or through a combination of multiple sensors, often accessed via centralized platforms such as Google Earth Engine (Gorelick et al. 2017). Next, data preprocessing steps are performed. Although recent work suggests that self-attention and recurrent architectures can outperform CNNs

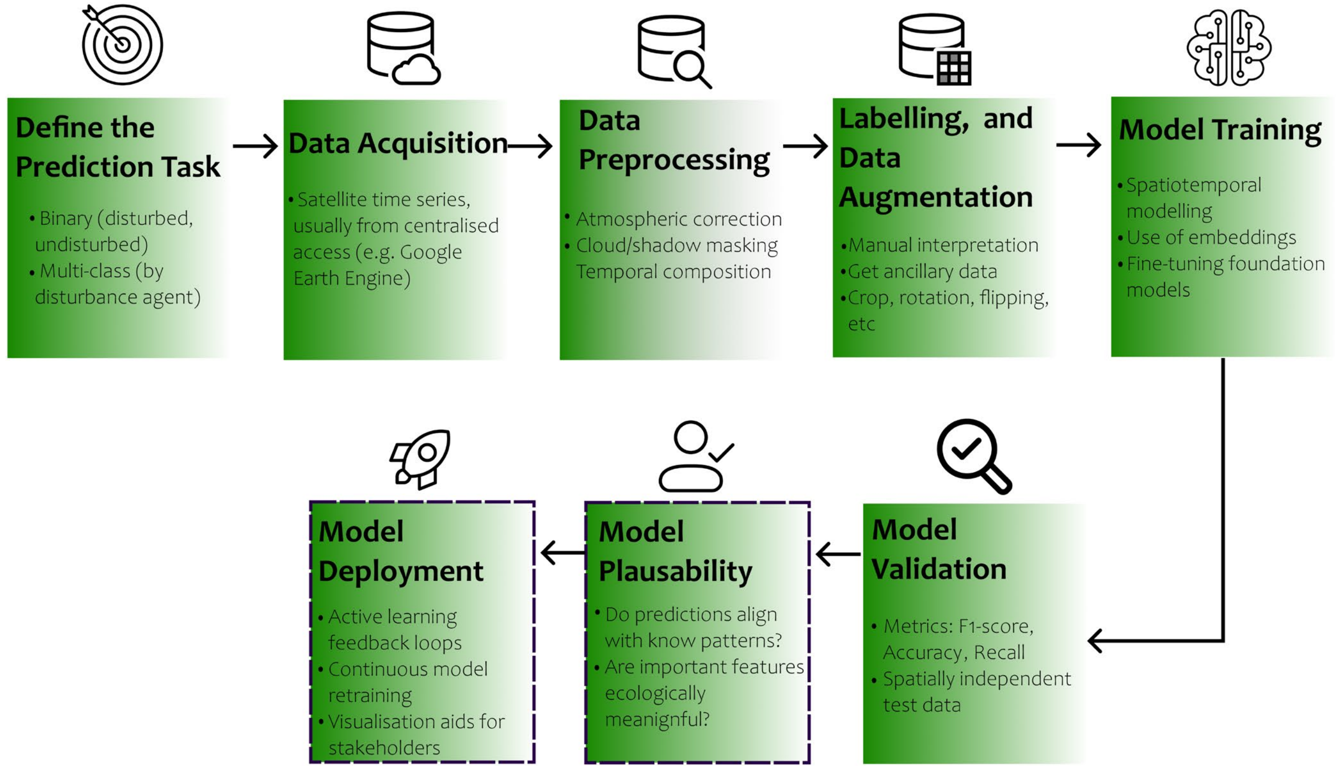

FIGURE 7 | Conceptual workflow for supervised deep learning in forest disturbance monitoring. Steps within dashed rectangles are optional.

when trained directly on raw satellite time-series (i.e., without precomputing VIs) (Rußwurm and Körner 2020; Schiller et al. 2024), preprocessing steps such as atmospheric correction and automated cloud filtering remain a standard practice in the field (Du et al. 2023; Dalagnol et al. 2023; Schiller et al. 2024), and continue to play an important role in improving DL model performance (Rußwurm and Körner 2020). Nonetheless, feature engineering can still be beneficial when training data are scarce or when simpler/shallower network architectures are used. To mitigate limited sample sizes, data augmentation techniques such as cropping, rotation, flipping, or noise injection are widely employed (Chen et al. 2023). In addition, exploring generative AI to synthesize training samples, and weakly supervised learning to improve model performance under limited reference data represent promising research directions. The inclusion of ancillary variables as input features, such as topography (e.g., slope, elevation), forest type, or socioeconomic indicators, may provide additional contextual information that purely spectral inputs may lack, potentially improving disturbance attribution, and overall model performance and transferability. However, their added value remain under-investigated. Furthermore, incorporating precomputed embeddings offers an additional avenue for capturing spatiotemporal dependencies and enhancing model generalization across scales, or simply achieving higher performance even when using a small volume of training data. Finally, following advances in other fields (Allen et al. 2025), integrating complementary remote sensing modalities is expected to become increasingly important in forest monitoring workflows. Multispectral data provide rich spectral information on vegetation condition, radar offers structural and all-weather sensitivity, and LiDAR contributes three-dimensional canopy metrics. Recent studies have demonstrated the advantages of multi-modal fusion, for example, combining SAR and optical imagery to capture forest mortality patterns (Agersborg et al. 2022) or integrating GEDI LiDAR with Landsat time series to expand canopy change data to the global scale (Lang et al. 2023). Data fusion enriches the spectral and structural information available to DL models while mitigating challenges such as cloud contamination, sensor failure, and seasonal data gaps (Du et al. 2023). Recent missions such as BIOMASS and NISAR will further expand the available data, particularly important to address challenges related to estimating logging intensities and carbon losses.

After data preparation, DL models are trained and evaluated to estimate their expected performance on unseen data. Recent literature highlights the advantages of fine-tuning GFMs for downstream tasks, rather than training task-specific models from scratch, particularly due to the small data volume on forest disturbances. Following model training, rigorous evaluation is essential to avoid misleading conclusions. In geospatial applications, the design-based approach by Olofsson et al. (2014) is widely recommended, advocating probability-based sampling to obtain an independent test set and thus more reliable accuracy estimates than random data splits. Standard reporting includes overall accuracy, precision, recall, F1-score, and area under the ROC curve, along with user's and producer's accuracy, area estimates, and uncertainty intervals. Because forest disturbances are often rare, class imbalance must be explicitly addressed. Accuracy alone can be misleading if a model predicts "no disturbance" for all pixels in a dataset with only 1% disturbed area. In such cases, metrics sensitive to minority classes, such as the F1-score or class-weighted measures, should be preferred. The choice of metrics depends on the application's tolerance for errors—for instance, high recall may be prioritized for early deforestation alerts to minimize false negatives, while high precision may be more relevant for stable forest monitoring to avoid false alarms.

Spatial autocorrelation introduces an additional challenge in DL model validation. If training and test samples are spatially dependent, model performance may be systematically overestimated. To mitigate this bias, approaches such as spatial blocking, distance buffers, or spatial cross-validation are recommended (Roberts et al. 2017; Brenning 2023; Ploton et al. 2020). The optimal validation design depends on the prediction goal—whether retrospective mapping or forecasting—and should be selected carefully. When using k-fold cross-validation, hyperparameter tuning must be performed within each fold to prevent data leakage, a detail often neglected in performance reporting. Comprehensive evaluation should also assess model plausibility and interpretability, and these aspects are increasingly examined (Natel et al. 2025; Becker et al. 2026). Ecological validation, for example, by verifying that predicted spatial patterns and feature importance align with known disturbance processes and biophysical principles, strengthens model credibility (Steger et al. 2015). For a sustainable operational use, active learning and feedback mechanisms should be implemented to maintain model accuracy and ensure that performance meets operational requirements. Finally, transparent communication of uncertainty is essential. Probabilistic outputs, entropy maps, bootstrapping, or conformal prediction methods can be used to quantify and visualize uncertainty, helping end users understand the confidence and limitations associated with model predictions.

