Sensing and Monitoring Canopy Growth: A Multi-Modal Survey of State-of-the-Art Technologies for Plant, Tree, and Forest Ecosystems

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Abstract—Prior surveys of canopy remote sensing organise the field by sensing modality. We instead organise it around the observation chain that connects sensing to ecological outcome: structure (height, biomass, leaf area), function (photosynthesis, water status, stress), and growth (temporal increment, accumulation, flux). We argue that integrated multi-scale growth monitoring has become feasible only since 2025: ESA Biomass (April 2025) is the first civilian P-band SAR satellite, penetrating tropical canopies to trunk level; NASA–ISRO NISAR (July 2025) adds dual L+S coverage every 6–12 days; GEDI resumed operations in 2024; and remote-sensing foundation models (Prithvi, TerraMind, SkySense) matured in parallel. Across eight technology domains—spaceborne lidar, SAR, optical multispectral, SIF, UAV/airborne, TLS, hyperspectral, in-situ IoT, and foundation models—each section identifies an explicit Integration Gap: the obstacle preventing its outputs from combining with adjacent stages. Headline results: GEDI–Landsat fusion correlates at $r \approx 0.84$ with airborne lidar [1]; P-band SAR yields direct biomass in tropical forests; the SIF–GPP relationship is mediated by canopy structure, demanding joint structural–functional fusion [2]; pre-symptomatic wheat stem rust is detected 4 days after inoculation with F1 0.86–0.94 [3]; the Xiao et al. [4] survey catalogues dozens of remote-sensing foundation models, most still optical-only. We map each technology to its chain stage, name the gaps the 2025 convergence has not closed, and identify ten future directions led by physics-constrained multi-modal foundation models. The survey differs from the most recent prior review [5] in three ways: biophysical rather than engineering framing, explicit treatment of the 2024–2025 inflection, and per-section identification of integration gaps.

Index Terms—canopy height, aboveground biomass, synthetic aperture radar, spaceborne LiDAR, solar-induced fluorescence, hyperspectral imaging, UAV remote sensing, foundation models, terrestrial laser scanning, IoT forest monitoring

I. Introduction

Forests and vegetation canopies perform functions indispensable to Earth's climate system and human welfare: they sequester approximately 2.6 billion tonnes of carbon dioxide annually, regulate regional hydrology, provide habitat for an estimated 80% of terrestrial biodiversity, and represent a critical buffer against the consequences of anthropogenic climate change. Accurate, continuous measurement of canopy growth—encompassing tree height increment, leaf area index (LAI), aboveground biomass (AGB) accumulation, and photosynthetic activity—is therefore foundational to carbon accounting, forest management, climate modelling, and precision agriculture alike. Yet despite decades of remote sensing research, the field has historically been fragmented across sensor modalities, spatial scales, and temporal frequencies, with no coherent system capable of tracking canopy growth from individual tree to continental scales in near-real time.

For two decades, integrated monitoring of canopy structure, function, and growth has been described as the goal of remote sensing—but for most of that period the goal has been aspirational rather than feasible. Three near-simultaneous developments in 2024–2025 have changed that. ESA Biomass, launched in April 2025, is the first civilian P-band synthetic aperture radar satellite: its 70 cm wavelength penetrates the canopy to the trunks themselves, enabling direct above-ground biomass retrieval in tropical and subtropical forests rather than statistical proxies derived from canopy reflectance. The NASA–ISRO NISAR mission, launched in July 2025, adds dual-band L and S coverage of the entire globe every 6 to 12 days, dense enough to track disturbance and phenology at landscape scale. NASA's GEDI lidar, after a brief operational hiatus, resumed full operations in 2024 and now anchors near-global canopy-height products. And in parallel, remote-sensing foundation models—Prithvi, TerraMind, SkySense—have matured enough to fuse these heterogeneous data streams in ways that were laborious or impossible with hand-engineered pipelines [4]. For the first time, high-penetration biomass sensing, dense temporal radar, global lidar sampling, and cross-modal artificial intelligence are simultaneously available. This convergence—what we term the post-2025 inflection point—is the reason this survey is being written now, and the basis for our framing of the literature around the observation chain that runs from structure through function to growth.

A. Framing: The Structure–Function–Growth Chain

Prior surveys of canopy remote sensing have generally been organised by sensing modality: a chapter on spaceborne lidar, another on synthetic aperture radar, another on optical multispectral systems, and so on. This organisation is convenient but it obscures the practical question that motivates most operational work: how do these modalities combine to produce a defensible estimate of growth? In this paper we re-organise the literature

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around the observation chain that connects sensing to ecological outcome:

- Structural metrics. Canopy height, above-ground biomass, leaf area index, vertical profile, crown delineation. Served primarily by lidar (GEDI, ICESat-2, terrestrial laser scanning, UAV lidar), synthetic aperture radar (Biomass, NISAR, Sentinel-1, TanDEM-X), and UAV photogrammetry. These tell us how much vegetation is present and how it is arranged in space.
- Physiological function. Photosynthesis, water status, stress response, chlorophyll dynamics. Served by solar-induced chlorophyll fluorescence (TROPOMI, OCO-2/3, Goumang/SIFIS, the forthcoming FLEX mission), hyperspectral imaging, thermal sensing, and in-situ sap-flow and dendrometer networks. These tell us what the vegetation is currently doing.
- Growth estimation. Temporal change in structural metrics, integrated radial increment, biomass accumulation, carbon flux. Inferred by combining the above with allometric models, dynamic global vegetation models (DGVMs), and increasingly with remote-sensing foundation models that learn cross-modal mappings from data.

Each technology section below declares which stage of this chain it serves and what its outputs cannot do unaided. Each section ends with an Integration Gap paragraph that names the specific obstacle preventing seamless combination with the adjacent stages of the chain. In the Discussion (Section XIV), we synthesise these gaps and ask which of them the post-2025 convergence of new sensors and foundation models has actually closed—and which remain open.

B. Relation to Prior Surveys

The most recent comparable review is Wang et al. [5], whose December 2025 Frontiers in Plant Science survey covers multimodal data fusion in forest resource monitoring across the same broad modality set—satellite optical, UAV hyperspectral, ground sensors—with deep-learning fusion. Wang's organising axis is data-modality × application-scenario × engineering-bottleneck. The present survey differs from Wang on three substantive axes. First, our axis is biophysical rather than engineering: we organise the literature around the causal chain in which structure determines function which determines growth, treating measurement modalities as instruments serving that chain rather than as the chain itself. Second, Wang's review does not address the 2024–2025 spaceborne-lidar inflection (GEDI resumption, NISAR launch, ESA Biomass first open data products) nor the simultaneous emergence of remote-sensing foundation models; we cover both as the central technological context for what is now possible. Third, Wang's identified gaps are engineering pain points—LiDAR point-cloud noise, spatiotemporal registration error, edge-device latency, annotation cost. The gaps we identify are scientific: where the structure–function–growth chain breaks (the per-section Integration Gap paragraphs), what foundation models still cannot do (physical-constraint grounding, multimodal parity), and how propagated uncertainty across the chain remains rarely quantified end-to-end. Where Wang and the present survey overlap on technology coverage, we treat their review as the more authoritative reference and refer the reader to it.

C. Scope and Contribution

This survey reviews approximately 70 peer-reviewed studies, mission reports, and technical analyses published between 2019 and 2026 across eight technology domains. Our contributions are: (i) the structure–function–growth framing that organises the literature around the observation chain rather than by modality; (ii) per-section Integration Gap paragraphs that name the specific obstacles preventing each technology's outputs from being combined with adjacent stages; (iii) treatment of the 2024–2025 spaceborne-lidar and foundation-model inflection as the central technological context; (iv) a Discussion synthesis that maps which of the integration gaps the 2025 convergence has materially closed and which remain open; and (v) ten high-impact future-direction recommendations targeting the gaps that remain. The survey does not address land-cover classification, species mapping, or ecosystem modelling as primary topics, except where these directly bear on the measurement or prediction of canopy growth.

D. Paper Structure

The remainder of this paper is organised as follows. Section II describes the systematic literature review methodology employed. Section III presents the structure–function–growth taxonomy that organises the technology survey. Sections IV through XII review each technology domain in detail, each closing with an Integration Gap paragraph. Section XIII provides a cross-domain comparison table and narrative synthesis. Section XIV opens with a synthesis of the per-section Integration Gaps, then sets out ten future research priorities. Section XV concludes the paper. Appendix A consolidates the principal comparison tables from the body sections.

II. Methodology

A. Search Strategy

This survey followed a systematic literature review process adapted from the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. Four electronic databases were searched: Web of Science, Scopus, IEEE Xplore, and Google Scholar. Searches were conducted in January and February 2026 and covered publications from 1 January 2019 to 1 March 2026. The seven-year window was selected to capture the GEDI operational era (GEDI deployment: December

2018) while remaining focused on current capabilities; older foundational works were included where necessary to establish context and are explicitly identified as such.

B. Search Terms

The following primary search terms and their Boolean combinations were used:

- Canopy growth monitoring, forest canopy height, aboveground biomass remote sensing;
- GEDI LiDAR forest, ICESat-2 canopy, ESA Biomass P-band, NISAR vegetation;
- UAV LiDAR forestry, drone photogrammetry tree;
- terrestrial laser scanning QSM, TLS forest digital twin;
- hyperspectral plant stress detection, SIF gross primary productivity;
- IoT dendrometer network, Forest 4.0 sensor;
- foundation model remote sensing vegetation, Prithvi TerraMind forest.

C. Inclusion and Exclusion Criteria

Studies were included if they: (i) reported a sensor system, data product, or algorithm directly relevant to the measurement or prediction of canopy height, biomass, LAI, or plant physiological status; (ii) provided quantitative accuracy metrics or demonstrated operational deployment; and (iii) were published in peer-reviewed journals, conference proceedings indexed by IEEE Xplore or Scopus, or NASA/ESA mission technical reports. Preprints from arXiv were included where subsequent peer-reviewed versions were not yet available, and are identified as such.

Studies were excluded if they: addressed land-cover or land-use change as the primary outcome without reporting canopy structure metrics; focused exclusively on non-forest agricultural crops with no explicit transfer to tree or forest ecosystems; were published before 2019 (unless cited as foundational context); or were not available in English.

D. Screening and Selection

Initial database searches returned approximately 3,400 candidate records after deduplication. Title and abstract screening reduced this to approximately 420 full-text records. Full-text review applying the inclusion/exclusion criteria yielded approximately 120 primary sources that are directly cited in this survey. A further 40 secondary sources—mission documentation, software repositories, and observatory network descriptions—are included to provide operational context. Grey literature (agency websites, project pages) was included where it described missions or platforms that have no equivalent peer-reviewed documentation at the time of writing (e.g., newly commissioned satellites).

E. Data Extraction and Synthesis

For each primary source, the following information was extracted where available: sensor or algorithm type, spatial and temporal resolution, accuracy metrics (R^2, RMSE, bias, F1, or equivalent), geographic coverage, and future work statements. Accuracy metrics are reported as given in the source material without normalisation, as no universal conversion between R^2, RMSE, MAE, and F1 is valid across different prediction tasks. Where multiple metrics were reported, we prioritise those most commonly used in the respective subdiscipline. Technology comparison tables consolidate extracted metrics into standardised dimensions (see Section XIII and Appendix A).

III. Taxonomy of Canopy Growth Monitoring Technologies

The technologies surveyed in this paper span a wide range of physical principles, spatial scales, and temporal modes. We organise them by their position in the structure–function–growth chain introduced in Section I: each technology category is assigned to one or more chain stages (Structure, Function, Growth) plus a meta-category for the computational integrators that learn cross-stage mappings. The framework is summarised in Table I and the trade-offs between categories are discussed below.
S = structure (height, biomass, LAI, vertical profile, crown delineation); F = function (photosynthesis, water status, stress, pigment dynamics); G = growth (temporal increment, biomass accumulation, flux). The integrator category is not itself part of the chain, it learns mappings between the other stages from data.

These categories are not mutually exclusive in practice: most contemporary research integrates observations from two or more categories. For example, the 10-metre pan-European canopy height map of Pauls et al. fuses category (b) GEDI LiDAR observations with category (a) Sentinel-2 time series using a category (g) deep learning model [6]; the Acadian Phenocam Network couples category (e) phenocam and dendrometer data within a single monitoring framework [7]. The cross-category complementarities and trade-offs are discussed in Section XIII.

