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Review

A Trait-Based Framework for Monitoring Forest Land Use Intensity with Remote Sensing: A Conceptual Review

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Abstract

Forest Land Use Intensity (F-LUI) is a multidimensional and dynamic property of forest ecosystems that cannot be directly observed by Remote Sensing (RS). Existing approaches commonly quantify individual management activities, forest attributes or ecological responses and therefore capture only specific dimensions of forest-use intensity. This concept-driven narrative review proposes a trait-based conceptual framework in which forest traits constitute the common observational interface linking anthropogenic forest use, ecosystem responses and RS observations. Based on this principle forest traits and their spatial, temporal and functional expressions are interpreted within six complementary F-LUI indicator families: Trait, Genesis, Structure, Taxonomy, Function and Socio-economics. Rather than defining a universal F-LUI index, the framework provides a multidimensional, sensor-independent architecture for integrating RS with in situ observations, forest inventories, management information and environmental data. Emerging approaches including Artificial Intelligence (AI) and Foundation Models, multi-sensor data fusion, semantic technologies, Knowledge Graphs and Digital Twins may support its operationalisation. Key challenges remain in standardisation, uncertainty quantification, attribution of management effects and transferability across forest types, management regimes and spatial and temporal scales. The proposed framework provides an open and extensible basis for harmonised, reproducible and operational trait-based monitoring of F-LUI.

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1. Introduction

Forests cover approximately one-third of the terrestrial land surface and are among the most important ecosystems on Earth [1]. They regulate global carbon, water and energy cycles, support biodiversity, and provide renewable resources and numerous other ecosystem services (Millennium Ecosystem Assessment, 2005; [2]). At the same time, forest ecosystems are increasingly affected by climate change, extreme weather events and biotic disturbances, while demands for timber production, biodiversity conservation and the bioeconomy continue to grow. Their role as a terrestrial carbon sink is becoming increasingly important for climate-change mitigation, yet this function is itself threatened by intensifying climatic extremes and disturbances [3]. Against this background, sustainable forest management and standardised forest monitoring are gaining importance, as reflected in the Paris Agreement, the Kunming–Montreal Global Biodiversity Framework, the European Green Deal and the EU Forest Strategy for 2030. These challenges require approaches capable of consistently assessing the intensity, spatial distribution and ecological consequences of anthropogenic forest use across scales.

Assessing anthropogenic influences on forest ecosystems therefore requires more than quantifying forest area, biomass or growing stock. It is necessary to consider the intensity, spatial distribution and temporal dynamics of forest use together with the resulting changes in forest structure, biodiversity and ecosystem functioning. The concept of Land Use Intensity (LUI) provides a theoretical basis for such an assessment. Erb et al. [4] conceptualised LUI through the interaction of inputs, outputs and resulting system-level impacts, while Kuemmerle et al. [5] emphasised the spatial and temporal dynamics of land-use systems and the interactions among anthropogenic interventions, environmental conditions and ecological feedbacks. Together, these concepts provide a basis for analysing anthropogenic land-use systems and their application to forests. From a Remote Sensing (RS) perspective, however, these impacts are not directly observable but must be inferred from changes in measurable ecosystem properties.

Building on this conceptual foundation, Forest Land Use Intensity (F-LUI) has emerged as an approach for characterising the intensity of anthropogenic forest use and its ecological consequences. Despite its increasing scientific relevance, neither a generally accepted definition nor a harmonised conceptual framework has yet been established. In forest science, anthropogenic use is commonly described through Forest Management Intensity (FMI) [6]. The Silvicultural Management Intensity (SMI) index subsequently provided a quantitative measure of silvicultural intensity based on stand and management characteristics [7]. In contrast, state- and impact-based approaches assess changes in forest structure, biodiversity and ecosystem functioning [8,9]. Although both perspectives provide important insights into anthropogenic forest use, neither alone fully captures the relationships among management interventions, forest condition and ecological processes.

In parallel, RS has fundamentally transformed forest monitoring by enabling spatially continuous and temporally repeated observations from individual trees to the global scale. Applications include the assessment of forest structure, vegetation cover, biomass, biochemical vegetation properties, biodiversity, soil characteristics, and natural and anthropogenic disturbances [10]. Multi-temporal Landsat and Sentinel time series further enable the detection of forest disturbance and degradation [11], while advances in

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multispectral, hyperspectral, thermal, Light Detection and Ranging (LiDAR) and SAR observations, together with missions such as GEDI, have substantially expanded opportunities for cross-scale forest monitoring [12]. However, RS does not observe forest management itself; it primarily captures its effects on observable ecosystem properties. The key challenge is therefore not simply to develop additional RS indicators, but to place these observations within a coherent conceptual framework for quantifying F-LUI.

From this perspective, forest traits provide a key conceptual interface between forest management, forest ecosystems and RS. They comprise observable morphological, structural, biochemical, physiological and phenological properties that respond to both environmental conditions and anthropogenic use. Management interventions can therefore become observable through changes in these traits. Trait-based approaches are well established in functional ecology and increasingly in RS because they link ecological processes to measurable ecosystem properties and allow observations from different sensor systems to be integrated within a common conceptual framework [13–15]. Forest traits can thus provide a common observational layer through which heterogeneous RS, in-situ, inventory and management information can be interpreted in relation to F-LUI.

Against this background, this conceptual review develops a trait-based framework for monitoring F-LUI using RS. We synthesise existing definitions and conceptual approaches, monitoring programmes, and in-situ and RS-based observation methods, and evaluate their potential and limitations for quantifying F-LUI. Building on this synthesis, forest traits are positioned as the central interface linking forest management, ecosystem responses and RS observations, and six complementary F-LUI indicator families—Trait, Genesis, Structure, Taxonomy, Function and Socio-economics—are integrated within a multidimensional framework. We further assess the potential of AI and Foundation Models, Multi-sensor Data Fusion, Semantic Web and Knowledge Graphs, and Digital Twins to support its future operationalisation. Rather than proposing a universal single F-LUI index, this conceptual review aims to establish an open, sensor- and scale-independent architecture for harmonised, reproducible and ultimately operational F-LUI monitoring.

The approach used to identify and synthesise the literature and to develop the six indicator families is described in Section 2.

2. Review Approach and Framework Development

The present study was conducted as a concept-driven narrative review rather than a systematic review. Its conceptual starting point was provided by established research on land-use intensity, forest management, forest traits and remote sensing, together with previous trait-based frameworks developed for monitoring agricultural and urban land-use intensity [16–18]. Building on this foundation, relevant literature was identified iteratively through targeted thematic searches and the screening of reference lists from pertinent publications. No lower temporal limit was applied because foundational conceptual studies were considered essential. The search included relevant publications available up to 2026 and addressed Land Use Intensity, Forest Management Intensity, Forest Traits, monitoring programmes, in-situ observations, remote-sensing methods and emerging forest-monitoring technologies.

Publications were selected according to their conceptual relevance to F-LUI, their contribution to the definition or observation of forest traits and management effects, their representation of major observation methods and sensor systems, and their potential to support the development or operationalisation of the proposed framework. The six F-LUI indicator families were not derived from a statistical classification or frequency analysis of the literature. Instead, they emerged from a concept-driven synthesis of the principal ways in which anthropogenic forest use and its ecological consequences can be observed

and interpreted: forest properties, temporal trajectories, spatial and three-dimensional organisation, biological identity and composition, ecosystem processes, and socio-economic and management context. Representative indicators were assigned according to their primary interpretative role, while recognising that individual indicators may contribute to more than one family.

3. Definition, Standards and Programmes for Monitoring F-LUI

3.1. Definition of F-LUI

The term Land Use Intensity describes the extent of anthropogenic intervention in land-use systems and its consequences for ecological processes, biodiversity and the provision of ecosystem services. Although the concept was initially developed primarily for agricultural production systems, it has increasingly been applied to forests. However, a generally accepted definition of F-LUI has yet to be established. Instead, F-LUI has been operationalised in different ways depending on the scientific context, including through management activities, forest condition and structure, or ecological responses.

A fundamental conceptual basis was provided by Erb et al. [4], who described LUI as a multidimensional concept comprising inputs, outputs and system-level impacts. From this perspective, land-use intensity cannot be characterised adequately by individual management activities or production outputs alone, but emerges from the interactions among resources invested in land use, goods and services produced, and the resulting ecological changes. Kuemmerle et al. [5] further emphasised that LUI should be understood as a spatially and temporally dynamic property of land-use systems, shaped by interactions among anthropogenic interventions, environmental conditions and ecological feedbacks. Consequently, a comprehensive assessment of LUI requires consideration of both management pressure and the resulting ecosystem responses.

Transferring this general concept to forest ecosystems leads to F-LUI. Existing approaches, however, emphasise different components of the management–ecosystem relationship. Some primarily quantify the intensity of forest management, whereas others assess changes in forest structure, biodiversity or ecosystem functioning. F-LUI should therefore not be regarded as a single management variable or universal index, but as a multidimensional property of forest ecosystems whose operationalisation depends on the dimensions and processes under consideration. This distinction is particularly important for RS, because management itself is generally not directly observable; rather, RS captures changes in forest properties resulting from the combined effects of management, environmental conditions and ecological processes.

Accordingly, in this review we define F-LUI as: F-LUI is a continuous, multidimensional, and spatially and temporally dynamic property of forest ecosystems that reflects the extent and intensity of anthropogenic use, management and transformation, together with their effects on forest structure, composition, functioning and ecological processes.

This definition deliberately integrates management pressure and ecosystem response rather than treating them as separate representations of land-use intensity. It serves as the core conceptual definition throughout this review, while Section 4 translates it into an RS-oriented operational framework by specifying the observable forest traits and ecosystem responses through which F-LUI can be detected and interpreted. It therefore provides the conceptual basis for the trait-based framework developed in this review, in which forest traits serve as the common observational interface linking forest management, ecosystem responses and RS observations. This distinction is central to the novelty of the proposed framework: existing approaches quantify management intensity, individual forest properties or ecological responses, whereas the framework developed here integrates these perspectives within a common multidimensional observational architecture.

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3.2. Existing Conceptual Approaches to Forest Land Use Intensity (F-LUI)

Although F-LUI is increasingly understood as a multidimensional concept (Section 3.1), different approaches have been developed for its description and quantification. These approaches differ in their scientific focus, the indicators employed, and the spatial and temporal scales considered. They share, however, the objective of characterising anthropogenic interventions in forest ecosystems and their ecological consequences. Their development reflects a conceptual transition from predominantly management-oriented approaches towards the assessment of ecosystem states and ecological impacts and, more recently, their spatially explicit observation through RS (Figure 1). The principal conceptual approaches and observational perspectives relevant to F-LUI—including management-, pressure-, state- and impact-based approaches as well as RS-based observation—are compared in Table A1 with respect to their primary focus, typical indicators, strengths and limitations.

Management-based approaches quantify the intensity of silvicultural interventions and therefore represent the most direct perspective on anthropogenic forest use. Typical variables include harvesting and biomass removal, thinning, rotation length, tree-species selection, regeneration practices and other management inputs. Schall and Ammer [6] for example, developed the SMI indicator, which combines tree-species selection, stand age and living and dead aboveground woody biomass to quantify management intensity along silvicultural gradients. Subsequent approaches extended the operational assessment of forest management intensity by incorporating additional stand and management characteristics [7,19]. More recently, Staab et al. [20] proposed the Forest Management IndeX (ForMIX), integrating altered tree-species composition, tree removal, deadwood availability and stand maturity relative to unmanaged old-growth reference conditions. Management-based approaches therefore provide comparatively direct and interpretable measures of anthropogenic intervention, but their ability to represent the realised ecological consequences of management remains limited because similar interventions may result in different ecosystem responses depending on site conditions, stand history and disturbance regimes.

A complementary perspective is provided by pressure-based approaches, which conceptualise land-use intensity through anthropogenic inputs, outputs and pressures associated with resource use. General Land Use Intensity frameworks have distinguished, for example, management inputs, extraction or production outputs and resulting changes in ecosystem properties, while emphasising their spatial and temporal variation [4,5]. When transferred to forests, this perspective encompasses variables such as harvesting and felling rates, wood extraction, accessibility, management inputs and disturbance frequency. Pressure-based approaches are particularly useful for characterising multiple dimensions of human intervention and linking forest use to production systems. However, anthropogenic pressure does not necessarily translate directly into ecological effects, because ecosystem responses depend on forest structure, environmental conditions, management history and ecological resilience.

With the increasing adoption of close-to-nature management systems, particularly Continuous Cover Forestry (CCF), the limitations of management- and pressure-based indicators become increasingly apparent. In contrast to conventional even-aged forestry, CCF maintains continuous forest cover and promotes structurally heterogeneous stands through individual-tree or group-based harvesting and regeneration [21,22]. Under such conditions, individual management variables or harvesting events may provide only incomplete information on F-LUI. Greater emphasis must therefore be placed on the realised condition of forest ecosystems and the ecological manifestations of management.

State-based approaches characterise the resulting condition of forest ecosystems through measurable structural, compositional and ecological properties. Relevant

indicators include biomass, stand maturity, canopy and vertical structure, deadwood, tree-species composition, regeneration and forest naturalness. Winter [23] and McRoberts et al. [24] for example, demonstrate how forest naturalness and related ecosystem properties can be assessed through observable forest characteristics. McRoberts et al. [24] explicitly investigated harmonised variables for assessing forest naturalness using National Forest Inventory data. Such approaches are ecologically interpretable and closely connected to measurable forest properties. Nevertheless, similar ecosystem states may result from different management histories, natural disturbances, succession or environmental conditions, which limits the direct attribution of observed states to management intensity.

Impact-based approaches extend this perspective from ecosystem condition towards the ecological consequences associated with different levels and forms of land-use intensity. They assess responses such as biodiversity, carbon storage, productivity, functional composition, ecosystem multifunctionality and ecosystem services [4,8,9]. These approaches are particularly important for understanding how anthropogenic pressures translate into ecological change and altered ecosystem functioning. However, observed ecological impacts cannot necessarily be attributed uniquely to forest management because climate, natural disturbances, site conditions and ecological succession may produce similar responses. State- and impact-based approaches therefore provide complementary information: the former describe the realised condition of the forest ecosystem, whereas the latter focus on the ecological consequences associated with land-use intensity.

In parallel with these conceptual developments, RS-based observational approaches have fundamentally transformed the monitoring of forest ecosystems. Satellite, LiDAR, SAR and imaging spectroscopy systems enable spatially continuous, standardised and temporally repeated observations of structural, biophysical, biochemical and functional forest properties. Observable characteristics such as canopy cover and height, Aboveground Biomass (AGB), Leaf Area Index (LAI), vegetation productivity, biochemical and physiological properties, and disturbance and recovery dynamics can increasingly be quantified across spatial and temporal scales [10,12,14,25]. RS therefore provides an important observational perspective for F-LUI because it enables many ecological manifestations of forest use to be monitored repeatedly and spatially explicitly.

However, RS also exposes a fundamental conceptual limitation of existing F-LUI approaches: forest management itself is generally not directly observable from RS. Instead, sensors record the structural, spectral, biochemical, physiological and temporal manifestations resulting from the combined effects of management, environmental conditions and ecological processes. Consequently, the same RS-observed forest state may originate from different management histories, while different ecosystem responses may follow similar management interventions. The interpretation of RS observations therefore requires an explicit conceptual link between anthropogenic interventions, measurable forest properties and their ecological consequences.

This limitation highlights the need for an integrative observational framework. Forest traits provide a suitable common interface because they represent measurable structural, morphological, biochemical, physiological and phenological properties of forest ecosystems that respond to both environmental conditions and anthropogenic use [16,26]. Forest traits can therefore connect management and pressure-based information with state- and impact-based ecological responses while simultaneously representing properties that can be observed or inferred through RS. In this way, they provide a common observational basis for integrating previously separate conceptual perspectives on F-LUI.

Taken together, existing approaches should therefore be regarded as complementary rather than mutually exclusive. Management- and pressure-based approaches primarily characterise anthropogenic interventions, state-based approaches describe the resulting condition of forest ecosystems, and impact-based approaches quantify their ecological consequences. RS adds a spatially explicit and temporally repeatable observational perspective but predominantly observes the manifestations of management rather than management itself. Figure 1 summarises this conceptual development and illustrates how these complementary perspectives can be integrated through forest traits within the proposed F-LUI framework. Table A1 compares their primary focus, indicators, strengths and limitations, whereas Table A2 traces the broader development from general LUI concepts and forest-specific management-intensity approaches towards integrated and multidimensional F-LUI concepts. Together, Figure 1 and Tables A1 and A2 provide the conceptual basis for the trait-based framework developed in Section 5.

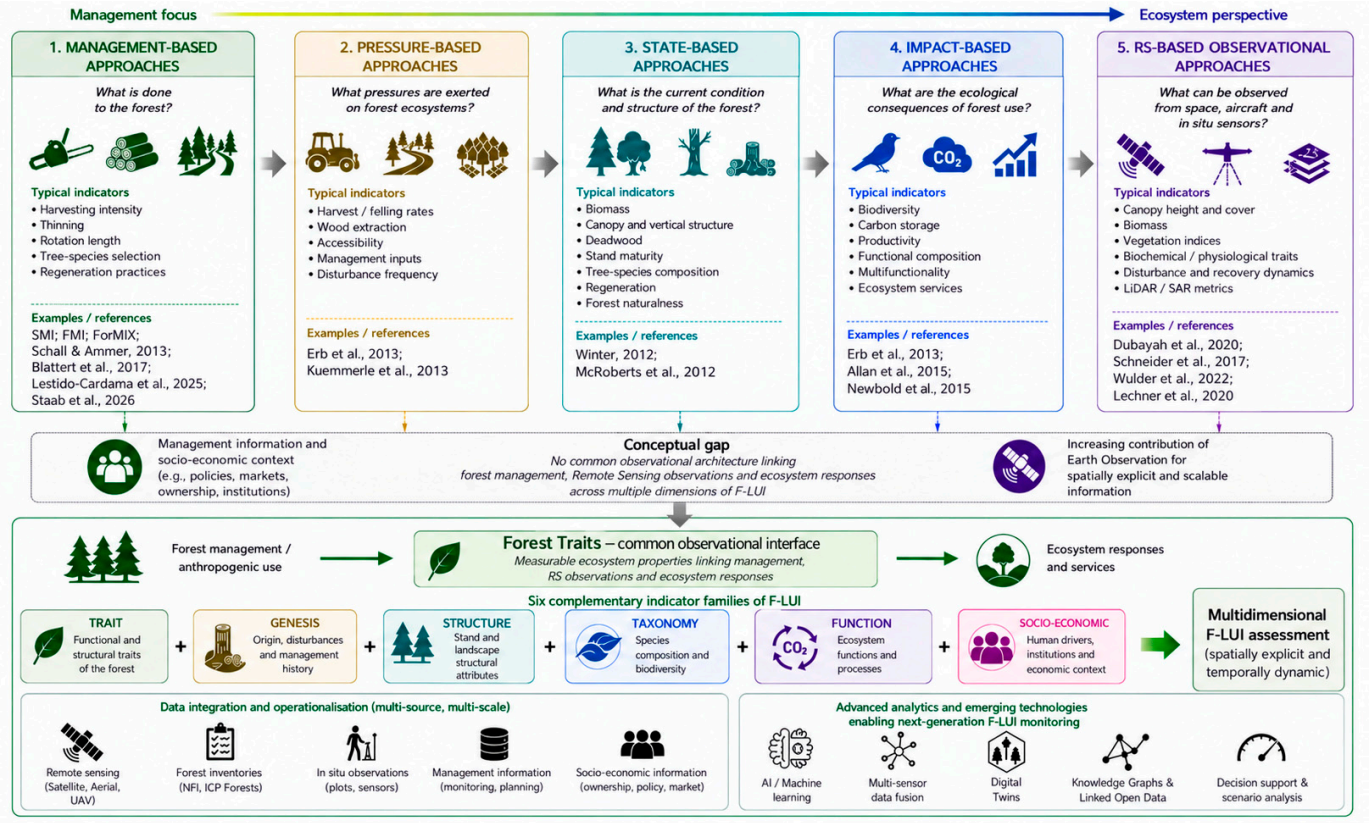


Figure 1. Evolution of conceptual approaches for describing Forest Land Use Intensity (F-LUI), ranging from management- and pressure-based approaches to state-, impact- and Remote Sensing (RS)-based observational approaches, and their integration within the proposed trait-based framework. Forest traits provide the common observational interface linking anthropogenic forest use, RS observations and ecosystem responses across six complementary F-LUI indicator families. References: Schall & Ammer 2013 [6], Blattert et al., 2017 [7], Lestido-Cardama et al., 2025 [19], Staab et al., 2026 [20], Erb et al., 2013 [4], Kuemmerle et al., 2013 [5], Winter 2012 [23], McRoberts et al., 2012 [24], Allan et al., 2015 [8], Newbold et al., 2015 [9], Dubayah et al., 2020 [12], Schneider et al., 2017 [14], Wulder et al., 2024 [25], Lechner et al., 2020 [10]. Conceptual visualisation generated using OpenAI ChatGPT (GPT-6; image generation) based on concepts defined by Angela Lausch; scientific validation and final revision by Angela Lausch.

3.3. Programmes for Monitoring Forest Land Use Intensity (F-LUI) at National (Germany), European and Global Scales

The quantification of F-LUI does not currently rely on dedicated F-LUI monitoring programmes, but on a range of national, European and global forest monitoring systems that capture different properties of forest ecosystems. These programmes were primarily developed to assess forest resources, biodiversity, forest condition, carbon dynamics, climate-related impacts and sustainable forest management rather than F-LUI itself. Nevertheless, they provide essential information on several dimensions of F-LUI and therefore represent an important basis for its operationalisation. The programmes differ in their objectives, spatial coverage, temporal frequency and data sources. National systems generally provide detailed inventory and management information, European programmes promote harmonisation across countries, and global programmes enable international comparison and reporting. From the perspective of the trait-based framework developed in this review, these monitoring systems provide complementary information for the six F-LUI indicator families—Trait, Genesis, Structure, Taxonomy, Function and Socio-economics—but each covers only part of the overall concept. Table A3 compares the major national (Germany), European and global forest monitoring programmes and information systems with respect to their primary purpose, main variables, data sources, spatial and temporal coverage, and their principal contributions to the six F-LUI indicator families.

3.3.1. National Monitoring Programmes in Germany

Germany has a well-established system of national forest inventories and environmental monitoring programmes that provides important information for assessing several dimensions of F-LUI. The German National Forest Inventory (Bundeswaldinventur, BWI) represents the principal nationwide forest inventory. It provides standardised information on forest area, tree species composition, stand structure, growing stock, increment, regeneration, deadwood and biomass. The most recent inventory, BWI 2022 [27], forms the basis for assessing current forest structure and resources and for analysing long-term changes in German forests. It is complemented by the Carbon Inventory (Kohlenstoffinventur) and by the Forest Development and Timber Resource Model (Waldentwicklungs- und Holzaufkommensmodellierung, WEHAM), which uses BWI information to model future forest development and timber availability under defined management assumptions. The current WEHAM modelling period extends from 2023 to 2062.

Forest condition and environmental responses are monitored through the national Forest Condition Survey (Waldzustandserhebung, WZE), Intensive Forest Monitoring (Level II) and the National Forest Soil Inventory (Bodenzustandserhebung im Wald, BZE). The WZE has been conducted annually since 1984 and primarily assesses crown condition and forest vitality, whereas Level II monitoring provides more detailed information on environmental pressures and ecosystem processes. The BZE complements these observations with information on soil chemistry, nutrient status, acidification, carbon stocks and related site characteristics. The third BZE began in 2022, with field sampling conducted until 2024.

Together, these programmes provide complementary information relevant to F-LUI, ranging from forest management and structural attributes to ecosystem condition, soil properties and carbon dynamics. However, they were not designed specifically to quantify F-LUI and differ considerably in spatial coverage, temporal resolution and observational focus. Their integration with spatially continuous RS observations therefore provides considerable potential for extending plot-based measurements across space and time and for linking national forest monitoring to the multidimensional F-LUI framework developed in this review. The principal characteristics and contributions of these programmes are summarised in Table A3.

3.3.2. European Monitoring Programmes

At the European scale, forest monitoring is based on a combination of harmonised field networks, national reporting systems and increasingly RS-based monitoring programmes. One of the most important long-term infrastructures is the International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests (ICP Forests), established in 1985 under the UNECE Air Convention. Its Level I network comprises approximately 6000 plots for large-scale monitoring of forest condition, while more than 600 Level II plots provide intensive observations of atmospheric deposition, soil and soil-water chemistry, foliar chemistry, tree growth, phenology, ground vegetation and other ecosystem properties. This combination provides a particularly valuable basis for analysing long-term changes in forest condition and ecosystem responses to environmental stressors.

At the policy and reporting level, FOREST EUROPE provides a pan-European framework for assessing sustainable forest management using harmonised criteria and indicators covering forest resources, biodiversity, productive and protective functions and socio-economic dimensions. These data are complemented by the Forest Information System for Europe (FISE), which integrates forest-related information from national and European sources and increasingly incorporates information derived from Copernicus.

RS-based monitoring is provided particularly through the Copernicus Land Monitoring Service (CLMS), including High Resolution Layers for Tree Cover Density and Forest Type, while CORINE Land Cover (CLC) provides long-term harmonised information on land-cover change. The Land Use/Cover Area Frame Survey (LUCAS) contributes standardised in situ observations that are also important for the calibration and validation of RS products. Disturbance monitoring is complemented by the European Forest Fire Information System (EFFIS), which provides information on fire danger, active fires and burnt areas. These programmes are also included in the monitoring architecture summarised in Table A3.

Together, European monitoring systems provide complementary observations of forest condition, structure, biodiversity, environmental pressures, management and disturbances. However, as at the national level, they were developed for different purposes and do not constitute an integrated F-LUI monitoring system. Their combination with RS and forest traits therefore provides an important basis for harmonising observations across countries and linking them to the multidimensional F-LUI framework developed in this review.

3.3.3. Global Monitoring Programmes

At the global scale, forest monitoring is primarily coordinated through the FAO Global Forest Resources Assessment (FRA), which provides harmonised information on forest extent and change, biomass and carbon stocks, disturbances, management, ownership and other dimensions of sustainable forest management. The most recent FRA 2025 [28] is based on official national data from 194 countries and areas and represents the principal global reference for assessing long-term changes in forest resources, management and use. The FRA is complemented by its RS survey, which provides spatially consistent information on forest and land-use dynamics and strengthens the integration of national reporting with satellite-based observations. The FRA 2020 RS survey [29], for example, analysed approximately 400,000 samples with contributions from experts in 126 countries.

In addition, National Forest Monitoring Systems (NFMS), particularly those developed in the context of REDD+, combine forest inventories, RS and other national data sources to monitor forest-cover change, degradation and carbon dynamics. FAO supports countries in developing such systems and increasingly promotes the integration

of RS and cloud-based processing with national forest information. Global RS-based platforms further complement these systems. Global Forest Watch (GFW) integrates numerous global and regional datasets on forest cover, land use and disturbance and provides near-real-time information on vegetation and forest loss. Its current integrated disturbance alerts combine several optical- and radar-based alert systems, illustrating the increasing importance of multi-sensor observations for global forest monitoring. The Global Wildfire Information System (GWIS) additionally contributes information on fire occurrence and disturbance dynamics. These programmes are summarised in Table A3.

Together, these global monitoring systems provide essential information on forest resources, management, carbon dynamics and disturbances across countries and biomes. However, their spatial and temporal resolutions, indicator definitions and underlying data sources differ considerably, and none was designed specifically to quantify the multiple dimensions of F-LUI. Their integration with forest traits and RS therefore provides an important basis for translating heterogeneous global forest observations into a harmonised, multidimensional F-LUI monitoring framework.

4. Approaches for Monitoring F-LUI

Monitoring F-LUI requires observations that capture both anthropogenic forest use and the resulting changes in forest ecosystem properties. Because F-LUI is multidimensional and cannot be measured directly by a single variable, its assessment relies on complementary observational approaches. These range from field-based measurements and forest inventories to spatially continuous RS observations.

In situ approaches provide detailed measurements of forest structure, composition, biomass, regeneration, deadwood, soil properties, biodiversity and ecosystem functioning and can additionally incorporate information on management history and silvicultural interventions. They therefore provide an essential ecological reference for interpreting F-LUI, but their spatial coverage and temporal repetition are generally limited. In contrast, RS approaches enable spatially continuous, standardised and repeated observations across scales and provide information on spectral, structural, biochemical, physiological and temporal properties of forest ecosystems. However, RS primarily captures observable ecosystem properties and changes rather than management decisions themselves.

The two approaches should therefore be considered complementary rather than alternative. In situ observations provide ecological interpretation, calibration and validation, whereas RS enables their spatial and temporal extension. Figure 2 illustrates this complementary observational architecture and shows how in situ measurements and RS observations can be linked through forest traits to capture different dimensions of F-LUI across spatial and temporal scales. Their integration is particularly important for the trait-based perspective developed in this review, because forest traits provide measurable ecosystem properties that can be characterised both in situ and through RS.

4.1. In-Situ Approaches

In situ observations provide the ecological reference for quantifying F-LUI. They deliver direct information on forest structure, species composition, biodiversity, ecosystem functions and forest management activities, thereby enabling the actual effects of anthropogenic use on forest ecosystems to be assessed. Owing to their high measurement accuracy and ecological interpretability, in situ data provide an indispensable basis for the calibration, validation and interpretation of RS-based F-LUI indicators [30,31]. The most important data source is provided by National Forest Inventories (NFIs), which periodically record information on forest area, tree species composition, tree dimensions, growing stock, biomass, increment, natural regeneration and deadwood. Repeated inventories enable long-term changes in forest resources and

their use to be analysed and, at the same time, provide a basis for numerous national and international reporting systems related to sustainable forest management, biodiversity and climate mitigation [30,31].

An important complement is provided by long-term forest condition monitoring programmes. The European ICP Forests network has monitored the condition of forest ecosystems since 1985 using harmonised methods across extensive Level I plots and intensively investigated Level II sites. Recorded variables include crown condition, tree growth, foliar chemistry, soil and soil-solution chemistry, atmospheric deposition, meteorological conditions and biodiversity-related characteristics. These observations make it possible to investigate long-term changes in forest condition as well as interactions among air pollution, climate change, natural disturbances, forest management and ecological responses across broad spatial and temporal scales [32].

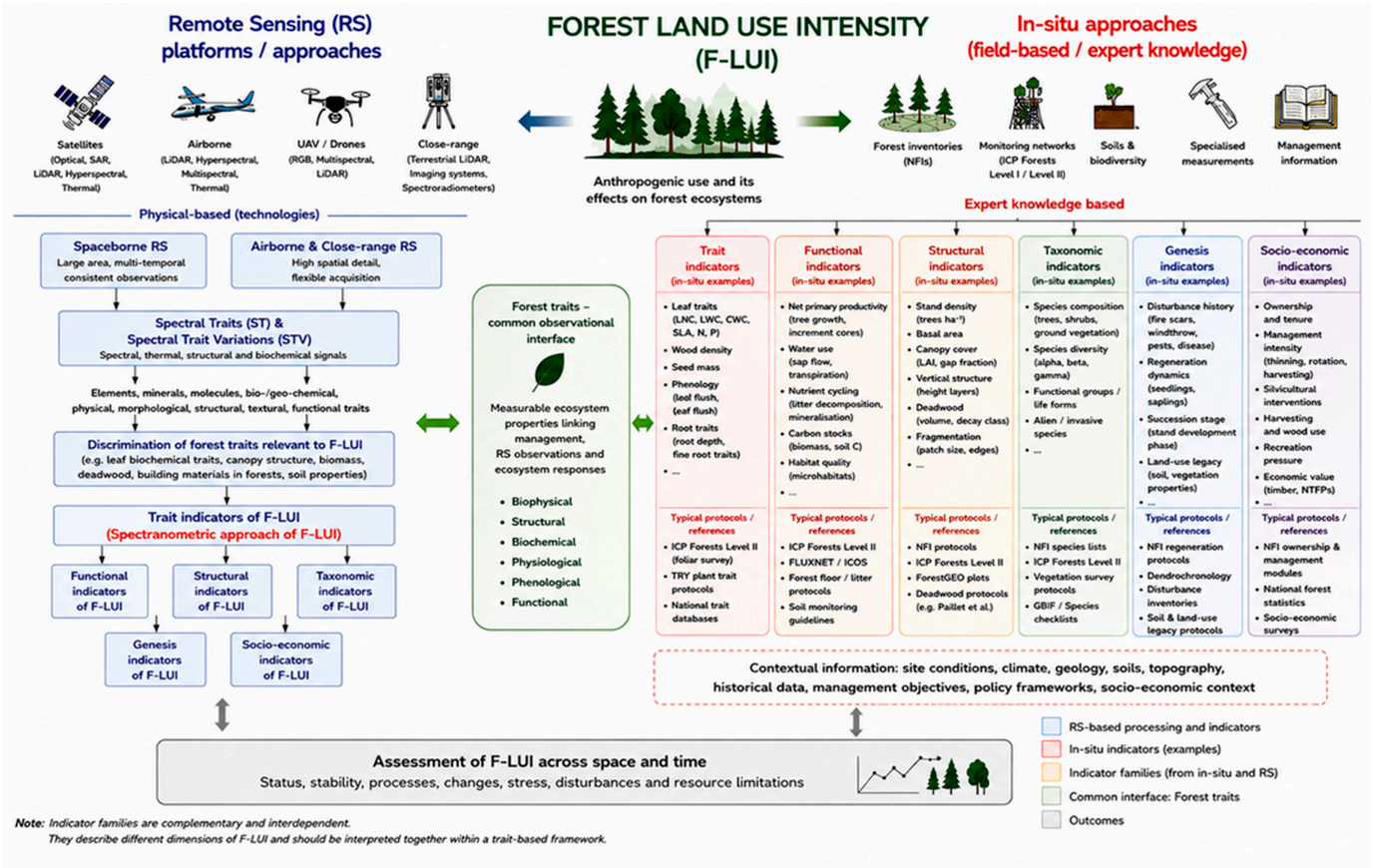


Figure 2. Complementary observational approaches for monitoring Forest Land Use Intensity (F-LUI). Remote Sensing (RS) provides spatially continuous and multitemporal observations from spaceborne, airborne, Unmanned Aerial Vehicle (UAV) and close-range platforms, whereas in situ approaches provide field measurements, inventories, long-term monitoring and management information. Forest traits form the common observational interface linking these approaches to six complementary F-LUI indicator families: Trait, Functional, Structural, Taxonomic, Genesis and Socio-economic. In the colour key, orange denotes indicator families informed by both RS and in situ observations; the purple box identifies the socio-economic indicator family, including ownership, management and use context. Together, the families support multidimensional assessment of F-LUI across space and time. Conceptual visualisation generated using OpenAI ChatGPT (GPT-6; image generation) based on concepts defined by Angela Lausch; scientific validation and final revision by Angela Lausch.To assess the ecological consequences of different levels of forest-use intensity, vegetation, biodiversity and habitat surveys are also conducted. These include assessments of species composition across different organism groups, habitat structures,

deadwood, microhabitats and other biodiversity indicators. Complementary soil inventories provide information on physical, chemical and biological soil properties, including soil moisture, forest-floor characteristics, carbon and nitrogen stocks, pH, nutrient availability and soil compaction. These measurements enable the long-term effects of forest management on nutrient cycling, soil functioning, carbon storage and forest ecosystem stability to be assessed [33].