5.3 | Lessons for Practitioners

From the reviewed applications, several overarching lessons emerged for building robust and generalizable DL-based forest disturbance models, which are summarized below:

1. Training data availability is critical: DL models are data-hungry. Before investing in complex architectures, practitioners should evaluate whether sufficient labeled data exist at the desired spatial and temporal resolution. For example, dividing the study area by patch size helps estimate whether hundreds to thousands of training patches can be obtained. If such data are unavailable and unfeasible to create, simpler pixel-based models may be more appropriate. To compensate for small data volume, the use of embeddings (Section 3.3), learning under limited data strategies (Section 3.2), and pretrained models or GFMs (Section 3.4) could be explored.
2. Minimal feature engineering is often sufficient: Unlike classical ML approaches such as RFs, DL models can learn feature representations directly from imagery, instead of relying for instance on precomputed VIs. A promising avenue is including embeddings as features in the training process. Basic preprocessing steps like cloud masking or temporal interpolation still remain important though.
3. The best model is not always the fanciest: More complex architectures do not guarantee success. More important is a clear understanding of the ecological target and the availability of well-curated training data. Before jumping to the fanciest model, we recommend starting with the state-of-the art model for a targeted task, for instance using simpler spatiotemporal models rather than the latest developed model (e.g., a “vanilla” transformer before a Temporal Fusion Transformer (Lim et al. 2021)).
4. Leverage model feedback during annotation: False positives and false negatives often reveal annotation errors. Active learning approaches—iteratively refining training data with model feedback—can substantially improve accuracy.
5. Adopt a phased approach to model deployment: Begin with local detection, then scale spatially, and finally extend temporally while monitoring error accumulation and retraining needs. A practical workflow involves three stages: (i) ensuring the model can detect the target disturbance locally, (ii) scaling inference to the full study area while reducing false positives by incorporating additional training labels for disturbance-absent conditions, and (iii) extending the model temporally to evaluate whether the rate of false positives remains acceptable or requires retraining.

5.4 | Benchmarks, Standardization and Reproducibility

Large-scale and spatially explicit databases of forest disturbances will become essential to train and evaluate global-scale DL models that perform well across environmental settings and forest types. Standardizing annotation protocols, data formats, and evaluation metrics reduces methodological variability and facilitates objective comparisons between studies and algorithms. Well-curated benchmarks also alleviate redundant preprocessing, allowing researchers to focus on algorithmic innovation rather than data harmonization. Furthermore, they allow the recognition of persistent challenges—such as distinguishing subtle or overlapping disturbances and generalizing across biomes—that remain obscured when models are trained on localized datasets.

For Earth observation products such as Landsat, model evaluation often relies on two major disturbance benchmarks—LandTrendr and Global Forest Change (GFC) (Kennedy et al. 2010; Hansen et al. 2013; Du et al. 2023). More recent benchmark datasets for forest disturbances include the global forest disturbance dataset (GFD) (Wang et al. 2025), which includes 11 disturbance types, the European Forest Disturbance Atlas (Viana-Soto and Senf 2025), including disturbance agent and disturbance severity, and the Tropical Moist Forest dataset (TMF) (Vancutsem et al. 2021). At national and regional scales, initiatives such as Brazil's DETER, SIMEX, and MapBiomas Fire complement these global datasets, alongside various disturbance-specific datasets such as for winds (Forzieri et al. 2020). However, the lack of unified disturbance definitions, harmonized spatial–temporal resolutions, and transparent labeling standards limits comparability across these datasets. Lessons from other remote sensing domains—such as BigEarthNet (Sumbul et al. 2021), Sen12MS (Schmitt et al. 2019), Sen4AgriNet (Sykas et al. 2021), and CropHarvest (Tseng et al. 2021)—exemplify the role of comprehensive benchmarks in driving advances in modeling development. Emerging efforts such as FORTY (Jiang and

Neumann 2025), which is a benchmark dataset for forest type, and FoMo (Bountos et al. 2025), which compiles several datasets to build a foundation model, serve as a robust resource for training and evaluating ML models and could be expanded for forest disturbance research. Another promising example is the deadtrees.earth initiative (Mosig et al. 2026), which is an open access community effort to share labeled aerial and satellite data on tree mortality to help ensure robust training data for ML models. Efforts of this kind, combining high-resolution imagery, consistent labeling, and global geographic coverage, represent an important example for future initiatives aimed at advancing spatiotemporal monitoring of forest disturbances.

Additionally, reproducibility continues to pose a significant challenge. According to Paulino et al. (2024), fewer than 10% of forest disturbance detection studies currently share their datasets publicly, which severely limits external validation and cumulative progress. To address this, the community must converge toward FAIR-compliant data-sharing standards. Implementing interoperable metadata frameworks, shared ontologies, and consistent disturbance taxonomies would enable reproducible workflows and ultimately accelerate the pace of methodological advances. Developing a web-based platform that facilitates external data contributions to curate open access databases in a consistent form, for example by accepting labeled data uploads according to certain common standards, would be a promising path forward (Fassnacht et al. 2024).

5.5 | From Scientific Models to Practitioner Tools

Estimating the extent of forest disturbances and identifying their agents are fundamental to monitoring forest change. These tasks inform decision-making in forest management, risk assessment, policy development, and carbon accounting aimed at reducing greenhouse gas emissions. Recent studies emphasize the need for improved quantification of disturbances and uncertainties, including the integration of novel large-scale and long-term datasets on ecosystem disturbances, to enhance global carbon cycle models (Forkel et al. 2019; Pugh et al. 2019). Disturbances remain one of the least certain components of the global forest carbon cycle. Moreover, over recent decades, various forest management paradigms have emerged—such as sustainable timber management, multiple-use forestry, ecosystem management, sustainable forest management, and climate-smart forestry. Forest management practices altering forest composition, for instance, can significantly influence carbon turnover rates (Ferretto et al. 2025), yet their effects remain poorly documented due to limited supporting data.

Decision Support Systems (DSS)—computer-based platforms that integrate data with modeling and analytical tools—have long supported forest managers, but most address very narrow, well-defined problems. Looking ahead, DSS must evolve into more general, multifunctional systems capable of tackling emerging disturbance regimes driven by the combined effects of climate change, forest management practices, and the growing demand for multiple forest ecosystem services. The increasing availability of high-resolution data combined with advanced DL methods presents an opportunity to make these systems more valuable for forest owners and managers by helping them understand a wider range of forest-related changes, impacts, and potential actions to enhance forest resilience—for example, susceptibility to disturbances such as spruce bark beetle outbreaks, windthrow, and root rot (Lämås et al. 2023). However, the reviewed methods presented in this paper do not automatically translate into useful tools to practitioners, which often require accessible and interpretable tools rather than raw model outputs. Bridging the gap between research prototypes and operational applications requires not only methodological advances but also participatory design involving end users (Xu and Jiang 2025). Engaging forestry agencies, conservation organizations, and local communities ensures that models address real-world needs—from timber harvest oversight to carbon credit verification—and can be embedded within established management systems (Paulino et al. 2024). Furthermore, explainable AI (xAI) techniques can strengthen user trust by clarifying how DL models reach their conclusions, thereby supporting informed decision-making. Therefore, we highlight that much progress in translating scientific DL models into operational monitoring systems will be required. Further research should emphasize usability, transparency, and integration within existing decision-support workflows. Interactive web platforms that combine DL-based disturbance maps with ancillary data—such as topography, reference imagery, and uncertainty layers—illustrate this principle by enabling users to validate, interpret, and act upon model outputs. Finally, consistent and transparent guidelines for assessing and communicating map accuracy remain essential, as both producers and users must be able to evaluate and convey the reliability of derived products (Olofsson et al. 2014).