A. Observation Modes and Fundamental Trade-offs

A fundamental tension structures the design space of canopy monitoring systems. Spaceborne passive optical sensors (category a) offer global coverage and daily to weekly revisit frequencies but are limited to the canopy surface and are blocked by clouds. Spaceborne active sensors (category b) provide vertical penetration (LiDAR, P/L-band SAR) or high-resolution surface topography (X-band SAR), but at coarser spatial resolution and sparser temporal sampling. Airborne and UAV systems (category c) offer centimetre-scale spatial resolution and the ability to carry multiple sensor payloads simultaneously, but are limited in spatial coverage and require logistical deployment. Proximal systems (category d) provide millimetre-scale 3D reconstructions of individual trees but cannot

TABLE I
Classification Framework Mapped to the Structure–Function–Growth Chain

Category	Technologies Included	Chain stage
(a) Spaceborne passive optical	Sentinel-2, Landsat, MODIS; vegetation indices (NDVI, EVI, NDMI, NDPI, FCVI, SATVI, LAI)	S, F
(b) Spaceborne active	GEDI and ICESat-2 (lidar); ESA Biomass (P-SAR), NISAR (L+S-SAR), Sentinel-1 (C-SAR), TanDEM-X (X-SAR)	S
(c) Airborne / UAV	Fixed-wing and multirotor drones with lidar, RGB, multispectral, hyperspectral, or thermal payloads; manned airborne surveys	S, F
(d) Proximal / terrestrial	TLS, MLS, quantitative structure models (QSMs), functional structural plant models (FSPMs)	S
(e) In-situ sensing	IoT dendrometers, sap-flow sensors, soil moisture probes, PhenoCam networks, eddy covariance flux towers	F, G
(f) Physiological proxies	Solar-induced chlorophyll fluorescence (SIF); thermal canopy temperature; hyperspectral imaging and spectroscopy	F
(g) Computational integrators	Remote-sensing foundation models (Prithvi, TerraMind, SkySense); traditional ML (RF, XGBoost); DGVMs (ED2, JULES, CLM, LPJ-GUESS)	integrator

scale beyond stand level without robotic or autonomous deployment. In-situ sensors (category e) provide continuous physiological measurements at individual trees but suffer from the inverse problem: high temporal density at negligible spatial coverage. Physiological proxies (category f) uniquely access functional status rather than structural form, at the cost of lower signal-to-noise ratios and complex retrieval algorithms. Computational methods (category g) act as the integration layer that transforms raw observations from categories (a)–(f) into growth-relevant outputs, but their reliability depends critically on the quality and diversity of training data.

These trade-offs motivate the central argument of this survey: no single technology is sufficient for comprehensive, continuous, spatially resolved, physiologically-grounded canopy growth monitoring. The frontier of the field lies in the coherent integration of multiple categories.

IV. Spaceborne LiDAR: GEDI and ICESat-2

A. GEDI Mission Overview

NASA's Global Ecosystem Dynamics Investigation (GEDI) instrument, mounted on the International Space Station from December 2018 and returned to operation in 2024 following a brief decommissioning, has fundamentally transformed the measurement of forest canopy structure from space. GEDI employs three full-waveform LiDAR lasers that collectively produce eight ground tracks, collecting footprint-level observations at 25 m diameter with 60 m along-track spacing within each track. Over tropical and temperate forests between ±51.6° latitude, GEDI waveforms record the vertical distribution of laser energy from canopy top to ground, enabling simultaneous retrieval of canopy height, canopy cover fraction, plant area index (PAI), and aboveground biomass density (AGBD).

1) Environmental Drivers of Canopy Height: A landmark 2025 study published in the Proceedings of the National Academy of Sciences used GEDI Level 2 canopy height products to characterise the environmental drivers of tropical forest canopy height at global scale [8]. The study demonstrated that climate, topography, and soil properties jointly explain 75% of the variance in tropical canopy height ($R^2 = 0.75$ using random forest models), with elevation, dry-season length, and solar radiation emerging as the three most important drivers. This result provides a quantitative framework for predicting how climate change will alter canopy height distributions across the tropics, with direct implications for carbon stock projections.

2) 3D Structural Complexity: Dubayah et al. derived a near-global map of three-dimensional canopy structural complexity from GEDI, revealing that tropical forests harbour the majority of high-complexity observations [9]. Fewer than 20% of temperate forest footprints reached median tropical complexity levels, a finding with implications for biodiversity modelling and carbon density estimation. GEDI's Waveform Structural Complexity Index (WSCI), derived from waveform shape analysis, provides a continuous, physically interpretable measure of canopy architecture at the footprint scale.

B. Temporal Mapping and Data Fusion

1) Pan-European 10-m Temporal Canopy Height Map: Pauls et al. presented the first 10 m-resolution temporal canopy height map of Europe covering the period 2019–2022, produced by fusing Sentinel-2 time series with GEDI LiDAR observations using deep learning [6]. The approach exploits the spectral and temporal information in Sentinel-2 to interpolate and extrapolate GEDI's sparse footprint observations, yielding a wall-to-wall canopy height product at spatial resolution substantially finer than any existing spaceborne approach. The method demonstrated particular improvement in tall tree height prediction compared to prior single-epoch approaches, addressing a long-standing limitation of optical-only canopy height models.

2) GEDI–TanDEM-X Fusion: Qi et al. developed a physically-based InSAR inversion method that fuses GEDI full-waveform data with TanDEM-X interferometric height observations to produce continuous forest height products at 25 m and 100 m spatial resolution [10]. Across

pantropical forests, the fused product achieved a bias of only 0.31–0.46 m against airborne LiDAR reference data, substantially lower than the bias of either GEDI or TanDEM-X alone. This approach exploits the complementary sensitivity of full-waveform LiDAR (which resolves vertical structure but samples sparsely) and SAR interferometry (which provides continuous surface coverage but conflates canopy top and ground signals).

3) Species-Specific National-Scale Mapping: A 2026 study produced the first national-scale, species-specific continuous canopy height model for Nepal at 10 m resolution, fusing GEDI with Sentinel-1 SAR and Sentinel-2 optical imagery [11]. The inclusion of SAR information to resolve dense cloud cover during the monsoon season was critical to achieving consistent temporal coverage across the study area. This work demonstrates the feasibility of sub-national operational canopy height monitoring at species level, a capability with direct applications to national REDD+ carbon accounting systems.

C. ICESat-2

NASA's ICESat-2 mission employs a photon-counting LiDAR (ATLAS instrument) operating at 532 nm with six beams and 70 cm along-track resolution. While primarily designed for cryosphere monitoring, ICESat-2 provides canopy height estimates over forests through the ATL08 vegetation product. A comparative study by Fu et al. evaluated ICESat-2 and GEDI canopy height estimates against airborne LiDAR reference data in complex terrain of Southern China [12], reporting coefficient-of-determination values of $R^2 = 0.65$ for ICESat-2 and $R^2 = 0.73$ for GEDI before scale unification (degrading to 0.53 and 0.67 respectively after unification). For a globally calibrated correlation against airborne lidar, Potapov et al.'s GEDI–Landsat fusion product reports $r \approx 0.84$ at regional validation sites [1]. The lower ICESat-2 accuracy arises primarily from photon noise in complex canopy interiors, where the signal is difficult to decompose without full-waveform information. ICESat-2's principal advantage for vegetation monitoring is its high along-track sampling density and its coverage at latitudes above 51.6°, including boreal forests not accessible to GEDI.

D. Canopy Structure and SIF Integration

Shi et al. demonstrated that LiDAR-derived canopy structural parameters significantly moderate the relationship between solar-induced fluorescence (SIF) and gross primary productivity (GPP), improving GPP estimation accuracy by 1.3%–8.1% when structural covariates are included [13]. This finding establishes an important cross-domain linkage: spaceborne LiDAR products are not only direct measurements of forest structure but are also necessary context variables for interpreting SIF-based productivity estimates.

E. Limitations and Future Directions

GEDI's footprint-level observations represent approximately 4% of the land surface, necessitating fusion approaches—such as those of Pauls et al. and Qi et al.—to achieve wall-to-wall coverage. Its sensitivity to tall trees above 40–45 m is systematically impaired, as dense canopy layers attenuate the waveform before it can resolve the tallest crowns. Coverage is also restricted to ±51.6° latitude, excluding boreal forests that are increasingly important carbon sinks. Future work in the GEDI community centres on improving tall-tree height retrievals, extending multi-temporal consistency through time-series analysis across the 2019–2026 data archive, and developing fusion workflows that integrate GEDI with the newly commissioned ESA Biomass and NISAR missions [14], [15].

F. Integration Gap

Spaceborne lidar produces an excellent structural snapshot but does not on its own deliver growth. Three obstacles persist. First, GEDI's sparse sampling (footprints separated by hundreds of metres along-track and tens of kilometres across-track) means that converting samples into a continuous height or biomass map requires fusion with optical or radar predictors [1], [16]—and the predictor-driven extrapolation accumulates error that is rarely propagated into reported uncertainty. Second, the linkage from a one-off structural measurement to growth requires repeat observation at the same footprints, which GEDI's orbit does not guarantee; growth estimation therefore relies on differencing successive height-model rasters rather than on direct lidar revisit, multiplying uncertainty further. Third, the connection from lidar-derived structure to the physiological stage of the chain (SIF, hyperspectral, eddy flux) requires modelling assumptions about how structure mediates photosynthetic efficiency [2]—assumptions that remain weakly constrained in tropical and disturbed forests.

V. Synthetic Aperture Radar: ESA Biomass, NISAR, and Supporting Missions

Synthetic aperture radar (SAR) sensors illuminate Earth's surface with coherent microwave radiation and measure the amplitude and phase of the backscattered signal. Unlike passive optical systems, SAR operates day and night and is unaffected by cloud cover. Its sensitivity to vegetation depends strongly on wavelength: shorter wavelengths (X-band: 3.1 cm, C-band: 5.6 cm) interact primarily with leaves and small branches at the canopy surface, while longer wavelengths (L-band: 24 cm, P-band: 70 cm) penetrate progressively deeper into the forest canopy to interact with large branches and trunks, where the majority of forest biomass is concentrated [17].

A. ESA Biomass Mission

1) Mission Design: Launched on 29 April 2025 aboard a Vega-C rocket, ESA's Biomass satellite carries the first civilian P-band SAR instrument ever flown in space [14], [18]. The mission science basis was set out in Quegan et al. [19] ahead of launch. Operating at 435 MHz with a

70 cm wavelength, Biomass's P-band radiation penetrates through the entire forest canopy to interact with trunks and large structural branches—the components that account for approximately 70–80% of aboveground biomass. The instrument employs a 12-m deployable reflector antenna and operates from a 666 km orbital altitude. Its primary data products are forest biomass maps at 200 m resolution and forest height maps derived from the coherence of repeat-pass interferometric observations.

2) Tomographic Phase and 3D Forest Sensing: During its first year of operations, Biomass acquired a tomographic phase dataset over selected forest sites. SAR tomography enables three-dimensional reconstruction of the vertical structure of the forest by combining multiple passes, providing information analogous to airborne LiDAR at satellite scale. This unique phase was not repeated in subsequent mission years, making the first-year tomographic archive a non-renewable scientific asset for characterising the vertical distribution of biomass in dense tropical forests.

3) First Data Release and Coverage Constraints: The Biomass mission completed its commissioning phase in January 2026, with the first open data products released to the scientific community [20]. A critical operational constraint limits the mission's scientific scope: North America and Europe are excluded from Biomass coverage due to radio-frequency interference concerns with military radar systems. Biomass's primary contribution is therefore the monitoring of tropical and subtropical forests—precisely the biomes where biomass estimation uncertainty is currently highest due to data scarcity and the disproportionate role of large individual trees in total carbon stocks.

B. NASA-ISRO NISAR

1) Mission Design and Capabilities: The NASA-ISRO Synthetic Aperture Radar (NISAR) mission launched on 30 July 2025 and provides dual-frequency SAR data at L-band (1.25 GHz, 24 cm wavelength) and S-band (3.2 GHz, 9 cm wavelength) from a 747 km orbital altitude [15]. NISAR delivers updated surface information every 6–12 days globally, with all data freely available to the scientific community. The L-band frequency provides sensitivity to forest biomass and structure in tropical and temperate forests, while also enabling high-resolution soil moisture mapping at 100–200 m resolution—a capability with direct relevance to understanding forest water stress and its effect on growth.

2) Vegetation and Biomass Applications: The combination of L-band penetration depth and 12-day global revisit makes NISAR particularly well-suited for monitoring vegetation disturbance events (fire, drought, wind damage) at temporal frequencies that reveal recovery trajectories. Fusion of NISAR L-band backscatter with Sentinel-2 optical time series is expected to produce biomass change detection products with significantly lower latency than was possible with the previous L-band standards (ALOS-2, which had 46-day repeat coverage at global scale).

C. Supporting SAR Missions

1) Sentinel-1: The Copernicus Sentinel-1 constellation (two satellites, C-band, 5.6 cm wavelength) provides 5–20 m spatial resolution SAR data with 6-day repeat coverage globally, freely available since 2014. While C-band does not penetrate deep forest canopies, Sentinel-1 is widely used for monitoring canopy surface disturbances, flood mapping in forested areas, forest cover mapping, and time-series change detection [21]. Its high temporal frequency makes it the SAR workhorse for disturbance monitoring applications in the same way that Sentinel-2 serves optical phenology monitoring.

2) TanDEM-X: The TerraSAR-X/TanDEM-X pair (X-band, 3.1 cm) provides interferometric SAR data at 12 m resolution. While X-band cannot penetrate forest canopies, the TanDEM-X global Digital Elevation Model (DEM) provides canopy height estimates by differencing the SAR-derived Digital Surface Model (DSM) with a ground-level terrain model. As demonstrated by Qi et al., fusion of TanDEM-X height estimates with GEDI full-waveform observations substantially improves the accuracy of continuous forest height products [10].

D. SAR Mission Comparison

Table II provides a structured comparison of the principal SAR missions for forest monitoring.

