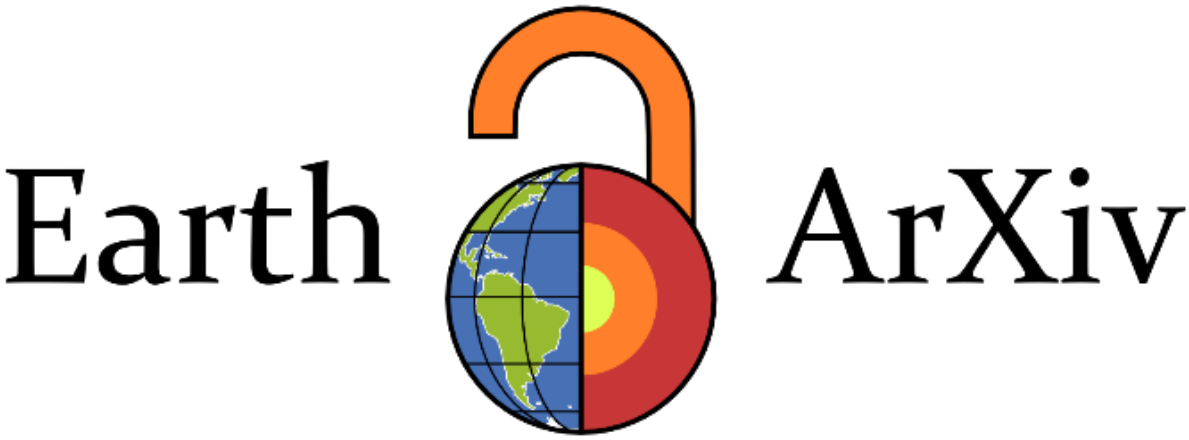

Remote sensing and deep learning for standing dead-tree detection and mapping: A review of advances, challenges, and future directions

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Abstract

Standing dead trees are visible indicators of recent tree mortality and an important transitional component linking forest disturbance to future lying deadwood, habitat availability, and carbon storage. As drought, insect outbreaks, pathogens, and climate extremes intensify tree mortality worldwide, scalable methods are needed to detect and map standing dead trees consistently across forest landscapes. Recent advances in high-resolution remote sensing and computer-vision-based deep learning, including object detection, semantic segmentation, instance segmentation, and transformer-based models, are making large-scale standing dead-tree detection increasingly feasible. This review synthesizes 38 studies from 2019 to 2026 that apply deep learning to optical and LiDAR data acquired from UAV-borne, airborne, satellite, and multi-sensor remote sensing platforms for standing dead-tree detection and mapping. We identify five major advances: 1) object-detection models have become central for identifying dead trees, especially where mortality is spatially scattered and dead trees occur at low density, with transformer-based frameworks emerging as a promising development; 2) U-Net derivatives and hybrid or ensemble models are widely used for segmentation in dense canopies; 3) multi-sensor fusion can improve detection robustness, particularly where spectral and structural cues are complementary; 4) transfer learning and domain adaptation are important for scaling across regions, although cross-biome generalization remains limited by differences in forest structure, dead-tree appearance, and sensor characteristics; and 5) model comparability is constrained by inconsistent annotations, varying definitions of standing dead trees, and the lack of standardized benchmark datasets. Despite substantial progress, operational deployment remains limited by canopy occlusion, class imbalance, annotation variability, and uncertain transferability. By linking ecological monitoring needs with recent methodological advances, this review outlines a pathway toward scalable, transferable, and benchmarked deep-learning systems for standing dead-tree monitoring, supported by standardized datasets, domain-invariant and self-supervised learning, and open databases such as deadtrees.earth.

Keywords: Tree mortality; Deadwood; Forest health; UAV; LiDAR; Multi-sensor fusion

Highlights

- Synthesizes recent deep learning advances for standing dead-tree detection and mapping.
- Object detection models support identification of scattered and low-density dead trees.
- U-Net derivatives and segmentation models are important for dense canopy conditions.
- Multi-sensor fusion and transfer learning can improve robustness and scalability.
- Standardized benchmarks are needed for operational, large-scale standing dead-tree monitoring.

1 Introduction

Forests cover approximately 31% of the global land surface and support a large share of global biodiversity, providing habitat for about 80% of all amphibians, 75% of all birds, and 68% of all mammals (Brockerhoff et al., 2017; FAO & UNEP, 2020; Mori et al., 2017). They also regulate atmospheric carbon through photosynthetic sequestration, absorbing roughly 25% of anthropogenic CO_2 emissions annually (Lv et al., 2025; Pan et al., 2011). However, increasing anthropogenic pressures and climate-driven disturbances including drought, extreme heat, insect outbreaks, pathogens, and wildfires are intensifying tree mortality across tropical, temperate, and boreal forests (Beloiu et al., 2026; Gazol et al., 2025; Hartmann et al., 2022; Seidl et al., 2017). Regional patterns highlight the scale of these changes: drought-related mortality has increased across 43% of Canada's boreal forests since 2002 (Junttila et al., 2024; Liu et al., 2023), while recurrent drought and compound disturbances have driven mortality in tropical forests (Boulton et al., 2022; Losso et al., 2022; Walden et al., 2023; Yang et al., 2018). In Europe, bark beetle outbreaks have become a dominant mortality driver, with timber losses increasing from 2.9 million m^3 annually during 1950–2000 to tens of millions of cubic meters during recent outbreaks across Central and Northern Europe (Hartmann et al., 2025; Hlásny et al., 2021; Schelhaas et al., 2003). These mortality processes generate substantial quantities of deadwood, including standing dead trees, a key structural component of forest ecosystems that strongly influences biodiversity, nutrient cycling, and carbon storage (Aakala et al., 2024; Harmon et al., 2020; Oberle et al., 2018).

Deadwood, including standing dead trees and fallen coarse woody debris, plays a central role in forest ecosystem functioning (Aakala et al., 2024; Oberle et al., 2018). Deadwood increases structural complexity and provides nesting, shelter, and foraging habitats for birds, bats, small mammals, fungi, and invertebrates (Jutras-Perreault et al., 2023; Löfroth et al., 2023). Many associated organisms are saproxylic species dependent on decaying wood and essential for decomposition and nutrient recycling processes (Rondeux and Sanchez, 2010; Shannon et al., 2022). Coarse woody debris also functions as a long-term carbon reservoir, decomposing over decades to centuries and contributing significantly to forest carbon storage and energy flow (Fraver et al., 2013; Harmon et al., 2020; Luo et al., 2025; Zhou et al., 2007). As decomposition progresses, gradients in moisture, temperature, and nutrient availability create diverse microhabitats colonized by specialized microbial and fungal communities that redistribute nutrients and enrich surrounding soils (Brabcová et al., 2022; Zhang et al., 2025b; Zheng et al., 2025). These processes influence regeneration, soil development, and successional dynamics (Piaszczyk et al., 2019; Wijas et al., 2024), while the quantity and spatial distribution of deadwood are widely recognized as key indicators of biodiversity and ecosystem integrity (Mansuy et al., 2024; Merganičová et al., 2012). In this review, we focus specifically on standing dead trees, defined as upright dead trees that remain visible or potentially detectable from above-canopy remote sensing data, rather than on fallen deadwood or concealed deadwood components below the canopy. This focus is important because standing dead trees represent a detectable transitional stage between tree mortality and the later recruitment of fallen coarse woody debris, and their monitoring may help anticipate future inputs to lying deadwood and broader deadwood pools that are currently difficult to observe directly from above-canopy Earth observation data.

Despite their ecological importance, standing dead trees remain difficult to monitor consistently across large spatial scales. Field inventories provide accurate measurements of standing dead trees and other deadwood components but are labor-intensive, costly, and spatially limited, particularly in remote or hazardous terrain (Ni

et al., 2025; Zhou et al., 2024). A central challenge is that tree mortality is often gradual rather than instantaneous. Trees may pass through intermediate decline stages characterized by crown thinning, discoloration, partial dieback, and structural degradation before they become clearly identifiable as dead. As a result, remote sensing observations may capture a continuum of canopy conditions rather than a simple alive/dead distinction. This progression is illustrated in Fig. 1, which shows how mortality signatures vary across decay stages and between coniferous and broadleaf species, from early spectral changes such as crown discoloration to later structural changes such as crown loss and snag formation. In advanced decay stages, standing dead trees may be reduced to trunk snags with little or no visible crown, making them difficult to detect in medium-resolution imagery and challenging even in some high-resolution datasets.

Remote sensing therefore provides an important complementary approach for mapping forest disturbance and mortality patterns over broad spatial extents, although direct detection of individual standing dead trees remains constrained by sensor resolution, canopy structure, tree condition, and decay stage. Long-term optical satellite missions such as MODIS, Landsat, and Sentinel-2 provide observations of forest condition and disturbance dynamics through stand- or canopy-level indicators such as canopy greenness, spectral change, and vegetation indices (Antoniadis et al., 2025; Campbell et al., 2020; Hall et al., 2016). However, their spatial resolutions generally limit their ability to identify individual standing dead trees, meaning that mortality is often inferred indirectly from aggregated canopy signals (Eliades et al., 2024). While effective for identifying large-scale disturbance events, these aggregated indicators can mask fine-scale spatial heterogeneity and limit ecological interpretation of mortality processes at the individual-tree scale.

Recent advances in high-resolution remote sensing and deep learning have substantially improved the potential for detecting standing dead trees at finer spatial scales (Fig. 2). UAV and airborne imagery can provide centimeter- to decimeter-scale observations of crown condition, while LiDAR adds three-dimensional structural information related to canopy height, crown geometry, and gap formation (Manfreda et al., 2018; Krzystek et al., 2020; Briechle et al., 2021; Polvivaara et al., 2024). Very-high-resolution satellite imagery and dense satellite time series further support broader-scale monitoring, although usually at coarser spatial detail than UAV or airborne data (Liu et al., 2021; Dixon et al., 2023; Schiefer et al., 2023; Shields et al., 2025). At the same time, deep learning approaches, including CNN-based classification, U-Net-based semantic segmentation, object detection, instance segmentation, and transformer-based models, have enabled increasingly automated detection and mapping of individual standing dead trees, dead crowns, and canopy mortality patterns (Jiang et al., 2023; Junttila et al., 2024; Lucas et al., 2024; Zhou et al., 2024; Möhring et al., 2025; Rahman et al., 2025). These developments create new opportunities for scalable standing-dead-tree monitoring, but also raise questions about sensor choice, model transferability, annotation quality, and benchmark comparability (Kattenborn et al., 2021; Fassnacht et al., 2024; Yun et al., 2024; Lines et al., 2022).

Despite these advances, comprehensive syntheses specifically focused on standing dead-tree detection remain limited. Existing reviews have addressed adjacent topics, including remote sensing of tree mortality and forest health (Eliades et al., 2024; Junttila, 2025; Ni et al., 2025), broader developments in forestry remote sensing and vegetation-oriented deep learning (Fassnacht et al., 2024; Kattenborn et al., 2021; Yun et al., 2024), individual tree-crown detection and delineation (Zhao et al., 2023), sensor-specific perspectives on laser scanning and satellite platforms (Cotrozzi, 2022; Marchi et al., 2018; Shields et al., 2025), and the ecological importance of deadwood (Steinebrunner et al., 2025; Wijas et al., 2024). However, these studies do not provide

a dedicated synthesis of standing dead-tree detection and mapping that jointly considers ecological relevance, sensor capabilities, and algorithmic developments. As a result, important questions remain regarding how different sensors and data-fusion strategies compare, how well deep learning models generalize across biomes, how differences in standing dead-tree definitions and annotation protocols affect comparability among studies, and to what extent current approaches can support large-scale operational monitoring. More broadly, operational deployment remains constrained by several factors, including canopy occlusion, annotation variability, and limited transferability (see Section 6).