6 | Conclusion

The rapid expansion of satellite Earth observation has created unprecedented opportunities for automated and scalable approaches to forest monitoring. Despite growing interest in DL, current research has yet to fully leverage its capabilities to develop models that are both generalizable and effective at detecting low-severity disturbances and attributing them to specific causal agents.

In this review, we have examined AI and DL opportunities for forest disturbance monitoring, while also highlighting key limitations and challenges that practitioners must be aware of when building and validating these systems. Although state-of-the-art models have achieved notable success in segmenting disturbance areas and analyzing temporal patterns through spatiotemporal methods, the field remains constrained by a predominant focus on localized, single-disturbance studies, often restricted to a few disturbance agents, and by reliance on data-rich regions. These limitations significantly reduce model transferability across diverse forest ecosystems and disturbance types. We have identified three primary technical avenues with promise to address limitations regarding disturbance detection, attribution, and the scarcity of training data: (a) spatiotemporal architectures, (b) embeddings and GFMs, and (c) learning approaches designed for limited labeled data.

Moreover, the path forward requires a shift in research direction toward large-scale, multi-disturbance models. Several critical gaps must be addressed to achieve this goal. First, the field needs standardized benchmark datasets that encompass a variety of disturbance agents across different ecosystems. To complement current efforts, citizen science and LLMs could be explored to expand ground-truth data collection. Second, approaches such as SSL should be explored to mitigate data scarcity in underrepresented regions. Third, closer collaboration between DL experts and remote sensing and forest researchers is essential to develop algorithms capable of handling the complex data characteristics of forest disturbances. Finally, the forest monitoring research community is urged to prioritize a transparent, FAIR-compliant data sharing that will not only accelerate scientific progress but also foster the development of generalizable DL models that can effectively support global forest monitoring goals.

These developments are particularly critical given the growing impacts of climate and land-use change on global forests, where understanding disturbance regimes is vital for maintaining carbon sequestration capacity and other forest ecosystem services.

Author Contributions

Christoph Molnar: writing – review and editing. **Peer Nowack:** writing – review and editing. **Ricardo Dalagnol:** writing – review and editing. **Carolina Natel:** conceptualization, writing – review and editing, writing – original draft, investigation.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

References

Acil, N., J. P. Sadler, C. Senf, S. Suvanto, and T. A. M. Pugh. 2025. "Landscape Patterns in Stand-Replacing Disturbances Across the World's Forests." *Nature Sustainability* 8, no. 1: 86–98.

Agersborg, J. A., L. T. Luppino, S. N. Anfinsen, and J. U. Jepsen. 2022. "Toward Targeted Change Detection With Heterogeneous Remote Sensing Images for Forest Mortality Mapping." *Canadian Journal of Remote Sensing* 48, no. 6: 826–848. https://doi.org/10.1080/07038992.2022.2135497.

Alkin, B., M. Beck, K. Pöppel, S. Hochreiter, and J. Brandstetter. 2024. "Vision-Lstm: Xlstm as Generic Vision Backbone." arXiv Preprint arXiv:2406.04303.

Allen, A., S. Markou, W. Tebbutt, et al. 2025. "End-To-End Data-Driven Weather Prediction." *Nature* 641, no. 8065: 1172–1179.

Altman, J., P. Fibich, V. Trotsiuk, and N. Altmanova. 2024. "Global Pattern of Forest Disturbances and Its Shift Under Climate Change." *Science of the Total Environment* 915: 170117.

Andresini, G., A. Appice, and D. Malerba. 2024. "A Deep Semantic Segmentation Approach to Map Forest Tree Dieback in Sentinel-2 Data." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 17: 17075–17086. https://doi.org/10.1109/JSTARS.2024.3460981.

Asner, G. P., S. R. Loarie, and U. Heyder. 2010. "Combined Effects of Climate and Land-Use Change on the Future of Humid Tropical Forests." *Conservation Letters* 3, no. 6: 395–403.

Bai, S., J. Z. Kolter, and V. Koltun. 2018. "An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling." arXiv Preprint arXiv:1803.01271.

Ball, J. E., D. T. Anderson, and C. S. Chan. 2017. "Comprehensive Survey of Deep Learning in Remote Sensing: Theories, Tools, and Challenges for the Community." *Journal of Applied Remote Sensing* 11, no. 4: 42609.

Beck, M., K. Pöppel, M. Spanring, et al. 2024. "Xlstm: Extended Long Short-Term Memory." *Advances in Neural Information Processing Systems* 37: 107547–107603.

Becker, P., C. N. de Moura, and P. J. Nowack. 2026. "Assessing and Explaining Temporal Deep Learning Models for Wildfire Danger Prediction." In *Assessing and Explaining Temporal Deep Learning Models for Wildfire Danger Prediction*, vol. 2, 15014. Machine Learning: Earth.

Boulila, W., H. Ghandorh, S. Masood, et al. 2024. "A Transformer-Based Approach Empowered by a Self-Attention Technique for Semantic Segmentation in Remote Sensing." *Heliyon* 10, no. 8: e29396.

Bountos, N. I., A. Ouaknine, I. Papoutsis, and D. Rolnick. 2025. "Fomo: Multi-Modal, Multi-Scale and Multi-Task Remote Sensing Foundation Models for Forest Monitoring." In *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 39, 27858–27868. AAAI.

Bragagnolo, L., R. V. Da Silva, and J. M. V. Grzybowski. 2021. "Amazon Forest Cover Change Mapping Based on Semantic Segmentation by U-Nets." *Ecological Informatics* 62: 101279. https://doi.org/10.1016/j.ecoinf.2021.101279.

Brenning, A. 2023. "Spatial Machine-Learning Model Diagnostics: A Model-Agnostic Distance-Based Approach." *International Journal of Geographical Information Science* 37, no. 3: 584–606.

Burns, P., C. R. Hakkenberg, and S. J. Goetz. 2024. "Multi-Resolution Gridded Maps of Vegetation Structure From Gedi." *Scientific Data* 11, no. 1: 881.

Castro, A., J. Pinto, L. Reino, P. Pipek, and C. Capinha. 2024. "Large Language Models Overcome the Challenges of Unstructured Text Data in Ecology." *Ecological Informatics* 82: 102742.

Chen, L., W. Jing, Y. Xie, E. Chen, and X. Zhang. 2023. "Discriminative Feature Constraints via Supervised Contrastive Learning for Few-Shot Forest Tree Species Classification Using Airborne Hyperspectral Images." *Remote Sensing of Environment* 295: 113710. https://doi.org/10.1016/j.rse.2023.113710.

Chen, Y., Z. Yang, L. Zhang, and W. Cai. 2025. "A Semi-Supervised Boundary Segmentation Network for Remote Sensing Images." *Scientific Reports* 15: 2007. https://doi.org/10.1038/s41598-025-85125-9.

Chicco, D. 2021. "Siamese Neural Networks: An Overview." *Artificial Neural Networks. Methods in Molecular Biology*, edited by H. Cartwright, vol. 2190, 73–94. Humana.

Choi, E., S. Biswal, B. Malin, J. Duke, W. F. Stewart, and J. Sun. 2017. "Generating Multi-Label Discrete Patient Records Using Generative

Adversarial Networks." In *Machine Learning for Healthcare Conference*, 286–305. PMLR.

