Advancing vegetation monitoring with virtual laser scanning of dynamic scenes (VLS-4D): Opportunities, implementations and future perspectives

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Hannah Weiser
3DGeo Research Group, Institute of Geography
Interdisciplinary Center for Scientific Computing (IWR)
Heidelberg University
Heidelberg, Germany

Bernhard Höfle
3DGeo Research Group, Institute of Geography
Interdisciplinary Center for Scientific Computing (IWR)
Heidelberg University
Heidelberg, Germany

Abstract

1. Virtual Laser Scanning (VLS) is an established and valuable research tool in forestry and ecology, widely used to simulate labelled LiDAR point cloud data for sensitivity analysis, model training and method testing. In VLS, vegetation has traditionally been modelled as static, neglecting the influence of vegetation dynamics on LiDAR point cloud representations and limiting applications to mono-temporal analyses.

2. In this review, we formalise VLS-4D, a framework that extends traditional VLS by using dynamic (i.e., 4D: 3D + time) input scenes. This advancement has opened new avenues for research on vegetation monitoring. We outline key concepts for representing dynamic scenes in LiDAR simulations, review technical implementations, and present innovative VLS-4D applications.

3. We find that current simulation frameworks suitable for vegetation applications do not yet fully support dynamic scenes. While LiDAR time series of vegetation growth can be generated from static scene snapshots, simulating the effects of vegetation movement during a scan remains a challenge. We group the reviewed applications of VLS-4D into three key methodological areas: i) investigating LiDAR data acquisition and vegetation movement effects, ii) testing and validating new methods for change detection and analysis, and iii) generating labelled training data for machine and deep learning.

4. We recommend that future efforts focus on extending the functionality of current LiDAR simulators and increasing the availability of open-source tools for modelling dynamic vegetation to enable more realistic simulations. Used as a complement, not a replacement, to real data, VLS-4D has the potential to significantly advance LiDAR-based vegetation monitoring by improving our understanding of point cloud representations, enabling reliable algorithm validation, and providing high-quality training data for deep learning.

Keywords 3D Animation · LiDAR Simulation · Machine Learning · Point Cloud Change Analysis · Synthetic Training Data · Vegetation Dynamics · Vegetation Monitoring · Virtual Laser Scanning

1 Introduction

Understanding vegetation and its dynamics is crucial in our rapidly changing world, as vegetation underpins a wide range of ecosystem services essential for human well-being. Among remote sensing technologies for vegetation monitoring, Light Detection and Ranging (LiDAR) stands out for its ability to capture the full 3D structure of vegetation because the laser beam can penetrate canopies. Researchers use repeated LiDAR acquisitions from ground-based and airborne platforms to assess tree health and damage [*Coops et al.*, 2009; *Jacobs et al.*, 2022; *Wulder et al.*, 2009], vegetation growth [*Bienert et al.*, 2024; *Tompalski et al.*, 2021; *Zhao et al.*, 2018], and plant physiology [*Herrero-Huerta et al.*, 2018; *Zlinszky et al.*, 2017].

Each LiDAR acquisition produces a unique 3D point cloud representation, from which vegetation properties such as shape, structure, and vitality can be derived. However, point cloud representations of the exact same scene can vary significantly depending on the acquisition parameters, affecting point distribution, density, occlusions, ranging accuracy and noise levels [*Soudarissanane et al.*, 2011]. Directly relating point clouds to biological and physical characteristics of plants is therefore challenging, especially without reliable reference data. Fig. 1 illustrates how a decrease in flight altitude alone can make vegetation appear much denser. In change analysis, multi-temporal LiDAR data captured with different sensors or settings complicates distinguishing between LiDAR acquisition effects (Fig. 1a and b) and actual change signals (Fig. 1c and d).

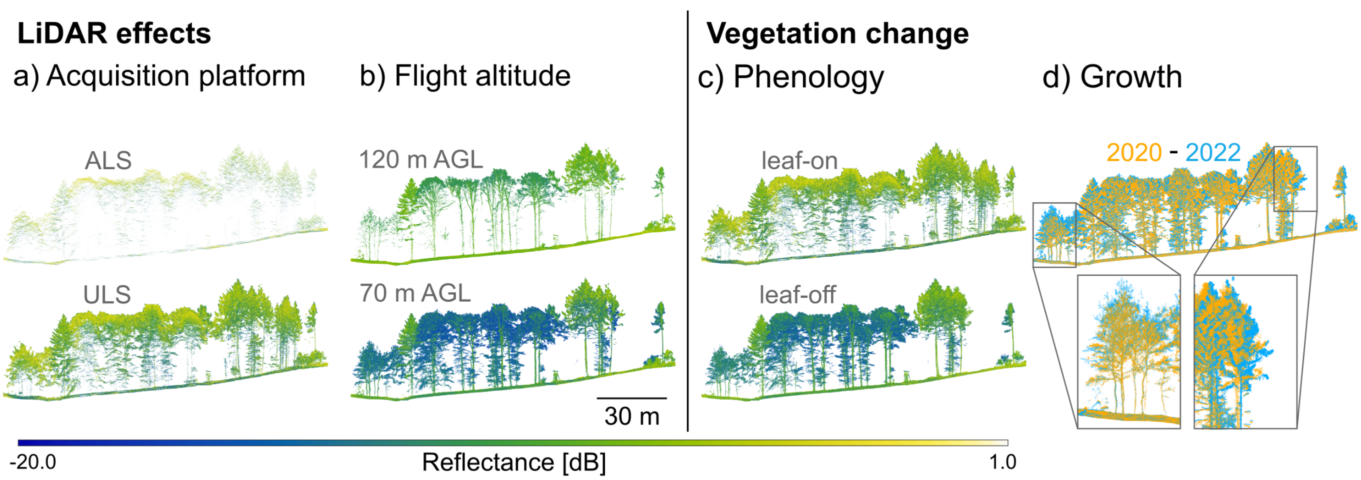

Figure 1: Real-world point cloud cross-sections demonstrating how LiDAR acquisition parameters (left) and vegetation changes (right) affect LiDAR representations. a) Acquisition platform and sensor: ALS vs. ULS, acquired approximately two months apart; b) Flight altitude: ULS on the same day and with the same device, but different flight altitudes and trajectories; c) Phenology: ULS with the same sensor and survey settings, but in leaf-on conditions and leaf-off conditions; d) Vegetation growth: Bi-temporal ULS point clouds acquired two years apart. ALS = airborne laser scanning, ULS = UAV-borne laser scanning, AGL = above ground level.

Uncertainty in the measurements arises not only from acquisition settings but also from vegetation movement during acquisition, compromising data quality. In mono-temporal Terrestrial Laser Scanning (TLS), for example, branch movement manifests as distortions in individual scans (Fig. 2a) or as duplication of branches ('ghosting effects'; *Wilkes et al.*, 2017 or 're-occurrence'; *Medic et al.*, 2023) in merged scans (Fig. 2b). These effects can result in unnoticed errors in downstream tasks (co-registration, vegetation parameter estimation, etc.). While *Medic et al.* [2023] propose several solutions to this problem, they emphasise that further scientific effort is required to adopt and develop these approaches.