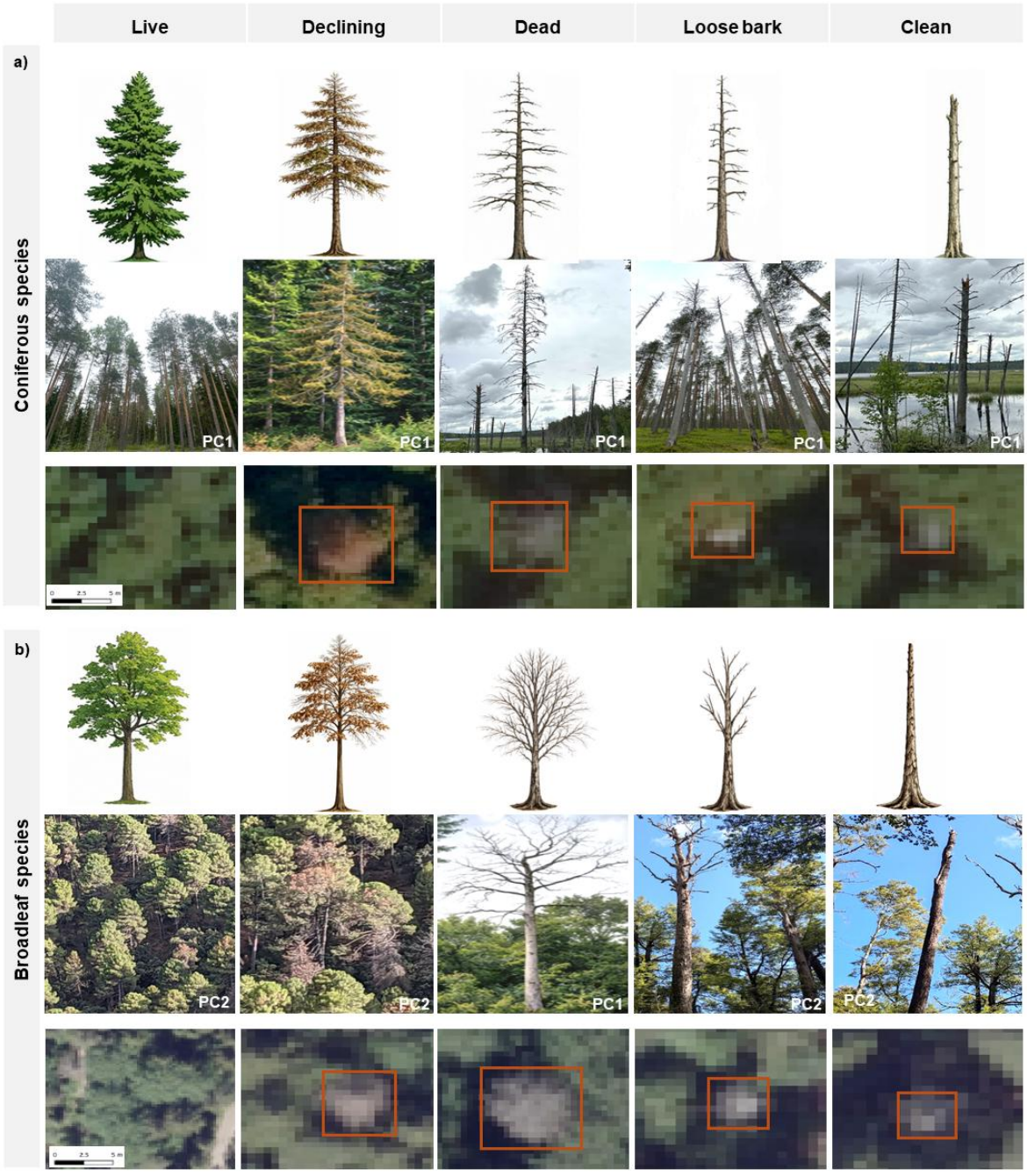

Fig. 1. Visual representation of living, declining, and dead forest trees at different decay stages for coniferous a) and broadleaf b) species across forest stands, individual tree structure, and aerial imagery (~50 cm). The figure highlights how mortality signatures evolve from spectral changes (e.g., crown discoloration) to structural features, with late-stage snags often lacking visible crowns and becoming difficult to detect, particularly in medium-resolution imagery. Adapted from Zielewska-Büttner et al. (2018). Photo credits: PC1, Anwarul Chowdhury; PC2, Clemens Mosig; illustrations by Anwarul Chowdhury.

In this review, we focus on scalable detection and mapping of standing dead trees using remote sensing and deep learning approaches. Specifically, we aim to (1) synthesize current datasets and remote sensing technologies for standing dead-tree detection, (2) review methodological frameworks and deep learning approaches applied to optical, LiDAR, UAV, airborne, satellite, and multi-sensor data, (3) evaluate ecological and management implications of spatially explicit standing dead-tree information, and (4) identify research gaps and priorities for developing scalable standing dead-tree monitoring systems.

2 Literature search and study selection

We reviewed 38 studies published, accepted, or publicly released between 2019 and 2026 that applied deep learning to remotely sensed data for standing dead-tree detection, segmentation, classification, or mapping. Literature was retrieved from Scopus and Google Scholar. The literature search was conducted in December 2025 and updated in February 2026; therefore, the review includes studies available up to February 2026. In Scopus, the search was applied to titles, abstracts, and keywords using the following search string: TITLE-ABS-KEY ("dead tree*" OR "deadwood" OR "tree mortality") AND TITLE-ABS-KEY ("deep learning" OR "neural network" OR "CNN") AND TITLE-ABS-KEY (detection OR segmentation OR mapping) AND TITLE-ABS-KEY ("aerial image*" OR "laser scanning" OR "lidar" OR "UAV" OR multispectral OR satellite OR hyperspectral OR "remote sensing"). In Google Scholar, simplified combinations of the terms “dead tree”, "deadwood", “tree mortality”, “deep learning”, “neural network”, “CNN”, “detection”, “segmentation”, “mapping”, “aerial imagery”, “laser scanning”, “LiDAR”, “UAV”, “multispectral”, “hyperspectral”, “satellite”, and “remote sensing” were used because Google Scholar does not support the same structured Boolean syntax as Scopus. Google Scholar results were screened in order of relevance until no additional eligible studies were identified within the retrieved records.

The database searches retrieved 139 records, including 59 from Scopus and 80 from Google Scholar. After removing duplicates and clearly irrelevant records, 65 records were retained for title and abstract screening. Seven records were excluded at this stage. The remaining 58 full-text records were assessed for eligibility, and 20 were excluded because they did not meet the inclusion criteria (Table A1). The final review included 38 studies. Studies were included if they applied a deep learning method, used remotely sensed data, and focused on detecting, segmenting, classifying, or mapping standing dead trees, dead-tree crowns, snags, or canopy mortality related to standing dead trees. Studies were excluded if they did not apply deep learning, did not use remotely sensed data, focused only on fallen deadwood, addressed general forest disturbance without standing dead-tree detection, or lacked sufficient methodological detail.

For each selected study, we extracted information on biome or forest type, spatial resolution, sensor modality, remote-sensing platform, model architecture, task type, validation approach, and reported performance metrics where available. Screening and data extraction were conducted by the lead author. Ambiguous cases, particularly studies addressing broader forest disturbance or canopy mortality, were discussed with co-authors when needed. Together, the selected studies show a rapid expansion of deep-learning-based standing-dead-tree monitoring across sensors, spatial resolutions, forest types, and modelling approaches. Because this review synthesizes studies with different sensors, annotation units, validation designs, and performance metrics, quantitative comparisons are interpreted descriptively rather than as direct benchmark-based rankings.

Table 1. Overview of studies included in the review for standing dead-tree detection and mapping. Spatial resolution is reported where available; NR indicates values not reported numerically.

No	Study	Biome/ Forest	Spatial resolution / GSD (cm)	Modality/ Bands	Models	Approach type
1	Mosig et al., 2026a	Global	1000	Multispectral	Per-pixel transformer model with HL-Gauss loss	Sub-pixel mapping
2	Ferrari et al., 2026	Temperate	10–25	RGB	SegFormer encoder + U-Net decoder	Semantic segmentation
3	Möhring et al., 2025	Global	1–28	RGB	SegFormer-B5 + U-Net decoder	Semantic segmentation
4	Mäyrä et al., 2025	Boreal	3.9–4.9	RGB + LiDAR	YOLOv8	Instance segmentation
5	Ahishali et al., 2025	Boreal / Temperate	50–60	RGBI	Flair U-Net + ADA-Net (domain adaptation)	Semantic segmentation
6	Wang et al., 2025a	Temperate	NR	RGB	DSFI-YOLO (Dual-Stream Feature Integration YOLO)	Object detection
7	Rahman et al., 2025	Boreal	25	RGBI	TreeMort-3T-UNet	Semantic segmentation
8	Yang et al., 2025	Subtropical	5–10	RGB	YOLOv5 (YOLOv5 + SE attention + BiFPN)	Object detection
9	Zhang et al., 2025a	Temperate	4	RGB	YOLOv9-ECA (YOLOv9 + Efficient Channel Attention)	Object detection
10	Leidemer et al., 2025	Temperate	1.4–2.1	RGB	YOLOv8n	Object detection
11	Gonzalez and Wallner, 2025	Temperate	20	RGBI	Attention U-Net; U-Net with ResNet34, ResNet101, EfficientNet-B7, InceptionV3 backbones	Semantic segmentation
12	Junttila et al., 2024	Boreal	50	RGBI	U-Net modification with inversed residual blocks and ASPP	Semantic segmentation

13	Wong et al., 2024	Temperate	20	LiDAR + CIR	CNN: 4 conv layers	Classification
14	Cheng et al., 2024	Temperate	25–60	RGBI	Custom EfficientUNet + deep watershed algorithm	Semantic segmentation + instance separation
15	Zhou et al., 2024	Temperate	12	RGB	Improved YOLOv7 + SimAM	Object detection
16	Matejčíková et al., 2024	Temperate	20	RGBI	CNN: 2 layers	Classification
17	Yao et al., 2024	Temperate	4	RGBI + red edge	Mask R-CNN (ResNet-50 backbone)	Instance segmentation
18	Lucas et al., 2024	Temperate	20	RGBI	Mask R-CNN (ResNet-50 + FPN backbone)	Instance segmentation
19	Khatri-Chhetri et al., 2024	Temperate	10	Multispectral + hyperspectral	CNN: 3 layers	Classification
20	Jääskeläinen, 2024	Boreal	300	RGB	U-Net	Semantic segmentation
21	Schwarz et al., 2024	Temperate	10–25	RGBI	EfficientUNet++	Semantic segmentation
22	Jin et al., 2023	Temperate	NR	RGB	Lightweight YOLOv4 (MobileNetV3 backbone)	Object detection
23	Jiang et al., 2023	Subtropical	4	RGB	Improved Faster R-CNN with Swin-Transformer backbone, FPN, and balance enhancement modules	Object detection
24	Dixon et al., 2023	Temperate	300	RGB	A custom 3D Spatio-Temporal Convolutional Neural Network	Classification
25	Schiefer et al., 2023	Temperate	6–33.9	RGB	U-Net + LSTM	Semantic segmentation + temporal modeling
26	Turkulainen et al., 2023	Boreal	3–6	RGB + multispectral + hyperspectral	2D CNN, 3D-CNN, and YOLO	Classification
27	Sani-Mohammed et al., 2022	Temperate	20	CIR	Mask R-CNN (ResNet-101 + FPN backbone)	Instance segmentation
28	Han et al., 2022	Temperate	10	RGBI	MSSCN with atrous blocks and spatial attention	Object detection
29	Wang et al., 2022	Temperate	5	RGB	LDS-YOLO	Object detection
30	Hell et al., 2022	Temperate	11–22	LiDAR + multispectral	PointCNN; 3DmFV-Net	Classification
31	Briechle et al., 2021	Temperate	10–20	LiDAR + RGBI	Silvi-Net: A dual-CNN (ResNet-18) approach	Classification

32	Tao et al., 2020	Subtropical	8.47	RGB	AlexNet & GoogLeNet	Object detection
33	Chiang et al., 2020	Temperate	NR	RGB	Mask R-CNN with transfer learning (ResNet-FPN backbone)	Instance segmentation
34	Briechle et al., 2020	Temperate	8.6	LiDAR + multispectral	3D deep neural network (DNN) PointNet++	Classification
35	Deng et al., 2020	Temperate	NR	RGB	Faster R-CNN	Object detection
36	Sylvain et al., 2019	Temperate	20	RGBI	VGG16S and ensemble learning	Classification
37	Fricker et al., 2019	Temperate	100	LiDAR + hyperspectral	CNN: 8 conv layers	Classification
38	Jiang et al., 2019	Temperate	20	CIR	FCN-DenseNet	Semantic segmentation

