Ecological Indicators 169 (2024) 112970

Contents lists available at ScienceDirect

Ecological Indicators

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

Original Articles

Towards consistently measuring and monitoring habitat condition with airborne laser scanning and unmanned aerial vehicles

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ARTICLE INFO

Keywords:
Biodiversity monitoring
Conservation management
Deep learning
Drone remote sensing
Geospatial data
Photogrammetry pipeline
Vegetation mapping

ABSTRACT

Indicators of habitat condition are essential for tracking conservation progress, but measuring biotic, abiotic and landscape characteristics at fine resolution over large spatial extents remains challenging. In this *viewpoint* article, we provide a comprehensive synthesis of the challenges and solutions for consistently measuring and monitoring habitat condition with remote sensing using airborne Light Detection and Ranging (LiDAR) and affordable Unmanned Aerial Vehicles (UAVs) over multiple sites and transnational or continental extents. Key challenges include variability in sensor characteristics and survey designs, non-transparent pre-processing workflows, heterogeneous and complex data, issues with the robustness of metrics and indices, limited model generalizability and transferability across sites, and difficulties in handling big data, such as managing large volumes and utilizing parallel or distributed computing. We suggest that a collaborative cloud virtual research environment (VRE) for habitat condition research and monitoring could provide solutions, including tools for data discovery, access, and data standardization, as well as geospatial processing workflows for airborne LiDAR and UAV data. A VRE would also improve data management, metadata standardization, workflow reproducibility, and transferability of structure-from-motion algorithms and machine learning models such as random forests and convolutional neural networks. Along with best practices for data collection and adopting FAIR (findability, accessibility, interoperability, reusability) principles and open science practices, a VRE could enable more consistent and transparent data processing and metric retrieval, e.g., for Natura 2000 habitats. Ultimately, these improvements would support the development of more reliable habitat condition indicators, helping prevent habitat degradation and promoting the sustainable use of natural resources.

1. Introduction

Habitat condition can be measured by quantifying the biotic, abiotic and landscape characteristics of an ecosystem (Turner and Gardner, 2015). A good habitat condition allows species to meet their needs for resources, shelter, and successful reproduction and promotes the conservation of habitats with their wild fauna and flora, including the diversity, distribution and abundance of a variety of animals, plants and other organisms (Moeslund et al., 2019; Nagendra et al., 2013; Tews et al., 2004; Turner and Gardner, 2015). Indicators of habitat condition can be derived from measurements of vegetation structure, cover and composition (Lorimer, 2024; Magee et al., 2019), topography (Assmann et al., 2022; Davies and Asner, 2014; Moeslund et al., 2013), microclimate (Zellweger et al., 2019), soil heterogeneity (Guerra et al., 2021), hydrology (Rolls et al., 2018), biotic resources such as deadwood (Seibold et al., 2015), dung, litter, carcasses and flower abundance (Brunbjerg et al., 2017; Sookhan et al., 2024), and landscape elements such as hedgerows, tree lines, stonewalls and flower strips (Albrecht et al., 2021; Broughton et al., 2021). Habitat extent and condition continue to decline at alarming rates, facing deteriorating trends from changes in land use, eutrophication, unsustainable management practices and other human-induced pressures, which contributes substantially to the ongoing loss of biodiversity (Díaz et al., 2019). While some habitats show improvements, progress is generally not sufficient to meet conservation targets and policy goals (European Environment Agency, 2020; Leclère et al., 2020; Moersberger et al., 2024). Effective

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https://doi.org/10.1016/j.ecolind.2024.112970
Received 20 September 2024; Received in revised form 20 November 2024; Accepted 5 December 2024
Available online 10 December 2024

monitoring is therefore key to capture these trends and inform restoration and conservation programs (Dalton et al., 2023).