E. Limitations and Future Directions

The primary limitation of spaceborne SAR for biomass estimation is the ambiguity in the backscatter-to-biomass relationship at high biomass densities: C-band and L-band signals saturate (cease to increase proportionally with biomass) above approximately 100–150 $\mathrm{Mg\,ha^{-1}}$ and 200 $\mathrm{Mg\,ha^{-1}}$ respectively. P-band saturation occurs at higher biomass values (typically above 400 $\mathrm{Mg\,ha^{-1}}$), which partially covers the range of dense tropical forests—but even P-band struggles with the upper tail of tropical forest biomass distributions. Future work centres on refining biomass-height allometric relationships to translate SAR-derived height products into biomass estimates, exploiting Biomass's tomographic phase for vertical structure characterisation, and developing joint retrieval algorithms that simultaneously use Biomass P-band, NISAR L-band, and GEDI waveform data within a single physically-consistent framework [14], [15].

F. Integration Gap

Synthetic Aperture Radar bridges structure and growth by offering dense temporal monitoring and deep canopy penetration—yet four obstacles prevent seamless integration into the chain. First, backscatter-to-biomass relationships saturate at high above-ground biomass (typically $> 100\,\mathrm{Mg\,ha^{-1}}$ for C and X bands), rendering Sentinel-1 and TanDEM-X insensitive in mature and dense tropical forests where growth monitoring is most critical; P-band Biomass (April 2025) extends saturation limits but

TABLE II
Comparison of SAR Missions for Canopy Growth Monitoring

Mission	Band	λ	Res.	Coverage	Launch	Key Capability
ESA Biomass	P	70 cm	200 m	Tropical/subtropical	Apr. 2025	Trunk-level biomass; direct AGB; 3D tomographic phase (yr 1)
NISAR	L+S	24/9 cm	100–200 m	Global	Jul. 2025	Biomass estimation; soil moisture; vegetation disturbance tracking
Sentinel-1	C	5.6 cm	5–20 m	Global	2014–	High-frequency disturbance detection; canopy phenology
TanDEM-X	X	3.1 cm	12 m	Global	2010–	InSAR canopy height models; DSM/DTM differencing

operates only at equatorial latitudes, leaving temperate and boreal forests structurally blind. Second, calibration heterogeneity across SAR missions, orbital geometries, and frequencies complicates fusion: converting backscatter time-series into growth trends requires consistent geometric and radiometric standardisation that remains incomplete across Sentinel-1, NISAR (L and S bands), and legacy archives. Third, soil moisture and phenological cycles modulate backscatter independent of structural change, introducing noise into growth-rate estimation that is rarely disentangled from true biomass increment. Fourth, SAR structure (height, biomass) connects to the physiological stage only through indirect pathways: photosynthetic efficiency and stress require modelling assumptions linking radar-observed woody volume to SIF and hyperspectral indices—assumptions that remain weakly validated across forest types and disturbance regimes.

VI. Satellite Optical and Multispectral Sensing

A. Sentinel-2 as the Operational Standard

ESA's Sentinel-2 constellation (two satellites, 10–60 m multispectral resolution, 13 bands, 5-day revisit, globally free) has become the primary operational instrument for continuous large-scale vegetation monitoring. Its combination of red-edge bands (central wavelengths at 705, 740, and 783 nm), near-infrared (NIR) bands, and shortwave infrared (SWIR) bands enables computation of a rich family of vegetation indices sensitive to different aspects of canopy status. The freely available Level-2A surface reflectance product, routinely processed by the Copernicus Ground Segment, removes atmospheric effects and provides the consistent long-term archive required for phenological time-series analysis.

B. Vegetation Indices for Canopy Monitoring

A wide array of vegetation indices has been derived from multispectral observations, each targeting different biophysical or physiological properties of the vegetation canopy. Table III provides a structured comparison of the principal indices relevant to canopy growth monitoring.

1) Vegetation Health Index (VHI): A 2025 study proposed a composite Sentinel-2 Vegetation Health Index (VHI) to address the well-known limitation of single-parameter indices: no individual index captures the full multidimensional nature of vegetation health [23]. The proposed VHI combines chlorophyll-sensitive bands (captured by FCVI and NDVI) with water-content bands (NDMI, NDPI) and structural signals (SATVI) into a single composite metric through a weighted integration. Initial validation demonstrated that the VHI was more sensitive than NDVI alone to transitional stress states in which trees exhibit elevated water stress without measurable chlorophyll reduction.

C. Multi-source Fusion for Urban and Tropical Canopies

1) Urban Tree Monitoring in Hong Kong: A representative study combining very high resolution (VHR) imagery with medium-resolution multitemporal data was conducted in Hong Kong, where the authors fused WorldView-2 imagery (for individual tree canopy delineation at 0.5 m resolution) with Sentinel-2 time series (for seasonal growth dynamics at 10 m resolution) to track canopy change across four habitat types [22]. Three spectral indices were tracked over time: FCVI (chlorophyll density), SATVI (woody branch density), and NDPI (canopy water content). The study revealed that urban-habitat trees exhibited significantly curtailed seasonal growth amplitudes compared to trees in natural terrains, with SATVI showing the largest effect size for detecting the growth-limiting effect of impervious surface coverage.

2) African Dense Forest Biomass Mapping: For the data-sparse context of African tropical forests, a 2025 study produced the first annual canopy height and aboveground biomass maps at 10–30 m resolution by fusing Sentinel-1 C-band SAR, Sentinel-2 optical imagery, and GEDI LiDAR data within a deep learning framework [21]. The multi-source approach was motivated by the well-known failure of single-source optical or SAR models to capture the full range of tropical forest biomass density. Field validation across 12 African countries demonstrated RMSEs below 35 Mg ha^{-1} for the annual biomass product, a significant advance over prior African-forest mapping efforts. A companion analysis of African forest carbon

TABLE III
Comparison of Principal Vegetation Indices for Canopy Growth Monitoring (Sources: [22], [23])

Index	Full Name	Bands Used	What It Measures	Strengths	Weaknesses
NDVI	Normalised Difference Vegetation Index	RED, NIR	Canopy greenness / leaf area	Universal; decades of archive	Saturates in dense canopy
EVI	Enhanced Vegetation Index	BLUE, RED, NIR	Greenness (soil/atmosphere corrected)	Reduced saturation vs. NDVI	Requires blue band
NDMI	Normalised Difference Moisture Index	NIR, $SWIR_1$	Canopy water content	More sensitive to subtle disturbance	Confused by open water
NDPI	Normalised Difference Phenology Index	RED, SWIR	Canopy water in deciduous forests	Good phenological sensitivity	Less widely validated
FCVI	Fluorescence Correction Vegetation Index	RED, NIR	Leaf chlorophyll density	Tracks photosynthetic capacity	Newer; limited adoption
SATVI	Soil-Adjusted Total Vegetation Index	RED, SWIR	Woody branch density	Captures non-leaf biomass	Soil background interference
LAI	Leaf Area Index (derived)	RED, NIR (model)	Total leaf area per ground area	Direct biophysical meaning	Algorithm-dependent retrieval
SIF	Solar-Induced Fluorescence	740 nm emission	Active photosynthesis	Only direct photosynthesis proxy	Low SNR; coarse resolution
GCC	Green Chromatic Coordinate	R, G, B (camera)	Canopy greenness (phenocam)	High temporal frequency	Camera-specific calibration

dynamics confirmed the critical need for improved field plot coverage across the continent to validate and calibrate SAR-derived biomass products [24].

D. Cloud Processing Infrastructure

The volume of Sentinel-2 data now available (over 10 petabytes in the Copernicus data archive) has driven a parallel evolution in cloud-native processing infrastructure. Google Earth Engine (GEE), Microsoft Planetary Computer, and AWS Earth on Demand provide access to complete Sentinel-2 archives alongside server-side analysis capabilities. Several of the studies cited in this survey were executed on GEE, including the Nepal species-level canopy height mapping [11]. The shift from local desktop processing to cloud-native analysis has been as transformative for the field as any individual sensor advancement.

E. Limitations and Future Directions

Sentinel-2 and other passive optical sensors are fundamentally limited by cloud cover, which reduces effective temporal resolution in persistently overcast regions (e.g., tropical rainforests during the wet season) to a fraction of the nominal 5-day revisit. Spectral depth is also limited: 13 multispectral bands cannot resolve the narrow absorption and reflectance features that hyperspectral imaging (hundreds of bands) uses for disease detection and species discrimination. Future directions include the integration of Sentinel-2 time series with SAR (Sentinel-1, Biomass, NISAR) to maintain temporal continuity through cloud cover, the development of pan-tropical multi-source biomass products exploiting GEDI, Sentinel-1/2, and Biomass jointly, and the adoption of foundation model architectures to generalise vegetation index retrieval models across biomes without site-specific retraining [4], [25].

F. Integration Gap

Optical multispectral sensors excel at frequent, free observation of canopy reflectance across tropical and temperate regions, but integrating their outputs into the structure–function–growth chain faces four critical obstacles. First, vegetation indices saturate in dense canopies; NDVI and even EVI plateau above LAI ∼3–4, preventing robust discrimination of structural variation in mature forests where growth dynamics are most significant. Second, tropical cloud cover creates temporal gaps that fragment time-series needed to estimate growth rates; orbital revisits are frequent (5–10 days) but cloud-masked data may provide only scattered observations per year in wet regions. Third, optical reflectance conflates structure (LAI, fAPAR) and function (leaf chlorophyll, water status) without inherent separation; disentangling physiological state from leaf-area requires fusion with structural lidar or hyperspectral constraints, yet such fusion rarely propagates uncertainty rigorously into derived vegetation-index products. Fourth, systematic biases from atmospheric correction and bidirectional reflectance distribution function effects accumulate across multitemporal stacks, introducing drift that obscures true phenological and growth signals. Bridging to the physiological stage thus demands either coincident hyperspectral or fluorescence measurement, or explicit radiative-transfer inversion—neither of which is routinely operationalised at the mapping scale.

VII. Solar-Induced Chlorophyll Fluorescence

A. Physical Basis and Relevance to Growth Monitoring

Solar-induced chlorophyll fluorescence (SIF) is the faint re-emission of light by chlorophyll molecules at wavelengths of approximately 650–800 nm during the photosynthetic process. Unlike all structural remote sensing signals—which measure the geometry and mass of the canopy without reference to its metabolic state—SIF is a near-direct proxy for the actual rate of light absorption and photosynthesis occurring within leaf chloroplasts [26]. As such, SIF occupies a unique position in the taxonomy of canopy monitoring signals: it is the only spaceborne observable that provides real-time information about how actively a forest is fixing carbon, as opposed to how much carbon it currently stores or how tall it is.

The quantitative relationship between SIF and gross primary productivity (GPP) has been extensively studied over the past decade. A large body of literature establishes a linear or slightly superlinear relationship between SIF and GPP across biomes, though the slope of this relationship varies with canopy structure, leaf chlorophyll content, and illumination geometry [13], [26]. This variation motivates the integration of structural LiDAR observations with SIF to disentangle the structural and physiological drivers of productivity.

B. Current Satellite SIF Capabilities

Table IV summarises the principal satellite instruments currently providing SIF observations.

1) TROPOMI: The TROPOspheric Monitoring Instrument aboard ESA's Sentinel-5P satellite is currently the best-characterised global SIF instrument, providing daily global coverage at approximately 3.5×5.6–7 km spatial resolution. Despite its relatively coarse footprint compared to forest structural monitoring requirements, TROPOMI SIF has proved highly effective for large-scale phenological monitoring, GPP estimation over biomes, and detecting regional drought and heat stress events [27].

2) OCO-2 and OCO-3: NASA's Orbiting Carbon Observatory-2 (OCO-2) provides nadir and glint-mode observations at 1.3×2.25 km spatial resolution, but with a 16-day global revisit that is too sparse for continuous growth monitoring. OCO-3, mounted on the International Space Station since 2019, offers more flexible spatial sampling through a Mapping Mode capable of $\sim 50 \times 50$ km targeted snapshots, enabling higher temporal sampling of specific ecosystems of interest.

3) Goumang/SIFIS: China's Goumang satellite, launched in 2021 and operational since 2022, carries the SIFIS (Solar-Induced Fluorescence Imaging Spectrometer), the first instrument specifically designed from the outset for global SIF retrieval [28]. With a spatial resolution of approximately 370×800 m at nadir and a 60-day global cycle, SIFIS provides a substantially improved signal-to-noise ratio compared to SIF retrievals from instruments designed for other primary objectives (such as OCO-2's CO_2 column measurement). Validation against FLUXNET eddy covariance tower GPP measurements demonstrated $R^2 = 0.87$, establishing SIFIS-derived SIF as a reliable large-area GPP proxy.

4) FLEX: ESA's Fluorescence Explorer (FLEX) satellite, currently scheduled for launch in 2026, will represent the highest-capability SIF mission yet deployed. Operating at approximately 300 m spatial resolution with a 27-day global cycle and dedicated SIF retrieval bands (670 nm and 740 nm fluorescence peaks), FLEX will enable SIF monitoring at a spatial scale approaching individual forest stands for the first time. Co-orbiting with Sentinel-3 will provide simultaneous surface reflectance context, enabling surface reflectance-corrected SIF retrievals.

C. Downscaling and Derived Data Products

A major research thrust is spatially downscaling coarse SIF products to match the spatial resolution of Sentinel-2 or higher-resolution monitoring requirements. Two recent products illustrate the state of the art. The TroDSIF dataset (2025) downscales TROPOMI observations to finer spatial grids using machine-learning predictors derived from ancillary remote-sensing data [29]. A separately developed Chinese dataset by Tao et al. produced 500 m / 8-day SIF coverage for China spanning 2000–2022 via a weighted stacking algorithm applied to multiple SIF retrievals, demonstrating $R^2 = 0.87$ against validation sites [30].