A further important monitoring component is provided by ecophysiological and ecohydrological measurement networks that continuously record functional processes such as photosynthesis, transpiration and carbon, water and energy fluxes. International research infrastructures such as the Integrated Carbon Observation System (ICOS) and FLUXNET provide harmonised long-term observations of the exchange of carbon dioxide, water and energy between forest ecosystems and the atmosphere. These data enable functional responses of forest ecosystems to climate variability, extreme events, disturbances and different management regimes to be analysed [34,35].

Of particular importance for quantifying F-LUI are management and operational data, because they directly document anthropogenic interventions. These include information on timber harvesting, thinning, clear-cutting, skid trails, machinery use, tree species selection, afforestation, natural regeneration, conservation measures and game-management interventions. Such information is derived primarily from forest enterprises, management plans or administrative databases and represents the most direct source of information for describing the actual intensity of forest use. At the same time, management data are frequently spatially incomplete, methodologically heterogeneous and only partly harmonised among countries, forest enterprises and ownership types, which limits their international comparability [6,7,19].

With the increasing digitalisation of forest ecology, automated in situ sensor networks are becoming increasingly important. Continuously operating dendrometers, sap-flow sensors, soil-moisture and microclimate sensors, automatic weather stations and phenocams provide high-resolution time series of structural, physiological and phenological processes. Compared with periodic forest inventories, they capture short-term responses of forest ecosystems to environmental change, extreme events and management interventions. At the same time, they bridge the temporal gap between discrete field measurements and continuous RS observations and provide reference information for the development, calibration and validation of RS-based products and AI-supported monitoring approaches [36,37].

In addition to established inventory and monitoring approaches, specialised in situ methods are used, including dendrochronological analyses, destructive biomass measurements and experimental manipulation studies. These methods provide detailed information on growth history, biomass allometry, genetic diversity, physiological responses and the ecological mechanisms operating within forest ecosystems. Owing to their high demands in terms of labour, time and cost, and their generally limited spatial coverage, they are mainly suitable for experimental, process-oriented or site-specific investigations. Their applicability to spatially comprehensive monitoring of F-LUI is therefore limited.

Taken together, these in situ methods provide high-quality reference information for the derivation and ecological interpretation of forest traits and for the calibration and validation of RS-derived forest traits. They therefore form a critical interface between forest management, forest ecosystems and RS. At the same time, they serve as ground reference data for the calibration, validation and ecological interpretation of RS observations [38]. This complementary role of in situ and RS approaches is illustrated in Figure 2.

Despite their high accuracy, in situ methods have inherent limitations in terms of spatial coverage and temporal repeatability. Because field surveys are labour-intensive, time-consuming and costly, they are generally conducted on sample plots and often at multi-year intervals. Consequently, spatially comprehensive and continuous quantification of F-LUI cannot be achieved using field methods alone. Future monitoring concepts therefore require close integration of in situ observations, RS and model-based approaches. In situ data provide the indispensable reference for the calibration, validation and ecological interpretation of RS-based F-LUI indicators and thereby establish the basis for harmonised, cross-scale monitoring of F-LUI.

4.2. Remote Sensing Approaches

4.2.1. Principles of Monitoring F-LUI Using RS

RS provides the principal basis for spatially continuous monitoring of F-LUI. Through the non-contact measurement of electromagnetic radiation, modern RS systems enable standardised, objective and repeatable observations of forest ecosystems across spatial scales ranging from individual trees to the global level. Depending on the application, ground-based sensor systems, Unmanned Aerial Vehicle (UAVs), airborne sensors and satellite missions provide multispectral, hyperspectral, thermal, radar (SAR) and LiDAR observations.

The increasing availability of high-resolution and long-term observations from missions such as Landsat, Sentinel-1/-2, GEDI, ICESat-2, EnMAP and PRISMA has substantially expanded the potential for consistent, spatially explicit and cross-scale forest monitoring. In particular, long-term Landsat time series and their integration with more recent multi-sensor RS systems have contributed substantially to the development of contemporary approaches for monitoring forest structure, dynamics and disturbances [12,39].

In contrast to in situ approaches, however, RS does not necessarily observe F-LUI directly. Sensors record the physical properties of the Earth's surface and their spatial and temporal variation. Anthropogenic interventions such as timber harvesting, thinning, changes in tree species composition, reforestation or forest degradation are therefore generally detected through their effects on the biophysical properties and dynamics of forest ecosystems. Consequently, the primary observational units of RS are not the management decisions themselves, but the measurable ecosystem properties, processes and changes through which management becomes observable [40].

Forest traits provide a conceptual basis for describing these observable properties. They encompass, for example, structural, morphological, biochemical, physiological and phenological properties of vegetation, soils and other components of forest ecosystems. Because these properties respond to both natural environmental conditions and anthropogenic use, forest traits constitute a central observational level through which the effects of forest management can be detected and quantified using RS [14–16,41].

Examples include horizontal and vertical stand structure, canopy architecture, AGB, LAI, leaf pigment and nitrogen content, vegetation water status, primary productivity and surface temperature. Forest management can modify these properties, and the resulting changes become detectable through spectral, thermal and structural RS signals. Forest traits therefore provide an observable interface linking forest management, ecosystem responses and RS, as conceptually illustrated in Figure 2.

An important advantage of the trait-based approach is its sensor independence. Different RS technologies capture complementary manifestations of ecosystem properties. Multispectral and hyperspectral sensors provide information on spectral characteristics and biochemical vegetation properties; thermal sensors characterise aspects of ecosystem energy and water dynamics; radar systems (SAR) are particularly sensitive to vegetation

structure and moisture conditions; and LiDAR systems enable direct characterisation of the three-dimensional architecture of forest stands. Combining these complementary information sources therefore enables a more multidimensional representation of forest ecosystems and substantially improves the potential to derive robust indicators of F-LUI [12,15]

The increasing availability of multi-sensor RS data is further complemented by recent advances in AI. Deep Learning, Self-supervised Learning, Foundation Models and multimodal data fusion increasingly enable heterogeneous satellite, LiDAR and forest inventory data to be analysed jointly. These developments are shifting RS from the retrieval of individual forest variables towards more integrated representations of forest traits and their spatial and temporal dynamics [42–45]. These emerging methodological developments and their potential contribution to operational F-LUI monitoring are discussed in greater detail in Section 7.

From this perspective, RS-based F-LUI monitoring focuses not primarily on forest management activities themselves, but on their manifestations in the observable properties and dynamics of forest ecosystems. F-LUI can therefore be characterised through the spatial and temporal variability of forest traits that reflect ecosystem responses to different forms and intensities of anthropogenic use. The trait-based approach consequently provides the conceptual basis for the framework developed in this review, in which heterogeneous RS observations are interpreted as measurable expressions of forest traits and integrated into a sensor-independent, standardisable and cross-scale framework for assessing F-LUI.

4.2.2. Challenges of Monitoring F-LUI Using RS

RS provides unique opportunities for spatially continuous, standardised and repeatable observations of forest ecosystems. Nevertheless, substantial conceptual, ecological and methodological challenges remain in quantifying F-LUI. These arise primarily because land-use intensity itself cannot be observed directly. Instead, RS systems primarily capture the manifestations of anthropogenic interventions in the biophysical properties and dynamics of forest ecosystems. Developing robust, scalable and internationally comparable F-LUI indicators therefore requires not only appropriate sensor technologies, but also a conceptual framework that consistently links forest management, forest traits and their observable RS signals.

Conceptual challenges: The fundamental conceptual challenge is that RS does not observe forest management decisions themselves, but primarily their manifestations in observable ecosystem properties. Management activities such as timber harvesting, thinning or changes in tree species composition can therefore generally be inferred only indirectly from changes in structural, biochemical, physiological or thermal properties. At the same time, there is currently neither a universally accepted definition of F-LUI nor an internationally harmonised indicator system that consistently integrates forest management, ecosystem state and ecosystem functioning. Many existing studies focus on individual parameters such as biomass, productivity, forest structure or timber harvesting, which substantially limits comparability among studies and complicates the consistent quantification of F-LUI.

Ecological challenges: A further major challenge is that forest traits respond to both anthropogenic use and natural environmental processes. Changes in canopy structure, biomass, leaf chemistry, productivity or surface temperature may result from forest management, but equally from drought stress, storms, wildfires, insect outbreaks, diseases or natural succession. Moreover, responses differ considerably among forest ecosystems. Identical management interventions may produce markedly different biophysical responses in boreal, temperate and tropical forests, as well as among stands

of different ages, structures and species compositions. Conversely, similar RS signals may result from different ecological or anthropogenic processes. Disentangling anthropogenic management effects from natural environmental and disturbance-driven variability therefore represents one of the principal challenges in RS-based F-LUI assessment.

Spatial and temporal scales: F-LUI is a dynamic and scale-dependent phenomenon. Forest management operates across spatial levels ranging from individual trees and stands to entire landscapes, while its ecological effects unfold over markedly different timescales. Clear-cutting, for example, may become immediately apparent in RS observations, whereas the effects of thinning, changes in tree species composition or long-term management regimes may develop over years or decades. Forest traits also differ in their response times: structural properties may respond relatively rapidly to management interventions, whereas some functional or physiological responses may emerge gradually or with a temporal lag. At the same time, RS systems differ in their spatial, spectral and temporal resolutions, meaning that individual processes and traits cannot be observed equally well by all sensors. Selecting appropriate spatial and temporal observation scales is therefore essential for deriving reliable and ecologically meaningful F-LUI indicators.

Methodological challenges: Different RS technologies capture different properties of forest ecosystems. Multispectral and hyperspectral sensors provide information on spectral signatures and biochemical vegetation properties; thermal sensors characterise aspects of ecosystem energy and water dynamics; radar systems (SAR) are particularly sensitive to vegetation structure and moisture conditions; and LiDAR systems provide direct information on three-dimensional forest structure. However, no single sensor technology can capture all dimensions of F-LUI. Instead, each sensor observes different and complementary manifestations of forest traits that collectively provide information on forest ecosystem state and dynamics. Moreover, many traits are not measured directly but are estimated using vegetation indices, physically based inversion methods or data-driven models. The accuracy of these products depends on sensor characteristics, model assumptions, calibration data and retrieval algorithms, inevitably introducing uncertainties throughout the processing chain.

Validation and data integration: The development of robust RS-based F-LUI indicators requires extensive reference data from forest inventories, permanent monitoring plots, sensor networks and forest management databases. However, such datasets are often regionally restricted, methodologically heterogeneous and collected at different temporal intervals. Differences in inventory designs, definitions and measurement protocols further constrain the transferability of models among regions, countries and forest types. Information on specific management interventions may also be incomplete, inaccessible or subject to data-protection and ownership restrictions. Modern data-fusion approaches, together with Machine Learning and AI, provide new opportunities for integrating heterogeneous sources such as RS, forest inventory, climate and management data. At the same time, these approaches increase requirements for data harmonisation, uncertainty quantification, model robustness, transferability and interpretability.

Standardisation and international comparability: In addition to these methodological limitations, there remains a substantial need for standardised concepts and procedures for assessing F-LUI. Although a rapidly growing range of RS products is available, an internationally harmonised observational framework that consistently connects different sensor technologies, forest types, management systems and spatial scales is still lacking. A trait-based, multidimensional and sensor-independent framework is therefore not merely a methodological extension of existing RS approaches, but a conceptual prerequisite for harmonised, cross-scale and internationally comparable monitoring of F-LUI.

Taken together, these challenges demonstrate that neither individual RS sensors nor isolated indicators are sufficient to characterise F-LUI consistently. What is required instead is a conceptual framework that positions forest traits as the common observational interface linking forest management, observable ecosystem responses and RS. This concept provides the basis for the trait-based F-LUI framework developed in the following section.

5. Conceptual Definition of F-LUI Using RS

5.1. Conceptual Definition of F-LUI

F-LUI describes the intensity of anthropogenic use, management and transformation of forest ecosystems and the resulting consequences for ecosystem structure, functioning and dynamics. While the concept of Land Use Intensity has been extensively developed for agricultural and other land-use systems [4], no universally accepted definition or conceptual framework currently exists for forest ecosystems that consistently links management activities, ecological processes and RS observations. Existing approaches predominantly quantify either the intensity of forest management activities or their ecological consequences and therefore capture different, but only partial, dimensions of F-LUI. Recent developments illustrate this distinction particularly clearly. Lestido-Cardama et al. [19] proposed a harmonised approach to Forest Management Intensity based on extractive impact, financial resources and management inputs, whereas Staab et al. [20] introduced the Forest Management Intensity Index (ForMIX), which integrates tree species composition, tree removal, deadwood availability and stand maturity to quantify forest land-use intensity. These approaches represent important advances in quantifying management intensity and forest-use intensity, but they do not provide a common observational architecture linking management, ecosystem responses and RS observations across multiple F-LUI dimensions.

From an RS perspective, F-LUI is fundamentally not directly observable as a single ecosystem property. Satellite-, airborne- and UAV-based sensor systems do not directly observe management decisions or management intensity itself; rather, they measure changes in the observable properties of forest ecosystems through which management effects become detectable. Changes in forest management can manifest in structural, morphological, biochemical, physiological, functional and phenological ecosystem properties that can either be observed directly or inferred from RS data. The primary observational units of RS-based F-LUI assessment are therefore not management activities themselves, but the measurable ecosystem properties and responses through which anthropogenic interventions become observable.

This perspective leads to a fundamental conceptual interpretation of F-LUI. Rather than treating F-LUI as an individual management activity or simply as the cumulative amount of silvicultural intervention, we conceptualise it as an emergent property of forest ecosystems arising from interactions among anthropogenic use, environmental conditions and ecological responses. This distinction is important because identical management interventions may produce different ecosystem responses depending on forest type, stand structure, site conditions, management history and disturbance regime. Conversely, similar observable forest states may result from different combinations of anthropogenic and natural processes. Consequently, RS does not simply measure forest use itself; it captures the spatial and temporal manifestations of forest use within the observable properties and dynamics of forest ecosystems.

Building on the core conceptual definition introduced in Section 3.1, we operationalise F-LUI for RS-based assessment as a multidimensional property that becomes observable through changes in structural, morphological, biochemical, physiological, phenological, functional and socio-ecological forest traits. These traits

represent the measurable manifestations through which anthropogenic use, management and transformation—and their interactions with environmental conditions and ecological processes—can be detected or inferred using RS. This operational interpretation does not constitute a separate definition of F-LUI; rather, it specifies how the general concept can be translated into observable indicators. This operational interpretation extends existing concepts of land-use and Forest Management Intensity by positioning forest traits as the common observational interface between forest management, ecosystem responses and RS. Forest traits encompass measurable properties of forest ecosystems that respond to both anthropogenic interventions and environmental conditions and can be characterised using complementary in situ and RS observations [14–16,41]. They therefore provide the fundamental observational level upon which the framework developed in this review is constructed.

Importantly, this framework does not replace existing indices of forest management or land-use intensity. Rather, approaches such as Forest Management Intensity and ForMIX quantify particular dimensions of management or forest-use intensity, whereas the trait-based framework addresses a different question: how can the multiple manifestations of F-LUI be observed, integrated and compared across sensors, spatial scales and time? This distinction is particularly relevant because recent work continues to highlight the need for harmonised approaches to quantifying Forest Management Intensity [19], while ForMIX demonstrates the value of integrating several complementary ecological and management-related dimensions rather than relying on a single forest attribute [20].

Accordingly, the framework developed here does not seek to derive a universal single F-LUI index. Instead, it provides a multidimensional observational architecture in which forest traits connect anthropogenic forest use with measurable ecosystem responses and their observation through RS. These observations are subsequently organised into six complementary indicator families—Trait, Genesis, Structure, Taxonomy, Function and Socio-economics—which together form the conceptual basis for the multidimensional assessment of F-LUI developed in the following sections.

5.2. Forest Traits as the Conceptual Interface Between Forest Ecosystems and Remote Sensing

Forest traits provide the conceptual foundation of the framework proposed in this review for assessing F-LUI.

In contrast to management activities, which cannot generally be observed directly by RS, forest traits represent directly or indirectly observable properties of forest ecosystems that can be measured or inferred from RS observations. They encompass structural, morphological, biochemical, physiological, phenological and functional properties of vegetation, soils and other components of forest ecosystems and thereby provide the physically measurable interface between ecological processes and RS observations [13–15].

The fundamental premise of the trait-based approach is that RS can only observe those manifestations of forest use that become expressed in measurable ecosystem properties. Forest management activities such as timber harvesting, thinning, changes in tree species composition or reforestation modify the structure, composition, functioning and dynamics of forest ecosystems. These changes are manifested in forest traits and subsequently become detectable through spectral, thermal or structural RS signals. RS therefore does not directly observe forest management or F-LUI itself, but the forest traits through which anthropogenic use and its ecological consequences become observable. Forest traits consequently constitute the fundamental observational units of RS-based F-LUI monitoring.

A major advantage of this approach is its sensor independence. Different RS technologies capture complementary manifestations of forest traits. Multispectral and hyperspectral sensors provide information on spectral characteristics and biochemical vegetation properties; thermal sensors characterise traits related to ecosystem energy and water dynamics; radar systems (SAR) are particularly sensitive to structural and moisture-related traits; and LiDAR systems provide information on three-dimensional structural traits of forest stands. No individual sensor technology can capture the full range of forest traits. Combining complementary observations therefore enables a multidimensional characterisation of forest ecosystems and substantially strengthens the assessment of F-LUI [12].

Forest traits also have a direct ecological meaning. Rather than representing abstract RS variables, they describe measurable properties of forest organisms and ecosystems and thereby facilitate the ecological and process-based interpretation of RS observations. This perspective is closely related to established trait-based approaches in functional ecology and to concepts such as Essential Biodiversity Variables (EBVs), which seek to represent complex biodiversity patterns and ecosystem changes through standardised and ecologically interpretable observational variables [15,46–48].

Importantly, the trait concept in the framework developed here is not restricted to the Trait indicator family itself. Rather, forest traits provide the common observational basis from which all six complementary F-LUI indicator families are derived and interpreted. The Trait family represents individual measurable ecosystem properties; Genesis indicators are derived from temporal changes and trajectories of forest traits that reveal disturbance, regeneration, succession and land-use legacies; Structural indicators describe the spatial and three-dimensional organisation and configuration of structural; Taxonomic indicators use trait expressions and their spatial patterns to distinguish tree species, forest types, communities and ecological classes; Functional indicators integrate traits associated with ecosystem processes such as productivity, water cycling, carbon dynamics and resilience; and Socio-economic indicators infer manifestations of anthropogenic use from trait patterns associated with harvesting, accessibility, management regimes and other spatial expressions of human forest use. Thus, although the six families represent different dimensions of F-LUI, their RS-based observation ultimately depends on measurable forest traits and their spatial, temporal and functional relationships.

This distinction is particularly important for the Genesis and Socio-economic dimensions. RS does not directly observe forest history, ownership, governance or management decisions. Instead, these dimensions become accessible to RS only where they leave detectable expressions in forest traits or in their spatial and temporal patterns. Similarly, taxonomic and functional properties are inferred from characteristic combinations, distributions or dynamics of observable traits rather than being directly measured as abstract ecosystem categories or processes. The trait concept therefore provides the common observational language through which otherwise heterogeneous dimensions of F-LUI can be related to RS.

Forest traits are themselves not necessarily measured directly. Many are inferred from spectral, thermal, radar or LiDAR observations using physically based retrieval models, statistical approaches or AI. Their expression is additionally influenced by climate, site conditions, forest developmental stage and natural disturbances. Consequently, an observed trait pattern cannot automatically be attributed to anthropogenic use. Reliable interpretation requires temporal information and, where available, complementary in situ observations, forest inventories, environmental information and management data. Nevertheless, RS-based F-LUI assessment remains fundamentally trait-based because these additional data support the interpretation and

attribution of observed forest traits rather than replacing them as the RS observational unit.

The conceptual relationship underlying the framework can therefore be expressed as: Forest management and anthropogenic use → ecosystem responses → forest traits → RS observations → trait-based interpretation within the six F-LUI indicator families → multidimensional F-LUI assessment.

Forest traits thus provide more than one category of F-LUI indicators. They constitute the common observational foundation of the entire framework, enabling heterogeneous RS observations to be organised and ecologically interpreted across the Trait, Genesis, Structure, Taxonomy, Function and Socio-economic dimensions. This common trait basis distinguishes the proposed framework from approaches that combine independent RS indicators without an overarching ecological observational concept. It also reflects the central novelty emerging from the conceptual synthesis: the integration of forest traits as the common observational interface linking forest management, RS observations and ecosystem responses within a multidimensional F-LUI architecture.

On this basis, the following section introduces the six complementary F-LUI indicator families—Trait, Genesis, Structure, Taxonomy, Function and Socio-economics—and demonstrates how each can be operationalised through forest traits and their spatial, temporal and functional expressions in RS observations.

5.3. The Six Trait-Based F-LUI Indicator Families

Because F-LUI is a continuous, multidimensional and dynamic property of forest ecosystems, it cannot be adequately characterised by a single RS parameter or management variable. Different forms and intensities of forest management simultaneously affect multiple ecosystem properties, resulting in changes in forest structure, composition, functioning and biophysical condition. These changes are expressed through forest traits and their spatial and temporal patterns, which can be observed or inferred using different RS technologies. A consistent assessment of F-LUI therefore requires a conceptual framework that systematically integrates these complementary trait-based observations.

Building on the concept of forest traits introduced above, we propose a trait-based framework that organises RS-observable or RS-derived ecosystem properties and their spatial, temporal and functional expressions into six complementary F-LUI indicator families: Trait, Genesis, Structure, Taxonomy, Function and Socio-economics (Figure 3). Importantly, forest traits constitute the common observational basis of all six families. The families therefore do not represent independent types of RS information; rather, they provide complementary perspectives through which individual traits and their spatial patterns, temporal trajectories and ecological relationships can be interpreted in relation to F-LUI.

- Trait indicators. Trait indicators represent directly observable or RS-derived structural, morphological, biochemical, physiological, phenological and thermal properties of forest ecosystems and their spatial and temporal variability. They constitute the fundamental observational level of the framework and provide the physically measurable interface between forest ecosystems and RS. Changes in these traits may reflect both environmental conditions and anthropogenic use and provide the primary observational basis from which the other F-LUI indicator families can be derived and interpreted.
- Genesis indicators. Genesis indicators characterise the origin, historical development and temporal dynamics of forest ecosystems through changes and trajectories in observable forest traits. They capture long-term patterns associated with disturbance history, regeneration, succession, historical land use and different management

regimes. Genesis indicators therefore place present-day trait expressions, forest structure and ecosystem functioning within their temporal and historical context. Rather than observing forest history directly, RS reconstructs aspects of this history from temporal trajectories, persistence and transitions in forest traits.

- Structural indicators. Structural indicators characterise the spatial organisation and three-dimensional architecture of forest ecosystems through structural forest traits and their spatial configuration. They include horizontal composition and configuration as well as vertical layering, canopy height, structural complexity and related properties. Structural indicators therefore describe how forest traits are organised in space and how this organisation is modified by natural processes and anthropogenic forest use.
- Taxonomic indicators. Taxonomic indicators describe the composition, diversity and spatial distribution of biological entities within forest ecosystems. RS does not observe taxonomy itself; rather, tree species, forest types, vegetation communities and ecological forest classes are identified from characteristic combinations and spatial patterns of spectral, structural, biochemical and phenological forest traits. Taxonomic indicators thus translate observable trait variation into information on the biological composition and organisation of forest ecosystems.
- Functional indicators. Functional indicators characterise ecological processes and ecosystem functions related to the carbon, water and energy dynamics of forest ecosystems. These include primary production, photosynthetic activity, carbon sequestration, evapotranspiration, water cycling and energy exchange. Such functions are not necessarily observed directly by RS but are inferred from individual forest traits or combinations and temporal dynamics of traits that are mechanistically related to ecosystem processes. Functional indicators therefore provide information on how different forms and intensities of forest use affect ecosystem functioning and functional performance.
- Socio-economic indicators. Socio-economic indicators characterise the anthropogenic dimension of forest use and the spatial manifestations of its social, economic and management context. The socio-economic family differs from the five RS-centred families in its observational basis. Core variables such as land tenure, ownership, governance, management objectives and economic decisions have no intrinsic spectral or structural signature and cannot be derived directly from RS observations. They must therefore be obtained from government databases, forest-management plans, cadastral records, administrative statistics or other ancillary sources. RS can nevertheless provide spatially explicit proxies and manifestations of human use, including harvesting patterns, accessibility, infrastructure and management-related forest configurations. Socio-economic information is consequently represented as an outer contextual layer that conditions the attribution and interpretation of the five RS-centred indicator families.

For practical application, indicators are assigned according to their primary interpretative role and the principal question they address. Trait indicators describe what measurable biophysical property is observed; Genesis indicators explain how the observed condition originated or changed over time; Structural indicators describe how forest properties are organised horizontally and vertically in space; Taxonomic indicators identify which biological entities or communities are present; Functional indicators represent which ecosystem processes or functional responses occur; and Socio-economic indicators characterise which human activities, management decisions or institutional contexts drive or shape forest use. Where an indicator addresses more than one of these questions, it is assigned to the family corresponding to its principal analytical purpose,

while relevant secondary associations with other families are retained. The classification is therefore based on interpretative priority rather than mutual exclusivity.

The six indicator families are therefore not independent but form an interconnected trait-based observational system. Changes in forest management generally affect multiple forest traits simultaneously, and individual traits may contribute to more than one indicator family depending on their spatial, temporal and ecological interpretation. For example, canopy height may constitute a structural trait, its temporal decline may indicate a disturbance event within the Genesis family, its spatial variation may contribute to structural complexity, and its relationship with biomass and productivity may contribute to the interpretation of functional responses. The multidimensional character of F-LUI therefore emerges not simply from the number of available indicators, but from the integration of complementary information derived from forest traits.

This distinction is fundamental to the proposed framework: Forest traits are the common observational basis, whereas the six indicator families represent complementary dimensions for interpreting those traits in relation to F-LUI. The framework therefore does not assume that RS directly observes forest-use intensity, management history, taxonomy, ecosystem functioning or socio-economic processes. Rather, these dimensions become accessible to RS through measurable traits and their spatial, temporal and functional relationships. This common observational architecture distinguishes the framework from approaches based on collections of otherwise independent RS indicators and represents the principal conceptual contribution of this review. The underlying conceptual synthesis likewise identified the integration of forest traits as the common interface between management, RS observations and ecosystem responses as the strongest defensible novelty of the framework.

Figure 3 summarises this conceptual framework. It illustrates how anthropogenic forest use and natural environmental conditions modify forest ecosystems and how these changes become manifested in observable forest traits. RS technologies capture different expressions of these traits, which are subsequently organised and interpreted within the six complementary F-LUI indicator families. Together, these families provide the basis for a multidimensional, sensor-independent and cross-scale assessment of F-LUI. This framework provides the conceptual foundation for Section 6, in which the six indicator families are systematically examined with respect to representative forest traits and RS indicators, their derivation, ecological interpretation and suitability for monitoring F-LUI.



Figure 3. Trait-based conceptual framework for monitoring Forest Land Use Intensity (F-LUI) using Remote Sensing (RS). Forest traits constitute the common observational basis linking anthropogenic forest use and ecosystem responses to RS observations. Their individual expressions, spatial patterns, temporal trajectories and functional relationships are organised into six complementary F-LUI indicator families—Trait, Genesis, Structure, Taxonomy, Function and Socio-economics—which together enable a multidimensional assessment of F-LUI. Conceptual visualisation generated using OpenAI ChatGPT (GPT-6; image generation) based on concepts defined by Angela Lausch; scientific validation and final revision by Angela Lausch.

6. The Six F-LUI Indicator Families Monitored Using RS

Building on the conceptual framework defined in Section 5.3, this section examines representative RS-based indicators for each of the six F-LUI indicator families. For each indicator, the underlying forest traits, their relevance to F-LUI, suitable observation approaches, limitations and future development opportunities are discussed. Table A4 provides a consolidated overview of five key indicators per family, their relevance to F-LUI, principal data sources and representative references.

The following sections examine the principal RS-based indicators within each of the six indicator families. For each indicator, the underlying forest traits, their ecological relevance to F-LUI and suitable RS approaches are discussed, together with their potential, limitations and future development opportunities (Figure 4).

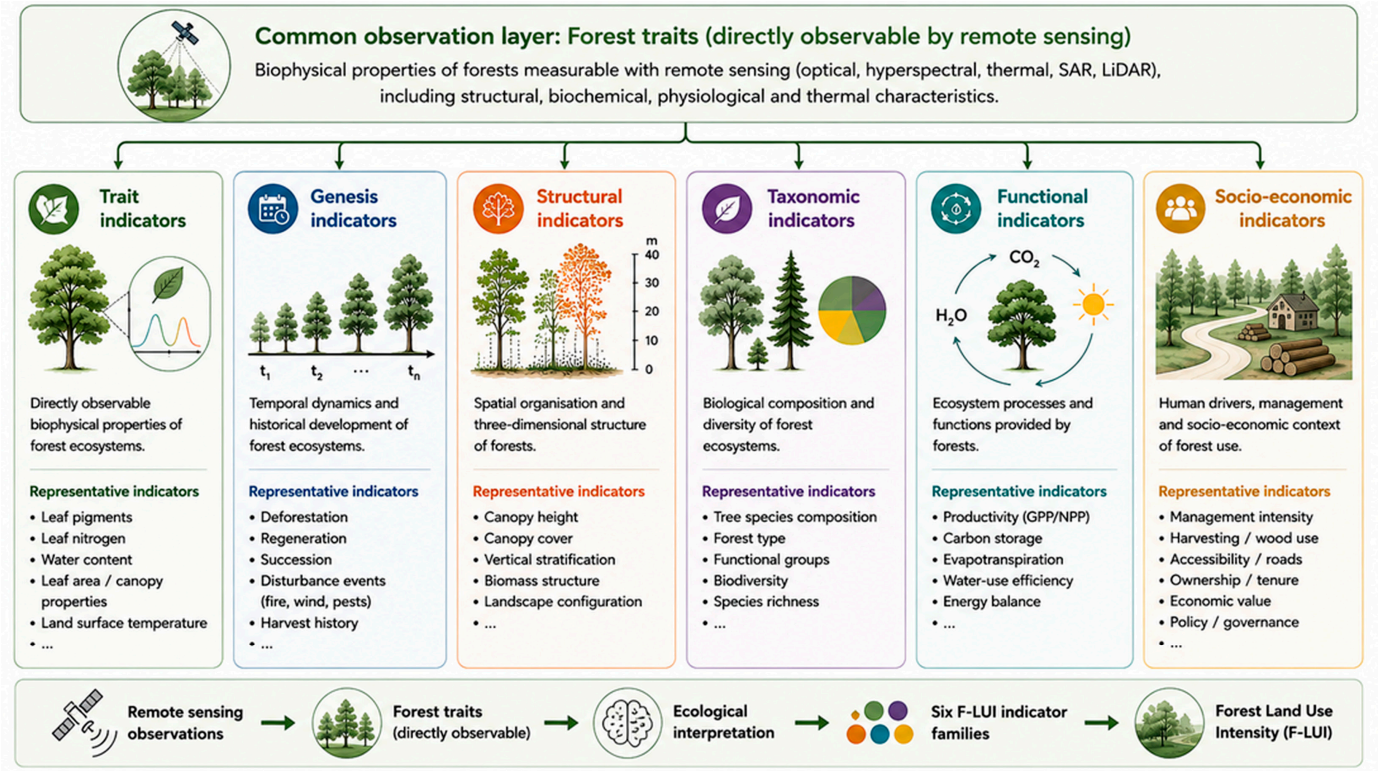


Figure 4. Conceptual overview of the six trait-based indicator families for monitoring Forest Land Use Intensity (F-LUI) using Remote Sensing (RS). Forest traits constitute the common observational layer of the framework and represent measurable forest ecosystem properties that can be observed or inferred from multi-source RS data. These trait observations, together with their spatial patterns, temporal trajectories and functional relationships, are interpreted within six complementary indicator families—Trait, Genesis, Structure, Taxonomy, Function and Socio-economics—which represent different ecological and anthropogenic dimensions of F-LUI. Together, the six families provide a multidimensional, sensor-independent and cross-scale framework for the consistent assessment and monitoring of F-LUI. Conceptual visualisation generated using OpenAI ChatGPT (GPT-6) (image generation) based on concepts defined by Angela Lausch; scientific validation and final revision by Angela Lausch.

