Advances in tree species identification from high-resolution aerial imagery and deep learning

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Abstract

Tree species diversity shapes forest functioning, carbon storage, and ecosystem resilience, yet species-level inventories remain limited outside local studies. High-resolution aerial imagery and deep learning now enable individual tree crowns to be mapped at high spatial detail, offering new pathways for biodiversity and climate impact assessments. We synthesize 103 studies (2017–2024), representing 671 deep learning–based species identification tasks using aerial imagery and associated multimodal data across ecosystems and sensor types. Current research is regionally imbalanced and relies heavily on multi-stage classification workflows, with sparse use of multi-temporal or multimodal inputs in end-to-end workflows. We identify core methodological gaps and highlight the need for cross-biome standardized curation, multimodal fusion, automated workflows, and advanced model architectures to achieve scalable species mapping.

Introduction

The composition and distribution of tree species is one of the most critical components of forest science. They provide essential information for ecological research and effective forest management, which are directly linked to forest biodiversity [1], ecological and economic value of forests [2], forest succession dynamics [3], and invasive species monitoring [4]. As global forests face escalating pressures from climate change and land-use alteration, accurate and timely species mapping is increasingly demanded by researchers and forest managers to support evidence-based decision-making and sustainable resource management. Meeting this need requires tools capable of delivering detailed, repeatable, and scalable insights, which are scarcely attainable through traditional ground surveys.

Remote sensing imagery plays a vital role in forest species mapping. Over the past few decades, advances in image resolution and sensor technology have allowed spectral and textural forest characteristics to be captured with unprecedented details [5]. These developments prompted the use of pattern recognition approaches, enabling tree species to be identified at the level of crown clusters, and increasingly at the scale of individual tree crowns [6,7], which has opened up new opportunities for forestry, ecological research, and practical operations, delivering more detailed information than ever before. However, despite the promise of this paradigm, pattern recognition approaches often entail limited transferability, complex workflows and manual data engineering processes.

The complexity persisted until deep learning-based computer vision began to offer an effective solution for remote sensing imagery analysis around 2018 [8,9]. By learning high-dimensional representations directly from imagery, deep learning models bypass hand-crafted feature engineering, capture subtle multi-scale patterns, and can generalize across heterogeneous environments when supported by sufficient training data [10–12]. As a result, detecting and identifying crowns on high-resolution aerial imagery leveraging modern computer vision techniques has rapidly become one of the most active frontiers in tree species mapping.

Tree species identification at the crown level (hereafter "TSI") using high-resolution aerial imagery and computer vision is an emerging research field, positioned at the intersection of forestry, remote sensing, and artificial intelligence. The field is expanding quickly: growing diversity of targeted forests, data sources, and modeling approaches has made it difficult to synthesize findings or identify optimal methods[13,14]. Therefore, a systematic and quantitative assessment is needed to clarify current progress and chart future directions.

To address this gap, we compiled a database and conducted a meta-analysis based on 671 tree species identification tasks reported in 103 peer-reviewed studies published between 2017 and 2024. Our analysis provides a synthesis of this interdisciplinary field and addresses three overarching questions: (1) Forest: what tree species have been identified across forest biomes or forest types? (2) Remote sensing data: how do imagery types, sensors, platforms, and data fusion influence model performance? (3) Deep learning: which deep learning approaches and models have been applied? Our results present the global landscape of TSI research, reveal persistent imbalances across geographic regions and taxonomic classes, and highlight opportunities where coordinated data efforts and advances in model architectures and learning strategies will be the crucial pathway forward.

Results and discussion

Global and taxonomic patterns

Research on TSI spans the five major forest biomes, encompassing a total of 352 tree species from 200 genera. This breadth implies the existence of a potentially vast database in the TSI community for future continental or global-scale studies, provided that data-sharing and collaborative efforts can be strengthened. Nonetheless, given the global estimate of over 73,000 tree species [15], current TSI research remains deficient and imbalanced, with a bias toward common, easy-to-identify, and economically valuable tree species, primarily concentrated in temperate and subtropical forests (Fig. 1).

Further statistics on species representation across biomes reinforce this imbalance. In arid and boreal regions, only five and eight species, respectively, have been studied, while 40 species have been studied in tropical forests, 165 in temperate forests, and as many as 175 in subtropical forests (Supplementary Table 3). This disparity is driven by several interacting factors: (1) the economic relevance of particular tree species, (2) the inherent differences in species richness across biomes, (3) unequal levels of economic investment, research capacity, and scientific motivation across geographical regions, and (4) the relative ease of identifying certain species from aerial imagery.

For example, in boreal forests, all identifications concentrate on cold-adapted genera such as *Pinus*, *Picea*, and *Betula*. These taxa dominate structurally homogeneous, species-poor boreal ecosystems [16], and their ecological importance, coupled with their strong difference in visual appearance , make them natural priorities for TSI research [17,18]. Conversely, in tropical forests, most identified species are economically salient broadleaf trees, valued for their edible, medicinal, or oil-producing properties. In these cases, TSI often serves as a practical tool for the inventorying of specific plantations or orchards [13,19].

The imbalance is also attributable to the varying degrees of forest structural complexity and land-use. For instance, trees in urban or plantation contexts are typically situated in orderly spatial arrangements and are often sharply contrasted against visually distinct ground surfaces in aerial imagery, while plantations generally involve single-species detection tasks. Both settings predictably yield high model performance. In contrast, natural mountain forests exhibit significant variance in canopy density and structure, species heterogeneity, and background complexity. Collectively, these factors impede and influence TSI model accuracy.

Beyond broad forest structure, model performance and species representation are also driven by differences in individual tree structure and plant functional types. Our results reveal that more coniferous species exhibit higher per-class F1-scores than broadleaved species (Fig. 1d; Supplementary Table 4). This superior performance is attributable to the conifers' less variable but more compact and characteristic crown shapes, spectral properties, and textures. Intriguingly, the two highest-ranked deciduous species, *Delonix regia* and *Ginkgo biloba*, also possess highly recognizable crown architectures and colors. These findings further underscore the bias in current TSI research: model performance leans toward optimistically reported because computer vision-based TSI tended to concentrate on visually distinctive and easy species. In contrast, the actual performance ceiling for the majority of the world's tree species, especially those with subtle crown morphology or occurring in structurally complex forests, remains much lower. Future TSI research should prioritize these more challenging species and forest types, where accurate and reliable identification remains difficult.

To realize the full potential of TSI, future efforts must address its significant geographical and methodological imbalance. First, we advocate a strategic shift towards underrepresented regions and forest types, particularly the vast boreal forests and the biodiverse tropical forests of the Global South. This involves introducing new species samples to expand the ecological scope and deploying more advanced remote sensing approaches. Second, it is critical to develop robust model transferability. Techniques such as transfer learning and incremental learning offer a path to enable knowledge acquired from data-rich regions (e.g., temperate and subtropical forests) to be transferred to data-scarce regions (see Box 1). For example, the subtropical biome, with its high data availability and high genus overlap with temperate zones (Fig. 1c; Supplementary Table 2), presents an ideal testbed for developing these transferability capabilities.

Finally, we assert that tropics warrant greater research attention and methodological advancement. Despite hosting the highest tree species richness and largest forest area [20], tropical forests account for only 15% of all TSI studies. The extreme species diversity, complex structure, and dense canopy cover in the tropics, particularly in rainforests and mangroves, demand a concerted effort: acquisition of very high-resolution imagery, precise reference data, coupled with methodological and architectural advances in deep learning to overcome intricate segmentation and classification issues. Equally important is the imperative for equitable scientific collaboration to ensure fair funding distribution, rigorous capacity building, and academic empowerment for researchers in less affluent regions [21,22], enabling sustainable and mutually beneficial progress in TSI research.

