Environmental Challenges 24 (2026) 101634

Contents lists available at ScienceDirect

Environmental Challenges

journal homepage: www.elsevier.com/locate/envc

From tree-wise monitoring to action: a digital forest carbon twin framework for forest carbon MRV and climate-smart forest management

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ARTICLE INFO

Keywords:
Digital forest carbon twin
Digital twin
Forest carbon MRV
Uncertainty propagation
Interoperability
Governance
Climate-smart forestry

ABSTRACT

Forests are increasingly expected to deliver climate mitigation together with productivity, resilience, and biodiversity outcomes, yet forest carbon monitoring, reporting, and verification (MRV) remain constrained by fragmented data workflows, weak traceability, and limited links between measurement and management action. This conceptual framework paper defines the Digital Forest Carbon Twin (DFCT) as a carbon-specialized digital twin whose minimum operational condition is a persistent tree-wise state that is repeatedly updated by observations and models. From this state, carbon accounting, uncertainty propagation, verification evidence, and decision support are generated through one versioned architecture. We propose a six-layer framework covering data acquisition, processing and integration, tree-wise state and carbon, MRV, decision support, and stakeholder/governance interfaces. The framework is operationalized through an auditor-facing verification workflow, a protocol-harmonization strategy, and a maturity pathway from pilot implementation to a scaled platform. An illustrative pilot in the City of Joensuu, Finland, demonstrates how ground laser scanning, UAV data, field measurements, tree-object reconstruction, and web visualization can be connected within one implementation pathway; the pilot is presented as evidence of integration feasibility rather than as a completed validation of carbon-accounting accuracy. Comparison with conventional inventories, remote-sensing workflows, MRV systems, generic digital twins, and decision-support systems shows that the defining DFCT features are persistent tree identities, versioned state updating, explicit uncertainty, reproducible lineage, and shared monitoring-to-action logic. The framework provides a practical research agenda for interoperable, verifier-ready, and climate-smart forest management systems.

Terminology used in this paper:

Digital twin: A synchronized virtual representation of a physical system that is updated through observations and models and supports analysis or feedback.

Forest digital twin: A digital twin applied to a forest system; it may operate at tree, stand, or landscape level and is not necessarily carbon-specific.

Digital Forest Carbon Twin (DFCT): The carbon-specialized architecture proposed in this paper, defined by persistent tree-wise identities, state updating, explicit uncertainty, verification-ready lineage, and decision support generated from the same digital core.

Persistent tree identity: A stable identifier that links observations and modeled states of the same physical tree across measurement events.

Lineage: The versioned and reproducible chain linking raw observations, processing steps, model assumptions, state updates, and reported outputs.

Monitoring, reporting and verification (MRV): The process through which environmental outcomes are measured, documented, and independently assessed.

1. Introduction

Forest management is being respecified by climate targets, evolving carbon accounting demands, and heightened scrutiny of monitoring and verification practices (Lopatin and Robins, 2026; Lopatin et al., 2026a). Across these pressures lies a shared constraint: decision-making and reporting frequently rely on heterogeneous data streams and model assumptions that are difficult to reconcile across spatial scales, update cycles, and verification requirements. Forestry digital twin literature suggests that a true digital twin—distinct from visualization or static

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https://doi.org/10.1016/j.envc.2026.101634
Received 18 April 2026; Received in revised form 21 August 2026; Accepted 23 August 2026
Available online 24 August 2026

digital models—requires a synchronized virtual representation updated through assimilation of observations and coupled to dynamic modeling and feedback (Döllner et al., 2023; Liu et al., 2023; Khan et al., 2025). Yet the same synthesis indicates that integration into MRV frameworks remains conceptually and operationally incomplete, constrained by interoperability gaps, heterogeneous data standards, and limited evidence of verifier-oriented deployments (Maimour et al., 2024; Tagarakis et al., 2024; Kondratev et al., 2025). The environmental challenge addressed in this paper is the absence of forest carbon monitoring systems that connect repeated measurements, uncertainty, verification, and management action within a single decision-ready architecture. In practice, this gap limits the ability of forest managers, project developers, and verifiers to translate monitoring into timely and credible management responses.

In parallel, drone-enabled monitoring has rapidly expanded the feasible design space for high-resolution forest measurement (Lopatin et al., 2026b). The drone MRV literature highlights accelerating capability for individual-tree detection and attribute estimation using UAV LiDAR, photogrammetry, and multispectral sensing, including under-canopy systems that navigate GNSS-denied forest interiors (Hyyppä et al., 2020a; Hyyppä et al., 2020b; Liang et al., 2024; Karjalainen et al., 2024). These advances matter not merely because they improve maps but because they enable repeated observations at resolutions compatible with tree-wise state updating and because they change detection in structurally complex forests (Krůček et al., 2020; Puliti and Granhus, 2021; Zhao et al., 2005). This paper develops a framework intended to unify these trajectories into a distinct scientific proposition: the digital forest carbon twin (DFCT). The novelty claim is architectural rather than incremental. The DFCT is defined not as "MRV plus drones" and not as "digital twin plus carbon outputs," but as a system in which carbon MRV, uncertainty propagation, verification-ready evidence, and climate-smart decision support are coordinated functions of the same evolving, tree-wise forest state representation. This reframing is motivated by the literature's repeated identification of (i) weak interoperability between digital twins and MRV systems (Maimour et al., 2024; Tagarakis et al., 2024), (ii) the need for explicit uncertainty handling and sampling-bias diagnosis (Kondratev et al., 2025; Ehlers, 2017), and (iii) growing feasibility of individual-tree data streams from drones and dense point clouds (Hyyppä et al., 2020a; Hyyppä et al., 2020b; Kellner et al., 2019; Bennett et al., 2020).

The proposed framework leads to four testable propositions:

1. Implementations that assimilate repeated observations at the individual tree level will reduce bias and improve the characterization of uncertainty in carbon change estimates compared to approaches that rely primarily on periodic sampling without maintaining a stateful update of observations.
2. Architectures that incorporate explicit versioning of data processing steps and full lineage tracking will reduce verification efforts and improve audit reproducibility compared to systems in which model assumptions and processing parameters are documented inconsistently or only in narrative form.
3. Decision-support outputs will be more consistent with monitoring, reporting, and verification (MRV) outcomes when both are derived from a shared tree-level state representation and a common uncertainty framework, rather than from separate and independently implemented model systems.
4. The use of autonomous under-canopy unmanned aerial vehicle (UAV) observations will measurably increase the operational feasibility of repeated tree-level updates in forest environments in which canopy occlusion and limited GNSS availability constrain above-canopy data acquisition.

1.1. Decision contexts and intended use cases

The framework is intended for three immediate decision contexts: (i) project-level forest carbon MRV in which repeated observations must support auditable carbon updates; (ii) climate-smart forest management in which tree-level interventions such as retention, thinning, deferment, and regeneration must be evaluated against carbon, productivity, and diversity objectives; and (iii) disturbance-triggered monitoring systems in which satellite or airborne signals initiate targeted tree-wise remeasurement and updating. These use cases define the management pathway of the DFCT and anchor the framework in implementation rather than theory alone.