6.1. Monitoring Trait Indicators of F-LUI Using RS

Trait indicators constitute the primary observational level of the proposed framework for assessing F-LUI. They encompass structural, morphological, biochemical, physiological, phenological and thermal properties of forest ecosystems whose spatial and temporal variation can be observed or inferred using RS. Changes in these forest traits reflect responses to both environmental conditions and anthropogenic interventions and therefore provide an ecologically interpretable basis for assessing forest condition, functioning and dynamics [16,26].

RS-based Forest Trait retrieval encompasses a broad range of ecosystem properties, including canopy height and architecture, biomass, LAI, pigment and nitrogen concentrations, vegetation water status, photosynthetic activity, phenology and surface temperature. Different sensor technologies capture complementary trait dimensions: multispectral and hyperspectral systems are particularly suited to biochemical and physiological properties, thermal sensors provide information related to ecosystem energy and water dynamics, SAR is sensitive to structural and moisture-related properties, and LiDAR characterises three-dimensional forest architecture. Recent developments in high-resolution UAS observations, multi-sensor data fusion and cross-scale integration are further expanding the range and consistency of observable forest

traits. For example, Spiers et al. [49] demonstrated the potential of UAS observations for morphological and physiological traits such as canopy structure and leaf chemistry, thereby providing an important observational bridge between field measurements and airborne or satellite RS. At the same time, standardised and spatially continuous retrieval of forest attributes is becoming increasingly important for operational forest inventories and monitoring programmes [38]. The following sections examine representative trait indicators with respect to their ecological relevance to F-LUI, sensitivity to anthropogenic use and retrieval using contemporary RS approaches.

6.1.1. Trait Indicators of F-LUI—Spectranomic Approach

The Spectranomics approach developed by Asner and Martin [50] provides an important conceptual and methodological foundation for trait-based RS of forest ecosystems. In contrast to conventional land-cover or object-based classification approaches, Spectranomics focuses not primarily on identifying tree species or forest types, but on the quantitative retrieval of functional vegetation traits from spectral information. It is based on the premise that vegetation reflectance is governed by biochemical, structural and physiological properties. Spectral signatures and thermal manifestation on forest ecosystem condition and functioning are derived.

The theoretical basis of Spectranomics lies in the coupling between leaf chemistry, plant physiology and electromagnetic radiation. Leaf pigments, nitrogen and water content, lignin and cellulose concentrations, leaf morphology and canopy structure influence reflectance across the visible (VIS), near-infrared (NIR) and shortwave-infrared (SWIR) spectral regions. Because these properties represent ecologically meaningful forest traits, imaging spectroscopy provides a means of quantifying and spatially mapping their variation [51,52].

A defining feature of the Spectranomics concept is the integration of extensive in situ measurements of functional traits with imaging spectroscopy. Measurements of leaf, canopy and stand properties are linked to hyperspectral reflectance observations to establish physically and ecologically interpretable relationships between spectral signals and vegetation properties. Contemporary retrieval approaches combine field observations with radiative transfer models, including PROSPECT and PROSAIL, and statistical or Machine Learning methods. This enables the spatial retrieval of multiple biochemical, structural and physiological forest traits, including leaf chlorophyll, nitrogen and water content, polyphenols, lignin, cellulose, LAI, Leaf Mass per Area (LMA), canopy height and biomass. Hybrid approaches combining physically based models with Machine Learning have further improved the robustness and transferability of trait retrieval [53,54].

The increasing availability of spaceborne imaging spectroscopy from operational missions such as PRISMA [52] and EnMAP [55], together with forthcoming missions such as Copernicus CHIME [56] and NASA's Surface Biology and Geology hyperspectral visible-to-shortwave infrared mission (SBG-VSWIR) [57], is expected to substantially expand regional-to-global retrieval of biochemical and physiological forest traits. In combination with the complementary SBG Thermal Infrared (SBG-TIR) observations, these missions will increasingly enable spectral and thermal manifestations of forest functioning, water status and physiological stress to be investigated within a common trait-based monitoring framework. Multi-sensor data fusion and AI-supported retrieval approaches further increase the potential for producing spatially and temporally consistent trait products across sensor platforms [58,59].

For F-LUI, Spectranomics is particularly relevant because anthropogenic interventions can modify biochemical, structural and physiological forest traits. Rather than attempting to observe management intensity directly, Spectranomics provides a methodological basis for characterising its ecological manifestations through continuous variation

in measurable vegetation properties and relating these changes to forest condition, biodiversity and ecosystem functioning.

6.1.2. Trait Indicators of F-LUI—Leaf Chlorophyll Content (Cab)

Cab is one of the most important biochemical forest traits and among the most frequently retrieved vegetation properties from RS observations. As a principal photosynthetic pigment, chlorophyll regulates light absorption and is closely associated with photosynthetic capacity, primary production, leaf nitrogen status and plant physiological performance. Cab therefore provides a sensitive indicator of vegetation vitality, nutrient status and physiological condition and plays an important role in trait-based forest monitoring [50,54].

For F-LUI assessment, Cab is relevant because management interventions such as thinning, harvesting, changes in tree species composition and reforestation alter light availability, competition, nutrient cycling and water availability. These changes can affect canopy chlorophyll status and thereby provide information on physiological responses to different management regimes and intensities. Cab thus complements structural indicators by providing a biochemical and physiological response dimension and may reveal changes in forest condition before substantial structural changes become apparent.

RS retrieval of Cab exploits strong chlorophyll absorption in the blue and red spectral regions and particularly the sensitivity of the red-edge region (approximately 680–750 nm). The position, slope and shape of the red edge respond strongly to chlorophyll concentration. Retrieval accuracy, however, is affected by LAI, canopy geometry, shadowing, understory vegetation and background reflectance, making explicit consideration of canopy structural effects essential [60].

Current retrieval approaches increasingly combine radiative transfer models such as PROSPECT and PROSAIL with statistical and Machine Learning algorithms. Hybrid methods exploit the physical interpretability of radiative transfer modelling together with the predictive capacity of data-driven approaches, while probabilistic methods such as Gaussian Process Regression (GPR) additionally allow retrieval uncertainty to be quantified [53]. Spaceborne imaging spectroscopy from PRISMA and EnMAP further facilitates retrieval of Cab together with complementary traits such as LNC, LWC, LMA and LAI across forest types [52].

Recent developments increasingly focus on simultaneous multi-trait retrieval and explicit consideration of phenological dynamics and canopy structural effects. Hybrid look-up-table approaches and adaptive retrieval strategies can improve chlorophyll estimation in deciduous forests and its transferability across sensors, phenological stages and forest types [61]. Nevertheless, species-specific leaf optical properties, phenology, water stress, understory vegetation and climatic conditions remain important sources of uncertainty. Cab should therefore be interpreted together with complementary biochemical, structural and functional forest traits when assessing F-LUI.

6.1.3. Trait Indicators of F-LUI—Leaf Nitrogen Content (LNC)

LNC is a key functional Forest Trait because nitrogen strongly regulates photosynthetic capacity, carbon assimilation and resource-use strategies in forest ecosystems. A substantial proportion of leaf nitrogen is associated with chloroplasts, including Rubisco and other photosynthetically active proteins. LNC is therefore closely related to photosynthetic capacity, growth and primary production and represents an important indicator of plant functional performance. Leaf nitrogen is also among the major plant functional traits used to characterise ecological strategies, resource acquisition and plant adaptation [13].

LNC is relevant to F-LUI because forest management can alter ecosystem nitrogen cycling and resource availability. Thinning, changes in tree species composition, regeneration and changes in stand density modify light availability, competition, mineralisation and nutrient cycling, which can subsequently affect nitrogen uptake and allocation within vegetation. LNC can therefore provide information on site nutrient availability, productivity and regeneration or successional dynamics associated with different management regimes.

Unlike chlorophyll, nitrogen cannot be retrieved from a single strong and unique absorption feature. Spectral features associated with nitrogen-containing proteins are comparatively weak and overlap with absorption by water, cellulose and lignin. LNC retrieval therefore relies strongly on hyperspectral information, particularly in the red-edge and SWIR regions, together with multivariate retrieval approaches capable of separating interacting biochemical signals [54].

An important methodological advance was the development of PROSPECT-PRO, which explicitly represents proteins and carbon-based constituents as separate biochemical components of leaf optical properties. This enables physically based retrieval of protein-related traits and provides an improved basis for estimating nitrogen-related vegetation properties from imaging spectroscopy [54].

Spaceborne hyperspectral missions such as PRISMA and EnMAP are increasingly enabling operational retrieval of nitrogen-related vegetation traits. Hybrid methods combining radiative transfer modelling with Machine Learning approaches such as Gaussian Process Regression, Kernel Ridge Regression (KRR) and Support Vector Regression (SVR) can improve the accuracy and transferability of LNC retrieval across forest types [52]. Increasingly, LNC is retrieved as part of multivariate trait products together with chlorophyll, water content, LMA, LAI and other functional properties. Such multi-trait approaches are particularly relevant to F-LUI because management effects are unlikely to be expressed through a single biochemical property but through coordinated changes across multiple forest traits.

6.1.4. Trait Indicators of F-LUI—Leaf Water Content (LWC) and Canopy Water Content (CWC)

LWC and CWC are important water-related forest traits with high relevance to F-LUI assessment. Whereas LWC characterises water content at leaf level, CWC integrates leaf water status with canopy-level properties such as LAI and biomass and therefore characterises vegetation water storage at the canopy scale. These traits are closely associated with fundamental ecophysiological processes including photosynthesis, stomatal conductance, transpiration, evaporative cooling and carbon uptake and respond sensitively to changes in forest structure and to natural and anthropogenic stressors [13].

Within the context of F-LUI, water-related traits can reflect management-induced changes in forest water relations. Thinning, harvesting, changes in tree species composition and reforestation alter canopy closure, stand density and radiation regimes and may consequently affect evapotranspiration, soil moisture and canopy water storage. In contrast to biochemical traits such as Cab and LNC, LWC and CWC provide a more direct indication of forest hydraulic status and can therefore contribute information on drought stress, vitality, resilience and post-management regeneration.

RS retrieval of vegetation water content exploits pronounced water-absorption features in the near- and shortwave infrared, particularly around 970, 1200, 1450 and 1940 nm. The introduction of the Normalized Difference Water Index (NDWI) by Gao [62] provided an important basis for operational estimation of vegetation water status from multispectral observations. Physically based radiative transfer models such as PROSPECT and PROSAIL subsequently enabled explicit modelling of interactions among leaf optics,

water content and canopy structure, while hybrid approaches combining radiative transfer modelling with Machine Learning have further improved retrieval accuracy, robustness and transferability [53,63].

Recent developments increasingly address cross-sensor consistency and the separation of leaf- and canopy-scale effects. Ma et al. [64] developed a sensor-independent approach for retrieving CWC from Sentinel-2, Landsat-8 and MODIS observations by combining PROSAIL simulations with artificial neural networks, facilitating consistent estimation across different satellite systems and climatic regions. Fang et al. [65] proposed a physically based downscaling strategy for hyperspectral observations in which leaf spectra are reconstructed from canopy spectra to reduce confounding effects of canopy structure and background reflectance before PROSPECT-based retrieval.

Recent evidence also demonstrates that satellite and in situ estimates may represent different components of forest water status and should therefore be interpreted as complementary rather than interchangeable observations [66]. Moreover, temporal and spatial variation in CWC may arise from different underlying trait components: Allen et al. [67] showed that temporal variation can be dominated by changes in LWC, whereas spatial differences are strongly influenced by canopy structure and LAI. This distinction is particularly important for F-LUI because management-induced structural changes could otherwise be misinterpreted as physiological changes in vegetation water status.

6.2. Monitoring Genesis Indicators of F-LUI Using RS

Genesis indicators describe the historical development and temporal dynamics of forest ecosystems resulting from anthropogenic management as well as natural disturbance and regeneration processes. Whereas Trait indicators primarily characterise current forest conditions through observable biophysical properties, Genesis indicators describe the temporal trajectories of forest traits. They thereby enable the reconstruction of forest development, management history, succession and disturbance processes and represent the historical dimension of F-LUI.

Genesis indicators are derived from multitemporal changes in forest traits. Temporal variation in canopy structure, biomass, LAI, vegetation vitality, water status or thermal properties can be quantified from RS observations and related to processes such as harvesting, thinning, reforestation, natural succession, windthrow, wildfire or insect disturbance. The magnitude, rate, frequency, persistence and recovery of these trait changes provide information on the intensity and spatial extent of management and disturbance processes.

Long-term multispectral satellite archives, particularly Landsat and increasingly Sentinel-2, provide the principal observational basis for reconstructing these trajectories over years to decades. Their integration with SAR, LiDAR and other complementary RS observations increasingly enables both abrupt disturbances and gradual ecosystem changes, as well as subsequent recovery trajectories, to be characterised. Genesis indicators therefore extend static trait observations into the temporal domain and enable a process-oriented interpretation of F-LUI.

6.2.1. Genesis Indicators of F-LUI—Forest Disturbance History

Forest disturbance history describes the timing, frequency, magnitude and spatial extent of disturbance events that shape the long-term development of forest ecosystems. Within the F-LUI framework, it represents a central Genesis indicator because anthropogenic interventions—including thinning, timber harvesting and clear-cutting—as well as natural disturbances such as windthrow, wildfire, drought and insect outbreaks produce characteristic changes in structural and functional forest traits. Because RS does not directly observe the underlying management decision or disturbance process, disturbance

history is reconstructed from temporal changes in traits such as canopy closure, LAI, biomass, vegetation water content, chlorophyll status and three-dimensional stand structure.

Multitemporal Landsat and Sentinel observations, complemented by SAR and increasingly LiDAR data, provide the principal basis for detecting and reconstructing forest disturbances. Established time-series approaches such as LandTrendr [68], BFAST [69] and CCDC [70] enable disturbance and recovery trajectories to be reconstructed over several decades. More recent approaches combine ensemble methods, multi-sensor RS observations and Machine Learning, improving both disturbance detection and the reconstruction of subsequent recovery trajectories [39,71].

Whereas early large-scale applications focused predominantly on detecting forest-cover loss [72], recent research increasingly addresses the attribution and characterisation of disturbance processes. Machine Learning approaches can increasingly distinguish among disturbance agents such as harvesting, fire, windthrow and insect outbreaks [73]. Accordingly, the methodological focus is shifting from binary change detection towards forest disturbance characterisation, in which disturbance cause, magnitude, spatial extent and subsequent recovery are considered jointly [74].

Within the trait-based F-LUI framework, forest disturbance history therefore represents more than the detection of forest change. It reconstructs when, where, how frequently and how strongly forest traits changed and, where attribution is possible, which anthropogenic or natural processes caused those changes. This temporal information is essential for distinguishing different disturbance and management regimes and provides a process-based dimension of F-LUI.

6.2.2. Genesis Indicators of F-LUI—Forest Regeneration Dynamics

Forest regeneration dynamics describe the recovery of structural and functional forest traits following anthropogenic or natural disturbances. Whereas forest disturbance history characterises the timing, magnitude and, where possible, cause of disturbance, regeneration dynamics focus on the subsequent trajectory of ecosystem recovery. Within the F-LUI framework, regeneration is therefore particularly relevant because it captures the long-term ecological consequences of forest use rather than merely its immediate effects.

The rate and completeness of recovery may vary substantially with disturbance and management intensity. Selective harvesting or less intensive management may retain structural and biological legacies that facilitate recovery, whereas severe or repeated disturbances can delay regeneration or redirect ecosystems towards alternative trajectories. Regeneration dynamics can therefore complement disturbance history by describing the rate, direction and completeness of ecological recovery [75]. Importantly, these relationships are context-dependent and also influenced by climate, forest type, site conditions and disturbance history.

RS characterises regeneration through temporal trajectories of structural and functional forest traits. Structural properties such as canopy closure, canopy height, LAI and AGB describe the re-establishment of forest structure, whereas biochemical and physiological traits such as chlorophyll (Cab), LNC and LWC or CWC can provide complementary information on the recovery of photosynthetic functioning, nutrient status and vegetation water relations. Consequently, the return of greenness or canopy cover alone does not necessarily indicate complete ecological recovery.

Recent research increasingly conceptualises regeneration as a recovery trajectory rather than as a single reforestation event. Maurent et al. [75] provide a framework for comparing recovery pathways, while global analyses demonstrate that disturbance severity can strongly influence the duration and completeness of ecosystem recovery. For example, [76] analysing 3281 large wildfires worldwide showed that increasing fire severity

prolonged the recovery of vegetation density, canopy structure and primary production and reduced the probability of complete recovery, particularly in boreal forests.

The integration of dense Landsat and Sentinel time series with LiDAR, SAR and imaging spectroscopy can further extend recovery monitoring from predominantly greenness-based measures towards structural and functional trait trajectories. Almeida et al. [77] for example, demonstrated the value of integrating LiDAR and hyperspectral information for characterising structural and functional aspects of forest recovery. Recent global analyses additionally indicate that functional recovery may lag behind apparent canopy recovery. Yan et al. [78] reported slower recovery of CWC than of conventional greenness indicators, illustrating why hydraulic forest traits can provide information that is not captured by vegetation indices alone.

Within the proposed framework, regeneration dynamics therefore connect disturbance history with the subsequent functional and structural state of the forest. Whereas disturbance history identifies when and how strongly a forest changed, regeneration dynamics describe how rapidly, completely and along which trajectory forest traits recover.

6.2.3. Genesis Indicators of F-LUI—Forest Succession

Forest succession represents the longer-term reorganisation of forest ecosystems following natural or anthropogenic disturbance and constitutes the third temporal dimension of the Genesis indicator family. Whereas disturbance history characterises disturbance events and regeneration dynamics describe subsequent recovery, succession encompasses longer-term changes in structural, functional and taxonomic forest traits over decades to centuries. These trajectories are shaped by species interactions, resource availability, disturbance regimes, climate and forest management and ultimately determine the long-term development of forest structure, biodiversity and ecosystem functioning [79,80].

Contemporary ecological understanding increasingly moves beyond a simple linear progression from pioneer vegetation towards a single stable climax state. Recurrent disturbances, management, fragmentation and climatic change can generate alternative successional trajectories differing in species composition, structural complexity, functional diversity and ecosystem resilience. This is particularly relevant to F-LUI because repeated or intensive management may alter the rate, direction and endpoint of forest development, potentially delaying or preventing the emergence of structurally complex and functionally diverse forest states [81].

Succession itself cannot be observed directly by RS. Rather, it is reconstructed from long-term trajectories and combinations of structural, functional and taxonomic forest traits. Particularly informative properties include canopy height, LAI, AGB, canopy complexity, Cab, LWC/CWC and trait-based measures of functional and taxonomic diversity. Long-term Landsat and Sentinel observations combined with LiDAR and SAR can therefore characterise transitions from early regeneration stages towards increasingly complex mature forest structures [39,58].

Methodologically, the emphasis is consequently shifting from mapping discrete successional classes towards analysing continuous successional trajectories. Multi-sensor approaches integrate complementary structural, functional and taxonomically informative forest traits, while Machine Learning facilitates the analysis of large multitemporal datasets and the identification of long-term changes in forest structure and functioning [74].

Importantly, different forest traits may recover or develop at different rates during succession. Hydraulic traits such as CWC, for example, may follow trajectories distinct from conventional greenness metrics [78]. Succession should therefore not be characterised solely by vegetation cover or biomass accumulation. Integrating structural, biochemical, physiological and taxonomically informative traits provides a more comprehensive

representation of long-term ecosystem development and enables the effects of different management regimes on forest trajectories to be assessed.

6.2.4. Genesis Indicators of F-LUI—Land-Use Legacy

Land-use legacy describes the persistent effects of historical land use and forest management on the present state and functioning of forest ecosystems. Whereas the preceding Genesis indicators describe disturbance, regeneration and succession as temporal processes, land-use legacy integrates their long-term cumulative consequences. It represents the ecological 'memory' of forest ecosystems and helps explain why forests subject to similar contemporary management may nevertheless differ substantially in structure, species composition, biodiversity, functional diversity and ecosystem functioning. Within the F-LUI framework, land-use legacy therefore connects historical forest use with present-day forest traits.

Historical management practices such as coppicing, coppice-with-standards systems, clear-cutting, afforestation, drainage or former agricultural use can leave persistent signatures in forest structure, tree species composition, soil development and ecosystem functioning. Such effects may remain detectable for decades or centuries. Persistent manifestations can include differences in canopy height, vertical structural complexity, AGB, canopy architecture, functional diversity and landscape configuration. Land-use legacy therefore does not describe an individual historical event, but the cumulative imprint of past land use on contemporary forest traits.

The ecological importance of historical land use was established by Foster et al. [82], who demonstrated that past land use can influence biodiversity, ecosystem structure, biogeochemical cycling and ecosystem functioning over very long periods. Subsequent work showed persistent effects on plant species composition, soils and forest development [83,84]. More recent trait-based research extends this perspective to below-ground ecosystem properties. Mejía et al. [85], for example, showed along a secondary-succession gradient on former agricultural land that land-use legacies can influence contemporary tree composition, functional root traits and mycorrhizal associations. Present-day forest traits may therefore reflect not only current management, but also historical land use and subsequent ecological development.

Because historical land use itself cannot be observed retrospectively by contemporary RS, its reconstruction requires the integration of historical information with present and long-term trait observations. Historical maps, aerial photographs, forest inventories and management records can establish past land-use conditions, while satellite time series and contemporary LiDAR, SAR or UAV observations characterise their persistent manifestations in forest traits. Three-dimensional structure, canopy complexity, biomass and functional diversity may retain information on past management that is no longer evident from conventional greenness metrics alone [49,77].

Within the trait-based F-LUI framework, land-use legacy therefore provides the long-term integrative dimension of Genesis. It explicitly acknowledges that contemporary trait patterns cannot always be explained by present-day management or environmental conditions alone. Incorporating historical land use is consequently essential for avoiding incorrect attribution of persistent Forest Trait patterns to current F-LUI.

6.3. Monitoring Structural Indicators of F-LUI Using RS

Structural indicators describe the spatial organisation and horizontal and vertical architecture of forest ecosystems and constitute one of the six indicator families of the trait-based framework proposed for quantifying F-LUI. Whereas Trait indicators represent individual observable properties of forest ecosystems, structural indicators integrate one or more forest traits into measures of stand organisation, spatial configuration and structural

complexity. They therefore represent the spatial manifestation of ecosystem changes resulting from forest management, natural disturbances and successional processes.

Their derivation is based primarily on structural forest traits such as canopy height, canopy cover, vertical layering, crown architecture, canopy roughness, gap structure and the spatial distribution of AGB. These properties respond directly or indirectly to thinning, harvesting, regeneration, changes in management systems and landscape fragmentation. Within the trait-based F-LUI framework, these observable forest traits constitute the measurement basis, whereas structural indicators provide their ecological interpretation at stand and landscape scales.

RS provides unique capabilities for repeatedly characterising forest structure across spatial scales ranging from individual trees to landscapes. Very-high-resolution optical imagery, Synthetic Aperture Radar (SAR), LiDAR and increasingly multi-sensor data fusion provide complementary information on horizontal and vertical forest organisation. The following sections focus on five particularly relevant structural dimensions of F-LUI: horizontal forest structure and fragmentation, vertical forest structure, spatial tree-species configuration, deadwood and AGB.

6.3.1. Structural Indicators of F-LUI—Horizontal Forest Structure, Landscape Configuration and Fragmentation

Horizontal forest structure describes the spatial composition and configuration of forest landscapes. Here, composition refers not to taxonomic tree-species composition, but to the relative abundance and spatial distribution of structural landscape elements such as closed forest, canopy gaps, core forest, forest edges, openings and linear infrastructure. Configuration describes their size, shape, arrangement, isolation and connectivity. Forest management, infrastructure development and land-use change modify these properties and can generate characteristic patterns of perforation, dissection and fragmentation, with consequences for microclimate, biodiversity, biomass and ecosystem functioning [86].

Within the trait-based F-LUI framework, these indicators are derived from spatially explicit forest traits such as canopy cover, canopy closure, gap size, edge position, stand density and vegetation continuity. Their aggregation at stand and landscape scales enables the quantification of forest amount, patch size and density, edge density, core forest area, shape complexity, gap density, isolation and connectivity. Considering both forest amount and forest configuration is particularly important because landscapes with identical forest cover can exhibit fundamentally different degrees of fragmentation and therefore different ecological manifestations of land-use intensity [87].

Optical, SAR and increasingly LiDAR observations provide the principal RS basis for deriving forest masks, canopy-cover products and spatial structural information. Long-term Landsat observations are particularly valuable for reconstructing fragmentation dynamics, whereas Sentinel-2 and very-high-resolution imagery provide finer spatial information on contemporary forest configuration. Global products such as GLC_FCS30D provide long-term land-cover information from dense Landsat observations, while approaches based on semantic segmentation and Deep Learning increasingly improve the detection of complex forest boundaries and small-scale structural elements. Dynamic World provides high-frequency 10-m land-cover information from Sentinel-2, although its probabilistic land-cover estimates should be interpreted carefully when used for forest-fragmentation analysis [88–90].

Landscape metrics can subsequently be calculated at patch, class and landscape levels. FRAGSTATS [91] remains a widely established framework for quantifying landscape pattern, complemented by Morphological Spatial Pattern Analysis (MSPA), graph-based connectivity metrics and least-cost or circuit-theory approaches. MSPA distinguishes structural elements such as core areas, edges, bridges and isolated fragments [92], whereas

indices such as the Probability of Connectivity (PC) and Integral Index of Connectivity (IIC) combine habitat amount and spatial connectivity [93]. For F-LUI monitoring, a combination of forest amount, core forest area, edge density, effective mesh size and structural connectivity may therefore provide substantially more information than any individual fragmentation metric.

Fragmentation is particularly relevant to F-LUI because it integrates cumulative spatial consequences of forest use beyond forest-cover loss alone. Increasing edge exposure and decreasing connectivity can alter forest microclimate, biomass and ecological integrity. Global analyses have demonstrated the pervasive exposure of forests to edge effects, while recent work indicates substantial reductions in AGB towards forest edges [86]. The Forest Landscape Integrity Index further illustrates how fragmentation, anthropogenic pressure and connectivity can be combined to characterise landscape-scale forest integrity [94].

However, fragmentation metrics are strongly scale-dependent. Spatial resolution, forest definitions, canopy-cover thresholds, minimum mapping units and analysis-window size can substantially affect estimated patterns. Dynamic analyses of changes in patch structure, edge density and connectivity are therefore preferable to static snapshots when the objective is to infer F-LUI dynamics. Increasingly, semantic segmentation also enables roads, skid trails, clearings and other linear infrastructure to be detected directly, potentially capturing subtle forest perforation before extensive canopy loss occurs.

6.3.2. Structural Indicators of F-LUI—Forest Vertical Structure

Vertical forest structure is particularly sensitive to forest management because harvesting, thinning, regeneration systems and tree-species selection directly modify the three-dimensional organisation of forest stands. These interventions affect canopy height, vertical layering, canopy closure, biomass distribution and structural heterogeneity, thereby influencing light availability, microclimate, carbon storage, habitat quality and biodiversity [95].

Within the trait-based framework, vertical structure indicators are derived from observable forest traits including canopy and stand height, vertical foliage distribution, canopy layering, canopy roughness, gap fraction and vertical biomass distribution. Rather than interpreting a single height measurement as F-LUI, combinations of these traits describe the three-dimensional structural complexity resulting from management, disturbance and succession.

Optical sensors provide primarily indirect information on vertical structure through texture, shadowing, stereoscopy and crown characteristics, whereas active sensors enable more direct three-dimensional observations. Airborne Laser Scanning (ALS) remains one of the most powerful approaches for retrieving canopy height, crown architecture, vertical layering and gaps at stand-to-landscape scales. Terrestrial Laser Scanning (TLS) provides complementary high-resolution information on stem geometry, understory structure and within-stand architecture [96]. UAV-based LiDAR increasingly bridges these observation scales by combining centimetre-to-decimetre spatial detail with flexible acquisition.

SAR provides complementary structural information, particularly at longer wavelengths. L-band and especially P-band observations penetrate deeper into forest canopies than shorter-wavelength radar and are sensitive to woody vegetation structure and biomass. Polarimetric and interferometric approaches, including PolSAR, InSAR and PolInSAR, can further support retrieval of forest height and vertical structural properties. Importantly, the ESA BIOMASS mission is no longer a forthcoming mission: it was launched in April 2025. Your original sentence should therefore be updated. Its P-band SAR observations provide an important new source of information on woody biomass and forest structure, particularly in high-biomass forests.

Spaceborne LiDAR has further transformed large-scale forest-structure monitoring. The Global Ecosystem Dynamics Investigation (GEDI) provides waveform-derived metrics such as Relative Height (RH) measures and Plant Area Volume Density (PAVD), enabling vertical forest structure to be sampled consistently across broad geographical regions [12]. These measurements are particularly valuable for characterising structural complexity and linking three-dimensional forest traits to habitat quality, biodiversity, biomass and ecosystem functioning.

Accordingly, current research is moving beyond individual measures such as canopy height towards multidimensional descriptions of three-dimensional structural complexity. Foliage Height Diversity (FHD), PAVD, gap fraction, canopy roughness and vertical heterogeneity capture aspects of stand organisation that cannot be represented by mean canopy height alone. This is particularly relevant to F-LUI because forests with similar mean heights may differ substantially in vertical layering and structural complexity as a consequence of contrasting management histories.

Multi-sensor fusion represents the logical next step. Combining GEDI with ALS, Sentinel-1/-2, UAV-LiDAR and imaging spectroscopy can extend discrete or locally available structural measurements towards spatially continuous products. Machine Learning and Deep Learning increasingly facilitate this spatial upscaling, although model transferability, reference-data quality and uncertainty remain critical limitations [58].

6.3.3. Structural Indicators of F-LUI—Spatial Tree-Species Configuration

Forest species composition and its spatial configuration represent an important structural dimension of F-LUI. Within the trait-based F-LUI framework, however, they are not directly observable forest traits, but higher-level response indicators derived from the classification and spatial organisation of species-specific trait expressions. Tree species differ in morphological, biochemical, phenological and structural properties, including crown architecture, leaf and needle morphology, pigment composition, water content, seasonal phenology and vertical crown organisation. RS captures these forest traits and their spatial and temporal variability; their classification and spatial aggregation enable the derivation of indicators describing tree-species dominance, mixture and spatial organisation at stand and landscape scales. Changes in these patterns can reflect the long-term effects of species selection, forest conversion, natural regeneration, succession and management and therefore provide important information for assessing F-LUI.

Operational mapping of tree-species composition increasingly relies on multispectral and hyperspectral RS observations. Multitemporal Sentinel-2 time series exploit species-specific differences in budburst, leaf development and senescence, thereby improving the discrimination of deciduous and coniferous tree species. Hemmerling et al. [97] demonstrated the potential of dense Sentinel-2 time series for tree-species mapping in temperate forests. At national scale, Blickensdörfer et al. [98] developed a Germany-wide tree-species map by integrating Sentinel-1, Sentinel-2 and German National Forest Inventory data. Schulz et al. [99] further demonstrated that combining spectral and phenological time-series information enables the discrimination of a large number of Central European tree species, highlighting the value of phenological forest traits for large-scale species mapping.

The increasing availability of imaging spectroscopy extends this approach beyond conventional species classification by providing information on biochemical and functional differences among species. Hyperspectral observations are sensitive to forest traits related to pigments, leaf chemistry and vegetation water content, whereas LiDAR provides complementary information on crown architecture, canopy height and vertical stand structure. Combining spectral and three-dimensional structural traits can substantially improve species discrimination, particularly in structurally heterogeneous forests.

Mäyrä et al. [100], for example, demonstrated highly accurate individual-tree species classification by integrating airborne hyperspectral and LiDAR data with three-dimensional Convolutional Neural Networks. Similar developments increasingly exploit UAV-based sensor fusion and Deep Learning to characterise individual crowns and fine-scale species mixtures.

At the same time, tree-species mapping is shifting from discrete species classification towards continuous representations of species composition. This is particularly important in mixed forests, where individual pixels or canopy objects may contain signals from several species and discrete classifications can inadequately represent compositional heterogeneity. Continuous approaches estimate species-specific cover, crown or biomass fractions and therefore provide a more realistic representation of transitions between monospecific and mixed stands. Spectral-spatial Deep Learning approaches can further exploit both spectral information and neighbourhood structure to characterise heterogeneous forest composition [101].

The resulting species maps and fractional estimates can be aggregated into structural indicators relevant to F-LUI. Species composition describes the relative abundance and dominance of tree species, whereas species configuration describes how these species are spatially arranged within stands and landscapes. Relevant metrics include species proportions, dominance and evenness, mixing indices and spatial configuration measures such as patch size, patch density, aggregation, adjacency and connectivity. Diversity measures such as Shannon and Simpson indices or Hill numbers can additionally characterise compositional heterogeneity, although their interpretation overlaps with the Taxonomic indicator family. Within the Structural family, their principal relevance lies in describing how species mixtures are spatially organised—for example, as extensive monospecific stands, fine-scale mixtures, group-wise mixtures or heterogeneous forest mosaics.

This distinction is particularly relevant to F-LUI. Forest management can alter not only which species are present, but also their relative dominance and spatial arrangement. Species selection, planting, thinning, rotation systems, conversion of monospecific plantations, natural regeneration and CCF can generate markedly different spatial patterns even where overall species richness is similar. Consequently, species configuration can reveal structural manifestations of management that cannot be represented by taxonomic composition alone.