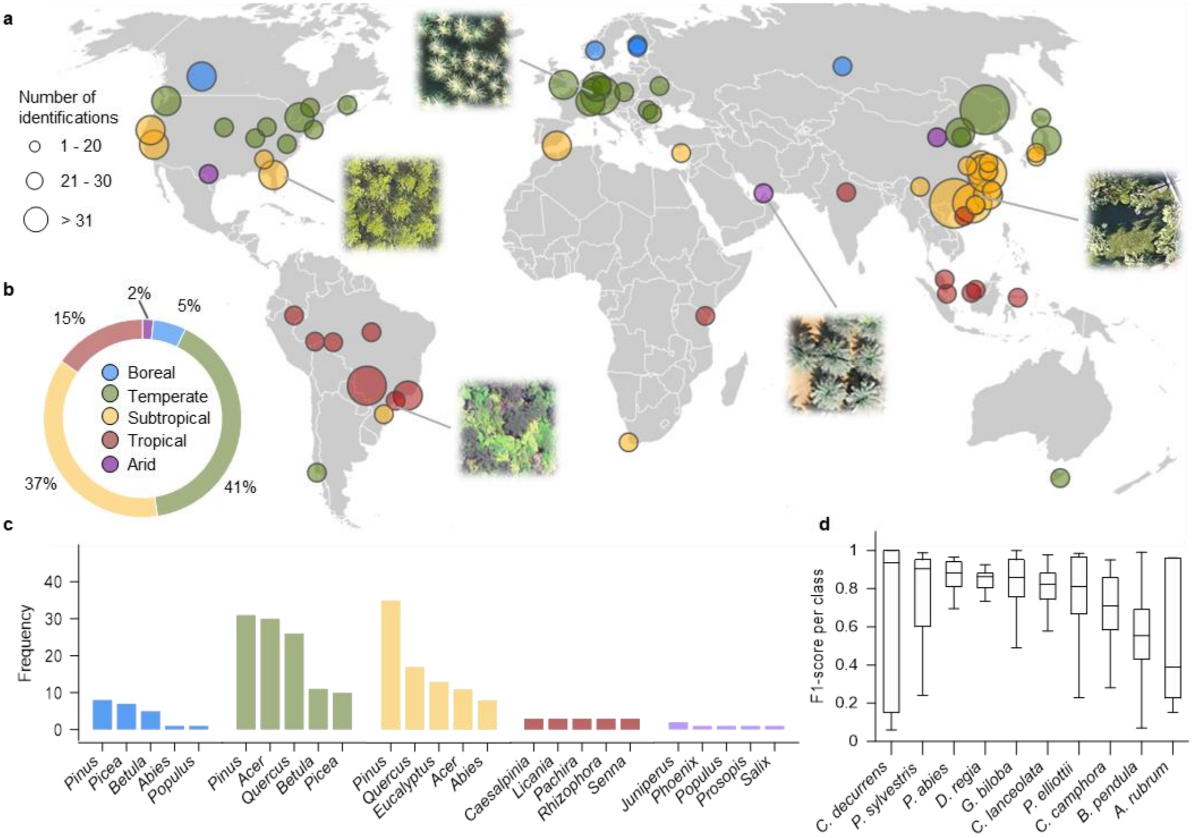

Fig. 1 Global pattern of crown-level tree species identification research. a Global map and number of tree species identifications per site (polar regions omitted), with example aerial images: temperate conifer forest [23], subtropical mixed forest, tropical rainforest [24], arid palm plantation [25], and urban forest in

subtropic [26]. **b** Proportional distribution of identifications across the five biomes. **c** Top five most frequently classified genera in each biome. **d** The 10 most frequently identified species and their average per-class accuracy. Full names of the species (from left to right) are *Calocedrus decurrens*, *Pinus sylvestris*, *Picea abies*, *Delonix regia*, *Ginkgo biloba*, *Cunninghamia lanceolata*, *Pinus elliottii*, *Cinnamomum camphora*, *Betula pendula*, and *Acer rubrum.*

Remote sensing data

Aerial imagery as the baseline

Results revealed that TSI models predominantly rely on single image data sources (74% of identifications). Among the studies that use imagery only, standard true-color RGB (Red, Green, and Blue) images constituted the dominant majority (49%) (Fig. 2a). This prevalence stems from the cost-effective and processing simplicity afforded by RGB imagery. Moreover, RGB imagery covers the visible spectrum, where solar irradiance is highest, enabling large signal-to-noise ratios and, therefore, finest spatial resolutions (Fig. 2c). The spatial resolution in turn is the key feature for species-related pattern recognition tasks [23,10]. TSI models trained solely on RGB data achieved a satisfactory average F1-scores of 0.75, with one-third achieving ≥0.8, establishing a robust baseline capability for the visible spectrum.

Spectral gains and trade-offs

Moving beyond visible light, 25% of identifications investigated additional spectral information, namely RGB-NIR (Red, Green, Blue, and Near infrared), hyperspectral, or multispectral imagery. Relative differences (Δ_{Rel}) uniformly demonstrated that models leveraging these extended spectral data achieved higher classification accuracy than RGB alone (Fig. 2b). This observation aligns with established theory suggesting that increased spectral bands, particularly the high spectral resolution provided by hyperspectral data, can supply the model with richer ecological and biological information, such as subtle variations in leaf greenness, pigment composition and water content, thereby facilitating higher classification accuracy [27,28].

However, multispectral and hyperspectral sensors are considerably more costly, complex to calibrate, and provide lower native spatial resolution than comparable RGB systems, which risks missing distinctive patterns. Furthermore, the challenge of effectively inputting this high-dimensional data to balance model efficacy and complexity remains an unresolved challenge. While some studies explored band pre-selection using manual, PCA-based, or deep learning based strategies, findings are inconclusive and highly case-dependent [29,28]. Optimal band selection also varied by species and image resolutions [30,27]. Intriguingly, studies that directly used full band input already achieved good results (average F1-score > 0.8), suggesting that modern deep learning models may autonomously learn useful bands, implying that pre-selection may be redundant.

The critical role of spatial resolution and platform

Spatial resolution is a critical determinant in TSI performance, which is one of the prerequisites of precise crown segmentation. 92% of reviewed identifications used imagery with a resolution of $\leq$ 50 cm, and 50% used a resolution of $\leq$ 10 cm. The most fine-grained imagery (0.22 cm) was from uncrewed aerial vehicles (UAVs) [31], whereas the coarser resolution (up to 200 cm) mostly originated from WorldView satellite imagery [32]. Experimental evidence consistently demonstrates a degradation in model performances as spatial resolution increased beyond 10 cm [33,34,23,35]. This decline is more pronounced for broadleaf tree species compared to conifers, underscoring the stricter spatial resolution requirements for complex canopy structures [23].

Application of data acquisition platforms for TSI studies mirrors the stringent benefit of high spatial resolution. Therefore, across all reviewed research, UAVs constitute the substantial majority (71% overall, and 83% in 2024), providing an average spatial resolution of 13 cm (Fig. 2e). This trend aligns with broader literature [36,37], which recognizes the UAV's compelling advantages: capacity to provide high resolution at sub-centimeter level, flexible sensor configurations, and customizable acquisition schedules [38,39]. Additionally, their relatively low cost and ease of deployment have made them a preferred tool for localized, fine-scale TSI research [40].