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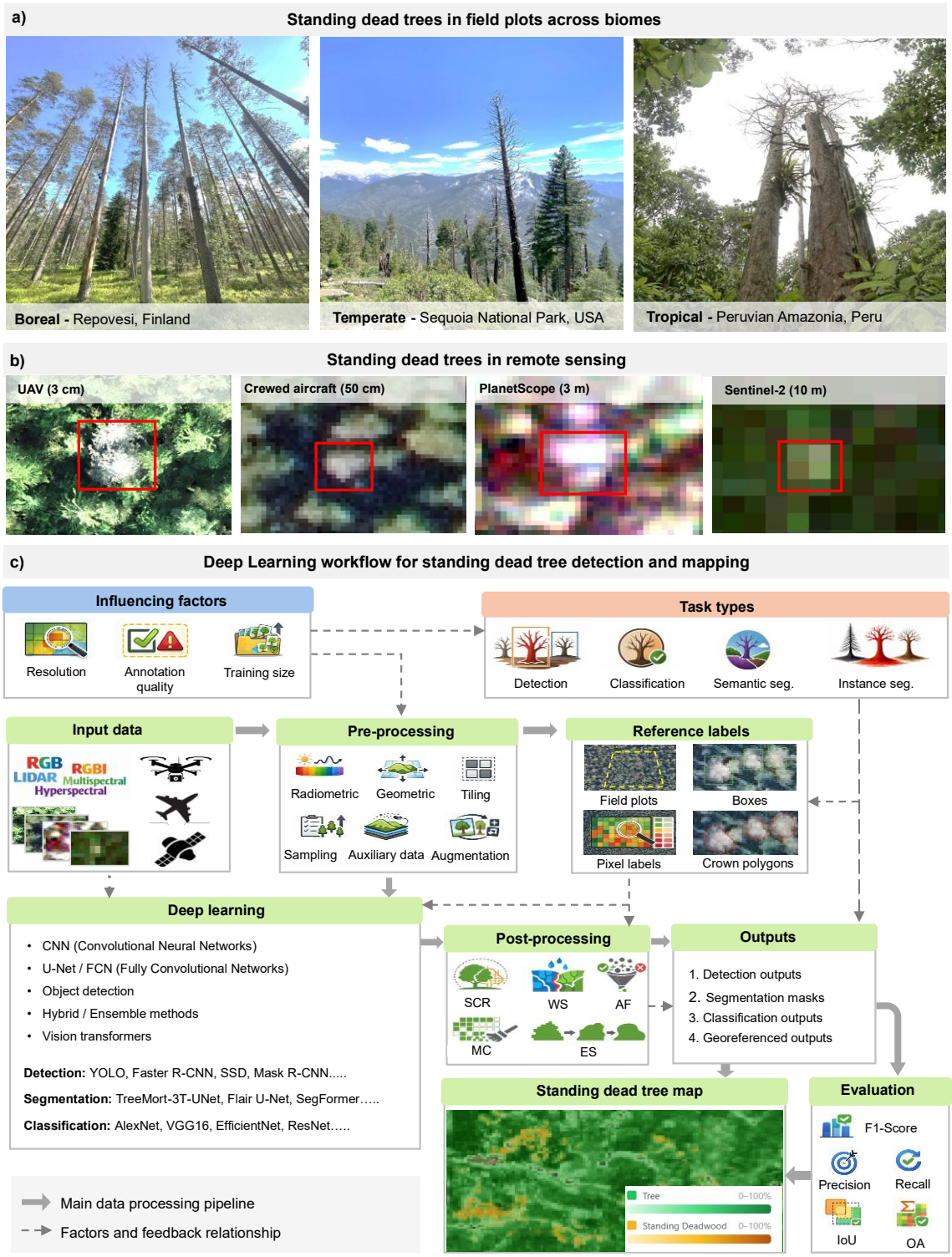


Fig. 2. Standing dead trees across biomes and spatial scales. (a) Field examples from boreal, temperate, and tropical forests. (b) Representation of standing dead trees in remote sensing imagery across spatial scales, from UAV imagery to Sentinel-2 observations. (c) Conceptual deep learning workflow for standing dead-tree detection and mapping. Image credits: boreal, Anwarul Chowdhury; temperate, Yan Cheng; tropical, Evan Gora.

3 Remote sensing platforms and methodological advances in standing dead-tree mapping

3.1 Advances in remote sensing platforms and data integration

The reviewed literature shows that standing dead-tree mapping has been conducted using UAV, crewed aircraft, and satellite platforms, with clear differences in spatial resolution, spatial extent, and analytical purpose (Fig. 3). Most studies relied on high-resolution optical imagery for crown- or tree-level detection, with 42.1% (16) using RGB imagery only and 34.2% (13) using extended optical data such as RGBI, CIR, or red-edge bands. In contrast, LiDAR-integrated approaches accounted for 15.8% (6) of the reviewed studies, while multispectral or hyperspectral data without LiDAR represented 7.9% (3) (Fig. 3a). Most studies also relied on fine spatial resolution, with 42.1% (16) using data in the 10–25 cm range, 15.8% (6) using imagery finer than 5 cm, and 10.5% (4) using imagery in the 5–10 cm range (Fig. 3a). Taken together, these patterns indicate that the reviewed literature is centered primarily on high-resolution aerial image analysis, whereas broader-scale satellite observations appear mainly in complementary or upscaling contexts.

Until recently, detecting and mapping standing dead trees beyond small scales was constrained by limited scalability and insufficient automated processing over large areas. Only in the last decade has the convergence of fine spatial resolution, frequent revisit capability, and efficient large-scale data processing made broader and more automated standing dead-tree monitoring increasingly feasible. Advances in miniaturized sensors, high-performance computing, and AI-driven image analysis have now enabled forest monitoring at resolutions previously achievable only through field surveys (Lines et al., 2022; Schiefer et al., 2025; Xu and Jiang, 2025). Modern UAVs can collect imagery with ground sampling distances down to approximately 1 cm, capturing fine details such as crown structure, branch exposure, and canopy gaps. UAVs are particularly advantageous for small to medium-sized monitoring areas, offering flexibility, low-cost, and the possibility of repeated temporal surveys (Manfreda et al., 2018). UAV-based remote sensing commonly captures RGB, multispectral, hyperspectral, and LiDAR data. LiDAR has been extensively employed for detecting standing dead trees (Briechle et al., 2021; Polvivaara et al., 2024). However, its performance may decline when identifying small, densely branched, or partially occluded targets (Miltiadou et al., 2018). At an intermediate scale, crewed airborne platforms equipped with high-resolution digital cameras, multispectral sensors, or LiDAR complement UAV surveys by extending coverage to thousands of hectares while retaining fine spatial detail. At broader regional to continental scales, satellite remote sensing provides the widest spatial coverage and the most consistent temporal observations. Very high-resolution commercial satellites such as WorldView-3 and SkySat provide sub-meter imagery, while systems such as PlanetScope offer frequent revisit times for repeated monitoring over large areas (Baldin and Casella, 2024; Liu et al., 2021; Shields et al., 2025). In addition, medium-resolution missions such as Sentinel-2 and Landsat, although coarser in spatial resolution, provide regular revisit schedules and dense time series that can partly offset this limitation by improving the detection of standing dead tree dynamics through time. In the broader tree-mortality remote sensing literature, Ni et al. (2025) reported that satellite-based data dominate previous studies, with optical imagery accounting for most applications. This contrasts with the deep-learning-based standing dead-tree studies reviewed here, which are more strongly centered on high-resolution UAV and airborne imagery.

The different remote sensing platforms are better understood as components of a multi-scale monitoring framework that supports distinct use cases. UAVs are particularly valuable for local assessments, where very high spatial resolution is needed to characterize fine-scale standing dead tree patterns. In other cases, local UAV-based assessments are used as reference information for model development, calibration, and validation, and are subsequently linked to airborne or satellite observations to support upscaling to broader areas. By contrast, studies focused on regional to continental standing dead tree patterns typically rely on airborne surveys, satellite observations, or upscaled products derived from these data sources. In this context, combinations such as crewed aircraft or satellite optical imagery with UAV optical or UAV LiDAR data are better understood as cross-scale integration for calibration, validation, and upscaling, rather than sensor fusion. UAVs are therefore not typically used as a standalone source for wall-to-wall large-scale monitoring but instead provide high-resolution reference data that can improve broader-scale standing dead-tree mapping products.

Moreover, standing dead-tree detection can benefit from integrating optical, spectral, and structural information, although the relative importance of each data source depends not only on the specific objective (e.g., presence detection versus structural quantification) but also on forest type, biome, canopy complexity, and tree growth form. Each sensor type contributes complementary insights:

- Optical sensors capture visible and near-infrared reflectance, revealing changes in color and texture associated with chlorophyll degradation or defoliation (Catalão et al., 2022; Liu et al., 2021; Ni et al., 2025).
- Multispectral and hyperspectral sensors measure narrow spectral bands related to pigment status, moisture conditions, and stress responses (Bergmüller and Vanderwel, 2022; Campbell et al., 2020; Cotrozzi, 2022; Jutras-Perreault et al., 2023). Their usefulness for standing dead-tree detection depends on the specific application as well as forest type, canopy structure, and operational scale. In particular, while hyperspectral data may help identify subtle physiological differences, their broader operational use for large-scale standing dead-tree monitoring remains limited by calibration requirements and large data volumes.
- LiDAR provides three-dimensional structure, enabling the estimation of canopy height, crown volume, and gap formation. This level of detail is particularly valuable for identifying standing dead trees that are partially obscured by overlapping crowns (Korpela et al., 2023; Krzystek et al., 2020; Kuzmin et al., 2026; Miltiadou et al., 2020). High-resolution photogrammetric point clouds can also recover tree structural attributes when image overlap, spatial resolution, and canopy conditions are favorable, although LiDAR is generally more robust in dense or structurally complex forests due to its capability to penetrate the upper canopy layers (Filippelli et al., 2019; McNicol et al., 2021; White et al., 2013).

Overall, integrating these datasets, often referred to as sensor fusion, can produce synergistic improvements in detection accuracy. Fusion can occur at multiple levels, including the data and feature levels. Combination approaches integrating LiDAR and optical data have shown strong potential for improving standing dead-tree detection, although results are not directly comparable across studies because they depend on dataset characteristics and evaluation metrics (Briechle et al., 2020; see also Section 6). As sensor technology becomes more accessible, such integrative frameworks are expected to become standard practice.

3.2 From visual interpretation to deep learning automation

Early approaches to standing dead-tree mapping relied either on field-plot measurements linked with remotely sensed data to extrapolate standing dead tree patterns or on manual and semi-automatic interpretation of aerial imagery, where analysts visually identified discolored or defoliated crowns (International Tree Mortality Network, 2025; Polewski et al., 2015a). While plot-based approaches provided reliable ground information, they were limited by sparse sampling and scaling uncertainties, whereas visual interpretation of imagery, although effective at small scales, was labor-intensive and prone to observer bias (International Tree Mortality Network, 2025; Wulder et al., 2012). The introduction of machine learning marked an initial step toward automated image-based detection by incorporating spectral indices (e.g., NDVI, NBR) and textural metrics into classifiers such as Random Forest and Support Vector Machines. However, these approaches depended heavily on handcrafted feature engineering and often struggled to generalize across forest types and environmental conditions (Sheykhmousa et al., 2020).

The transition to deep learning substantially advanced automated standing dead-tree mapping. By learning hierarchical spatial and spectral representations directly from imagery, deep learning models reduce reliance on manual feature design and enable more robust detection of crown discoloration, defoliation, and structural degradation (Chowdhury et al., 2025; Weinstein et al., 2019). Numerous recent studies have applied deep learning methods to detect standing dead trees in UAV and airborne imagery (Jiang et al., 2023; Joshi and Witharana, 2025; Junttila et al., 2024; Lucas et al., 2024; Möhring et al., 2025; Schiefer et al., 2023; Schwarz et al., 2024; Yao et al., 2024; Zhang et al., 2025a; Zhou et al., 2024). Furthermore, transfer learning and domain adaptation strategies enhance model portability across regions and forest types, improving the potential for scalable monitoring of standing dead trees (see Section 4.3). Detailed comparisons of specific architectures and their performance characteristics are discussed in Section 4.