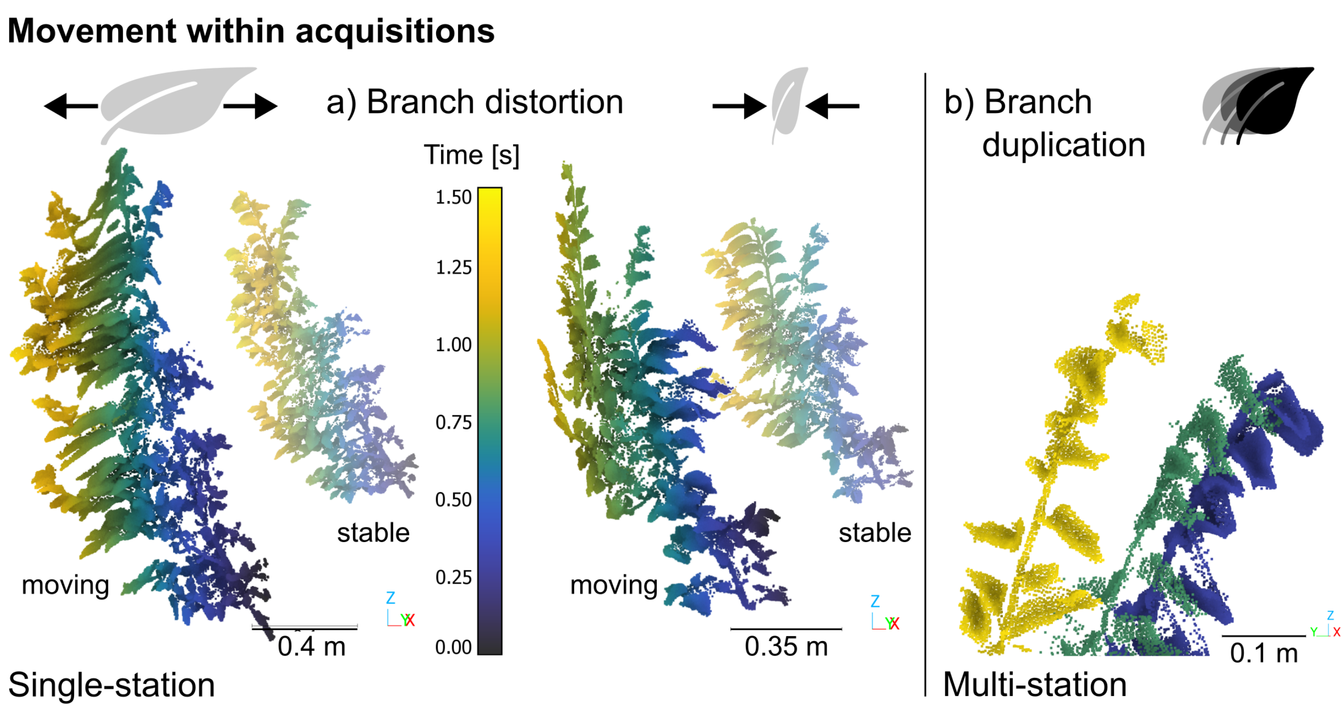

Figure 2: Examples of wind effects in terrestrial laser scanning point clouds due to branch movement during acquisition. a) Branch distortion, showing stretching (left) and compression (right) in a single scan from one station. The smaller semi-transparent images on the right show the same branches scanned under stable conditions for comparison. b) Branch duplication in a merged point cloud from multiple scan stations, with distinct colours indicating individual scans.

In machine learning (ML) applications, the effects of sensor, survey settings and wind on analysis results can be mitigated by training models on large datasets that incorporate these influences (e.g., *Puliti et al.*, 2025 for species recognition). This approach involves substantial efforts for data acquisition, processing, and labelling and remains largely unexplored in the context of vegetation change analysis. In addition, these costly benchmark datasets can quickly become outdated and less valuable as new LiDAR sensor systems are developed rapidly. To better understand the relationships between survey parameters, plant dynamics and point cloud representations, controlled experiments and sensitivity analyses offer valuable insights [*Hopkinson*, 2007]. In practice, the resources for empirical experiments are often too limited to comprehensively explore the input space of acquisition parameters and environmental settings. Also, since fully replicating a given LiDAR acquisition is impossible, unavoidable variations in survey characteristics make it difficult to isolate the effects of individual variables [*Roberts et al.*, 2020].

Due to these limitations, researchers have added LiDAR simulation as an additional research tool to their studies to investigate the influence of scanning configurations [*Hämmerle et al.*, 2017; *Roberts et al.*, 2020; *Stocker et al.*, 2023], to validate methods for quantifying forest biometrics [*Jiang et al.*, 2021; *Wu et al.*, 2021; *Zhu et al.*, 2020], or to generate training data for segmentation tasks [*Bryson et al.*, 2024; *Esmorís et al.*, 2024; *Liu et al.*, 2025]. LiDAR simulation, or Virtual Laser Scanning (VLS), comes with error-free reference data on scene geometry and semantics, enables the controlled variation of individual parameters, and lets us create scenarios that mimic real or fictional acquisitions [*Winiwarter et al.*, 2022b]. In addition, VLS does not face many of the challenges associated with real data acquisition, such as high costs, labelling difficulties, inaccessibility of study sites, or the limitation to specific available or affordable hardware [*Liu et al.*, 2025]. VLS is a scientific tool that perfectly complements and interacts with real data in a feedback loop. Real data guides the development of dynamic digital LiDAR twins and to assess their realism. In turn, simulated data helps to improve experimental designs, operational field campaigns, and computational methods for real-world data.

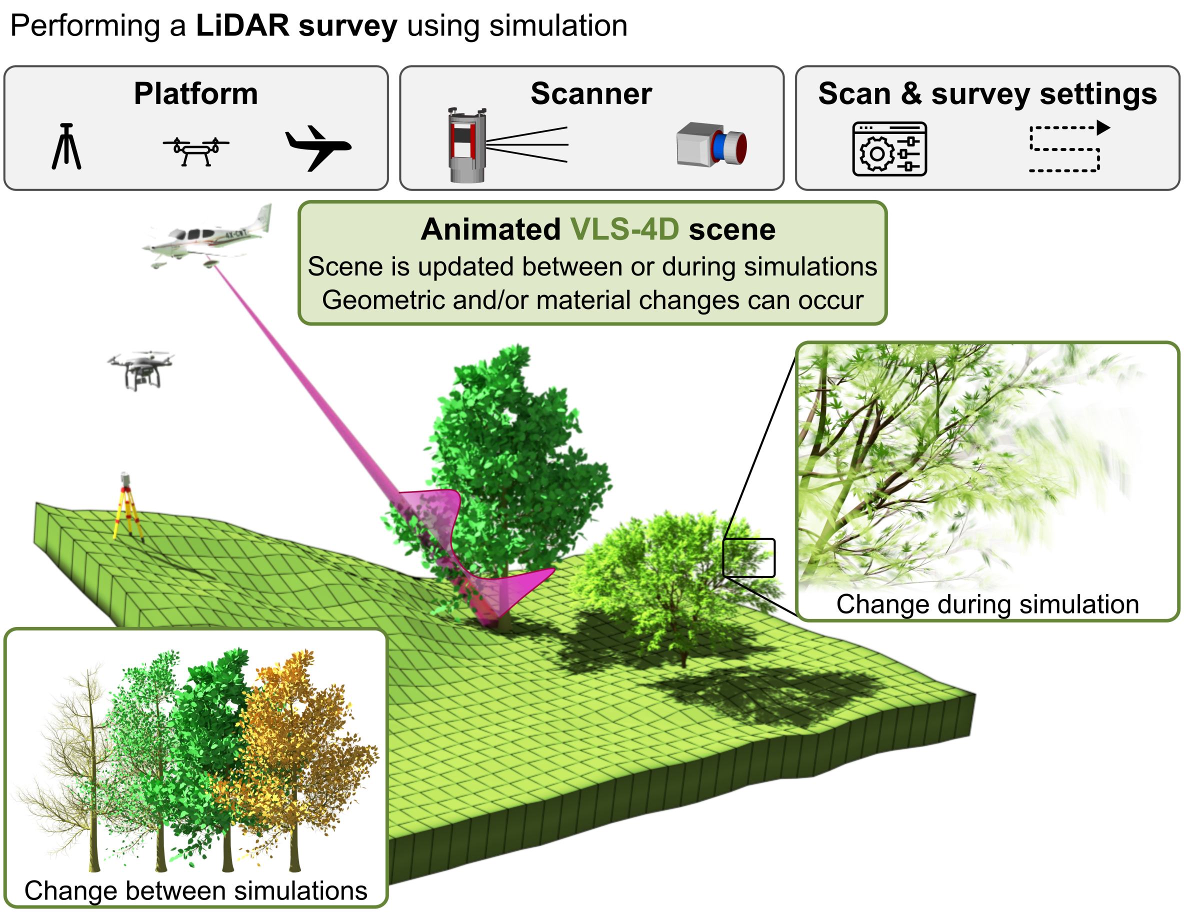

Figure 3: Schematic overview of the core modules (boxes) of VLS: The platform, the scanner which is mounted on the platform, the scan and survey settings and the scene. The novelty about VLS-4D is that the scene is dynamic (green outlined boxes). The rendered scene in the background is a modified version of Fig. 1 published in *Winiwarter et al.* [2022b] under the CC BY 4.0 licence (`https://creativecommons.org/licenses/by/4.0/`).