Despite the dominance of UAVs, satellite imagery (15% of identifications), primarily from WorldView and Planet, remains advantageous for regional and global-scale data with high temporal resolution. Meanwhile, several advancements are narrowing the resolution gap between platforms: recent initiatives in low Earth orbit constellations aiming to deliver 10-cm satellite imagery, and the growing use of AI-based enhancement techniques (e.g., super-resolution) to refine existing satellite image resolution [41]. Importantly, high-resolution UAV observations serve as valuable local training data to calibrate and enhance satellite-based large-scale TSI models [42], pointing toward an integrated, cross-platform framework as the future of TSI research.

Integrating multi-modal data

Among the identifications using multi-modal data, the majority (20%) incorporated 3D LiDAR data alongside imagery, while a smaller fraction (6%) fused additional 2D image sources or metrics extracted from them, which we categorize as *other fusion*. The Δ_{Rel} indicated that, overall, both types of data fusion improved model performance compared to single 2D image input (Fig. 2d). For instance, UAV-RGB data offers very high spatial resolution for detailed crown, branch or even leaf structures, whereas satellite multispectral data supplies additional spectral and temporal information. This combination is the most common within *other fusion* [43–45], and improved model performance was consistently observed (Fig. 2d).

3D data fusion most commonly involves adding canopy height models or digital surface models (DSMs) [46–48]. A smaller number of studies integrated other products, such as intensity, curvature, or leaf area index estimates [49–51]. While 3D data can provide forest structural cues, such as treetop locations, canopy height and shapes, the efficacy of 3D data fusion, particularly with LiDAR products, shows only modest improvements. Furthermore, identifications incorporating 3D data derived from image photogrammetry sometimes reported a negative influence (Fig. 2d; Supplementary Table 5).

Decreased performance when fusing 3D data has been attributed to four main factors: (1) the relevant information for species classification provided by the 3D products may already be adequately covered by the illumination differences and geometrical cues visible in imagery data[30,52]; (2) the structural differences (e.g., crown size or height) between different species may be minimal in some forests[49,50]; (3) providing species-specific information at the individual crown level imposes higher demands on LiDAR data quality (e.g., high point density)[30]; and (4) potential misalignment exists between the LiDAR and image datasets that could confuse models.

Data fusion strategy is a critical factor influencing model performance. Depending on the stage at which fusion occurs, existing strategies are typically categorized into early fusion (input-level combination), late fusion (decision-level integration), and hybrid fusion [53,54]. Virtually all reviewed studies employing data fusion used early fusion, which means stacking all feature bands from different sources before inputting them into classification models. Early fusion carries the risk of misalignment between different sources, especially when fusing data with disparate spatial resolutions or combining 2D and 3D modalities [55,56]. For small objects such as individual crowns, this strategy may fail to optimally utilize the most informative aspects of all modalities, and the potential misalignment could undermine model performance.

In future TSI work, effective data fusion requires careful consideration of four key factors: (1) ensuring the added modality provides genuinely complementary information to avoid unnecessary model complexity; (2) accurate co-registration and harmonization on spatial resolution and timestamp across modalities; (3) designing deep neural network architectures capable of accommodating the distinct characteristics of each modality; and (4) implementing modality- and task-specific preprocessing, including appropriate data augmentation.

The importance of multi-temporal data

Multi-temporal data can capture phenological information, which provides strong cues for distinguishing tree species, yet, only 7% of the identification employed multi-temporal data. Among these, six publications systematically compared the influence of multi-temporal against single-temporal data on model performance, all of which demonstrated a positive impact (Fig. 2f). This significant gain is directly attribute to the capture of phenological traits, such as color and foliation status of trees, which constitute a highly significant and unique spectral signature for species classification [45,57,58]. Consequently, multi-seasonality data facilitates more accurate species identification. This also highlights that for single-temporal data acquisition, the choice of season is paramount and highly dependent on the target forest ecosystem [57,31,32]. Therefore, a strategic selection of the data acquisition season, tailored to the specific phenological characteristics under investigation, is necessary for maximizing TSI accuracy.

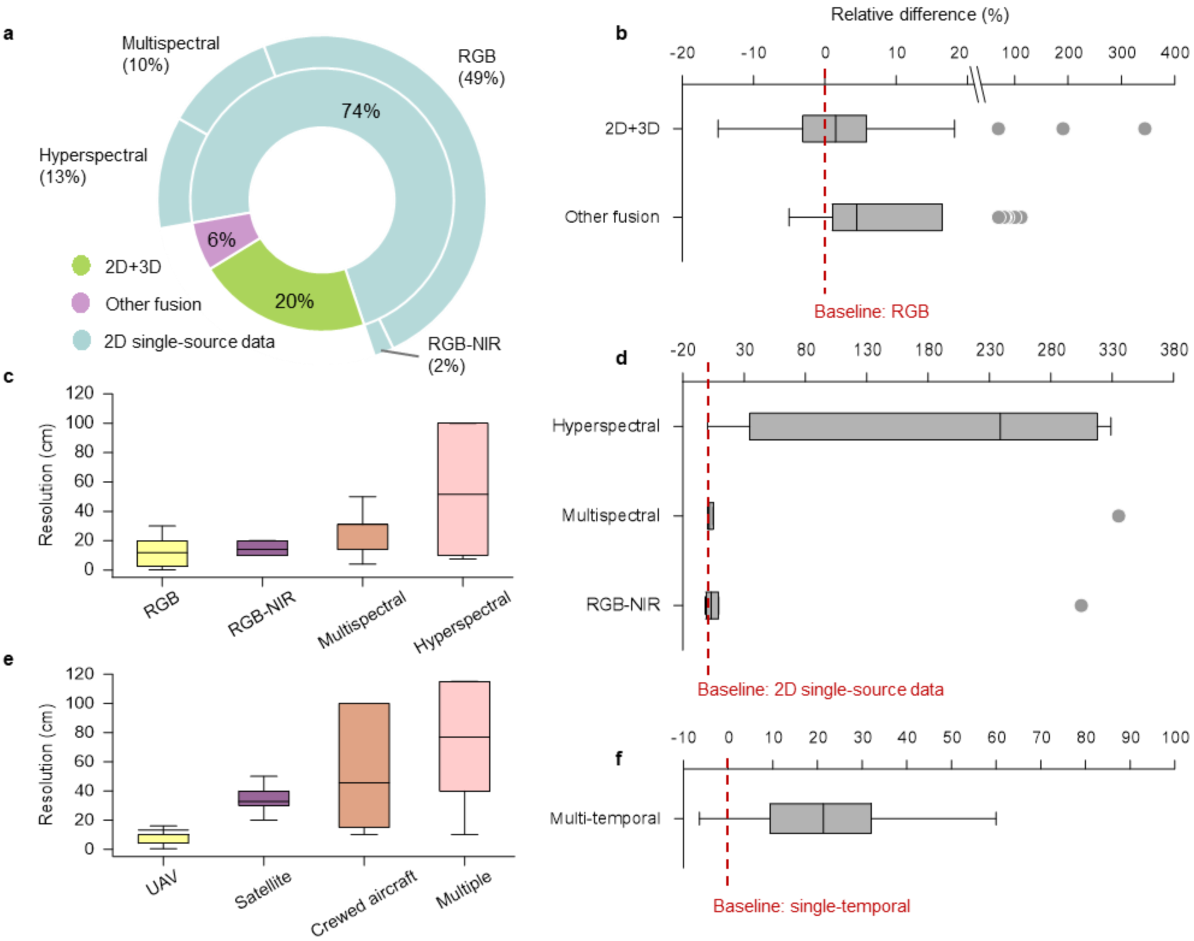

Fig. 2 Usage of remote sensing data in crown-level tree species identification. a Proportional distribution of model input data types in reviewed identifications. The inner circle represents the proportions of three broad data types: 2D, data fusion of 2D + 3D, and other fusion. The outer circle further categorizes 2D single data sources into hyperspectral, multispectral, RGB and RGB-NIR. **b** Relative difference of different spectral data, comparing hyperspectral, multispectral, and RGB-NIR, against the baseline of RGB. **c** The average spatial resolution of imagery data types in TSI research. **d** Relative difference of different data fusion, comparing fusing 3D data with 2D (2D+3D) and other fusion, against

the baseline of 2D single data source. **e** The average spatial resolutions of data acquisition platforms in TSI research. **f** Relative difference of multi-temporal data against the baseline of single temporal data.