3.3 Validation practices and the role of field observations

Validation remains an underdeveloped aspect of standing dead-tree mapping. Most reviewed studies assessed performance using manually annotated imagery or withheld image tiles from the same remotely sensed dataset. Although such approaches are useful for evaluating agreement with expert interpretation, they do not fully establish whether mapped standing dead trees correspond to standing dead trees actually present in the field. Only a limited number of studies incorporated field observations into validation, either directly or in combination with image-based reference data (Table A2). Examples include Mäyrä et al. (2025), who compared UAV-interpreted deadwood with field-measured deadwood; Matejčíková et al. (2024), who used a ground-truth dataset produced with partial field verification; and Fricker et al. (2019), who linked field-based tree observations to manually delineated image labels used for training and testing. Together, these studies show that field data can reveal omission and visibility biases that are not captured by image-based validation alone.

4 Model architectures and performance patterns in standing dead-tree detection

Deep learning has become increasingly important in remote-sensing-based standing dead-tree detection. Among the reviewed studies, object detection approaches were the most common category (39.5%), followed by CNN-based classification models (23.7%), hybrid or ensemble methods (15.8%), FCN/U-Net architectures (13.2%), and vision transformer-based models (7.9%) (Fig. 3a). In addition, more than two-thirds of the reviewed studies were conducted in temperate biomes (Fig. 3a). However, these model categories are not always directly comparable because they often target different outputs, including patch-level classification, pixel-wise segmentation, crown-level localization, instance segmentation, and sub-pixel mapping. Reported performance also depends strongly on forest structure, sensor modality, spatial resolution, annotation quality, evaluation protocol, and pre- or post-processing choices. Therefore, differences among model families should be interpreted as descriptive patterns rather than direct evidence of superiority across studies.

4.1 Deep learning architectures for standing dead-tree detection

Table 2. Overview of deep learning architectures used for standing dead-tree detection, including their main advantages, limitations, typical applications, and input-data flexibility reported in the literature.

Architecture	Main advantages	Key limitations	Use	Input data & flexibility
CNNs	Capture localized spectral and textural features; effective for crown-level classification; adaptable to high-resolution UAV imagery	Limited global context; patch-based approaches reduce spatial precision; sensitive to training data quality	Crown-level classification; localized mortality signals; well-represented training data	Flexible with raster inputs beyond RGB, including multispectral, hyperspectral, LiDAR-derived layers, and temporal stacks.
FCN / U-Net	Pixel-wise segmentation with accurate boundary delineation; preserves spatial detail; effective in complex canopies	Requires large, high-quality annotated datasets; weaker performance in sparse mortality conditions	Dense canopy segmentation; precise crown delineation; boundary-sensitive tasks	Accept arbitrary multi-channel raster inputs and are widely used with multispectral, RGBI, and temporal data.
Object detection	Instance-level detection; high recall; effective for counting and mapping individual trees; strong performance in recent YOLO variants	Limited boundary precision; challenges with overlapping crowns in dense canopies	Individual tree detection and counting; sparse or patchy mortality; operational mapping	Most often applied to RGB/RGBI imagery; multi-channel use is possible but less common and usually requires adaptation.
Hybrid / Ensemble	Combines complementary model strengths;	High computational	Heterogeneous forests; complex	Most flexible; can combine imagery,

	improved robustness in complex environments; integrates spatial and structural information	cost; complex workflows; potential error propagation between stages; results often study-specific	canopy structures; multi-stage detection and delineation	structural data, and temporal information across stages.
Vision transformers	Capture global context and long-range dependencies; robust in heterogeneous and mixed-species conditions	High data and computational requirements; less efficient for small datasets	Mixed-species forests; large-scale heterogeneous datasets; complex spatial patterns	Support multi-channel and multi-temporal inputs but usually need more data and computation.

4.1.1 Convolutional neural networks (CNNs)

CNNs formed an early foundation for crown- or patch-level standing dead-tree classification, where the goal is to label crowns or image patches as dead, damaged, or alive (Schwenke et al., 2025). CNNs are well suited to this task because they capture localized spatial and spectral patterns associated with tree mortality, such as crown discoloration, thinning, or structural collapse. Early applications using standard architectures such as AlexNet and GoogLeNet demonstrated the feasibility of CNN-based standing dead-tree detection, while also highlighting limitations related to feature representation and dataset constraints (Tao et al., 2020). Subsequent studies have shown that performance can benefit from architectures tailored to the characteristics of domain-specific imagery rather than simply increasing model depth. For example, lightweight or shallow CNNs have been successfully applied to high-resolution UAV imagery, suggesting that carefully optimized models may be particularly suitable for crown-focused detection tasks (Khatri-Chhetri et al., 2024; Wong et al., 2024). Incorporating temporal information can further enhance detection: Dixon et al. (2023) developed a 3D spatio-temporal CNN that integrates multi-date imagery to track gradual crown deterioration, highlighting the value of temporal feature learning for long-term forest monitoring. Hybrid CNN designs extend applicability to more challenging environments. Silvi-Net (Briechle et al., 2021), a dual-stream CNN, improves robustness in mixed-species forests by handling variability in crown shape and spectral characteristics. Similarly, Fricker et al. (2019) showed that an 8-layer CNN reliably distinguishes healthy and dead crowns across diverse forest types (F1-score 0.87).

Despite their strengths, standard CNN classifiers can be limited by restricted receptive fields, which may reduce their ability to incorporate broader spatial context. In patch-based frameworks, predictions are made at the patch level, assigning a single label per tile and thereby limiting spatial localization and precise crown delineation. While fully convolutional segmentation architectures address this through dense pixel-wise predictions, CNN-based approaches remain highly dependent on high-quality training data and may underperform in dense mixed forests without domain-specific tuning. Overall, CNNs are most suitable for crown- or patch-level classification when mortality signals are localized and well represented in the training data, whereas they are less suitable for dense-canopy segmentation or instance-level mapping requiring precise crown boundaries.

4.1.2 Fully convolutional networks (FCNs) and U-Net derivatives

Fully Convolutional Networks (FCNs), particularly U-Net and its variants, are widely used for pixel-wise standing dead tree crown segmentation because their encoder–decoder architecture with skip connections preserves spatial detail and enables precise localization (Long et al., 2014; Ronneberger et al., 2015). This makes them well suited to delineating crown boundaries and capturing subtle spectral and structural characteristics in dense or complex canopies. Enhanced U-Net architectures, such as those incorporating atrous spatial pyramid pooling and inverted residual blocks (Junttila et al., 2024) achieve F1-scores of up to 0.93, demonstrating improved multi-scale feature extraction, boundary precision, and robustness against shadows or heterogeneous canopy structures.

Attention mechanisms and post-processing further enhance performance. The TreeMort-3T-UNet (Rahman et al., 2025) combines self-attention with watershed filtering to isolate standing dead crowns in overlapping canopies, achieving an F1-score of 0.59, highlighting its ability to address structural complexity despite lower overall accuracy. Lightweight models like EfficientUNet++ (Schwarz et al., 2024) maintain segmentation quality while improving computational efficiency. FCNs have limitations in sparse-mortality settings, where isolated standing dead trees occupy few pixels; their sensitivity to local context can cause missed detections or false positives. Performance also depends on high-quality, large-scale annotated datasets, as inconsistent or limited labels reduce generalization. Overall, U-Net and FCN derivatives are particularly useful for dense-canopy segmentation, benefiting from boundary-preserving skip connections, multi-scale feature learning, and attention/post-processing enhancements.

4.1.3 Object detection frameworks

Object detection frameworks have become popular for standing dead-tree detection, particularly for identifying and counting individual trees. Unlike CNN classifiers or FCNs, these models generate bounding boxes or instance masks, allowing them to isolate discrete crowns—a key advantage in sparse-mortality or dense mixed forests. YOLO-based models are prominent in recent studies due to their real-time performance and high detection accuracy. For example, Yang et al. (2025) enhanced YOLOv5 with SE attention, BiFPN, and EIoU loss, achieving an F1-score of 0.83, while Zhou et al. (2024) improved YOLOv7 with SimAM and WIoU optimization, reaching 0.94. Zhang et al. (2025a) developed YOLOv9-ECA, integrating Efficient Channel Attention, and reported one of the highest F1-scores among the reviewed local case studies. These studies demonstrate that attention mechanisms and multi-scale feature fusion enable object detectors to capture subtle spectral and structural cues associated with standing dead trees. Lightweight variants, such as YOLOv4 with a MobileNetV3 backbone (Jin et al., 2023, F1-score 0.97) and LDS-YOLO (Wang et al., 2022), further show that high accuracy can be maintained while reducing computational cost, supporting operational UAV-based mapping.

Mask R-CNN is widely used when instance segmentation and detailed crown geometry are required, whereas Faster R-CNN is more suitable for bounding-box-based object localization. Lucas et al. (2024) reported an F1-score of 0.91 using Mask R-CNN with a ResNet-50 backbone, while Yao et al. (2024) achieved 0.71. Although slower than YOLO, these models provide precise crown shapes useful for biomass estimation and crown-level analysis. Object detectors often report strong performance in sparse or patchy mortality conditions, particularly

where the objective is to localize and count individual dead crowns. However, in dense-canopy forests, overlapping crowns can challenge bounding-box precision, making FCNs or U-Net derivatives more effective for boundary-sensitive segmentation. Overall, the choice of detection framework should consider forest structure, standing dead-tree distribution, annotation format, and mapping objective. YOLO-based models are well suited to rapid localization and counting, whereas Mask R-CNN and related instance-segmentation models are preferable when crown geometry is important.

4.1.4 Hybrid and ensemble models

In this review, hybrid models refer specifically to approaches that combine two or more model architectures or processing stages within a single detection workflow, rather than to the combination of different data sources or sensors. Ensemble models refer to approaches that combine predictions from multiple models to improve robustness. Hybrid and ensemble architectures combine the strengths of multiple deep learning models, enabling simultaneous modeling of local textures, global context, and temporal dynamics, which are critical in forests with complex mortality patterns or highly variable canopy structures. For example, TreeMort-3T-UNet (Rahman et al., 2025) represents an architecture-level hybrid workflow that integrates a self-attention U-Net with multi-stage post-processing, including watershed and adaptive filtering. Related multi-stage workflows, such as the EfficientUNet and deep watershed approach of Cheng et al. (2024), similarly aim to improve instance separation in dense or overlapping canopies. These hybrid workflows address common FCN limitations by incorporating structural priors, which are essential for precise counting and delineation of standing dead trees.

Another common hybrid strategy combines object detection and segmentation in multi-stage pipelines. YOLO or Mask R-CNN models first localize potential standing dead tree crowns, followed by U-Net variants or deep watershed algorithms to refine boundaries. This strategy can outperform standalone models in some case studies, although gains are workflow- and dataset-dependent. Ensemble approaches can further improve robustness by aggregating predictions from multiple models or repeated realizations of the same model; for example, Sylvain et al. (2019) combined predictions from multiple CNN runs with different random initializations to reduce random variation and produce smoother dead forest cover maps. In contrast, methods such as ADA-Net (Ahishali et al., 2025) are better characterized as domain-adaptation frameworks rather than ensemble models, as they are designed to improve transferability across varying forest types or sensor conditions.

However, these methods come with trade-offs: they are computationally intensive, require larger datasets and model parameters, and may propagate errors between stages if initial detection fails. Overall, hybrid and ensemble models are particularly relevant for heterogeneous forests and complex canopy conditions, although their reported advantages are often study-specific and should therefore be interpreted cautiously across different datasets and evaluation settings (Zhao et al., 2023).

4.1.5 Vision transformer-based models

Vision Transformers (ViTs) and transformer-based hybrids have recently emerged as promising alternatives to CNNs for standing dead-tree detection, largely due to their global self-attention mechanisms, which capture long-range dependencies and contextual relationships across entire images. Unlike CNNs, whose receptive fields are limited, ViTs can help capture subtle variations in crown coloration, texture, or structure that may be overlooked by conventional models. SegFormer-based architectures may offer advantages under variable illumination and mixed-species conditions, effectively distinguishing healthy from unhealthy crowns over large spatial extents (Joshi and Witharana, 2025). Hybrid designs, such as SegFormer-B5 combined with a U-Net decoder, leverage transformer feature extraction while preserving fine-grained crown boundaries, achieving competitive F1-scores (~0.71; Möhring et al., 2025).