In addition to explicit species mapping, spectral diversity provides a complementary approach. Spectral diversity describes spatial variation in spectral trait expressions and can be associated with taxonomic, functional and structural heterogeneity. Spectral diversity metrics may therefore provide indirect information on tree-species composition and stand heterogeneity, particularly where complete species-level classification is not feasible. However, spectral diversity should not be equated directly with species diversity because spectral variation is also influenced by canopy structure, phenology, illumination, physiological condition and environmental heterogeneity. Reduced spectral and structural heterogeneity may indicate increasing stand homogenisation under particular management regimes, but such patterns are not uniquely attributable to management and should therefore be interpreted together with Genesis, Functional and other Structural indicators.

Important methodological challenges remain. Closely related tree species may exhibit similar spectral characteristics, while phenological variability, crown overlap, illumination and viewing geometry can substantially affect classification. Model transferability among regions, forest types and sensor systems also remains limited. Multiseasonal observations, sensor fusion, high-quality in situ reference data and advanced Machine Learning and AI-based classification approaches are therefore essential for robust and transferable tree-species mapping [102,103].

Within the trait-based F-LUI framework, forest species composition and configuration should therefore be interpreted as higher-level indicators derived from species-specific forest traits and their spatial organisation rather than as directly observable RS properties. Their particular value for the Structural indicator family lies in revealing how forest management modifies the dominance, mixture and spatial arrangement of tree species, thereby linking observable trait variation to the structural consequences of F-LUI.

6.3.4. Structural Indicators of F-LUI—Deadwood

Deadwood is a particularly informative structural response indicator of F-LUI because its amount, diversity and spatial organisation integrate long-term effects of forest management, mortality, natural disturbance and succession. Relevant properties include standing and downed deadwood, snags, coarse woody debris, stumps, size classes, decay stages and their spatial distribution. These characteristics are closely linked to habitat provision, biodiversity, nutrient cycling and carbon dynamics and can therefore reveal management effects that are not captured by living canopy structure alone.

In many forest systems, increasing management intensity and systematic removal of dead or damaged trees reduce deadwood quantity and structural diversity, whereas unmanaged or less intensively managed forests generally contain larger and more heterogeneous deadwood pools. Paillet et al. [104], for example, demonstrated substantial biodiversity differences between managed and unmanaged European forests, particularly for taxa associated with deadwood and old-growth structures. Deadwood can therefore provide an important long-term structural indication of management history, although disturbance history and salvage logging must be considered when interpreting its abundance.

RS observes deadwood through combinations of forest traits associated with mortality and structural change. Multispectral and hyperspectral observations capture changes in pigments, water content and exposed woody material, whereas LiDAR provides information on the three-dimensional geometry of standing dead trees, crown degradation and larger downed woody material. ALS supports landscape-scale detection of snags and canopy mortality, while TLS provides highly detailed measurements of geometry, volume and decay-related structural properties. Combining ALS and TLS can therefore substantially improve the characterisation and validation of coarse woody debris and standing deadwood [105–107].

Current developments increasingly integrate UAV imagery, LiDAR and spectral information with Machine Learning and Deep Learning. High-resolution aerial or UAV imagery can support object-level detection of individual dead trees, whereas Sentinel-2 and other satellite observations provide complementary information for broader-scale mortality monitoring. The combination of spectral and three-dimensional forest traits is particularly promising for distinguishing living vegetation, standing dead trees and different stages of canopy deterioration.

Nevertheless, deadwood remains substantially more difficult to quantify by RS than living canopy structure or AGB, particularly for downed material beneath closed canopies. Consequently, RS-derived deadwood indicators require strong in situ calibration and should be interpreted together with disturbance history, forest structure and management information.

6.3.5. Structural Indicators of F-LUI—Aboveground Biomass (AGB)

AGB is a central structural response indicator of F-LUI because it integrates the cumulative effects of forest growth, mortality, disturbance and management within the contemporary forest state. Harvesting, thinning, rotation length, tree-species selection and regeneration alter both biomass stocks and their spatial and temporal distribution. Within

the trait-based framework, AGB is inferred from combinations of observable forest traits, particularly canopy height, crown dimensions, vertical vegetation structure and related structural properties, supported by field-based allometric relationships. It thereby links the structural dimension of F-LUI to carbon storage and ecosystem productivity.

AGB should not, however, be interpreted as a direct or monotonic measure of management intensity. High biomass can occur both in old, relatively undisturbed forests and in highly productive managed stands, whereas low biomass may result from harvesting, young stand age, low site productivity or natural disturbance. Biomass therefore gains diagnostic value for F-LUI primarily when interpreted together with vertical structure, species composition, deadwood, disturbance history and regeneration dynamics.

Optical, SAR and LiDAR systems provide complementary information for AGB estimation. Optical observations characterise canopy cover, leaf area and vegetation condition but tend to saturate in dense forests and have limited direct sensitivity to woody biomass. SAR responds to vegetation structure, moisture and volume scattering, with longer wavelengths generally providing greater sensitivity to woody components. LiDAR has particular value because canopy height and vertical vegetation profiles are strongly related to biomass, although retrieval accuracy remains dependent on forest type, field reference data, allometric models and spatial scale [108].

GEDI represents a major advance in large-scale AGB estimation. Its waveform LiDAR observations provide structural measurements within discrete footprints that are linked with field and airborne LiDAR reference data to derive AGB density estimates and associated uncertainties. Because GEDI samples rather than continuously images the Earth's surface, its observations are increasingly integrated with spatially continuous optical and SAR data to produce wall-to-wall biomass products [12,109].

The ESA BIOMASS mission, launched in 2025, adds a particularly important complementary capability. Its spaceborne P-band SAR observations are designed to provide information on forest biomass and structure, with particular relevance to high-biomass forests where shorter-wavelength radar and optical approaches frequently saturate. The combination of BIOMASS, GEDI, Landsat, Sentinel-1/-2 and airborne or UAV LiDAR therefore provides a powerful emerging basis for multi-sensor AGB monitoring.

Within the F-LUI framework, the greatest value of AGB lies not in a single biomass estimate but in its spatial and temporal trajectory. Changes in biomass stocks, their spatial heterogeneity and their relationship to disturbance, regeneration and three-dimensional forest structure can reveal cumulative consequences of forest use. Multi-sensor fusion and AI-supported upscaling are increasingly enabling these relationships to be quantified consistently across stands, landscapes and regions.

6.4. Monitoring Taxonomic Indicators of F-LUI Using RS

Taxonomic indicators describe the biological composition of forest ecosystems and provide information on tree species, forest types, their diversity and their spatial distribution. In contrast to structural indicators, which characterise the spatial organisation and architecture of forests, taxonomic indicators focus on the biological identity and composition of vegetation and their changes in response to anthropogenic use. They therefore enable changes in biological diversity and the ecological characteristics of forest ecosystems to be assessed as an important dimension of F-LUI.

Within the trait-based F-LUI framework, taxonomic entities are not directly observed by RS. RS sensors initially record physical properties of vegetation from which observable forest traits, such as crown structure, leaf chemistry, pigment content, water status and phenology, can be derived. Only the combination and ecological interpretation of these traits enable the classification of tree species, forest types and other taxonomic entities.

Taxonomic indicators therefore represent higher-level classifications derived from forest traits rather than directly observable RS properties.

In particular, high-resolution multispectral and hyperspectral sensors, together with LiDAR and SAR observations, have considerably expanded the potential for deriving taxonomic information in recent years. The following sections present the principal RS-based taxonomic indicators for characterising forest cover and forest types, tree species and taxonomic diversity, forest communities and habitat types, and ecological integrity and naturalness in the context of F-LUI.

6.4.1. Taxonomic Indicators of F-LUI—Forest Land Cover and Forest Type Classification

The classification of forest land cover and forest types constitutes the fundamental taxonomic level for assessing F-LUI. Whereas land-cover classifications primarily distinguish forest from non-forest areas, forest-type classifications describe the biological identity of forest ecosystems according to dominant tree species, vegetation formations, stand composition or management-related forest categories. Within the trait-based F-LUI framework, forest types are not directly observable forest traits but taxonomic classes derived from characteristic combinations of structural, biochemical, phenological and spectral forest traits. Changes in forest cover and forest types resulting from deforestation, reforestation, forest conversion, plantation forestry, natural regeneration or succession reflect long-term consequences of different management intensities and therefore constitute taxonomic response indicators of F-LUI.

For quantifying F-LUI, however, a simple forest/non-forest classification is insufficient. Of particular relevance is the differentiation of biologically and management-relevant forest types, for example deciduous, coniferous and mixed forests; primary and secondary forests; semi-natural forests; plantations; and agroforestry systems. These forest types differ not only in their biological composition but also in stand age and structure, biodiversity, carbon storage, productivity and resilience. Their differentiation therefore provides an important basis for national forest inventories, international biodiversity programmes and global climate and forest monitoring.

RS now enables standardised and consistent mapping of forest cover and forest types from local to global scales. Multispectral satellite systems such as Landsat and Sentinel-2 provide the basis for operational forest-type mapping because of their long time series and frequent repeat observations. Sentinel-1 complements these observations with radar information related to forest structure and moisture and can improve classification, particularly in persistently cloudy regions and structurally heterogeneous forests. Combining optical and radar time series can provide more robust differentiation of forest types than individual observations [110]. Multitemporal Sentinel-2 observations further improve forest-type classification by capturing seasonal differences in vegetation spectral and phenological traits. For complex deciduous forests, Shirazinejad et al. [111] demonstrated the value of multidate Sentinel-2 observations for differentiating forest types.

Global datasets have substantially advanced operational forest monitoring. The global forest-cover-change maps developed by Hansen et al. [72] remain an important reference for monitoring changes in forest extent. ESA WorldCover provides globally harmonised land-cover maps for the reference years 2020 and 2021 at 10-m spatial resolution, derived from combined Sentinel-1 and Sentinel-2 observations and distinguishing eleven land-cover classes [112]. In Europe, the Copernicus High Resolution Layer Forest and associated forest-type products provide complementary operational information for differentiating broadleaved, coniferous and mixed forests and support consistent monitoring of biological forest types. For F-LUI assessment, datasets that distinguish relatively natural forests from anthropogenically modified forest systems are of particular relevance.

Lesiv et al. [113] developed a global forest-management map for 2015 at 100-m spatial resolution. The dataset distinguishes different forms of forest management and thereby extends conventional forest/non-forest classifications by incorporating management-related categories. For F-LUI monitoring, it provides an important basis for spatially explicit assessment of anthropogenic influences on forest ecosystems. However, its comparatively coarse spatial resolution and differences in classification accuracy among management classes limit its application at stand level. Combined with higher-resolution information on forest types, tree species and forest structure, such management maps can nevertheless contribute substantially to quantifying taxonomic changes associated with different levels of forest-use intensity.

In parallel, forest-type classification is increasingly shifting from static land-cover maps towards continuous and probabilistic classification approaches. Modern products increasingly provide class probabilities and uncertainty information in addition to the most probable forest class. Such approaches can represent transition zones between forest types and gradual changes in biological forest identity more effectively than conventional discrete classifications.

Current developments are increasingly driven by multi-sensor data fusion and AI. Deep Learning models, including Convolutional Neural Networks (CNNs), Vision Transformers (ViTs) and hybrid architectures, can integrate multispectral, hyperspectral, LiDAR and SAR observations with multitemporal time series, thereby improving both classification accuracy and transferability across forest regions. Recent reviews indicate that the integration of complementary sensor systems with multimodal Deep Learning is increasingly shaping forest-type classification and is likely to play an important role in operational forest inventories and monitoring of biological forest types [114,115].

6.4.2. Taxonomic Indicators of F-LUI—Tree Species and Taxonomic Diversity

Tree-species composition and taxonomic diversity constitute a central taxonomic dimension of F-LUI because they describe the biological identity of forest ecosystems. Management practices such as species selection, afforestation, natural regeneration, forest conversion, selective harvesting and the promotion of economically important species can alter species composition, dominance relationships and stand diversity over long periods. Within the trait-based F-LUI framework, tree species and their diversity therefore represent taxonomic response indicators reflecting the biological consequences of different management intensities. In contrast to the Structural indicators discussed in Section 6.3, which focus on the spatial organisation and configuration of forest stands and species mixtures, the emphasis here is on species identity and taxonomic diversity.

RS does not directly observe tree species. Instead, it captures species-specific combinations of morphological, structural, biochemical and phenological forest traits. Differences in crown architecture, leaf and needle morphology, pigment and water content, leaf chemistry, seasonal phenology and vertical canopy structure produce characteristic spectral and structural signals. Taxonomic information emerges only through the combination, classification and ecological interpretation of these trait expressions. Relevant F-LUI indicators include the occurrence of individual tree species, species proportions, species richness, dominance relationships, taxonomic diversity and temporal changes in species composition. These properties are also closely associated with biodiversity, habitat quality, productivity and ecosystem resilience [15,116].

Operational tree-species mapping has advanced substantially through the increasing availability of multitemporal satellite time series. Sentinel-2 captures species-specific differences in phenology and biochemical and spectral forest traits, whereas Sentinel-1 provides complementary information on canopy structure and vegetation moisture. Their combination enables increasingly robust mapping of dominant tree species from regional

to national scales. For Germany, Blickensdörfer et al. [98] developed a nationwide tree-species map based on multitemporal Sentinel-1 and Sentinel-2 observations combined with German National Forest Inventory reference data, demonstrating the potential of satellite time series for monitoring taxonomic forest patterns. Schulz et al. [99] further showed that phenological time series can improve the differentiation of numerous Central European tree species and particularly support the identification of less abundant species.

For high-resolution applications, imaging spectroscopy and LiDAR currently provide particularly powerful complementary information. Hyperspectral sensors capture species-specific biochemical traits related to pigments, nitrogen and water content, whereas LiDAR provides three-dimensional information on crown architecture and vertical canopy structure. Combining these complementary biochemical and structural forest traits can substantially improve the discrimination of morphologically or spectrally similar tree species [102].

The concept of spectral diversity has become an important approach for indirectly assessing taxonomic and functional diversity using RS. Numerous studies have demonstrated relationships between spatial spectral variability and biological diversity. However, these relationships are not universal and depend on spatial scale, habitat type, phenology and the spectral diversity metrics applied [117]. Empirical studies have further shown that the original Spectral Variability Hypothesis (SVH) does not apply consistently across all landscapes and spatial scales, emphasising the need for ecologically differentiated interpretation of spectral diversity metrics [118].

Current developments are increasingly shaped by multi-sensor data fusion and AI. CNNs, ViTs, self-supervised learning and multimodal Foundation Models enable the joint analysis of optical, hyperspectral, LiDAR and SAR observations and have the potential to improve both classification accuracy and model transferability across forest regions. Recent reviews indicate that combining complementary sensor systems with Deep Learning is increasingly defining the state of the art in tree-species classification and may become an important component of operational biodiversity monitoring [115].

6.4.3. Taxonomic Indicators of F-LUI—Forest Communities and Habitat Types

The effects of F-LUI often become particularly apparent at the level of forest communities and habitat types. Whereas individual tree species may respond relatively rapidly to management interventions, forest communities integrate the longer-term effects of management, succession and site conditions. Transitions from semi-natural forest communities towards species-poorer production forests, the loss of characteristic associated species or the transformation of protected habitat types can therefore reflect cumulative effects of F-LUI and constitute informative taxonomic response indicators.

Mapping forest communities is among the more challenging applications of RS because habitat types are defined by the combined characteristics of tree, shrub and herb layers together with environmental site conditions. Modern approaches therefore integrate multitemporal Sentinel-2 time series, Sentinel-1 SAR, LiDAR, digital terrain models and climatic and soil information with Machine Learning and Deep Learning methods. Gafurov et al. [119] demonstrated that forest communities based on the Braun-Blanquet system can be mapped objectively and reproducibly using Landsat time series and unsupervised Machine Learning. Similarly, the hierarchical-modular approach of Punalekar et al. [120] illustrates how integrating RS observations with topographic, edaphic and ecological contextual information can improve national-scale habitat mapping.

For Europe, standardised classification systems such as the European Nature Information System (EUNIS) habitat classification and the Natura 2000 habitat types are particularly important because they enable harmonised description and assessment of forest habitats across national boundaries and underpin numerous conservation and monitoring

programmes (EEA, 2020) [121]. At the same time, phytosociological classification according to Braun-Blanquet remains an important scientific basis for many national vegetation maps and forest-community classifications. A recent global review indicates that the Braun-Blanquet approach continues to be one of the most widely used reference systems for describing and classifying plant communities internationally [122]. Increasing integration of these established ecological classification systems with RS observations and AI-supported classification approaches offers new opportunities for standardised, large-scale mapping of forest communities and habitat types.

In parallel, rapid developments in AI are transforming habitat mapping. Deep Learning models, ViTs and multimodal data fusion enable the joint analysis of optical, radar and LiDAR observations and can improve the delineation of complex forest communities. A recent review by Matyukira and Mhangara [123] highlights the rapidly growing role of AI-supported approaches in vegetation mapping. For F-LUI, these developments offer the opportunity not only to map forest communities at individual points in time but also to track their temporal trajectories, thereby facilitating the detection of gradual management-related changes.

6.4.4. Taxonomic Indicators of F-LUI—Ecological Integrity and Naturalness Classes

F-LUI affects not only tree species, forest communities and habitat types but, over longer periods, also the overall ecological condition of forest ecosystems. Concepts such as ecological integrity, naturalness, hemeroby, primary forests and Intact Forest Landscapes (IFLs) describe this condition along gradients ranging from near-natural to strongly anthropogenically modified forests. Within the trait-based F-LUI framework, these concepts do not constitute directly observable taxonomic properties but represent the highest level of taxonomic integration, combining information on species composition, habitat types, forest structure, ecological processes and anthropogenic influences into an integrated assessment of biological identity and conservation condition. Naturalness and ecological integrity are therefore emergent ecosystem properties derived from the joint interpretation of taxonomic, structural and functional forest traits.

This integrative perspective is supported by international assessment frameworks. The IUCN Global Ecosystem Typology describes ecosystems through characteristic combinations of their biota, structure, functions and disturbance regimes and thereby provides a scientifically grounded framework for assessing ecological conditions across ecosystem types [124]. Concepts such as Primary Forests and Intact Forest Landscapes (IFLs) provide reference conditions for comparatively undisturbed forest ecosystems and therefore constitute important baselines for assessing naturalness, ecological integrity and anthropogenic modification of managed forests along continuous gradients [125,126]. Unlike conventional forest types, these concepts do not primarily describe the taxonomic identity of a forest, but rather the degree of its ecological integrity and anthropogenic modification.

Standardised assessment approaches for quantifying ecological integrity have been developed in recent years. The Forest Landscape Integrity Index (FLII) integrates direct human pressures, fragmentation, loss of connectivity and modelled indirect pressures into a continuous measure of integrity, enabling globally comparable assessment of forest landscape condition [94]. Building on broader ecosystem-condition concepts, Maes et al. [127] developed a European Forest Condition Index aligned with the international System of Environmental-Economic Accounting—Ecosystem Accounting (SEEA EA) framework. The index integrates RS-derived information on productivity, forest connectivity, tree-cover density and landscape naturalness with soil-carbon and biodiversity-related indicators, illustrating that ecological integrity can only be assessed comprehensively by integrating multiple biotic and abiotic ecosystem properties.

RS is consequently moving from the mapping of individual forest attributes towards the integrated assessment of ecological condition. Multitemporal Sentinel-1 and Sentinel-2 time series, Landsat, GEDI, airborne LiDAR, UAV systems and very-high-resolution aerial imagery enable complementary characterisation of fragmentation, canopy structure, habitat continuity, biomass, successional dynamics and disturbance processes. Multi-sensor fusion of these observations can support the derivation of continuous integrity indicators that characterise forest condition more comprehensively than individual structural or diversity parameters. Emerging approaches such as phenospectral similarity assess the spectral-phenological similarity of a forest stand to near-natural reference ecosystems and may provide opportunities to quantify degrees of naturalness continuously rather than exclusively through discrete classes [128].

In parallel, GeoAI, multimodal data fusion and geospatial Foundation Models are shaping the next generation of forest monitoring. Pre-trained models can learn transferable representations from multisensor RS observations and facilitate the joint analysis of optical, radar and LiDAR information across large spatial scales [129]. This development may shift the focus from classifying individual forest attributes towards the semantic characterisation of ecological states and their temporal dynamics. Nevertheless, ecological interpretation remains dependent on high-quality reference information from forest inventories, habitat surveys and records of management and disturbance history.

Within the trait-based F-LUI framework, ecological integrity and naturalness classes therefore represent the highest taxonomic level of integration. They synthesise information on forest types, tree species, forest communities and structural and functional ecosystem properties into an integrated assessment of the biological condition of forest ecosystems. Combining standardised integrity concepts with multisensor RS and AI-supported data fusion provides a basis for consistent, cross-scale monitoring of the biological consequences of different forest-use intensities and establishes the conceptual transition to the Functional indicators of F-LUI discussed in the following section.

6.5. Monitoring the Functional Indicators of F-LUI with RS

Functional indicators describe ecological processes within forest ecosystems and provide information on how F-LUI alters forest functioning and ecosystem performance. In contrast to Structural indicators, which characterise the spatial organisation of forest ecosystems, or Taxonomic indicators, which describe their biological composition, Functional indicators address processes such as primary production, carbon sequestration, water cycling, energy exchange and ecosystem resilience. They therefore enable assessment of the functional consequences of different management intensities and complement the structural, taxonomic and historical dimensions of F-LUI with a process-oriented perspective.

From an RS perspective, ecosystem functions are not directly observable. Their quantification relies on functional forest traits and their spatial and temporal dynamics. These include, for example, photosynthetic activity, vegetation water status, canopy temperature, biomass production and vertical vegetation structure. Through the integration and ecological interpretation of these observable traits, key ecosystem processes such as productivity, carbon cycling, evapotranspiration and resilience can be derived spatially. Functional indicators therefore do not represent properties measured directly by RS; rather, they constitute the process-oriented interpretation of functional trait patterns and form the functional level of the trait-based F-LUI framework.

6.5.1. Functional Indicators of F-LUI—Forest Productivity and Ecosystem Metabolism

Forest productivity describes the capacity of forest ecosystems to assimilate atmospheric carbon through photosynthesis, accumulate biomass and convert solar energy into organic matter. It represents one of the most immediate functional responses to changes

in F-LUI and underpins key ecosystem processes including carbon storage, water and nutrient cycling, and long-term stand development. In contrast to Structural or Taxonomic indicators, productivity does not describe the spatial organisation or biological composition of a forest, but rather its ecophysiological performance. Within the trait-based F-LUI framework, productivity therefore represents a functional response indicator that integrates the effects of different management intensities on forest ecosystem functioning.

Forest productivity is determined by numerous functional forest traits, including leaf chlorophyll, nitrogen and water content, LAI, crown architecture, Light Use Efficiency (LUE), leaf-angle distribution and phenological characteristics. Changes in these traits resulting from harvesting, thinning, species selection or forest conversion directly affect photosynthesis, biomass increment and carbon uptake. Productivity indicators thus provide a functional link between the forest traits described in Section 6.1 and subsequent water and carbon fluxes. As integrative measures of vegetation functioning, they respond sensitively to forest management, climatic extremes and natural disturbances and are therefore particularly relevant for quantifying the functional dimension of F-LUI. Recent research further indicates that the composition of functional traits at stand and ecosystem levels strongly influences forest productivity and associated carbon and water fluxes, with hydraulic and resource-economic trait syndromes playing a key role in ecosystem responses to management and environmental change [130].

Key functional indicators include Gross Primary Productivity (GPP), Net Primary Productivity (NPP), Net Ecosystem Productivity (NEP), Absorbed Photosynthetically Active Radiation (APAR), Light Use Efficiency (LUE) and phenological metrics such as the onset, duration and end of the growing season. Whereas GPP describes total photosynthetic carbon uptake, NPP additionally accounts for autotrophic respiration and therefore represents net biomass production. NEP extends this concept by accounting for both autotrophic and heterotrophic respiration and describes the net carbon gain of an ecosystem. APAR and LUE provide the theoretical basis of modern light-use-efficiency vegetation models and enable the physiological performance of forest ecosystems to be quantified from local to global scales [131–133].

Satellite-based observation of vegetation functioning has advanced substantially in recent years. Classical vegetation indices such as the Normalised Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), and particularly the Near-Infrared Reflectance of Vegetation (NIRv), provide robust proxies for vegetation activity, leaf-area development and photosynthetic potential. NIRv is closely related to APAR and GPP and has become a powerful indicator of vegetation functioning [134].

Multitemporal Landsat, MODIS and Sentinel-2 time series further enable continuous characterisation of seasonal and interannual variations in vegetation activity and provide the basis for operational productivity models. A major advance has been the satellite-based observation of Solar-Induced Chlorophyll Fluorescence (SIF). In contrast to conventional reflectance-based vegetation indices, SIF is more directly linked to photosynthetic processes and can respond to changes in photochemical functioning before structural changes in vegetation become apparent. It is therefore particularly valuable for detecting physiological responses to drought, heat stress and potentially management-induced changes in forest condition. The integration of SIF, NIRv, APAR and LUE provides increasingly powerful approaches for estimating GPP and represents an important component of modern satellite-based systems for quantifying vegetation functioning and carbon uptake [133,135,136].

The ESA FLEX (Fluorescence Explorer) mission will provide the first satellite mission specifically designed for global observations of vegetation fluorescence and, in synergy with Sentinel-3, is intended to enable operational monitoring of photosynthetic functioning and vegetation stress [137]. In addition to optical observations, other RS systems

provide complementary information on vegetation functioning. Airborne and spaceborne LiDAR characterise stand height, crown architecture and the vertical distribution of photosynthetically active vegetation, thereby improving productivity modelling. SAR provides information on biomass, vegetation moisture and structural change, whereas thermal sensors such as ECOSTRESS provide information on canopy temperature, transpirational cooling and stomatal regulation. Together with missions such as GEDI, FLEX and LSTM (Land Surface Temperature Monitoring), satellite RS is developing towards an integrated observation system capable of jointly characterising structural, biochemical and physiological properties of forest ecosystems [12,137].

In parallel, the integration of multisensor RS observations with Machine Learning, Deep Learning and process-based vegetation models is transforming the quantification of forest productivity. Modern models integrate optical, hyperspectral, thermal, radar and LiDAR observations with meteorological information and Eddy-Covariance measurements from FLUXNET to derive spatially continuous estimates of GPP and vegetation functioning. Multisensor data fusion can improve both accuracy and transferability across forest types and climatic regions. Geospatial Foundation Models additionally provide new opportunities for jointly analysing multimodal RS observations and learning transferable relationships between functional forest traits, productivity and environmental conditions.

RS is therefore increasingly moving from the observation of individual vegetation properties towards a process-oriented characterisation of vegetation functioning and forest ecosystem metabolism.

6.5.2. Functional Indicators of F-LUI—Water Cycling and Ecohydrological Functioning

Water cycling represents a central functional response dimension of F-LUI, because forest management directly influences water exchange among vegetation, soil and the atmosphere. Changes in tree-species composition, stand density, crown architecture, root distribution and soil structure affect interception, evapotranspiration, infiltration, soil-water storage, groundwater recharge and runoff generation and thereby determine the ecohydrological functioning of forest ecosystems. These processes simultaneously regulate water availability to vegetation, resistance to drought and numerous other ecosystem services and therefore constitute an important functional dimension of F-LUI [138,139].

Within the trait-based F-LUI framework, these processes are controlled by functional forest traits. Key traits include LAI, LWC, stomatal conductance, xylem hydraulic conductivity, rooting depth and architecture, and hydraulic safety and efficiency traits. Changes in these traits resulting from harvesting, thinning, species selection or forest conversion directly influence transpiration, water transport along the Soil–Plant–Atmosphere Continuum (SPAC) and the coupling of water and carbon fluxes. Productivity, water cycling and carbon uptake are therefore functionally interconnected and should not be interpreted independently within the F-LUI framework. Recent research indicates that hydraulic and resource-economic trait syndromes are particularly important in determining the stability of water and carbon fluxes and the capacity of forests to respond to drought stress [130].

Important functional indicators include evapotranspiration (ET), potential and actual evapotranspiration, soil moisture, water availability, precipitation interception, infiltration, groundwater recharge, runoff generation and indicators of plant water stress. Whereas ET represents the total loss of water through evaporation and transpiration, soil moisture and infiltration provide information on water storage and availability within the rooting zone. Together, these variables characterise the ecohydrological functioning of forests and respond sensitively to changes in stand structure and management intensity [138,140].

Satellite-based monitoring of forest water cycling has advanced substantially in recent years. Thermal RS provides spatially explicit information on actual ET and vegetation water stress. In particular, ECOSTRESS enables high-resolution observations of canopy temperature and provides information on transpirational cooling and stomatal regulation. Sentinel-2 and Landsat complement these observations by capturing changes in LAI, vegetation development and vegetation water status, whereas Sentinel-1 SAR is sensitive to changes in soil and vegetation moisture. Soil-moisture missions such as SMAP and SMOS provide additional large-scale information on water availability and complement optical observations, particularly under cloudy conditions, although retrievals beneath dense forest canopies remain challenging [141].

Beyond the observation of individual components of the water cycle, RS is increasingly contributing to a process-oriented analysis of the entire SPAC. Modern approaches combine thermal observations, radar, LiDAR, satellite soil-moisture products and meteorological reanalysis data to characterise water fluxes throughout the hydrological continuum. GEDI provides three-dimensional information on canopy structure and vertical vegetation distribution that can improve the parameterisation of water transport and ET, whereas LiDAR and SAR contribute information on crown architecture, biomass and moisture conditions [12]. The integration of these complementary observations enables increasingly consistent characterisation of interactions among vegetation structure, water availability and physiological functioning from local to global scales.

Current developments increasingly integrate multisensor RS observations with Machine Learning, physics-informed Machine Learning and process-based land-surface models. These approaches combine thermal, optical, radar and LiDAR observations with Eddy-Covariance measurements, soil-moisture data and meteorological information to derive spatially continuous estimates of ET, water stress and plant water availability. Such integration can improve both the spatial representation of hydrological processes and model transferability among forest types and climatic regions. Geospatial Foundation Models may further facilitate the joint analysis of multimodal RS data and the identification of complex relationships among vegetation structure, functional traits and ecohydrological processes.

For F-LUI quantification, these developments offer important new perspectives. Changes in forest water cycling need no longer be characterised solely through individual variables such as ET or soil moisture but can increasingly be interpreted as manifestations of altered functional forest traits and their consequences for the ecohydrological system. This creates new opportunities to disentangle management effects from climate-driven changes and to quantify spatially the consequences of different management regimes for water cycling, drought resistance and hydrological stability.

Overall, water cycling and ecohydrological functioning represent major functional dimensions of F-LUI. The combination of thermal RS, radar, LiDAR, soil-moisture missions, Eddy-Covariance measurements and AI-supported multisensor data fusion enables increasingly process-oriented monitoring of forest water fluxes and provides an important basis for evaluating the functional consequences of different forest-management intensities.

6.5.3. Functional Indicators of F-LUI—Carbon Cycling and Climate Regulation

Carbon storage and exchange represent central functional dimensions of F-LUI, because forest management directly affects both the magnitude of ecosystem carbon pools and the greenhouse-gas balance of forest ecosystems. Changes in tree-species composition, stand structure, biomass, deadwood stocks and soil properties influence long-term carbon storage and the exchange of carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) between forests and the atmosphere. Within the trait-based F-LUI framework,

carbon storage and greenhouse-gas fluxes therefore constitute functional response indicators integrating the cumulative effects of different management intensities on the climate-regulation function of forests.

Carbon storage is determined by numerous forest traits, including wood density, tree height, biomass allocation, crown architecture, LAI, root systems, deadwood and soil-carbon stocks. These properties determine the magnitude and residence time of carbon pools while also influencing respiration, litter production and decomposition. Changes in these traits resulting from harvesting, thinning, species selection, forest conversion or natural succession alter both above- and below-ground carbon pools and consequently long-term climate regulation. Recent research further suggests that functional trait composition plays an important role in determining the stability of carbon storage and forest resistance to climatic extremes [130].

Key functional indicators include Aboveground Carbon (AGC), AGB, below-ground and soil carbon, deadwood stocks, Net Ecosystem Exchange (NEE), Net Ecosystem Productivity (NEP) and fluxes of CO_2, CH_4 and N_2O. Whereas above- and below-ground carbon pools describe the long-term sequestration of atmospheric carbon, NEE and NEP characterise ecosystem-atmosphere carbon exchange and indicate whether forests function as net carbon sinks or sources. Together, these indicators enable an integrated assessment of the climatic consequences of different management regimes and provide a basis for contemporary forest carbon accounting [133,138].

Satellite-based assessment of forest carbon stocks has advanced considerably. Airborne and spaceborne LiDAR provide information on stand height, vertical vegetation structure and biomass and constitute an important basis for estimating above-ground carbon stocks. In particular, the GEDI mission provides extensive observations of three-dimensional forest structure and has substantially improved large-scale estimates of above-ground biomass and carbon stocks [12]. L-band and P-band SAR provide complementary sensitivity to forest biomass and structure and are particularly relevant for biomass estimation in dense forests. The ESA BIOMASS mission, based on P-band SAR, was specifically developed for global mapping of forest biomass and its temporal change [142].

Beyond carbon stocks, satellite-supported assessment of carbon and greenhouse-gas dynamics is becoming increasingly important. Combining optical observations, SIF, thermal RS, LiDAR and radar enables complementary analysis of carbon uptake, biomass development and vegetation stress. When integrated with Eddy-Covariance measurements from FLUXNET, these observations support spatial modelling of carbon fluxes and their temporal dynamics. This increasingly enables changes in ecosystem carbon balance to be related to forest management, natural disturbances and climatic extremes and their consequences for the climate-regulation function of forests to be assessed spatially [133].