2. Conceptual background

2.1. Digital twins in environmental systems

Forestry digital twins are increasingly discussed as synchronized virtual representations of forest systems that couple (a) state representation, (b) ongoing observation-driven updating, and (c) dynamic simulation supporting scenario analysis and management feedback (Döllner et al., 2023; Qiu et al., 2023). Broader ecological digital twin frameworks emphasize modularity, data-driven updating, and real-time feedback as prerequisites for robust deployment across complex natural systems (Khan et al., 2025). Across the forestry-focused literature, a consistent barrier is the lack of standardized architectures and semantic alignment across data streams that would allow digital twins to interoperate with operational monitoring and reporting infrastructures (Tagarakis et al., 2024; Lopatin et al., 2026a; Chen and Roßmann, 2022). Another recurring boundary is conceptual: "virtual forests" and 3D data products can improve visualization and user interaction but do not necessarily constitute a digital twin unless they implement systematic updating and decision-relevant feedback (Lopatin et al., 2026b; Qiu et al., 2023; Murtiyoso et al., 2024). This distinction matters for carbon MRV because verification depends on traceability through time—what changed, why it changed, and how uncertainty evolved—rather than on a single 3D snapshot.

2.2. Forest monitoring and growth systems

If carbon outcomes are to be linked credibly to observed forests and management decisions, digital representations must embody growth and change through time. The forestry digital twin literature includes approaches that merge remote sensing and modeling to improve growth prediction fidelity and management optimization, including interactive environments and learning-based approaches (Qiu et al., 2023; Qin et al., 2023). Yet it also highlights persistent weaknesses: limited incorporation of mortality and below-ground processes in some growth models, sensitivity of outcomes to implementation assumptions, and computational difficulty when optimization seeks tree-level detail (Vanclay, 2014; Pukkala et al., 2025; Pardos and Calama, 2025). A key conceptual bridge for DFCTs is data assimilation: the formal integration of forecasts and new measurements under correlated errors and constrained observation frequencies (Ehlers, 2017). Digital forest twins have also been used to expose biases and uncertainty limitations in traditional sampling strategies, emphasizing that uncertainty is not a reporting afterthought nor is it straightforward to diagnose without richer spatial information (Kondratev et al., 2025). Longitudinal growth studies combining tree-ring analysis with remote sensing further support the need to resolve forest change through time at fine biological granularity when building predictive management systems (Lopatin et al., 2006).

2.3. Carbon MRV and decision-support context

The drone MRV literature positions UAV systems as increasingly central contributors to carbon monitoring strategies, particularly by enabling repeatable high-resolution data acquisition and by supporting multi-source fusion with ground and satellite observations (Dainelli et al., 2021; Leoni et al., 2025). Under-canopy UAV systems and autonomous navigation approaches aim to address persistent measurement gaps in dense and structurally complex forests, though occlusion, point-density variability, and interoperability barriers remain significant (Hyyppä et al., 2020a; Hyyppä et al., 2020b; Tienaho et al., 2022; Liang et al., 2025). From a policy-facing perspective, the literature emphasizes that new monitoring capabilities will affect forest carbon governance only if they align with evolving demands for transparency, standardization, and credible reporting (Leoni et al., 2025; Migliavacca, 2025). Decision support in forestry has a long history of simulation and optimization across scales, ranging from landscape planning to explicitly tree-level optimization in continuous cover forestry (Pukkala et al., 2025; Kaya et al., 2016; Orazio et al., 2017). The digital twin proposition extends the conventional decision-support system (DSS) by insisting on synchronization and feedback: decisions affect the physical forest, which must then trigger measurement and model updating in the digital counterpart (Khan et al., 2025; Qiu et al., 2023). For carbon, this means decision support must remain consistent with MRV outputs and uncertainty statements, or it risks generating management recommendations that cannot be reconciled with reported carbon outcomes.

The practical consequence is that a DFCT is designed not only to document a carbon claim, but to determine when and how management or remeasurement should occur after new evidence is received.

3. Toward a digital forest carbon twin

3.1. Definition

We define a digital forest carbon twin as:

A continuously updated digital twin of a forest system in which each tree is represented as a persistent digital entity with a state that is repeatedly updated through observation and modeling, and in which carbon accounting, uncertainty propagation, verification-ready lineage, and climate-smart decision support are co-produced as coordinated functions of this evolving tree-wise state representation.

This definition inherits the core digital twin requirements emphasized in forestry: synchronized representation, data assimilation, and dynamic modeling with feedback (Döllner et al., 2023; Khan et al., 2025; Qiu et al., 2023). It specializes them for carbon MRV and decision support by making three commitments explicit: (i) carbon estimation is a first-order design objective; (ii) uncertainty is tracked through time as part of the state; and (iii) lineage and verifiability are system functions rather than reporting add-ons (Kondratev et al., 2025; Ehlers, 2017). Recent low-cost UAV photogrammetry results further show that the tree stem diameter can be estimated without relying exclusively on premium LiDAR platforms, widening the practical basis for tree-wise DFCT implementations (García-Pascual et al., 2025).

3.2. Tree-wise granularity as a required DFCT condition

This paper advances a mandatory condition: tree-wise granularity is not optional in a DFCT; it is definitional. Two lines of evidence from the curated literature motivate this requirement.

First, measurement feasibility is moving toward consistent individual-tree detection and tree attribute retrieval at operationally relevant resolutions. The drone MRV literature documents transferable individual-tree monitoring using UAVs (Bennett et al., 2020), large-area mapping of individual trees from ultra-high-density drone LiDAR (Krůček et al., 2020; Kellner et al., 2019), individual-tree diameter estimation with UAV laser scanning (Hao et al., 2021), and end-to-end UAV monitoring workflows that include individual-tree detection and carbon dynamics simulation (Fujimoto et al., 2019). Under-canopy UAV laser scanning further expands feasibility in dense forests where canopy occlusion complicates above-canopy inference (Hyyppä et al., 2020a; Hyyppä et al., 2020b; Liang et al., 2025; Lopatin et al., 2023; Lopatin et al., 2025). Second, management optimization and decision support increasingly require tree-level representation when the aim is to support multi-objective forest management, because only tree-level state representation allows trade-offs among carbon sequestration, productivity, and diversity to be balanced explicitly at the level where interventions, competition, growth, and mortality occur. Tree-level optimization is explicitly developed in continuous cover contexts, but it is also recognized as computationally demanding, implying that digital systems must manage scale, uncertainty, and tractability without collapsing essential heterogeneity (Pukkala et al., 2025; Kaya et al., 2016). The digital twin literature likewise emphasizes coupling detailed individual-tree data with stand and landscape processes as a pathway to richer modeling and decision paradigms (Khan et al., 2025; Pukkala et al., 2025; Wang et al., 2024). On this basis, we argue a strong hypothesis consistent with the scope of Hypothesis and Theory: only tree-wise granularity can simultaneously support accurate carbon accounting and carbon-optimized management because both tasks require attribution and updating at the level at which growth, mortality, competition, and interventions manifest as discrete changes. Stand- or pixel-aggregated approaches can be useful for coarse monitoring, but they tend to conflate within-stand heterogeneity and obscure the link between interventions and carbon outcomes. This claim should be treated as a DFCT design postulate that is empirically testable (see Section 7), and it is advanced here as a necessary condition for a DFCT to be meaningfully distinguishable from enhanced MRV mapping systems.

For DFCT applications aimed at intervention-specific carbon accounting, uncertainty attribution, and management optimization at the level of retained, removed, damaged, or regenerated trees, tree-wise granularity becomes the minimum defensible state representation. Stand- and pixel-based systems should therefore be understood as complementary layers rather than reduced forms of a DFCT: they support large-scale model-based or model-assisted inference on forest resources and can provide automated near-real-time change detection that triggers remeasurement and updating of the tree-wise state. On their own, however, they do not satisfy the definitional requirements of a DFCT, because they do not preserve persistent tree identities at the level where management interventions and carbon responses must be attributed.

3.3. Core components

A DFCT requires at least five coupled component classes.