Remote sensing provides a promising tool for habitat monitoring (Vanden Borre et al., 2011). In the context of global biodiversity change, habitat measurements derived from satellite data offer synoptic (regional to near-global) coverage with pre-defined temporal lags (Skidmore et al., 2021). Openly accessible satellite remote sensing data are therefore widely used to map the spatial extent and fragmentation of habitats and vegetation types (Skidmore et al., 2021), but they are less able to provide information on changes in habitat condition and fine-scale habitat disturbances (Nagendra et al., 2013). Open-access airborne Light Detection and Ranging (LiDAR) data and imagery from affordable Unmanned Aerial Vehicles (UAVs) are increasingly becoming available (Stankov et al., 2019; Stereńczak et al., 2020), offering an additional source of spatially-explicit data for area-based conservation and land management. For instance, LiDAR point clouds collected with crewed aircraft through (sub)national airborne laser scanning (ALS) surveys can be used to derive various biotic, abiotic, and landscape-level characteristics (Table 1). Similarly, site-level flight campaigns with UAVs or small fixed-wing aircraft offer an increasing range of spatially detailed observations (Dronova et al., 2021; Zhang and Zhu, 2023; Zlinszky et al., 2015), including multispectral, hyperspectral and thermal imaging as well as LiDAR point clouds. The most affordable and cost-effective UAVs record imagery in the Red, Green and Blue (RGB) and Near-Infrared (NIR) spectrum at mm to cm resolution, enabling the mapping of specific plant species, vegetation structure, and abiotic characteristics (Table 1). Examples of habitat condition derived from LiDAR point clouds and affordable UAVs include measurements of vertical vegetation structure, tree species composition, deadwood, linear landscape elements such as hedges and stonewalls, invasive plants, woody encroachment, and plant biomass (Fig. 1). While these technologies and sensor systems have the potential to transform site-based habitat assessments, the lack of harmonized and standardized approaches currently limits their consistent repeat use over large spatial extents, e.g. for multi-site, transnational and continental-scale monitoring programs (Dronova et al., 2021; Koontz et al., 2022; Vanden Borre et al., 2011).

Table 1
Examples of quantifying habitat condition with Light Detection and Ranging (LiDAR) point clouds and Unmanned Aerial Vehicle (UAV) imagery.

Habitat condition	Examples	References
LiDAR point clouds		
Biotic characteristics	Canopy height and cover, vertical and horizontal variability of vegetation, understory density, forest biomass, tree stem diameters	Bakx et al. (2019); Davies and Asner (2014); Koma et al. (2021a), Wieser et al. (2017)
Abiotic characteristics	Soil moisture, hydrology, wetness, elevation, aspect, slope, terrain texture	Assmann et al. (2022); Davies and Asner (2014); Moeslund et al. (2013); Zlinszky et al. (2015)
Landscape characteristics	Hedges & tree lines, stonewalls, tree inventories, amount of deadwood, open vegetation patches, edge extent	de Vries et al. (2021); Duan et al. (2017); Graham et al. (2019); Lucas et al. (2019); Marchi et al. (2018); Martinuzzi et al. (2009); Suh and Ouimet (2023); Wang et al. (2018)
UAV imagery		
Plant species mapping	Invasive, rare, or protected species	Bakacsy et al. (2023); Hill et al. (2017); James and Bradshaw (2020); Oldeland et al. (2021); Zhang et al. (2020)
Biotic characteristics	Understory biomass, woody plant distribution and biomass, vegetation height, woody encroachment, scrub vegetation cover	Cunliffe et al. (2016); Gonçalves et al. (2016); Olariu et al. (2022); van Iersel et al. (2018); Jordan et al. (2024)
Abiotic characteristics	Bare ground, micro-topography, soil moisture and wetness	Barnas et al. (2019); Eischeid et al. (2021); Ikkala et al. (2022); Lendzioch et al. (2021)

In this *viewpoint* article, we provide a perspective on how to advance habitat condition research and monitoring with ALS surveys and UAVs. We first synthesize the challenges and potential solutions for consistently measuring habitat condition with LiDAR point clouds and UAV imagery across multiple sites and transnational or continental extents. We then outline how a cloud-based virtual research environment (VRE) could advance the consistent monitoring of habitat condition, e.g., by providing the necessary services for data management and metadata standardization and by enhancing the reproducibility of geospatial processing workflows and the transferability of models. Throughout our *viewpoint*, we emphasize the FAIR (Findability, Accessibility, Interoperability, and Reusability) guiding principles (Wilkinson et al., 2016) and focus on the condition monitoring of natural and semi-natural habitats. We illustrate this with examples from the EU Natura 2000 network of protected areas (European Commission Directorate-General for Environment et al., 2008), but also include examples from non-European studies (e.g., North America, China, Brazil, and Australia). The European Natura 2000 network contains around 25,000 sites across the EU's member states and supports endangered, vulnerable, rare, endemic and indicator animal and plant species across Europe. While the EU member states regularly report the conservation status for habitats and species with an emphasis on Natura 2000 sites, the methods for habitat monitoring and reporting vary widely among EU member states, often with a poor data quality, little harmonization and a lack of accessible data (Ellwanger et al., 2018; Moersberger et al., 2024; Pereira et al., 2022).