Transformer-CNN hybrids, particularly those incorporating Swin-Transformer backbones, may also improve detection performance in object detection workflows. Jiang et al. (2023) reported an F1-score of 0.94 using a Swin-Transformer backbone with Faster R-CNN, suggesting that transformer-based feature extraction can support robust crown-level localization. Beyond standing dead-tree detection, transformer models have shown strong potential in broader remote sensing applications (Wang et al., 2024). However, ViTs generally require larger training datasets and higher computational resources than many CNN-based models, which can limit their operational use in small annotated datasets. Overall, transformer-based models are promising, but their advantages for standing dead-tree detection should be evaluated more rigorously using shared benchmarks, cross-site validation, and multi-sensor datasets.

Our analysis included 31 studies that reported comparable quantitative metrics, including F1-score, precision, recall, or overall accuracy (Fig. 3b). Because these metrics were extracted from heterogeneous studies rather than a common benchmark, they should be interpreted as descriptive summaries rather than direct evidence of superiority among model families. Across model categories, reported mean F1-scores ranged from 0.68 to 0.81, precision from 0.71 to 0.91, recall from 0.65 to 0.90, and overall accuracy from 0.77 to 0.96. Object detection models showed high mean values across several metrics, while transformer-based models showed the highest mean overall accuracy. However, these patterns should be interpreted cautiously because studies differed in sensor modality, spatial resolution, forest type, annotation protocol, validation design, and task definition. Standardized benchmark datasets and shared evaluation protocols are therefore needed before robust conclusions can be drawn about the relative performance of different model families.

Box 1. Key synthesis findings from the reviewed literature

- Most reviewed studies rely on high-resolution RGB or RGBI UAV/airborne imagery.
- Object detection models are most common for individual-tree localization and counting.
- U-Net-type architectures are widely used for semantic segmentation of dead crowns or canopy mortality.
- Field validation remains rare; most studies rely on image interpretation.
- Cross-biome and cross-sensor transferability remains weakly demonstrated.
- Standardized benchmark datasets are the most urgent requirement for robust model comparison.

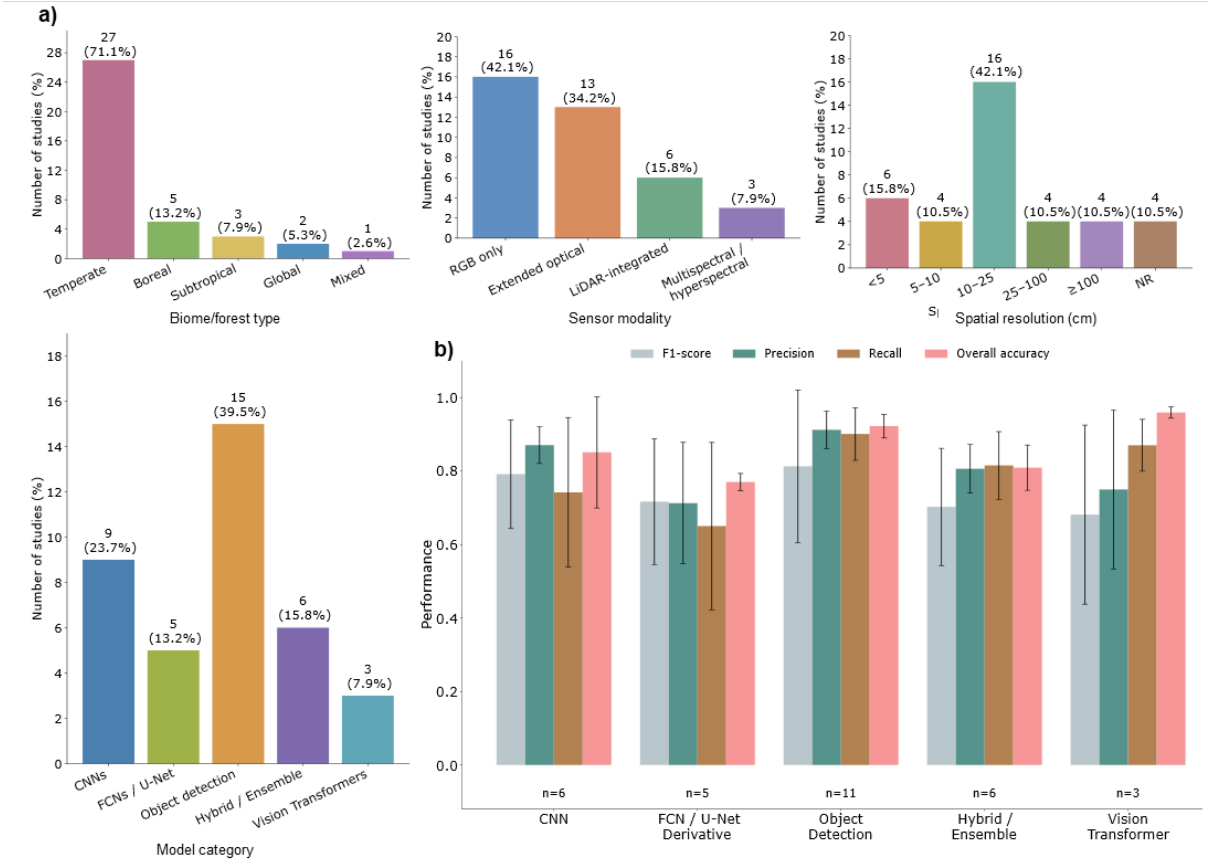


Fig. 3. Overview of the reviewed studies and model performance across deep learning categories. a**)** Distribution of the total number of reviewed studies (*n = 38*) according to biome/forest type, sensor modality, spatial resolution, and model category. b**)** Performance comparison across model categories based on studies that reported quantitative metrics (*n = 31*), showing mean F1-score, precision, recall, and overall accuracy; error

bars indicate variability (standard deviation) across studies, and *n* denotes the number of publications per category.

4.2 Factors influencing model accuracy

Model performance depends not only on architecture but also on data characteristics, preprocessing, post-processing, and evaluation design.

4.2.1 Data-related factors: resolution, training size, and annotation quality

Model performance in standing dead-tree detection is fundamentally constrained by data characteristics. Resolution across spatial, spectral, and temporal dimensions, together with dataset size and diversity, and annotation quality influence not only what a model can learn, but also how reliably its performance can be evaluated. These factors therefore determine both predictive capacity and the extent to which model performance can be validly demonstrated. If indicators of death are not visible at the available resolution, or if annotations are weak, inconsistent, or incomplete, neither training nor evaluation can fully capture true model capability. The following sections examine how spatial detail, dataset composition, and annotation design jointly influence model generalization, error patterns, and the validity of reported results across forest conditions.

Resolution

Spatial resolution determines how clearly diagnostically relevant canopy features are represented in the imagery and therefore directly influences the detectability of standing dead trees. High-resolution UAV or airborne imagery can capture fine-scale characteristics such as crown boundaries, branch structure, canopy gaps, and partial defoliation, all of which are important indicators of tree death (Matejčíková et al., 2024). In contrast, coarser imagery may obscure small, partially occluded, or early-stage standing dead trees, thereby reducing detection sensitivity. While reported ground sampling distances (GSD) have varied from centimeter-level to several meters (Fig. 3a), GSDs of approximately 4–8 cm have been reported as effective for standing dead tree segmentation in some contexts, although no universally optimal resolution can yet be identified (Möhring et al., 2025). In general, finer spatial resolution improves the visibility of crown-level indicators relevant to standing dead-tree detection. However, the benefits of very high-resolution imagery are constrained by the reduced spatial context that can be processed within computationally feasible image patches. Higher spatial resolution often necessitates smaller patches, which can limit the contextual information available to the model even when fine-scale features are well resolved (Kattenborn et al., 2021; Möhring et al., 2025; Schiefer et al., 2020). As discussed in Section 3.1, spectral resolution provides complementary information by capturing differences in reflectance related to canopy condition, including pigment degradation and moisture status, which can support the detection of standing dead trees beyond what is visible from structural features alone. Temporal resolution further influences detectability by determining whether the progression of tree mortality can be observed. Standing dead trees may transition through multiple stages, and their detectability can depend on the timing of image acquisition. Multi-temporal observations can improve detection by capturing change dynamics, such as gradual decline or sudden canopy loss, and by helping to distinguish mortality from seasonal or short-term variability (Dixon et al., 2023).

However, temporal data are often limited by acquisition frequency, consistency, and challenges related to co-registration and phenological variation, and many studies therefore rely on single-date imagery.

Training size and dataset diversity

Beyond resolution, dataset size and heterogeneity strongly influence model generalization. In computer vision, stable performance often requires on the order of 10^3–10^4 annotated instances per class, depending on model complexity (Krizhevsky et al., 2012). However, ecological applications typically operate with far fewer samples (e.g., 150–1000 instances per class), making dataset diversity across sites, species composition, canopy structure, illumination, and phenological stages particularly important for improving transferability (Shahinfar et al., 2020). Large-scale initiatives, such as the 100-million-crown dataset by Weinstein et al. (2021), demonstrate clear performance gains when models are trained on extensive and heterogeneous annotations.

However, standing dead tree occurrences are typically rare, leading to pronounced class imbalance. Limited representation of standing dead trees biases models toward the dominant healthy class and increases omission errors. Expanding annotated samples through multi-site data collection, targeted sampling of standing dead tree cases, or synthetic augmentation can improve detection performance (Khatri-Chhetri et al., 2024). High-capacity architectures such as Mask R-CNN, U-Net variants, and transformer-based models particularly depend on sufficient data diversity to avoid amplifying site-specific biases.

Annotation quality and format

Data quantity alone does not ensure reliability, but robust standing dead-tree detection does not necessarily require precise or complete manual labels (Weinstein et al., 2019). In practice, crown-level annotation often does not scale across large and heterogeneous forest settings (Wang et al., 2026). Although inaccurate delineations, misclassified standing dead trees, and omission of small or partially dead trees can introduce label noise, recent AI frameworks increasingly address these limitations directly. Weakly supervised learning, semi-supervised learning, active learning, and human-in-the-loop refinement can work with incomplete, noisy, or weak labels while reducing annotation effort (Polewski et al., 2015a; Weinstein et al., 2019). Annotation quality therefore remains important, but not as an absolute prerequisite for effective modeling. Rather, reliable performance depends on how well the annotation strategy matches the model architecture, learning framework, and forest structure. Instance segmentation networks generally benefit from precise crown polygons, whereas detection-oriented models may work effectively with weaker supervision such as bounding boxes, centroids, points, or coarse labels (Zhao et al., 2023). Automatic and semi-automatic annotation methods can further support scalable dataset generation and iterative improvement (Wang et al., 2026). As Steier et al. (2024) show, annotation errors can still distort training signals and ecological inference, so uncertainty must be managed explicitly. Overall, reliable performance depends less on label perfection alone than on the compatibility among annotation strategy, learning framework, model type, and forest structure.

4.2.2 Pre-processing: ensuring spectral consistency and training robustness

Pre-processing prepares remote-sensing imagery for model training by standardizing data where necessary, organizing it into usable inputs, and introducing transformations that improve generalization (Sani-Mohammed et al., 2022; Weinstein et al., 2019). In standing dead-tree detection, model performance does not depend on

spectral information alone, but may instead rely on a combination of spectral, textural, structural, and contextual cues (Möhring et al., 2025; Zhao et al., 2023). Accordingly, pre-processing should not be understood simply as preserving radiometric fidelity, but as balancing input consistency with sufficient variability to reduce overfitting across different acquisition and forest conditions (Han et al., 2022).

The relevance of radiometric correction depends on sensor type, acquisition workflow, and modelling objective. While normalization or calibration can improve comparability between images acquired under different conditions, exact spectral fidelity is not always critical in high-resolution UAV-based standing dead-tree detection, where texture, crown shape, branching structure, and local canopy context may be equally or more informative (Schiefer et al., 2023). Accordingly, many workflows deliberately introduce spectral variability during training through augmentations such as brightness or contrast in order to improve robustness to changing acquisition conditions (Han et al., 2022; Sani-Mohammed et al., 2022).