Current developments are increasingly shaped by multisensor data fusion and GeoAI. Machine-Learning and Deep-Learning models integrate LiDAR, SAR, optical and thermal RS observations with forest inventories and process-based carbon models to derive spatially continuous estimates of biomass, carbon stocks and carbon fluxes. Foundation Models may further facilitate the joint analysis of multimodal RS data and improve transferability across forest types and climatic regions. These developments provide an important basis for future Measurement, Reporting and Verification (MRV) systems supporting international and national climate-policy frameworks, including REDD+ and LULUCF accounting.

Forest climate regulation, however, is not determined solely by carbon storage. Changes in crown structure, leaf area and tree-species composition also influence albedo, evapotranspiration, turbulent energy fluxes and surface temperature, thereby affecting regional and global climate processes. The climate-regulation function of forest ecosystems therefore emerges from interactions between biogeochemical processes associated

with carbon cycling and biophysical processes governing water and energy exchange [138]. For F-LUI quantification, carbon storage and greenhouse-gas exchange should consequently be interpreted together with the Structural, Productivity and Water-cycling indicators described above.

Overall, forest carbon storage, greenhouse-gas exchange and climate regulation constitute a distinct functional dimension of F-LUI. Integrating LiDAR, radar, optical and thermal RS, satellite biomass mapping, Eddy-Covariance measurements and AI-supported multisensor data fusion enables increasingly spatially explicit monitoring of forest carbon stocks, greenhouse-gas dynamics and climate-regulation functions and provides an essential basis for assessing the long-term consequences of different management intensities.

6.5.4. Functional Indicators of F-LUI—Ecosystem Multifunctionality, Resilience and Stability

The effects of F-LUI ultimately cannot be assessed solely through individual ecosystem functions but require consideration of their combined behaviour. Concepts such as ecosystem multifunctionality, ecosystem resilience and ecosystem stability describe the capacity of forest ecosystems to provide multiple functions simultaneously—including carbon storage, productivity, water regulation, habitat provision and biodiversity conservation—and to maintain or recover these functions under disturbance. Within the trait-based F-LUI framework, these concepts therefore represent the highest level of functional integration. They integrate the processes described in the preceding sections into an overarching assessment of forest ecosystem performance and enable evaluation of the long-term effects of management on forest functioning.

Forest ecosystem multifunctionality emerges from interactions among functional forest traits, forest structure, taxonomic composition and the coupling of water, carbon and energy cycles. Changes in management intensity therefore rarely affect individual processes in isolation but instead alter multiple ecosystem functions simultaneously. Current syntheses indicate that functional diversity and structural complexity can promote the simultaneous provision of multiple ecosystem functions and contribute to ecosystem stability under climatic extremes [143,144]. For F-LUI assessment, this implies that sustainable forest management cannot be evaluated solely through the maximisation of individual ecosystem services, but must also consider the long-term maintenance of ecosystem multifunctionality.

RS is increasingly moving from the observation of individual variables towards the integrated quantification of multiple ecosystem functions. Multitemporal observations from Sentinel-1, Sentinel-2, Landsat, GEDI and ECOSTRESS, together with SIF and airborne and UAV LiDAR, enable complementary characterisation of vegetation activity, biomass, carbon storage, water cycling, habitat structure and disturbance dynamics. Through multisensor data fusion, Analysis Ready Data (ARD) and Earth Observation Data Cubes, these observations can be integrated consistently across broad spatial and temporal scales, providing a basis for deriving composite functional indicators.

A particular focus of current research is the RS-based quantification of forest ecosystem resilience. Whereas traditional approaches predominantly described static ecosystem states, modern time-series analyses increasingly examine ecosystem dynamics using metrics such as resistance, recovery, recovery rate, recovery time, critical slowing down and early-warning signals. Dense Landsat and Sentinel time series, Vegetation Optical Depth (VOD), SIF, radar and LiDAR observations provide new opportunities to monitor forest responses and recovery following drought, storms, fire and insect disturbances. Such temporal resilience metrics may provide more sensitive information on changes associated with F-LUI than purely static structural indicators [145,146].

In parallel, rapid developments in GeoAI are transforming the assessment of forest ecosystem functioning. Modern Machine-Learning, Deep-Learning and Transformer models integrate optical, thermal, radar and LiDAR observations with forest inventories, Eddy-Covariance measurements and process-based ecosystem models. These approaches enable complex relationships among functional traits, productivity, water cycling, carbon storage and biodiversity to be analysed jointly. Physics-informed Machine Learning, Self-supervised Learning and geospatial Foundation Models are increasingly being explored to learn more transferable representations of forest ecosystems and improve generalisation across forest types and climatic regions.

A further development is the integration of RS with Digital Twins and data-driven ecosystem models. Through continuous assimilation of multisensor observations, virtual representations of forest ecosystems can be developed to simulate management scenarios and predict their consequences for multifunctionality, resilience and stability. This development has the potential to shift RS from the retrospective description of ecosystem states towards predictive assessments of future forest trajectories under alternative management and climate scenarios.

For F-LUI, this development represents an important conceptual shift. Whereas conventional approaches often considered individual structural or functional indicators in isolation, modern RS and AI methods increasingly enable an integrated assessment of forest ecosystem functioning. Ecosystem multifunctionality, resilience and stability therefore constitute the highest functional level of the F-LUI framework. They connect observable forest traits with productivity, water cycling, carbon storage and biodiversity to provide an integrated assessment of forest ecosystem performance and establish a basis for cross-scale monitoring of sustainable forest management under global environmental change.

6.6. Monitoring Socio-Economic Indicators of F-LUI with RS

F-LUI is determined not only by ecological and biophysical processes but also, to a substantial extent, by socio-economic decisions and institutional conditions. Management objectives, timber demand, ownership structures, accessibility, institutional regulations and economic incentives influence where, when, how and at what intensity forests are used. These factors shape management interventions such as timber harvesting, thinning, tree-species selection, regeneration and infrastructure development and thereby indirectly affect forest traits, forest structure, species composition and ecosystem functioning. The socio-economic dimension thus provides an important link between the drivers of anthropogenic forest use and the ecological responses of forest ecosystems represented by the preceding indicator families.

In contrast to Trait, Genesis, Structural, Taxonomic and Functional indicators, however, socio-economic properties are only partly observable through RS. Forest ownership, governance structures, market prices, timber demand, operational decisions and policy regulations have no unique spectral, thermal or structural signature. Consequently, RS generally cannot observe the underlying socio-economic processes themselves, but can capture their spatially and temporally manifested consequences or proxies. These include harvesting and thinning, changes in canopy and stand structure, skid trails and forest roads, fragmentation, reforestation and spatial patterns associated with different management intensities.

A particular strength of RS lies in the spatial explicitness and temporal repeatability of these observations. Multitemporal Landsat and Sentinel time series can reveal the timing, spatial extent and recurrence of harvesting and stand changes, whereas high-resolution optical observations, SAR, LiDAR and UAV data can provide additional information on infrastructure, canopy openings, skid trails and small-scale interventions. These observations can be used to derive spatial proxies for management activity, harvesting

intensity, accessibility and management pressure. However, an unambiguous socio-economic interpretation is often impossible from RS alone because similar changes may result from forest management, storms, fire, drought or biotic disturbances.

For the socio-economic dimension of F-LUI, the integration of RS with in situ, inventory, administrative and socio-economic data is therefore particularly important. National Forest Inventories and operational forestry data provide information on timber removals, increment, growing stock and management interventions; cadastral and ownership data describe property structures; road networks and topographic data characterise accessibility; management plans and protected-area data document institutional management regimes; and production, trade, price and company statistics provide information on timber demand and forest-based economic activity. RS complements these plot-based or administratively delineated information sources by providing spatially continuous observations of forest use as manifested on the ground and its ecological consequences.

The Socio-economic indicator family therefore differs conceptually from the other F-LUI indicator families. Its purpose is not to infer socio-economic processes from RS alone, but to link RS-observable patterns of forest use and forest traits with information on the underlying human decision-making, accessibility, governance and economic systems. Only this integration enables the socio-economic driver of forest use, the realised management activity, and its observable ecological response to be distinguished. Accordingly, the socio-economic indicator family constitutes a distinct contextual dimension that supports the interpretation and attribution of the five predominantly RS-centred indicator families.

6.6.1. Socio-Economic Indicators of F-LUI—Forest Management Activity and Harvesting Intensity

The intensity of actual forest-management interventions, and timber harvesting in particular, represents one of the most direct socio-economic indicators of F-LUI. It describes when, where, how frequently and to what extent biomass is removed through thinning, single-tree or group selection, partial harvesting or complete stand harvesting. Management and harvesting intensity can therefore be characterised by variables such as harvested area, harvested volume, intervention frequency, harvest severity, spatial harvest pattern and recurrence interval. Based on 182,649 inventory plots across eleven European countries, Suvanto et al. [147] showed that the combination of the frequency and intensity of individual harvesting interventions can distinguish different harvesting regimes and provides a considerably more differentiated description of realised forest use than aggregated harvest volumes alone.

RS enables spatially explicit and repeatable observation of such management activities, although neither the intervention itself nor the actual volume of timber removed is necessarily observed directly. Instead, RS primarily records its biophysical consequences, including changes in canopy closure, stand density, biomass, vertical structure and spectral properties. Large and intensive interventions in particular generate pronounced RS signals and can be characterised using multitemporal Landsat and Sentinel observations in terms of timing, spatial extent and recurrence. Ceccherini et al. [148], for example, demonstrated the large-scale satellite-based assessment of changes in harvested forest area and associated biomass losses across Europe.

For F-LUI quantification, however, it is not sufficient to determine whether a management intervention has occurred; its intensity, spatial expression and temporal recurrence are equally important. Multitemporal Landsat and Sentinel time series enable the derivation of harvest frequency, severity, patch size, recurrence and recovery time and can therefore characterise different harvesting and management regimes. Long Landsat time series are particularly valuable for retrospectively reconstructing repeated interventions, whereas the higher spatial and temporal resolution of Sentinel-1 and Sentinel-2

enables more detailed monitoring of recent management activities. Xulu et al. [149], for example, demonstrated that combined Sentinel-1 SAR and Sentinel-2 observations can be used for automated detection of harvesting events in managed forests. Sentinel-1 time series are particularly valuable for continuous monitoring of abrupt forest changes because of their relative independence from cloud cover [150].

Very-high-resolution optical time series extend these capabilities to smaller intervention areas. PlanetScope, with a spatial resolution of approximately 3 m and near-daily revisit capability, offers particular potential for timely detection of small-scale forest change. Francini et al. [151], for example, developed a near-real-time forest-change detection approach based on PlanetScope time series. A recent synthesis confirms the increasing potential of PlanetScope for high-resolution and near-real-time forest monitoring, while also highlighting challenges related to radiometric harmonisation and time-series consistency [152].

The detection of partial and small-scale timber removals remains particularly challenging because thinning and single-tree or group selection generate considerably weaker spectral and structural changes than clear-cutting. High-resolution optical observations can therefore be combined with SAR, ALS, UAV and multisensor approaches to detect changes in canopy closure, canopy gaps, tree height, stand density and vertical structure. This is particularly relevant to CCF, in which continuous forest cover is maintained. In their review specifically addressing CCF, Stoddart et al. [153] showed that conventional area-based RS approaches have limitations under these conditions and that high-resolution LiDAR, UAV and multisensor approaches are particularly important for detecting structurally heterogeneous and often subtle management effects. Recent ALS analyses further indicate that LiDAR metrics can identify uneven-aged stand structures characteristic of CCF and provide information on understory structure [154].

The combination of long-term Landsat time series, high-frequency Sentinel-1/-2 and PlanetScope observations, and structure-sensitive LiDAR and UAV data therefore increasingly enables a multidimensional characterisation of management activity and harvesting intensity. Nevertheless, an important limitation remains, particularly for partial harvesting: a weak or absent RS disturbance signal must not automatically be interpreted as low or absent management activity, because interventions that retain canopy cover may be only weakly visible in satellite observations. Robust quantification of actual timber removals therefore continues to require integration with inventory and management data.

A further challenge is distinguishing forest-management interventions from natural disturbances. Canopy and biomass losses can also result from storms, fire, drought, disease or insect outbreaks. Detection of forest change therefore does not in itself provide unequivocal evidence of timber harvesting. Similarly, RS-derived harvested area, canopy loss or spectral change magnitude should not be equated directly with the actual volume of timber removed. The debate surrounding the satellite-derived increase in European harvested forest area reported by Ceccherini et al. [148]illustrates this uncertainty and highlights the need for independent inventory and harvest statistics to validate RS-based estimates.

Robust quantification of forest management activity and harvesting intensity therefore requires integration of RS with forest inventories, georeferenced harvesting records, forest-management plans and operational management data. Whereas RS primarily captures the location, timing, spatial extent, recurrence and biophysical severity of an intervention, in situ and management data provide information on the type of intervention and the actual volume of timber removed. The importance of this combination is further demonstrated by Suvanto et al. [147]: harvesting patterns observed on permanent forest-inventory plots show that regions with similar overall harvesting rates may exhibit

markedly different combinations of frequent low-intensity and infrequent high-intensity interventions.

For F-LUI monitoring, forest management activity and harvesting intensity should therefore be understood as a multidimensional indicator comprising harvested area, harvested volume, intervention frequency, harvest severity, spatial harvest pattern and recurrence interval. RS provides the spatial and temporal observation of realised forest use and its biophysical consequences, whereas in situ, inventory and management data remain essential for quantifying and unequivocally attributing actual management and harvesting intensity.

6.6.2. Socio-Economic Indicators of F-LUI—Forest Ownership and Governance

Forest ownership and governance structures strongly influence the objectives pursued on forest land, how decisions are made and which forms of management are implemented. Public, private, municipal and community-managed forests may differ in management objectives, planning horizons, utilisation intensity and conservation orientation. In a synthesis of temperate forests in Europe and North America, Mölder et al. [155] showed that ownership patterns can be closely associated with long-term management practices and characteristic patterns of forest structure and biodiversity. For F-LUI, ownership and governance therefore do not represent directly observable biophysical properties but rather institutional contexts within which different intensities and forms of forest use emerge.

Governance extends beyond formal ownership. It encompasses legal regulations, ownership and use rights, institutional responsibilities, management plans, protection requirements, and public and private governance instruments. Using a historical database for the Nordic countries, Fridén et al. [156] demonstrated how governmental regulation, private governance and forest-policy instruments have changed over two centuries, creating different institutional conditions for forest management. Different forms of governmental, private, Indigenous or community governance are also not always clearly separable; Zhang et al. [157] emphasised, particularly for protected and community-managed areas, that governance often involves overlapping institutional responsibilities and that its ecological effects are strongly context dependent.

RS cannot observe forest ownership or governance itself. Property boundaries, ownership status, use rights, legal restrictions and decision-making processes have no intrinsic spectral or structural signature. Their relevance to F-LUI therefore emerges through the spatial integration of external governance information with RS-observed forest traits and forest change. Ownership and cadastral boundaries, protected-area categories, concession areas or management units can, for example, be overlaid with RS-derived information on forest structure, tree-species composition, biomass, forest loss and regeneration. This enables assessment of whether different institutional or ownership contexts are systematically associated with differences in forest traits and their temporal dynamics.

RS offers a particular advantage in this context because satellite- and airborne-derived products can provide spatially continuous and standardised forest information across institutional boundaries. Wulder et al. [25], for example, demonstrated how satellite-derived information on forest condition, structure, disturbance and regeneration can be attributed to management units or polygon-based forest stands. Such approaches make it possible to calculate identical RS indicators for different ownership or governance units and thereby compare their forest conditions and change dynamics using a common observational basis.

This integration is particularly relevant to forest management planning. Ulvdal et al. [158] showed for large Swedish forest-owning companies that strategic, tactical and operational decisions rely strongly on spatial forest inventories and stand data and that RS-

derived information is increasingly used to update these planning datasets. Fassnacht et al. [38] similarly emphasised that the operational use of RS in forest management depends not only on sensor technology but also on ownership structures, management traditions, regulatory frameworks, information requirements and institutional capacities. Ownership and governance therefore influence not only forest management itself but also how RS-derived information is incorporated into decision-making processes.

For F-LUI, forest ownership and governance should therefore primarily be considered contextual socio-economic indicators. Relevant variables include ownership type, parcel size and fragmentation, management responsibility, protection status, concession status, management-plan coverage, and institutional restrictions or prescriptions governing forest use. These data originate primarily from cadastral, administrative, forest-management and governance databases. RS complements them with spatially and temporally consistent observations of forest structure and development. Only through their integration can the relationships between institutional conditions and different manifestations of F-LUI be assessed.

6.6.3. Socio-Economic Indicators of F-LUI—Forest Accessibility, Infrastructure and Management Pressure

Forest accessibility and forestry infrastructure strongly influence where and at what cost forest resources can be managed and therefore constitute an important socio-economic dimension of F-LUI. Roads and forest tracks provide access for machinery, timber transport and other management operations and consequently influence both the costs and spatial distribution of forest management. Relevant indicators include road density, distance to roads, road-network connectivity, relative openness, extraction distance and road expansion. A recent synthesis by Đuka et al. [159] confirms that road-network density and accessibility are fundamental prerequisites for efficient forest utilisation and, together with topography and technical constraints, determine the actual accessibility of forest areas. Fraefel et al. [160] similarly demonstrated for Switzerland that the usability of forest roads, together with terrain and transport conditions, substantially determines which forest areas are accessible to different harvesting and transport systems.

From an F-LUI perspective, however, accessibility must be distinguished from realised management activity. High road density or short distance to the nearest forest road increases the technical and economic feasibility of forest use but does not demonstrate that a forest is actually managed intensively. Conversely, poorly accessible or steep forest areas may be less intensively used because of high extraction and transport costs. Infrastructure indicators should therefore primarily be interpreted as proxies for potential management pressure. At the same time, roads themselves can generate ecological effects through habitat fragmentation, soil disturbance and increased human accessibility and can therefore contribute directly to F-LUI. As emphasised by Đuka et al. [159], actual accessibility depends not merely on road-network length but on its spatial distribution, technical usability and relationship to terrain.

RS can spatially characterise important components of this infrastructure. High- and very-high-resolution optical and multisensor satellite observations increasingly enable automated mapping of forest roads and road networks using Machine-Learning and Deep-Learning methods. Particularly relevant is the study by Slagter et al. [161], who combined Sentinel-1 and Sentinel-2 time series with Deep Learning to map the monthly development of roads across the Congo Basin at 10-m spatial resolution. Between 2019 and 2022, they mapped 35,944 km of road development, at least 78% of which was associated with industrial selective logging. This demonstrates that RS can capture not only existing infrastructure but also road construction, expansion and reopening through time and relate these dynamics to forest use.

Very-high-resolution satellite imagery, aerial photography and UAV observations can further improve the detection of narrow forest tracks and secondary infrastructure, whereas LiDAR and ALS are particularly advantageous where roads and skid trails are partially obscured by canopy cover. High-resolution digital terrain models can reveal linear terrain structures and anthropogenic modifications of the ground surface that are difficult to detect in optical satellite imagery beneath closed canopies. Operational F-LUI monitoring can therefore benefit particularly from multisensor approaches in which optical and SAR time series capture the temporal dynamics of infrastructure while high-resolution aerial, UAV or LiDAR observations provide complementary information on fine-scale spatial structures.

RS-based infrastructure mapping enables the derivation of spatial F-LUI proxies such as road density, distance to roads, road expansion, road-network connectivity and roadless area. Temporal dynamics are particularly informative: the construction or reopening of forest roads may indicate imminent or increasing utilisation of previously less accessible forest areas. Slagter et al. [161], for example, demonstrated that satellite observations of road development in the Congo Basin can be closely related to the spatial dynamics of selective logging. RS-based infrastructure indicators can therefore provide not only a static description of accessibility but increasingly also an assessment of how accessibility changes through time.

Actual forest accessibility, however, is not determined by the road network alone. Topography, slope, surface roughness, soil conditions and the suitability of different harvesting systems determine whether forests can be accessed by machinery and whether timber can be transported economically. Fraefel et al. [160] developed a spatially explicit approach for Switzerland that links road-network characteristics with the requirements of different timber-harvesting and transport systems. RS-derived digital elevation models and terrain parameters can therefore be combined with road information to characterise functional accessibility more realistically than road density or simple Euclidean distance alone.

For F-LUI monitoring, forest accessibility, infrastructure and management pressure should therefore be conceptualised as a multidimensional indicator comprising road density, distance to roads, road connectivity, road expansion, roadless area, terrain accessibility, and their temporal changes. RS plays an important role because road development and spatial accessibility patterns can increasingly be monitored continuously and over large areas. Nevertheless, infrastructure remains primarily an enabling or pressure indicator rather than direct evidence of realised management intensity. Robust interpretation therefore requires RS-derived infrastructure and terrain information to be integrated with inventory, harvesting, management and administrative geodata.

6.6.4. Socio-Economic Indicators of F-LUI—Forest Management Regimes and Spatial Management Patterns

Different forest management regimes represent long-term strategies of forest use, ranging from largely unmanaged forests through close-to-nature and multifunctional management systems to intensively managed production forests and plantations. In contrast to Section 6.6.1, which addresses the intensity of individual management and harvesting events, a management regime describes the long-term combination and spatial organisation of different management practices. It therefore represents a higher-level socio-economic dimension of F-LUI.

RS cannot directly observe a forest management regime, because management objectives and silvicultural concepts have no unique spectral or structural signature. Long-term management, however, modifies forest structure, tree-species composition, stand age, biomass distribution and spatial heterogeneity and can therefore generate characteristic RS-

observable management signatures. The relevant information consequently lies not in a single RS parameter but in the multivariate combination of forest traits and spatial structural characteristics.

Asbeck and Frey [162], for example, investigated the relationship between a field-based ForMIX and structural complexity measured using TLS. Individual management components were associated with three-dimensional stand structure, but the overall relationship between management intensity and structural complexity was weak. This result is particularly important for F-LUI because it demonstrates that management regimes cannot be reliably inferred from a single structural RS characteristic.

LiDAR-based approaches nevertheless enable increasingly detailed characterisation of such structural management signatures. Neudam et al. [163] used Mobile Laser Scanning to quantify three-dimensional structural complexity in differently managed and formerly managed beech forests and demonstrated that management-related differences in vertical and horizontal stand structure can be captured using LiDAR metrics. Batchelor et al. [164] additionally developed TLS-derived metrics such as depth, openness and isovist, from which characteristic structural signatures of different forest structures can be derived. Such three-dimensional information is particularly relevant to F-LUI because long-term management affects not only mean tree height or biomass but, importantly, the distribution and complexity of vegetation within three-dimensional space.

The temporal development of structural complexity can also contribute to differentiating management regimes. Using repeated terrestrial laser scans of differently managed and unmanaged European beech forests, Willim et al. [165] showed that structural complexity develops differently depending on management. For F-LUI, this provides an opportunity to characterise management regimes not solely through static forest condition but through the trajectories of structural forest traits.

At landscape and continental scales, such local structural information must be integrated with spatially continuous datasets. An important recent approach is provided by Scherpenhuijzen et al. [166], who developed a high-resolution map of European forest-management regimes distinguishing five classes: unmanaged, close-to-nature, combined-objective, intensive and very intensive forestry. At the same time, their study illustrates an important methodological limitation: continental-scale attribution of forest-management regimes does not rely on a single RS signal but on the integration of multiple spatial data layers and comparison with National Forest Inventory information. Management-regime mapping should therefore be considered a data-integration problem in which RS-derived forest characteristics are combined with inventory and management information.

For such integration, multivariate management signatures are particularly promising. Rather than relying on individual parameters, combinations of canopy-height distribution, vertical complexity, structural heterogeneity, tree-species composition, biomass distribution, canopy openness, stand homogeneity, and their spatial configuration can be used. The capacity to quantify three-dimensional forest complexity objectively continues to expand through advanced LiDAR approaches. Batchelor et al. [164], for example, showed that different height strata within a forest stand can exhibit distinct structural signatures, whereas Neudam et al. [163] demonstrated that mobile LiDAR observations can quantitatively characterise complex three-dimensional stand structures. RS-derived structural characteristics can thus increasingly serve as components of an overarching management-regime signature.

Unambiguous attribution nevertheless remains difficult. Similar forest structures can result from different management regimes, natural succession, site conditions or disturbances; conversely, the same management system can generate different RS signatures depending on tree species, site conditions and stand history. The weak relationships between a continuous management-intensity index and individual TLS-derived structural measures reported by Asbeck and Frey [162] illustrate this limitation particularly clearly.

Classification of forest-management regimes should therefore not rely exclusively on RS, but should combine RS-derived Trait and Structural information with National Forest Inventory, forest-management planning and operational management data.

7. Emerging Approaches for Next-Generation F-LUI Monitoring

Rapid advances in RS are creating new opportunities for the assessment and monitoring of F-LUI. Whereas conventional RS approaches have often relied on individual sensors or indicators, emerging methods increasingly enable the integration of heterogeneous data sources, automated knowledge extraction and the analysis of complex relationships among forest management, ecosystem structure and ecosystem functioning. In particular, advances in AI, multimodal data fusion and semantic data integration are creating the conditions for more standardised, scalable and operational F-LUI monitoring. The following sections review these developments and discuss their potential contribution to future monitoring systems.

7.1. Artificial Intelligence and Foundation Models for F-LUI Monitoring

Rapid advances in AI are fundamentally changing the analysis of RS data and creating new opportunities for monitoring complex forest ecosystems. Whereas conventional Machine Learning and Deep Learning approaches have predominantly been developed for individual tasks such as tree-species classification, biomass estimation or disturbance detection, research is increasingly shifting towards Foundation Models. These models are pre-trained on large datasets, often using Self-supervised Learning, to learn generalisable spatial, spectral and temporal representations that can subsequently be transferred to a wide range of RS applications [43,44]. At the same time, Lu et al. [43] identify sensor heterogeneity, differences in spatial and spectral resolution, temporal dynamics and transferability to previously unseen regions as major challenges for RS Foundation Models.

This development is particularly relevant to F-LUI monitoring. F-LUI is not a directly observable RS variable but a latent, multidimensional system property emerging from interactions among anthropogenic forest management, natural disturbances and structural, taxonomic and functional ecosystem changes. Its assessment therefore requires the joint consideration of multiple forest traits and their spatial and temporal dynamics. From the perspective of the framework proposed here, the principal value of Foundation Models consequently lies not merely in improving the accuracy of individual classification or regression tasks, but in their potential to learn shared representations of complex forest ecosystems from which multiple forest traits can subsequently be derived.

Recent multimodal Foundation Models illustrate this potential. SkySense integrates optical and SAR time series within a common spatio-temporal representation model and was pre-trained on 21.5 million temporal sequences [167]. The model demonstrates the potential to combine different sensor modalities and temporal contexts within transferable representations. This temporal dimension is particularly relevant to F-LUI because land-use intensity is characterised not only by current forest condition but also by trajectories of harvesting, regeneration, succession, tree-species change and disturbance.

Particularly relevant to forest monitoring are FoMo-Bench and FoMo-Net. Bountos et al. [168] developed FoMo-Bench as a benchmark comprising 15 datasets covering different regions, spatial scales and sensor modalities, together with FoMo-Net, a pre-training framework capable of handling different combinations of RS modalities and spectral bands. FoMo therefore illustrates how heterogeneous forest observations can be incorporated into a common model architecture for multiple monitoring tasks.

For the trait-based F-LUI framework, this development creates the possibility of representing variables that have previously been modelled separately—such as biomass, canopy structure, tree-species composition, biochemical traits and disturbance dynamics—within shared representation spaces. These forest traits subsequently provide the observational basis

for the six F-LUI indicator families Trait, Genesis, Structure, Taxonomy, Function and Socio-economics. Foundation Models may therefore provide a scalable methodological bridge between high-dimensional RS observations and the multidimensional characterisation of F-LUI.

These opportunities are, however, accompanied by substantial limitations. Foundation Models may inherit biases from their training data and lose transferability when applied to forest types, regions or sensor systems that are poorly represented during pre-training. For F-LUI, ecological interpretability, uncertainty quantification and independent validation are therefore essential. Latent representations must not be equated directly with ecological traits or management intensity but require validation against in situ observations, forest inventories and management information.

AI and Foundation Models should consequently not be regarded as substitutes for ecological process understanding, but rather as a representation and inference layer within trait-based F-LUI monitoring. Their principal potential lies in transforming heterogeneous observations into transferable Forest-Trait representations and thereby supporting scalable, dynamic and ultimately operational F-LUI monitoring. Accordingly, improvements in predictive accuracy alone are insufficient; AI-derived F-LUI information must also be calibrated, independently validated, ecologically plausible and traceable to its underlying training and observation data.

7.2. Multi-Sensor Data Fusion and Digital Twins

The increasing availability of complementary RS observations creates new opportunities for multidimensional monitoring of F-LUI. Individual sensor systems capture only specific properties of forest ecosystems: multispectral and hyperspectral observations provide information on biochemical and physiological vegetation properties, LiDAR characterises three-dimensional stand structure, whereas SAR is particularly sensitive to structural properties and vegetation moisture. Combining these complementary observations can therefore improve the retrieval of tree species, canopy structure, stand height, biomass and other forest traits. A recent synthesis by Balestra et al. [58], for example, highlighted the substantial potential of integrating LiDAR with multispectral, hyperspectral and radar observations for tree and crown segmentation, biomass estimation, stand-height retrieval, tree-species identification and structural forest characterisation.

For F-LUI, however, the importance of data fusion extends beyond improving estimates of individual forest variables. Of particular relevance is the integration of RS observations with forest inventories, in situ sensor networks, management information, climate and site data, and process-based models. Such integration enables forest traits not only to be characterised spatially but also to be interpreted in relation to their underlying causes. This is essential because similar changes in forest structure or functioning may result from fundamentally different processes. Timber harvesting, storms, drought, fire and insect outbreaks, for example, may all produce comparable changes in canopy structure or biomass. Joint analysis of multiple data sources and their temporal dynamics can therefore improve attribution of observed trait changes to anthropogenic or natural drivers.

Recent work on multimodal data fusion in forest monitoring increasingly describes integrated space–air–ground observation systems combining satellite, UAV and terrestrial observations [169]. The next stage of integration is to couple these observations continuously with dynamic models of forest ecosystems. Digital Twins provide a particularly promising architecture for this purpose. A Digital Twin can be understood as a dynamic virtual representation of a real system that is continuously or repeatedly updated using observational data and thereby supports not only description of current system state but also simulation of potential future developments. Digital-Twin concepts are increasingly being explored in both agriculture and forestry [170].

Within a trait-based F-LUI monitoring system, a Forest Digital Twin could integrate RS-derived forest traits, forest inventories, management data, sensor networks and process models within a dynamic system representation. Unlike a static forest map, such a system would not merely represent the current state of biomass, canopy structure, tree-species composition or productivity, but would follow their temporal trajectories. New RS and in situ observations could be assimilated regularly to update the digital representation of the forest ecosystem. Management interventions and disturbances could then be incorporated as events, allowing their consequences for the six F-LUI indicator families—Trait, Genesis, Structure, Taxonomy, Function and Socio-economics—to be analysed.

Particularly important is the transition from monitoring to scenario simulation. Digital Twins could, for example, simulate alternative thinning intensities, harvesting strategies, tree-species conversions or regeneration measures and compare their potential consequences for biomass, carbon storage, biodiversity, water cycling and resilience. The potential of such systems is already becoming evident in wildfire management, where Digital Twins can integrate RS, meteorological, sensor and simulation data to support analyses of fire development, prevention and management scenarios [171].

For F-LUI, however, Digital Twins should currently be regarded primarily as a prospective integration architecture rather than an established operational monitoring method. Major challenges include the spatial and temporal harmonisation of heterogeneous datasets, differences in measurement uncertainty, incomplete management information, model errors, continuous data assimilation and independent validation. Nevertheless, the integration of multi-sensor observations, forest traits and dynamic ecosystem models offers an important perspective: F-LUI monitoring could evolve from a predominantly retrospective description of anthropogenic forest use towards a dynamic and scenario-based monitoring framework. Multi-sensor fusion should therefore provide not only harmonised estimates but also explicit information on uncertainty propagation, sensor-specific limitations and the conditions under which the resulting products remain valid.

The semantic integration of the heterogeneous observations, traits and management information required for such systems is addressed in Section 7.3.

7.3. Semantic Web, Linked Open Data and Knowledge Graphs

Operationalising F-LUI requires not only the integration of heterogeneous data sources but also their semantic harmonisation. RS products, forest inventories, in situ observations, management data and ecological models differ in terminology, spatial and temporal resolution, measurement units and data structures. Moreover, identical terms may be defined differently among monitoring programmes, whereas different terms may refer to the same ecological property. For internationally comparable F-LUI monitoring, purely technical data fusion is therefore insufficient. The meaning, provenance and relationships of forest traits and F-LUI indicators must also be described explicitly and in machine-readable form.

The Semantic Web and Linked Open Data (LOD) provide a suitable conceptual framework for this purpose. Semantic technologies represent data not only as values but connect them to explicitly defined concepts and relationships. Standards such as the Resource Description Framework (RDF) and the Web Ontology Language (OWL) enable such relationships to be represented formally, whereas SPARQL and particularly GeoSPARQL support semantic and spatial querying. GeoSPARQL was specifically developed to represent spatial objects and relationships in a standardised manner within the Semantic Web [172].

For the trait-based F-LUI framework, the ontological description of the observational layer is particularly important. A Forest Trait could, for example, be represented together with its definition, unit, spatial scale, observation method, sensor source and temporal validity. Transferable semantic standards already exist for this purpose. The SOSA/SSN

ontology, jointly developed within the W3C/OGC context, provides a modular semantic model for sensors, observations, procedures, observed properties and features of interest [173]. The Environment Ontology (ENVO) similarly demonstrates how environmental conditions and entities can be formally represented and linked to biological information [174].