Clay. Clay-foundation/model. 2025. "Clay Foundation." https://github.com/Clay-foundation/model.

da Luz, E. F. P., R. S. Felipe, D. L. Correa, F. G. González, and F. M. Ramos. 2014. "The Forestwatchers: A Citizen Cyberscience Project for Deforestation Monitoring in the Tropics." *Human Computation* 1, no. 2: 137–145.

Dalagnol, R., F. H. Wagner, L. S. Galvão, et al. 2023. "Mapping Tropical Forest Degradation With Deep Learning and Planet Nicfi Data." *Remote Sensing of Environment* 298: 113798.

Dallaqua, F. B. J. R., F. A. Faria, and A. L. Fazenda. 2018. "Active Learning Approaches for Deforested Area Classification." In *2018 31st SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)*, 48–55. IEEE. https://doi.org/10.1109/SIBGRAPI.2018.00013.

Dallaqua, F. B. J. R., Á. L. Fazenda, and F. A. Faria. 2019. "Foresteyes Project: Can Citizen Scientists Help Rainforests?" In *2019 15th International Conference on eScience (eScience)*, 18–27. IEEE.

Deng, J., W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. 2009. "Imagenet: A Large-Scale Hierarchical Image Database." In *2009 IEEE Conference on Computer Vision and Pattern Recognition*, 248–255. Ieee.

Di Giuseppe, F., J. McNorton, A. Lombardi, and F. Wetterhall. 2025. "Global Data-Driven Prediction of Fire Activity." *Nature Communications* 16, no. 1: 2918.

Dixon, D. J., Y. Zhu, C. F. Brown, and Y. Jin. 2023. "Satellite Detection of Canopy-Scale Tree Mortality and Survival From California Wildfires With Spatio-Temporal Deep Learning." *Remote Sensing of Environment* 298: 113842. https://doi.org/10.1016/j.rse.2023.113842.

Dosovitskiy, A., L. Beyer, A. Kolesnikov, et al. 2020. "An Image Is Worth 16 × 16 Words: Transformers for Image Recognition at Scale." In International Conference on Learning Representations (ICLR).

Drusch, M., U. Del Bello, S. Carlier, et al. 2012. "Sentinel-2: ESA'S Optical High-Resolution Mission for GMES Operational Services." *Remote Sensing of Environment* 120: 25–36. https://doi.org/10.1016/j.rse.2011.11.026.

Du, B., Z. Yuan, Y. Bo, and Y. Zhang. 2023. "A Combined Deep Learning and Prior Knowledge Constraint Approach for Large-Scale Forest Disturbance Detection Using Time Series Remote Sensing Data." *Remote Sensing* 15, no. 12: 2963.

Dunn, K. W., F. Chichen, D. J. Ho, et al. 2019. "Deepsynth: Three-Dimensional Nuclear Segmentation of Biological Images Using Neural Networks Trained With Synthetic Data." *Scientific Reports* 9: 18295.

Edwards, T., C. B. Jones, and P. Corcoran. 2022. "Identifying Wildlife Observations on Twitter." *Ecological Informatics* 67: 101500.

FAO. 2004. "Global Forest Resources Assessment Update 2005: Terms and Definitions."

Fassnacht, F. E., J. C. White, M. A. Wulder, and E. Næsset. 2024. "Remote Sensing in Forestry: Current Challenges, Considerations and Directions." *Forestry: An International Journal of Forest Research* 97, no. 1: 11–37.

Feng, Z., C. Atzberger, S. Jaffer, et al. 2025. "Tessera: Precomputed Fair Global Pixel Embeddings for Earth Representation and Analysis." arXiv Preprint arXiv:2506.20380.

Ferretto, A., P. Anthoni, T. A. M. Pugh, et al. 2025. "The Impact of Changing Forest Composition in Europe-Longest Carbon Turnover Time in Unmanaged and Broadleaved Deciduous Forests." *PLoS One* 20, no. 10: e0334118.

Figueroa-Mata, G., and E. Mata-Montero. 2020. "Using a Convolutional Siamese Network for Image-Based Plant Species Identification With Small Datasets." *Biomimetics* 5, no. 1: 8.

Forkel, M., M. Drüke, M. Thurner, et al. 2019. "Constraining Modelled Global Vegetation Dynamics and Carbon Turnover Using Multiple Satellite Observations." *Scientific Reports* 9, no. 1: 18757.

Forzieri, G., M. Pecchi, M. Girardello, et al. 2020. "A Spatially Explicit Database of Wind Disturbances in European Forests Over the Period 2000–2018." *Earth System Science Data* 12, no. 1: 257–276.

Foster, D. R., D. H. Knight, and J. F. Franklin. 1998. "Landscape Patterns and Legacies Resulting From Large, Infrequent Forest Disturbances." *Ecosystems* 1, no. 6: 497–510.

Gevaert, C. M., A. A. Pedro, K. Ou, et al. 2025. "Explainable Few-Shot Learning Workflow for Detecting Invasive and Exotic Tree Species." *Scientific Reports* 15: 23238.

Gnilke, A., and T. G. M. Sanders. 2022. "Distinguishing Abrupt and Gradual Forest Disturbances With Modis-Based Phenological Anomaly Series." *Frontiers in Plant Science* 13: 863116.

Gorelick, N., M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore. 2017. "Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone." *Remote Sensing of Environment* 202: 18–27.

Gougherty, A. V., and H. L. Clipp. 2024. "Testing the Reliability of an AI-Based Large Language Model to Extract Ecological Information From the Scientific Literature." *npj Biodiversity* 3: 13.

Grabska, E., P. Hawryło, and J. Socha. 2020. "Continuous Detection of Small-Scale Changes in Scots Pine Dominated Stands Using Dense Sentinel-2 Time Series." *Remote Sensing* 12, no. 8: 1298.

Gui, J., T. Chen, J. Zhang, et al. 2024. "A Survey on Self-Supervised Learning: Algorithms, Applications, and Future Trends." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 46, no. 12: 9052–9071.

Hansen, M. C., P. V. Potapov, R. Moore, et al. 2013. "High-Resolution Global Maps of 21st-Century Forest Cover Change." *Science* 342, no. 6160: 850–853. https://doi.org/10.1126/science.1244693.

He, K., X. Zhang, S. Ren, and J. Sun. 2016. "Deep Residual Learning for Image Recognition." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 770–778. IEEE.

Hennessy, A., K. Clarke, and M. Lewis. 2021. "Generative Adversarial Network Synthesis of Hyperspectral Vegetation Data." *Remote Sensing* 13, no. 12: 2243.

Hilker, T., M. A. Wulder, N. C. Coops, et al. 2009. "A New Data Fusion Model for High Spatial- and Temporal-Resolution Mapping of Forest Disturbance Based on Landsat and Modis." *Remote Sensing of Environment* 113, no. 8: 1613–1627.

Hirschmugl, M., H. Gallaun, M. Dees, et al. 2017. "Methods for Mapping Forest Disturbance and Degradation From Optical Earth Observation Data: A Review." *Current Forestry Reports* 3, no. 1: 32–45.

Hislop, S., A. Haywood, S. Jones, M. Soto-Berelov, A. Skidmore, and T. H. Nguyen. 2020. "A Satellite Data Driven Approach to Monitoring and Reporting Fire Disturbance and Recovery Across Boreal and Temperate Forests." *International Journal of Applied Earth Observation and Geoinformation* 87: 102034.

Hochreiter, S., and J. Schmidhuber. 1997. "Long Short-Term Memory." *Neural Computation* 9, no. 8: 1735–1780.

Hosseiny, B., M. Mahdianpari, M. Hemati, A. Radman, F. Mohammadimanesh, and J. Chanussot. 2023. "Beyond Supervised Learning in Remote Sensing: A Systematic Review of Deep Learning Approaches." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 17: 1035–1052.