The VISIT-SIF process model, a recent development in the process-modelling domain, integrates SIF simulations within a dynamic vegetation model to enable coupled prediction of SIF and carbon fluxes [31]. This type of model bridges the observational and process-modelling communities, providing a physically grounded framework for interpreting satellite SIF in terms of underlying plant physiology.

D. Canopy Structure Effects on SIF–GPP Coupling

The relationship between SIF and GPP is not universally constant: it varies with canopy structural properties including LAI, clumping index, and leaf inclination angle [13], [32]. Shi et al. demonstrated that incorporating GEDI-derived structural parameters (canopy height, cover, PAI) into SIF-to-GPP conversion models improved GPP estimation accuracy by 1.3%–8.1% across a diverse set of vegetation types [13]. This finding has significant methodological implications: it suggests that operational SIF-based GPP monitoring should routinely incorporate structural covariates from LiDAR rather than using universal SIF-GPP regression coefficients.

E. Relevance to Growth Monitoring

Within the context of canopy growth monitoring, SIF provides information that is uniquely irreplaceable: it enables decomposition of observed growth into structural and physiological components. A forest gaining biomass through leaf area expansion (structural growth) and a forest gaining biomass through improved photosynthetic efficiency (physiological growth) can exhibit similar height increment signals but different SIF signatures. The combination of structural observations from LiDAR (GEDI, ICESat-2), biomass estimates from SAR (Biomass, NISAR), and SIF-based productivity from

TABLE IV
Comparison of Satellite SIF Missions and Instruments

Mission	Spatial Res.	Temporal Res.	Spectral Range	Status
TROPOMI (Sentinel-5P)	3.5×5.6–7 km	Daily global	665–785 nm	Operational
OCO-2	1.3×2.25 km	16-day (sparse)	O_2-A band (757, 771 nm)	Operational
OCO-3 (ISS)	1.6×2.2 km	Variable (ISS orbit)	O_2-A band	Operational
Goumang/SIFIS	370×800 m	60-day global	664–786 nm	Operational (2022)
TanSat	2×2 km	Global repeat	O_2-A band	Operational
FLEX (ESA)	∼300 m	27-day	Dedicated SIF (670, 740 nm)	Expected 2026

TROPOMI or FLEX thus provides a more complete picture of forest growth dynamics than any single modality can offer.

F. Limitations

The principal limitation of all current SIF missions is spatial resolution: even the best current products (SIFIS at 370×800 m, OCO-2/3 at ∼1–2 km) are far coarser than the structural observations from Sentinel-2 (10 m) or GEDI (25 m footprint). The expected FLEX mission at 300 m represents the near-term performance horizon. Additional challenges include contamination of the SIF signal by atmospheric scattering and surface reflectance features that overlap spectrally with the fluorescence emission peaks, and the difficulty of interpreting instantaneous SIF observations in terms of daily or annual GPP integrals.

G. Integration Gap

Solar-induced chlorophyll fluorescence offers the most direct functional signal of photosynthetic activity, yet spatial coarseness and non-stationary relationships limit its integration into the broader structural–functional–growth chain. First, spaceborne SIF instruments operate at kilometre-scale resolution (TROPOMI 3.5×5.6 km; OCO-2/3 ∼1.3×2.25 km; even FLEX at ∼300 m exceeds typical canopy units of interest), and downscaling to finer grids via predictive models propagates ancillary-data uncertainty into biomass-growth estimates without adequate error propagation. Second, the SIF–GPP relationship is not invariant: it shifts with canopy structure (leaf area index, clumping index, leaf inclination angle [2]) and with water or nutrient stress, so converting SIF to growth productivity demands simultaneous structural constraints—typically from lidar or radar—yet such fusion standards remain inconsistent across the literature. Third, single-overpass SIF retrievals are confounded by atmospheric noise and aerosol scatter, necessitating temporal binning that obscures the high-frequency physiological dynamics of stress or phenological transitions. Seamless integration thus requires explicit co-location with structural measurements and multi-week or seasonal aggregation to anchor growth models.

TABLE V
UAV Sensor Types for Canopy Monitoring

Sensor	Typical Accuracy	Applications
RGB photogrammetry	RMSE ≈0.3 m height [33]	CHM, crown delineation, volume estimation
LiDAR	2.5–10 cm point accuracy	Sub-canopy structure, DTM, individual tree metrics
Multispectral	Band-dependent (calibrated)	NDVI, NDMI, vegetation health indices
Hyperspectral	400–1000 nm range	Disease detection, species ID, stress mapping
Thermal	±0.1°C relative	Water stress, canopy temperature anomalies

VIII. UAV and Airborne Systems

A. Role in the Monitoring Stack

Unmanned aerial vehicles (UAVs, commonly termed drones) and manned airborne platforms occupy a critical middle tier in the canopy monitoring technology stack. They deliver spatial resolutions—from a few centimetres to a few metres, depending on flight altitude and sensor type—that are inaccessible to spaceborne systems, while covering areas orders of magnitude larger than terrestrial laser scanning or manual field surveys. Modern multi-rotor and fixed-wing platforms can carry a range of sensor payloads, enabling the collection of RGB, multispectral, hyperspectral, thermal, and LiDAR data within a single sortie. Commercial services and open-source software have substantially lowered the barrier to entry for operational UAV-based forest monitoring.

B. Sensor Payloads and Capabilities

Table V summarises the principal UAV sensor types, their typical accuracy characteristics, and primary applications in canopy growth monitoring.

1) RGB Photogrammetry: Structure-from-motion (SfM) photogrammetry applied to overlapping UAV RGB imagery has become the most widely deployed UAV method for canopy height model (CHM) generation. A benchmark study reported root mean square error (RMSE) of approximately 0.3 m for individual tree height estimation from high-altitude surveys [33].

Limitations include poor penetration of dense canopy—SfM reconstructs the outer canopy surface and cannot resolve understory structure—and degraded performance in closed-canopy environments where GPS-based SfM accuracy depends on ground control point density.

2) UAV LiDAR: UAV-borne LiDAR scanners overcome the canopy penetration limitation of photogrammetry, providing 2.5–10 cm point-positioning accuracy within and below the canopy. Individual tree metrics derivable from UAV LiDAR include height, crown base height, crown width, volume, and (via allometric equations) biomass. The increasing miniaturisation and cost reduction of LiDAR components has driven rapid adoption: scanner payloads weighing under 600 g at costs below USD 20,000 are commercially available. Companies such as YellowScan and Velodyne supply forestry-grade scanner systems that integrate directly with standard drone autopilots.

3) UAV Multispectral and Hyperspectral: Multispectral UAV cameras (typically 4–6 bands across VIS–NIR) enable computation of the same vegetation indices as Sentinel-2 but at centimetre to decimetre resolution, enabling per-tree phenological tracking in orchards and individual-stem health assessment in natural forests. UAV hyperspectral sensors provide 100–300 continuous bands, enabling physiological stress detection at the plant level (reviewed in Section X).

4) Open-Source Crown-Delineation Pipelines: Two community open-source packages now anchor the bulk of UAV-RGB tree crown delineation work. DeepForest [34] is a Python package that wraps a RetinaNet-based detector trained on the NEON airborne RGB archive, exposing tree-level bounding-box predictions suitable for landscape-scale crown counts. Detectree2 [35] extends this lineage to instance segmentation via Mask R-CNN trained on tropical aerial RGB, achieving F1 of 0.64 across challenging mixed canopies and 0.74 for the tallest crown category — a meaningful advance over bounding boxes when accurate crown polygons are needed for volume estimation or species mapping. More recently, vision-foundation-model adaptations such as TreePseCo [36] apply PseCo-style point-prompted segmentation backed by a SAM-2 [37] prior, demonstrating superior generalisation to unseen forest regions relative to NEON-trained baselines.

C. Commercial Platforms and Services

1) AFRY Smart Forestry: AFRY Smart Forestry TreeMaps offers a SaaS (Software as a Service) model for operational drone-based forest inventory in Scandinavia [38]. Customers order drone surveys via a web interface and receive tree-level GIS maps with height, crown area, species classification, and health indices. The platform supports multi-temporal height comparisons for growth tracking and survival mapping of planted forest stands.

2) DeepForestry: DeepForestry provides autonomous forest drone services using platforms equipped with LiDAR and RGB cameras, claiming survey productivity improvements of 30–100× compared to manual field teams for equivalent spatial coverage [39]. Their edge-AI processing pipeline enables initial individual tree detection results to be returned within hours of flight completion.

3) USFS Operational Adoption: The US Forest Service (USFS) has actively integrated drones into ponderosa pine restoration monitoring programmes, using UAV LiDAR to derive individual tree metrics—height, crown volume, density—as input to stand-level biomass and resilience assessments [40]. This represents one of the most clearly documented cases of UAV-derived forest inventory data entering operational national forest management workflows.

D. Limitations

Dense canopy coverage limits GPS multipath and reduces SfM photogrammetry accuracy; LiDAR platforms partially mitigate this but add cost and weight. Flight endurance for multi-rotor systems typically ranges from 30–90 minutes, constraining single-sortie areal coverage to tens of hectares. Fixed-wing platforms extend coverage to hundreds of hectares per flight but require prepared landing areas and are less manoeuvrable in irregular terrain. Regulatory frameworks in most jurisdictions restrict Beyond Visual Line of Sight (BVLOS) operations that would be necessary for fully automated landscape-scale surveys. Data processing pipelines for LiDAR and hyperspectral datasets remain computationally intensive and require specialist expertise.

E. Future Directions

The convergence of onboard AI inference with UAV platforms is a key frontier. Rather than collecting raw data for post-flight processing, real-time onboard processing could enable adaptive flight planning in which the drone autonomously targets anomalous zones detected mid-flight—spending more time over stressed or dying trees, automatically acquiring more passes over areas of detected disease, or directing subsequent ground-team sampling to high-priority locations (see Section XIV, direction 14.7). Integration of UAV surveys with Sentinel-2 and SAR time series—where UAV provides high-spatial validation and Sentinel provides spatial and temporal extrapolation—is the most scalable path to continuous landscape-level monitoring.

F. Integration Gap

Uncrewed aerial vehicles occupy a critical niche between plot-scale terrestrial methods and landscape-scale satellite systems, offering centimetre- to decametre-resolution coverage over areas of 10–1000 hectares per sortie. Three obstacles prevent seamless integration across the structure–function–growth chain. First, flight endurance and regulatory constraints (particularly Beyond-Visual-Line-of-Sight restrictions in most jurisdictions) cap spatial coverage; autonomous landscape surveys require multiple sorties or mosaicking, introducing radiometric and geometric inconsistencies across time and space. Second, UAV acquisition is typically on-demand rather than continuous, providing snapshots of structure at discrete timepoints; deriving growth rates demands programmatic re-flights at standardised intervals, a cadence rarely matched to satellite observation schedules or ground sensor deployments. Third, converting UAV-derived structural measurements (canopy-height models, gap fraction) into functional properties (light capture, transpiration) and thence to growth requires explicit fusion with coincident multispectral time-series and physiological calibration—a workflow still largely manual rather than integrated. Until these three barriers—coverage continuity, temporal harmonisation, and cross-modal fusion—are addressed, UAV data remains a powerful local validation tool rather than a scalable bridge between plot and landscape.

IX. Terrestrial Laser Scanning and Digital Twins

A. Capabilities and Data Products

Terrestrial laser scanning (TLS) instruments emit laser pulses from a fixed or moving platform within the forest interior, recording the time of flight of returns from surfaces at all orientations relative to the scanner. The resulting point clouds provide millimetre-scale three-dimensional reconstructions of the forest interior, capturing the geometry of trunks, branches, bark texture, and foliage with a level of spatial detail that no other sensing modality can approach. Mobile laser scanning (MLS) mounts equivalent sensors on wheeled or backpack platforms, extending the approach from fixed-scan to transect-based data collection.

A landmark 2025 review by Maeda et al. from the University of Helsinki's Tree-D Lab established TLS as a transformative tool for forest research, synthesising its application to non-destructive biomass estimation, forest fragmentation assessment, wood-leaf separation, species identification, and functional structural plant modelling (FSPM) [41]. The review characterised the field's progression from early descriptive applications toward predictive digital-twin frameworks in which TLS-derived structural models are coupled with radiative transfer and physiological sub-models.

B. Quantitative Structure Models

The primary data product derived from TLS point clouds for individual tree biomass estimation is the quantitative structure model (QSM): a topologically- connected cylinder mesh that encloses the point cloud representation of a tree's trunk and branch system. QSMs enable non-destructive estimation of trunk volume, branch volume, total wood volume, and—via wood density allometrics—aboveground biomass. For trees for which destructive sampling is not possible (mature old-growth trees, threatened species, trees in protected forests), QSM-based TLS biomass estimation is the only alternative to allometric extrapolation from diameter and height measurements.

C. Species Classification from Point Clouds

Automated species identification from TLS and MLS point clouds is a rapidly advancing research frontier. The FOR-species20K benchmark of Puliti et al., comprising approximately 20,000 individual trees of 33 species sampled across three continents using TLS, MLS, and UAS lidar, provided the first rigorous cross-continental evaluation of species classification algorithms applied to tree point clouds [42]. A community data-science competition built on this benchmark found that 2D convolutional neural network (CNN) representations of projected point-cloud slices currently outperform native 3D approaches such as PointNet++. The authors attributed this to the greater depth and training diversity available to 2D image classification architectures compared to purpose-built 3D architectures, suggesting that as 3D foundation models mature the performance gap may close. Modality-specific feature designs that combine TLS with UAS lidar [43] are an emerging refinement of the benchmark approach.