Deep learning approaches for tree species identification

Computer vision tasks

Current research in TSI employed diverse deep learning approaches, which are categorized into four computer vision tasks (Fig. 3): patch-wise classification (51%), semantic segmentation (21%), object detection (15%), and instance segmentation (13%). The choice of approach critically dictates the balance between workflow manageability and end-to-end automation.

Patch-wise classification is the mostly used approach in TSI research (51%), relying on a two-stage process: pre-processing to crop image chips representing individual tree crowns (often using ancillary geometric references like canopy height models, rule-based segmentation [30,59]), followed by classification on image chips (Fig. 3a). This approach is prevalent due to its intuitive workflow and flexibility in managing training data imbalances (as training unit is ‘one image to one class’). However, the dependency on site-specific pre-processing and external crown detection algorithms diminishes the overall scalability and automation of the workflow, and the output fundamentally lacks spatial context for mapping large orthomosaics.

Semantic segmentation operates on the principle of classifying every image pixel. While semantic segmentation does not inherently delineate individual tree crowns, pixel-wise outputs can be segmented or aggregated into crowns using subsequent object recognition or post-processing methods, such as majority voting, distance mapping, or watershed segmentation [60–62,19] (Fig. 3a). Similarly, the reliance on separate processing limits full automation and shifts the burden to custom pipelines. However, in practical applications where individual crown detection and quantification are either not required or not feasible due to forest structure, TSI at the crown cluster level is sufficient without requiring post-processing. In this case, semantic segmentation proves to be more useful and advantageous [63], by providing coherent classification maps with precise class locations and areas, while enabling higher model simplicity and efficiency [31].

Conversely, **object detection** and **instance segmentation** models integrate crown detection, localization, and species classification into a single pipeline [64]. Object detection models predict bounding boxes for each tree crown that contain class information and coarse relative position (quadratic boxes), while instance segmentation further advances this by segmenting the exact individual tree crown extents. This high degree of automation minimizes manual data engineering and simplifies the transferability of models across domains, marking a significant methodological advance.

The major drawback of object and instance segmentation approaches is their sensitivity to data quality and annotation effort. In practice, the model performance is highly sensitive to issues such as missing labelled trees in an image chip [65,66], imbalanced class distribution in training data [67], and disparities in image resolutions and sizes. Similar issues also risk the performance of instance segmentation models, yet high-quality pixel-accurate annotations for instance segmentation models require higher labor intensity and data volume demands [68]. Furthermore, the reported detection accuracy of object and instance detection methods was questioned to be overly optimistic, especially in dense forests, when training data lacks robust ground-truth or terrestrial sensor support [69]. This vulnerability highlights the critical trade-off between full automation and substantial data quality demands required for reliable performance.

In essence, TSI consists of two coupled tasks: detecting crowns and classifying their species. This makes the overall task fundamentally complex and requires more training data. Current evidence from comparative studies is inconsistent and no single approach outperform others across all scenarios [70,71]. Future methodological efforts should focus on two directions: first, integrating specialized detection/segmentation models (e.g., DeepForest [72], Detectree2 [73], or broader models like DETR and SAM [74,75]) as an automated upstream module into the currently dominant patch-wise classification pipelines, achieving higher automation while preserving classification flexibility. Second, developing more robust object detection and instance segmentation architectures that are resilient to common data limitations, thus realizing fully automated, high-fidelity mapping. The optimal choice of approaches in application will ultimately be guided by the specific forest characteristics and the quality and volume of available data.

Table 1. Summary of different computer vision approaches in reviewed studies.

Approach	Advantages	Limitations
Patch-wise classification	● High flexibility in combining segmentation and classification methods. ● High flexibility in training and testing data division. Incomplete and missing ground truth labeled objects can be easily removed. ● Require simpler models.	● Creating patches of individual crowns is inefficient. ● Details are limited to patch-level, cannot resolve individual pixels or instances. ● Relies heavily on external CHMs/DSMs for pre-segmentation.
Semantic segmentation	● Efficient at the tree-cluster level, providing precise tree-cluster extents and locations. ● Produces coherent classification maps on large image tiles. ● Require simpler models.	● Requires post-processing for individual crown delineation.

Object detection	● Simultaneous crown localization, quantification, and classification. ● Good performance in simple forests. ● Requires less annotation effort than masks.	● Sensitive to high-quality annotations. ● Limited precision in crown boundaries. ● Less effective in dense or heterogeneous forests.
Instance segmentation	● Simultaneous crown localization, delineation, quantification, and classification. ● Good performance in dense and complex forests. ● Strong transferability potential.	● Annotation-intensive. ● Higher computational demand.

CHM = canopy height models; DSM = digital surface model.

Convolutional, graph, and transformer architectures

Convolutional neural networks (CNNs) are a class of deep neural networks designed to process grid-like data (such as images) by applying learnable convolutional filters across local regions, extracting hierarchical features like edges, textures, and patterns [76]. CNNs underpin 92% of all identifications, spanning over 35 architectural variants (Supplementary Table 6). Classic CNN architectures like ResNet and Unet are most widely employed in TSI, providing backbones for dedicated, continuously upgraded architectures such as RetinaNet, Faster-RCNN, and Mask-RCNN. Additionally, DeepLab and YOLO are also among the most commonly used for semantic segmentation and object detection, respectively. The popularity of these pre-trained and open-source architectures stems from their ease of application and customization.

Most identifications deployed custom CNN designs (16%), collectively referred to as *custom CNN* in Supplementary Table 6. These modifications include the integration of blocks that enhance feature extraction, such as feature pyramid network [77], single shot detector [78], adaptive sample selection [79], and attention mechanisms [44,80]. A crucial strategy for measurable accuracy gains is the implementation of ensemble frameworks, combining multiple models [81]. For instance, [82] developed Silvi-Net, which integrates two independently trained ResNets for multi-source feature extraction, followed by an MLP classifier. Another noteworthy ensemble model is a hierarchical CNN proposed by [57], which combines architectures (e.g., ResNet, GoogLeNet, and DenseNet) to perform classification across taxonomic levels: coarse-level classification by dividing all tree species into coniferous and broadleaf groups, followed by finer species-level classification within each group. All of the ensemble strategies showed measurable accuracy gains, underscoring the role of architectural customization and innovation in advancing TSI performance.