(1) **Tree-wise identity and state model:** persistent identifiers and state variables for each tree, enabling repeated updating and attribution through time (Bennett et al., 2020; Hao et al., 2021).
(2) **Observation and updating mechanisms:** repeatable observation streams (UAV, under-canopy and above-canopy LiDAR, multispectral, field references) and assimilation logic reflecting correlated errors and temporal constraints (Hyyppä et al., 2020a; Ehlers, 2017).
(3) **Carbon accounting module coupled to state:** carbon estimation as an explicit mapping from tree-wise state and growth trajectories to carbon-relevant indicators, with assumptions logged and sensitivity-managed (Vanclay, 2014; Pardos and Calama, 2025).
(4) **Uncertainty propagation through time:** uncertainty tracked as part of state updating, not appended only at reporting time (Kondratev et al., 2025; Ehlers, 2017).
(5) **Verification-ready lineage and governance interfaces:** traceable data flows and auditable processing decisions that enable verification (Buonocore, 2022).

3.4. Boundaries of the concept

The DFCT is intentionally distinguished from bordering system classes.

A DFCT is conceptually distinct from conventional forest inventory. Conventional inventories are designed to produce statistically defensible area-level estimates from relatively simple and robust measurements, typically treating trees as sampling units and focusing on distributions and their associated sampling errors rather than on persistent individual-tree identities. By contrast, a DFCT starts from tree-wise persistent digital entities and aggregates upward only when stand- or landscape-level inference is required. This bottom-up logic enables more precise attribution of growth, mortality, interventions, and carbon change, but it also limits direct generalization beyond observed areas unless supported by explicit sampling, model-assisted inference, or assimilation design. At the same time, rapid advances in UAV and laser-scanning workflows are expanding the feasible spatial extent and refresh rate of tree-wise observations, making them increasingly suitable as operational complements to airborne and satellite monitoring systems (Kondratev et al., 2025; Kellner et al., 2019; Leoni et al., 2025).

A DFCT is not merely a remote sensing workflow. Remote sensing can serve as an auxiliary data source for model-based or model-assisted inference and as an efficient trigger for automated change detection, but it does not by itself satisfy the definitional requirements of a DFCT unless it is coupled to a stateful, updateable forest representation with persistent tree identities and feedback logic linking new observations to carbon estimation and management decisions (Döllner et al., 2023; Matiza et al., 2023; Fol et al., 2025). A DFCT is not an MRV system alone: MRV systems are designed to produce auditable reporting outputs, whereas a DFCT is designed to maintain the evolving tree-wise state from which MRV and decision outputs jointly derive (Maimour et al., 2024; Tagarakis et al., 2024). A DFCT is not a generic DSS: a DSS may optimize plans but often relies on static inputs and is not inherently synchronized or verifiable in the manner required for carbon claims (Pukkala et al., 2025; Orazio et al., 2017).

4. Framework architecture

The DFCT framework is organized into six layers (Fig. 1; Table 1). The design principle is that each layer is independently evolvable but semantically aligned, and that the tree-wise state is the digital "spine" that binds carbon MRV, uncertainty, and decision support.

The present DFCT framework is centered on live-tree, aboveground, tree-wise state representation as the minimal operational core. Deadwood, below-ground carbon, soil carbon, and harvested-wood-product accounting should be treated as linked modules; the accounting is not assumed to be fully resolved by the tree-wise layer itself.

4.1. Data acquisition layer

The data acquisition layer comprises multi-source observations capable of supporting tree-wise representation and repeated updating. UAV LiDAR and photogrammetry enable flexible revisits and high-resolution structural information, while under-canopy UAV systems address GNSS-denied environments and provide complementary perspectives to canopy-top observations (Hyyppä et al., 2020a; Hyyppä et al., 2020b; Liang et al., 2024; Karjalainen et al., 2024). Ultra-high-density drone LiDAR and supervised segmentation for individual-tree mapping expand practical pathways for tree-wise data at larger areas (Krůček et al., 2020; Kellner et al., 2019). Field references and terrestrial data remain essential to anchor calibration and validation, particularly under structural complexity and occlusion (Dainelli et al., 2021; Tienaho et al., 2022). Earlier UAV-based work in Finland on energy biomass mapping also supports the operational relevance of drone-derived biomass products as a bridge between spatial biomass estimation and future tree-wise carbon workflows (Lopatin and Lopatina, 2017).

4.2. Processing and integration layer

In the processing and integration layer, raw data are transformed into aligned tree-wise features and updates. This includes georeferencing (including SLAM-based trajectories and ray tracing approaches), point-cloud normalization, tree detection and segmentation, trait extraction, and multi-source fusion. The drone MRV literature emphasizes both algorithmic gains and persistent processing constraints, including occlusion, variable point density, and standardization gaps that limit comparability (Tienaho et al., 2022; Liang et al., 2025). Benchmark datasets and community validation resources are framed as important for method maturity and transferability (Puliti and Granhus, 2021; Schladebach et al., 2025).

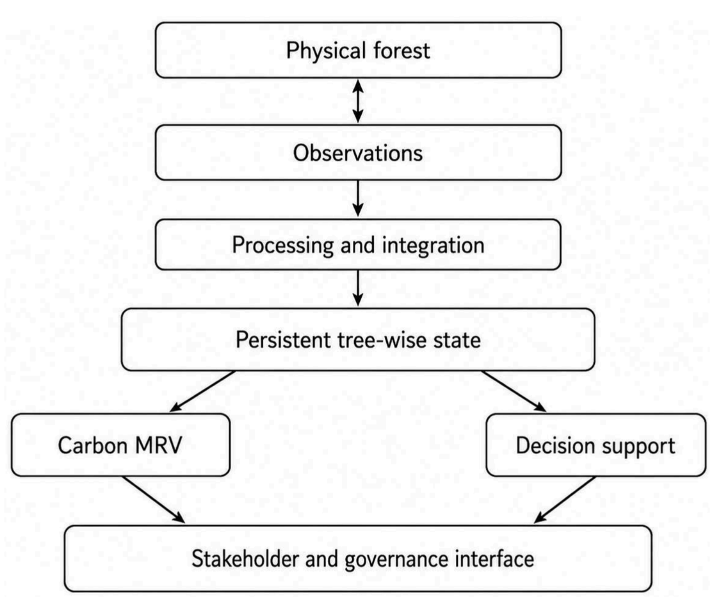

Fig. 1. Conceptual architecture of the Digital Forest Carbon Twin.

Table 1
Proposed DFCT architecture.