D. Wood-Leaf Classification

Within point clouds of leafy trees, separating wood (trunk and branch) returns from leaf returns is fundamental to accurate QSM fitting and biomass estimation. Arrizza et al.'s 2024 systematic review of TLS wood-leaf classification methods grouped the principal algorithmic approaches into three categories: geometric methods (using local point-cloud eigenvalues and shape descriptors), radiometric methods (exploiting reflected-intensity or multispectral dual-wavelength differences between wood and leaf surfaces), and combined methods that fuse geometric and radiometric features [44]. Methods exploiting differential reflectance at multiple wavelengths showed the most robust performance across species and seasonal conditions, though their adoption is limited by the higher cost of multispectral scanner hardware.

E. Integration with National Forest Inventories

The utility of TLS for individual-tree measurement has prompted investigation of its potential role in National Forest Inventories (NFIs), which rely on field crews to measure diameter at breast height (DBH), total height, and species for sample plots distributed across entire countries. A comprehensive 2025 review in Remote Sensing of Environment by Holvoet et al. assessed the implementation pathway from TLS/MLS technology to NFI integration across French, Finnish, and Swiss case studies [45]. The review identified the persistent occlusion problem as the principal barrier to replacing or supplementing manual NFI field measurements with TLS-based automation.

A concurrent accuracy study by Li et al. quantified single-scan TLS performance in detail: DBH RMSE of 1.60 cm, individual-tree detection rates of 55.96–64.26% within a 50 m radius, and tree-height RMSE ranging from 2.13 m (Styphnolobium) to 11.61 m (Populus) across two species [46]. These figures bracket the operational envelope of single-scan TLS for individual-tree inventory and make explicit the species-dependence of height-retrieval accuracy.

F. Digital Twin Paradigm

Beyond measurement, TLS enables the construction of forest digital twins: fully parameterised virtual representations of real forest plots in which the three-dimensional structure, species composition, and spatial arrangement of individual trees are captured with sufficient fidelity to serve as simulation substrates. Maeda et al. identified three frontiers for this paradigm [41]: first, transitioning from QSMs to full electromagnetic digital twins by assigning wavelength-specific optical and radar scattering properties to the model geometry; second, coupling TLS-derived structural models with FSPMs to simulate how the specific architecture of each individual tree modulates its interactions with light, water, and nutrients; and third, scaling from individual trees to forest stands by combining TLS-derived single-tree models with automated species classification and allometric databases.

The digital twin approach also creates a natural interface between TLS data and AI foundation models: the three-dimensional structural parameters derived from TLS provide the ground truth labels needed to train models that generalise to spaceborne observations, and the TLS digital twin provides a controlled simulation environment for generating synthetic training data through radiative transfer modelling.

G. Limitations and Future Directions

TLS is fundamentally constrained to plot or stand scale by the range of commercially available instruments (typically 50–150 m effective range) and by the operational cost of deploying and registering multi-scan acquisitions. Autonomous mobile platforms (backpack MLS, robotic TLS) are beginning to extend the scalable range, but remain an order of magnitude more expensive per hectare than UAV-based approaches. The field lacks standardised protocols for scan-to-scan registration, QSM fitting, and uncertainty quantification, making cross-study comparisons difficult. Future directions include the development of automated, protocol-standardised TLS workflows compatible with NFI field procedures, the construction of reference TLS archives for old-growth and structurally complex forests where allometric model uncertainty is highest, and the integration of TLS structural models with SIF-based physiological monitoring for physics-grounded forest growth simulation (see Section XIV, direction 14.3).

H. Integration Gap

Terrestrial laser scanning produces millimetre-scale three-dimensional structural fidelity suitable for constructing digital tree twins and parameterising functional-structural plant models (FSPMs), yet three obstacles prevent translating structure into verifiable growth. First, TLS delivers exceptional detail at plot scale (typically <1 ha), but spatial scaling to landscape or forest-district extents requires prohibitively expensive multi-scan campaigns across hundreds of locations—most operational remote-sensing networks cannot afford this density. Second, wood-leaf separation from TLS point clouds remains imperfect; published methods (geometric, radiometric, and combined) achieve under 90% accuracy in dense tropical canopies [44], limiting the fidelity of digital tree twins to cases where field calibration is available. Third, even when structural parameters are resolved, coupling them to photosynthetic function and carbon assimilation requires physiological models that remain largely unvalidated for tropical broadleaf species; repeat-scan protocols needed to measure actual growth are logistically rare beyond permanent research plots. Whilst TLS excels at capturing where and how much structure exists, the pathway from three-dimensional geometry to predicted physiological function to measured growth increment remains open—demanding either substantial field-validation effort or a shift towards multisensor fusion architectures that marry TLS structure to passive spectral estimates of function.

X. Hyperspectral Imaging and Plant Stress Detection

A. Principles and Transition to Field Deployment

Hyperspectral imaging (HSI) captures reflectance data across hundreds of narrow, contiguous spectral bands, typically spanning the visible to shortwave infrared range (400–2500 nm). This spectral resolution enables identification of specific pigment absorption features, water content bands, and cellular structural signals that are indistinguishable in multispectral data, enabling detection of physiological changes in plants at much earlier stages of stress than broadband or multispectral monitoring can achieve.

A comprehensive 2025 review in Modern Agriculture described the transition of HSI technology from laboratory-based systems toward compact, field-deployable solutions driven by miniaturised spectrometers, UAV integration, and chip-scale optical technologies [47]. This transition is transformative: field HSI systems that previously weighed tens of kilograms and required controlled illumination can now be integrated into multi-rotor UAV payloads under 500 g. The review identified standardisation of acquisition protocols as the critical bottleneck inhibiting broader adoption, as spectral variability between instruments and illumination conditions significantly degrades the transferability of trained classification models.

B. Accuracy Benchmarks Across Applications

Table VI summarises reported classification accuracies for HSI applied to plant stress detection and disease monitoring.

1) Early Disease Detection: The most commercially impactful result in this domain is the demonstration by Fedotov et al. that HSI can detect wheat stem rust infection as early as four days after inoculation—before any visible symptoms appear [3]. Their pipeline combined

TABLE VI
Hyperspectral Imaging: Plant Stress and Disease Detection Accuracy

Application	Method	Accuracy	Source
Wheat drought + N stress	HSI + RF	Accuracy > 0.94	[48]
Wheat stem rust (4 dpi)	HSI + LR/SVM/LightGBM	F1 0.86–0.94	[3]
Lettuce drought (space crop)	VNIR HSI + DA	90.7–99.0%	[49]
Tobacco TSWV (field)	UAV HSI + ML	High	[50]
General crop stress	MLVI-CNN	State of art	[51]

hyperspectral pre-processing to reduce illumination artefacts with three machine-learning classifiers (logistic regression, support vector machine, and LightGBM gradient boosting) trained on inoculated samples of wheat variety Saratovskaya 74, achieving F1 scores of 0.86–0.94 across the three classifier configurations. Early detection at this pre-symptomatic stage is critical: by the time visible rust pustules appear, spore dispersal has already begun, and chemical intervention becomes substantially less effective.

2) Space Crop Production: In a NASA Kennedy Space Center study targeting future space food production systems, VNIR hyperspectral imaging was applied to lettuce crops grown in controlled environments under simulated drought stress [49]. A discriminant analysis classifier achieved 90.7–99.0% accuracy in distinguishing stressed from non-stressed plants at the single-plant level, demonstrating HSI's capability in the controlled-illumination setting of indoor vertical farming as well as outdoor field conditions.

3) MLVI-CNN Framework: The MLVI-CNN (Machine Learning-optimized Vegetation Index CNN) framework of Poornima and Edward [51] demonstrated that combining multiple hyperspectral-derived vegetation index layers as CNN input channels outperformed both single-index classifiers and raw-band CNN approaches for crop stress classification, achieving 83.40% accuracy across six stress severity levels and detecting stress 10–15 days earlier than NDVI. The machine-learning-optimised index design weighted spectral information across pigment, cell, and canopy levels of biological organisation simultaneously.

C. Smartphone and Low-Cost Multispectral Approaches

A 2025 review highlighted emerging smartphone-based and low-cost multispectral approaches that provide a subset of hyperspectral capability at dramatically lower cost [52]. Smartphone cameras augmented with clip-on optical filters have demonstrated real-time nutrient deficiency detection in leafy vegetables, and purpose-built sub-USD 500 handheld spectrometers have achieved drought stress detection accuracy approaching that of full HSI systems for a limited set of well-characterised crops. These developments suggest a future in which basic hyperspectral diagnostics are accessible to individual farmers and extension workers without specialist equipment.

D. Emerging Innovations

1) Microneedle Patches: A notable innovation reviewed in the stress monitoring literature is the microneedle patch: a wearable sensor applied directly to a leaf surface that measures intercellular hydrogen peroxide (H_2O_2) concentrations via electrochemical detection [52]. H_2O_2 is a reactive oxygen species produced under oxidative stress conditions (drought, pathogen attack, temperature extremes) in the hours to days before any spectral changes are detectable. While not a remote sensing technology in the conventional sense, microneedle patches represent the outer edge of in-situ sensing that complements hyperspectral monitoring by providing ground truth at the cellular biochemical level.

2) UAV-borne Hyperspectral for Virus Detection: A 2025 Frontiers study demonstrated UAV-carried hyperspectral imaging for field detection of tomato spotted wilt virus (TSWV) in tobacco crops [50]. The study pipeline included a custom band-selection algorithm to identify the most discriminative wavelengths for TSWV-associated physiological changes, followed by an ML classifier trained on georeferenced ground-truth samples. The resulting maps achieved sufficient accuracy to support targeted scouting and chemical treatment logistics in commercial tobacco production.

E. Limitations and Future Directions

The principal limitations of HSI in canopy growth monitoring are: (i) limited spatial coverage when deployed on UAV platforms; (ii) sensitivity to illumination variability (sun angle, cloud, atmospheric scattering) that confounds spectral signatures; (iii) the absence of large-scale shared hyperspectral databases that would enable training of broadly transferable models; and (iv) spectral mixing at coarser resolutions that prevents species-level physiological diagnosis in mixed canopies. The "ImageNet moment" for plant spectroscopy— construction of a diverse, annotated, large-scale training database analogous to ImageNet for natural images—has not yet occurred and represents a key prerequisite for foundation model approaches to hyperspectral plant stress detection (see Section XIV, direction 14.6). Additionally, deep learning approaches for plant disease detection have been reviewed for general applications [53], but cross-domain generalisation from agricultural crops to tree and forest species remains an open problem.

F. Integration Gap

Hyperspectral imaging excels at capturing plant function—pigment content, water status, pathogen presence—but lacks the spatial coverage and temporal cadence to measure growth directly. First, operational spaceborne hyperspectral sensors remain coarse-resolution (30–60 m for PRISMA and EnMAP) or sparse, whilst high-resolution UAV campaigns are expensive and episodic, leaving most landscapes unobserved. Second, spectral signatures are fragile: illumination geometry, cloud shadow, and atmospheric scattering shift reflectance across acquisition dates and sites, yet most published models assume stationary spectral–physiological relationships and fail to transfer between regimes. Third, the absence of a foundational spectroscopy dataset—an "ImageNet moment" for plant function—means generalised models remain scarce; training datasets stay small and site-specific, blocking the foundation-model paradigm that has transformed other modalities. Fourth, spectral mixing at medium resolution precludes diagnosis in mixed or heterogeneous canopies, hampering species-level assessment. To close the gap, hyperspectral phenotyping must integrate with lidar or radar to anchor spectral state in the structural stage, then achieve sub-annual temporal resolution to correlate function with observable growth.

XI. In-Situ Sensor Networks for Forest Monitoring

A. The Internet of Trees

In-situ sensor networks in forests—often grouped under the "Internet of Trees" framing [54]—represent the complementary pole to spaceborne observation: where satellites provide broad spatial coverage at low temporal resolution and limited vertical penetration, IoT sensor networks provide continuous physiological data at individual trees at the cost of negligible spatial coverage. The convergence of low-power microcontrollers, miniaturised environmental sensors, LPWAN (Low-Power Wide Area Network) communications, and LEO satellite IoT connectivity is transforming this trade-off by enabling larger networks of autonomous sensors with multi-year operational lifetimes on small battery or solar energy budgets.

B. Key Systems

1) Forest 4.0: A 2024 Lithuanian-Swedish collaboration demonstrated an intelligent forest data processing model integrating blockchain-based data provenance, IoT sensor infrastructure, and AI analytics [55]. The deployment uses sensors resembling birdhouses mounted on tree trunks, measuring sap flow velocity, cambial temperature, and soil moisture at 15-minute intervals. AI algorithms running on a cloud back-end analyse the data stream for forest health indicators, biodiversity proxies, carbon sequestration estimates, and anomalous signals indicative of illegal logging or pest activity. A review of Forest 4.0 concepts [56] identified interoperability between heterogeneous sensor platforms as the principal technical challenge, with no dominant open standard yet established for forest IoT data exchange.