Huang, C., S. N. Goward, K. Schleeweis, N. Thomas, J. G. Masek, and Z. Zhu. 2009. "Dynamics of National Forests Assessed Using the Landsat Record: Case Studies in Eastern United States." *Remote Sensing of Environment* 113, no. 7: 1430–1442.

Illarionova, S., A. Trekin, V. Ignatiev, and I. Oseledets. 2021. “Tree Species Mapping on Sentinel-2 Satellite Imagery With Weakly Supervised Classification and Object-Wise Sampling.” *Forests* 12, no. 10: 1413.

Ishikawa, T., C. Bonannella, B. J. W. Lerink, and M. Rußwurm. 2025. “Deep Pre-Trained Time Series Features for Tree Species Classification in the Dutch Forest Inventory.” arXiv preprint arXiv:2508.18829.

Jakubik, J., R. Sujit, C. E. Phillips, et al. 2023. “Foundation Models for Generalist Geospatial Artificial Intelligence.” arXiv preprint arXiv:2310.18660.

Jakubik, J., F. Yang, B. Blumenstiel, et al. 2025. “Terramind: Large-Scale Generative Multimodality for Earth Observation.” arXiv Preprint arXiv:2504.11171.

Jelas, I. M., M. A. Zulkifley, M. Abdullah, and M. Spraggon. 2024. “Deforestation Detection Using Deep Learning-Based Semantic Segmentation Techniques: A Systematic Review.” *Frontiers in Forests and Global Change* 7: 1300060. https://doi.org/10.3389/ffgc.2024.1300060.

Jiang, Y., and M. Neumann. 2025. “Not Every Tree Is a Forest: Benchmarking Forest Types From Satellite Remote Sensing.” In *International Geoscience and Remote Sensing Symposium—IGARSS*, vol. 2025. IGARSS.

Jonnarth, A., and M. Felsberg. 2022. “Importance Sampling Cams for Weakly-Supervised Segmentation.” In *ICASSP 2022–2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2639–2643. IEEE.

Kacic, P., F. Thonfeld, U. Gessner, and C. Kuenzer. 2023. “Forest Structure Characterization in Germany: Novel Products and Analysis Based on GEDI, Sentinel-1 and Sentinel-2 Data.” *Remote Sensing* 15, no. 8: 1969. https://doi.org/10.3390/rs15081969.

Kaselimi, M., A. Voulodimos, I. Daskalopoulos, N. Doulamis, and A. Doulamis. 2023. “A Vision Transformer Model for Convolution-Free Multilabel Classification of Satellite Imagery in Deforestation Monitoring.” *IEEE Transactions on Neural Networks and Learning Systems* 34, no. 7: 3299–3307. https://doi.org/10.1109/TNNLS.2022.3144791.

Kattenborn, T., J. Leitloff, F. Schiefer, and S. Hinz. 2021. “Review on Convolutional Neural Networks (CNN) in Vegetation Remote Sensing.” *ISPRS Journal of Photogrammetry and Remote Sensing* 173: 24–49. https://doi.org/10.1016/j.isprsjprs.2020.12.010.

Kennedy, R. E., W. B. Cohen, and T. A. Schroeder. 2007. “Trajectory-Based Change Detection for Automated Characterization of Forest Disturbance Dynamics.” *Remote Sensing of Environment* 110, no. 3: 370–386.

Kennedy, R. E., Z. Yang, and W. B. Cohen. 2010. “Detecting Trends in Forest Disturbance and Recovery Using Yearly Landsat Time Series: 1. Landtrendr—Temporal Segmentation Algorithms.” *Remote Sensing of Environment* 114, no. 12: 2897–2910.

Kirillov, A., E. Mintun, N. Ravi, et al. 2023. “Segment Anything.” In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 4015–4026. IEEE.

Kleinman, J. S., J. D. Goode, A. C. Fries, and J. L. Hart. 2019. “Ecological Consequences of Compound Disturbances in Forest Ecosystems: A Systematic Review.” *Ecosphere* 10, no. 11: e02962.

Klemmer, K., E. Rolf, C. Robinson, L. Mackey, and M. Rußwurm. 2025. “Satclip: Global, General-Purpose Location Embeddings With Satellite Imagery.” *Proceedings of the AAAI Conference on Artificial Intelligence* 39: 4347–4355.

Kondylatos, S., I. Prapas, M. Ronco, et al. 2022. “Wildfire Danger Prediction and Understanding With Deep Learning.” *Geophysical Research Letters* 49: e2022GL099368.

Kong, Y.-L., Q. Huang, C. Wang, J. Chen, J. Chen, and D. He. 2018. “Long Short-Term Memory Neural Networks for Online Disturbance Detection in Satellite Image Time Series.” *Remote Sensing* 10, no. 3: 452.

Krawchuk, M. A., G. W. Meigs, J. M. Cartwright, et al. 2020. “Disturbance Refugia Within Mosaics of Forest Fire, Drought, and Insect Outbreaks.” *Frontiers in Ecology and the Environment* 18, no. 5: 235–244.

Kuzu, R. S., O. Antropov, M. Molinier, C. O. Dumitru, S. Saha, and X. X. Zhu. 2024. “Forest Disturbance Detection via Self-Supervised and Transfer Learning With Sentinel-1&2 Images.” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 17: 4751–4767.

Lai, L., J. Chen, H. Huang, and W. Qingyao. 2021. “Exploring a Cam-Based Approach for Weakly Supervised Fire Detection Task.” In *2021 IEEE International Conference on e-Business Engineering (ICEBE)*, 134–138. IEEE.

Lämås, T., L. Saengstuvall, K. Öhman, et al. 2023. “The Multi-Faceted Swedish Heureka Forest Decision Support System: Context, Functionality, Design, and 10 Years Experiences of Its Use.” *Frontiers in Forests and Global Change* 6: 1163105.

Lang, N., W. Jetz, K. Schindler, and J. D. Wegner. 2023. “A High-Resolution Canopy Height Model of the Earth.” *Nature Ecology & Evolution* 7, no. 11: 1778–1789.

Layegh, N. F., R. Darvishzadeh, A. K. Skidmore, C. Persello, and N. Krüger. 2022. “Integrating Semi-Supervised Learning With an Expert System for Vegetation Cover Classification Using Sentinel-2 and RapidEye Data.” *Remote Sensing* 14, no. 15: 3605. https://doi.org/10.3390/rs14153605.

LeCun, Y., and Y. Bengio. 1998. “Convolutional Networks for Images, Speech, and Time Series.” In *The Handbook of Brain Theory and Neural Networks*, edited by M. A. Arbib. MIT Press.

Li, W., H. Lee, S. Wang, C.-Y. Hsu, and S. T. Arundel. 2023. “Assessment of a New Geoai Foundation Model for Flood Inundation Mapping.” In *Proceedings of the 6th ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery*, 102–109. ACM.

Li, Y., X. Xiao, W. Zhenzi, H. Fan, X. Tong, and J. Liu. 2022. “A Forest Type-Specific Threshold Method for Improving Forest Disturbance and Agent Attribution Mapping.” *GIScience & Remote Sensing* 59, no. 1: 1624–1642.

Li, Y., H. Zhang, X. Xue, Y. Jiang, and Q. Shen. 2018. “Deep Learning for Remote Sensing Image Classification: A Survey.” *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 8, no. 6: e1264.

Lim, B., S. Ö. Arık, N. Loeff, and T. Pfister. 2021. “Temporal Fusion Transformers for Interpretable Multi-Horizon Time Series Forecasting.” *International Journal of Forecasting* 37, no. 4: 1748–1764.

Liu, Y., X. Wang, Y. Wang, et al. 2025. “Representation Learning for Geospatial Data.” *Annals of GIS* 31, no. 4: 557–583.