DFCT layer	Primary function	Data inputs	Outputs	Dominant uncertainties	Implementation challenges
Data acquisition layer	Collect repeatable multi-source observations at resolution compatible with tree-wise updating	UAV LiDAR (above/under canopy), UAV multispectral, field references, ALS/satellite context	Raw observations + metadata	Occlusion, seasonal effects, navigation constraints in GNSS-denied environments	Robust under-canopy operations; repeatability; mission design under weather/phenology windows (Hyyppä et al., 2020b; Liang et al., 2025; Brown et al., 2024).
Processing and integration layer	Convert raw data to aligned, tree-wise features; fuse sources; capture pipeline versions	Point clouds, imagery, trajectories/SLAM, ground references	Tree detection/ segmentation products; matched tree identities; fused feature sets; lineage records	Algorithm conditionality; point-density variability; modality-specific biases	Standardized processing; benchmarked segmentation; interoperability across tools and schema (Tagarakis et al., 2024; Puliti and Granhus, 2021; Tienaho et al., 2022).
Tree-wise forest state and carbon layer	Maintain persistent tree identities and evolving state; assimilate updates; map state to carbon indicators	Fused tree-wise features; growth model forecasts	Updated tree states; carbon indicators derived from state; uncertainty fields	Correlated errors; model assumption; missing processes (mortality, below-ground)	Assimilation under heterogeneity; assumption transparency and sensitivity testing; computational scaling (Ehlers, 2017; Vanclay, 2014; Pardos and Calama, 2025).
MRV layer	Produce reports and verification-ready evidence linked to lineage and uncertainty	State histories; pipeline versions; uncertainty outputs	MRV indicators, reporting packages, reproducible evidence bundles	Propagation and reporting of uncertainty; boundary choices	Harmonizing outputs with evolving MRV expectations; audit interfaces; ensuring reproducibility (Kondratev et al., 2025; Leoni et al., 2025).
Decision-support layer	Scenario analysis and optimization using the same state and uncertainty logic as MRV	Tree-wise state; management options; constraints	Scenarios, prescriptions, carbon-aware optimization outputs	Scenario uncertainty; optimization trade-offs	Tree-wise optimization tractability; user-centered design; explaining recommendations (Qiu et al., 2023; Pukkala et al., 2025; Kaya et al., 2016).
Stakeholder/ governance layer	Provide roles, permissions, governance controls, and trust mechanisms	MRV outputs; lineage; standards constraints; stakeholder needs	Audit tools; access-controlled interfaces; governance artifacts	Institutional variability; confidentiality constraints	Standardization and interoperability across actors; trust and traceability mechanisms; policy alignment (Migliavacca, 2025; Buonocore, 2022).

4.3. Tree-wise forest state and carbon layer

The tree-wise forest state and carbon layer is the DFCT core: it stores and updates the evolving state of each tree (and associated stand/ landscape contexts), with explicit links to carbon estimation. Assimilation logic integrates new observations with forecasts while managing correlated errors and update frequency constraints (Ehlers, 2017). The layer must also expose model assumptions and support sensitivity reasoning since forest simulation outcomes can shift materially under hidden assumptions (Vanclay, 2014). Where models are incomplete in ecological representation—such as limited mortality or below-ground processes—DFCTs must encode this as an explicit limitation and uncertainty rather than as a silent omission (Pardos and Calama, 2025).

4.4. MRV layer

The MRV layer compiles standardized monitoring indicators, reporting outputs, and verification-ready evidence packages. The forestry digital twin literature suggests that digital inventories can reveal and reduce biases in traditional sampling under certain conditions, reinforcing the value of a system that can carry uncertainty and sampling design logic into reporting outputs (Kondratev et al., 2025). For instance, transparency-oriented architectures—sometimes coupled to blockchain—are proposed to strengthen traceability and trust in measurement-to-claim pathways (Buonocore, 2022; Niță, 2021). For DFCTs, the key requirement is not a particular technology choice but an auditable chain linking raw observations, processing versions, state updates, and reported carbon outcomes. This governance requirement is consistent with remote-sensing-based assessment of certification indicators, where the credibility of digital monitoring depends on the explicit linkage between measurements and certification-relevant criteria (Lopatin et al., 2016).

4.5. Decision-support layer

The decision-support layer couples simulation and optimization to the same tree-wise state and uncertainty logic used for MRV. Interactive digital twin environments support scenario evaluation and feedback loops (Qiu et al., 2023), while optimization methods—especially tree-level—support carbon-aware silviculture but impose computational and data requirements that must be explicitly managed (Pukkala et al., 2025; Kaya et al., 2016). Climate-smart forestry perspectives emphasize aligning management with adaptation and mitigation outcomes and highlight the growing role of AI-enabled monitoring and planning systems (Wang, 2024; Das, 2025). From a management perspective, this also connects to spatial optimization problems beyond stand boundaries since road access and biomass mobilisation can materially affect which carbon-oriented interventions are feasible in practice (Havimo et al., 2017).

4.6. Stakeholder and governance layer

A DFCT must be usable by managers and legible to auditors, which requires a stakeholder and governance layer. The literature repeatedly identifies stakeholder integration and the lack of standardized protocols as barriers to operational digital twin deployment and MRV integration (Döllner et al., 2023; Tagarakis et al., 2024). Policy-facing syntheses emphasize that monitoring technologies will only affect climate goals if accompanied by harmonization, interoperability, and credible governance (Lopatin and Robins, 2026; Leoni et al., 2025; Migliavacca, 2025). DFCTs, therefore, require role-based access, structured audit interfaces, and system-level governance choices that convert technical outputs into trusted decisions and verified claims. Related work on due diligence under the EU Timber Regulation likewise suggests that traceability systems are only credible when data provenance and compliance logic are operationally auditable, not merely technically sophisticated (Trishkin et al., 2015; Trishkin et al., 2017a).

4.7. Illustrative implementation: Joensuu city forest pilot

To demonstrate how the six-layer architecture can be instantiated in practice, we use the ongoing Joensuu City Forest pilot as an illustrative implementation vignette (forestdigitaltwin.ai). The pilot was developed within the FORESTCARBOVISION Living Lab on a municipal forest site in Joensuu, Finland. It combines ground laser scanning for stem and lower-canopy structure, UAV data for canopy geometry and spatial context, and field measurements for calibration and validation. The same physical forest site is therefore represented through complementary observation streams rather than through a single sensor product.

The pilot processing pathway moves from raw observations to digital tree objects through point-cloud quality control and classification, tree and crown segmentation, Quantitative Structure Model (QSM) or other tree-object reconstruction, matching between field-measured and detected trees, and publication of tree-level objects and attributes in a web-based visualization environment. The current prototype can display the forest area, individual tree objects, field measurement locations, and initial links between physical and digital trees.

This implementation operationalizes several DFCT layers: multi-source data acquisition, processing and integration, initial tree-wise state representation, and a stakeholder-facing visualization interface. Its practical benefit is that the same digital core can subsequently support monitoring, management scenarios, biodiversity indicators, and stakeholder communication without rebuilding separate spatial data pipelines for each use case.

The Joensuu vignette (Fig. 2) should not be interpreted as a completed validation study or as evidence that the current prototype can issue verified forest carbon claims. Carbon calibration, persistent tree matching across repeated observations, formal uncertainty propagation, and auditor reproduction remain under development. The pilot is included to demonstrate integration feasibility in a real municipal forest setting and to identify the empirical tests required for subsequent DFCT maturity stages.

5. Operationalization pathways

5.1. Drone-enabled MRV workflows

Drone-enabled workflows provide an immediate operational pathway for DFCT updating because they can produce repeated, high-resolution structural and trait metrics. Under-canopy UAV laser scanning, including SLAM-based approaches, enables tree attribute estimation in dense stands and supports forest-interior mapping (Hyyppä et al., 2020a; Hyyppä et al., 2020b; Karjalainen et al., 2024). Further, transferable individual-tree monitoring and segmentation methods extend these capabilities toward broader forest structures and continuous cover conditions (Krůček et al., 2020; Bennett et al., 2020). Additionally, multispectral integration supports species and condition inference relevant to carbon dynamics and disturbance response (Khan et al., 2025; Kukkonen et al., 2019; Vignali et al., 2024; Trishkin et al., 2016). A DFCT-specific workflow differs from a conventional UAV mapping workflow because it treats each data acquisition as an update event to a tree-wise state rather than as a product-generation event.