Geometric pre-processing is mainly relevant where spatial distortions or misalignment affect crown representation, annotation accuracy, or the integration of auxiliary layers. Orthorectification and co-registration can improve alignment between imagery, labels, and additional data sources, whereas misregistration may shift crown boundaries and introduce training noise. At the same time, geometric variability is often introduced deliberately through augmentations such as rotation, flipping, and patch shifts to improve robustness and reduce overfitting (Sani-Mohammed et al., 2022; Yao et al., 2024), with rotation and flipping being the most frequently reported augmentation strategies in previous studies (Fig. A1).

Pre-processing also includes tiling, patch extraction, and sampling design. Tiling large orthomosaics into smaller patches improves computational feasibility, but patch size must preserve crown integrity and sufficient spatial context while avoiding boundary artefacts (Han et al., 2022; Polewski et al., 2015b; Schiefer et al., 2023). Because standing dead trees are often rare, pre-processing workflows must also address class imbalance. Oversampling minority-class patches, targeted patch selection, weighted loss functions, and synthetic augmentation or copy-paste strategies can reduce bias toward the dominant healthy class and improve sensitivity to standing dead tree occurrences (Han et al., 2022; Zhou et al., 2024).

Finally, pre-processing may include the integration of complementary structural information, such as canopy height data or digital surface models (DSMs), to enrich feature representation beyond spectral imagery alone. Such auxiliary layers can improve discrimination between dead and healthy crowns, especially where structural differences are more consistent than spectral responses (Yao et al., 2024).

4.2.3 Post-processing: refining ecological realism and boundary precision

While deep learning models generate increasingly accurate pixel- or object-level predictions, their raw outputs often require refinement to achieve ecologically realistic crown delineations. Post-processing techniques therefore play a complementary role in improving boundary precision, reducing false positives, and enforcing geometrically plausible crown structures. Broadly, these approaches aim to shift predictions from purely data-driven segmentation toward structurally coherent tree representations. However, post-processing parameters should be reported transparently because thresholding, filtering, and watershed settings can substantially affect omission and commission errors.

Shape-constrained refinement

One class of post-processing methods incorporates explicit shape constraints to regularize crown geometry. For example, Shelton et al. (2021) combine model-derived probability maps with an active contour (level set) framework, in which contours evolve by minimizing an energy function that balances image-based likelihoods with smoothness and shape priors. This approach reduces irregular boundaries and regularizes crown geometry, particularly in heterogeneous canopy conditions. Similarly, Polewski et al. (2020) integrate generative adversarial network (GAN)-based shape priors into the segmentation process, constraining predicted crowns to a learned manifold of realistic tree geometries. By embedding structural expectations directly into refinement, such approaches mitigate spurious shapes that arise from local spectral noise or canopy overlap. These methods highlight an important conceptual shift: rather than relying solely on pixel-wise confidence, segmentation is guided by ecological knowledge of crown morphology.

Instance-boundary refinement

Another widely used strategy focuses on improving separation between adjacent crowns. Watershed segmentation is often applied in a marker-controlled manner and has proven effective in refining instance boundaries and reducing crown merging. In a recent dual-task U-Net framework, Rahman et al. (2025) apply watershed post-processing combined with adaptive filtering to reduce over-segmentation and suppress false positives. Such approaches are particularly valuable in dense forests where crown overlaps complicate instance-level detection.

Noise reduction and structural cleanup

Morphological filtering operations, such as opening and closing, are commonly used to remove small, isolated pixel clusters and smooth crown edges. Although comparatively simple, these operations can substantially improve map readability and reduce artefactual detections, especially in high-resolution imagery where pixel-level noise may propagate into fragmented predictions.

4.3 Transfer learning and large-scale mapping

Scaling standing dead-tree detection from localized UAV surveys to regional or global monitoring is challenged by domain shift: systematic differences in spectral characteristics, sensor types, forest structure, and acquisition conditions that reduce model transferability. Transfer learning can support scalability by initializing networks with pretrained weights from large visual datasets (e.g., ImageNet), enabling stable, generalizable feature representations that accelerate convergence, reduce annotation requirements, and improve performance under limited data (Ma et al., 2024). By pre-training models on forest species classification, networks can learn transferable representations that accelerate convergence when fine-tuned for standing dead-tree detection (Rahman et al., 2025). Large-scale workflows typically follow a three-stage paradigm: broad pretraining, localized fine-tuning with site-specific annotations, and lightweight domain adaptation to harmonize spectral or seasonal differences, mirroring successful strategies in tree-crown delineation, forest-type classification, and canopy-health assessment (Kattenborn et al., 2021).

Despite its advantages, transfer learning alone cannot fully overcome domain discrepancies. Integrating domain adaptation methods, self-supervised representation learning, and few-shot approaches allows models

to align feature distributions across regions and leverage unlabeled imagery for scalable training (Ahishali et al., 2025; Gevaert et al., 2025; Rahman et al., 2025). Open, standardized datasets such as deadtrees.earth (Mosig et al., 2026b) further enhance model generalization by exposing networks to diverse forest types, mortality stages, and disturbance gradients, while enabling benchmarking and reproducibility. Together, these strategies could help shift standing dead-tree detection from site-specific modelling toward more transferable and scalable mapping, paving the way for continuous, global forest health assessment with minimal dependence on manual annotation.

5 Implications of standing dead-tree mapping

The ability to map standing dead trees across extensive forest landscapes has substantially improved the quantification of disturbance regimes and patterns of standing dead-tree occurrence. Traditional approaches based on field plots or coarse-resolution satellite indices captured disturbance only at aggregated scales, often obscuring fine-scale standing dead tree patterns driven by species-specific physiology, microsite variability, or competition. Advances in high-resolution remote sensing and deep learning now enable tree-crown–level detection across hundreds to thousands of hectares. For example, LiDAR- and multispectral-based assessments revealed that more than 25% of trees in drought-exposed areas of the Sierra Nevada died between 2013 and 2017, with strong spatial clustering linked to elevation, water stress, and stand density (Hemming-Schroeder et al., 2023). Similar improvements have been reported using fused LiDAR and multispectral data in Central Europe (Krzystek et al., 2020; Liu et al., 2021) and UAV-based deep learning approaches (Rahman et al., 2025). As shown in Fig. 4, these maps can provide metrics such as affected area, canopy size, mortality intensity, and mortality rates. These spatially explicit standing dead tree data provide new insights into forest health, resilience, and biogeochemical processes. Tree mortality represents a key transition in carbon cycling, shifting biomass from live pools to necromass and influencing respiration, nutrient mineralization, and carbon turnover. High-resolution standing dead-tree maps reduce uncertainty in deadwood pool initialization, particularly where field data are limited, and remote sensing increasingly complements and extends ground monitoring for representing carbon stock transitions (Bueno et al., 2025; Martinuzzi et al., 2009; Ni et al., 2025). Tree mortality also alters transpiration, canopy interception, snow dynamics, albedo, and aerodynamic roughness, affecting surface energy balance and evapotranspiration. Spatially explicit standing dead-tree maps further improve attribution of carbon and water cycle anomalies by distinguishing acute disturbances from background mortality (Senf and Seidl, 2021). These spatial products make the ecological functions of deadwood measurable by quantifying standing dead-tree density, spatial configuration, and decay heterogeneity relevant to biodiversity, including cavity-nesting birds, saproxylic insects, fungi, and microbial decomposers (Bujoczek et al., 2021; Löfroth et al., 2023; Marchi et al., 2018; Seibold and Thorn, 2018; Seidling et al., 2014).

When integrated with multi-scale data and modelling approaches, standing dead-tree maps support prediction and management of forest dynamics. While satellite time series capture large-scale disturbance patterns, standing dead-tree maps provide the spatial detail needed to resolve local stand conditions. Combining these datasets links standing dead-tree patterns to climatic drivers and landscape-scale disturbance regimes, although interpretation still requires ancillary ecological and field data. Spatially explicit models show that incorporating fine-scale standing dead tree patterns improves predictions of future die-off hotspots under

climate stress (Ganz et al., 2025). These insights support management applications including early detection of disturbances, intervention planning, wildfire risk assessment through fuel mapping, and adaptive management strategies (Bell et al., 2021; Cheng et al., 2024; Junttila et al., 2024; Mahanta et al., 2024; Schiller et al., 2024; Turkulainen et al., 2023). Standing dead-tree mapping also supports policy frameworks such as the EU Biodiversity Strategy and REDD+, where standing dead tree data improve disturbance attribution and reduce uncertainty in greenhouse gas inventories (Mansuy et al., 2024). Together, these dimensions highlight the feedback between data acquisition, ecological interpretation, predictive modelling, and decision-making, as summarized in Fig. 4.

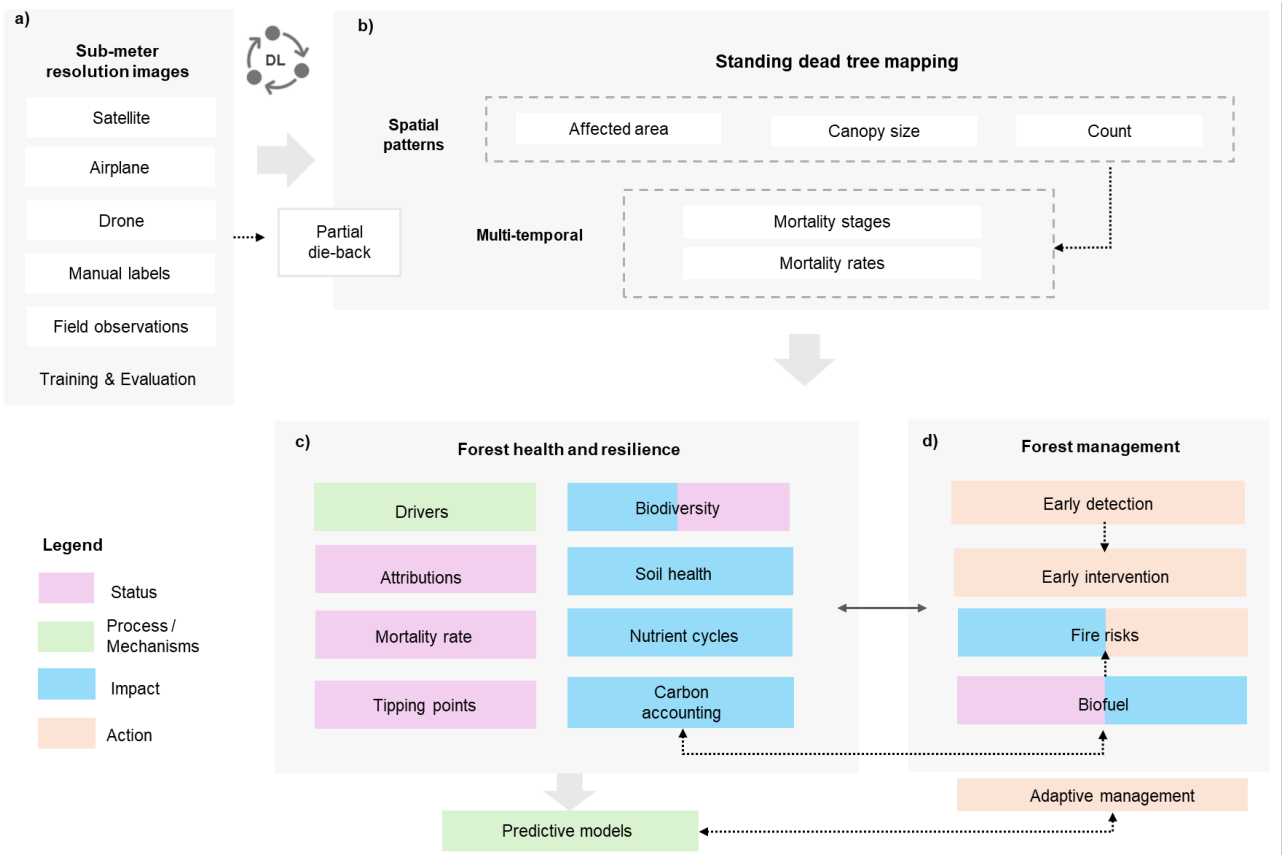


Fig. 4. Conceptual framework illustrating how standing dead-tree mapping supports ecological analysis and forest management. a) Multi-source data inputs (e.g., remote sensing imagery, field observations, and manual annotations) support model training and evaluation for standing dead-tree mapping. b) Standing dead tree-derived metrics (e.g., affected area, canopy size, mortality stages, and mortality rates) obtained from high-resolution mapping. c) Ecological interpretation of these metrics, informing forest health and resilience, including biodiversity, nutrient cycling, and carbon dynamics. d) Applications in forest management and prediction, including early detection, intervention, wildfire risk assessment, and adaptive management strategies.