Matricardi, E. A. T., D. L. Skole, M. A. Cochrane, M. Pedlowski, and W. Chomentowski. 2007. “Multi-Temporal Assessment of Selective Logging in the Brazilian Amazon Using Landsat Data.” *International Journal of Remote Sensing* 28, no. 1: 63–82.

Matricardi, E. A. T., D. L. Skole, O. B. Costa, M. A. Pedlowski, J. H. Samek, and E. P. Miguel. 2020. “Long-Term Forest Degradation Surpasses Deforestation in the Brazilian Amazon.” *Science* 369, no. 6509: 1378–1382.

Meigs, G. W., H. S. J. Zald, J. L. Campbell, W. S. Keeton, and R. E. Kennedy. 2016. “Do Insect Outbreaks Reduce the Severity of Subsequent Forest Fires?” *Environmental Research Letters* 11, no. 4: 045008.

Mitchell, A. L., A. Rosenqvist, and B. Mora. 2017. “Current Remote Sensing Approaches to Monitoring Forest Degradation in Support of Countries Measurement, Reporting and Verification (MRV) Systems for REDD+.” *Carbon Balance and Management* 12: 1–22. https://doi.org/10.1186/s13021-017-0078-9.

Molnar, C. 2022. *Modeling Mindset: The Many Cultures of Learning From Data*. Independently published.

Montréal Process. 2015. "The Montréal Process Criteria and Indicators for the Conservation and Sustainable Management of Temperate and Boreal Forests. Montreal Process Liaison Office." In *A Framework to Diagnose Barriers to Climate Change Adaptation*, edited by S. Moser and J. Ekstrom, vol. 107, 22026–22031. Proceedings of the National Academy of Sciences of the United States of America. https://www.montrealpro.

Moraes, D., M. L. Campagnolo, and M. Caetano. 2025. "A Weakly Supervised and Self-Supervised Learning Approach for Semantic Segmentation of Land Cover in Satellite Images With National Forest Inventory Data." *Remote Sensing* 17(4):711: 711.

Mosig, C., J. Vajna-Jehle, M. D. Mahecha, et al. 2026. "Deadtrees. Earth—An Open-Access and Interactive Database for Centimeter-Scale Aerial Imagery to Uncover Global Tree Mortality Dynamics." *Remote Sensing of Environment* 332: 115027.

Nagrani, A., S. Yang, A. Arnab, A. Jansen, C. Schmid, and C. Sun. 2021. "Attention Bottlenecks for Multimodal Fusion." *Advances in Neural Information Processing Systems* 34: 14200–14213.

Natel, C., D. M. Belda, P. Anthoni, N. Haß, S. Rabin, and A. Arneth. 2025. "Emulating Grid-Based Forest Carbon Dynamics Using Machine Learning: An Lpj-Guess v4. 1.1 Application." *Geoscientific Model Development* 18, no. 14: 4317–4333.

Natel, C., J. S. de Moura, and D. H. M. Detzel. 2022. "Evaluating the Long Short-Term Memory (Lstm) Network for Discharge Prediction Under Changing Climate Conditions." *Hydrology Research* 53, no. 5: 657–667.

Nesha, K., M. Herold, V. De Sy, et al. 2021. "An Assessment of Data Sources, Data Quality and Changes in National Forest Monitoring Capacities in the Global Forest Resources Assessment 2005–2020." *Environmental Research Letters* 16, no. 5: 54029. https://doi.org/10.1088/1748-9326/abd81b.

Olivier, C., S. Bernhard, and Z. Alexander. 2006. "A Discussion of Semi-Supervised Learning and Transduction." In *Semi-Supervised Learning*, edited by O. Chapelle, B. Scholkopf, and A. Zien, 473–478. MIT Press. https://doi.org/10.7551/mitpress/9780262033589.003.0025.

Olofsson, P., G. M. Foody, M. Herold, S. V. Stehman, C. E. Woodcock, and M. A. Wulder. 2014. "Good Practices for Estimating Area and Assessing Accuracy of Land Change." *Remote Sensing of Environment* 148: 42–57.

Osco, L. P., W. Qiusheng, E. L. De Lemos, et al. 2023. "The Segment Anything Model (SAM) for Remote Sensing Applications: From Zero to One Shot." *International Journal of Applied Earth Observation and Geoinformation* 124: 103540. https://doi.org/10.1016/j.jag.2023.103540.

Ouaknine, A., T. Kattenborn, E. Laliberté, and D. Rolnick. 2025. "Openforest: A Data Catalog for Machine Learning in Forest Monitoring." *Environmental Data Science* 4: e15.

Parra, A., and M. Simard. 2023. "Evaluation of Tree-Growth Rate in the Laurentides Wildlife Reserve Using GEDI and Airborne-LiDAR Data." *Remote Sensing* 15, no. 22: 5352. https://doi.org/10.3390/rs15225352.

Pasquarella, V. J., B. A. Bradley, and C. E. Woodcock. 2017. "Near-Real-Time Monitoring of Insect Defoliation Using Landsat Time Series." *Forests* 8, no. 8: 275. https://doi.org/10.3390/f8080275.

Paulino, E. R., M. Schlerf, A. Roeder, J. Stoffels, and T. Udelhoven. 2024. "Forest Disturbance Characterization in the Era of Earth Observation Big Data: A Mapping Review." *International Journal of Applied Earth Observation and Geoinformation* 128: 103755.

Perbet, P., L. Guindon, J.-F. Côté, and M. Béland. 2024. "Evaluating Deep Learning Methods Applied to Landsat Time Series Subsequences to Detect and Classify Boreal Forest Disturbances Events: The Challenge of Partial and Progressive Disturbances." *Remote Sensing of Environment* 306: 114107.

Ploton, P., F. Mortier, M. Réjou-Méchain, et al. 2020. "Spatial Validation Reveals Poor Predictive Performance of Large-Scale Ecological Mapping Models." *Nature Communications* 11, no. 1: 4540.

Potapov, P., X. Li, A. Hernandez-Serna, et al. 2021. "Mapping Global Forest Canopy Height Through Integration of GEDI and Landsat Data." *Remote Sensing of Environment* 253: 112165. https://doi.org/10.1016/j.rse.2020.112165.

Praveena, K., R. J. Anandhi, S. Gupta, A. Jain, A. Kumar, and A. M. Saud. 2024. "Application of Zero-Shot Learning in Computer Vision for Biodiversity Conservation Through Species Identification and Tracking." In *2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies*, 1–6. IEEE. https://doi.org/10.1109/TQCEBT59414.2024.10545030.

Price, I., A. Sanchez-Gonzalez, F. Alet, et al. 2025. "Probabilistic Weather Forecasting With Machine Learning." *Nature* 637, no. 8044: 84–90.

Pugh, T. A. M., M. Lindeskog, B. Smith, et al. 2019. "Role of Forest Regrowth in Global Carbon Sink Dynamics." *Proceedings of the National Academy of Sciences* 116, no. 10: 4382–4387.

Puthumanaillam, G., and U. Verma. 2023. "Texture Based Prototypical Network for Few-Shot Semantic Segmentation of Forest Cover: Generalizing for Different Geographical Regions." *Neurocomputing* 538: 126201. https://doi.org/10.1016/j.neucom.2023.03.062.

Qiu, D., Y. Liang, R. Shang, and J. M. Chen. 2023. "Improving Landtrendr Forest Disturbance Mapping in China Using Multi-Season Observations and Multispectral Indices." *Remote Sensing* 15, no. 9: 2381.

Rafiq, K., S. Beery, M. S. Palmer, Z. Harchaoui, and B. Abrahms. 2025. "Generative Ai as a Tool to Accelerate the Field of Ecology." *Nature Ecology & Evolution* 9, no. 3: 378–385.