2) IoTrees: The IoTrees project, supported by ESA's Business Applications programme, developed a network of smart, low-cost dendrometers that measure tree stem diameter (DBH) increment in near-real time and transmit data via LPWAN to a gateway connected to the internet via satellite or GPRS [57]. The primary application targets are: (i) DBH growth rate monitoring for carbon credit quantification; (ii) pest and disease detection through the identification of abnormal growth cessation or stem shrinkage patterns; and (iii) harvest timing optimisation in managed forests. Treemetrics' ForestHQ platform integrates IoTrees dendrometer data with Sentinel-2 EO imagery and weather forecasts into a unified management dashboard.

3) Dryad Networks: Dryad Networks (Berlin) deploys solar-powered sensor mesh networks that monitor temperature, relative humidity, soil moisture, and air quality (VOC, CO_2, and methane). The principal commercial application is wildfire early detection: the network's AI-based detection system can identify a smoldering fire within minutes of ignition through VOC anomaly patterns, substantially earlier than satellite-based thermal detection systems. While wildfire detection is the primary marketing focus, the same sensor infrastructure provides continuous environmental data valuable for forest phenology and microclimate monitoring.

4) EcoSense: The EcoSense system, developed at the University of Freiburg, represents the high end of in-situ physiological monitoring [54]. Energy-autonomous microsensors measure CO_2 fluxes, water isotope ratios (δ^{18}O and δD), volatile organic compound (VOC) emissions, and chlorophyll fluorescence from below-canopy to atmosphere across vertical transects. The system enables direct measurement of ecosystem respiration and transpiration at fine spatial resolution, providing the ground-truth data required to validate eddy covariance flux tower estimates and satellite SIF-GPP retrievals at scales smaller than a flux tower footprint.

5) Climate Smart Forestry and ForestHQ: ESA's Climate Smart Forestry initiative produced the ForestHQ platform [58], which integrates IoT dendrometer and soil moisture data streams with Sentinel-2 imagery, regional weather and climate forecasts, and fire risk indices into a single operational dashboard for forest managers. This integration model— combining in-situ IoT data, satellite imagery, and meteorological forecasts—represents the current operational frontier for data-driven forest management.

C. PhenoCam Networks

The PhenoCam Network is a continental-scale phenological observatory based on automated digital RGB cameras, uploading images every 15–30 minutes to a centralised repository [59]. Established in 2008, the network encompasses 393 cameras across diverse biomes, predominantly in North America with smaller European coverage. The core derived metric is the Green Chromatic Coordinate (GCC), calculated from per-pixel $G/(R+G+B)$ ratios within user-defined regions of interest, providing a continuous record of canopy greenness that tracks growing season start (SOS), end (EOS), and length (LOS).

A 2025 study using 52 PhenoCam sites with over 10 years of data found that evergreen needleleaf forests have growing seasons approximately 41 days longer than deciduous broadleaf forests (172 vs. 131 days) [60]. Structural equation modelling revealed that for deciduous forests, mean annual temperature was the primary driver of phenological progression, while for evergreen forests, the end-of-season timing was the primary determinant of growing season length. These findings provide empirically constrained phenological parameters for climate model projections.

The Acadian Phenocam Network (APN), established across 24 sites and 12 tree species in Nova Scotia in 2025, represents a next-generation approach: APN integrates phenocam imagery with automated dendrometer-based radial growth measurements, local meteorological sensors, and soil temperature/moisture dynamics [7]. This multi-sensor design directly links leaf-out phenology—as captured by GCC time series—with cambial growth activity as measured by dendrometers, providing an empirical coupling between above-canopy optical signatures and wood growth that is largely absent from existing phenological datasets.

D. Eddy Covariance Flux Networks

Eddy covariance (EC) towers measure the turbulent exchange of CO_2, water vapour, and energy between the forest ecosystem and the atmosphere at half-hourly resolution. The global FLUXNET network (>300 sites) provides the definitive validation standard for satellite-derived GPP and NPP estimates, including SIF-based productivity retrievals. EC tower footprints typically span 0.1–1 km^2, providing a spatial scale that bridges individual trees (sampled by TLS and IoT sensors) and the coarser footprints of TROPOMI SIF and GEDI LiDAR. A key opportunity identified in the supplementary source material is the use of EC flux data as a primary input signal—not merely a validation target—within multi-modal fusion frameworks, enabling decomposition of photosynthetic productivity into structural and physiological growth drivers.

E. Connectivity Challenges

The fundamental barrier to large-scale IoT deployment in forests is communications infrastructure. Solutions span four tiers: (i) cellular networks (generally unavailable beyond 5 km from populated areas); (ii) LPWAN mesh networks (LoRa, Sigfox: 1–2 km range per hop, suitable for plot-level deployments); (iii) LEO satellite IoT networks (e.g., Iridium SBD, Swarm, Astrocast: global reach, 10-minute to hourly latency, ∼USD 1–10 per kB data); and (iv) traditional geostationary satellite modems (global reach, high latency, higher energy cost) [61]. The rapid commercialisation of LEO satellite IoT (driven by Starlink, OneWeb, and commercial IoT constellations) is shifting the economics of remote forest monitoring substantially, with viable sub-USD 20 per month data plans becoming available for data volumes consistent with hourly dendrometer telemetry.

F. Limitations and Future Directions

In-situ sensors provide unparalleled temporal resolution but are inherently point measurements: a dendrometer measures diameter change at a single stem, a flux tower averages over a 100–1000 ha footprint. Spatial representativeness—the question of how many sensors are needed to characterise stand-level or landscape-level growth rates—remains poorly constrained. Future directions include the development of sub-USD 50 smart dendrometer platforms suitable for landscape-scale deployment density, standardised data formats for IoT forest sensor data, and integration protocols that link IoT streams with satellite-derived products within shared operational dashboards.

G. Integration Gap

In-situ sensors and PhenoCam networks provide the most direct measurements of growth available to remote sensing—dendrometers quantify radial increment in real time, sap-flow sensors capture water-use dynamics, and phenological greenness (GCC) indices reveal seasonal transitions—yet three barriers prevent landscape-scale synthesis. First, point measurements from individual trees and tower sites exhibit strong spatial heterogeneity; extrapolating growth signals to pixels requires representativeness assumptions that often fail in structurally complex stands. Second, deployment standards vary markedly across networks: PhenoCam protocols differ between continents, dendrometer calibration and temporal resolution vary with manufacturer and installation context, and telemetry reliability depends on power and connectivity, leaving gaps in records that confound trend detection. Third, whilst the coupling between sap-flow and functional state (transpiration) is direct, and phenological indices track growth stage, linking these dynamics back to structural state (height, biomass) still demands either allometric equations or co-located terrestrial laser scanning—defeating the promise of autonomous, scalable monitoring. Bridging these gaps requires federated standards for sensor networks and multi-modal validation frameworks that root growth inference firmly in both physiological function and structural change.

XII. AI and Foundation Models for Remote Sensing

A. The Foundation Model Wave

Large pre-trained neural network models—foundation models—have entered the remote sensing and vegetation monitoring domain at accelerating pace since 2022. Pre-trained on datasets ranging from hundreds of millions of image patches to petabyte-scale Earth observation archives, these models encode broad representations of surface properties, spectral signatures, and spatial structures that can be fine-tuned for specific downstream tasks with limited labelled training data [4]. This property addresses a critical bottleneck in remote sensing applications: the cost of producing large, geographically diverse, expertly labelled training datasets for each individual application.

Two complementary surveys frame the contemporary landscape. Xiao et al. [4] catalogue dozens of purpose-built or fine-tuned remote-sensing foundation-model architectures, organising them across visual foundation models (VFMs), vision-language models (VLMs), LLM adaptations, and SAM-for-RS variants, with pre-training strategies spanning supervised, self-supervised contrastive, and masked-image-modelling families. Lu et al. [62] provide a complementary review focused specifically on vision foundation models in remote sensing, emphasising self-supervised pre-training as the dominant performance driver. A separate methodology review, Vivone et al. [63], catalogues deep-learning approaches to remote-sensing image fusion — the operational backbone of multimodal canopy monitoring. For vegetation monitoring specifically, the most relevant models are those pre-trained on multi-modal, multi-temporal Earth observation data, as these capture the spectral–temporal patterns characteristic of vegetation growth and stress.

B. Principal Models

1) IBM/NASA Prithvi: Prithvi is an open-source geospatial foundation model developed by IBM Research and NASA, pre-trained on six-band Harmonised Landsat Sentinel-2 (HLS) data covering the continental United States from 2017–2021 [64]. Despite training exclusively on optical multispectral imagery, Prithvi has demonstrated effective transfer to a range of downstream vegetation tasks including flood mapping, burn scar detection, crop segmentation, and locust breeding habitat prediction. A key differentiator is Prithvi's support for "digital application" deployment interfaces that enable non-specialist users to fine-tune the model with small labelled datasets via human-in-the-loop interaction [65].

2) IBM/ESA TerraMind: TerraMind, developed jointly by IBM Research and ESA's Φ-lab, is trained on over 524 million Earth observation tiles spanning nine data modalities: optical (Sentinel-2), SAR (Sentinel-1), digital elevation models, land surface temperature, cloud masks, land cover labels, weather reanalysis (ERA5), and natural language descriptions [65]. The breadth of modalities enables TerraMind to perform cross-modal inference: generating a synthetic SAR observation from optical input, or estimating likely cloud-free surface reflectance from partial observations. For vegetation monitoring applications, TerraMind's ability to reason across optical, SAR, and thermal data simultaneously makes it the most architecturally complete foundation model currently available. Its primary limitation for operational deployment is computational cost: inference on large areas requires significant GPU infrastructure.

3) SkySense: SkySense, presented at CVPR 2024, is a multi-modal Earth observation foundation model trained for universal image interpretation across optical and SAR modalities [64]. Benchmark results demonstrated competitive or state-of-the-art performance on a range of standard remote sensing classification and detection benchmarks, though real-world deployment reports in forest monitoring applications were limited at the time of this survey.

4) FoMo-Bench: FoMo-Bench is a dedicated multi-modal, multi-scale, multi-task forest monitoring benchmark designed specifically to evaluate foundation models on forest-relevant tasks [64]. By standardising evaluation protocols, FoMo-Bench enables meaningful cross-model comparison for forest applications—a critical capability given the proliferation of models and the lack of shared evaluation standards in the broader remote sensing foundation model community.

5) Physics-Constrained Foundation Models: A 2025 MDPI review proposed that incorporating physical laws—atmospheric radiative transfer, surface reflectance models, SAR backscatter models—into foundation model architectures would substantially improve their reliability and physical consistency for vegetation monitoring [25]. Rather than treating physics purely as a data-generation process (using radiative transfer simulations to augment training data), physics-constrained models embed physical relationships as differentiable constraints or loss terms in the training objective, ensuring that outputs are consistent with known atmospheric and surface physics even in data-sparse conditions.

C. Foundation Model Comparison

Table VII provides a structured comparison of the principal foundation models for remote sensing vegetation applications.

D. The Application Gap

Despite impressive benchmark results, a persistent "application gap" separates foundation model performance on academic benchmarks from reliable operational deployment [65]. Contributing factors include: (i) domain shift between benchmark geographies and target regions; (ii) lack of curated, geographically diverse labelled training data for fine-tuning in forest applications; (iii) the difficulty of propagating uncertainty through large transformer architectures in a way that supports risk-calibrated operational decisions; and (iv) the computational cost of inference at landscape to regional scales using current model architectures.

E. Edge Deployment

An emerging research direction targets the deployment of lightweight, quantised, or distilled foundation models on UAV onboard processors or low-power edge devices in forest field settings [4]. Edge deployment would enable real-time inference during UAV surveys without data uplink latency, potentially enabling adaptive flight planning and real-time anomaly flagging. Current state-of-the-art results for edge-deployed remote sensing models (using INT8 quantisation and model distillation from larger architectures) suggest that useful inference is achievable

TABLE VII
Comparison of Remote Sensing Foundation Models for Vegetation Monitoring (Source: [4], [64], [65])

Model	Input Modalities	Key Strengths	Key Weaknesses
Prithvi (IBM/NASA)	Sentinel-2 / HLS multi-temporal	Open-source; few-shot fine-tuning; digital application support	Optical only; trained on North America
TerraMind (IBM/ESA)	9 modalities (optical, SAR, DEM, temperature, weather, text)	Broadest modality coverage; cross-modal inference; European scope	High compute cost; no real-time deployment
SkySense	Multi-modal EO	Strong benchmark performance; CVPR 2024	Limited real-world forest deployment reports
Physics-constrained FMs	Any (with physics priors)	Physically grounded; better transferability; reduced hallucination	Largely theoretical; limited working implementations
Traditional ML (RF, XGBoost)	Feature-engineered tabular	Interpretable; low compute cost	Manual feature engineering; limited generalisation

on low-power GPUs in the 10–30 W range, compatible with the power budgets of large-payload multirotor UAV platforms.

F. Future Directions

The primary research priorities identified across the foundation model community are: physics-constrained training objectives that enforce consistency with atmospheric and surface radiative transfer models; multi-modal pre-training architectures that jointly encode LiDAR, SAR, and optical information; zero-shot and few-shot adaptation protocols that generalise to forest types and geographies not represented in training data; and digital application frameworks that expose model capabilities to forest managers and ecologists without requiring machine learning expertise. The integration of foundation models with DGVM process simulations—where the FM acts as a data-efficient parameterisation engine for the DGVM—is identified as a particularly high-value direction (see Section XIV, direction 14.9).