Beyond CNNs, two emerging model types are demonstrating specialized advantages. Graph neural networks (GNNs) operate by explicitly modeling data as a graph, where nodes represent entities (like tree crowns or points in a cloud) and edges represent relationships (spatial proximity or feature similarity), allowing the network to learn both individual features and structural context. GNNs are proven to be suited for learning the structural and topological information of trees embedded in high-dimensional data, such as multispectral and point cloud fusion [83,84]. Transformers entered TSI research in 2024, with models such as DETR, SegFormer, Swin Transformer, and Vision Transformer [79,85,86]. Their ability to model long-range dependencies and adapting to variable image scales [87] strengthens feature extraction and offers clear advantages for tree detection in complex forests. Beyond directly using Transformers, a common design strategy integrates Transformer blocks into established CNN-based object detection or instance segmentation frameworks. Models such as Fast R-CNN and DeepLab provide flexible architectures that can be readily customized this way [88,89,80]. We anticipate that Transformers or hybrid CNN-Transformer approaches will constitute an increasing share of future TSI research.

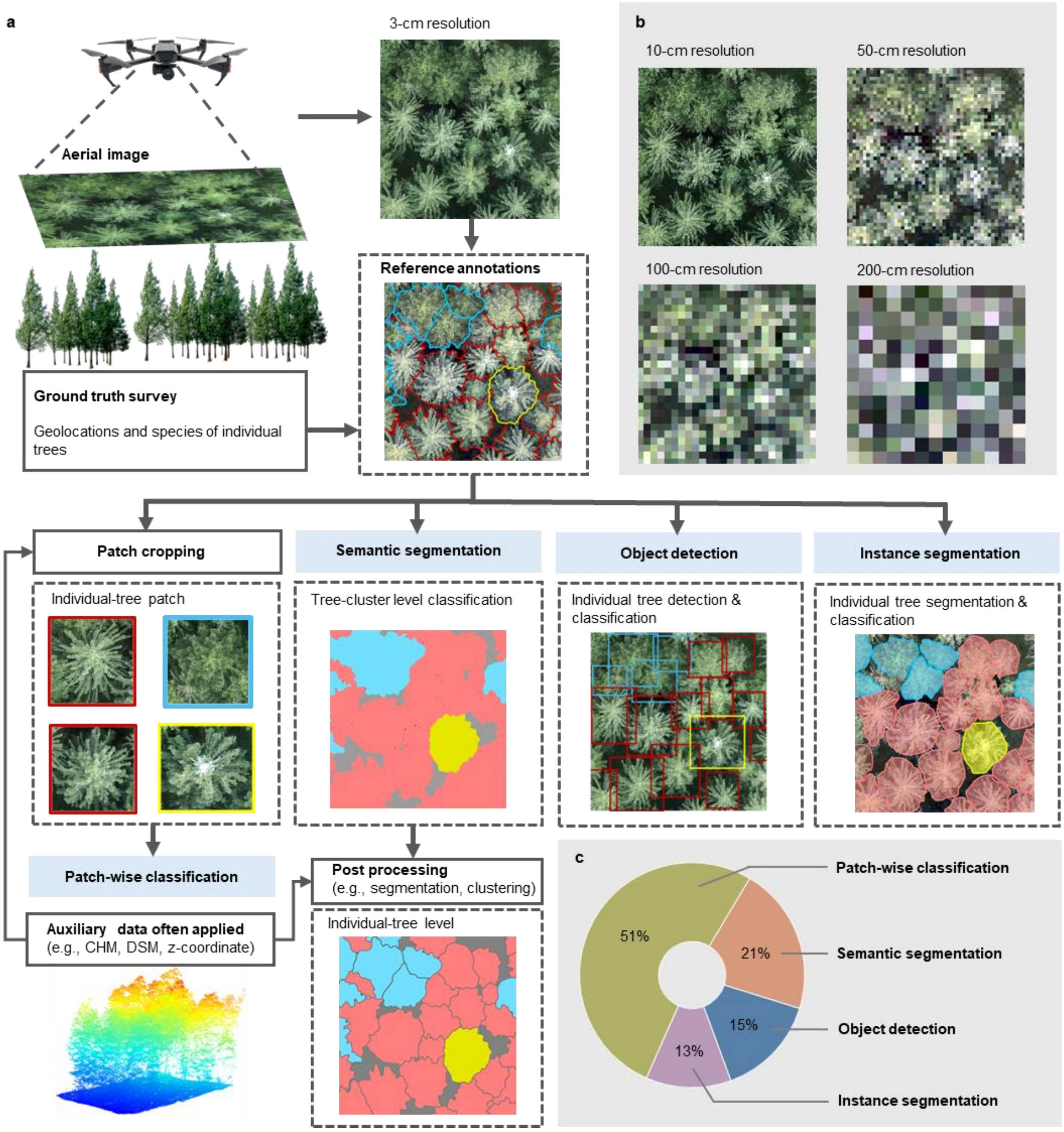

Fig. 3 Computer vision tasks applied to crown-level tree species identification. a Workflow of each computer vision approach. Aerial imagery source: TreeAI [90]. **b** The image resolution is a determinant for tree detection and classification. **c** Proportional distributions and illustration of computer vision approaches.

Challenges and perspectives

Deep learning has advanced crown-level tree species identification, but performance remains constrained by properties inherent to forest data. Strong phenological and structural variability, overlapping species signatures, heterogeneous sensors, and inconsistent annotations continue to limit model robustness and generalization. The following sections outline the main data and methodological challenges identified across current studies and outline research directions for overcoming them.

Addressing data limitations

Deep learning model robustness is fundamentally tied to data volume and quality. Yet in forestry research, collecting well-annotated ground truth data is challenging [91]. Our review underscores that TSI research is data-imbalanced, both in quantity and standardization. Strengthening data-sharing practices and developing standardized, domain-specific databases are crucial [92]. We strongly encourage researchers to deposit datasets on open platforms (e.g., Hugging Face, Zenodo) to foster a community-wide resource pool. Several existing TSI-specific databases are listed in Table 2.

Table 2. Open-access reference datasets for crown-level tree species identification.

No.	Data	Description
1.	NEON Tree Species Predictions[93]	Species predictions at the individual tree level for 100 million trees in the National Ecological Observatory Network, the United States.
2.	Tree detection in UAV LiDAR and RGB image data [94]	The dataset contains 3,600 trees from seven species across 10 ground plots in Perm Krai, Russia, accompanied by a LiDAR point cloud and an RGB orthophoto.
3.	Quebec Trees Dataset [95]	The dataset comprises over 22,000 trees from 20 species and RGB imagery in Quebec, Canada.
4.	TreeAI Global Initiative [90]	The dataset provides over 100,000 tree annotations across 70 species in COCO format and RGB imagery from diverse locations worldwide.

Meanwhile, attention must be raised to the absence of a consensus standard for annotation and quality control within the TSI domain. As diverse and massive data streams converge, this lack of standard poses a profound negative impact on the cleanliness, completeness, and balance of training data, which can severely misguide models. Common sources of noise include: (1) the lack of an agreed class list, with researchers adopting different taxonomic systems [96]; (2) inconsistent naming conventions (e.g., *Picea abies* and *Picea abies* L. treated as separate classes). (3) mixed taxonomic levels within the same dataset (e.g., *Picea* spp. and *Picea abies*, without ensuring mutual exclusivity, or assigning species labels to dead trees). (4) the absence of hierarchical class structures in databases (e.g., tree > conifer > *Picea* > *Picea abies*). (5) variable fidelity in crown delineation, which often relies on manual interpretation of aerial imagery, which is increasingly questioned by recent studies [69]. Moreover, the completeness issue arises when not all trees in an image patch are labelled. These missed ground truth trees will be learnt as a void or background class that can weaken models. Lastly, the imbalance issue is pervasive, manifesting as stark quantitative disparities at the regional, forest-type, and species class levels, often displaying a long-tail distribution.