Reiche, J., A. Mullissa, B. Slagter, et al. 2021. "Forest Disturbance Alerts for the Congo Basin Using Sentinel-1." *Environmental Research Letters* 16, no. 2: 024005.

Reichstein, M., G. Camps-Valls, B. Stevens, et al. 2019. "Deep Learning and Process Understanding for Data-Driven Earth System Science." *Nature* 566, no. 7743: 195–204.

Roberts, D. R., V. Bahn, S. Ciuti, et al. 2017. "Cross-Validation Strategies for Data With Temporal, Spatial, Hierarchical, or Phylogenetic Structure." *Ecography* 40, no. 8: 913–929. https://doi.org/10.1111/ecog.02881.

Rogers, P. 1996. *Disturbance Ecology and Forest Management: A Review of the Literature*. US Department of Agriculture.

Ronneberger, O., P. Fischer, and T. Brox. 2015. "U-Net: Convolutional Networks for Biomedical Image Segmentation." In *Medical Image Computing and Computer-Assisted Intervention—MICCAI 2015*, edited by N. Navab, J. Hornegger, W. M. Wells, and A. F. Frangi, 234–241. Springer International Publishing.

Rußwurm, M., and M. Körner. 2020. "Self-Attention for Raw Optical Satellite Time Series Classification." *ISPRS Journal of Photogrammetry and Remote Sensing* 169: 421–435.

Saah, D., G. Johnson, B. Ashmall, et al. 2019. "Collect Earth: An Online Tool for Systematic Reference Data Collection in Land Cover and Use Applications." *Environmental Modelling & Software* 118: 166–171.

Scheepens, D., J. Millard, M. Farrell, and T. Newbold. 2024. "Large Language Models Help Facilitate the Automated Synthesis of Information on Potential Pest Controllers." *Methods in Ecology and Evolution* 15, no. 7: 1261–1273.

Schiefer, F., S. Schmidtlein, A. Frick, et al. 2023. "UAV-Based Reference Data for the Prediction of Fractional Cover of Standing Deadwood From Sentinel Time Series." *ISPRS Open Journal of Photogrammetry and Remote Sensing* 8: 100034. https://doi.org/10.1016/j.ophoto.2023.100034.

Schiller, C., J. Költzow, S. Schwarz, F. Schiefer, and F. E. Fassnacht. 2024. “Forest Disturbance Detection in Central Europe Using Transformers and Sentinel-2 Time Series.” *Remote Sensing of Environment* 315: 114475. https://doi.org/10.1016/j.rse.2024.114475.

Schleeweis, K. G., G. G. Moisen, T. A. Schroeder, et al. 2020. “US National Maps Attributing Forest Change: 1986–2010.” *Forests* 11: 653.

Schmitt, M., L. H. Hughes, C. Qiu, and X. X. Zhu. 2019. “Sen12ms: A Curated Dataset of Georeferenced Multi-Spectral Sentinel-1/2 Imagery for Deep Learning and Data Fusion.” In *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. IV-2/W7, 153–160. ISPRS. https://doi.org/10.5194/isprs-annals-IV-2-W7-153-2019.

Schroeder, T. A., K. G. Schleeweis, G. G. Moisen, et al. 2017. “Testing a Landsat-Based Approach for Mapping Disturbance Causality in Us Forests.” *Remote Sensing of Environment* 195: 230–243.

Sebald, J., C. Senf, and R. Seidl. 2021. “Human or Natural? Landscape Context Improves the Attribution of Forest Disturbances Mapped From Landsat in Central Europe.” *Remote Sensing of Environment* 262: 112502.

Seidl, R., D. Thom, M. Kautz, et al. 2017. “Forest Disturbances Under Climate Change.” *Nature Climate Change* 7, no. 6: 395–402.

Senf, C. 2022. “Seeing the System From Above: The Use and Potential of Remote Sensing for Studying Ecosystem Dynamics.” *Ecosystems* 25, no. 8: 1719–1737. https://doi.org/10.1007/s10021-022-00777-2.

Senf, C., A. Buras, C. S. Zang, A. Rammig, and R. Seidl. 2020. “Excess Forest Mortality Is Consistently Linked to Drought Across Europe. *Nature*.” *Communications* 11, no. 1: 6200. https://doi.org/10.1038/s41467-020-19924-1.

Senf, C., and R. Seidl. 2020. “Mapping the Forest Disturbance Regimes of Europe.” *Nature Sustainability* 4, no. 1: 63–70. https://doi.org/10.1038/s41893-020-00609-y.

Shah, M., M. S. Raval, and S. Divakaran. 2025. “A Systematic Review on Deep Learning for Atmospheric Correction of Satellite Images.” *Archives of Computational Methods in Engineering* 33: 4059–4089.

Shi, X., Z. Chen, H. Wang, D.-Y. Yeung, W.-K. Wong, and W.-c. Woo. 2015. “Convolutional Lstm Network: A Machine Learning Approach for Precipitation Nowcasting.” *Advances in Neural Information Processing Systems* 28: 1–9.

Shimabukuro, Y. E., R. Beuchle, R. C. Grecchi, and F. Achard. 2014. “Assessment of Forest Degradation in Brazilian Amazon due to Selective Logging and Fires Using Time Series of Fraction Images Derived From Landsat Etm+ Images.” *Remote Sensing Letters* 5, no. 9: 773–782.

Shu, D., and A. B. Farimani. 2024. “Zero-Shot Uncertainty Quantification Using Diffusion Probabilistic Models.” arXiv Preprint arXiv:2408.04718.

Slagter, B., J. Reiche, D. Marcos, et al. 2023. “Monitoring Direct Drivers of Small-Scale Tropical Forest Disturbance in Near Real-Time With Sentinel-1 and -2 Data.” *Remote Sensing of Environment* 295: 113655.

Smith, M., L. Fleming, J. Geach, R. Roberts, F. Kalaitzis, and J. Banister. 2025. “Dargana: Fine-Tuning Earthpt for Dynamic Tree Canopy Mapping From Space.” In *ICLR 2025 Workshop on Tackling Climate Change With Machine Learning*. ICLR. https://www.climatechange.ai/papers/iclr2025/11.

St. Peter, J., J. Drake, P. Medley, and V. Ibeanusi. 2021. “Forest Structural Estimates Derived Using a Practical, Open-Source Lidar-Processing Workflow.” *Remote Sensing* 13, no. 23: 4763. https://doi.org/10.3390/rs13234763.

Steger, S., R. Bell, H. Petschko, and T. Glade. 2015. “Evaluating the Effect of Modelling Methods and Landslide Inventories Used for Statistical Susceptibility Modelling.” In *Engineering Geology for Society and Territory-Volume 2: Landslide Processes*, 201–204. Springer.

Sumbul, G., A. De Wall, T. Kreuziger, et al. 2021. “Bigearthnet-Mm: A Large-Scale, Multimodal, Multilabel Benchmark Archive for Remote Sensing Image Classification and Retrieval [Software and Data Sets].” *IEEE Geoscience and Remote Sensing Magazine* 9, no. 3: 174–180.

Sykas, D., I. Papoutsis, and D. Zografakis. 2021. “Sen4agrinet: A Harmonized Multi-Country, Multi-Temporal Benchmark Dataset for Agricultural Earth Observation Machine Learning Applications.” In *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, 5830–5833. IEEE.

Szegedy, C., W. Liu, Y. Jia, et al. 2015. “Going Deeper With Convolutions.” In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1–9. IEEE.

Szegedy, C., V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. 2016. “Rethinking the Inception Architecture for Computer Vision.” In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2818–2826. IEEE.

Thom, D., and R. Seidl. 2016. “Natural Disturbance Impacts on Ecosystem Services and Biodiversity in Temperate and Boreal Forests.” *Biological Reviews* 91, no. 3: 760–781.