Building on these standards, Knowledge Graphs could explicitly represent relationships among the components of the F-LUI framework. Nodes within an F-LUI Knowledge Graph could include, for example, Forest Trait, tree species, forest structure, management intervention, disturbance, sensor, RS product and ecosystem function. Relationships could then specify which sensor observes a particular trait, which management intervention influences that trait, or which trait contributes to a particular ecosystem function. This would create a transparent knowledge chain: Management/Disturbance → Forest Trait → RS Observation → F-LUI Indicator → Ecosystem Response. This explicit representation distinguishes a Knowledge Graph from a conventional database: not only observational values, but also their ecological meaning and relationships within the F-LUI concept are represented formally.

A comparable principle is already applied in global biodiversity monitoring. EBVs were developed as a standardised observational layer between heterogeneous primary data sources and higher-level biodiversity indicators [175,176] further demonstrated that integration and harmonisation of different observation sources are essential prerequisites for representative EBV datasets. For forest ecosystems, Latifi et al. [177] showed, using a comprehensive data infrastructure for the Bohemian Forest ecosystem, how heterogeneous in situ and RS observations can be integrated to support the development of EBVs.

Semantic technologies are also an important prerequisite for implementing the FAIR principles—Findable, Accessible, Interoperable and Reusable [178]. These principles explicitly emphasise the machine-actionable discoverability, interpretability and reuse of scientific data. For F-LUI, their implementation could substantially improve comparability among forest inventories, RS products, research projects and national or international monitoring programmes. The Semantic Web, LOD and Knowledge Graphs therefore do not constitute an additional F-LUI indicator family, but rather a semantic integration layer of the trait-based framework. Their central function is to link forest traits, observation methods, management information and the six F-LUI indicator families unambiguously. This provides the basis for transparent, reproducible and machine-readable F-LUI products and ultimately supports the operational implementation of the trait-based framework proposed in Section 7.4.

As illustrated in Figure 5, an F-LUI ontology provides the semantic interface between heterogeneous data sources and the six indicator families of the trait-based F-LUI framework. Formal descriptions of forest traits, management information and RS products create the basis for interoperable data integration, automated knowledge extraction and AI-supported analyses, thereby supporting the development of standardised and reproducible F-LUI monitoring systems.

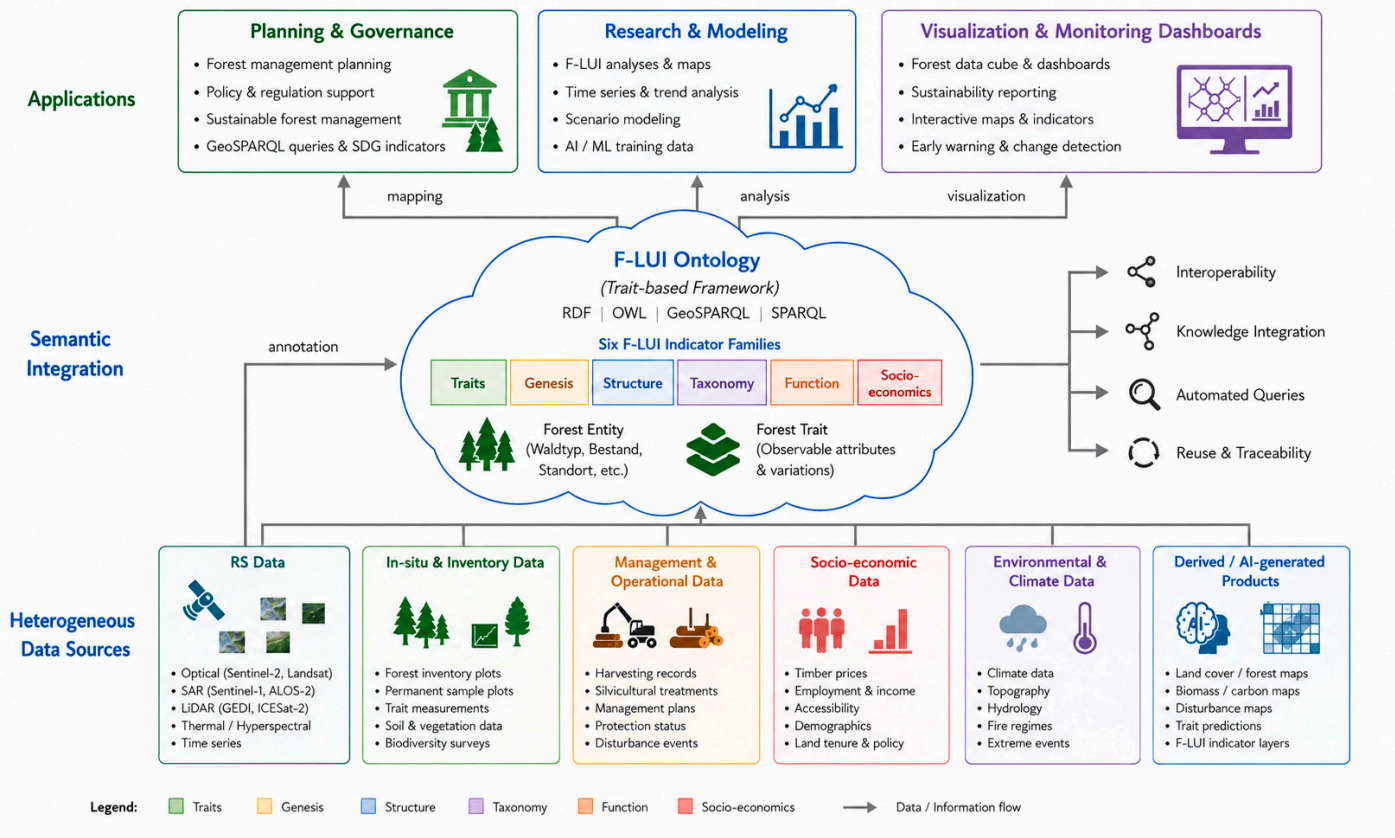


Figure 5. Conceptual framework for the semantic integration of heterogeneous data sources within trait-based Forest Land Use Intensity (F-LUI) monitoring. Conceptual visualisation generated using OpenAI ChatGPT (GPT-6; image generation) based on concepts defined by Angela Lausch; scientific validation and final revision by Angela Lausch.

7.4. Towards an Operational Trait-Based F-LUI Monitoring Framework

The principal challenge for future operational monitoring of F-LUI is not primarily the availability of additional sensors or individual indicators, but the standardised transformation of heterogeneous observations into comparable and ecologically interpretable F-LUI information. Continuous RS time series, forest inventories and in situ observations now provide extensive information on forest ecosystems, yet a common reference framework that systematically connects these observations with anthropogenic forest use and its ecological consequences is still lacking. The trait-based F-LUI framework proposed in this review addresses this gap by establishing forest traits as the common observational layer linking heterogeneous data sources, ecological processes and the six F-LUI indicator families.

Conceptually, this approach follows the logic of EBVs. EBVs provide an intermediate layer between heterogeneous primary observations and higher-level indicators, thereby enabling harmonisation across different observation systems [175]. Proença et al. [176] similarly demonstrated that field observations, monitoring networks and RS provide complementary contributions to standardised EBVs. For satellite-supported EBVs, Pettorelli et al. [179] further emphasised that operational monitoring requires clearly defined variables, user requirements and long-term coordination among ecology, RS and data providers.

Applied to F-LUI, this results in a hierarchical monitoring architecture: RS + in situ + inventories + management and environmental data → forest traits → six F-LUI indicator families → multidimensional F-LUI assessment → management and policy applications.

At the first level, heterogeneous primary observations from multispectral and hyperspectral sensors, SAR, LiDAR and thermal RS are integrated with forest inventories, sensor networks and management and environmental information. At the second level, these

observations are used to derive or characterise standardised forest traits, such as canopy height, biomass, leaf chemistry, vegetation water status and phenological properties. This observational layer is fundamental because traits can be defined largely independently of any particular sensor: conceptually, a Forest Trait remains the same ecological property regardless of whether it is measured in situ, retrieved from LiDAR or imaging spectroscopy, or characterised by a future sensor system.

Where higher-level properties such as tree-species composition are considered, they are derived from characteristic combinations of underlying forest traits rather than treated as directly observable RS properties. This distinction maintains the trait-based logic of the framework across all subsequent levels.

At the third level, forest traits and their spatial configurations, temporal trajectories and functional relationships are interpreted within the six F-LUI indicator families—Trait, Genesis, Structure, Taxonomy, Function and Socio-economics. For the socio-economic dimension, external management, ownership, governance and administrative information provides essential contextual information for attributing RS-observable trait patterns to anthropogenic drivers. F-LUI is therefore explicitly not reduced to a universal single index. Instead, the framework produces a multidimensional F-LUI profile representing different forms and ecological consequences of anthropogenic forest use. This is important because similar overall levels of use intensity may result from different management regimes and may generate substantially different ecological outcomes. The framework therefore retains information on individual dimensions while enabling their standardised joint assessment.

The technologies discussed in Sections 7.1–7.3 provide the methodological infrastructure required for this architecture. Foundation Models can support scalable and transferable Forest-Trait representations; multi-sensor data fusion integrates complementary observations; Semantic Web technologies and Knowledge Graphs provide explicit definitions and relationships among data, traits and indicators; and Digital Twins can dynamically update these representations and support scenario simulation. Importantly, these technologies do not define the conceptual framework itself but support its operationalisation.

For an operational system, F-LUI products must additionally meet defined requirements for spatial and temporal resolution, uncertainty, validation, reproducibility and interoperability. Uncertainty must be assessed throughout the complete processing chain rather than only for the final F-LUI product. Relevant sources include sensor noise and calibration, atmospheric and topographic effects, differences in spatial, spectral and temporal resolution, geolocation and co-registration errors, missing observations, optical and radar saturation, reference-data uncertainty, model transferability and the propagation of errors during multi-sensor fusion. These uncertainties should be quantified, where possible, using independent spatial and temporal validation, ensemble modelling, probabilistic prediction intervals, sensitivity analysis and error-propagation procedures. F-LUI products should therefore provide uncertainty layers and quality flags alongside estimated traits and indicators, rather than presenting model outputs as ecologically certain values.

AI-supported inference must additionally be auditable and ecologically contextualised. Each product should document the sensors and acquisition dates used, preprocessing and fusion procedures, training and validation data, model version, applicability domain and performance across forest types and environmental conditions. Historical RS time series, forest inventories, disturbance records and management information should be incorporated to distinguish persistent management effects from short-term anomalies or natural disturbances. Where several ecological interpretations remain plausible, these alternatives should be reported explicitly and subjected to expert evaluation. This audit trail links mathematical model confidence with ecological plausibility and enables users to trace each F-LUI inference back to its underlying observations, assumptions and uncertainties.

Experience from the EBV concept demonstrates that standardised metadata, interoperable data structures and reproducible workflows are essential prerequisites for global trait-based data products [180]. Similarly, every F-LUI product should provide information on data provenance, sensors used, model uncertainty, spatial and temporal validity, and the basis for validation.

The proposed framework therefore does not constitute a finished global F-LUI index, but an open reference architecture for its future operationalisation. Its principal conceptual contribution is to establish forest traits as a stable interface between continuously evolving observation technologies and the ecologically relevant dimensions of forest-use intensity. New sensors, AI models and data sources can therefore be incorporated without altering the underlying conceptual structure of the monitoring framework. In the longer term, this provides a pathway from fragmented individual indicators towards harmonised, dynamic and internationally comparable trait-based F-LUI monitoring.

Figure 6 summarises this architecture and illustrates how heterogeneous observations can be transformed through forest traits and the six F-LUI indicator families into AI-supported operational F-LUI monitoring.

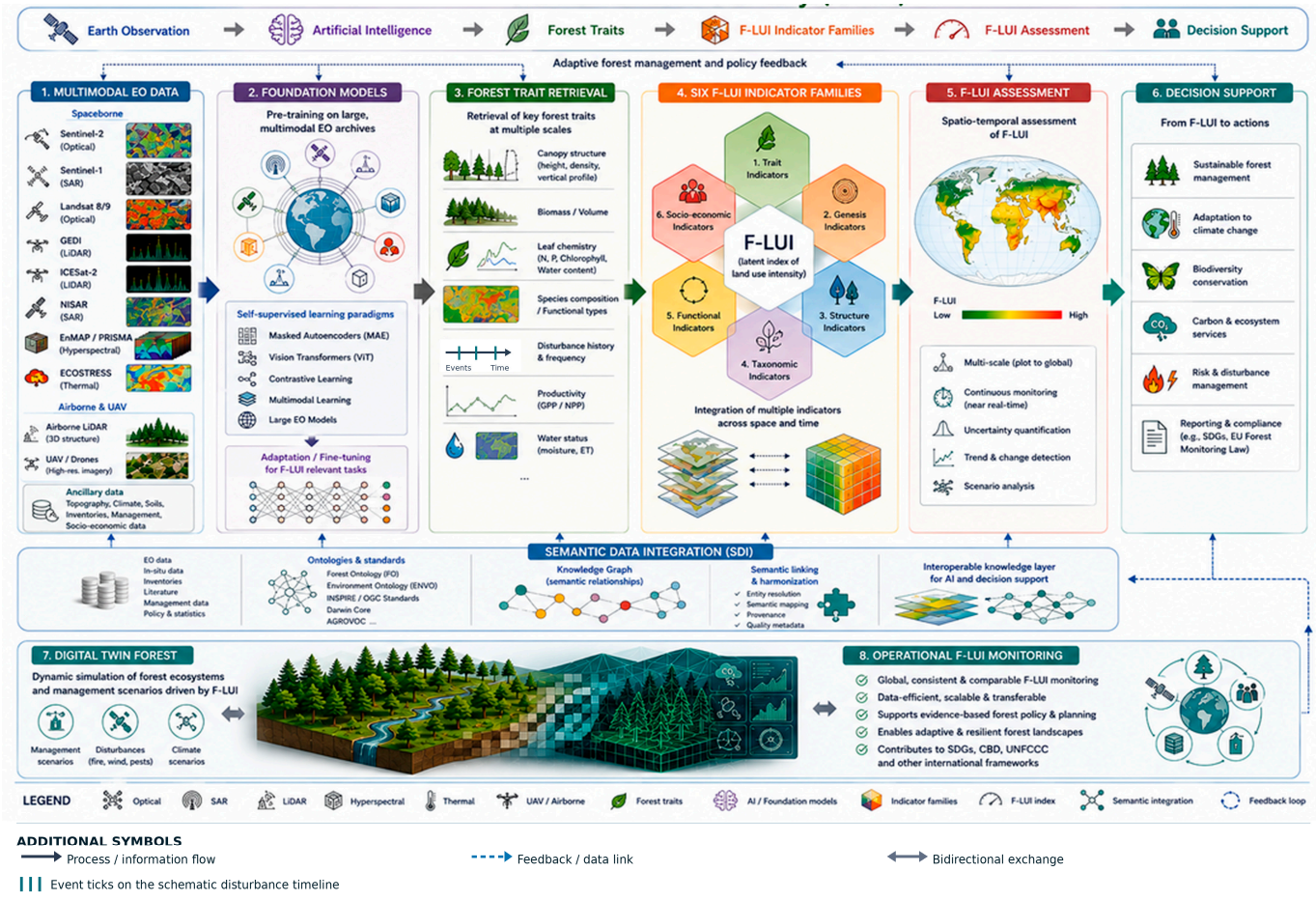


Figure 6. AI-enabled, trait-based framework for operational monitoring of Forest Land Use Intensity (F-LUI). Solid arrows indicate process and information flow; dotted blue arrows show feedback and data links; double-headed arrows indicate bidirectional exchange involving the digital twin and operational monitoring. The event marks in the disturbance-history panel represent a schematic timeline. Conceptual visualisation generated using OpenAI ChatGPT (GPT-6) (image generation) based on concepts defined by Angela Lausch; scientific validation and final revision by Angela Lausch.

A practical application of this operational architecture is illustrated in Section 7.5 using the transition from clear-cutting to continuous-cover forestry as an example.

7.5. From the Conceptual Framework to Management Decision Support: An Illustrative Continuous-Cover Forestry Scenario

To illustrate how the proposed framework can support practical decision-making, the transition from a commercial forest managed through clear-cutting towards continuous-cover forestry is considered as an illustrative scenario. This example is conceptual rather than empirical and demonstrates how the six indicator families can be combined without requiring a universally applicable F-LUI index. The management objective is to maintain timber production while increasing structural continuity, tree-species diversity, carbon storage and ecosystem resilience.

Implementation begins with the definition of the management objective, spatial assessment unit and monitoring period. A baseline is established using historical RS time series, forest-inventory data, management records and relevant socio-economic information. Indicators are then selected from each family according to their sensitivity to the intended management transition, their availability and their relevance to local management objectives. This selection should remain parsimonious, because operational decision support does not require every indicator described in this review.

Trait indicators provide the primary observational basis and may include LAI, canopy water status, foliar biochemical properties and canopy temperature. These indicators can reveal changes in vegetation condition and stress during harvesting, regeneration and stand development. Genesis indicators use temporal trajectories to distinguish abrupt clear-cutting events from smaller and more frequent interventions associated with continuous-cover forestry. They also capture regeneration dynamics, disturbance legacies and the continuity of forest development.

Structural indicators describe expected changes in canopy cover, vertical stratification, gap-size distribution, stand density and above-ground biomass. Under successful continuous-cover management, large homogeneous openings should decline, whereas vertical and horizontal structural heterogeneity should increase. Taxonomic indicators can assess changes in tree-species composition, functional groups and forest-community diversity. Their interpretation generally requires the integration of RS with forest inventories or field observations. Functional indicators evaluate consequences for productivity, carbon storage, evapotranspiration, water-use efficiency and energy exchange. They help determine whether structural and compositional changes translate into the intended ecosystem functions.

Socio-economic indicators provide the management context needed to interpret these ecological changes. Relevant information may include harvesting intensity, timber removals, road accessibility, ownership, management plans, regulatory constraints, operational costs and timber-market conditions. While RS can identify spatial proxies such as canopy openings, skid trails and harvesting patterns, ownership, economic objectives and management decisions must be obtained from cadastral records, administrative databases, forest-management plans or stakeholder information.

For decision support, the selected indicators can first be evaluated separately against the baseline, management targets or ecologically defined thresholds. Indicators may subsequently be normalised to a common scale and aggregated within each family. The six family-level results should initially be presented as a multidimensional dashboard or map rather than immediately collapsed into a single score. This preserves information on trade-offs, for example where improved structural diversity is accompanied by temporarily reduced timber output or increased operational costs.

If a particular decision requires alternatives to be ranked, context-specific weighting may be applied using a transparent Multi-Criteria Decision Analysis procedure. Weights should be defined according to the management objective, site conditions, legal requirements and stakeholder priorities rather than prescribed universally by the framework. Sensitivity analysis should then be used to determine whether the ranking changes under alternative weighting schemes. Any resulting composite score represents a decision-specific assessment and should not be interpreted as a universal F-LUI index. The scenario demonstrates that the framework can be implemented using currently available RS, inventory and management information. Digital Twins may extend this workflow by assimilating repeated observations and simulating future management alternatives, but they are not a prerequisite for operational application. Table 1 illustrates how the six-family F-LUI framework can be applied to the transition from clear-cutting to continuous-cover forestry by linking representative indicators, expected responses, principal data sources and their relevance to management decisions.

Table 1. Illustrative application of the six-family F-LUI framework to the transition from clear-cutting to continuous-cover forestry.

Indicator Family	Illustrative Indicators	Expected Response Under Continuous-Cover Forestry	Principal Data Sources	Management Relevance
Trait	LAI, canopy water status, canopy temperature	Improved continuity of canopy condition; reduced stress after intervention	Optical, hyperspectral and thermal RS; field data	Early detection of stress and recovery
Genesis	Harvesting events, regeneration and disturbance trajectories	Fewer abrupt stand-replacing changes; more continuous development	Landsat/Sentinel time series; management records	Verification of temporal continuity
Structure	Canopy cover, height diversity, gap size, biomass	Smaller gaps and greater vertical and horizontal heterogeneity	LiDAR, SAR, optical RS; inventories	Assessment of target stand structure
Taxonomy	Tree-species composition and diversity	Greater compositional diversity and mixed-species structure	Hyperspectral and multispectral RS; inventories	Evaluation of diversification and naturalness
Function	Productivity, carbon storage, evapotranspiration	More stable ecosystem functioning and carbon retention	Multi-sensor RS; flux and ecosystem models	Assessment of functional outcomes
Socio-economics	Harvest intensity, accessibility, ownership, costs	Modified harvest cycles, operational requirements and economic trade-offs	Management plans, cadastral and administrative data; RS proxies	Integration of ecological and operational objectives

8. Conclusions and Further Research

F-LUI is a multidimensional and dynamic property of forest ecosystems that cannot be adequately represented by individual management variables or RS indicators. Although RS enables spatially continuous and temporally repeated observations of forest ecosystems, F-LUI itself is not directly observable. This review therefore proposes forest traits as the common observational interface linking forest management, RS observations and ecosystem responses.

Building on this principle, the proposed trait-based framework distinguishes six complementary F-LUI indicator families: Trait, Genesis, Structure, Taxonomy, Function and Socio-economics. These families represent different interpretative dimensions of forest traits and their spatial and temporal dynamics rather than independent RS observation

domains. Instead of reducing F-LUI to a single index, the framework enables different dimensions and ecological consequences of forest use to be assessed within a common and sensor-independent architecture. The conceptual pathway observations → forest traits → F-LUI indicator families → multidimensional F-LUI assessment provides the basis for integrating RS with forest inventories, in situ observations, management information and environmental data.

Emerging approaches, including Foundation Models, multi-sensor data fusion, semantic data integration, Knowledge Graphs and Digital Twins, can support the operationalisation of this framework by improving trait retrieval, interoperability, attribution and dynamic monitoring. However, these technologies should be regarded as enabling methodological and computational layers rather than substitutes for ecologically interpretable forest traits, ecological process understanding and independent validation.

Future research should focus on standardising Forest Trait definitions and F-LUI indicators, quantifying and propagating uncertainties, distinguishing management effects from natural disturbances and environmental variability, and evaluating transferability across forest types, management regimes and spatial and temporal scales. Particular priority should be given to long-term validation sites that combine RS time series with repeated forest inventories, documented management histories and ecological observations. Such integrated datasets will be essential for determining which combinations of forest traits provide robust and transferable evidence of different dimensions of F-LUI.

The proposed trait-based framework thus provides an open and extensible conceptual basis for harmonised, reproducible and internationally comparable F-LUI monitoring. By positioning forest traits as the stable observational interface between heterogeneous data sources and multidimensional F-LUI indicators, it provides a pathway towards spatially and temporally consistent assessments of forest-use intensity and its ecological consequences.

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for graphical visualisation and not for scientific analysis, interpretation, or the generation of scientific conclusions.

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Abbreviations

The following abbreviations are used in this manuscript:

AGB	Aboveground Biomass
AGC	Aboveground Carbon
AI	Artificial Intelligence
ALS	Airborne Laser Scanning
APAR	absorbed photosynthetically active radiation
Cab	Leaf Chlorophyll Content
CCF	Continuous Cover Forestry
CWC	Canopy Water Content
EBV	Essential Biodiversity Variable
FMI	Forest Management Intensity
ForMIX	Forest Management Intensity Index
F-LUI	Forest Land Use Intensity
GPP	Gross Primary Production
GPR	Gaussian Process Regression
LAI	Leaf Area Index
LiDAR	Light Detection and Ranging
LMA	Leaf Mass per Area
LNC	Leaf Nitrogen Content
LOD	Linked Open Data
LUE	Light Use Efficiency
LUI	Land Use Intensity
LWC	Leaf Water Content
NDVI	Normalised Difference Vegetation Index
NDWI	Normalized Difference Water Index
NFI	National Forest Inventory
NIR	Near-Infrared
NIRv	Near-Infrared Reflectance of Vegetation
NEP	Net Ecosystem Productivity
NPP	Net Primary Productivity
OWL	Web Ontology Language
RDF	Resource Description Framework
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SIF	Solar-Induced Chlorophyll Fluorescence
SMI	Silvicultural Management Intensity
SPARQL	SPARQL Protocol and RDF Query Language
SWIR	Shortwave Infrared
TLS	Terrestrial Laser Scanning
UAV	Unmanned Aerial Vehicle

Appendix A

Table A1. Existing conceptual approaches and observational perspectives for assessing Forest Land Use Intensity (F-LUI).

Conceptual Approach	Key References	Primary Focus	Typical Indicators/Variables	Strengths	Limitations
Management-based	[6,7,19,20]	Intensity of silvicultural interventions and forest management	Harvesting and biomass removal; thinning; rotation length; tree-species selection; regeneration practices; management inputs	Directly characterises anthropogenic interventions and enables comparison among management regimes	Requires detailed management information and only partly captures resulting ecosystem responses
Pressure-based	[4,5]	Anthropogenic inputs, outputs and pressures associated with forest use	Harvest/felling rates; wood extraction; accessibility; management inputs; disturbance frequency	Captures multiple dimensions of human pressure and links forest use to production systems	Pressures do not necessarily correspond directly to realised ecological effects
State-based	[23,24]	Forest condition and ecosystem properties resulting from management and environmental processes	Biomass; canopy and vertical structure; deadwood; stand maturity; tree-species composition; regeneration; forest naturalness	Ecologically interpretable and closely linked to measurable forest properties	Similar forest states may result from different management histories, natural disturbances or environmental processes
Impact-based	[4,8,9]	Ecological consequences associated with land-use intensity	Biodiversity; carbon storage; productivity; functional composition; multifunctionality; ecosystem services	Links land use to ecological responses and ecosystem functioning	Attribution of observed impacts specifically to forest management is often difficult
RS-based observational	[10,12,14,25]	Spatially explicit observation of forest properties and their temporal dynamics	Canopy height and cover; biomass; vegetation indices; biochemical and physiological traits; disturbance and recovery dynamics; LiDAR and SAR metrics	Spatially continuous, repeatable, multi-scale and suitable for long-term monitoring	Primarily observes manifestations of management rather than management itself; requires ecological interpretation, reference data and attribution

Note: The approaches are complementary rather than mutually exclusive. Management- and pressure-based approaches primarily characterise anthropogenic interventions, whereas state- and impact-based approaches describe their realised ecological manifestations and consequences. RS provides an observational perspective that enables many of these manifestations to be monitored spatially and temporally but generally does not observe management intensity directly.

Table A2. Evolution of conceptual definitions and related concepts relevant to Forest Land Use Intensity (F-LUI).

Reference	Concept	Definition/Interpretation	Primary Focus	Main Dimensions/Indicators	Relevance and Limitations for F-LUI
Erb et al. [4]	Land Use Intensity (LUI)	LUI is conceptualised as a multidimensional property of land-use systems comprising inputs, outputs and system-level impacts.	General land-use systems	Inputs, outputs, changes in ecosystem properties	Provides a fundamental multidimensional basis for F-LUI, but was not developed specifically for forest ecosystems.

Kuemmerle et al. [5]	Land Use Intensity	LUI is considered a multidimensional and spatially explicit characteristic of land systems, requiring indicators of management intensity and its effects across spatial and temporal scales.	Land-system science and spatial LUI assessment	Management intensity, production, land-system properties, spatial and temporal dynamics	Establishes an important basis for spatially explicit LUI assessment, but does not provide a harmonised forest-specific framework.
Schall and Ammer [6]	Forest Management Intensity/Silvicultural Management Intensity (SMI)	Forest management intensity is quantified through measurable deviations of managed stands from reference conditions resulting from silvicultural decisions and interventions.	Forest and silvicultural management	Tree-species selection, stand development, biomass removal and management-related stand characteristics	Provides a quantitative forest-specific management perspective, but primarily represents silvicultural intervention rather than the broader ecological dimensions of F-LUI.
Blattert et al. [7]	Silvicultural Management Intensity (SMI)	Management intensity is quantified through indicators representing the degree and effects of silvicultural intervention at stand level.	Operational forest management	Stand and management characteristics, tree-species composition, growing stock, harvesting and stand development	Enables operational comparison of management intensity, but ecological responses and broader socio-ecological dimensions are represented only indirectly.
Lestido-Cardama et al. [19]	Forest Management Intensity (FMI)	FMI is conceptualised through the demands imposed by forest management schemes, integrating extractive impact, financial resources and management inputs.	Harmonised assessment of forest management intensity	Extractive impact, financial resources, management inputs	Broadens FMI beyond individual silvicultural variables and improves comparability among management schemes, but remains centred on management intensity rather than the full ecosystem response.
Staab et al. [20]	Forest Management Intensity Index (ForMIX)	Forest-use intensity is represented by combining complementary management-related and ecological forest attributes within an integrated index.	Ecologically informed forest management intensity	Tree-species composition, tree removal, deadwood availability, stand maturity	Integrates management and ecologically relevant forest properties, but does not provide a sensor-independent observational architecture for multidimensional F-LUI monitoring.
This review	Trait-based Forest Land Use Intensity (F-LUI)	F-LUI is conceptualised as a continuous, multidimensional and spatially and temporally dynamic property of forest ecosystems that reflects anthropogenic use, management and transformation and manifests in observable forest traits and ecosystem responses.	Integrated and RS-supported F-LUI assessment	Trait, Genesis, Structure, Taxonomy, Function and Socio-economics	Provides a sensor- and scale-independent observational framework linking forest management, forest traits, ecosystem responses and RS; operational implementation and harmonisation remain future challenges.

Table A3. Major national (Germany), European and global forest monitoring programmes and information systems relevant to Forest Land Use Intensity (F-LUI).

Scale	Programme/System	Organisation	Primary Purpose	Main Variables/Indicators	Main Data Sources	Main F-LUI Dimensions	Spatial and Temporal Coverage
Germany	**German National Forest Inventory (BWI)**	BMEL/Thünen Institute	National forest resource monitoring	Forest area, tree species, growing stock, increment, regeneration, deadwood, biomass	Systematic field inventory	Trait; Genesis; Structure; Taxonomy; Function	Nationwide systematic plot network; approximately decadal
Germany	**Forest Development and Timber Resource Modelling (WEHAM)**	Thünen Institute	Scenario-based projection of forest development and timber resources	Growing stock, timber potential, harvesting, forest development, carbon stocks	BWI data and forest development models	Genesis; Structure; Function; Socio-economics	Germany; scenario-based, multi-decadal projections
Germany	**Forest Condition Survey (WZE)**	BMEL/federal states	Long-term assessment of forest condition	Crown defoliation, discolouration, tree vitality and damage	Systematic field observations	Trait; Function	Germany; annual
Germany	**National Forest Soil Inventory (BZE)**	BMEL/Thünen Institute	Assessment of forest soil condition and change	Soil carbon, nutrients, pH, acidification, pollutants and soil properties	Systematic soil sampling and laboratory analyses	Trait; Function	Germany; periodic multi-year inventories
Europe	**ICP Forests**	UNECE ICP Forests	Long-term monitoring of forest condition and environmental pressures	Crown condition, growth, foliar chemistry, deposition, soil, phenology, biodiversity-related variables	Level I and intensive Level II plots	Trait; Structure; Taxonomy; Function	Pan-European; repeated to continuous depending on variable
Europe	**FOREST EUROPE**	FOREST EUROPE	Reporting on sustainable forest management	Forest resources, biodiversity, productive and protective functions, socio-economic indicators	Harmonised national statistics and reporting	Structure; Taxonomy; Function; Socio-economics	Pan-European; periodic reporting
Europe	**Forest Information System for Europe (FISE)**	European Commission/EEA	Integration and dissemination of European forest information	Forest resources, biomass, biodiversity, disturbances and other forest indicators	National, European and RS-derived datasets	Genesis; Structure; Taxonomy; Function; Socio-economics	Europe; continuously maintained information system
Europe	**Copernicus Land Monitoring Service (CLMS)**	European Commission/EEA	Operational satellite-based land and forest monitoring	Tree Cover Density, Forest Type, land cover and land-cover change	Sentinel and other RS data	Genesis; Structure; Taxonomy	Pan-European; product-dependent updates
Europe	**LUCAS**	Eurostat	Harmonised land-cover and land-use survey	Land cover, land use, vegetation and soil observations	Systematic field observations and photographs	Trait; Structure; Taxonomy; Socio-economics	EU-wide sampling network; periodic
Europe	**European Forest Fire Information**	European Commission/JRC	Monitoring and assessment of forest fires	Fire danger, active fires, burnt areas and fire impacts	Satellite observations,	Genesis; Structure; Function	Europe and neighbouring regions; near-

	System (EFFIS)				meteorological and national data		real-time to annual
Global	**Global Forest Resources Assessment (FRA)**	FAO	Harmonised global assessment of forest resources and management	Forest area and change, biomass, carbon, disturbances, management, ownership and designated functions	National reporting, NFIs and complementary RS information	Genesis; Structure; Taxonomy; Function; Socio-economics	Global; five-year reporting cycle
Global	**FRA Remote Sensing Survey (FRA RSS)**	FAO	Consistent assessment of global forest and land-use change	Forest area change, deforestation, afforestation and land-use transitions	Systematic satellite-based sample assessment	Genesis; Structure	Global sample-based assessment; linked to FRA cycles
Global/national	**National Forest Monitoring Systems (NFMS)**	National authorities/FAO support	National monitoring of forest extent, change and carbon, particularly for REDD+	Forest area and change, biomass, carbon stocks and degradation	Forest inventories, RS and national datasets	Genesis; Structure; Function	Country-specific; repeated monitoring
Global	**Global Forest Watch (GFW)**	World Resources Institute and partners	Near-real-time forest change and disturbance information	Forest-cover loss, disturbance alerts, fires and selected carbon indicators	Multi-source satellite observations and derived products	Genesis; Structure; Function	Global; annual to near-real-time depending on product
Global	**Global Wildfire Information System (GWIS)**	European Commission/JRC	Global wildfire information and monitoring	Active fires, burnt area, fire danger and emissions	Satellite and meteorological observations	Genesis; Function	Global; near-real-time and historical

Table A4. Key indicators for the six Forest Land Use Intensity (F-LUI) indicator families and representative references.