Over the past decade, VLS has become invaluable in forestry and ecology [*Bornand et al.*, 2024; *Cai et al.*, 2024; *Disney et al.*, 2010; *Hämmerle et al.*, 2017; *Liu et al.*, 2019, 2025; *Li et al.*, 2021b; *Liu et al.*, 2022; *Roberts et al.*, 2020; *Schäfer et al.*, 2023; *Wang*, 2020; *Wang et al.*, 2022; *Wu et al.*, 2021; *Zhao et al.*, 2023]. In most previous studies, VLS has been operated in a 'frozen' world where vegetation is assumed to be completely static. This simplification limits VLS to mono-temporal scenarios and neglects effects from the interactions between laser scanning and dynamic vegetation (Fig. 2). Moving to dynamic scenes, VLS can help us learn how different types of plant dynamics become visible in both mono-temporal and 4D point clouds (i.e., point cloud sequences; 4D = 3D + time) in different scenarios. This is highly relevant to virtually anyone using laser scanning in vegetated areas, as vegetation dynamics inherently affect real laser scanning data. These effects can either be the primary focus of analysis or introduce unwanted variability that impacts data quality. We therefore propose advancing traditional VLS (VLS-3D) to the concept of VLS-4D, in which objects change between or during virtual laser scans (Fig. 3). This new framework will push progress in 4D analysis of vegetation point clouds and has the potential to make laser scanning simulations more realistic.

VLS-4D realism is majorly influenced by two factors: a) the level of detail of the scene (geometry and dynamics) and b) the fidelity of the LiDAR simulation. For a), previousLiDAR simulation studies have modelled trees using simple crown archetypes [*Calders et al.*, 2013] or geometrically detailed 3D models [*Calders et al.*, 2018]. Likewise, plant dynamics can be implemented in a very simple way, e.g. by scaling whole plants, or in a very detailed way, e.g. by including the precise movement and deformation of individual branches. For b), the fidelity of the LiDAR simulation depends largely on the representation of realistic scan patterns and the modelling of beam divergence, which determines whether multiple returns can be recorded in the canopy [*Disney et al.*, 2010; *Manivasagam et al.*, 2023]. The appropriate degree of simplification of each component ultimately depends on the specific research objectives.

As VLS-4D has not yet been formulated as a scientific method and its application in vegetation studies is still in its early stages, the objectives of this review are as follows:

- to develop a conceptual framework for VLS-4D with respect to different types of vegetation dynamics and measurement scenarios (Section 2)
- to give an overview of tools for implementing VLS-4D, from modelling dynamic plants and ecosystems to conducting LiDAR surveys in a virtual environment (Section 3)
- to identify the main methodological areas for VLS-4D and review research questions in ecology and forestry where VLS-4D can have an impact (Section 4)
- to discuss remaining challenges and identify future developments that could make VLS-4D more accessible and fit for the identified purposes (Section 5)

2 THE CONCEPTUAL FRAMEWORK

VLS is the simulation of laser scanning using models of scenes, platforms, scanners, and the beam-scene interaction (Fig. 3; *Winiwarter et al.*, 2022b). While in traditional VLS-3D, the acquisition has always been dynamic, supporting mobile platforms, the virtual landscape (scene) has been static. With the term 'dynamic' in the VLS-4D framework, we specifically refer to the input scene. The scene model is a small and simplified section of the real or a fictional world. In VLS-4D, scene objects can undergo any changes that are relevant to the simulated ray-scene interaction, specifically changes to geometric or material properties. Geometric changes of objects in a scene can be categorised as rigid body displacement, deformation, or as the complete replacement, removal, or addition of objects. Material changes typically refer to changes in the spectral properties. Scene changes may occur between several acquisitions (epochs), between scans or flight strips of a single acquisition, or during a single scan (Fig. 5). We will give an overview of vegetation dynamics that can be observed with LiDAR and reproduced in VLS-4D (Section 2.1). Based on this, we will discuss three change logic concepts for VLS-4D and explain for which combinations of vegetation dynamics and LiDAR acquisition scenarios they are suitable (Section 2.2).

2.1 *Vegetation dynamics observable with LiDAR*

The use of VLS-4D requires data or knowledge about the dynamics of the object to be replicated and virtually observed. In this section, we discuss vegetation dynamics that can be observed with LiDAR, which are summarised in Fig. 4. These dynamics occur at different temporal and spatial scales, which often overlap. Plants move during the day related to water status or wind, change during the phenological cycle, and grow taller during their lifetime. In addition to geometric changes, plants also change in material properties, e.g., as a result of chlorophyll degradation. Many studies have shown that vegetation dynamics can be uncovered with laser scanning. Geometric and backscatter information from laser scanning point clouds have been used to investigate tree sway [*Vaaja et al.*, 2016; *Yun et al.*, 2025], diurnal branch and leaf movement [*Herrero-Huerta et al.*, 2018; *Puttonen et al.*, 2019; *Wang et al.*, 2022], phenological changes [*Bienert et al.*, 2024; *Calders et al.*, 2015; *Shcherbacheva et al.*, 2024], stress-induced changes [*Jacobs et al.*, 2022; *Junttila et al.*, 2019], as well as growth and biomass dynamics [*Tompalski et al.*, 2021; *Zhao et al.*, 2018]. Most of these studies rely on multi- or hyper-temporal datasets to quantify changes occurring during days, months, or years. In case of wind-induced vegetation movement, effects are visible in individual mono-temporal point clouds (Figs 2 and 4).