2. Materials and methods

Our synthesis of challenges for consistently measuring habitat condition is based on our experience and expertise with processing LiDAR point clouds and UAV imagery, especially in the context of ecology, biodiversity research, habitat monitoring, and software and workflow development. It should be considered as a *viewpoint* of the authors, rather than a structured review. An early manuscript draft was compiled as a deliverable for the MAMBO project ('Modern Approaches to the Monitoring of BiOdiversity') funded by the European Commission (Høye et al., 2023) in which the author team is responsible for developing workflows delivering consistent and standardized habitat condition metrics from airborne LiDAR or drone imagery for site-specific (e.g. Natura 2000) EU habitat monitoring. We first developed an outline in which the key challenges for consistently measuring habitat condition metrics were identified, centring around six major topics: lack of standardized survey reporting, findability and accessibility of raw data, interoperability and reusability of data, software and data processing, availability of computational resources, and robustness and transferability of metric calculations. We then synthesized the ideas and information into the following sub-sections: (1) variation in sensor characteristics and flight surveys, (2) transparency of pre-processing, (3) heterogeneity and complexity of data, (4) robustness of metric calculations, (5) generalizability and transferability of models, and (6) big data computing. Our synthesis was complemented by reviews on UAVs (Barbieri et al., 2023; Dronova et al., 2021; Singh and Frazier, 2018; Singh et al., 2024; Wyngaard et al., 2019; Zhang and Zhu, 2023), deep learning (Diab et al., 2022; Reichstein et al., 2019; Yun et al., 2024), LiDAR applications in animal ecology and forestry (Bakx et al., 2019; Balestra et al., 2024; Davies and Asner, 2014; Hyyppä et al., 2008), deadwood assessments (Marchi et al., 2018; Seibold et al., 2015), Natura 2000 habitat monitoring (Vanden Borre et al., 2011), and upscaling methods (Ge et al., 2019). We also consulted technical papers on ALS technology (Baltsavias, 1999; Wehr and Lohr, 1999), geospatial data