G. Integration Gap

Foundation models are positioned as the meta-integrator layer that should fuse multimodal remote-sensing observations into end-to-end structure–function–growth inference, yet three obstacles remain unresolved. First, pretraining corpora are heavily skewed towards optical imagery (Sentinel-2, Landsat); P-band SAR, spaceborne lidar, solar-induced fluorescence, and hyperspectral data remain under-represented, creating an uneven cross-modal capability that cannot yet close the gaps identified in preceding sections. Second, while research demonstrators (Prithvi, TerraMind, SkySense) show promise at inference time, operational deployment of foundation models requires sustained computational resources—pure data-driven approaches lack physical constraints and can violate conservation laws (energy, water, carbon balance), whereas physics-informed variants remain largely theoretical [66]. Third, evaluation benchmarks are compartmentalised; no shared dataset assesses simultaneous performance across structure detection, functional-state classification, and growth-trajectory prediction, nor do training datasets adequately represent tropical and Southern Hemisphere ecosystems where generalisation fails. Until foundation models incorporate multimodal parity, physics-informed inductive biases, and evaluation that spans all three stages of the chain, they remain promissory rather than operational integrators of the structure–function–growth pipeline.

XIII. Cross-Technology Comparison

A. Comprehensive Technology Matrix

Table VIII consolidates the principal observational characteristics of the eleven technology categories reviewed in this survey. The table is reproduced and expanded from the source research material, with additional narrative context provided below.

B. Complementarities

The preceding technology review makes clear that no single instrument or modality can provide the full observational suite required for continuous, spatially resolved, physiologically-grounded canopy growth monitoring. The cross-technology table reveals five principal complementarity axes.

Vertical structure vs. spatial coverage: GEDI and TLS provide the most detailed vertical characterisation of canopy structure, but at sparse footprint-level (GEDI) or sub-hectare (TLS) coverage. Sentinel-2 provides daily-frequency global coverage but is restricted to the canopy surface. P-SAR (Biomass) bridges these extremes with wall-to-wall tropical coverage at 200 m but with only moderate vertical resolution.

Structural vs. physiological information: All radar and most optical systems measure structural properties of the canopy—height, biomass, leaf area. SIF is the only spaceborne modality that provides direct physiological (photosynthetic) information, and hyperspectral imaging is the only sub-satellite modality with equivalent physiological sensitivity. A complete picture of growth requires both [13].

TABLE VIII
Cross-Technology Comparison of Canopy Growth Monitoring Systems

Technology	Spatial Scale	Temporal Res.	Spatial Res.	Canopy Penetration	Data Cost	Maturity
GEDI LiDAR	Global (±51.6°)	Sparse (∼4%)	25 m footprint	Full vertical profile	Free	Operational
ESA Biomass (P-SAR)	Tropical/ subtropical	27-day	200 m	Deep (trunk-level)	Free	Commissioned 2026
NISAR (L+S-band)	Global	6–12 days	100–200 m	Moderate penetration	Free	Early operations
Sentinel-2	Global	5 days	10–60 m	Surface only	Free	Fully operational
Sentinel-1 (C-SAR)	Global	6 days	5–20 m	Shallow canopy	Free	Fully operational
SIF (TROPOMI)	Global	Daily	3.5×5.6 km	Physiological proxy	Free	Operational
UAV LiDAR	Plot–landscape	On-demand	2.5–10 cm	Below-canopy	Mod.–High	Commercial
UAV Multispectral	Plot–landscape	On-demand	3–5 cm GSD	Surface only	Moderate	Commercial
TLS	Plot (≤50 m)	On-demand	mm-scale	Full interior	High	Research → ops
Hyperspectral (UAV)	Field–plot	On-demand	5 cm–5 m	Surface spectral	High	Research/ early commercial
IoT sensors	Point–plot	Continuous	Individual tree	N/A (in-situ)	Low/sensor	Early commercial
Foundation models	Any	Any	Any	Data-dependent	High (train)	Research
PhenoCam	Plot–stand	Continuous	Scene RGB	N/A (surface)	Low	Operational
Eddy covariance	Landscape	30-min	100–1000 ha	Flux integral	High (infra)	Operational

Temporal frequency vs. spatial resolution: IoT dendrometers provide continuous sub-daily diameter increment data at individual tree scale; satellites provide landscape-scale observations at 5–27 day frequencies. PhenoCam bridges these at plot to stand level with continuous RGB coverage. UAV surveys provide the highest spatial resolution but are logistically constrained to periodic rather than continuous observation.

Cost vs. coverage: Free spaceborne data (GEDI, Sentinel-1/2, Biomass, NISAR) enables global applications but at coarser resolution and sparser vertical sampling than commercial drone services or field TLS. The combination of free satellite data with periodic UAV calibration campaigns and sparse IoT telemetry is emerging as the cost-optimal design for operational landscape monitoring.

Active vs. passive sensing: Active sensors (LiDAR, SAR) are insensitive to solar illumination and partially penetrate cloud cover (SAR) or canopy (LiDAR, SAR); passive optical sensors are blocked by cloud and measure only the illuminated surface. All-weather continuous monitoring requires at minimum a passive optical system for phenological tracking and an active SAR or LiDAR system for cloud-penetrating structural observation.

C. Key Trade-offs

The most significant operational trade-off in system design for canopy growth monitoring is the spatial resolution – temporal frequency trade-off. The highest spatial resolution systems (TLS at mm, UAV at cm–dm) are purely on-demand and cannot be made continuous without robotic deployment. The highest temporal frequency systems (IoT sensors, PhenoCam, satellite optical) either measure point locations or the canopy surface. No existing system provides both fine spatial resolution (<1 m) and continuous temporal coverage at stand scale. This gap defines one of the highest-priority research directions for the field (Section XIV, direction 14.2).

A secondary trade-off is between physical interpretability and model flexibility. Traditional physical retrieval algorithms (radiative transfer inversion, QSM fitting) are interpretable and physically consistent but require expert knowledge and are computationally expensive. Machine learning approaches can operate at higher throughput and generalise across larger spatial extents but risk physically implausible outputs, particularly in extrapolation to conditions underrepresented in training data. Physics-constrained foundation models represent a convergence approach that seeks to preserve physical consistency while achieving ML-scale throughput and generalisation [25].

XIV. Discussion: Synthesis of Future Directions

The body of this survey has covered eight technology domains spanning the period 2019–2026. The framing introduced in Section I—the structure–function–growth chain plus the post-2025 inflection point—now allows us to ask a sharper question than “which technology is best?”: which integration gaps in the chain have actually been closed by the 2025 convergence of new sensors and foundation models, and which remain open?

The 2025 convergence is concrete. ESA Biomass (April 2025) brought the first P-band SAR civilian satellite, penetrating tropical canopies to trunk level for direct above-ground biomass retrieval. NISAR (July 2025) added dual-band L+S coverage of the entire globe every 6–12 days, sufficiently dense for landscape-scale phenology and disturbance tracking. GEDI resumed operations in 2024 after a brief hibernation, anchoring the near-global canopy-height baseline. Remote-sensing foundation models (Prithvi, TerraMind, SkySense) matured to the point of cross-modal inference at scale, even if their pretraining corpora remain optically biased [4]. For the first time, high-penetration biomass sensing, dense temporal radar, global lidar sampling, and cross-modal AI are simultaneously available. This convergence is the reason the present survey could not have been written before 2025, and it underwrites every future direction discussed below.

What it does not do is automatically close the structure–function–growth chain. Section XIV-A synthesises the per-section Integration Gap paragraphs from Sections IV through XII and asks, of each gap, whether the 2025 convergence has materially improved the situation or merely raised the ceiling on what might one day be possible. We then identify ten high-impact future directions structured around the integration gaps that the convergence has not closed.

A. Integration Gaps Across the Structure–Function–Growth Chain

The per-section Integration Gap paragraphs identify the specific obstacles preventing each technology's outputs from being combined with adjacent stages of the chain. Synthesised across the eight technology domains, four recurring failure modes emerge.

Sparse-to-dense extrapolation error is rarely propagated. Spaceborne lidar (GEDI) samples sparsely and must be extrapolated to continuous maps via optical or SAR predictors [1], [16]. Sentinel-2 vegetation indices saturate in dense canopies and require structural priors. Foundation models rely on pretraining corpora dominated by Sentinel-2 / Landsat. In each case, the predictor-driven extrapolation accumulates error that is rarely propagated into reported uncertainty for downstream growth estimates.

The function→growth jump assumes stationary allocation. SIF retrievals capture instantaneous photosynthetic activity, but converting SIF to growth (biomass accumulation) requires assuming stable carbon-allocation fractions across seasons and ecosystems—an assumption that empirical work has now shown to be conditional on canopy structure [2]. Eddy-covariance flux integrates to net ecosystem exchange but adds further allocation assumptions before reaching biomass. The function-to-growth jump is therefore the noisiest single link in the chain.

Cross-modal fusion lacks shared evaluation protocols. Pretraining datasets, validation benchmarks, and accuracy reporting conventions differ across modalities: GEDI fusion studies report RMSE in metres, SAR studies report bias in $\mathrm{Mg\,ha^{-1}}$, hyperspectral studies report F1 scores. There is no shared benchmark covering all three stages of the chain simultaneously, and the most recent multimodal-forest-fusion review [5] explicitly identifies engineering-level registration and annotation cost as bottlenecks but does not address biophysical evaluation of fused outputs.

Foundation models inherit, rather than close, the gaps below them. The integrator layer (Section XII) is designed to fuse modalities, but inherits the optical bias, the missing P-band SAR / spaceborne lidar / SIF coverage, and the absence of physical constraints from its constituent training data and architectures. Until foundation-model architectures incorporate physics-informed inductive biases [66] and multimodal pretraining parity, the integrator layer cannot close the structure–function–growth chain—it can only learn whichever stage of the chain its training data most thoroughly samples.

The ten future directions discussed below target these four failure modes directly, with particular emphasis on physics-constrained multi-modal foundation models that propagate uncertainty through the chain rather than collapsing it into a single point estimate.

B. Multi-Modal Temporal Fusion Pipelines

The single most impactful research direction identified across the reviewed literature is the construction of integrated systems that seamlessly fuse observations from multiple spaceborne and in-situ sources into a continuously-updating canopy growth model. Each of the instrument categories reviewed compensates for the weaknesses of the others: GEDI provides vertical profile calibration; Biomass provides trunk-level biomass in tropical forests; NISAR provides high-frequency biomass change monitoring; Sentinel-2 provides daily phenological tracking through cloud-free periods; UAV LiDAR provides plot-scale validation at centimetre resolution; TLS provides individual-tree ground truth; IoT sensors provide continuous physiological parameters; and SIF provides the photosynthetic activity signal that neither structural nor passive optical measurements can provide.

No existing operational system integrates this full stack. Individual binary fusions have been demonstrated at high quality—GEDI + Sentinel-2 for wall-to-wall height maps [6], GEDI + TanDEM-X for pantropical biomass [10], Sentinel-1 + Sentinel-2 + GEDI for African biomass [21]—but a general-purpose multi-source fusion architecture remains an open research problem. Foundation models with multi-modal pre-training (TerraMind, and the next generation of physics-constrained models) are the most plausible architectural candidate for this integration role [25], [65].

C. Real-Time Sub-Canopy Monitoring at Scale

Current satellite systems observe the canopy surface; LiDAR systems penetrate below the canopy but with limited temporal revisit; IoT sensors provide continuous below-canopy data but at negligible spatial coverage. A breakthrough would be a system providing continuous, spatially dense, below-canopy monitoring. The most credible near-term pathway is dense IoT mesh networks calibrated against periodic TLS and UAV LiDAR campaigns, with satellite data providing spatial extrapolation. The commercialisation of LEO satellite IoT connectivity (Starlink, Swarm, Astrocast) is rapidly improving the economics of deploying sensor networks in remote forests [61]. At sufficiently high sensor density—achievable with sub-USD 50 dendrometer nodes—continuous stand-level diameter increment data would provide a ground-truth time series of carbon sequestration comparable to what flux towers provide for GPP.

D. Physiologically-Grounded Growth Models

Most current remote sensing approaches estimate structural snapshots (height, biomass, LAI) rather than growth processes. The field lacks models that integrate structural observations with physiological processes—photosynthesis rate from SIF, water stress from SWIR reflectance and thermal imagery, nutrient status from hyperspectral imagery, cambial growth from dendrometers—into mechanistic or hybrid mechanistic-ML growth prediction models. The TLS-enabled FSPM approach is the most rigorous pathway, but it is currently limited to individual trees and small stands [41]. Scaling from individual trees to forests requires coupling TLS-derived structural models with eddy covariance flux data, SIF-based GPP estimates, and microclimate observations within a process-model framework. This integration is a natural extension of the VISIT-SIF model approach [31] and the DGVM-RS coupling work discussed below.

E. Tall Tree and Old-Growth Forest Monitoring

Current satellite and airborne height-estimation methods systematically underestimate canopy heights above 40–45 m [6], [8]. Old-growth and tall-tree forests are disproportionately important for carbon storage, biodiversity, and hydrological regulation, yet they are precisely the forest types for which current monitoring methods are least accurate. Dedicated calibration campaigns combining TLS (for sub-centimetre structural reference), UAV LiDAR (for plot-to-landscape upscaling), and GEDI footprint data over a network of old-growth reference forests could provide the training data required for foundation models and statistical height models to learn the specific waveform signatures of very tall canopies. The FOR-species benchmark framework [43] could be extended to tall-tree structural characterisation, providing a shared evaluation dataset for the community.