While standardization is paramount, existing deep learning methods offer powerful ways to address current data deficiencies. Data-centric learning and active learning are highly relevant strategies for TSI. They emphasize iterative data refinement (e.g., filtering poor-quality samples) and selective labeling of the most informative, uncertain samples, respectively[97,98]. This approach maximizes annotation quality and minimizes the effort required to build high-fidelity datasets. Furthermore, current modeling can be optimized to tolerate data noise. Techniques such as pseudo-labeling [26,99], soft sampling, ignore masking[100], and strategic refinement of attention mechanisms and loss functions can be employed to effectively mitigate the impact of incomplete or imbalanced ground truth data [101,102].

To realize the full potential of deep learning on a global scale, the field must prioritize the creation of shared, heterogeneous datasets through community-wide collaboration. Integrating diverse research groups via data hosting platforms and large-scale projects is the only viable path to generate benchmarks that are truly representative of the world's biomes. Such initiatives serve a dual purpose: curating the vast training data necessary for high-performance models while simultaneously establishing best practices for data quality and standardization. This approach has already proven transformative in related domains, exemplified by the 20forK LiDAR dataset [103], which addresses tree species classification with LiDAR data, or the global deadtrees.earth initiative [104], which focuses on tree vitality mapping with drones and satellites. Embracing such collaborative paradigms is essential for bridging the generalization gap in crown-level species identification.

Standardizing reporting metrics

Cross-study comparison and benchmarking are hampered by the non-uniform reporting of essential parameters and model performance. To facilitate progress, we mandate the explicit use of binomial scientific names for all species and the clear reporting of fundamental imagery metrics: the spectral bands and spatial resolution. Crucially, evaluation reports are often fragmented across disparate metrics. To establish a coherent domain standard, we advocate for the mandatory reporting of per-class metrics (mAP, Recall, Precision, and F1-score), complemented by the overall performance indicators such as IoU and Overall accuracy. However, these metrics are not representative or comparable unless they are derived from truly independent datasets that minimize spatial and temporal autocorrelation [105,106]. Therefore, we strongly recommend implementing robust validation techniques, such as spatial block cross-validation, to ensure that training and testing partitions are spatially independent and the reported metrics are reliable and transferable across studies.

Table 3. Summary of evaluation metrics with respective equations and descriptions.

Evaluation metrics	**Equation**	**Description**
Precision	$\frac{TP}{TP+FP}$	The proportion of model-predicted objects that are correct.
Recall	$\frac{TP}{TP+FN}$	The proportion of true objects that are correctly detected by models.
F1-score	$2 \times \frac{Precision \times Recall}{Precision + Recall}$	The harmonic mean of Precision and Recall.
IoU	$\frac{Area\ of\ Overlap}{Area\ of\ Union}$	The ratio between the intersecting area and the total combined area of the predicted bounding box (or mask) and the ground truth box (or mask).
AP	$\int_0^1 p(r)dr$	Average precision equals to the area under the Precision-Recall curve for each class.
mAP	$\frac{1}{N}\sum_{i=1}^{n} x_{ii}$	Unweighted average AP across all classes.
Overall accuracy	$\frac{1}{N}\sum_{i=1}^{n} AP_i$	The ratio of all correctly classified objects to the total number of true objects across all classes

Note the TP represents the true positive, FP represents the false positive, FN represents the false negative, $p(r)$ represents the maximum precision at a given recall level, n is the number of classes, x_{ii} is the number of correct predictions in class i.

Model generalization, robustness, and transferability

Generalization, robustness, and transferability describe related but distinct performance dimensions in deep learning for TSI (see Box 1). Current TSI models often generalize well but show limited robustness and very low transferability, largely due to domain shift [107]. Improving transferability requires more than domain-invariant features; it depends on understanding which factors, sensor properties, taxonomic overlap, phenological timing, or structural complexity, govern cross-site performance. Methods such as transfer learning, which reuses learned visual features from a pre-trained model, and domain adaptation, which explicitly reduces discrepancies between source and target data distributions, can facilitate adaptation to new environments [108,109]. Self-supervised pretraining, which learns generalizable representations from unlabeled data, offers an additional route to mitigate data scarcity. Meanwhile continual and incremental learning strategies are essential when new species or biomes must be incorporated without retraining from scratch [110]. Addressing these three dimensions jointly is critical for developing operational TSI models that function across diverse environments and sensor conditions towards the development of a universal tree species identification DL model.

Box 1 - Key performance concepts in deep learning

Generalization: DL model's ability to perform well on unseen data drawn from the *same* distribution as the training set, such as new crowns of the *same species* within the same forest type [111].

Robustness: The stability of a DL model's performance under perturbations, including changes in illumination, season, view angle, or sensor noise, which are common in aerial imagery and can significantly distort spectral and textural cues [112].

Transferability: A model's ability to maintain performance when applied to different forests, biomes, or sensor conditions, where species composition, canopy structure, and imaging geometry may differ substantially from the training data. Transferability does not mean that a model trained on a given species (e.g., spruce) can recognize new species elsewhere. Rather, a transferable model can (i) continue to recognize the same species in new environments, and (ii) reuse its learned visual representations, such as texture, shape, or canopy-structure cues, to be efficiently adapted to different species through fine-tuning, domain adaptation, or continual learning, which all require additional data from the target environment (labelled data for new species in fine-tuning and continual learning, and labelled or unlabeled target-domain data for domain adaptation). Because these situations involve large domain gaps, transferability represents the most challenging performance dimension [113,114].

Domain shift: The mismatch between the statistical properties of training data and those encountered during deployment, often caused by differences in forest structure, species composition, acquisition geometry, seasonality, or sensor characteristics. Domain shift affects all three performance dimensions: it has minimal impact on generalization, moderate impact on robustness, and is the primary cause of poor transferability.

Transfer learning: A method that reuses visual features learned by a pre-trained model to improve performance on a new task or in a new environment, reducing the need for extensive additional training data. Transfer learning is used mainly to improve transferability by counteracting domain shift and can also enhance robustness by promoting more domain-invariant feature learning [113,115].

Advances in high spatial and temporal resolution data

The growing availability of open, high-resolution aerial and LiDAR data is rapidly expanding the possibilities for crown-level species identification. Several European countries now provide nationwide or regional very high-resolution aerial imagery (5–25 cm), including Switzerland, Austria, Germany, the Netherlands, Denmark, Poland, Spain, parts of the Nordic countries, and France [116–118], which additionally operate airborne LiDAR programmes. Globally, the United Nations Strategic Plan for Forests and the EU Forest Strategy for 2030 highlight the need for harmonized, high-resolution forest monitoring systems to support biodiversity and climate objectives [119]. Further, incorporating non-orthorectified, multi-view imagery, combining high-nadir with low-oblique views, has been shown to preserve vertical structure and bark characteristics that improve taxonomic classification [26,86]. Likewise, high-volume leaf- and branch-level texture data from citizen-science photographs can enhance model performance when tested to aerial imagery [31,120].

Achieving global-scale, high-resolution imagery for TSI depends on narrowing the resolution gap between satellite and UAV data. Super-resolution has recently garnered significant attention and offers a promising path forward [121,122]. While high-ratio super-resolution upscaling still carries uncertainty, and current studies capable of refining sub-meter imagery to the 10 cm resolution required for TSI remain scarce [122,123]. Looking ahead, increasing sub-meter resolution satellite imagery, combined with advances in super-resolution that can bridge both spatial resolution and coverage gaps, holds the potential to produce continental- or global-scale very-high resolution imagery. Importantly, such developments would not only improve spatial detail but also enable the integration of multispectral and multitemporal satellite information with UAV data, which would benefit large-scale and real-time TSI research.