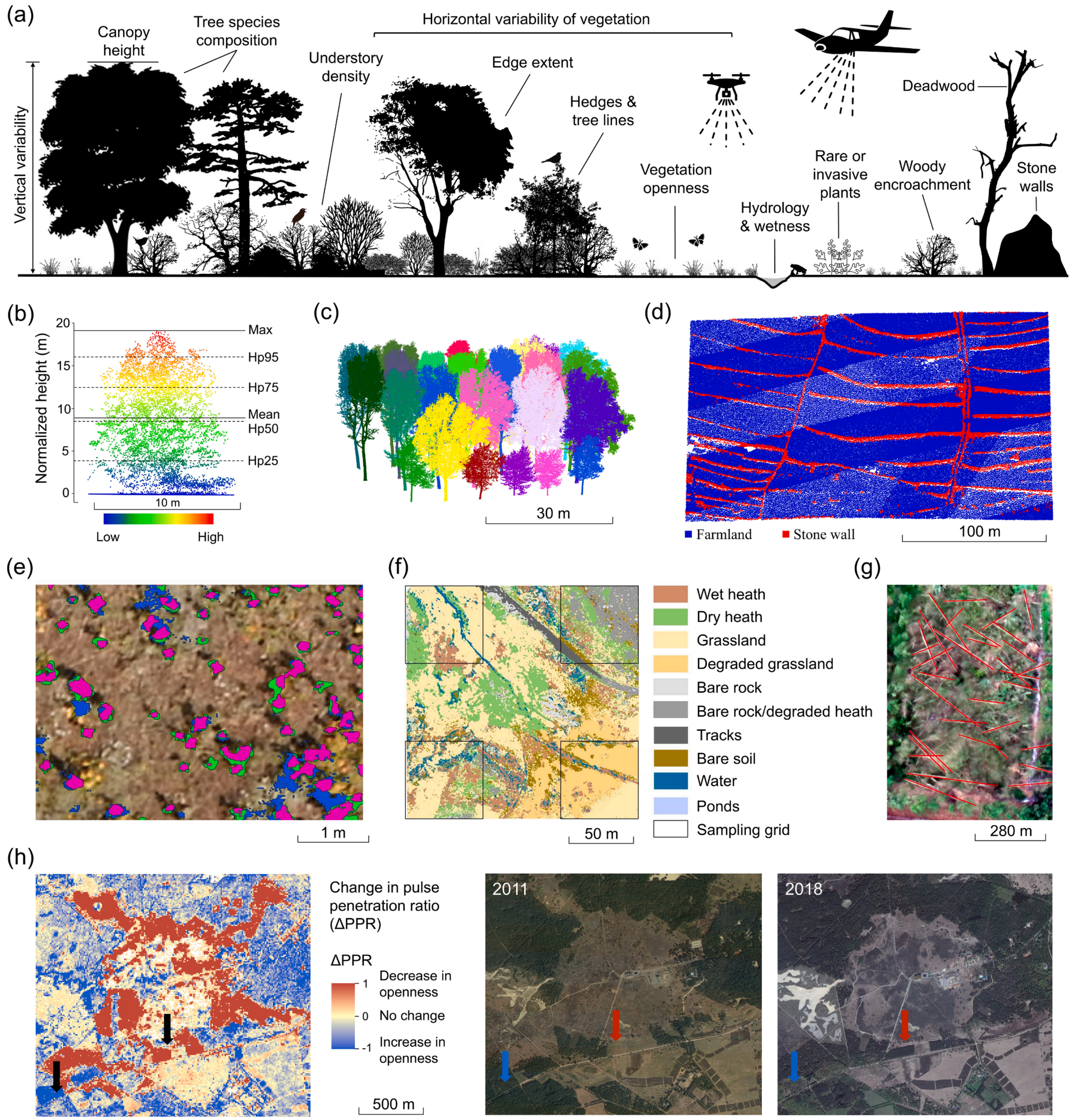

Fig. 1. Measuring and monitoring habitat condition with imagery and LiDAR point clouds obtained from UAVs and crewed aircraft, including examples from European Natura 2000 sites. (a) General examples of characterising habitat condition (see Table 1 for relevant references). (b) Measurements of vegetation height from point clouds. For metric calculations see Meijer et al. (2020), Kissling et al. (2022), and Kissling et al. (2023). (c) 3D mapping and segmentation of individual trees in point clouds of woodland habitats (Natura 2000 habitat code N26). For methodology see Wang et al. (2018). (d) Linear landscape elements such as stonewalls in agricultural habitats of Malta (Natura 2000 habitat code N27) mapped from LiDAR point clouds (35.870960 N, 14.569285 E). For methodological examples see Lucas et al. (2019), Graham et al. (2019) and Suh and Ouimet (2023). (e) Invasive plant species mapping with UAV imagery in the Pannonic sand steppes of Hungary (Natura 2000 habitat code 6260). Purple = true positive, green = false negative, and blue = false positive areas. See Bakacsy et al. (2023). (f) Mapping habitat condition and degradation through woody encroachment using UAV imagery in *Nardus* grasslands (Natura 2000 habitat code 6230) and Atlantic wet heathlands (Natura 2000 habitat code 4020). See Gonçalves et al. (2016). (g) Deadwood mapping by extracting windthrown trees from UAV images. See Duan et al. (2017). (h) Monitoring changes in vegetation openness in the nature reserve 'De Veluwe' (Natura 2000 site code NL9801023) composed of heath and scrub (Natura 2000 habitat code N08) and coniferous and mixed woodlands (Natura 2000 habitat codes N17 and N19). Shown are differences over two time periods (delta, Δ) in the pulse penetration ratio (PPR) from two country-wide airborne LiDAR point clouds (Wang et al., 2022). Red indicates decreasing openness (e.g., denser vegetation through re-growth or plantation) whereas blue shows increasing openness (e.g., tree cutting). Two examples are visually indicated with arrows in satellite images from Google Maps.

processing (Deibe et al., 2020; Kissling et al., 2022), open source LiDAR and UAV software (Coetzee et al., 2020; Meijer et al., 2020; Pereyra Irujo et al., 2023; Pirotti, 2019; Roussel et al., 2020), metadata catalogues (Schindler et al., 2023; Zhao et al., 2021b), and reproducible workflows (Hardisty et al., 2019; Kissling et al., 2022; Wang et al., 2022; Zhao et al., 2022). Additionally, we compiled an overview of existing open-access ALS point clouds from European countries (Appendix A), performed an analysis on the robustness of LiDAR vegetation metrics to varying point densities and spatial resolutions (Appendix B), and summarized examples from different Natura 2000 habitats (Table 2). Based on this synthesis, we present our view on how a cloud-based VRE could contribute to advance habitat condition research and monitoring with airborne LiDAR and UAV remote sensing.