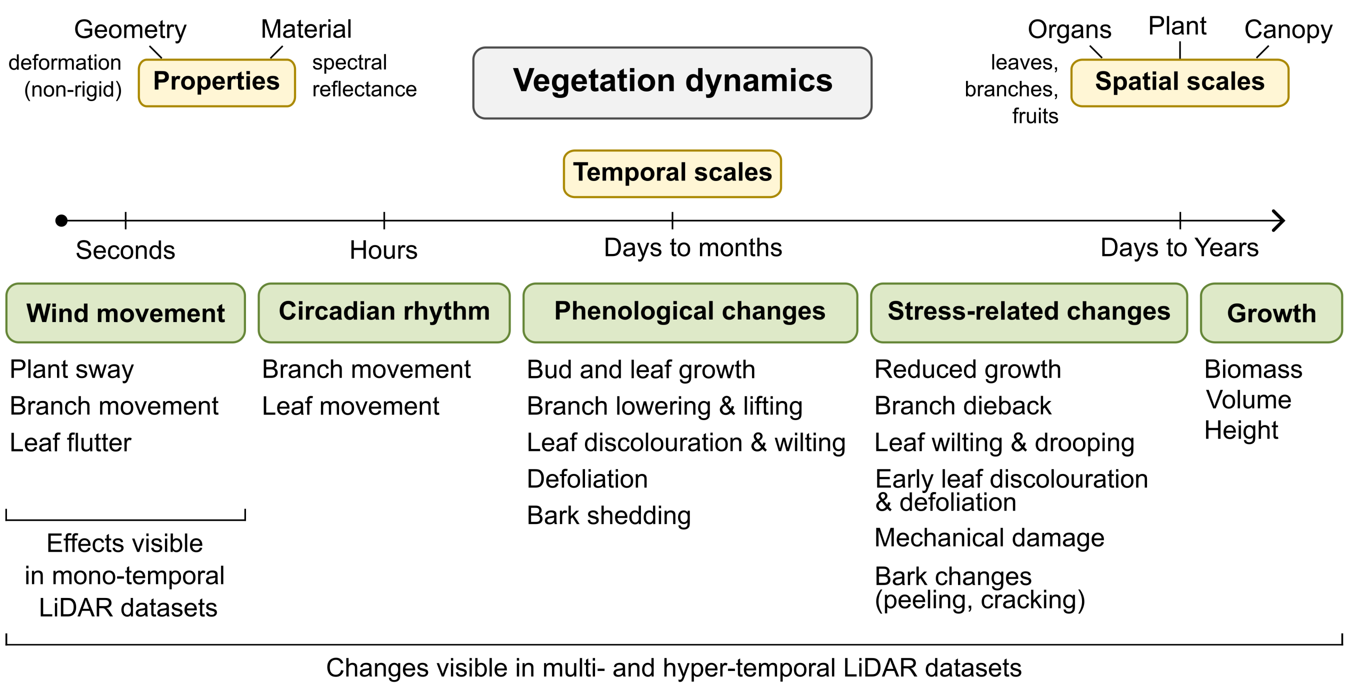

Figure 4: Overview of vegetation dynamics that can be observed with LiDAR and have been described in the literature. Changes can affect geometric and material properties, and often occur simultaneously at overlapping spatial and temporal scales (yellow boxes). Examples of vegetation dynamics are listed, grouped by their drivers and temporal scales (green boxes). Wind-induced motion can affect single acquisitions, whereas dynamics over longer time scales are only visible between epochs.

For most of these vegetation dynamics, reference data is difficult to collect in the real world. This is why we propose the simulation of LiDAR surveys in virtual scenes with defined geometric, material and dynamic properties (VLS-4D) as a complementary approach to generate point clouds with (virtual) 'ground truth'. To ensure fitness for purpose, VLS-4D must be implemented using use case-specific approaches (Sections 2.2 and 3).

2.2 *Scene change logic*

In order to implement the vegetation changes described in Section 2.1, we propose three main concepts and illustrate them with examples (Fig. 5).

2.2.1 *Concept of one static snapshot per epoch*

Monitoring dynamics such as forest growth [*Tompalski et al.*, 2021] or tree phenology [*Wittke et al.*, 2024] requires multi- or hyper-temporal LiDAR datasets, as acquired by repeated Airborne Laser Scanning (ALS) or permanent TLS. These datasets can be simulated using an updated static scene snapshot, assuming that minor changes during individual acquisitions, such as tree movement caused by wind, can be neglected. This can be justified either by the spatial resolution being too low to register such changes or by their magnitude being insignificant relative to the changes between epochs. In this approach, the scene remains unchanged during a single simulation run and the simulation is repeated across different versions of a scene to capture changes over time (Fig. 5a).

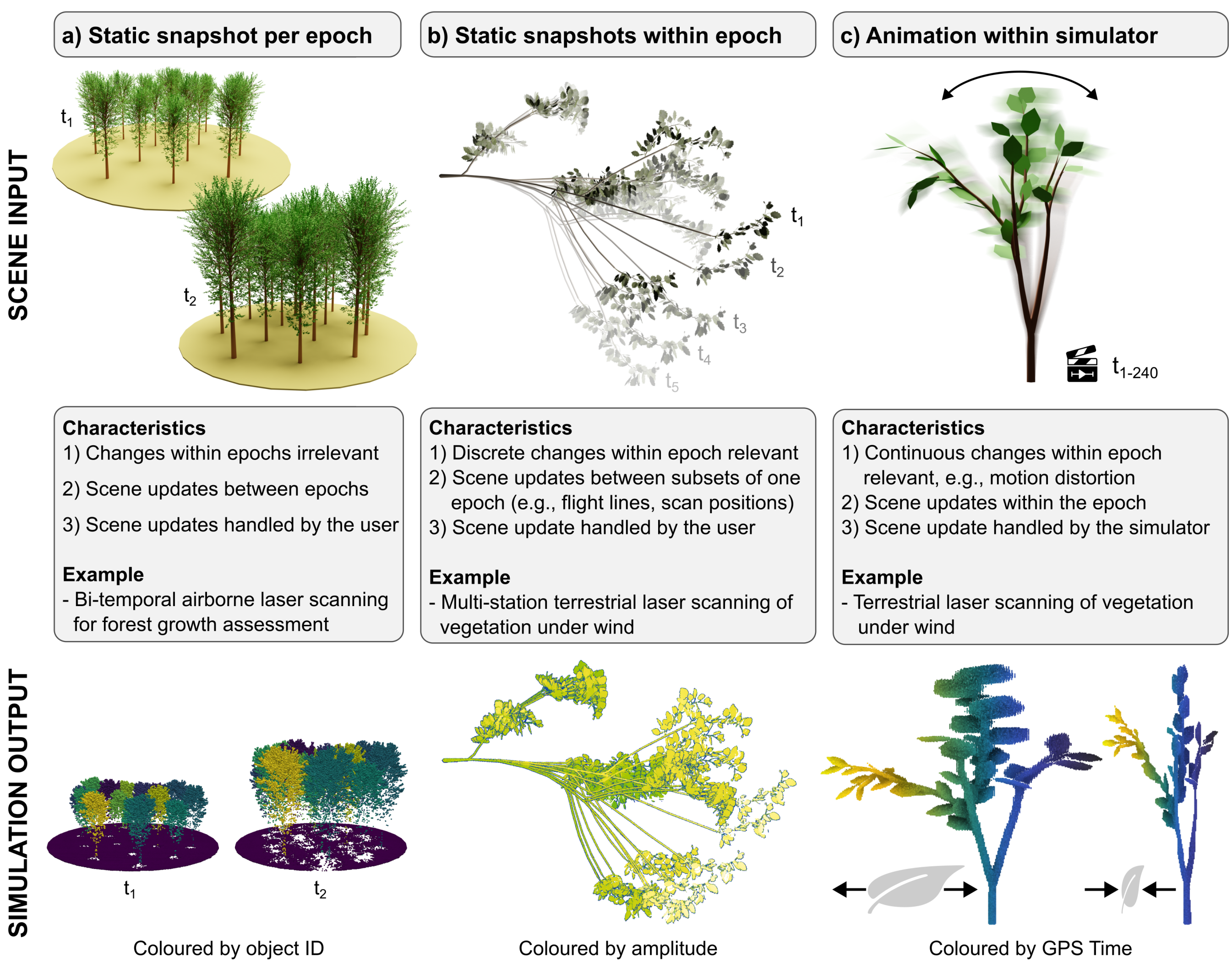

Figure 5: Overview of the three change logic concepts. The first row shows exemplary dynamic input scenes, the second row names the characteristics of each concept and suitable VLS-4D scenarios, and the bottom row shows exemplary VLS-4D point clouds, simulated with HELIOS++ v2.0.2.

2.2.2 Concept of several static snapshots within an epoch

We propose the second concept to study effects from wind-induced vegetation movement between individual flight lines of an ALS campaign or between individual scan positions of a multi-station TLS survey. In this concept, several static scene snapshots are created for one epoch and used to simulate different subsets (i.e., flight lines or scan positions) of a survey.

In the example of multi-station TLS, using an updated scene snapshot for each scan position enables recreating duplication effects, where branches appear in different positions across scans (Figs 2b and 5b). Snapshots may be sampled from a 3D animation of a tree swaying in the wind. With this approach, both windless and wind-affected point clouds can be generated for the same plant, which would require controlled lab experiments in the real world.

2.2.3 Concept of animation within the simulator

The third concept is essential for simulating movement effects within a single scan, such as a branch being displaced by a gust of wind, which leads to point cloud distortions (Figs 2a and 5c). In this case, the virtual scene needs to change continuously during a single simulation run and therefore requires frequent scene updates. This implies that the animation must be integrated into the simulator (Fig. 5c), where the simulation engine manages scene updates automatically based on the definition of the dynamic scene behaviour and the update frequency.