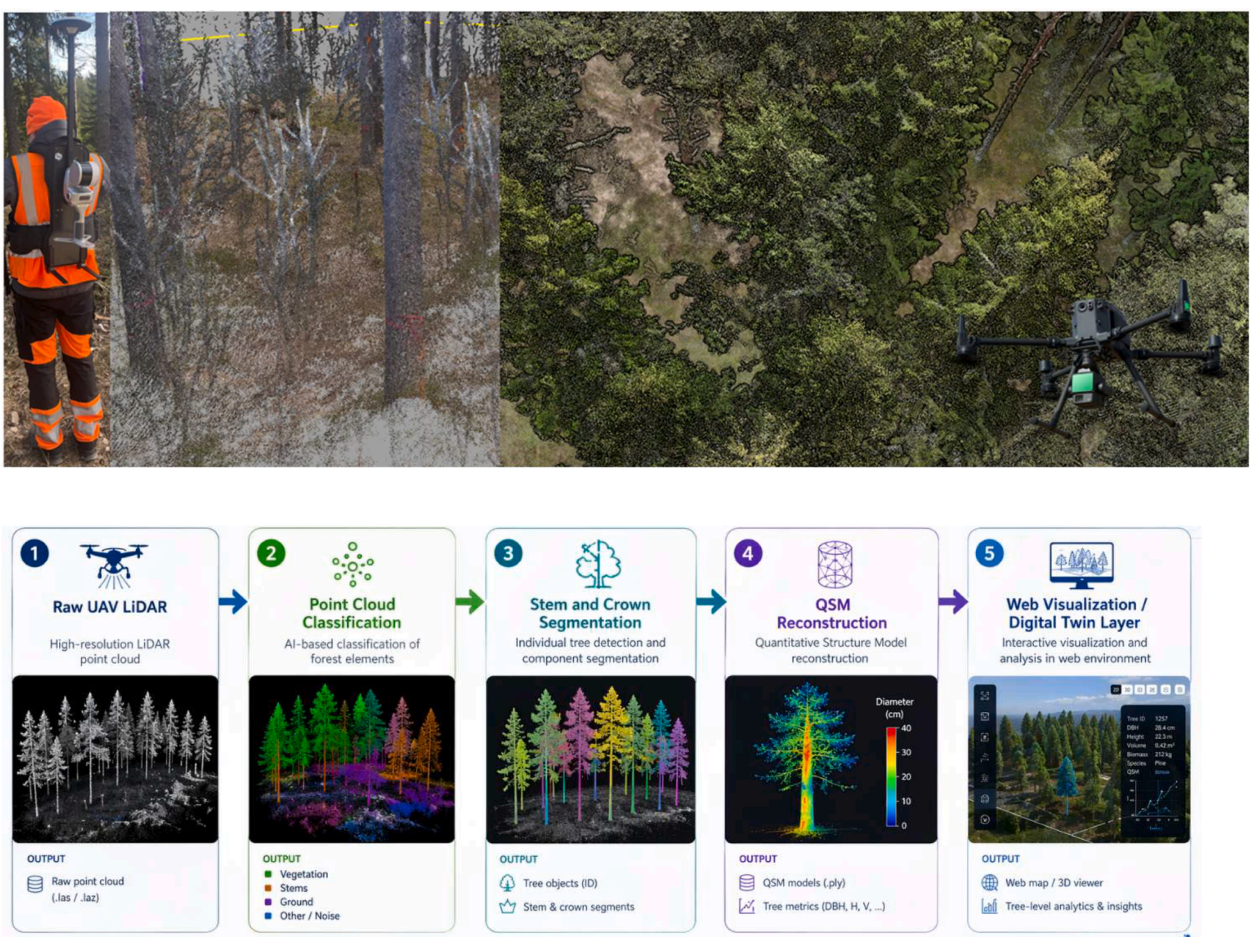

Fig. 2. Illustrative implementation of the Digital Forest Carbon Twin architecture in the Joensuu City Forest pilot. (a) Complementary observation streams with web-based prototype: ground laser scanning provides stem and lower-canopy structure, UAV sensing provides canopy geometry and spatial context, and field measurements provide calibration and validation references. (b) Processing pathway from raw UAV LiDAR through classification, tree segmentation, QSM/tree-object reconstruction, and Digital Forest Twin visualization. The pilot demonstrates integration feasibility; calibrated carbon accounting and formal verification remain under development. Images and project materials: authors, © Natural Resources Institute Finland.

Practically, this implies persistent tree identifiers, repeated-measurement alignment, and update logic that distinguishes measurement error from biological change. Consumer drone workflows coupled with deep learning have also proven viable for regeneration-stage inventory, indicating that DFCT logic can extend from mature-stand carbon monitoring to early stand development (Lopatin and Poikonen, 2023).

For Environmental Challenges readers, the key distinction is operational: inventories support statistically defensible area-level estimates, whereas DFCTs are intended to support intervention-level updating and management response.

5.2. Integration with growth and carbon models

DFCT operationalization requires a modular modeling architecture in which growth models provide continuity between observation events and support decision-support simulations. Hybrid modeling approaches and learning-based methods are increasingly used in forestry digital twin contexts, but model assumptions and ecological omissions remain critical risk factors (Qiu et al., 2023; Vanclay, 2014; Pardos and Calama, 2025; Peng et al., 2027; Lopatin et al., 2008). The DFCT framework, therefore, advances an explicit requirement: modeling assumptions and parameter choices must be machine-readable and logged as part of the lineage since verification for carbon claims depends on the ability to reproduce or audit how estimates were produced and updated (Buonocore, 2022). For cases in which the curated reviews do not provide explicit carbon accounting standards, the DFCT framework treats carbon estimation as assumption-explicit mapping from the tree-wise state and modeled trajectories to carbon-relevant indicators, with methodological conformity treated as a configurable module.

5.3. Spatial and temporal updating

Updating is a defining characteristic of DFCTs. The digital twin literature emphasizes the value—and difficulty—of real-time or iterative updating, especially under heterogeneous data sources and limited interoperability (Maimour et al., 2024; Tagarakis et al., 2024). Drone MRV literature similarly emphasizes that seasonality and operational windows influence data quality, affecting when and how updates should occur (Dainelli et al., 2021; Brown et al., 2024). Operationally, DFCT updating can be decomposed into three modes: periodic updates (scheduled campaigns), event-driven updates (triggered by management or disturbance), and assimilation-based interim updates (model-dominant periods). Concepts linking small- and large-scale digital twins provide an approach to reconcile tree-wise updates in sampled areas with landscape-scale context and calibration (Durrant et al., 2025).

5.4. Uncertainty and verification

Uncertainty is not a reporting artifact in DFCTs; it is a state variable. For instance, work using digital forest twins to assess bias and uncertainty in traditional sampling underscores that uncertainty diagnosis requires spatially explicit, independently checkable representations (Kondratev et al., 2025). Data assimilation highlights correlated errors and the fact that update frequency interacts with uncertainty evolution (Ehlers, 2017). Further, drone-based measurement introduces additional uncertainty structures related to occlusion, variable point densities, and algorithm conditionality (Tienaho et al., 2022; Liang et al., 2025). Verification readiness, in DFCT terms, means that an auditor can trace from a carbon indicator back to (i) the observation events and sensor configurations, (ii) processing pipeline versions and parameters, (iii) state update rules and model assumptions, and (iv) uncertainty propagation logic. The literature proposes blockchain-enabled traceability and transparency mechanisms as one possible implementation family, though the DFCT requirement is the verification-ready lineage itself rather than any specific technology stack (Buonocore, 2022; Niță, 2021).

5.4.1. Auditor-facing verification workflow

An auditor-facing DFCT workflow must enable independent reproduction of a reported carbon result without requiring access to undocumented expert choices. The minimum verification unit should therefore be a versioned evidence bundle containing: (i) the project boundary and baseline identifier; (ii) a manifest of observation events and sensor metadata; (iii) calibration and field-reference data; (iv) software, model, and parameter versions; (v) the persistent tree-identity table and state-update event log; (vi) carbon equations, conversion factors, and model assumptions; (vii) uncertainty models and aggregation rules; and (viii) machine-readable outputs, quality flags, and exception records.