3. Challenges and solutions for consistently measuring habitat condition with airborne LiDAR and UAV imagery

3.1. Variation in sensor characteristics and flight surveys

For each flight survey with an UAV, decisions must be made about the survey design and which platform and sensor to use (Fig. 2). The different options and the rapidly developing technology of platforms and sensors result in a large variation of flight parameters (e.g., flight altitude, duration, and stability), different sensor characteristics (e.g., pixel resolution, frame rates, spectral bandwidth and spectral range, lens types), and in a lack of compatibility between hardware and software of different sensor generations and platforms (Singh and Frazier, 2018; Zhang and Zhu, 2023). This is exacerbated by the short-lived maintenance support by manufacturers for older sensor and platform generations, accelerating their obsolescence. Moreover, decisions about survey designs vary widely because of differences in survey objectives (Dronova et al., 2021) and the deployed platform and sensor technology (Koontz et al., 2022; Zhang and Zhu, 2023). To our knowledge, there is currently no standard approach or best practice for sensor use procedures (Wyngaard et al., 2019), such as mounting requirements on different platforms, sample rates, altitude, flight patterns and ground observations for calibration. To improve UAV survey standardization and provisioning of FAIR data, a community-based development and adoption of best practice guidelines for sensor use procedures and survey designs is thus required (Barbieri et al., 2023). To support this, the Research Data Alliance (RDA; Berman and Crosas, 2020) has setup a Small Unmanned Aircraft Systems' Data Interest Group in 2024.

For ALS surveys, differences in sensor characteristics and acquisition specifications such as flight parameters (e.g., flight height, field of view, beam divergence and swath overlap) and utilized sensor hardware (e.g., wavelength, frequency and scanning pattern) also vary widely. For instance, different laser scanners with varying wavelengths, frequencies and fields of view are used in forestry studies (Yun et al., 2024). Scan angle differences can influence the density and distribution of returns, with wider scan angles decreasing the possibility of laser pulses penetrating through dense canopies, thereby reducing the number of returns from the understory and ground surface (Baltsavias, 1999). The power of the laser scanner also determines the energy of each emitted pulse and can affect the ability of LiDAR to detect small or distant objects. A stronger laser power increases the probability of multiple returns and thus leads to a more accurate representation of vegetation structure (Wehr and Lohr, 1999). Furthermore, the pulse repetition frequency and the flight altitude of LiDAR sensor system during data acquisition alters the obtained point density and distribution (Hopkinson, 2007; Hyyppä et al., 2008). Guidelines for standardizing flight attributes such as field-of-view, swath overlap, pulse rate, scan rate, and flight speeds would therefore be beneficial. Moreover, to improve the provisioning of FAIR data, information about ALS surveys (e.g., dates of data acquisition) and the equipment used (e.g., sensor characteristics) should be better reported in the documentations of the ALS data providers.

Even if UAV and LiDAR surveys and sensor use procedures cannot be

Table 2
Examples of habitat condition assessments in Natura 2000 sites based on Light Detection and Ranging (LiDAR) point clouds and/or Red, Green and Blue (RGB), multispectral or hyperspectral imagery obtained with crewed aircraft or Unmanned Aerial Vehicles (UAVs). This list is not intended to be exhaustive but to show examples from different European Natura 2000 sites, including habitats such as grasslands, heathlands, coastal dunes, wetlands, and forests. The Natura 2000 data (site network and habitat classification) are provided by the European Environment Agency (https://www.eea.europa.eu/en/datahub/datahubitem-view/6fc8ad2d-195d-40f4-bdec-576e7d1268e4).

Natura 2000 habitat description (habitat code)	Example and description	References
Grasslands		
Species-rich *Nardus* grasslands on silicious substrates in mountain areas (code 6230)	Mapping the spatial extent and arrangement of grassland and heath habitat types with RGB images and digital surface models from UAVs, evaluating habitat degradation through heath encroachment caused by decreased grazing pressure	Gonçalves et al. (2016)
Pannonic sand steppes (code 6260)	Mapping of areal cover and shoots and flowers of two invasive plant species in open sandy grasslands, using RGB images obtained with UAVs	Bakacsy et al. (2023)
Pannonic salt steppes and salt marshes (code 1530)	Mapping of grassland conservation status on alkaline soils, based on LiDAR point clouds obtained with crewed aircraft and derived raster products (e.g., digital terrain model, surface roughness, and point reflectance)	Zlinszky et al. (2015)
Heathlands		
Dry sand heaths with *Calluna* and *Genista* (code 2310) and European dry heaths (code 4030)	Assessing habitat condition of heathlands with hyperspectral and RGB images from UAVs by mapping *Calluna* coverage, stand structural diversity, and a species index (occurrence and coverage of key species)	Schmidt et al. (2017)
Northern Atlantic wet heaths with *Erica tetralix* (code 4010) and dry sand heaths with *Calluna* and *Genista* (code 2310)	Mapping heathland habitat types using airborne hyperspectral images obtained with crewed aircraft, and assessing habitat condition through measuring the percentage of tree and grass cover per patch	Haest et al. (2017)
Coastal dunes		
Coastal sand dunes, sand beaches, machair (code N04)	Mapping and classification of coastal dune habitats (including littoral sediment, sand beach, dune scrub, dune grasslands, and dune forest) with multispectral UAV imagery and data derived from airborne LiDAR point clouds (digital terrain model, intensity values)	Agrillo et al. (2023)
Coastal sand dunes, sand beaches, machair (code N04)	Mapping of native and alien invasive shrub species in coastal dunes using multispectral aerial photographs and canopy surface height derived from LiDAR point clouds, both obtained with crewed aircraft	Hantson et al. (2012)
Wetlands		
Reedbed habitats, included in the habitat class 'Bogs, Marshes, Water fringed	Mapping habitat condition and structure of reedbeds from national LiDAR point clouds obtained with crewed	Koma et al. (2021b)