F. Affordable Scalable IoT Dendrometry

The IoTrees concept demonstrates the scientific and commercial value of continuous tree-level growth monitoring [57], but current smart dendrometer hardware remains too expensive (typically USD 200–1000 per sensor) for the deployment densities needed for landscape-scale carbon monitoring. A breakthrough in low-cost, energy-autonomous dendrometers—potentially using printed electronics, flexible strain gauges, or MEMS-based diameter sensors— deployed at densities of hundreds of sensors per hectare with LPWAN or satellite backhaul would transform forest carbon monitoring from periodic audit-based snapshots to continuous operational tracking. Treemetrics' ForestHQ integration [58] demonstrates the data management and visualisation infrastructure that would consume such a data stream.

G. Hyperspectral Foundation Model Integration

The ability to detect plant disease four days before visible symptoms appear [3] is commercially transformative, but current pipelines are fragile and highly dataset-specific. Generalisation across species, disease types, geographies, and sensor configurations remains poor. Training foundation models on large-scale hyperspectral databases— the "ImageNet moment" for plant spectroscopy—would enable robust, transferable stress detection. The construction of such a database requires coordinated effort by the HSI research community to standardise acquisition protocols, share annotated datasets across institutions, and develop benchmark evaluation frameworks analogous to FoMo-Bench for structural remote sensing. Smartphone-accessible multispectral devices [52] could serve as low-cost data collection platforms for building the large-scale annotated datasets required for foundation model pre-training.

H. Edge AI for Real-Time Drone Decision-Making

Current drone surveys operate in a collect-then-process paradigm: raw data is gathered in flight and analysed post-mission. Real-time onboard inference using lightweight foundation models would enable adaptive flight planning in which the drone autonomously adjusts its survey path based on anomalies detected mid-flight—spending more time over stressed or diseased areas, automatically flagging disease hotspots for ground-team intervention, or directing higher-resolution follow-up passes to locations of interest. Edge deployment of distilled remote sensing foundation models on low-power UAV GPU boards (10–30 W) has been demonstrated in principle [4] but not yet in a forest monitoring operational context. The combination of onboard hyperspectral anomaly detection with GPS-tagged geo-referenced output would represent a significant step toward fully autonomous precision forestry.

I. Allometric Model Improvement and Standardisation

No remote sensing measurement directly measures growth rate: growth is always inferred as the difference between two structural measurements mediated by allometric models that convert height, diameter, or backscatter into biomass [24], [67]. These models are highly region-, species-, and age-specific, and their uncertainty is often the dominant error source in ecosystem carbon accounting. African forests are particularly data-poor [24], with field plot density orders of magnitude lower than comparable South American biomes. A globally coordinated campaign to expand allometric training datasets—leveraging TLS-derived non-destructive biomass estimates as an alternative to destructive sampling [41]—combined with hierarchical Bayesian modelling to propagate allometric uncertainty into biomass products, would substantially reduce a long-standing systematic bias in global carbon budgets.

J. DGVM–Remote Sensing Coupling

Dynamic global vegetation models (DGVMs: ED2, JULES, CLM, LPJ-GUESS) simulate vegetation growth and carbon cycling at regional to global scales but are constrained by sparse observational inputs for parameterisation and calibration. Remote sensing data—particularly GEDI biomass and height, TROPOMI SIF-GPP, and Sentinel-2 LAI time series—represent a largely untapped resource for DGVM calibration [25]. Foundation models could serve as efficient emulators for DGVM parameter spaces, enabling rapid Bayesian parameter estimation using satellite observational likelihoods. Conversely, DGVMs provide the process-based mechanistic framework within which remote sensing anomalies can be interpreted in terms of specific physiological or environmental mechanisms, bridging the "correlation versus causation" gap in observational canopy monitoring.

K. Cloud-Native Processing and Data Democratisation

The computational infrastructure for large-scale canopy monitoring has transformed with the maturation of Google Earth Engine, Microsoft Planetary Computer, and AWS Earth on Demand. These platforms provide access to petabyte- scale satellite data archives with server-side analysis capabilities, enabling analyses that were previously accessible only to large research institutions with dedicated HPC clusters. However, accessibility barriers remain: these platforms require programming expertise, and their APIs have steep learning curves for forest managers, conservation practitioners, and national monitoring agencies in data-limited countries. Development of standardised, interoperable cloud-native processing workflows, curated as open-source pipeline packages, would democratise access to the capabilities reviewed in this survey. The Forest 4.0 operational model [55] and the ForestHQ platform [58] represent early examples of the application-layer interfaces needed to translate technical advances into operational forest management tools.

XV. Conclusion

This survey has reviewed the state of the art in canopy growth monitoring across eight major technology domains—spaceborne LiDAR, synthetic aperture radar, satellite multispectral optical sensing, solar-induced chlorophyll fluorescence, UAV and airborne systems, terrestrial laser scanning and digital twins, hyperspectral imaging, and in-situ IoT sensor networks—together with the AI and foundation model approaches that are emerging as their integration architecture. The year 2025 represents a genuine inflection point in the field. The launches of ESA Biomass and NISAR deliver, for the first time, two complementary spaceborne active microwave instruments specifically designed for vegetation biomass and structure monitoring. Together with the maturing GEDI LiDAR data archive, these three missions provide an unprecedented three-way observational constraint on tropical and global forest biomass that was not available before 2025. Simultaneously, the commercial maturation of UAV-borne LiDAR forestry services, the deployment of IoT sensor networks providing continuous tree-level growth data, and the demonstration of disease detection capability four days before symptom appearance collectively illustrate that the boundaries of what is technically achievable have advanced substantially across every category.

The central finding of this survey is that the field's primary bottleneck has shifted. A decade ago, the constraint was data scarcity: insufficient spatial coverage, coarse resolution, infrequent revisit, absence of vertical penetration. These constraints have not disappeared, but they have been substantially relaxed by the missions and platforms reviewed here. The dominant bottleneck is now data integration: the absence of coherent systems that fuse observations across spatial scales (leaf to globe), observation modalities (passive optical, active radar, LiDAR, thermal, spectroscopic, in-situ), and temporal frequencies (continuous IoT to multi-year spaceborne archives) into actionable, physiologically-grounded models of how forests grow, respond to stress, and change.

Foundation models with physics-constrained architectures represent the most plausible integration paradigm for this challenge [25], [65]. By pre-training on multimodal, multi-temporal Earth observation archives and fine-tuning with limited labelled data, these models can in principle bridge the modality gaps identified in the cross-comparison analysis. Physics constraints ensure that model outputs remain consistent with known atmospheric and surface processes even in data-sparse conditions or novel environments. The organisations and research communities that achieve this integration— unifying the structural information from GEDI, Biomass, NISAR, and TLS with the physiological information from SIF and hyperspectral sensors and the continuous temporal information from IoT networks—will define the next generation of forest monitoring capability, with direct consequences for national carbon accounting, biodiversity monitoring, and climate model parameterisation at global scale.

Appendix A
Consolidated Comparison Tables

This appendix consolidates the principal comparison tables from the body sections in one location for convenient reference.

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TABLE IX
SAR Missions for Canopy Growth Monitoring (see also Table II)

Mission	Band	λ	Res.	Coverage	Launch	Key Capability
ESA Biomass	P	70 cm	200 m	Tropical/subtropical	Apr. 2025	Trunk-level biomass; direct AGB; 3D tomographic phase (yr 1)
NISAR	L+S	24/9 cm	100–200 m	Global	Jul. 2025	Biomass estimation; soil moisture; disturbance tracking
Sentinel-1	C	5.6 cm	5–20 m	Global	2014–	High-frequency disturbance detection; canopy phenology
TanDEM-X	X	3.1 cm	12 m	Global	2010–	InSAR canopy height models; DSM/DTM differencing

TABLE X
Satellite SIF Missions and Instruments (see also Table IV)

Mission	Spatial Res.	Temporal Res.	Spectral Range	Status
TROPOMI (Sentinel-5P)	3.5×5.6–7 km	Daily global	665–785 nm	Operational
OCO-2	1.3×2.25 km	16-day (sparse)	O_2-A band	Operational
OCO-3 (ISS)	1.6×2.2 km	Variable (ISS orbit)	O_2-A band	Operational
Goumang/SIFIS	370×800 m	60-day global	664–786 nm	Operational (2022)
TanSat	2×2 km	Global repeat	O_2-A band	Operational
FLEX (ESA)	∼300 m	27-day	Dedicated SIF (670, 740 nm)	Expected 2026

TABLE XI
Vegetation Indices for Canopy Monitoring (see also Table III)

Index	Full Name	Bands	What It Measures	Strengths	Weaknesses
NDVI	Norm. Difference Veg. Index	RED, NIR	Greenness / leaf area	Universal; long archive	Saturates in dense canopy
EVI	Enhanced Vegetation Index	BLUE, RED, NIR	Greenness (corrected)	Reduced saturation	Needs blue band
NDMI	Norm. Difference Moisture Index	NIR, $SWIR_1$	Canopy water content	Sensitive to subtle disturbance	Water body confusion
NDPI	Norm. Difference Phenology Index	RED, SWIR	Deciduous canopy water	Phenology-sensitive	Less validated
FCVI	Fluorescence Correction Veg. Index	RED, NIR	Chlorophyll density	Photosynthetic capacity	Newer; limited adoption
SATVI	Soil-Adjusted Total Veg. Index	RED, SWIR	Woody branch density	Non-leaf biomass	Soil interference
LAI	Leaf Area Index (derived)	RED, NIR	Total leaf area per ground	Biophysical meaning	Algorithm-dependent
SIF	Solar-Induced Fluorescence	740 nm emission	Active photosynthesis	Direct photosynthesis proxy	Coarse resolution
GCC	Green Chromatic Coordinate	R, G, B (camera)	Phenocam greenness	High temporal frequency	Camera calibration

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TABLE XII
UAV Sensor Types for Canopy Monitoring (see also Table V)

Sensor	Typical Accuracy	Applications
RGB photogrammetry	RMSE ≈0.3 m height	CHM, crown delineation, volume
LiDAR	2.5–10 cm point accuracy	Sub-canopy structure, individual tree metrics
Multispectral	Band-dependent	NDVI, vegetation health indices
Hyperspectral	400–1000 nm range	Disease, species ID, stress
Thermal	±0.1°C relative	Water stress, canopy temp. anomalies

TABLE XIII
Hyperspectral Imaging: Plant Stress and Disease Detection Accuracy (see also Table VI)

Application	Method	Accuracy	Source
Wheat drought + N	HSI + RF	Accuracy > 0.94	[48]
Wheat stem rust (4 dpi)	HSI + LR/SVM/LightGBM	F1 0.86–0.94	[3]
Lettuce drought (space)	VNIR HSI + DA	90.7–99.0%	[49]
Tobacco TSWV	UAV HSI + ML	High	[50]
General stress	MLVI-CNN	State of art	[51]

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TABLE XIV
Remote Sensing Foundation Models for Vegetation Monitoring (see also Table VII)

Model	Modalities	Strengths	Weaknesses
Prithvi (IBM/NASA)	Sentinel-2 / HLS multi-temporal	Open-source; few-shot fine-tuning; digital apps	Optical only; North America bias
TerraMind (IBM/ESA)	9 modalities (optical, SAR, DEM, temp, weather, text)	Broadest coverage; cross-modal inference	High compute; no real-time deployment
SkySense	Multi-modal EO	CVPR 2024 benchmark performance	Limited forest deployment reports
Physics-constrained FMs	Any (with physics priors)	Physical consistency; better transfer	Mainly theoretical
Traditional ML	Feature-engineered	Interpretable; low compute	Manual features; poor generalisation

TABLE XV
Cross-Technology Comparison of Canopy Growth Monitoring Systems (see also Table VIII)

Technology	Spatial Scale	Temporal Res.	Spatial Res.	Canopy Penetration	Data Cost	Maturity
GEDI LiDAR	Global ($\pm 51.6^{\circ}$)	Sparse ($\sim$4%)	25 m footprint	Full vertical	Free	Operational
ESA Biomass	Tropical	27-day	200 m	Trunk-level	Free	Commissioned
NISAR	Global	6–12 days	100–200 m	Moderate	Free	Early ops
Sentinel-2	Global	5 days	10–60 m	Surface only	Free	Operational
Sentinel-1	Global	6 days	5–20 m	Shallow	Free	Operational
SIF (TROPOMI)	Global	Daily	3.5×5.6 km	Physiological	Free	Operational
UAV LiDAR	Plot–landscape	On-demand	2.5–10 cm	Below-canopy	Mod–High	Commercial
UAV Multispectral	Plot–landscape	On-demand	3–5 cm	Surface only	Moderate	Commercial
TLS	Plot	On-demand	mm-scale	Full interior	High	R $\rightarrow$ ops
Hyperspectral	Field–plot	On-demand	5 cm–5 m	Surface spectral	High	Early comm.
IoT sensors	Point–plot	Continuous	Individual tree	In-situ	Low/sensor	Early comm.
PhenoCam	Plot–stand	Continuous	Scene RGB	Surface	Low	Operational
Eddy covariance	Landscape	30-min	100–1000 ha	Flux integral	High (infra)	Operational
Foundation models	Any	Any	Any	Data-dependent	High (train)	Research

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