Verification can proceed in two passes. In the first pass, the auditor evaluates data integrity and lineage by checking file hashes, coordinate systems, timestamps, sensor configurations, missing-data flags, and correspondence between raw observations and processed tree objects. In the second pass, the auditor reproduces the reported result by rerunning, or independently reimplementing, the declared processing and carbon-calculation steps for a risk-based sample of trees, strata, and observation events.

The audit should then test whether tree identities have been matched defensibly across time, whether management and disturbance events have been attributed correctly, whether calibration models remain valid, and whether uncertainty has been propagated consistently from observation through aggregation. The reproduced result should be compared with the submitted carbon claim using predefined confidence and materiality criteria.

Failed checks should not be hidden by overwriting previous states. Instead, the DFCT should generate an exception record, preserve the rejected version, and issue a new version only after corrective processing. The final verification statement (Fig. 3.) should identify the evidence-bundle version, reproduced result, detected deviations, unresolved exceptions, and scope of auditor assurance. In this way, auditability becomes a reproducible system function rather than a narrative appendix.

5.5. Interoperability and protocol harmonization

Data heterogeneity should be managed by separating sensor-specific acquisition formats from a sensor-independent DFCT core schema. Each observation enters through an adapter that preserves the raw source file while mapping its essential information to a common observation record. At minimum, this record should include the spatial reference system, vertical datum, observation time, sensor and trajectory metadata, processing status, quality flags, and links to the original files.

Derived tree objects should be stored in a common tree-state schema containing a persistent identifier, geometry, species and status fields, attribute values and units, observation time, source lineage, uncertainty, quality flags, and relationships to earlier or subsequent states. The relationship model should accommodate tree matching, mortality, recruitment, split or merged detections, and corrections to previously assigned identities.

Protocol fragmentation should be addressed through a versioned transformation registry rather than by forcing all projects to use one sensor, algorithm, or software package. Each processing step should have a stable identifier, software or container version, parameter file, input and output hashes, and declared validation status. Sensor- and vendor-specific workflows can therefore coexist, provided that they produce the same minimum core fields and quality metadata.

A tiered protocol can reduce implementation burden. Tier 1 can use standardized field and area-level data with conservative defaults. Tier 2 adds repeated UAV or airborne observations and tree-level matching. Tier 3 adds persistent tree-wise assimilation, explicit uncertainty

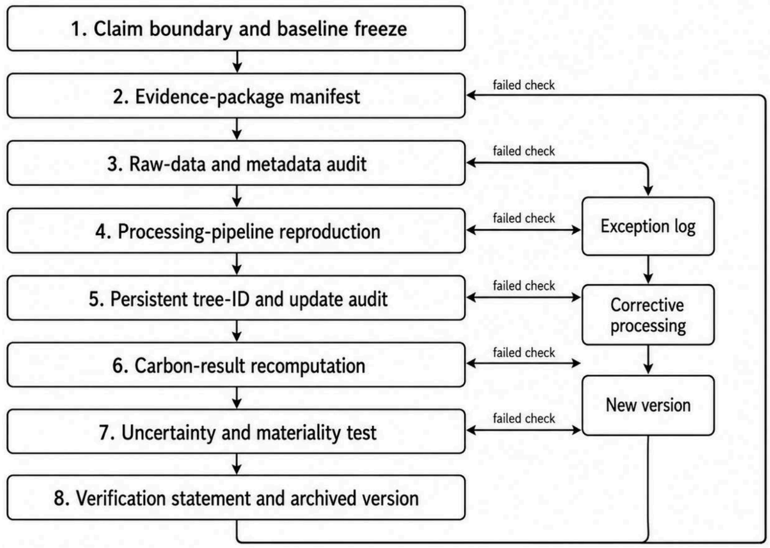

Fig. 3. Auditor-facing verification workflow for a Digital Forest Carbon Twin. Verification begins by freezing the claim boundary and baseline version, proceeds through data-lineage and processing checks, and culminates in independent carbon-result reproduction and uncertainty assessment. Failed checks produce versioned exception records rather than overwriting previous states.

propagation, full versioned lineage, and independent auditor reproduction. Projects can consequently enter the DFCT architecture at different maturity levels without losing compatibility with the common reporting and verification structure.

At governance level, a DFCT protocol profile should distinguish mandatory, recommended, and optional fields and define rules for unit conversion, missing data, calibration, validation, access permissions, and retirement of obsolete versions (Fig. 4, Table 2). This enables methodological innovation while maintaining interoperability and comparability across DFCT implementations.

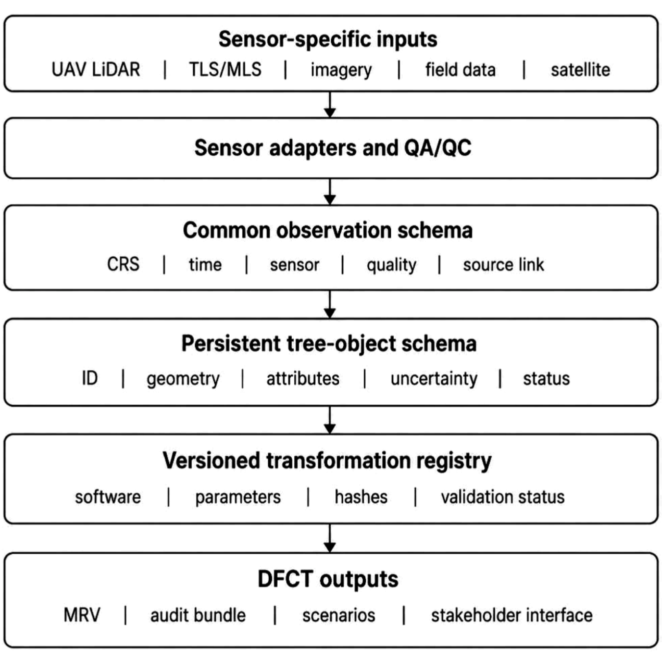

Fig. 4. Proposed harmonization pattern for heterogeneous DFCT data and protocols. Sensor-specific data remain available in their original formats, while adapters map essential metadata and derived attributes to common observation and persistent tree-object schemas. Versioned transformations connect these schemas to interoperable MRV, verification, and decision-support outputs.

6. Comparison with existing approaches

Table 3 differentiates forest inventory, remote sensing workflows, MRV systems, digital twins, and DSSs. The DFCT proposition is that no system class, on its own, closes the loop between repeated observation, tree-wise state updating, carbon accounting consistency, uncertainty propagation, verification, and action.

The expanded comparison shows that no adjacent system class combines all defining DFCT properties. Forest inventories and remote-sensing workflows can support calibration, mapping, and area-level estimates, but they do not generally maintain persistent tree states. MRV systems provide audit-oriented outputs, but they are normally claim-centered rather than state-centered. Generic forest digital twins and decision-support systems can update or simulate forest conditions, but they do not necessarily embed carbon accounting, uncertainty propagation, and auditor reproduction.

The DFCT novelty therefore rests in the joint requirement for persistent tree identity, stateful updating, versioned lineage, explicit uncertainty, reproducible carbon calculation, and management feedback generated from the same digital core. Tree-wise persistence alone is not sufficient; it becomes distinctive when combined with carbon-specialized state variables and verification-ready system design.