(continued on next page)

Table 2 (*continued*)

Natura 2000 habitat description (habitat code)	Example and description	References
vegetation, Fens' (code N07)	aircraft, separating water reed, structurally poor land reed, and structurally rich land reed	
Various peatland habitats, especially blanket bogs (code 7130) and active raised bogs (code 7110)	Mapping plant functional types and microforms to derive habitat distribution (ecotopes) and habitat condition (peat accumulation status) for five Irish peatlands, with RGB imagery and digital terrain models obtained with UAVs	Steenvoorden et al. (2024)
Forests		
Coniferous woodland (code N17) and mixed woodland (code N19)	Individual tree segmentation using airborne LiDAR point clouds (acquired by a helicopter) and multispectral aerial imagery, differentiating coniferous trees (e.g., pines), deciduous trees (e.g., birch and alder), standing dead trees with crowns, and snags	Briechle et al. (2021); Hell et al. (2022)
Broad-leaved deciduous woodland (code N16)	Measuring diameter at breast height (DBH) in alluvial forests with LiDAR point clouds derived from laser scanners on board of an UAV	Wieser et al. (2017)

fully standardized, a standardized reporting of their metadata would already improve the consistent measurement of habitat condition (Fig. 2). For instance, for UAVs there is a lack of standards and guidelines for generating metadata describing calibration, training and validation procedures during the flight campaign and how to report the flight parameters in a standardized way (Barbieri et al., 2023; Dronova et al., 2021; Koontz et al., 2022). The lack of standardized metadata for observations and calibration can significantly affect the comparability of UAV surveys (Singh and Frazier, 2018). For instance, the parameters set by the pilot for the flight (e.g., flight line overlap, flight height, direction and speed, and terrain following) or other characteristics during the flight survey (e.g., wind speed, sun light, flight time, humidity, and cloud cover) can have large implications for multi-site and multi-temporal comparisons. To allow a better comparison among datasets, metadata of survey variables, sensor information, and the date and time should therefore be reported in a standardized and machine-readable way (Table 3).

3.2. *Transparency of pre-processing pipelines*

The use of proprietary software during UAV data pre-processing results in little software transparency and interoperability (Fig. 2, right). Provenance information (i.e., lineage and processing history) and workflow metadata from the pre-processing are often not available (Wyngaard et al., 2019). For LiDAR point clouds collected with UAVs, each LiDAR sensor manufacturer stores the data on the instrument in its own way, which is then converted to a standard format (such as LAS) using the company's own software. In case of RGB imagery, structure-from-motion algorithms (when many highly overlapping image frames are combined to deliver 2-dimensional image mosaics and 3-dimensional point clouds) use photogrammetric data contained within UAV images to generate digital terrain models (DTMs) and digital surface models (DSMs) with high spatial resolution. Many different algorithms are available for generating DTMs, parameter choices and uncertainties are often not well documented, and the use of proprietary software makes pre-processing workflows and photogrammetry pipelines not very transparent (Jiang et al., 2020; Zhang and Zhu, 2023). However, an increasing number of open-source software tools is becoming available for UAVs, including image processing and data management (Jiang et al., 2020; Jordan et al., 2024; Pereyra Irujo et al., 2023). Some of these open-source software packages (e.g., ColMap) allow reproducible open-source workflows for structure-from-motion pipelines, including feature extraction, feature matching, geometric verification, and structure and motion reconstruction. Such open source software and workflows for UAV data (Pereyra Irujo et al., 2023) are needed for a more transparent and interoperable pre-processing of UAV imagery (Table 3).