F-LUI Indicator Family	Key F-LUI Indicator	Main Relevance to F-LUI	Principal Observation/Data Source	Representative Reference Already Included in the Manuscript
Trait	**Leaf Area Index (LAI)**	Canopy foliage quantity, light interception and responses to thinning, harvesting and regeneration	Multispectral/hyperspectral RS; LiDAR; field measurements	[52]
Trait	**Leaf chlorophyll content (Cab)**	Photosynthetic condition, vegetation vitality and biochemical response to changing resource availability	Multispectral and hyperspectral RS; red-edge spectroscopy	[60]
Trait	**Leaf nitrogen content (LNC)**	Nutrient status, photosynthetic capacity and resource-acquisition strategy	Imaging spectroscopy; radiative-transfer inversion	[54]
Trait	**Leaf and canopy water content (LWC/CWC)**	Hydraulic status, drought response and	SWIR/hyperspectral and multispectral RS	[64]

		physiological effects of stand modification		
Trait	**Phenological traits**	Timing and duration of canopy activity and management-related changes in species and stand development	Multitemporal Sentinel-1/-2; phenological time series	[99]
Genesis	**Disturbance history**	Timing, magnitude and recurrence of anthropogenic and natural forest change	Long-term Landsat/Sentinel time series; change detection	[68]
Genesis	**Harvest and thinning history**	Frequency, severity and recurrence of biomass-removal interventions	Repeated inventories; multitemporal RS; harvest records	[147]
Genesis	**Regeneration and recovery dynamics**	Rate, direction and completeness of forest recovery following disturbance or management	Multitemporal optical RS; LiDAR; inventories	[75]
Genesis	**Successional trajectory**	Long-term reorganisation of structural, taxonomic and functional forest properties	Chronosequences; long-term RS; field observations	[85]
Genesis	**Land-use and management legacy**	Persistent ecological imprint of historical forest and land-use practices	Historical maps and inventories combined with contemporary observations	[83]
Structure	**Horizontal forest structure and fragmentation**	Patchiness, edges, connectivity and landscape-scale spatial consequences of forest use	Optical RS; forest masks; landscape metrics	[87]
Structure	**Vertical forest structure and canopy complexity**	Modification of height, layering and three-dimensional stand organisation by management	ALS, TLS, UAV-LiDAR, GEDI	[95]
Structure	**Spatial tree-species configuration**	Spatial dominance, mixture and arrangement of species produced by management and regeneration	Sentinel-1/-2; species maps; spatial metrics	[98]
Structure	**Deadwood amount and distribution**	Retention/removal of structural legacies and habitat elements	TLS/ALS; UAV; field inventory	[106]
Structure	**Aboveground biomass (AGB)**	Cumulative outcome of growth, mortality, harvesting and stand development	GEDI/ALS; SAR; optical RS; inventories	[109]
Taxonomy	**Forest type and biological forest class**	Differentiation of broadleaved, coniferous, mixed and other	Multitemporal Sentinel-2 and complementary RS	[111]

		biologically relevant forest types		
Taxonomy	**Tree-species composition**	Biological identity and management-induced changes in dominant and associated species	Sentinel-1/-2; hyperspectral RS; inventories	[98]
Taxonomy	**Taxonomic diversity**	Species richness, dominance and diversity responses to forest-use intensity	Species maps; spectral-diversity measures; inventories	[117]
Taxonomy	**Forest communities and habitat types**	Integrated biological response to management, succession and site conditions	Multitemporal RS + environmental and vegetation data	[119]
Taxonomy	**Ecological integrity and naturalness**	Degree of anthropogenic modification relative to near-natural forest conditions	Integrated RS, fragmentation, pressure and ecological datasets	[94]
Function	**Forest productivity/GPP**	Photosynthetic carbon uptake and productive ecosystem performance	NIRv, SIF, optical time series; flux measurements	[134]
Function	**Water cycling and evapotranspiration**	Effects of management on transpiration, water availability and ecosystem water fluxes	Thermal RS; ECOSTRESS; optical/SAR; flux measurements	[140]
Function	**Carbon storage and sequestration**	Long-term effects of management on biomass and ecosystem carbon pools	LiDAR, SAR, inventories and carbon models	[109]
Function	**Ecosystem resilience and recovery**	Capacity to resist disturbance and recover structural and functional properties	Long-term RS trait trajectories	[76]
Function	**Ecosystem multifunctionality**	Simultaneous maintenance of multiple ecosystem functions under different land-use intensities	Integrated ecological, biodiversity and functional observations	[8]
Socio-economic	**Forest-management activity and harvesting intensity**	Realised frequency, extent and severity of timber-removal interventions	NFI/harvest records combined with multitemporal RS	[147]
Socio-economic	**Forest ownership and governance**	Institutional context determining management objectives, restrictions and decision-making	Cadastral, policy, administrative and governance data	[156]
Socio-economic	**Forest accessibility and infrastructure**	Physical and economic accessibility enabling forest-management operations	Road networks, DEMs, high-resolution RS and administrative data	[160]

Socio-economic	**Forest-management regime and spatial management pattern**	Long-term organisation of unmanaged, close-to-nature, multifunctional and production-oriented management	RS-derived forest attributes + inventories + management information	[166]
Socio-economic	**Management inputs and financial resources**	Resources and management inputs invested in forest utilisation and silvicultural intervention	Management, financial, operational and inventory data	[19]

References

1. FAO. Global Forest Resources Assessment. 2020 Available online: https://www.fao.org/interactive/forest-resources-assessment/2020/en/ (accessed on 21 September 2026).
2. Bonan, G.B. Forests, Climate, and Public Policy: A 500-Year Interdisciplinary Odyssey. *Annu. Rev. Ecol. Evol. Syst.* **2016**, *47*, 97–121. https://doi.org/10.1146/annurev-ecolsys-121415-032359.
3. Ruehr, S.; Keenan, T.F.; Williams, C.; Zhou, Y.; Lu, X.; Bastos, A.; Canadell, J.G.; Prentice, I.C.; Sitch, S.; Terrer, C. Evidence and Attribution of the Enhanced Land Carbon Sink. *Nat. Rev. Earth Environ.* **2023**, *4*, 518–534. https://doi.org/10.1038/s43017-023-00456-3.
4. Erb, K.H.; Haberl, H.; Jepsen, M.R.; Kuemmerle, T.; Lindner, M.; Müller, D.; Verburg, P.H.; Reenberg, A. A Conceptual Framework for Analysing and Measuring Land-Use Intensity. *Curr. Opin. Environ. Sustain.* **2013**, *5*, 464–470. https://doi.org/10.1016/j.cosust.2013.07.010.
5. Kuemmerle, T.; Erb, K.; Meyfroidt, P.; Müller, D.; Verburg, P.H.; Estel, S.; Haberl, H.; Hostert, P.; Jepsen, M.R.; Kastner, T.; et al. Challenges and Opportunities in Mapping Land Use Intensity Globally. *Curr. Opin. Environ. Sustain.* **2013**, *5*, 484–493. https://doi.org/10.1016/j.cosust.2013.06.002.
6. Schall, P.; Ammer, C. How to Quantify Forest Management Intensity in Central European Forests. *Eur. J. For. Res.* **2013**, *132*, 379–396. https://doi.org/10.1007/s10342-013-0681-6.
7. Blattert, C.; Lemm, R.; Thees, O.; Lexer, M.J.; Hanewinkel, M. Management of Ecosystem Services in Mountain Forests: Review of Indicators and Value Functions for Model Based Multi-Criteria Decision Analysis. *Ecol. Indic.* **2017**, *79*, 391–409. https://doi.org/10.1016/j.ecolind.2017.04.025.
8. Allan, E.; Manning, P.; Alt, F.; Binkenstein, J.; Blaser, S.; Blüthgen, N.; Böhm, S.; Grassein, F.; Hölzel, N.; Klaus, V.H.; et al. Land Use Intensification Alters Ecosystem Multifunctionality via Loss of Biodiversity and Changes to Functional Composition. *Ecol. Lett.* **2015**, *18*, 834–843. https://doi.org/10.1111/ele.12469.
9. Newbold, T.; Hudson, L.N.; Hill, S.L.L.; Contu, S.; Lysenko, I.; Senior, R.A.; Börger, L.; Bennett, D.J.; Choimes, A.; Collen, B.; et al. Global Effects of Land Use on Local Terrestrial Biodiversity. *Nature* **2015**, *520*, 45–50. https://doi.org/10.1038/nature14324.
10. Lechner, A.M.; Foody, G.M.; Boyd, D.S. Applications in Remote Sensing to Forest Ecology and Management. *One Earth* **2020**, *2*, 405–412. https://doi.org/10.1016/j.oneear.2020.05.001.
11. Hirschmugl, M.; Gallaun, H.; Dees, M.; Datta, P.; Deutscher, J.; Koutsias, N.; Schardt, M. Methods for Mapping Forest Disturbance and Degradation from Optical Earth Observation Data: A Review. *Curr. For. Reports* **2017**, *3*, 32–45. https://doi.org/10.1007/s40725-017-0047-2.
12. Dubayah, R.; Blair, J.B.; Goetz, S.; Fatoyinbo, L.; Hansen, M.; Healey, S.; Hofton, M.; Hurtt, G.; Kellner, J.; Luthcke, S.; et al. The Global Ecosystem Dynamics Investigation: High-Resolution Laser Ranging of the Earth's Forests and Topography. *Sci. Remote Sens.* **2020**, *1*, 100002. https://doi.org/10.1016/j.srs.2020.100002.
13. Díaz, S.; Kattge, J.; Cornelissen, J.H.C.; Wright, I.J.; Lavorel, S.; Dray, S.; Reu, B.; Kleyer, M.; Wirth, C.; Colin Prentice, I.; et al. The Global Spectrum of Plant Form and Function. *Nature* **2016**, *529*, 167–171. https://doi.org/10.1038/nature16489.
14. Schneider, F.D.; Morsdorf, F.; Schmid, B.; Petchey, O.L.; Hueni, A.; Schimel, D.S.; Schaepman, M.E. Mapping Functional Diversity from Remotely Sensed Morphological and Physiological Forest Traits. *Nat. Commun.* **2017**, *8*, 1441. https://doi.org/10.1038/s41467-017-01530-3.

15. Cavender-Bares, J.; Schneider, F.D.; Santos, M.J.; Armstrong, A.; Carnaval, A.; Dahlin, K.M.; Fatoyinbo, L.; Hurtt, G.C.; Schimel, D.; Townsend, P.A.; et al. Integrating Remote Sensing with Ecology and Evolution to Advance Biodiversity Conservation. *Nat. Ecol. Evol.* **2022**, *6*, 506–519. https://doi.org/10.1038/s41559-022-01702-5.
16. Lausch, A.; Erasmi, S.; King, D.J.; Magdon, P.; Heurich, M. Understanding Forest Health with Remote Sensing -Part I—A Review of Spectral Traits, Processes and Remote-Sensing Characteristics. *Remote Sens.* **2016**, *8*, 1029. https://doi.org/10.3390/rs8121029.
17. Lausch, A.; Bumberger, J.; Dong, X.; Haase, D.; Jung, A.; Pause, M.; Selsam, P.; Wellmann, T.; Trabert, T.; Banzhaf, E. Monitoring Urban Land Use Intensity with Remote Sensing and Urban Traits: A Review. *Smart Cities* **2026**, *9*, 107. https://doi.org/10.3390/smartcities9070107.
18. Lausch, A.; Bumberger, J.; Jung, A.; Pause, M.; Selsam, P.; Zhou, T.; Herzog, F. Monitoring Agricultural Land Use Intensity with Remote Sensing and Traits. *Agriculture* **2025**, *15*, 2233. https://doi.org/10.3390/agriculture15212233.
19. Lestido-Cardama, Y.; Rodríguez-Soalleiro, R.; Gonzalez-Benecke, C.A.; Tucker, G.; Sevilla-Martínez, F.; Cañellas, I.; Oliveira, N.; Alberdi, I.; Montes, F.; Molina-Valero, J.A.; et al. Towards a Common Approach to Defining Forest Management Intensity. *For. Ecol. Manage.* **2025**, *597*, 123176. https://doi.org/10.1016/j.foreco.2025.123176.
20. Staab, M.; Blüthgen, N.; Wehner, K.; Schall, P.; Ammer, C. Advancing the Quantification of Land-Use Intensity in Forests: The ForMIX Index Combining Tree Species Composition, Tree Removal, Deadwood Availability, and Stand Maturity. *Eur. J. For. Res.* **2026**, *145*, 416. https://doi.org/10.1007/s10342-025-01865-3.
21. Pommerening, A. *Continuous Cover Forestry: Theories, Concepts, and Implementation*; John Wiley & Sons, Ltd.: Hoboken, NJ, USA , 2024; ISBN 978-1-119-89530-5..
22. Routa, J.; Huuskonen, S. *Continuous Cover Forestry in Boreal Nordic Countries*; Rautio, P., Routa, J., Huuskonen, S., Holmström, E., Cedergren, J., Kuehne, C., Eds.; Managing Forest Ecosystems; Springer Nature: Cham, Switzerland, 2025; Volume 45; ISBN 978-3-031-70483-3.
23. Winter, S. Forest Naturalness Assessment as a Component of Biodiversity Monitoring and Conservation Management. *Forestry* **2012**, *85*, 291–304. https://doi.org/10.1093/forestry/cps004.
24. McRoberts, R.E.; Winter, S.; Chirici, G.; LaPoint, E. Assessing Forest Naturalness. *For. Sci.* **2012**, *58*, 294–309. https://doi.org/10.5849/forsci.10-075.
25. Wulder, M.A.; Hermosilla, T.; White, J.C.; Bater, C.W.; Hobart, G.; Bronson, S.C. Development and Implementation of a Stand-Level Satellite-Based Forest Inventory for Canada. *For. An Int. J. For. Res.* **2024**, *97*, 546–563. https://doi.org/10.1093/forestry/cpad065.
26. Lausch, A.; Borg, E.; Bumberger, J.; Dietrich, P.; Heurich, M.; Huth, A.; Jung, A.; Klenke, R.; Knapp, S.; Mollenhauer, H.; et al. Understanding Forest Health with Remote Sensing, Part III: Requirements for a Scalable Multi-Source Forest Health Monitoring Network Based on Data Science Approaches. *Remote Sens.* **2018**, *10*, 1120. https://doi.org/10.3390/rs10071120.
27. BMLEH Bundeswaldinventur. 2022 Available online: https://www.bundeswaldinventur.de/vierte-bundeswaldinventur-2022/ (accessed on 21 September 2026).
28. FAO. Global Forest Resources Assessment. 2025. Available online: https://openknowledge.fao.org/handle/20.500.14283/cd6709en (accessed on 21 September 2026).
29. FAO. FRA 2020 Remote Sensing Survey. 2022. Available online: https://openknowledge.fao.org/handle/20.500.14283/cb9970en (accessed on 21 September 2026).
30. Tomppo, E.; Gschwantner, T.; Lawrence, M.; McRoberts, R.E. *National Forest Inventories: Pathways for Common Reporting*; Springer: Dordrecht, The Netherlands, 2010; ISBN 978-90-481-3232-4.
31. Vidal, C.; Alberdi, I.A.; Hernández Mateo, L.; Redmond, J.J. *National Forest Inventories: Assessment of Wood Availability and Use*; Springer International Publishing: Cham, Switzerland, 2016; ISBN 978-3-319-44014-9.
32. Bontemps, J.-D.; Bouriaud, O.; Vega, C.; Bouriaud, L. Offering the Appetite for the Monitoring of European Forests a Diversified Diet. *Ann. For. Sci.* **2022**, *79*, 19. https://doi.org/10.1186/s13595-022-01139-7.
33. Cools, N.; De Vos, B. Forest Soil: Characterization, Sampling, Physical, and Chemical Analyses. In *Forest Monitoring: Methods for Terrestrial Investigations in Europe with an Overview of North America and Asia*; Elsevier: Amsterdam, The Netherlands, 2013; pp. 267–300.
34. Pastorello, G.; Trotta, C.; Canfora, E.; Chu, H.; Christianson, D.; Cheah, Y.-W.; Poindexter, C.; Chen, J.; Elbashandy, A.; Humphrey, M.; et al. The FLUXNET2015 Dataset and the ONEFlux Processing Pipeline for Eddy Covariance Data. *Sci. Data* **2020**, *7*, 225. https://doi.org/10.1038/s41597-020-0534-3.

35. Heiskanen, J.; Brümmer, C.; Buchmann, N.; Calfapietra, C.; Chen, H.; Gielen, B.; Gkritzalis, T.; Hammer, S.; Hartman, S.; Herbst, M.; et al. The Integrated Carbon Observation System in Europe. *Bull. Am. Meteorol. Soc.* **2022**, *103*, E855–E872. https://doi.org/10.1175/BAMS-D-19-0364.1.
36. Richardson, A.D. Tracking Seasonal Rhythms of Plants in Diverse Ecosystems with Digital Camera Imagery. *New Phytol.* **2019**, *222*, 1742–1750. https://doi.org/10.1111/nph.15591.
37. Richardson, A.D. PhenoCam: An Evolving, Open-Source Tool to Study the Temporal and Spatial Variability of Ecosystem-Scale Phenology. *Agric. For. Meteorol.* **2023**, *342*, 109751. https://doi.org/10.1016/j.agrformet.2023.109751.
38. Fassnacht, F.E.; White, J.C.; Wulder, M.A.; Næsset, E. Remote Sensing in Forestry: Current Challenges, Considerations and Directions. *For. An Int. J. For. Res.* **2024**, *97*, 11–37. https://doi.org/10.1093/forestry/cpad024.
39. Wulder, M.A.; Roy, D.P.; Radeloff, V.C.; Loveland, T.R.; Anderson, M.C.; Johnson, D.M.; Healey, S.; Zhu, Z.; Scambos, T.A.; Pahlevan, N.; et al. Fifty Years of Landsat Science and Impacts. *Remote Sens. Environ.* **2022**, *280*, 113195. https://doi.org/10.1016/j.rse.2022.113195.
40. Kennedy, R.E.; Andréfouët, S.; Cohen, W.B.; Gómez, C.; Griffiths, P.; Hais, M.; Healey, S.P.; Helmer, E.H.; Hostert, P.; Lyons, M.B.; et al. Bringing an Ecological View of Change to Landsat-based Remote Sensing. *Front. Ecol. Environ.* **2014**, *12*, 339–346. https://doi.org/10.1890/130066.
41. Lausch, A.; Bastian, O.; Klotz, S.; Leitão, P.J.; Jung, A.; Rocchini, D.; Schaepman, M.E.; Skidmore, A.K.; Tischendorf, L.; Knapp, S. Understanding and Assessing Vegetation Health by in Situ Species and Remote-sensing Approaches. *Methods Ecol. Evol.* **2018**, *9*, 1799–1809. https://doi.org/10.1111/2041-210X.13025.
42. Schneider, J.; Meske, C.; Kuss, P. Foundation Models. *Bus. Inf. Syst. Eng.* **2024**, *66*, 221–231. https://doi.org/10.1007/s12599-024-00851-0.
43. Lu, S.; Guo, J.; Zimmer-Dauphinee, J.R.; Nieusma, J.M.; Wang, X.; VanValkenburgh, P.; Wernke, S.A.; Huo, Y. Vision Foundation Models in Remote Sensing: A Survey. *IEEE Geosci. Remote Sens. Mag.* **2025**, *13*, 190–215. https://doi.org/10.1109/MGRS.2025.3541952.
44. Xiao, A.; Xuan, W.; Wang, J.; Huang, J.; Tao, D.; Lu, S.; Yokoya, N. Foundation Models for Remote Sensing and Earth Observation: A Survey. *IEEE Geosci. Remote Sens. Mag.* **2025**, *13*, 297–324. https://doi.org/10.1109/MGRS.2025.3576766.
45. Bodnar, C.; Bruinsma, W.P.; Lucic, A.; Stanley, M.; Allen, A.; Brandstetter, J.; Garvan, P.; Riechert, M.; Weyn, J.A.; Dong, H.; et al. A Foundation Model for the Earth System. *Nature* **2025**, *641*, 1180–1187. https://doi.org/10.1038/s41586-025-09005-y.
46. Pettorelli, N.; Laurance, W.F.; O'Brien, T.G.; Wegmann, M.; Nagendra, H.; Turner, W. Satellite Remote Sensing for Applied Ecologists: Opportunities and Challenges. *J. Appl. Ecol.* **2014**, *51*, 839–848. https://doi.org/10.1111/1365-2664.12261.
47. Jetz, W.; McGeoch, M.A.; Guralnick, R.; Ferrier, S.; Beck, J.; Costello, M.J.; Fernandez, M.; Geller, G.N.; Keil, P.; Merow, C.; et al. Essential Biodiversity Variables for Mapping and Monitoring Species Populations. *Nat. Ecol. Evol.* **2019**, *3*, 539–551. https://doi.org/10.1038/s41559-019-0826-1.
48. Skidmore, A.K.; Coops, N.C.; Neinavaz, E.; Ali, A.; Schaepman, M.E.; Paganini, M.; Kissling, W.D.; Vihervaara, P.; Darvishzadeh, R.; Feilhauer, H.; et al. Priority List of Biodiversity Metrics to Observe from Space. *Nat. Ecol. Evol.* **2021**, *5*, 896–906. https://doi.org/10.1038/s41559-021-01451-x.
49. Spiers, A.I.; Scholl, V.M.; McGlinchy, J.; Balch, J.; Cattau, M.E. A Review of UAS-Based Estimation of Forest Traits and Characteristics in Landscape Ecology. *Landsc. Ecol.* **2025**, *40*, 1–19. https://doi.org/10.1007/s10980-024-01991-0.
50. Asner, G.P.; Martin, R.E. Spectranomics: Emerging Science and Conservation Opportunities at the Interface of Biodiversity and Remote Sensing. *Glob. Ecol. Conserv.* **2016**, *8*, 212–219. https://doi.org/10.1016/j.gecco.2016.09.010.
51. Asner, G.P.; Martin, R.E. Airborne Spectranomics: Mapping Canopy Chemical and Taxonomic Diversity in Tropical Forests. *Front. Ecol. Environ.* **2009**, *7*, 269–276. https://doi.org/10.1890/070152.
52. Tagliabue, G.; Panigada, C.; Savinelli, B.; Vignali, L.; Rossini, M. Appraising Retrieval Schemes from Spaceborne Hyperspectral Imagery for Mapping Leaf and Canopy Traits in Forest Ecosystems. *Remote Sens. Environ.* **2026**, *333*, 115145. https://doi.org/10.1016/j.rse.2025.115145.
53. Verrelst, J.; Malenovský, Z.; Van der Tol, C.; Camps-Valls, G.; Gastellu-Etchegorry, J.-P.; Lewis, P.; North, P.; Moreno, J. Quantifying Vegetation Biophysical Variables from Imaging Spectroscopy Data: A Review on Retrieval Methods. *Surv. Geophys.* **2019**, *40*, 589–629. https://doi.org/10.1007/s10712-018-9478-y.
54. Féret, J.-B.; Berger, K.; de Boissieu, F.; Malenovský, Z. PROSPECT-PRO for Estimating Content of Nitrogen-Containing Leaf Proteins and Other Carbon-Based Constituents. *Remote Sens. Environ.* **2021**, *252*, 112173. https://doi.org/10.1016/j.rse.2020.112173.

55. Chabrillat, S.; Foerster, S.; Segl, K.; Beamish, A.; Brell, M.; Asadzadeh, S.; Milewski, R.; Ward, K.J.; Brosinsky, A.; Koch, K.; et al. The EnMAP Spaceborne Imaging Spectroscopy Mission: Initial Scientific Results Two Years after Launch. *Remote Sens. Environ.* **2024**, *315*, 114379. https://doi.org/10.1016/j.rse.2024.114379.
56. Nieke, J.; Rast, M. Towards the Copernicus Hyperspectral Imaging Mission For The Environment (CHIME). In *Proceedings of the IGARSS 2018—2018 IEEE International Geoscience and Remote Sensing Symposium*; IEEE: Piscataway, NJ, USA, 2018; pp. 157–159.
57. Cawse-Nicholson, K.; Townsend, P.A.; Schimel, D.; Assiri, A.M.; Blake, P.L.; Buongiorno, M.F.; Campbell, P.; Carmon, N.; Casey, K.A.; Correa-Pabón, R.E.; et al. NASA's Surface Biology and Geology Designated Observable: A Perspective on Surface Imaging Algorithms. *Remote Sens. Environ.* **2021**, *257*, 112349. https://doi.org/10.1016/j.rse.2021.112349.
58. Balestra, M.; Marselis, S.; Sankey, T.T.; Cabo, C.; Liang, X.; Mokroš, M.; Peng, X.; Singh, A.; Stereńczak, K.; Vega, C.; et al. LiDAR Data Fusion to Improve Forest Attribute Estimates: A Review. *Curr. For. Rep.* **2024**, *10*, 281–297. https://doi.org/10.1007/s40725-024-00223-7.
59. Samadzadegan, F.; Toosi, A.; Dadrass Javan, F. A Critical Review on Multi-Sensor and Multi-Platform Remote Sensing Data Fusion Approaches: Current Status and Prospects. *Int. J. Remote Sens.* **2025**, *46*, 1327–1402. https://doi.org/10.1080/01431161.2024.2429784.
60. Gao, S.; Yan, K.; Liu, J.; Pu, J.; Zou, D.; Qi, J.; Mu, X.; Yan, G. Assessment of Remote-Sensed Vegetation Indices for Estimating Forest Chlorophyll Concentration. *Ecol. Indic.* **2024**, *162*, 112001. https://doi.org/10.1016/j.ecolind.2024.112001.
61. Slaninákova, T.; Švik, M.; Rebok, T.; Hanousek, T.; Janoutová, R. Introducing a New Adaptive Look-up Table Subset Selection Method for Leaf Chlorophyll and Carotenoids Retrieval in Broadleaved Forests. *Remote Sens. Lett.* **2025**, *16*, 676–686. https://doi.org/10.1080/2150704X.2025.2495992.
62. Gao, B. NDWI—A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water from Space. *Remote Sens. Environ.* **1996**, *58*, 257–266. https://doi.org/10.1016/S0034-4257(96)00067-3.
63. Jacquemoud, S.; Verhoef, W.; Baret, F.; Bacour, C.; Zarco-Tejada, P.J.; Asner, G.P.; François, C.; Ustin, S.L. PROSPECT+SAIL Models: A Review of Use for Vegetation Characterization. *Remote Sens. Environ.* **2009**, *113*, S56–S66. https://doi.org/10.1016/j.rse.2008.01.026.
64. Ma, H.; Weiss, M.; Malik, D.; Berthelot, B.; Yebra, M.; Nolan, R.H.; Mialon, A.; Zeng, J.; Quan, X.; Tagesson, H.T.; et al. Satellite Canopy Water Content from Sentinel-2, Landsat-8 and MODIS: Principle, Algorithm and Assessment. *Remote Sens. Environ.* **2025**, *326*, 114801. https://doi.org/10.1016/j.rse.2025.114801.
65. Fang, M.; Hu, X.; Chen, J.M.; Zhao, X.; Tang, X.; Liu, H.; Xu, M.; Ju, W. A Down-Scaling Inversion Strategy for Retrieving Canopy Water Content from Satellite Hyperspectral Imagery. *Forests* **2024**, *15*, 1463. https://doi.org/10.3390/f15081463.
66. Kesselring, J.; Humphrey, V.; Niederberger, M.; Feigenwinter, I.; Shekhar, A.; Buchmann, N.; Damm, A. Divergence between in Situ and Satellite-Based Estimates of Forest Canopy Water Content. *Remote Sens. Environ.* **2026**, *332*, 115097. https://doi.org/10.1016/j.rse.2025.115097.
67. Allen, J.; Anderegg, L.D.L.; Roberts, D.; Trugman, A.T. Detecting Drought Stress from the Leaf to the Landscape: Is Canopy Structure or Leaf Desiccation More Influential in Tree Canopy Spectral Responses to Declining Water? *New Phytol.* **2026**. https://doi.org/10.1111/nph.71450.
68. Kennedy, R.E.; Yang, Z.; Cohen, W.B. Detecting Trends in Forest Disturbance and Recovery Using Yearly Landsat Time Series: 1. LandTrendr—Temporal Segmentation Algorithms. *Remote Sens. Environ.* **2010**, *114*, 2897–2910. https://doi.org/10.1016/j.rse.2010.07.008.
69. Verbesselt, J.; Hyndman, R.; Newnham, G.; Culvenor, D. Detecting Trend and Seasonal Changes in Satellite Image Time Series. *Remote Sens. Environ.* **2010**, *114*, 106–115. https://doi.org/10.1016/j.rse.2009.08.014.
70. Zhu, Z.; Woodcock, C.E. Continuous Change Detection and Classification of Land Cover Using All Available Landsat Data. *Remote Sens. Environ.* **2014**, *144*, 152–171. https://doi.org/10.1016/j.rse.2014.01.011.
71. Healey, S.P.; Cohen, W.B.; Yang, Z.; Kenneth Brewer, C.; Brooks, E.B.; Gorelick, N.; Hernandez, A.J.; Huang, C.; Joseph Hughes, M.; Kennedy, R.E.; et al. Mapping Forest Change Using Stacked Generalization: An Ensemble Approach. *Remote Sens. Environ.* **2018**, *204*, 717–728. https://doi.org/10.1016/j.rse.2017.09.029.
72. Hansen, M.C.; Potapov, P. V.; Moore, R.; Hancher, M.; Turubanova, S.A.; Tyukavina, A.; Thau, D.; Stehman, S. V.; Goetz, S.J.; Loveland, T.R.; et al. High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science* **2013**, *342*, 850–853. https://doi.org/10.1126/science.1244693.
73. Stahl, A.T.; Andrus, R.; Hicke, J.A.; Hudak, A.T.; Bright, B.C.; Meddens, A.J.H. Automated Attribution of Forest Disturbance Types from Remote Sensing Data: A Synthesis. *Remote Sens. Environ.* **2023**, *285*, 113416. https://doi.org/10.1016/j.rse.2022.113416.

74. Rodríguez Paulino, E.; Schlerf, M.; Röder, A.; Stoffels, J.; Udelhoven, T. Forest Disturbance Characterization in the Era of Earth Observation Big Data: A Mapping Review. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *128*, 103755. https://doi.org/10.1016/j.jag.2024.103755.
75. Maurent, E.; Hérault, B.; Piponiot, C.; Derroire, G.; Delgado, D.; Finegan, B.; Kientz, M.A.; Amani, B.H.K.; Bieng, M.A.N. A Common Framework to Model Recovery in Disturbed Tropical Forests. *Ecol. Modell.* **2023**, *483*, 110418. https://doi.org/10.1016/j.ecolmodel.2023.110418.
76. Lv, Q.; Chen, Z.; Wu, C.; Peñuelas, J.; Fan, L.; Su, Y.; Yang, Z.; Li, M.; Gao, B.; Hu, J.; et al. Increasing Severity of Large-Scale Fires Prolongs Recovery Time of Forests Globally since 2001. *Nat. Ecol. Evol.* **2025**, *9*, 980–992. https://doi.org/10.1038/s41559-025-02683-x.
77. Almeida, C.T. de; Galvão, L.S.; Ometto, J.P.H.B.; Jacon, A.D.; Pereira, F.R. de S.; Sato, L.Y.; Silva-Junior, Celso Henrique Leite Silva-Junior, Pedro H. S. Brancalion, L.E.O. e C. de A. Advancing Forest Degradation and Regeneration Assessment Through Light Detection and Ranging and Hyperspectral Imaging Integration. *Remote Sens.* **2024**, 1–26. https://doi.org/10.3390/rs16213935.
78. Yan, Y.; Hong, S.; Chen, A.; Peñuelas, J.; Allen, C.D.; Hammond, W.M.; Munson, S.M.; Myneni, R.B.; Piao, S. Satellite-Based Evidence of Recent Decline in Global Forest Recovery Rate from Tree Mortality Events. *Nat. Plants* **2025**, *11*, 731–742. https://doi.org/10.1038/s41477-025-01948-4.
79. Christensen, N.L. An Historical Perspective on Forest Succession and Its Relevance to Ecosystem Restoration and Conservation Practice in North America. *For. Ecol. Manag.* **2014**, *330*, 312–322. https://doi.org/10.1016/j.foreco.2014.07.026.
80. Lecina-Diaz, J.; Martínez-Vilalta, J.; Lloret, F.; Seidl, R. Resilience and Vulnerability: Distinct Concepts to Address Global Change in Forests. *Trends Ecol. Evol.* **2024**, *39*, 706–715. https://doi.org/10.1016/j.tree.2024.03.003.
81. Lecina-Diaz, J.; Turner, M.G.; Seidl, R. Forest Reorganisation After Natural Disturbance: A Synthesis. *Glob. Ecol. Biogeogr.* **2026**, *35*. https://doi.org/10.1111/geb.70220.
82. Foster, D.; Swanson, F.; Aber, J.; Burke, I.; Brokaw, N.; Tilman, D.; Knapp, A. The Importance of Land-Use Legacies to Ecology and Conservation. *Bioscience* **2003**, *53*, 77–88. https://doi.org/10.1641/0006-3568(2003)053[0077:TIOLUL]2.0.CO;2.
83. Dupouey, J.L.; Dambrine, E.; Laffite, J.D.; Moares, C. Irreversible Impact of Past Land Use on Forest Soils and Biodiversity. *Ecology* **2002**, *83*, 2978–2984. https://doi.org/10.1890/0012-9658(2002)083[2978:IIOPLU]2.0.CO;2.
84. Hermy, M.; Verheyen, K. Legacies of the Past in the Present-day Forest Biodiversity: A Review of Past Land-use Effects on Forest Plant Species Composition and Diversity. *Ecol. Res.* **2007**, *22*, 361–371. https://doi.org/10.1007/s11284-007-0354-3.
85. Mejía, G.A.; Su, C.; Allen, D.; Chaudhary, V.B.; Ong, T.W. Land-Use Legacies Affect the Composition and Distribution of Tree Species and Their Belowground Functions in a Succession from Old-Field to Mature Temperate Forest. *For. Ecosyst.* **2024**, *11*, 100249. https://doi.org/10.1016/j.fecs.2024.100249.
86. Yang, G.; Crowther, T.W.; Lauber, T.; Zohner, C.M.; Smith, G.R. A Globally Consistent Negative Effect of Edge on Aboveground Forest Biomass. *Nat. Ecol. Evol.* **2025**, *9*, 2036–2045. https://doi.org/10.1038/s41559-025-02840-2.
87. Ma, J.; Li, J.; Wu, W.; Liu, J. Global Forest Fragmentation Change from 2000 to 2020. *Nat. Commun.* **2023**, *14*, 3752. https://doi.org/10.1038/s41467-023-39221-x.
88. Brown, C.F.; Brumby, S.P.; Guzder-Williams, B.; Birch, T.; Hyde, S.B.; Mazzariello, J.; Czerwinski, W.; Pasquarella, V.J.; Haertel, R.; Ilyushchenko, S.; et al. Dynamic World, Near Real-Time Global 10 m Land Use Land Cover Mapping. *Sci. Data* **2022**, *9*, 251. https://doi.org/10.1038/s41597-022-01307-4.
89. Zhang, X.; Zhao, T.; Xu, H.; Liu, W.; Wang, J.; Chen, X.; Liu, L. GLC_FCS30D: The First Global 30 m Land-Cover Dynamics Monitoring Product with a Fine Classification System for the Period from 1985 to 2022 Generated Using Dense-Time-Series Landsat Imagery and the Continuous Change-Detection Method. *Earth Syst. Sci. Data* **2024**, *16*, 1353–1381. https://doi.org/10.5194/essd-16-1353-2024.
90. Xie, J.; Zhang, M.; Wu, H.; Lin, A.; Adami, M.; Mohamed Shariff, A.R.; Guo, Y. S2-IFNet: A Spatial-Semantic Information Fusion Network Integrated with Boundary Feature Enhancement for Forest Land Extraction from Sentinel-2 Data. *Int. J. Appl. Earth Obs. Geoinf.* **2025**, *139*, 104505. https://doi.org/10.1016/j.jag.2025.104505.
91. McGarigal, K. Landscape Pattern Metrics. In *Wiley StatsRef: Statistics Reference Online*; Wiley: Hoboken, NJ, USA, 2014.
92. Vogt, P.; Riitters, K.H.; Estreguil, C.; Kozak, J.; Wade, T.G.; Wickham, J.D. Mapping Spatial Patterns with Morphological Image Processing. *Landsc. Ecol.* **2007**, *22*, 171–177. https://doi.org/10.1007/s10980-006-9013-2.
93. Saura, S.; Pascual-Hortal, L. A New Habitat Availability Index to Integrate Connectivity in Landscape Conservation Planning: Comparison with Existing Indices and Application to a Case Study. *Landsc. Urban Plan.* **2007**, *83*, 91–103. https://doi.org/10.1016/j.landurbplan.2007.03.005.