The aforementioned theoretical considerations of scene dynamics in LiDAR simulation require methods for animating vegetation scenes, as well as support for such animations in existing LiDAR simulation software. These aspects will be addressed in the next section.

3 How VLS-4D can be implemented

To perform VLS, you need three fundamental steps: 1) the generation of a 3D scene, 2) the configuration of the scanner, platform behaviour and survey settings, and 3) the execution of the survey (Fig. 3). In VLS-4D, we must either model multiple versions of the scene that represent different points in time or create 3D animations. While repeated surveys with static snapshot scenes can be processed in any LiDAR simulator, some software also explicitly supports dynamic scenes.

In the following, we first give an overview of algorithms for modelling dynamic vegetation (Section 3.1) and then review LiDAR simulation software solutions for vegetation applications and their compatibility with dynamic scenes (Section 3.2).

3.1 Scene generation

We start this section by introducing approaches for automatically generating individual plants. We then present methods for transforming static tree models into animated ones, and finally review approaches for generating entire dynamic ecosystems.

3.1.1 Data-driven and procedural modelling

The two primary approaches for generating virtual plant models for VLS scenes are data-driven and procedural modelling. Data-driven modelling refers to the reconstruction of 3D tree models from real-world data, which allows generating digital copies of trees which exist in the real world. Procedural modelling refers to the (semi)automatic generation of 3D models by means of a procedure or a program [*Smelik et al.*, 2014], enabling the generation of large and structurally diverse datasets.

Table 1: Approaches for 3D modelling of individual trees by reconstruction from 2D or 3D data.

Input	**Output**	**Examples**
Tree point cloud	Voxel model	*Li et al.* [2024]; *Schäfer et al.* [2023]; *Weiser et al.* [2021]
Tree point cloud	Polygonal 3D tree model	AdTree [*Du et al.*, 2019] SimpleForest [*Hackenberg et al.*, 2021] TreeQSM [*Raumonen et al.*, 2013]
Tree image	Polygonal 3D tree model	Deep learning-based [*Li et al.*, 2021a] Image-guided non-parametric tree growing [*Tan et al.*, 2008]

In data-driven modelling, 3D tree models are typically reconstructed from 3D point clouds but also 2D images (Table 1). This approach is the basis for creating digital twins. A key advantage is that dynamics derived from real-world data can be incorporated into the digital model. Using point clouds for reconstruction also allows the assessment of realism by comparing simulated point clouds with their real-world counterparts. Several studies employing static-scene VLS or radiative transfer modelling have utilised tree models created from real-world point cloud data, in the form of cylinder models [*Calders et al.*, 2018; *Esmorís et al.*, 2024; *Stocker et al.*, 2023] or voxel models [*Schäfer et al.*, 2023; *Li et al.*, 2024]. Detailed cylinder models are essential for simulating close-range acquisitions, e.g., TLS, and for applications requiring precise branching structure or individual leaves, such as leaf-wood separation. These models demand high-resolution input data, typically from TLS. In contrast, voxel models are more suitable for ALS and UAV-based Laser Scanning (ULS) simulations. They should be reconstructed from point clouds of much higher resolution or quality than those to be simulated [*Weiser et al.*, 2021; *Winiwarter et al.*, 2022a], but are not limited to TLS data.

The key advantage of procedural modelling is that just a small set of parameters or rules results in a wide variety of complex models, a concept that *Smith* [1984] describes as database amplification. Compared to manual and data-driven modelling, procedural techniques significantly reduce the effort to create realistic virtual environments on larger scales. Table 2 lists tree modelling software based on procedural modelling that have been used in LiDAR simulation studies, specifying their dynamic features, their licence types and selected VLS case studies. Most of the solutions already support dynamics in the form of wind and growth animation, which makes them suitable for VLS-4D workflows.

3.1.2 From static to animated plants

Once a static base scene has been created, manual editing can be effective in creating new versions for VLS-4D scenarios: Branches can be removed from a tree to simulate branch dieback or pruning, or trees can be scaled, removed, or replaced to simulate growth, harvesting, and replanting.

Beyond that, several algorithms have been proposed to automatically convert static triangular meshes into animated models (Table 3). These animated plant models can be created by deriving motion from point cloud sequences and transferring it onto a mesh [*Li et al.*, 2013]. Other approaches aim to generate 'simulation-ready' tree models which, unlike the input polygonal tree model, are semantically segmented and hierarchically organised, enabling deformation through physical simulations of wind or

Table 2: Procedural modelling based tree generation software solutions, their support for wind and growth animation, their licence type and VLS case studies where they have been used.

Software	Wind animation	Growth animation	Licence type	Virtual laser scanning case studies
Arbaro	✗	✗	Free & open source	*Liu et al.* [2019]; *Zhu et al.* [2020]
Sapling Tree Gen	✓	✗	Free & open source	*Albert et al.* [2025]; *Bornand et al.* [2024]
Tree It	✓	✗	Free	*Raverta Capua et al.* [2025]
OnxyTREE	✓	✓	Commercial	*Cai et al.* [2024]; *Jiang et al.* [2021]; *Li et al.* [2021b]
AmapSim	✓	✓	Free	*Lecigne et al.* [2021]
xfrog	✓	✓	Commercial	*Grau et al.* [2017]; *Widlowski et al.* [2015]
TheGrove	✓	✓	Commercial	*Bornand et al.* [2024]
SpeedTree	✓	✓	Commercial	*Wang et al.* [2022]

`https://sourceforge.net/projects/arbaro/`, [*Weber and Penn*, 1995]
`https://docs.blender.org/manual/en/4.1//addons/add_curve/sapling.html`, [*Weber and Penn*, 1995]
`http://www.evolved-software.com/treeit/treeit`
`https://www.onyxtree.com/`
`https://amapstudio.cirad.fr/soft/amapsim/start`, [*Barczi et al.*, 2008]
`https://www.xfrog.com/xfrog-software`, [*Lintermann and Deussen*, 1999]
`https://www.thegrove3d.com/`
`https://store.speedtree.com/`
URLs last accessed: 2025-02-11.

gravity [*Li et al.*, 2013; *Zhao and Barbič*, 2013]. Finally, several studies generate models of developmental stages of trees [*Stava et al.*, 2014; *Pirk et al.*, 2012, 2014; *Zhou et al.*, 2024], which represent tree growth or environmental responses as sequences of static models. The static input 3D models of the approaches in Table 3 may be taken from public tree model libraries, generated using procedural modelling, or reconstructed from real-world data (Section 3.1.1).

Table 3: Examples of algorithms to turn static 3D tree models or 2D sequences into moving or evolving 3D tree models.

Input	Output	Description	Reference
2D video	Animated tree models	Probabilistic generative modelling and motion tracking	*Li et al.* [2011]
Static polygonal tree model and real-world captured growth sequences	Animated plant models	Motion and growth transfer	*Li et al.* [2013]
Static polygonal tree model	Simulation-ready tree models	Hierarchical organ segmentation	*Li et al.* [2013]
Static polygonal tree model	Simulation-ready plant model	Pre-processing (authoring) pipeline	*Zhao and Barbič* [2013]
Static polygonal tree model	Parameters of a procedural model	Inverse procedural model	*Stava et al.* [2014]
Static polygonal tree model	Arbitrary intermediate stages in tree development and animations	Developmental model	*Pirk et al.* [2012]
Static polygonal tree model, parameters of developmental model and parameters of wind emitter	Developmental stages with immediate and long-term wind response	Wind simulation	*Pirk et al.* [2014]
Static polygonal tree models (procedural) for training, and global priors (species, age, gravitropism)	Developmental stages (among others)	Iterative deep learning pipeline	*Zhou et al.* [2024]

3.1.3 From single plants to dynamic ecosystems

The previous approaches have focused on the individual plant level. When we want to perform multi-temporal VLS-4D on the stand level, e.g., for different scenarios of climate warming or silvicultural management, it is essential to simulate ecosystem dynamics and account for factors such as vegetation growth, environmental conditions, and competition. Approaches for this can be drawn from two distinct fields: forestry, which provides empirical or process-based models of forest growth, and computer graphics, which offers algorithms for generating visually realistic, explicit 3D models.