6 Current barriers in large-scale standing dead-tree detection

Detecting and mapping standing dead trees at large scales faces multiple ecological, computational, sensor-related, validation, annotation, and operational barriers. In this section, we focus on current barriers, while methodological opportunities and future research priorities are discussed separately in Section 7. Ecologically, forests differ widely in structure, composition, and disturbance regimes, producing standing dead-tree signatures that vary in crown color, foliage loss, and decay dynamics. Boreal conifer stands often exhibit compact crowns with clear discoloration or needle drop, whereas subtropical and tropical broadleaf forests feature multi-layered canopies where standing dead-tree crowns may be obscured by overlapping foliage or persistent understory. Phenology can also shift spectral and textural patterns across seasons. In tropical environments, additional complexities arise because trees may temporarily lose leaves due to seasonal dormancy or stress, and some individuals may resprout after partial defoliation. Standing dead trees can also collapse, fall, be removed, or become obscured by regrowth after initial detection, especially in fast-growing or highly dynamic forests. As a result, single-date observations may misclassify temporarily leafless trees as dead or fail to detect partially dead trees, reducing the temporal validity of mapped standing dead-tree locations. Disturbance processes, including beetle outbreaks, droughts, and windthrow, further shape standing dead-tree trajectories and complicate cross-biome model generalization.

Sensor and data limitations further constrain detection. Optical imagery can capture crown discoloration, defoliation, texture, and canopy gaps, but it is sensitive to illumination, shadow, viewing geometry, phenology, and canopy occlusion. Dense or overlapping canopies can obscure partially dead crowns, particularly where mortality occurs below the dominant canopy layer. LiDAR provides valuable structural information, including canopy height, crown geometry, and gap formation, but sparse or ambiguous returns may limit the detection of small, suppressed, or partially occluded standing dead trees. Spatial resolution also creates trade-offs: coarser imagery may obscure individual trees or early mortality symptoms, whereas very high-resolution imagery increases computational demands and may reduce the spatial context available within model input patches. Multi-sensor datasets can help address these limitations, but they also introduce practical challenges, including accurate sub-meter co-registration, compatible acquisition timing, and consistent preprocessing across data sources (Campbell et al., 2020; Marchi et al., 2018).

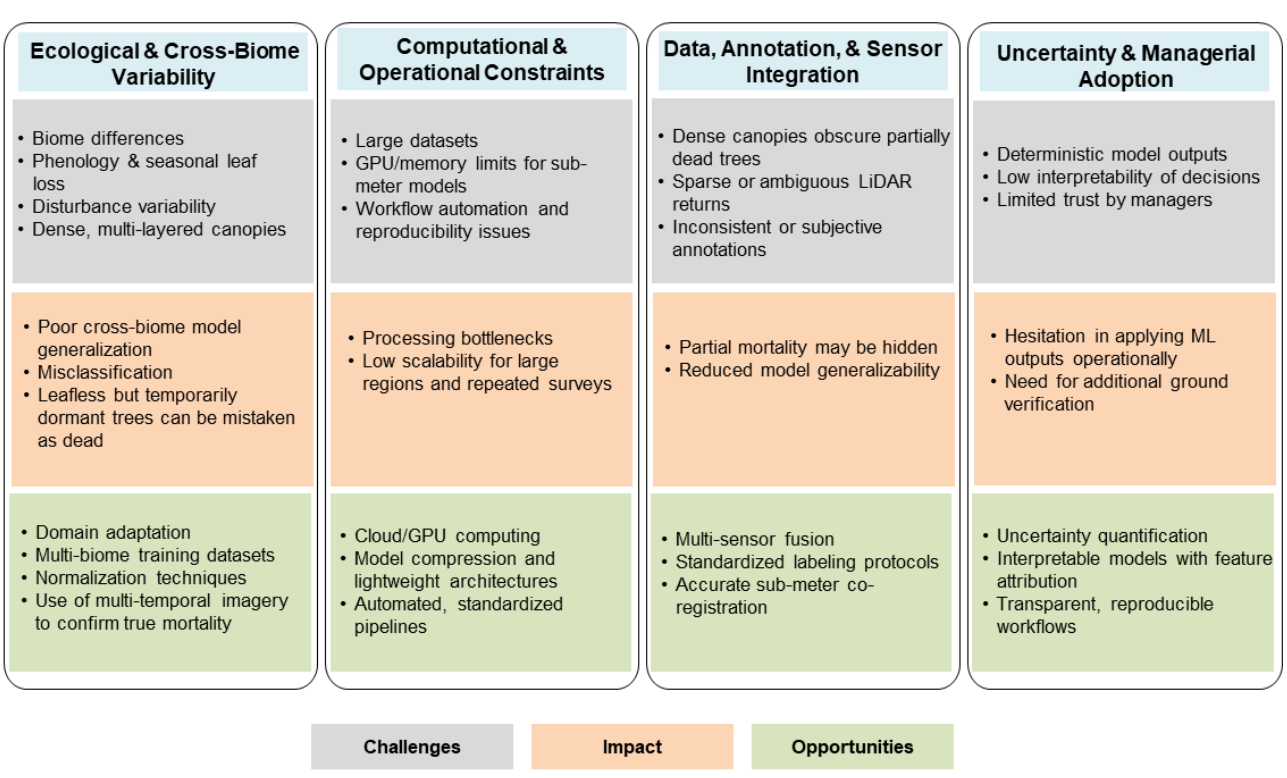
Computationally, high-resolution UAV and airborne datasets often reach hundreds of gigabytes or terabyte scale, creating storage, memory, and input/output bottlenecks. Models applied to sub-meter imagery are computationally intensive and often require GPU acceleration, cloud computing, or high-performance computing infrastructure. Large-area inference also requires efficient tiling, mosaicking, post-processing, and quality-control workflows. These requirements can limit reproducibility and operational adoption, especially for forest agencies or conservation organizations with limited computing resources. In addition, complex processing chains involving orthomosaic generation, radiometric normalization, tiling, model inference, post-processing, and map production may be difficult to reproduce unless workflows are clearly documented and standardized.

Validation and annotation remain major barriers to model comparability and operational reliability. Most reviewed studies rely primarily on expert image interpretation or withheld image tiles from the same remotely sensed dataset. Although these approaches are useful for evaluating agreement with image-based labels, they

765 do not necessarily confirm whether mapped objects correspond to standing dead trees actually present in the
766 field. Only a limited number of studies incorporated field observations directly or used mixed field- and image-
767 based validation. Annotation practices also vary substantially among studies, including pixel masks, crown
768 polygons, bounding boxes, centroids, patch labels, and canopy mortality fractions. These differences affect both
769 model training and reported performance, making it difficult to compare results across studies. Inconsistent
770 definitions of standing dead trees, uncertainty in decay-stage interpretation, omission of partially dead crowns,
771 and class imbalance further reduce comparability among studies. Therefore, reported performance metrics
772 often reflect study-specific annotation and validation choices rather than directly comparable model capability.

773 Operational deployment is further constrained by limited model transferability, uncertain reliability, and low
774 interpretability. Models trained in one region, forest type, biome, or sensor setting may perform poorly
775 elsewhere because of differences in canopy structure, species composition, illumination, phenology,
776 disturbance history, and sensor characteristics. Many models also produce deterministic outputs without
777 uncertainty estimates or interpretable explanations, which can limit trust among forest managers and decision-
778 makers. This is particularly important when outputs are used for sanitation harvesting, outbreak response,
779 biodiversity assessment, wildfire-risk planning, or carbon accounting. Large-scale use of UAV, airborne, or very-
780 high-resolution satellite imagery may also raise concerns related to privacy, land ownership, data access, and
781 governance. Together, these ecological, sensor-related, computational, validation, annotation, and operational
782 barriers currently limit the development of scalable and transferable standing dead-tree monitoring systems.
783 These barriers, their impacts, and the main methodological opportunities for overcoming them are summarized
784 in Fig. 5.

785



786

Fig. 5. Conceptual overview of major barriers, impacts, and opportunities in large-scale standing dead-tree detection. Gray boxes summarize current ecological, computational, sensor-related, annotation, and operational challenges. Orange boxes indicate their impacts on model performance, scalability, comparability, and management adoption. Green boxes highlight methodological opportunities discussed in the future research roadmap.

7 Discussion and future research roadmap

Future research should move beyond marginal improvements in accuracy metrics alone and focus on developing transferable, interpretable, ecologically meaningful, and operationally scalable standing dead-tree monitoring systems. The most important priorities include standardized benchmark datasets, transferable learning strategies, temporal mortality modelling, multi-sensor fusion, uncertainty quantification, explainability, and responsible data governance.

The most urgent need is a large, open, standardized benchmark dataset for standing dead-tree detection and mapping. Such a dataset should include multiple biomes, forest types, disturbance agents, sensor platforms, spatial resolutions, and decay stages. It should also provide clear target definitions, including distinctions among standing dead trees, dead crowns, snags, canopy mortality, fallen deadwood, and declining but not yet dead trees. Standardized annotation protocols are equally important. Future datasets should document whether labels represent crown polygons, bounding boxes, centroids, pixel masks, decay-stage classes, or canopy mortality fractions. Where possible, annotations should be supported by georeferenced field observations, multi-annotator validation, and uncertainty labels. Shared train-test splits and common evaluation metrics would allow more robust comparison among model architectures and reduce the current dependence on study-specific performance claims.

Improving model transferability across regions, sensors, and forest types is another central priority. Domain shift remains a major limitation because standing dead-tree appearance varies with biome, species composition, canopy structure, phenology, illumination, and sensor characteristics. Models trained in one landscape may therefore perform poorly when applied to another. Domain adaptation, self-supervised learning, contrastive learning, and few-shot learning offer promising ways to reduce dependence on site-specific annotations and improve cross-site generalization (Kuzu et al., 2024; Yun et al., 2024). These methods can exploit large volumes of unlabeled remote sensing imagery and learn more domain-invariant representations. Future studies should increasingly evaluate models using cross-site, cross-biome, and cross-sensor validation rather than relying only on random splits within the same study area. Such evaluation would provide a more realistic assessment of operational transferability.

Standing dead-tree detection should also move beyond simple binary live/dead classification where data allow. Tree mortality is often gradual, progressing through stages of stress, decline, partial dieback, recent death, crown loss, and snag formation. Binary labels can mask ecologically meaningful differences among temporary canopy stress, progressive decline, established mortality, and advanced decay. Multi-temporal remote sensing and deep learning time-series approaches could help distinguish temporary defoliation or seasonal dormancy from true mortality by tracking sequential changes in crown color, canopy density, texture, and structure. These

approaches may support earlier detection of tree decline and improve confidence in standing dead-tree classification. Stage-based or confidence-based labels could also improve ecological interpretation by linking detected standing dead trees to decay stage, biodiversity value, and future recruitment of lying deadwood.

Future monitoring systems should integrate optical, spectral, structural, and temporal information more effectively. RGB and RGBI imagery provide useful information on crown color and texture, multispectral and hyperspectral data can capture pigment- and moisture-related signals, and LiDAR provides three-dimensional structural information. Combining these data sources can improve detection robustness, especially in dense or heterogeneous forests where no single sensor is sufficient. However, multi-sensor fusion must be supported by scalable processing infrastructure, including automated preprocessing, accurate co-registration, reproducible quality control, cloud-based processing, model compression, and lightweight architectures suitable for large-area inference. UAV-based reference data can also be linked with airborne and satellite observations to support upscaling from local surveys to regional or national standing dead-tree monitoring.