94. Grantham, H.S.; Duncan, A.; Evans, T.D.; Jones, K.R.; Beyer, H.L.; Schuster, R.; Walston, J.; Ray, J.C.; Robinson, J.G.; Callow, M.; et al. Anthropogenic Modification of Forests Means Only 40% of Remaining Forests Have High Ecosystem Integrity. *Nat. Commun.* **2020**, *11*, 5978. https://doi.org/10.1038/s41467-020-19493-3.
95. Atkins, J.W.; Walter, J.A.; Stovall, A.E.L.; Fahey, R.T.; Gough, C.M. Power Law Scaling Relationships Link Canopy Structural Complexity and Height across Forest Types. *Funct. Ecol.* **2022**, *36*, 713–726. https://doi.org/10.1111/1365-2435.13983.
96. Liang, X.; Kankare, V.; Hyyppä, J.; Wang, Y.; Kukko, A.; Haggrén, H.; Yu, X.; Kaartinen, H.; Jaakkola, A.; Guan, F.; et al. Terrestrial Laser Scanning in Forest Inventories. *ISPRS J. Photogramm. Remote Sens.* **2016**, *115*, 63–77. https://doi.org/10.1016/j.isprsjprs.2016.01.006.
97. Hemmerling, J.; Pflugmacher, D.; Hostert, P. Mapping Temperate Forest Tree Species Using Dense Sentinel-2 Time Series. *Remote Sens. Environ.* **2021**, *267*, 112743. https://doi.org/10.1016/j.rse.2021.112743.
98. Blickensdörfer, L.; Oehmichen, K.; Pflugmacher, D.; Kleinschmit, B.; Hostert, P. National Tree Species Mapping Using Sentinel-1/2 Time Series and German National Forest Inventory Data. *Remote Sens. Environ.* **2024**, *304*, 114069. https://doi.org/10.1016/j.rse.2024.114069.
99. Schulz, C.; Förster, M.; Vulova, S.V.; Rocha, A.D.; Kleinschmit, B. Spectral-Temporal Traits in Sentinel-1 C-Band SAR and Sentinel-2 Multispectral Remote Sensing Time Series for 61 Tree Species in Central Europe. *Remote Sens. Environ.* **2024**, *307*, 114162. https://doi.org/10.1016/j.rse.2024.114162.
100. Mäyrä, J.; Keski-Saari, S.; Kivinen, S.; Tanhuanpää, T.; Hurskainen, P.; Kullberg, P.; Poikolainen, L.; Viinikka, A.; Tuominen, S.; Kumpula, T.; et al. Tree Species Classification from Airborne Hyperspectral and LiDAR Data Using 3D Convolutional Neural Networks. *Remote Sens. Environ.* **2021**, *256*, 112322. https://doi.org/10.1016/j.rse.2021.112322.
101. Bolyn, C.; Lejeune, P.; Michez, A.; Latte, N. Mapping Tree Species Proportions from Satellite Imagery Using Spectral–Spatial Deep Learning. *Remote Sens. Environ.* **2022**, *280*, 113205. https://doi.org/10.1016/j.rse.2022.113205.
102. Fassnacht, F.E.; Latifi, H.; Stereńczak, K.; Modzelewska, A.; Lefsky, M.; Waser, L.T.; Straub, C.; Ghosh, A. Review of Studies on Tree Species Classification from Remotely Sensed Data. *Remote Sens. Environ.* **2016**, *186*, 64–87. https://doi.org/10.1016/j.rse.2016.08.013.
103. Pu, R. Mapping Tree Species Using Advanced Remote Sensing Technologies: A State-of-the-Art Review and Perspective. *J. Remote Sens.* **2021**, *2021*. https://doi.org/10.34133/2021/9812624.
104. PAILLET, Y.; BERGÈS, L.; HJÄLTÉN, J.; ÓDOR, P.; AVON, C.; BERNHARDT-RÖMERMANN, M.; BIJLSMA, R.; DE BRUYN, L.; FUHR, M.; GRANDIN, U.; et al. Biodiversity Differences between Managed and Unmanaged Forests: Meta-Analysis of Species Richness in Europe. *Conserv. Biol.* **2010**, *24*, 101–112. https://doi.org/10.1111/j.1523-1739.2009.01399.x.
105. Marchi, N.; Pirotti, F.; Lingua, E. Airborne and Terrestrial Laser Scanning Data for the Assessment of Standing and Lying Deadwood: Current Situation and New Perspectives. *Remote Sens.* **2018**, *10*, 1356. https://doi.org/10.3390/rs10091356.
106. Yrttimaa, T.; Saarinen, N.; Luoma, V.; Tanhuanpää, T.; Kankare, V.; Liang, X.; Hyyppä, J.; Holopainen, M.; Vastaranta, M. Detecting and Characterizing Downed Dead Wood Using Terrestrial Laser Scanning. *ISPRS J. Photogramm. Remote Sens.* **2019**, *151*, 76–90. https://doi.org/10.1016/j.isprsjprs.2019.03.007.
107. Calders, K.; Adams, J.; Armston, J.; Bartholomeus, H.; Bauwens, S.; Bentley, L.P.; Chave, J.; Danson, F.M.; Demol, M.; Disney, M.; et al. Terrestrial Laser Scanning in Forest Ecology: Expanding the Horizon. *Remote Sens. Environ.* **2020**, *251*, 112102. https://doi.org/10.1016/j.rse.2020.112102.
108. Zolkos, S.G.; Goetz, S.J.; Dubayah, R. A Meta-Analysis of Terrestrial Aboveground Biomass Estimation Using Lidar Remote Sensing. *Remote Sens. Environ.* **2013**, *128*, 289–298. https://doi.org/10.1016/j.rse.2012.10.017.
109. Duncanson, L.; Kellner, J.R.; Armston, J.; Dubayah, R.; Minor, D.M.; Hancock, S.; Healey, S.P.; Patterson, P.L.; Saarela, S.; Marselis, S.; et al. Aboveground Biomass Density Models for NASA's Global Ecosystem Dynamics Investigation (GEDI) Lidar Mission. *Remote Sens. Environ.* **2022**, *270*, 112845. https://doi.org/10.1016/j.rse.2021.112845.
110. Belgiu, M.; Drăguţ, L. Random Forest in Remote Sensing: A Review of Applications and Future Directions. *ISPRS J. Photogramm. Remote Sens.* **2016**, *114*, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011.
111. Shirazinejad, G.; Javad Valadan Zoej, M.; Latifi, H. Applying Multidate Sentinel-2 Data for Forest-Type Classification in Complex Broadleaf Forest Stands. *For. An Int. J. For. Res.* **2022**, *95*, 363–379. https://doi.org/10.1093/forestry/cpac001.
112. Zanaga, D.; Van De Kerchove, R.; Daems, D.; De Keersmaecker, W.; Brockmann, C.; Kirches, G.; Wevers, J.; Cartus, O.; Santoro, M.; Fritz, S.; et al. ESA WorldCover 10 m 2021 V200. Available online: https://zenodo.org/records/7254221 (accessed on 21 September 2026).

113. Lesiv, M.; Schepaschenko, D.; Buchhorn, M.; See, L.; Dürauer, M.; Georgieva, I.; Jung, M.; Hofhansl, F.; Schulze, K.; Bilous, A.; et al. Global Forest Management Data for 2015 at a 100 m Resolution. *Sci. Data* **2022**, *9*, 199. https://doi.org/10.1038/s41597-022-01332-3.
114. Yun, T.; Li, J.; Ma, L.; Zhou, J.; Wang, R.; Eichhorn, M.P.; Zhang, H. Status, Advancements and Prospects of Deep Learning Methods Applied in Forest Studies. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *131*, 103938. https://doi.org/10.1016/j.jag.2024.103938.
115. Zhong, L.; Dai, Z.; Fang, P.; Cao, Y.; Wang, L. A Review: Tree Species Classification Based on Remote Sensing Data and Classic Deep Learning-Based Methods. *Forests* **2024**, *15*, 852. https://doi.org/10.3390/f15050852.
116. Jetz, W.; Cavender-Bares, J.; Pavlick, R.; Schimel, D.; Davis, F.W.; Asner, G.P.; Guralnick, R.; Kattge, J.; Latimer, A.M.; Moorcroft, P.; et al. Monitoring Plant Functional Diversity from Space. *Nat. Plants* **2016**, *2*, 16024. https://doi.org/10.1038/nplants.2016.24.
117. Fassnacht, F.E.; Müllerová, J.; Conti, L.; Malavasi, M.; Schmidtlein, S. About the Link between Biodiversity and Spectral Variation. *Appl. Veg. Sci.* **2022**, *25*. https://doi.org/10.1111/avsc.12643.
118. Schmidtlein, S.; Fassnacht, F.E. The Spectral Variability Hypothesis Does Not Hold across Landscapes. *Remote Sens. Environ.* **2017**, *192*, 114–125. https://doi.org/10.1016/j.rse.2017.01.036.
119. Gafurov, A.; Prokhorov, V.; Kozhevnikova, M.; Usmanov, B. Forest Community Spatial Modeling Using Machine Learning and Remote Sensing Data. *Remote Sens.* **2024**, *16*, 1371. https://doi.org/10.3390/rs16081371.
120. Punalekar, S.M.; Hurford, C.; Lucas, R.M.; Planque, C.; Chognard, S. Hierarchical-Modular Framework for Habitat Mapping through Systematic and Informed Integration of Remote Sensing Data with Contextual Information. *Ecol. Inform.* **2024**, *82*, 102714. https://doi.org/10.1016/j.ecoinf.2024.102714.
121. European Environment Agency (EEA). *State of Nature in the EU: Results from Reporting Under the Nature Directives 2013–2018, EEA Report No. 10/2020*; EEA: Copenhagen, Denmark, 2020. Available online: https://www.eea.europa.eu/en/analysis/publications/state-of-nature-in-the-eu-2020 (accessed on 21 September 2026).
122. Ivanova, N. Global Overview of the Application of the Braun-Blanquet Approach in Research. *Forests* **2024**, *15*, 937. https://doi.org/10.3390/f15060937.
123. Matyukira, C.; Mhangara, P. Advances in Vegetation Mapping through Remote Sensing and Machine Learning Techniques: A Scientometric Review. *Eur. J. Remote Sens.* **2024**, *57*, 2422330. https://doi.org/10.1080/22797254.2024.2422330.
124. Keith, D.A.; Ferrer-Paris, J.R.; Nicholson, E.; Bishop, M.J.; Polidoro, B.A.; Ramirez-Llodra, E.; Tozer, M.G.; Nel, J.L.; Mac Nally, R.; Gregr, E.J.; et al. A Function-Based Typology for Earth's Ecosystems. *Nature* **2022**, *610*, 513–518. https://doi.org/10.1038/s41586-022-05318-4.
125. Potapov, P.; Hansen, M.C.; Laestadius, L.; Turubanova, S.; Yaroshenko, A.; Thies, C.; Smith, W.; Zhuravleva, I.; Komarova, A.; Minnemeyer, S.; et al. The Last Frontiers of Wilderness: Tracking Loss of Intact Forest Landscapes from 2000 to 2013. *Sci. Adv.* **2017**, *3*. https://doi.org/10.1126/sciadv.1600821.
126. Sabatini, F.M.; Keeton, W.S.; Lindner, M.; Svoboda, M.; Verkerk, P.J.; Bauhus, J.; Bruelheide, H.; Burrascano, S.; Debaive, N.; Duarte, I.; et al. Protection Gaps and Restoration Opportunities for Primary Forests in Europe. *Divers. Distrib.* **2020**, *26*, 1646–1662. https://doi.org/10.1111/ddi.13158.
127. Maes, J.; Bruzón, A.G.; Barredo, J.I.; Vallecillo, S.; Vogt, P.; Rivero, I.M.; Santos-Martín, F. Accounting for Forest Condition in Europe Based on an International Statistical Standard. *Nat. Commun.* **2023**, *14*, 3723. https://doi.org/10.1038/s41467-023-39434-0.
128. Osei Darko, P.; Laliberté, E.; Kalacska, M.; Arroyo-Mora, J.P.; Gonzalez, A.; Zuloaga, J. Phenospectral Similarity as an Index of Ecological Integrity. *Front. Environ. Sci.* **2024**, *12*. https://doi.org/10.3389/fenvs.2024.1333762.
129. Mai, G.; Xie, Y.; Jia, X.; Lao, N.; Rao, J.; Zhu, Q.; Liu, Z.; Chiang, Y.-Y.; Jiao, J. Towards the next Generation of Geospatial Artificial Intelligence. *Int. J. Appl. Earth Obs. Geoinf.* **2025**, *136*, 104368. https://doi.org/10.1016/j.jag.2025.104368.
130. Anderegg, W.R.L.; Martinez-Vilalta, J.; Mencuccini, M.; Poyatos, R. Community Assembly Influences Plant Trait Economic Spectra and Functional Trade-Offs at Ecosystem Scales. *Proc. Natl. Acad. Sci.* **2024**, *121*. https://doi.org/10.1073/pnas.2404034121.
131. Monteith, J.L. Solar Radiation and Productivity in Tropical Ecosystems. *J. Appl. Ecol.* **1972**, *9*, 747. https://doi.org/10.2307/2401901.
132. Running, S.W.; Ramakrishna R. Nemani; Heinsch, F.A.; Zhao, M.; Reeves, M.; Hashimoto, H. A Continuous Satellite-Derived Measure of Global Terrestrial Primary Production. *Bioscience* **2004**, *54*, doi:doi.org/10.1641/0006-3568(2004)054[0547:ACSMOG]2.0.CO;2.
133. Prentice, I.C.; Balzarolo, M.; Bloomfield, K.J.; Chen, J.M.; Dechant, B.; Ghent, D.; Janssens, I.A.; Luo, X.; Morfopoulos, C.; Ryu, Y.; et al. Principles for Satellite Monitoring of Vegetation Carbon Uptake. *Nat. Rev. Earth Environ.* **2024**, *5*, 818–832. https://doi.org/10.1038/s43017-024-00601-6.

134. Badgley, G.; Field, C.B.; Berry, J.A. Canopy Near-Infrared Reflectance and Terrestrial Photosynthesis. *Sci. Adv.* **2017**, *3*. https://doi.org/10.1126/sciadv.1602244.
135. Mohammed, G.H.; Colombo, R.; Middleton, E.M.; Rascher, U.; van der Tol, C.; Nedbal, L.; Goulas, Y.; Pérez-Priego, O.; Damm, A.; Meroni, M.; et al. Remote Sensing of Solar-Induced Chlorophyll Fluorescence (SIF) in Vegetation: 50 Years of Progress. *Remote Sens. Environ.* **2019**, *231*, 111177. https://doi.org/10.1016/j.rse.2019.04.030.
136. Li, X.; Xiao, J.; He, B.; Altaf Arain, M.; Beringer, J.; Desai, A.R.; Emmel, C.; Hollinger, D.Y.; Krasnova, A.; Mammarella, I.; et al. Solar-induced Chlorophyll Fluorescence Is Strongly Correlated with Terrestrial Photosynthesis for a Wide Variety of Biomes: First Global Analysis Based on OCO-2 and Flux Tower Observations. *Glob. Chang. Biol.* **2018**, *24*, 3990–4008. https://doi.org/10.1111/gcb.14297.
137. Drusch, M.; Moreno, J.; Del Bello, U.; Franco, R.; Goulas, Y.; Huth, A.; Kraft, S.; Middleton, E.M.; Miglietta, F.; Mohammed, G.; et al. The FLuorescence EXplorer Mission Concept—ESA's Earth Explorer 8. *IEEE Trans. Geosci. Remote Sens.* **2017**, *55*, 1273–1284. https://doi.org/10.1109/TGRS.2016.2621820.
138. Bonan, G.B. Forests and Climate Change: Forcings, Feedbacks, and the Climate Benefits of Forests. *Science* **2008**, *320*, 1444–1449. https://doi.org/10.1126/science.1155121.
139. Ellison, D.; Morris, C.E.; Locatelli, B.; Sheil, D.; Cohen, J.; Murdiyarso, D.; Gutierrez, V.; Noordwijk, M. van; Creed, I.F.; Pokorny, J.; et al. Trees, Forests and Water: Cool Insights for a Hot World. *Glob. Environ. Chang.* **2017**, *43*, 51–61. https://doi.org/10.1016/j.gloenvcha.2017.01.002.
140. Fisher, J.B.; Lee, B.; Purdy, A.J.; Halverson, G.H.; Dohlen, M.B.; Cawse-Nicholson, K.; Wang, A.; Anderson, R.G.; Aragon, B.; Arain, M.A.; et al. ECOSTRESS: NASA's Next Generation Mission to Measure Evapotranspiration From the International Space Station. *Water Resour. Res.* **2020**, *56*. https://doi.org/10.1029/2019WR026058.
141. Entekhabi, D.; Njoku, E.G.; O'Neill, P.E.; Kellogg, K.H.; Crow, W.T.; Edelstein, W.N.; Entin, J.K.; Goodman, S.D.; Jackson, T.J.; Johnson, J.; et al. The Soil Moisture Active Passive (SMAP) Mission. *Proc. IEEE* **2010**, *98*, 704–716. https://doi.org/10.1109/JPROC.2010.2043918.
142. Quegan, S.; Le Toan, T.; Chave, J.; Dall, J.; Exbrayat, J.-F.; Minh, D.H.T.; Lomas, M.; D'Alessandro, M.M.; Paillou, P.; Papathanassiou, K.; et al. The European Space Agency BIOMASS Mission: Measuring Forest above-Ground Biomass from Space. *Remote Sens. Environ.* **2019**, *227*, 44–60. https://doi.org/10.1016/j.rse.2019.03.032.
143. Manning, P.; van der Plas, F.; Soliveres, S.; Allan, E.; Maestre, F.T.; Mace, G.; Whittingham, M.J.; Fischer, M. Redefining Ecosystem Multifunctionality. *Nat. Ecol. Evol.* **2018**, *2*, 427–436. https://doi.org/10.1038/s41559-017-0461-7.
144. Mori, A.S.; Furukawa, T.; Sasaki, T. Response Diversity Determines the Resilience of Ecosystems to Environmental Change. *Biol. Rev.* **2013**, *88*, 349–364. https://doi.org/10.1111/brv.12004.
145. Bathiany, S.; Bastiaansen, R.; Bastos, A.; Blaschke, L.; Lever, J.; Loriani, S.; De Keersmaecker, W.; Dorigo, W.; Milenković, M.; Senf, C.; et al. Ecosystem Resilience Monitoring and Early Warning Using Earth Observation Data: Challenges and Outlook. *Surv. Geophys.* **2025**, *46*, 265–301. https://doi.org/10.1007/s10712-024-09833-z.
146. Guo, J.; Zhu, Z.; Gong, P. Global Forest Resilience Change from 2001 to 2022. *Int. J. Remote Sens.* **2024**, *45*, 5889–5900. https://doi.org/10.1080/01431161.2024.2380546.
147. Suvanto, S.; Esquivel-Muelbert, A.; Schelhaas, M.; Astigarraga, J.; Astrup, R.; Cienciala, E.; Fridman, J.; Henttonen, H.M.; Kunstler, G.; Kändler, G.; et al. Understanding Europe's Forest Harvesting Regimes. *Earth's Futur.* **2025**, *13*. https://doi.org/10.1029/2024EF005225.
148. Ceccherini, G.; Duveiller, G.; Grassi, G.; Lemoine, G.; Avitabile, V.; Pilli, R.; Cescatti, A. Abrupt Increase in Harvested Forest Area over Europe after 2015. *Nature* **2020**, *583*, 72–77. https://doi.org/10.1038/s41586-020-2438-y.
149. Xulu, S.; Mbatha, N.; Peerbhay, K.; Gebreslasie, M. Detecting Harvest Events in Plantation Forest Using Sentinel-1 and -2 Data via Google Earth Engine. *Forests* **2020**, *11*, 1283. https://doi.org/10.3390/f11121283.
150. Ruiz-Ramos, J.; Marino, A.; Boardman, C.; Suarez, J. Continuous Forest Monitoring Using Cumulative Sums of Sentinel-1 Timeseries. *Remote Sens.* **2020**, *12*, 3061. https://doi.org/10.3390/rs12183061.
151. Francini, S.; McRoberts, R.E.; Giannetti, F.; Mencucci, M.; Marchetti, M.; Scarascia Mugnozza, G.; Chirici, G. Near-Real Time Forest Change Detection Using PlanetScope Imagery. *Eur. J. Remote Sens.* **2020**, *53*, 233–244. https://doi.org/10.1080/22797254.2020.1806734.
152. Shields, S.G.; Coops, N.C.; Achim, A.; Hamelin, R.C.; Mulverhill, C. A Review of PlanetScope CubeSats for Forest Monitoring. *Sci. Remote Sens.* **2025**, *12*, 100314. https://doi.org/10.1016/j.srs.2025.100314.
153. Stoddart, J.; Suarez, J.; Mason, W.; Valbuena, R. Continuous Cover Forestry and Remote Sensing: A Review of Knowledge Gaps, Challenges, and Potential Directions. *Curr. For. Reports* **2023**, *9*, 490–501. https://doi.org/10.1007/s40725-023-00206-0.

154. Maltamo, M.; Jukkara, H.; Kosunen, P.; Kymäläinen, H.; Uhlgren, V.-V.; Liimatainen, K.; Nummenmaa, T.; Korhonen, L. Mapping and Verifying Potential Continuous Cover Forestry Areas from LiDAR Data. *Trees, For. People* **2026**, *24*, 101196. https://doi.org/10.1016/j.tfp.2026.101196.
155. Mölder, A.; Tiebel, M.; Plieninger, T. On the Interplay of Ownership Patterns, Biodiversity, and Conservation in Past and Present Temperate Forest Landscapes of Europe and North America. *Curr. For. Reports* **2021**, *7*, 195–213. https://doi.org/10.1007/s40725-021-00143-w.
156. Fridén, A.; D'Amato, D.; Ekström, H.; Iliev, B.; Nebasifu, A.; May, W.; Thomsen, M.; Droste, N. Mapping Two Centuries of Forest Governance in Nordic Countries: An Open Access Database. *For. Policy Econ.* **2024**, *160*, 103142. https://doi.org/10.1016/j.forpol.2023.103142.
157. Zhang, Y.; West, P.; Thakholi, L.; Suryawanshi, K.; Supuma, M.; Straub, D.; Sithole, S.S.; Sharma, R.; Schleicher, J.; Ruli, B.; et al. Governance and Conservation Effectiveness in Protected Areas and Indigenous and Locally Managed Areas. *Annu. Rev. Environ. Resour.* **2023**, *48*, 559–588. https://doi.org/10.1146/annurev-environ-112321-081348.
158. Ulvdal, P.; Öhman, K.; Eriksson, L.O.; Wästerlund, D.S.; Lämås, T. Handling Uncertainties in Forest Information: The Hierarchical Forest Planning Process and Its Use of Information at Large Forest Companies. *For. An Int. J. For. Res.* **2023**, *96*, 62–75. https://doi.org/10.1093/forestry/cpac028.
159. Đuka, A.; Papa, I.; Proto, A.R.; Latterini, F.; Mederski, P.S.; Borz, S.A.; Iordache, E.; Sokolović, D.; Karišik, A.; Stojnić, D.; et al. Forest Accessibility and Road Network Density: A Global Overview with a Special Focus on Europe. *Curr. For. Reports* **2025**, *11*, 26. https://doi.org/10.1007/s40725-025-00259-3.
160. Fraefel, M.; Bont, L.G.; Fischer, C. Spatially Explicit Assessment of Forest Road Suitability for Timber Extraction and Hauling in Switzerland. *Eur. J. For. Res.* **2021**, *140*, 1195–1209. https://doi.org/10.1007/s10342-021-01393-w.
161. Slagter, B.; Fesenmyer, K.; Hethcoat, M.; Belair, E.; Ellis, P.; Kleinschroth, F.; Peña-Claros, M.; Herold, M.; Reiche, J. Monitoring Road Development in Congo Basin Forests with Multi-Sensor Satellite Imagery and Deep Learning. *Remote Sens. Environ.* **2024**, *315*, 114380. https://doi.org/10.1016/j.rse.2024.114380.
162. Asbeck, T.; Frey, J. Weak Relationships of Continuous Forest Management Intensity and Remotely Sensed Stand Structural Complexity in Temperate Mountain Forests. *Eur. J. For. Res.* **2021**, *140*, 721–731. https://doi.org/10.1007/s10342-021-01361-4.
163. Neudam, L.; Annighöfer, P.; Seidel, D. Exploring the Potential of Mobile Laser Scanning to Quantify Forest Structural Complexity. *Front. Remote Sens.* **2022**, *3*. https://doi.org/10.3389/frsen.2022.861337.
164. Batchelor, J.L.; Wilson, T.M.; Olsen, M.J.; Ripple, W.J. New Structural Complexity Metrics for Forests from Single Terrestrial Lidar Scans. *Remote Sens.* **2022**, *15*, 145. https://doi.org/10.3390/rs15010145.
165. Willim, K.; Ammer, C.; Seidel, D.; Annighöfer, P.; Schmucker, J.; Schall, P.; Ehbrecht, M. Short - Term Dynamics of Structural Complexity in Differently Managed and Unmanaged European Beech Forests. *Trees, For. People* **2022**, *8*, 100231. https://doi.org/10.1016/j.tfp.2022.100231.
166. Scherpenhuijzen, N.; West, T.A.P.; Debonne, N.; Oostdijk, S.; Adame, P.; Astrup, R.; Verburg, P.H. Mapping Forest Management Regimes in Europe. *For. Ecol. Manage.* **2025**, *594*, 122940. https://doi.org/10.1016/j.foreco.2025.122940.
167. Guo, X.; Lao, J.; Dang, B.; Zhang, Y.; Yu, L.; Ru, L.; Zhong, L.; Huang, Z.; Wu, K.; Hu, D.; et al. SkySense: A Multi-Modal Remote Sensing Foundation Model Towards Universal Interpretation for Earth Observation Imagery. In *Proceedings of the 2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*; IEEE: Piscataway, NJ, USA, 2024; pp. 27662–27673.
168. Bountos, N.I.; Ouaknine, A.; Papoutsis, I.; Rolnick, D. FoMo: Multi-Modal, Multi-Scale and Multi-Task Remote Sensing Foundation Models for Forest Monitoring. *Proc. AAAI Conf. Artif. Intell.* **2025**, *39*, 27858–27868. https://doi.org/10.1609/aaai.v39i27.35002.
169. Wang, M.; Zhang, Q.; Liu, X.; Zhang, J.; Yu, F.; Zhang, X.; Zhao, R. Research Progress on Multimodal Data Fusion in Forest Resource Monitoring. *Front. Plant Sci.* **2026**, *16*, 1710618. https://doi.org/10.3389/fpls.2025.1710618.
170. Tagarakis, A.C.; Benos, L.; Kyriakarakos, G.; Pearson, S.; Sørensen, C.G.; Bochtis, D. Digital Twins in Agriculture and Forestry: A Review. *Sensors* **2024**, *24*, 3117. https://doi.org/10.3390/s24103117.
171. Li, Y.; Zhang, T.; Ding, Y.; Wadhwani, R.; Huang, X. Review and Perspectives of Digital Twin Systems for Wildland Fire Management. *J. For. Res.* **2024**, *36*, 14. https://doi.org/10.1007/s11676-024-01810-x.
172. Battle, R.; Kolas, D. Enabling the Geospatial Semantic Web with Parliament and GeoSPARQL. *Semant. Web* **2012**, *3*, 355–370. https://doi.org/10.3233/SW-2012-0065.
173. Haller, A.; Janowicz, K.; Cox, S.J.D.; Lefrançois, M.; Taylor, K.; Le Phuoc, D.; Lieberman, J.; García-Castro, R.; Atkinson, R.; Stadler, C. The Modular SSN Ontology: A Joint W3C and OGC Standard Specifying the Semantics of Sensors, Observations, Sampling, and Actuation. *Semant. Web* **2018**, *10*, 9–32. https://doi.org/10.3233/SW-180320.

174. Buttigieg, P.; Morrison, N.; Smith, B.; Mungall, C.J.; Lewis, S.E. The Environment Ontology: Contextualising Biological and Biomedical Entities. *J. Biomed. Semantics* **2013**, *4*, 43. https://doi.org/10.1186/2041-1480-4-43.
175. Pereira, H.M.; Ferrier, S.; Walters, M.; Geller, G.N.; Jongman, R.H.G.; Scholes, R.J.; Bruford, M.W.; Brummitt, N.; Butchart, S.H.M.; Cardoso, A.C.; et al. Essential Biodiversity Variables. *Science* **2013**, *339*, 277–278. https://doi.org/10.1126/science.1229931.
176. Proença, V.; Martin, L.J.; Pereira, H.M.; Fernandez, M.; McRae, L.; Belnap, J.; Böhm, M.; Brummitt, N.; García-Moreno, J.; Gregory, R.D.; et al. Global Biodiversity Monitoring: From Data Sources to Essential Biodiversity Variables. *Biol. Conserv.* **2017**, *213*, 256–263. https://doi.org/10.1016/j.biocon.2016.07.014.
177. Latifi, H.; Holzwarth, S.; Skidmore, A.; Brůna, J.; Červenka, J.; Darvishzadeh, R.; Hais, M.; Heiden, U.; Homolová, L.; Krzystek, P.; et al. A Laboratory for Conceiving Essential Biodiversity Variables (EBVs)—The 'Data Pool Initiative for the Bohemian Forest Ecosystem.' *Methods Ecol. Evol.* **2021**, *12*, 2073–2083. https://doi.org/10.1111/2041-210X.13695.
178. Wilkinson, M.D.; Dumontier, M.; Aalbersberg, Ij.J.; Appleton, G.; Axton, M.; Baak, A.; Blomberg, N.; Boiten, J.-W.; da Silva Santos, L.B.; Bourne, P.E.; et al. The FAIR Guiding Principles for Scientific Data Management and Stewardship. *Sci. Data* **2016**, *3*, 160018. https://doi.org/10.1038/sdata.2016.18.
179. Pettorelli, N.; Wegmann, M.; Skidmore, A.; Mücher, S.; Dawson, T.P.; Fernandez, M.; Lucas, R.; Schaepman, M.E.; Wang, T.; O'Connor, B.; et al. Framing the Concept of Satellite Remote Sensing Essential Biodiversity Variables: Challenges and Future Directions. *Remote Sens. Ecol. Conserv.* **2016**, *2*, 122–131. https://doi.org/10.1002/rse2.15.
180. Kissling, W.D.; Walls, R.; Bowser, A.; Jones, M.O.; Kattge, J.; Agosti, D.; Amengual, J.; Basset, A.; van Bodegom, P.M.; Cornelissen, J.H.C.; et al. Towards Global Data Products of Essential Biodiversity Variables on Species Traits. *Nat. Ecol. Evol.* **2018**, *2*, 1531–1540. https://doi.org/10.1038/s41559-018-0667-3.

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