Forest growth models have been widely used for decades as operational tools to support decision making in forestry. These models help estimate forest growth and yield, predict the impacts of management practices, and study forest dynamics [*Porté and Bartelink*, 2002]. FORMIND [*Fischer et al.*, 2016] and TROLL [*Chave*, 1999], two popular individual tree-based forest growth models, both have a LiDAR simulation module implemented, which makes them particularly interesting for VLS-4D (Section 3.2). Building on processes implemented in FORMIND, *Henniger et al.* [2023] presented Forest Factory 2.0, a model to generate virtual dynamic forest stands for different biomes, which was used in several VLS studies for biomass estimation [*Schäfer et al.*, 2024; *Yu et al.*, 2024].

Ecosystem modelling approaches from computer graphics prioritise visual realism and aesthetics. These approaches usually include detailed geometric representations of plants, making them well-suited for direct use in LiDAR simulation. *Deussen et al.* [1998] present a multilevel modelling and rendering pipeline for plant ecosystems based on procedural modelling. Similarly, *Makowski et al.* [2019] present a multi-scale modelling approach to generate ecosystems, which dynamically adapt over time based on developmental traits, terrain characteristics, and climatic conditions. Another notable contribution is the work of *Pałubicki et al.* [2022], which focuses on modelling the climate response of vegetated ecosystems. While the algorithms presented here and in Section 3.1.2 show great potential to generate input for VLS-4D, they are not available as free software for researchers in forestry, ecology, and remote sensing (Section 5).

3.2 LiDAR simulation

The aim of LiDAR simulators used in remote sensing and vegetation research is to accurately model the geometric and radiometric properties of point clouds from survey-grade laser scanners. The input scenes to these simulators have traditionally been static, neglecting vegetation movement and growth. LiDAR simulators developed in other fields already focus on animated scenes as they are used for object detection and tracking tasks, e.g., for autonomous driving [*Gschwandtner et al.*, 2011; *Reitmann et al.*, 2021; *Rott*, 2022]. However, they implement simplified single-return LiDAR models (with zero beam divergence) that do not meet the typical requirements of VLS studies for vegetation. Simulation of multiple returns is important for vegetation applications, as illustrated by the point cloud section shown in Fig. 6. Here, 40% of the returns are intermediate or last returns that would be missing if beam divergence were neglected.

Table 4 lists LiDAR simulators commonly used in applications of remote sensing and vegetation. Regarding the sampling principle, these simulation frameworks fall into three categories: those based on Monte Carlo ray tracing (MCRT), those based on deterministic ray tracing, and those based on a simple probabilistic approach. MCRT relies on the statistical convergence of a large number of simulated rays, allowing it to handle multiple scattering events within the tree crown. This is physically

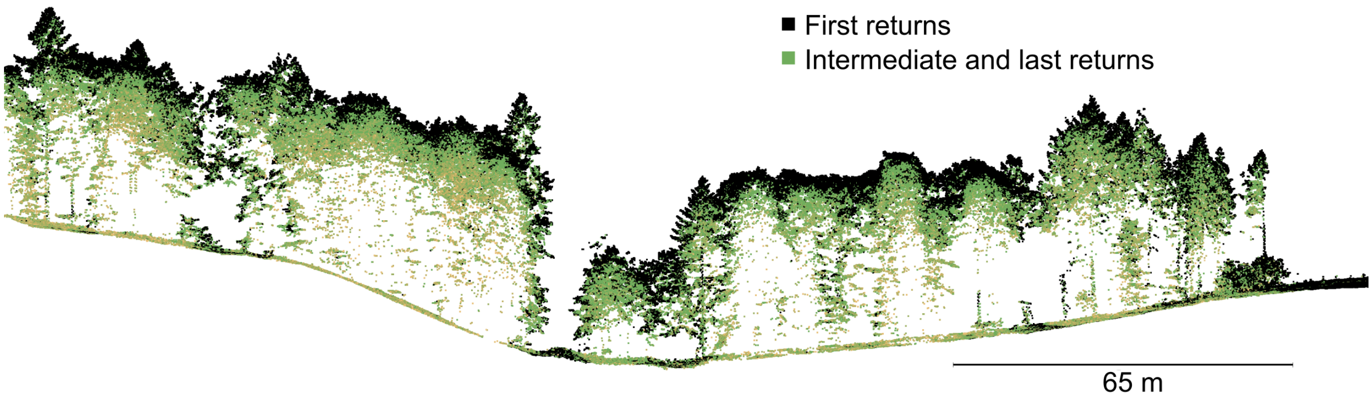

Figure 6: Real-world airborne laser scanning point cloud cross-section coloured by return number (first returns in black). 60% of the points are first returns and 40% are intermediate or last returns.

more accurate, but comes at a higher computational cost than deterministic ray tracing, which assumes that light is reflected only once before reaching the sensor [*Disney et al.*, 2000; *Gastellu-Etchegorry et al.*, 2016]. Deterministic ray tracing is usually sufficient if geometric point cloud features are of primary interest. MCRT-based LiDAR simulators of radiative transfer models are recommended for studies where radiometric and full-waveform (FWF) information are required (e.g., to support species classification from FWF ALS data; *Koenig and Höfle*, 2016) or where atmospheric effects should be considered (e.g., spaceborne LiDAR). Radiative transfer models like DART are used to simulate a wider range of remote sensing products, enabling the simulation of LiDAR point clouds and complementary satellite imagery of the same scene.

The simulators in Table 4 support two types of vegetation scenes: i) explicit 3D geometry and ii) primitives filled with turbid medium. Explicit geometry is represented as polygonal meshes with individual branches and leaves (cf. Section 3.1). Such representations are needed for simulating high-resolution acquisitions and have been used for studies on leaf-wood separation [*Vicari et al.*, 2019] or plant movement [*Wang et al.*, 2022]. Different optical properties, e.g., for the bark and the leaves, can be defined through material settings. Turbid medium approaches are used for simulations of lower resolution, i.e., airborne and spaceborne LiDAR. They use simplified crown shapes and/or voxelised representations. A turbid medium is a statistical representation of matter, commonly used to simulate fluids and foliage [*Gastellu-Etchegorry et al.*, 2015]. In radiative transfer models, the turbid medium of tree crowns is characterised by the structural parameters leaf area density and leaf angle distribution and the optical parameters transmittance and reflectance [*Gastellu-Etchegorry et al.*, 2016; *North*, 1996]. The turbid medium assumption is also the basis for the simple LiDAR sampling approach used by the forest growth models FORMIND and TROLL, which calculates probabilities for LiDAR returns in the medium based on the Beer-Lambert law [*Knapp et al.*, 2018; *Schmitt et al.*, 2023].

Vegetation dynamics of larger scale, such as tree growth, can be represented with both explicit geometry and turbid medium approaches. For turbid medium representations, multi-temporal virtual scenes can be parametrised by adjusting properties like leaf area density and reflectance [*Koetz et al.*, 2005], as well as scaling the bounding volumes of the medium. The turbid medium-based LiDAR simulators of FORMIND and TROLL can automatically generate a point cloud for each time step of the forest growth model, enabling the synthetisation of VLS time series of long-term forest dynamics. Fine-scale tree movement - such as branch lifting and lowering, tree sway and leaf flutter - are better represented by explicitly modelling individual branches and

Table 4: Overview of commonly used LiDAR simulation software in remote sensing and forest studies. The table details the sampling principle (RT = ray tracing), simulation of beam divergence and full waveforms (FWF), the possible scene object representations, and the supported scene dynamics. It is organised such that LiDAR simulators with similar features are grouped together, facilitating comparison between them.