Foundation models and interpretability

Foundation models are rapidly emerging as a potential solution for overcoming key challenges in TSI, such as ground truth data scarcity, imbalance, and poor model generalization. While foundation models like CLIP, DINO, and SAM dominate broad computer vision, the remote sensing field has developed specific counterparts, including RemoteCLIP, SpectralEarth, Prithvi-EO, and AlphaEarth [124–127]. These efforts aggregate a massive collection of Earth observation data and spectral information. For TSI, there are currently two main pathways for applying foundation models: (1) fine-tuning general object detection foundation models using TSI-specific data [128,129], and (2) combining segmentation-focused foundation models with dedicated classification models to allocate specialized, powerful models to their respective tasks [75,130]. Although a dedicated TSI-specific foundation model is currently absent, the concepts accompanying foundation models, such as self-supervised learning, contrastive learning, and zero-shot learning [67,131], offer abundant inspiration for the future workflow design and training strategies for TSI models [132,133].

Explainable AI and Causal AI are crucial for countering the 'black-box' nature of deep learning models in forestry remote sensing [98,134]. Rather than blindly expanding data sources, spectral bands, and data temporality, future TSI research must clarify how model inputs relate to the massive model input data and the vast heterogeneity of tree species and forest types. Explainable AI offers feature-importance analyses and attribution maps that reveal which spectral or structural cues drive model decisions and whether these cues align with ecological understanding [135]. These insights allow researchers to diagnose failure modes, eliminate redundant or misleading inputs, and refine both data acquisition and model training strategies. Thus, incorporating Explainable AI can elevate TSI from a purely detection and classification task into an ecologically informed decision-support framework [114].

Methods

Literature search

We conducted exhaustive searches across Scopus, Web of Science, and IEEE Explore. The search was limited to English language, peer-reviewed articles and conference proceeding published between 1 January 2012 and 30 September 2024. The search string, applied across the title, abstract, and author keywords, was structured as follows: ("tree" OR "forest" OR "canopy" OR "crown") AND ("individual" OR "single" OR "delineat*" OR "detect*" OR "discriminat*" OR "segment*" OR "map*") AND ("species classification" OR "species identification" OR "species detection" OR "species recognition") AND ("deep learning" OR "neural network" OR "DL" OR "CNN" OR "convolutional networks" OR "automat*" OR "instance segmentation" OR "object detection" OR "semantic segmentation"). After removing duplicates, the initial results yielded 683 studies (Supplementary Fig. 1).

Study screening

Two rounds of screening process are implemented to identify eligible articles. First, studies not primarily focused on trees are excluded, such as studies targeting other vegetation types (e.g., crops, flowers). Studies that included shrubs alongside trees were retained, given the morphological and ecological continuum between these growth forms and the frequent co-occurrence in remote sensing literature. For the second round, five predefined inclusion criteria was applied, aligning with the core scope of this review: (1) the target objects were individual trees or crown clusters as a species community; (2) species or genus labels were explicitly identified; (3) aerial imagery (UAV, aircraft, or satellite) was the *primary* model input, with spatial resolution < 2 m. Studies only using non-imagery data (such as LiDAR and SAR) are excluded; (4) a deep learning model was used for classification, detection, or segmentation. (5) valid accuracy evaluation metrics were explicitly reported. In total, 103 studies published between 2017 to 2024 met all criteria were included in the subsequent meta-analysis.

Data extraction

We treated each unique identification outcome reported within a publication, which represents distinct experiments (e.g., testing different models or applying the same models to different datasets), as an independent record for database construction. We ensured that all extracted identifications also adhered to the five inclusion criteria. For example, if a study primarily used imagery data but contained comparative experiments using only LiDAR data, only the identifications based on imagery data were retained.

For each valid identification, we extracted a total of 28 metadata attributes grouped into four key aspects (Supplementary Table 1): (1) forest: the location of study sites, biome designation[136], identified species and genera using scientific binomial names, and the total number of identified classes; (2) data sources: we identified whether the study used single imagery or data fusion, imagery data types (e.g., RGB, multispectral), spatial resolution, data acquisition platforms, and multi-temporal data usage; (3) deep learning models: the computer vision approach employed (e.g., object detection, instance segmentation) and the specific model architecture; (4) model performance for each identification, including precision, recall, F1-score, overall accuracy, and Kappa are recorded. When specific information was not explicitly reported, missing information was denoted as “NA”.

Data analysis

Descriptive statistics. We calculated the proportional distributions of identifications grouped by biomes, data types, and computer vision approaches. We computed the frequencies of identified species and genera and applied deep learning models. Specifically, species frequency was recorded once per species per study. Genus frequency was recorded once per unique species within that genus per study (e.g., *Pinus strobus* and *Pinus resinosa* in one study counted as two genus frequencies) (Supplementary Table 2).

Performance metrics. For the most frequently identified species, we extracted the per-class F1-score from relevant papers and computed the average per-class F1-score (Fig. 1; Supplementary Table 4). And to quantify the impact of remote sensing data properties on TSI models (e.g., data types, data fusions, and temporality), we calculated the relative difference (Δ_{Rel}) within each relevant studies, controlling for classification tasks and spatial resolution of data (Supplementary Table 5).

$$\Delta_{Rel} = \frac{Performance_{Proposed} - Performance_{Baseline}}{Performance_{Baseline}} \times 100\% \qquad \text{(Eq. 1)}$$

Where $Proposed$ is the accuracy of the proposed model, $Baseline$ is the accuracy of the baseline model. Impact of hyperspectral, multispectral and RGB-NIR, model performance based on RGB imagery served as the baseline; Impact of data fusion, model performance based on single-imagery data served as the baseline; Impact of multi-temporal data, model performance based on single-temporal data served as the baseline. Model performance (F1-score or Overall Accuracy) was held identical for each paired comparison within a study.

Data availability

The database, including the full list of publications and all extracted data used in the meta-analysis, is provided in the Supplementary Information.

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Author contributions

Z.X., and M.B. conceived the original ideas for this literature review and designed the research. Z.X. performed the literature search, compiled the database, extracted all data, and wrote the original draft of the manuscript with substantial inputs from MB. Z.X., and M.B. worked on data visualization. The original manuscript was substantially improved with conceptual and analytical inputs from T.K., J.D.W., A.G., and V.C.G. All authors discussed the results and edited the final manuscript together.

Competing interest

The authors declare no competing interests.

Supplementary Information for

Advances in tree species identification from high-resolution aerial imagery and deep learning

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Supplementary tables

Supplementary Table 1. The protocol of extracted metadata

Metadata types	No.	Metadata	Note
Basic information	1	Publication ID	
	2	Identification ID	
	3	Title	
	4	Authors	
	5	Journal	
	6	Year	
	7	DOI	
Tree species	8	Country	
	9	Continent	
	10	Biome	Boreal, temperate, subtropical, tropical, or arid
	11	Species	Scientific name
	12	Genus	Scientific name
	13	Number of Classes	
Remote sensing data	14	Single Data Source	Yes or No
	15	Data type	2D, 2D + 3D, Other
	16	Optical data input	
	17	Sensor platform	UAV, crewed aircraft, satellite etc.

	18	Resolution	Spatial resolution (cm)
	19	Multi-temporal data	Yes or No
	20	Data augmentation	Yes or No
Deep learning model	21	Computer vision approach	
	22	Deep learning model	
	23	Model architecture	
	24	F-score	
	25	Overall accuracy	
	26	Kappa	
	27	Precision	
	28	Recall	

Supplementary Table 2. Tree genera in TSI research and their frequencies grouped by biomes.