7. Discussion

7.1. Scientific contribution: Novelty and theory claim

This paper advances a theory-driven category distinction: a DFCT is not an enhanced MRV system and is not merely a digital twin with carbon outputs appended. The DFCT is defined by the architectural decision to treat carbon MRV, uncertainty, verification evidence, and decision support as coordinated functions of a single evolving, tree-wise state representation. This clarifies a recurring ambiguity identified in the digital twin literature, where systems of very different updating and governance structures are often labeled “digital twins” despite lacking synchronization, state updating, or feedback (Döllner et al., 2023; Tagarakis et al., 2024; Murtiyoso et al., 2024).

The second novelty of this paper is the explicit theorization of tree-wise granularity as a necessary condition for a DFCT. Individual-tree monitoring and segmentation capabilities are increasingly feasible and transferable in UAV contexts, including within continuous cover settings

Table 2
Minimum DFCT protocol-harmonization profile.

Fragmentation problem	Mandatory DFCT rule	Minimum recorded information	Verification benefit
Spatial incompatibility	Declare common spatial and vertical references	CRS, vertical datum, transformation, positional accuracy	Prevents untraceable coordinate shifts
Observation heterogeneity	Preserve raw data and use sensor adapters	Sensor, date/time, trajectory, acquisition settings, source link	Allows source-level inspection
Tree-identity inconsistency	Use persistent tree identifiers	Tree ID, observation event, matching confidence, status history	Supports change attribution
Attribute ambiguity	Use a shared data dictionary	Definition, unit, method, missing-value and quality codes	Enables comparison across workflows
Processing fragmentation	Version every transformation	Software, version, parameters, container/environment, hashes	Enables independent reproduction
Calibration variability	Link attributes to calibration records	Reference data, model version, validity domain, residual statistics	Exposes transfer limitations
Uncertainty inconsistency	Store uncertainty with each derived attribute	Error source, variance/confidence, covariance assumptions	Supports transparent aggregation
Baseline changes	Freeze and version baselines	Boundary, baseline date, model assumptions, event log	Prevents retrospective claim alteration
Access and confidentiality	Use role-based permissions	User role, accessible layer, change history	Protects data while preserving auditability

Table 3
Comparative properties of the DFCT and adjacent monitoring and decision-system classes.

System class	Core unit and persistence	Updating logic	Carbon/MRV and uncertainty	Audit reproduction	Decision feedback and principal limitation
Forest inventory	Plot/stand; trees usually not maintained as persistent digital entities	Periodic campaigns	Supports statistically defensible estimates and sampling uncertainty	Reproducible at inventory-method level	Supports planning, but lacks continuous tree-wise state
Remote-sensing workflow	Pixel, segment, or detected tree; persistence often absent	Episodic product generation	Biomass or trait maps depend on calibration and model validity	Variable; often pipeline-dependent	Efficient spatial monitoring, but commonly one-way
MRV system	Project, accounting area, or claim	Reporting-cycle oriented	Carbon accounting and verification are central	High for the declared methodology	Produces claims, but need not maintain a living forest state
Generic forest digital twin	Tree, stand, or landscape; persistence is implementation-dependent	Iterative synchronization and simulation	Carbon and explicit uncertainty may be optional	Variable	Strong scenario capability, but not necessarily carbon- or audit-ready
Decision-support system	Treatment unit, stand, or tree	Scenario-driven	Carbon may be one objective among several	Usually limited	Optimizes decisions, but can be disconnected from monitoring lineage
Digital Forest Carbon Twin	**Persistent tree entities aggregated to stand/ project levels**	**Periodic, event-driven, and assimilation-based state updating**	**Carbon calculation and uncertainty are functions of the shared state**	**Versioned evidence bundle enables independent reproduction**	**Monitoring, reporting, verification, and management feedback use the same digital core**

(Hyyppä et al., 2020a, 2020b; Krůček et al., 2020; Bennett et al., 2020). Tree-level optimization is simultaneously recognized as necessary for certain management objectives and as computationally demanding, motivating DFCT designs that can preserve tree-wise information while managing scale and tractability (Pukkala et al., 2025). The DFCT theory claim is, therefore, not that "trees can be measured" but rather that the system class enabling high-integrity carbon accounting and carbon-optimized forestry is one whose digital core is tree-wise, updateable, and verification-ready.

The Joensuu implementation vignette clarifies the practical meaning of this distinction. The pilot demonstrates that ground scanning, UAV data, field references, tree-object reconstruction, and stakeholder visualization can be connected through one implementation pathway. However, it also shows that visualization and initial tree-level reconstruction do not by themselves constitute a fully operational DFCT. Persistent cross-time identity, calibrated carbon attributes, formal uncertainty propagation, and auditor reproduction are required before the system can support verified carbon claims.

7.2. Testable hypotheses implied by the DFCT framework

Because this is a Hypothesis and Theory paper, the framework is offered with explicit empirical implications.

H1. DFCT implementations that assimilate repeated individual-tree observations will reduce bias and improve uncertainty characterization of carbon change estimates relative to workflows relying primarily on periodic sampling without stateful updating (Kondratev et al., 2025; Ehlers, 2017).

H2. DFCT architectures that encode versioned processing and lineage will reduce verification friction and enhance audit reproducibility relative to MRV implementations in which model assumptions and processing parameters are only documented narratively or are inconsistently documented (Buonocore, 2022).

H3. DFCT decision-support recommendations will be more consistent with reported MRV outcomes when both derive from the same tree-wise state and uncertainty logic, compared to cases in which decision support and MRV are implemented as separate model stacks (Qiu et al., 2023; Vanclay, 2014; Pukkala et al., 2025).

H4. Under-canopy autonomous UAV observation will measurably expand the operational feasibility of repeatable tree-wise updates in forests where canopy occlusion and GNSS denial constrain above-canopy inference (Liang et al., 2025; Hyyppä et al., 2021; Karjalainen et al., 2026). Climate-driven changes in technical forest accessibility may also alter when carbon-prioritizing interventions are operationally feasible, arguing for tighter coupling of DFCTs with accessibility models (Goltsev and Lopatin, 2013).

The Joensuu pilot does not yet test hypotheses H1–H4. Instead, it identifies the implementation components and observable endpoints required for future testing. Testing the hypotheses will require repeated observation events, frozen baseline versions, independently reproduced processing, quantified uncertainty, and comparison with conventional MRV and decision-support workflows.

7.3. Implementation challenges

The DFCT framework highlights several barriers that the curated literature emphasizes as decisive:

Interoperability remains a primary bottleneck. Forestry digital twin reviews identify heterogeneous data sources, a lack of unified standards, and semantic enrichment challenges as blocking operational integration with MRV systems (Döllner et al., 2023; Tagarakis et al., 2024; Chen and Roßmann, 2022). Drone MRV syntheses also emphasize that data fusion across drones, ground references, and satellites is technically demanding and often constrained by proprietary workflows and inconsistent protocols (Leoni et al., 2025; Niță, 2021).

Autonomy and robustness under canopy are still uneven. Under-canopy systems show promise, but operational reliability remains challenged by obstacle-rich environments, sensor limitations, and the need for robust navigation and route planning (Liang et al., 2024; Karjalainen et al., 2024; Liang et al., 2025; Karjalainen et al., 2026).

Tree-wise optimization is computationally demanding and has practical tractability limits. The tree-level optimization literature emphasizes both benefits and computational intensity, which implies that DFCT architectures must explicitly manage resolution, approximation, and uncertainty without collapsing the tree-wise state into coarse aggregates that defeat the DFCT premise (Pukkala et al., 2025; Kaya et al., 2016).

Model assumptions and ecological omissions can undermine credibility. The literature stresses that simulation outcomes can shift materially under untested assumptions and that models may omit key processes, motivating DFCT designs that treat assumptions as first-class, auditable entities (Vanclay, 2014; Pardos and Calama, 2025).