Name	**Sampling principle**	**Beam div. & FWF**	**Scene object representation**	**Scene dynamics**	**References**
FLIGHT	Monte Carlo RT	✓	Turbid medium	✗	*North* [1996]; *North et al.* [2010]
librat	Monte Carlo RT	✓	Explicit geometry, turbid medium	✗	*Lewis* [1999]
DART LiDAR	Quasi-Monte Carlo RT	✓	Explicit geometry, turbid medium	✗	*Gastellu-Etchegorry et al.* [2015, 2016]
LESS LiDAR	Deterministic RT	✓	Explicit geometry	✗	*Qi et al.* [2019]; *Luo et al.* [2023]
HELIOS++	Deterministic RT	✓	Explicit geometry, turbid medium	Rigid motions	*Winiwarter et al.* [2022b]
FORMIND LiDAR	Simple probabilistic approach based on Beer-Lambert law	✗	Turbid medium	Forest growth	*Knapp et al.* [2018]
TROLL LiDAR	Simple probabilistic approach based on Beer-Lambert law	✗	Turbid medium	Forest growth	*Schmitt et al.* [2023]

https://flight-rtm.github.io/index.html
https://github.com/profLewis/librat
https://dart.omp.eu/#/
http://lessrt.org/
https://github.com/3dgeo-heidelberg/helios
https://formind.org/
https://github.com/TROLL-code/TROLL, https://github.com/sylvainschmitt/rcontroll
URLs last accessed: 2025-02-11.

leaves. These detailed scenes can then be animated to simulate dynamics within a single simulation (Section 2.2.3). While all LiDAR simulators in Table 4 can be used in the VLS-4D concepts of static snapshots (Section 2.2), only HELIOS++ explicitly supports object dynamics during a single scan, but only rigid motions (as of version 2.0). For VLS-4D of vegetation, we can learn from other established LiDAR simulation tools that incorporate dynamic scene capabilities, such as those built into 3D modelling and robotics software (Section 5).

4 Where VLS-4D can make an impact: Applications in vegetation monitoring

In this section, we review previous studies using VLS-4D, extending beyond ecological applications, and propose further research directions for vegetation monitoring. We group the applications into three main methodological categories:

1. Investigating effects from LiDAR data acquisition and vegetation movement
2. Developing and evaluating new methods for vegetation change detection and analysis
3. Generating training and test data for supervised machine learning

4.1 LiDAR data acquisition and vegetation movement effects

Wind-induced vegetation movement can have a significant effect on LiDAR point clouds. This has been reported as a quality issue not only in TLS data [*Liang et al.*, 2022; *Vaaja et al.*, 2016], but also for strip alignment in ALS and ULS data [*Sun et al.*, 2023].

VLS serves as a valuable tool for investigating how the laser beam interacts with the scene and how vegetation is represented in the LiDAR point clouds, depending on the acquisition settings and vegetation dynamics. Unlike in real-world experiments, individual effects can be isolated and controlled, and reference data on the objects and their dynamics is available.

VLS-4D can help to better understand the distortion and duplication effects that can be observed in single-epoch TLS point clouds (Fig. 2; *Medic et al.*, 2023). *Weiser* [2024] and *Albert et al.* [2025] investigated how wind-induced tree movement during multi-station TLS affects the accuracy of point cloud-derived metrics and the performance of ML-based leaf-wood classification. They generated wind-affected simulated point clouds by virtually scanning an updated version of a tree from each position. This knowledge of wind effects can be used to develop algorithms to correct for such motion effects or to quantify and interpret motion to better understand plant dynamics (*Medic et al.*, 2023; Sections 4.2 and 4.3). Assessing the effects of vegetation movement on point cloud occlusion could be another research direction for VLS-4D.

Researchers can leverage VLS-4D to optimise data acquisition strategies. Using static scenes, *Li et al.* [2021b] have developed an iterative-mode scan design based on LiDAR simulation of virtual forest plots of different structure and complexity. Their proposed scan design aims to minimise occlusion effects and resulting errors in tree parameters. Such analysis could be extended to forest plots with tree sway, to optimise the acquisition design not only for completeness of coverage but also for mitigation of wind effects. For a geomorphological application, *Winiwarter et al.* [2022a] performed VLS-4D to investigate the detectability of rill erosion in ALS point cloud time series acquired at different flight altitudes. A similar study design could be adapted to forest mensuration. VLS-4D could also be used to find optimal LiDAR acquisition intervals to pinpoint the timing of leaf emergence and senescence, to study how these phenological events are affected by climate warming.

Simulation can also be used to experiment with sensors, and even allows implementing hypothetical specifications that sensors on the current market do not support. Using LESS [*Luo et al.*, 2023], *Zhao et al.* [2023] conducted a simulation study to assess the suitability of a prototype airborne hyperspectral LiDAR sensor for monitoring forest insect and disease stress. Their scenarios included different stages and locations of leaf damage, expressed by leaf spectra measured from real leaves at different levels of damage.

4.2 Method development for change detection and analysis

VLS-4D is a valuable tool for validating change analysis and change detection methods as it provides virtual 'ground truth' data on the states of the scene objects at each epoch. As demonstrated in previous static scenario VLS case studies, it is considered best practice to evaluate the performance of a novel method on both synthetic and real data (e.g., *Liu et al.*, 2022; *Vicari et al.*, 2019; *Wu et al.*, 2021). Synthetic data, with its inherent reference data, enables quantitative evaluation across arbitrary scenarios but suffers from a sim-to-real domain gap. Real-world data is therefore essential to confirm effectiveness, though evaluations are often limited to small datasets, specific scenarios, or qualitative assessments.

Recognising wind-induced plant movement as a source of uncertainty or error in point cloud measurements (Section 4.1), methods are needed to reliably mitigate wind effects. For the case of duplication of plant organs (Fig. 2b), this can be achieved with additional non-rigid registration [*Medic et al.*, 2023; *Wang et al.*, 2022] after conventional rigid point cloud registration. Non-rigid registration aims to align multiple point clouds while accounting for changes in plant shape. *Wang et al.* [2022] employed bi-temporal VLS to validate PlantMove, a tool for quantifying plant movement via coarse-to-fine non-rigid point cloud registration. They used a SpeedTree-generated tree model and created two static representations - before and after applying a non-linear transformation function. These were then scanned in two epochs, and the PlantMove motion fields compared with the known simulated motion fields. *Wang et al.* [2022] also demonstrated their method on real-world datasets, for which they however lacked accurate and full-coverage reference displacement values.

VLS-4D can also generate time series of sequential point clouds, which can be used to develop algorithms for change analysis [*Winiwarter et al.*, 2022a]. As introduced in Section 1 (Fig. 1), monitoring plant growth and health can often be complicated by the use of different sensor systems and acquisition setups over time. Here, VLS-4D provides the option to perform multi-temporal LiDAR simulations from different sensors and to include not only changes of interest (e.g., tree growth), but also other changes (e.g., wind movement, seasonal changes). This enables the development of methods that are targeted at specific changes and robust to change noise and inconsistent measurement scenarios. Future methods developed with the support of VLS-4D may even be able to disentangle signals from different change processes, e.g., wind sway and tree growth.

4.3 Training data generation

There are two main motivations for generating training data using VLS-4D. First, VLS-4D generates sequential data that is essential for change-related tasks, such as change detection, object tracking, or scan registration. Second, VLS-4D can be used to create so much variability in the simulated training data that the model can generalise to real-world data, a concept known as domain randomisation [*Tobin et al.*, 2017].