See attached supplementary Excel file "*Supplementary Table 2.xlsx*". This table is available from the corresponding author upon reasonable request.

Supplementary Table 3. Tree species in TSI research and their frequencies grouped by biomes.

See attached supplementary Excel file "*Supplementary Table 3.xlsx*". This table is available from the corresponding author upon reasonable request.

Supplementary Table 4. The ten most frequently studied tree species and their per-class F1-score across studies, ranked by Mean F1-score (high to low).

Species	**Min.**	**Max.**	**Mean**	**St.d**	**N**
Picea abies	0.6950	0.9655	0.8646	0.0911	44
Delonix regia	0.7338	0.9254	0.8442	0.0607	11
Ginkgo biloba	0.4202	1.0000	0.8286	0.1527	57
Pinus sylvestris	0.2400	0.9884	0.8168	0.1941	42
Cunninghamia lanceolata	0.1041	0.9778	0.7976	0.1412	51
Pinus elliottii	0.2280	0.9850	0.7255	0.2782	9
Cinnamomum camphora	0.2800	0.9510	0.7056	0.1924	22
Calocedrus decurrens	0.0601	1.0000	0.6657	0.4184	10
Betula pendula	0.0700	0.9909	0.5981	0.2504	37
Acer rubrum	0.1514	0.9613	0.4724	0.3695	4

"St.d", standard deviation; "N", number of identifications.

Supplementary Table 5. Relative differences.

Baseline	Proposed	Relative difference (%)					
		Min	**Max**	**Mean**	**Median**	**St.d**	**N**
RGB	Hyperspectral	0.29	329.00	183.00	239.00	144.00	10
	Multispectral	-51.50	335.00	36.90	1.24	122.00	8
	RGB-NIR	-1.69	305.00	45.90	3.23	11.40	7
Single imagery data	2D+3D (LiDAR)	-15.00	344.00	15.00	2.72	58.00	46
	2D+3D (Photogrammetry)	-8.53	7.35	-3.03	-3.08	4.42	13
	Other fusion	-5.02	112.00	23.80	4.48	37.00	26
Single-temporal data	Multi-temporal data	-6.41	59.70	22.20	18.50	18.10	30

"St.d", standard deviation; "N", number of identifications.

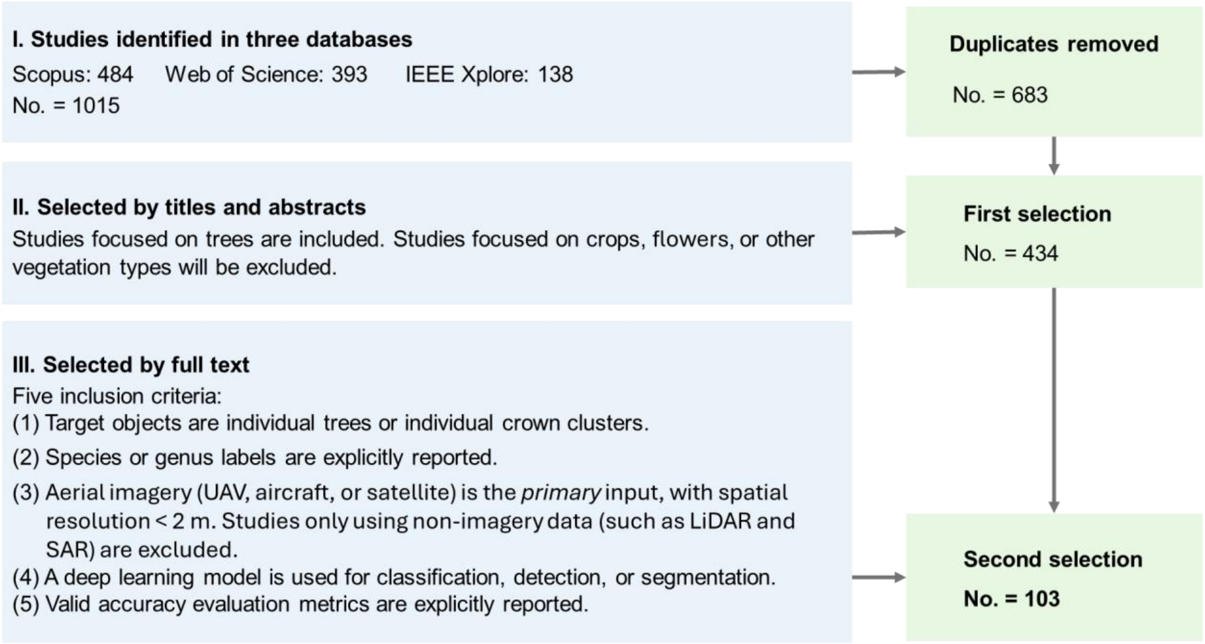
Supplementary Table 6. Full names and references for the architectures reviewed in the TSI studies and their frequencies.

Architecture	Full name	Number of identifications	Reference
ResNet	Residual Neural Network	79	He et al., 2016
DenseNet	Densely Connected Convolutional Network	66	Huang et al., 2017
Mask R-CNN		41	He et al., 2017
DeepLab		38	Chen et al., 2017
Unet	U-shaped Convolutional Neural Network	34	Ronneberger et al., 2015
YOLO	You Only Look Once	29	Redmon et al., 2016
GoogLeNet		28	Szegedy et al., 2014
Faster R-CNN		27	Ren et al., 2016
EfficientNet	Efficient Neural Network	22	Tan & Le, 2020
ResUNet		21	Diakogiannis et al., 2020
VGG	Visual Geometry Group Network	15	Simonyan & Zisserman, 2015
SegFormer		15	Xie et al., 2021
AlexNet	AlexNet Convolutional Neural Network	13	Krizhevsky et al., 2017
ConvNeXt	Convolutional Network Next	11	Liu et al., 2022

ACE R-CNN		9	Li et al., 2022
Inception	Inception Network	7	Szegedy et al., 2015
RetinaNet		7	Lin et al., 2018
DeepForest		5	Weinstein et al., 2020
PointNet++		4	Qi et al., 2017
MobileNet	Efficient Convolutional Neural Networks for Mobile Vision Applications	4	Howard et al., 2017
Swin Transformer		4	Liu et al., 2021
Vision Transformer		4	Dosovitskiy et al., 2021
LeNet		4	Lecun et al., 1998
PSPNet	Pyramid Scene Parsing Network	3	Zhao et al., 2017
SegNet		2	Badrinarayanan et al., 2016
PointNet		2	Qi, Su, et al., 2017
Xception	Extreme Inception Network	2	Chollet, 2017
BiSENet	Bilateral Segmentation Network	2	He & He, 2021
SSMD	Single Shot MultiBox Detector	1	Liu et al., 2016
RepPoints		1	Yang et al., 2019
SENet	Squeeze-and-Excitation Network	1	Hu et al., 2019
DETR		1	Carion et al., 2020
PAA	Probabilistic Anchor Assignment	1	Kim & Lee, 2020
Custom CNN		107	

“Custom CNN” refers to all originally designed CNN architectures in the reviewed literatur

Supplementary figures



Supplementary Figure 1. PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) flow diagram describing the selection phases (in blue) of this review and the final number (No.) of selected papers (in green).

Supplementary note: The full list of publications and all extracted data used in the meta-analysis

See attached supplementary Excel file “*Supplementary_Database_Review_ZX.xlsx*”

This table is available from the corresponding author upon reasonable request.

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