Consequently, companion digital twins for enabling infrastructure, such as forest roads and trafficability, may, therefore, become important complements to tree-wise DFCTs because accessibility conditions the timing and feasibility of carbon-oriented interventions (Väätäinen et al., 2026).

8. Management implications of tree-wise DFCTs

The management value of a tree-wise DFCT lies not only in estimating carbon more precisely but also in attributing carbon consequences to discrete interventions. Once individual trees become persistent digital entities, management can be optimized at the level at which silvicultural decisions actually act: retain, remove, release, regenerate, or defer intervention. This enables carbon-maximizing or carbon-prioritizing management to be formulated subject to biodiversity, operability, and productivity constraints, rather than as a stand-averaged reporting exercise.

8.1. Limitations

This manuscript primarily presents a conceptual architecture and does not claim fully validated performance of an operational DFCT. The Joensuu vignette demonstrates the feasibility of integrating multi-source observations, tree-object processing, field references, and web visualization within one pilot workflow, but it does not yet demonstrate validated forest carbon accounting, repeated tree-wise updating, or independent verification.

The framework is currently centered on live-tree, aboveground carbon as the minimum operational core. Soil carbon, below-ground biomass, deadwood, harvested wood products, leakage, and substitution effects require linked modules and are not resolved by tree-wise aboveground representation alone.

The paper also does not prescribe one carbon-accounting standard. Instead, methodological conformity is treated as a configurable module whose equations, factors, baselines, and uncertainty rules must be versioned and auditable. Finally, the framework and implementation vignette are influenced by boreal and European forestry contexts. Transferability to other biomes, ownership systems, sensor environments, and carbon methodologies remains an empirical question.

8.2. Governance and standardization

The curated literature repeatedly converges on a governance requirement: advanced monitoring technologies influence climate goals only if accompanied by harmonized protocols, interoperable systems, and trustworthy reporting structures (Leoni et al., 2025; Migliavacca, 2025). Digital twin frameworks propose transparency mechanisms, including blockchain-enabled traceability, but they also note integration complexity and policy alignment challenges (Buonocore, 2022). The DFCT framework treats governance as a layer: role-based access, audit interfaces, versioned pipelines, and explicit assumption records are designed into the system rather than retrofitted. Operational-level sustainability assessments further indicate that monitoring systems gain legitimacy only when they are embedded in day-to-day management practice rather than remaining external reporting overlays (Trishkin et al., 2017b).

8.3. Research agenda

The DFCT research agenda is summarized in Table 4 and is centered on five priorities: (i) standardization and interoperability across tree-wise representations and pipelines; (ii) robust under-canopy autonomy and repeatable measurement; (iii) uncertainty propagation through time and verifier-ready evidence designs; (iv) cross-scale linking of local tree-wise twins with regional monitoring contexts; and (v) user-centered decision support that remains consistent with MRV outputs (Tagarakis et al., 2024; Kondratev et al., 2025; Puliti and Granhus, 2021; Liang et al., 2025; Durrant et al., 2025).

The framework is therefore best understood as an implementation-oriented environmental monitoring architecture rather than as a purely conceptual digital twin typology.

9. Conclusion

This Hypothesis and Theory paper defines the digital forest carbon twin as a carbon-specialized digital twin. This digital twin's definitional distinguishing feature is tree-wise state representation that is continuously updated through observation and modeling, enabling carbon MRV, uncertainty tracking, verification-ready lineage, and decision support that is generated from the same evolving digital core. The framework is positioned against conventional MRV, remote sensing pipelines, and generic DSSs by emphasizing that DFCTs are state- and update-oriented systems in which MRV is a layer rather than the system identity.

The DFCT concept matters because it reframes forest carbon MRV from a reporting workflow into a function of continuous state estimation. Its practical implication is a coherent architecture by which drone-enabled individual-tree monitoring, assimilation, and governance interfaces can be assembled into operational infrastructure for climate-smart forestry. The next steps are empirical: implementing DFCT prototypes and evaluating whether tree-wise updating improves uncertainty characterization, auditability, and management outcomes while remaining operationally feasible at scale.

The Joensuu City Forest pilot illustrates how the architecture can begin to move from concept to implementation by linking ground scanning, UAV data, field measurements, tree-object reconstruction, and stakeholder visualization. The pilot does not yet constitute a verified

Table 4
Research gaps and future priorities for DFCTs.

Topic	Current limitation	Implication for science	Implication for implementation
Tree-wise identity persistence across time	Tree matching and cross-time identity linkage remains method- and site-dependent	Limits ability to formalize DFCT updating theory as repeatable state estimation	Weakens repeat-scan change detection and attribution needed for auditable carbon outcomes (Bennett et al., 2020; Liang et al., 2025).
Under-canopy autonomy and robustness	GNSS-denied navigation and obstacle-rich environments still constrain reliability	Restricts repeatability of tree-wise observation streams in complex stands	Increases costs and operator dependence; reduces feasibility for large-scale deployment (Liang et al., 2024; Karjalainen et al., 2026).
Standardized DFCT architectures and semantics	Fragmented definitions and weak interoperability standards	Slows theory convergence and cross-study comparability	Prevents integration with operational MRV systems and stakeholder systems (Tagarakis et al., 2024; Chen and Roßmann, 2022).
Uncertainty propagation and assimilation design	Correlated errors and update-frequency constraints complicate uncertainty tracking	Requires formal methodological advances to unify sensing errors with model uncertainty	Verification credibility depends on consistent and reproducible uncertainty statements (Kondratev et al., 2025; Ehlers, 2017).
Benchmark datasets and validation standards	Limited shared datasets and benchmarks for tree-wise segmentation across forest types	Hinders cumulative method development and replicability	Constrains QA/QC and verifier confidence; increases vendor lock-in risks (Puliti and Granhus, 2021; Schladebach et al., 2025).
Decision-support consistency with MRV	DSS outputs often rely on separate model stacks from MRV pipelines	Limits ability to test "consistency" hypotheses central to DFCT theory	Risk that recommended actions cannot be reconciled with reported carbon outcomes (Qiu et al., 2023; Pukkala et al., 2025).
Governance and verification-ready lineage	Traceability is often proposed but unevenly operationalized	Demands socio-technical research on "auditability by design"	Determines adoption by auditors and markets; requires transparent lineage and reproducibility mechanisms (Buonocore, 2022).

carbon-accounting system, but it demonstrates that the principal observation, processing, tree-state, and interface components can be connected in a real forest-management context.

The proposed auditor workflow and protocol-harmonization profile make the implementation implications more explicit. A DFCT should be considered operational only when its carbon results can be reproduced from a versioned evidence bundle and when heterogeneous observations can be mapped to common, uncertainty-qualified tree states.

For Environmental Challenges, the value of the DFCT lies less in proposing a new digital concept than in providing a monitoring-to-action architecture for climate-oriented land management. Its immediate relevance is in contexts where repeated forest measurements must be translated into auditable carbon updates, intervention choices, and management responses.

Funding

This work was supported by the Interreg Northern Periphery and Arctic Programme, co-funded by the European Union, project FORESTCARBOVISION (NPA0800248), project BIOGUARD (NPA1000322); funding from the Research Council of Finland, the Academy of Finland Flagship Programme (Forest–Human–Machine Interplay [UNITE]) Grant No. 337653; and funding from Business Finland, project Digital Forest Carbon Twins.

CRediT authorship contribution statement

Evgeny Lopatin: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Timo P. Pitkänen:** Writing – review & editing, Conceptualization. **Lauri Sikanen:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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