Tollefson, J. 2025. “Google Ai Model Creates Maps of Earth ‘at Any Place and Time’.” *Nature* 644: 313–314.

Tseng, G., R. Cartuyvels, I. Zvonkov, M. Purohit, D. Rolnick, and H. Kerner. 2023. “Lightweight, Pre-Trained Transformers for Remote Sensing Timeseries.” In *Proceedings of the NeurIPS 2023 Workshop on Tackling Climate Change With Machine Learning: Blending New and Existing Knowledge Systems*. NeurIPS. https://www.climatechange.ai/papers/neurips2023/87.

Tseng, G., I. Zvonkov, C. L. Nakalembe, and H. Kerner. 2021. “Cropharvest: A Global Dataset for Crop-Type Classification.” In *Thirty-Fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*. NeurIPS.

Turner, M. G., and R. Seidl. 2023. “Novel Disturbance Regimes and Ecological Responses.” *Annual Review of Ecology, Evolution, and Systematics* 54, no. 1: 63–83. https://doi.org/10.1146/annurev-ecolsys-110421-101120.

Vancutsem, C., A. Frédéric, J.-F. Pekel, et al. 2021. “Long-Term (1990–2019) Monitoring of Forest Cover Changes in the Humid Tropics.” *Science Advances* 7, no. 10: eabe1603.

Vaswani, A., N. Shazeer, N. Parmar, et al. 2017. “Attention Is All You Need.” *Advances in Neural Information Processing Systems* 30: 1–11.

Verbesselt, J., A. Zeileis, and M. Herold. 2012. “Near Real-Time Disturbance Detection Using Satellite Image Time Series.” *Remote Sensing of Environment* 123: 98–108.

Viana-Soto, A., and C. Senf. 2025. “The European Forest Disturbance Atlas: A Forest Disturbance Monitoring System Using the Landsat Archive.” *Earth System Science Data* 17, no. 6: 2373–2404. https://doi.org/10.5194/essd-17-2373-2025.

Wagner, F. H., R. Dalagnol, C. H. L. Silva-Junior, et al. 2023. “Mapping Tropical Forest Cover and Deforestation With Planet Nicfi Satellite Images and Deep Learning in Mato Grosso State (Brazil) From 2015 to 2021.” *Remote Sensing* 15, no. 2: 521.

Wang, J., X. Fan, X. Yang, T. Tjahjadi, and Y. Wang. 2022. “Semi-Supervised Learning for Forest Fire Segmentation Using UAV Imagery.” *Forests* 13, no. 10: 1573. https://doi.org/10.3390/f13101573.

Wang, L., S. Liu, W. Song, J. Zhang, and S. Ding. 2025. “Global High-Resolution Forest Disturbance Type Dataset.” *Earth System Science Data Discussions* 1–23: 2025.

Wang, S., W. Chen, S. M. Xie, G. Azzari, and D. B. Lobell. 2020. “Weakly Supervised Deep Learning for Segmentation of Remote Sensing Imagery.” *Remote Sensing* 12, no. 2: 207.

Wang, W., V. W. Zheng, H. Yu, and C. Miao. 2019. "A Survey of Zero-Shot Learning: Settings, Methods, and Applications." *ACM Transactions on Intelligent Systems and Technology* 10, no. 2: 1–37. https://doi.org/10.1145/3293318.

Wang, Y., C. M. Albrecht, N. A. A. Braham, L. Mou, and X. X. Zhu. 2022. "Self-Supervised Learning in Remote Sensing: A Review." *IEEE Geoscience and Remote Sensing Magazine* 10, no. 4: 213–247.

Wilkinson, M. D., M. Dumontier, I. J. J. Aalbersberg, et al. 2016. "The Fair Guiding Principles for Scientific Data Management and Stewardship." *Scientific Data* 3, no. 1: 1–9.

Wu, H., B. Xiao, N. Codella, et al. 2021. "Cvt: Introducing Convolutions to Vision Transformers." In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 22–31. IEEE.

Wu, K., Y. Zhang, R. Lixiang, et al. 2025. "A Semantic-Enhanced Multi-Modal Remote Sensing Foundation Model for Earth Observation." *Nature Machine Intelligence* 7: 1235–1249.

Wu, N., L. Huang, M. Zhang, Y. Dou, K. Mo, and J. Liu. 2025. "Remote Sensing Detection of Forest Changes in the South Ridge Corridor and an Attribution Analysis." *Forests* 16, no. 2: 205.

Wulder, M. A., T. R. Loveland, D. P. Roy, et al. 2019. "Current Status of Landsat Program, Science, and Applications." *Remote Sensing of Environment* 225: 127–147.

Xiao, A., W. Xuan, J. Wang, et al. 2025. "Foundation Models for Remote Sensing and Earth Observation: A Survey." *IEEE Geoscience and Remote Sensing Magazine* 13: 297–324.

Xu, Z., and D. Jiang. 2025. "AI-Powered Plant Science: Transforming Forestry Monitoring, Disease Prediction, and Climate Adaptation." *Plants* 14, no. 11: 1626.

Ye, S., J. Rogan, Z. Zhu, and J. R. Eastman. 2021. "A Near-Real-Time Approach for Monitoring Forest Disturbance Using Landsat Time Series: Stochastic Continuous Change Detection." *Remote Sensing of Environment* 252: 112167.

Zhang, L., L. Zhang, and B. Du. 2016. "Deep Learning for Remote Sensing Data: A Technical Tutorial on the State of the Art." *IEEE Geoscience and Remote Sensing Magazine* 4, no. 2: 22–40. https://doi.org/10.1109/MGRS.2016.2540798.

Zhang, X., and Y. Zhang. 2023. "Conv-Pvt: A Fusion Architecture of Convolution and Pyramid Vision Transformer." *International Journal of Machine Learning and Cybernetics* 14, no. 6: 2127–2136.

Zhang, Y., F. Ling, X. Wang, et al. 2021. "Tracking Small-Scale Tropical Forest Disturbances: Fusing the Landsat and Sentinel-2 Data Record." *Remote Sensing of Environment* 261: 112470. https://doi.org/10.1016/j.rse.2021.112470.

Zhao, F., R. Sun, L. Zhong, et al. 2022. "Monthly Mapping of Forest Harvesting Using Dense Time Series Sentinel-1 SAR Imagery and Deep Learning." *Remote Sensing of Environment* 269: 112822. https://doi.org/10.1016/j.rse.2021.112822.

Zhou, B., A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba. 2016. "Learning Deep Features for Discriminative Localization." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2921–2929. IEEE.

Zhou, Z.-H. 2018. "A Brief Introduction to Weakly Supervised Learning." *National Science Review* 5, no. 1: 44–53.

Zhu, X. X., D. Tuia, L. Mou, et al. 2017. "Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources." *IEEE Geoscience and Remote Sensing Magazine* 5, no. 4: 8–36. https://doi.org/10.1109/MGRS.2017.2762307.

Zhu, Z., and C. E. Woodcock. 2014. "Continuous Change Detection and Classification of Land Cover Using All Available Landsat Data." *Remote Sensing of Environment* 144: 152–171.

Zhu, Z., J. Zhang, Z. Yang, et al. 2020. "Continuous Monitoring of Land Disturbance Based on Landsat Time Series." *Remote Sensing of Environment* 238: 111116.

Ziegler, J. D., S. Subramaniam, M. Azzarito, O. Doyle, P. Krusche, and T. Coroller. 2022. "Multi-Modal Conditional Gan: Data Synthesis in the Medical Domain." In *NeurIPS 2022 Workshop on Synthetic Data for Empowering ML Research*. NeurIPS.

Ziv, R. S., and Y. LeCun. 2024. "To Compress or Not to Compress—Self-Supervised Learning and Information Theory: A Review." *Entropy* 26, no. 3: 252.