Simulated LiDAR training data has been exploited for various ML and deep learning (DL) applications in forestry and ecology such as tree instance segmentation [*Wang*, 2020; *Liu et al.*, 2025], semantic segmentation [*Cai et al.*, 2024; *Wang*, 2020; *Esmorís et al.*, 2024; *Liu et al.*, 2025; *Stocker et al.*, 2023] or biomass estimation [*Schäfer et al.*, 2024], but these studies have only used static scenarios. In other domains, VLS-4D training data have already been used successfully for change analysis. *de Gélis et al.* [2023] and *Zahs et al.* [2023] used bi-temporal VLS-4D training data for urban change analysis and building damage assessment, respectively. *de Gélis et al.* [2023] show that pre-training with their simulated point cloud dataset significantly reduces the amount of labelled data samples needed in the fine-tuning step on real data. In computer vision, sequential point cloud datasets have been simulated from animations of humanoids and animals [*Huang et al.*, 2023; *Li and Harada*, 2022]. These VLS-4D datasets are used to train and validate DL methods for non-rigid point cloud registration (Section 4.2). Such existing methods may be directly applied to multi-station TLS point clouds with vegetation wind effects, allowing windless representations to be computed. However, fine-tuning with targeted and domain-specific VLS-4D training and validation data of moving plants might further improve the results [*Medic et al.*, 2023] and we see this as a future research direction.

Knapp et al. [2018] used VLS-4D in conjunction with the forest growth model FORMIND to simulate a wide range of successional stages of a tropical rainforest under different disturbance regimes. This generated large amounts of simulated LiDAR data with corresponding inventory data. By further varying LiDAR acquisition settings, the approach could serve as domain randomisation, enabling effective training of DL-based biomass models. Virtual LiDAR time series based on forest growth models could also be employed to train models for quantifying forest succession, growth, and the impacts of disturbances. Models for assessing forest pests and diseases benefit from the combination of LiDAR metrics and hyperspectral metrics as predictors [*Stone* *and Mohammed*, 2017]. Hybrid (point cloud and image) multi-temporal datasets (e.g., *Zhao et al.*, 2023) can be generated by radiative transfer models such as DART or LESS, which can simulate both LiDAR data and multi- and hyperspectral imagery of the same synthetic scenes.

In general, there is still little literature on Artificial Intelligence (AI) for change detection at the point level [*de Gélis et al.*, 2024] and even less so for vegetation change detection. Reasons for this include a) the lack of open multi-temporal point clouds datasets and b) the difficulty of relating multi-temporal point cloud features to change signals due to the lack of reference data. With the current developments in sensing systems and AI, we expect more algorithms to be developed in the near future. Here, VLS-4D can be a means of accelerating methodological progress, complementing real-world benchmark datasets. VLS-4D can significantly enhance the volume, diversity and labelling quality of point cloud training datasets for vegetation change analysis, while also speeding up data provisioning.

5 Open Challenges

5.1 Closing the implementation gap of VLS-4D of vegetation

To date, there are only a few studies using VLS-4D to investigate vegetation dynamics [*Wang et al.*, 2022; *Albert et al.*, 2025] or other environmental processes. Besides the aspect of realism (Section 5.2), this is due to the limited accessibility of automated algorithms for dynamic scene generation and the limitations of current LiDAR simulation frameworks.

Regarding dynamic scene generation, we found that the software that can animate tree movement and growth with high geometric and dynamic realism is primarily commercial (Table 2). In addition to the potentially prohibitive cost of acquiring the software, software licences may also prohibit the sharing of generated 3D models and animations, which is contrary to many of the open data efforts currently practiced in the forestry community (e.g., *Ouaknine et al.*, 2025; *Puliti et al.*, 2025). In the fields of computer graphics, simulation, and animation, many technical solutions for creating dynamic vegetation scenes already exist, using real-data or procedural models, and from individual plants to entire ecosystems (Section 3.1). However, these methods are often not freely available. The remote sensing community would benefit from greater accessibility in the form of open-source software to reduce the effort required to create dynamic scenes.

Regarding simulation frameworks, there is currently no solution that combines sophisticated and realistic laser beam modelling (i.e., beam divergence, full waveforms) with support for arbitrary animations within the simulator (Section 3.2). In VLS-4D frameworks integrated with 3D modelling or robotics software, complex animations (e.g., skeleton animation and physics-based simulation) are possible, but scan patterns, LiDAR intensity computations and noise models are simplified, and beam divergence is completely neglected, which is problematic for vegetation applications. Nevertheless, these frameworks can serve as valuable templates and facilitate the further development of vegetation-oriented LiDAR simulators through knowledge and technology transfer.

5.2 Assessing and enhancing realism

The biggest challenge in VLS-4D remains the same as for VLS of static scenes: the reality gap between real and simulated data. On the one hand, VLS-4D can be a means to close this gap, since in many cases, neglecting scene dynamics results in unrealistic simplification of real scenes. On the other hand, VLS-4D adds additional complexity to VLS by including the temporal dimension. In addition to conventional VLS components - such as scene geometries, material properties, scan patterns, beam divergence, multiple returns, and sensor noise - VLS-4D requires realistic modelling of the type, speed and resolution of scene dynamics. If the dynamics are not modelled in a suitable way, VLS-4D point clouds may be even less realistic than their conventional VLS-3D counterparts. Further work is required to develop approaches and metrics for thoroughly analysing the realism and fitness for purpose of the simulated data (e.g. *Manivasagam et al.*, 2023). This highlights the need for accessible algorithms to generate animated models of real-world plants, enabling direct comparisons between real and simulated point clouds under controlled conditions. Such analyses can then identify the most effective adjustments to enhance the realism of simulations.

Several ML and DL studies have shown that there is a consistent performance gap between models trained on real data and models trained on simulated VLS data alone [*Liu et al.*, 2025; *Schäfer et al.*, 2023]. Considering this reality gap, we recommend the use of labelled simulated training data in three key ways: (1) in hybrid models trained on a small set of real data complemented by large amounts of simulated data [*de Melo et al.*, 2022; *Liu et al.*, 2025], (2) for pre-training DL models, which are later fine-tuned on real-world data [*Liu et al.*, 2025], and (3) by applying domain adaptation techniques [*Bryson et al.*, 2024; *de Melo et al.*, 2022].

Since the dynamics implemented in digital twins for VLS-4D shall closely resemble the real-world dynamics, good knowledge of vegetation processes is essential to ensure sufficient realism. To parametrise virtual scenes, VLS-4D benefits from basic research on vegetation dynamics, including tree phenology and tree sway, as quantified using numerical simulations [*Zanotto et al.*, 2024], complementary sensors such as accelerometers and strain gauges [*Jackson et al.*, 2021; *Jaeger et al.*, 2022] or cameras [*Gibbs et al.*, 2019; *Kattenborn et al.*, 2022].

6 Conclusion

Vegetation dynamics clearly affect mono- and multi-temporal LiDAR representations. The integration of vegetation dynamics into VLS therefore has significant potential to advance LiDAR-based vegetation monitoring, particularly in the context of multi-temporal and multi-sensor data analysis and the growing need for labelled training data for DL approaches. Our review highlights three key areas where VLS-4D can make a difference: (1) investigating LiDAR data acquisition and vegeation movement effects, (2) supporting the development of new methods for vegetation change analysis, and (3) generating training data for DL. Applications for VLS-4D can be primarily found in the study of vegetation movement and point cloud quality, the optimisation of data acquisition, and the monitoring of vegetation growth and health.

The concept of approximating dynamic scenes as a series of static representations is fully compatible with the current state-of-the-art high-fidelity LiDAR simulators used in forestry. In contrast, the direct support of animated virtual scenes remains an area for future innovation. To fully realize the potential of VLS-4D, increased availability of open-source tools to generate realistic large-scale dynamic vegetation scenes will be crucial.

VLS-4D will be a transformative tool for vegetation research, serving training data generation and method validation where real data is scarce or suitable reference measurements cannot be obtained. If fitness for purpose is ensured, this framework promises to improve our understanding of LiDAR representations of dynamic vegetation and to support more effective environmental monitoring and management.

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Fig. 3 shows a scene rendered in Blender with an airplane model CC-BY Emmanuel Beranger, a house model by free3d.com user `gerald3d`, and a drone model by cgtrader.com user `CGaxr`.

Conflict of interest

The authors declare no conflict of interest in relation to this paper.

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