In contrast to UAV-collected data, national and subnational LiDAR point clouds are collected with airplanes through ALS surveys, usually by specialized companies and service providers (e.g., geospatial surveying firms), and then made publicly available via a website, a geoportal, or an institutional repository within a country (see examples from European countries in Appendix A Fig. A1 and Table A1). The point clouds are typically provided in a standard open file format (LAS or compressed LAZ files) which has been designed for the interchange and archiving of LiDAR point clouds (ASPRS, 2019). This provides

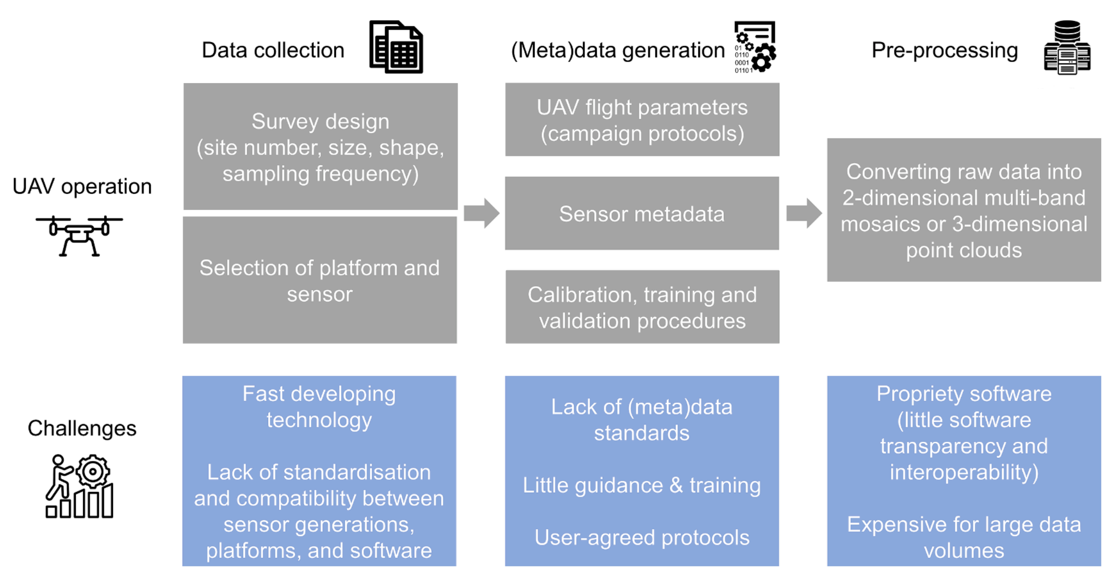

Fig. 2. Key aspects of unmanned aerial vehicle (UAV) operation (grey boxes) and related challenges for standardization (blue boxes) during data collection, (meta) data generation and pre-processing.

Table 3
Summary of challenges and potential solutions for consistently measuring and monitoring habitat condition metrics from airborne LiDAR and UAV remote sensing.

Challenges	Future needs	Potential solutions
Variation in sensor characteristics and flight surveys	• Development of standards and best practices for sensor use procedures and survey designs	• Best practice guidelines, community engagement, training workshops
	• Standardized and machine-readable meta-data of survey variables and sensor characteristics	• Metadata standards and formats, data integration, data management education
Transparency of pre-processing	• Transparent and interoperable UAV data pre-processing pipelines	• Open source software and workflows for UAV pre-processing
	• Detailed information on methodology for pre-processing airborne laser scanning point clouds	• Documentation of pre-processing and provenance of (sub)national LiDAR point cloud datasets
Heterogeneity and complexity of data	• Standardization and normalization of image reflectance	• Radiometric calibration, normalization of reflectance values, systematic inter-calibration
	• Multi-sensor data integration (e.g., RGB, NIR, hyperspectral and LiDAR)	• Open-source workflows for fusing multi-source data
	• Seasonal information from LiDAR point clouds and UAV imagery	• Laser scanning in leaf-on and leaf-off seasons, multiple UAV surveys during growing season
	• Consistent classification of vegetation in (sub) national LiDAR point clouds	• Open-source methods for semantic segmentation and classification
Robustness of metric calculations	• Comparable and robust metrics for habitat condition assessments (e.g., textural, spectral, spatial patch and topographical metrics, vegetation indices, LiDAR metrics)	• Testing metric robustness to parameter settings in pre-processing steps and varying point densities, spatial resolutions, habitats, etc.
Generalizability and transferability of models	• Transferability of machine and deep learning models across space and time (e.g., random forests, support vector machines, convolutional neural networks)	• Multi-site and multi-dataset testing of the accuracy and transferability of algorithms for habitat condition mapping
	• Large amounts of accessible data for model training and evaluation (e.g., benchmarking datasets, ground-reference data)	• Open-access training and validation datasets with manually labelled point clouds (including trees, shrubs, stonewalls, deadwood etc.)
Big data computing	• Efficient processing of multi-terabyte LiDAR and UAV datasets	• Reproducible, scalable, and distributed, open-source processing workflows
	• Computing resources and services on remote cloud infrastructures	• Big data storage, computing resources, and easy-to-use tools for data and workflow management