Operational monitoring requires more than accurate predictions. Models should provide uncertainty estimates, confidence maps, and interpretable outputs that help users understand where predictions are reliable and where field verification is needed. This is particularly important in complex forests, transitional mortality stages, and regions outside the model's training domain. Explainable AI methods, feature attribution, uncertainty-aware segmentation, and probabilistic outputs can improve trust among forest managers and decision-makers. These outputs could support practical applications such as prioritizing field surveys, detecting disturbance hotspots, planning sanitation harvesting, assessing habitat availability, estimating carbon impacts, and identifying areas of elevated wildfire risk. Future studies should therefore evaluate not only accuracy, but also usefulness for management decisions.

Large-scale standing dead-tree monitoring also requires responsible data governance. UAV, airborne, and very-high-resolution satellite imagery may raise concerns related to privacy, land ownership, data access, and equitable participation, especially in landscapes with fragmented ownership or Indigenous and local communities. Transparent communication, inclusive governance, and collaboration with landowners, Indigenous communities, conservation agencies, and forest managers are therefore necessary to ensure that standing dead-tree mapping supports ecological and management goals while respecting local rights and values. Open databases such as deadtrees.earth (Mosig et al., 2026b) and TreeFinder (Wang et al., 2025b) demonstrate the potential of shared, large-scale standing dead-tree resources for benchmarking, collaborative model development, and geographically diverse model training. However, such databases should be well documented, versioned, quality controlled, and maintained over the long term. Clear metadata on sensor type, acquisition date, spatial resolution, annotation protocol, field validation, and uncertainty will be essential for ensuring that these resources remain useful for both research and operational monitoring.

Table 3. Summary of future directions for large-scale standing dead-tree detection and monitoring.

Category	*Future research priorities*
Technical advances	Self-supervised learning; automated and semi-automated annotation; domain adaptation; multi-sensor fusion; temporal modelling; lightweight edge models; resolution benchmarking; uncertainty quantification; model explainability; standardized benchmarks
Ecological integration	Causes-of-death inference; species-specific responses; mortality trajectories; decay-stage classification; biodiversity-relevant deadwood indicators
Operational deployment	Cloud-based national monitoring systems; early-warning pipelines; UAV-to-satellite model transfer; standardized acquisition and validation protocols; reproducible processing pipelines
Governance and ethics	Privacy safeguards; harmonized legal frameworks; equitable data access; Indigenous and local data governance; transparent data stewardship

8 Conclusion

Recent advances in multi-sensor remote sensing and deep learning have substantially improved the detection and mapping of standing dead trees across a wide range of forest conditions. High-resolution imagery from uncrewed aerial vehicles, airborne platforms, and satellites, together with LiDAR, multispectral, and hyperspectral data, now support increasingly detailed assessments of standing dead tree patterns across local to broader spatial scales. Deep learning approaches, including convolutional neural networks, U-Net derivatives, object detection frameworks, hybrid models, and more recent transformer-based methods, have expanded the methodological toolbox available for standing dead-tree detection and mapping. At the same time, the reviewed studies acknowledge that no single approach is universally optimal, as performance depends strongly on forest structure, sensor characteristics, annotation quality, and the specific detection or mapping objective.

Despite this progress, large-scale operational monitoring of standing dead trees remains constrained by several persistent challenges. These include canopy occlusion, class imbalance, inconsistencies in standing dead tree definitions and annotation protocols, and limited transferability of models across regions, forest types, and sensor settings. In addition, the ecological complexity of tree mortality, which often develops gradually and varies among species, disturbance agents, and environments, is not always well captured by simplified live–dead classification frameworks. As a result, many current approaches remain effective mainly within site-specific or sensor-specific contexts.

Looking forward, operationalizing standing dead-tree mapping at national to global scales will benefit from integrated pipelines that combine automated preprocessing, multi-sensor data fusion, temporal modeling, and uncertainty-aware outputs. Embedding ecological knowledge into model design through decay-stage classification, species-specific spectral signatures, and structural priors can further enhance interpretability and

reliability for forest management applications. Open-access, large-scale databases of standing dead trees will accelerate cross-site benchmarking, support label-efficient learning, and facilitate scalable monitoring frameworks.

Overall, standing dead-tree mapping is emerging as an important component of forest monitoring, with clear relevance for biodiversity assessment, carbon accounting, disturbance analysis, and early-warning applications. By combining remote sensing, deep learning, and ecological knowledge within transparent and scalable workflows, future research can move the field closer to operational monitoring systems that support forest resilience and climate-adaptation strategies.

Acronyms & abbreviations

ADA-Net – Adversarial Domain Adaptation Network
AF – Adaptive Filtering
ASPP – Atrous Spatial Pyramid Pooling
BiFPN – Bidirectional Feature Pyramid Network
CCD – Charge-Coupled Device
CIR – Color-Infrared
CNN – Convolutional Neural Network
CO_2 – Carbon Dioxide
DMC – Digital Mapping Camera
DNN – Deep Neural Network
DSFI-YOLO – Dual-Stream Feature Integration YOLO
ECA – Efficient Channel Attention
EIoU – Efficient Intersection over Union
ES – Edge Smoothing
EU – European Union
FCN – Fully Convolutional Network
FPN – Feature Pyramid Network
GAN – Generative Adversarial Network
GPU – Graphics Processing Unit
I/O – Input / Output
IoU – Intersection over Union
LDS-YOLO – Lightweight Deep Supervision YOLO
LSTM – Long Short-Term Memory
MC – Morphological Cleanup
MODIS – Moderate Resolution Imaging Spectroradiometer
NBR – Normalized Burn Index
NDVI – Normalized Difference Vegetation Index
RGB – Red, Green, Blue
RGBI – Red, Green, Blue, Near-Infrared

REDD+ – Reducing Emissions from Deforestation and Forest Degradation
ResNet – Residual Network
RTK – Real-Time Kinematic
SCR – Shape-Constrained Refinement
SE – Squeeze-and-Excitation
UAV – Uncrewed Aerial Vehicle
U-Net – Convolutional Encoder–Decoder Network
ViTs – Vision Transformers
WIoU – Weighted Intersection over Union
WS – Watershed Separation
YOLO – You Only Look Once

CRediT authorship contribution statement

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Appendix A.

Table A1. Literature identification, screening, and inclusion process for the review

Review stage	Screening step	Records, n	Description / criteria
Identification	Records retrieved from Scopus	59	Search applied to titles, abstracts, and keywords using structured Boolean terms related to standing dead trees, deadwood, tree mortality, deep learning, and remote sensing.
Identification	Records retrieved from Google Scholar	80	Simplified keyword combinations were used because Google Scholar does not support the same structured Boolean syntax as Scopus.
Identification	Total records retrieved before deduplication	139	Total number of records retrieved from Scopus and Google Scholar before duplicate removal.
Deduplication / preliminary screening	Duplicate and clearly irrelevant records removed	74	Duplicate records and records clearly outside the scope of the review were removed before detailed screening.
Screening	Records screened by title and abstract	65	Records screened for relevance to standing dead trees, dead-tree crowns, snags, tree mortality, deep learning, and remotely sensed data.
Screening	Records excluded after title and abstract screening	7	Records excluded because they were unrelated to standing dead trees, did not use deep learning, did not use remote sensing, or focused only on general forest disturbance.
Eligibility	Full-text records assessed for eligibility	58	Full texts were assessed against the inclusion and exclusion criteria.
Eligibility	Full-text records excluded	20	Records excluded because they lacked a deep learning method, did not use remotely sensed data, focused only on fallen deadwood, addressed general disturbance without a standing-dead-tree target, or lacked sufficient methodological detail.

Included	Studies included in final review	38	Studies included in the final synthesis of deep-learning-based standing dead-tree detection and mapping.

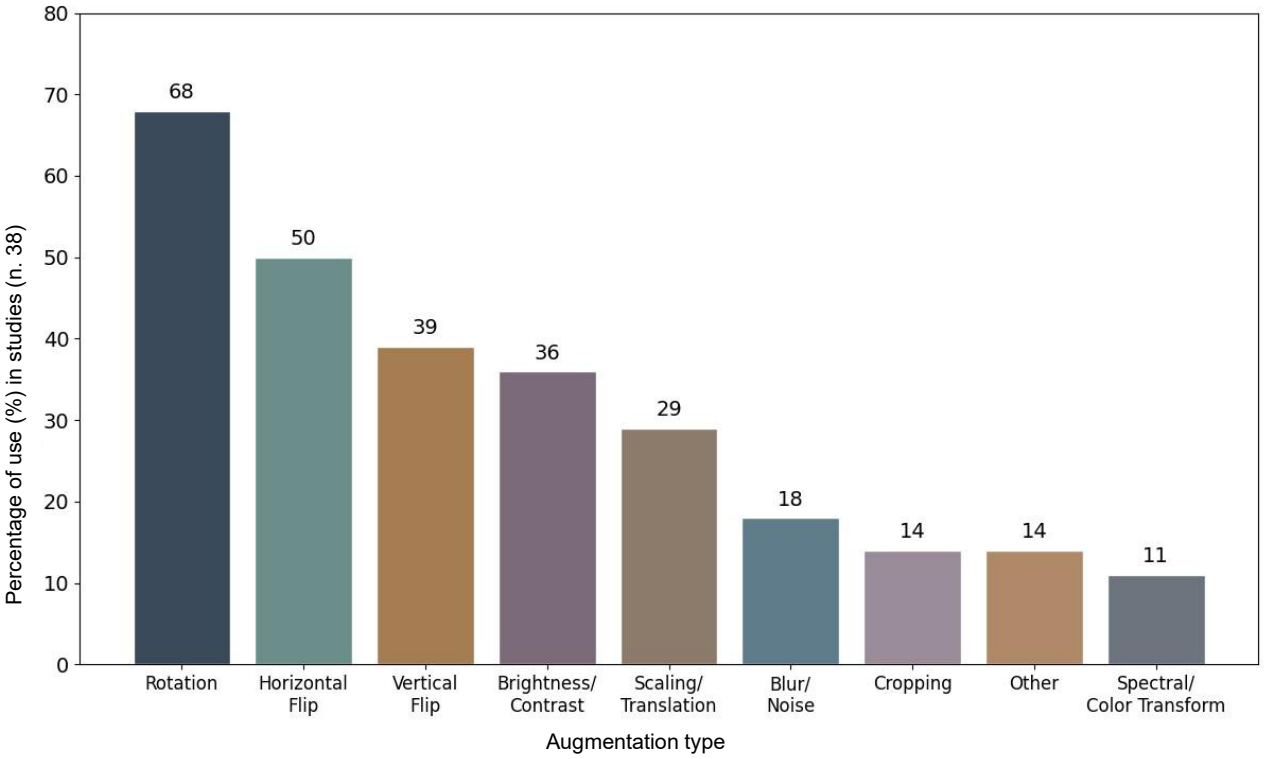

Fig. A1. Percentage of reviewed studies reporting each augmentation type; studies may report multiple augmentations.

Table A2. Validation approaches used in the reviewed standing dead-tree mapping studies.

Validation type	**Studies**
Image interpretation-based	Mosig et al., 2026; Ferrari et al., 2026; Möhring et al., 2025; Ahishali et al., 2025; Wang et al., 2025; Rahman et al., 2025; Yang et al., 2025; L. Zhang et al., 2025; Gonzalez and Wallner, 2025; Leidemer et al., 2025; Junttila et al., 2024; Wong et al., 2024; Cheng et al., 2024; Zhou et al., 2024; Yao et al., 2024; Lucas et al., 2024; Khatri-Chhetri et al., 2024; Schwarz et al., 2024; Jin et al., 2023; Jiang et al., 2023; Dixon et al., 2023; Schiefer et al., 2023; Turkulainen et al., 2023; Sani-Mohammed et al., 2022; Han et al., 2022; Wang et

Validation type	Studies
	al., 2022; Hell et al., 2022; Briechle et al., 2021; Tao et al., 2020; Chiang et al., 2020; Briechle et al., 2020; Deng et al., 2020; Sylvain et al., 2019; Jiang et al., 2019
Mixed (field + image)	Mäyrä et al., 2025; Matejčíková et al., 2024; Jääskeläinen, 2024; Fricker et al., 2019