standardized data and metadata on various point cloud properties such as the coordinate reference system (CRS) of the dataset, the attributes (X, Y, and Z values) of each point, intensity values (i.e., the magnitude of the pulse return), the pulse return number etc. (ASPRS, 2019). A classification field is also provided with information on whether a point belongs to the ground, vegetation, building, water etc. (Appendix A Fig. A1). However, the pre-processing of the LiDAR point clouds is usually not well documented because it is done by companies and not described in scientific publications. Information on the accuracy and methodology of the pre-processing of (sub)national LiDAR point clouds should therefore be better reported (Table 3) to increase the FAIRness of these datasets.

3.3. Heterogeneity and complexity of data

To our knowledge, there is currently no overview available about the type of UAV imagery that is collected in protected areas and European Natura 2000 sites. Some examples for different habitats are provided in Table 2. Most data acquisition is probably done with small, relatively inexpensive, and flexible UAVs that collect imagery in the visible spectrum (RGB), as it is done in Natura 2000 grasslands (Bakacsy et al., 2023; Gonçalves et al., 2016) and wetland habitats (Dronova et al., 2021; Steenvoorden et al., 2024). RGB imagery already results in heterogeneous data because sensor characteristics and flight surveys are not standardised (see above) and various factors will influence the spectral characteristics, including weather conditions (e.g., sun and shading), camera characteristics (e.g., lens imperfections and uneven illumination), and season of data acquisition (e.g., plant phenology in spring versus summer). A solution is to standardize image values (Table 3), e.g., through normalizing the RGB values or applying radiometric calibration to produce reflectance values. However, the latter is not trivial and both are currently not widely applied in ecological applications of UAV remote sensing (e.g., in invasive plant species mapping; Singh et al., 2024). Long-term monitoring with multi-temporal UAV imagery and regional multi-site applications would therefore require a systematic inter-calibration (Dronova et al., 2021; Singh and Frazier, 2018). Besides RGB cameras, additional sensor types such as NIR, multispectral, hyperspectral, and thermal cameras can add valuable information for habitat condition monitoring. By providing additional spectral bands they can improve the identification of vegetation, plant species, open water bodies and soil features (Agrillo et al., 2023; Schmidt et al., 2017; Steenvoorden et al., 2024; Zhang and Zhu, 2023) or measure surface temperatures and heat anomalies (Lendzioch et al., 2021). However, they are also more costly and are thus not yet as widely used as RGB imagery (Dronova et al., 2021; Singh et al., 2024). Nevertheless, cameras with NIR are increasingly becoming available and affordable. The added NIR band is essential to derive the commonly used normalized difference vegetation index (NDVI) which is linked to vegetation productivity, stress, and cover. NIR also helps to increase the spectral separability of certain vegetation types, plant species and open water bodies. This makes NIR sensors attractive for the large-scale UAV-based monitoring of certain habitats such as peatlands (Steenvoorden et al., 2024; Steenvoorden and Limpens, 2023) and other Natura 2000 habitats such as forests, wetlands, grasslands and coastal dunes (Agrillo et al., 2023; Šímová et al., 2023). Other types of UAV sensors such as hyperspectral cameras and LiDAR are more costly, result in additional data heterogeneity and complexity (e.g., tens to hundreds of spectral bands), and strongly increase the computational requirements. Nevertheless, the fusion of multi-sensor UAV data is promising, and applications will likely increase in the future. For instance, the fusion of 3D point clouds with RGB/NIR, multispectral, or hyperspectral data can improve individual tree or crown segmentation, aboveground biomass, canopy height, and vegetation structure derivation, tree species identification, and the mapping of various Natura 2000 habitats (Agrillo et al., 2023; Balestra et al., 2024; Haest et al., 2017; Shi et al., 2018; Šímová et al., 2023).

For LiDAR points clouds from ALS surveys, the LAS/LAZ format already provides a good basis for the standardization of (meta)data and the provisioning of FAIR data. However, ALS datasets from different countries or multiple time periods are heterogeneous because they are obtained with different budgets and requirements, for different purposes, with different sensors, and with different end products in mind. Hence, a major challenge for the consistent transnational or multi-temporal analysis of such datasets is that they come with a wide variety of characteristics (Fig. 3). For instance, some countries only provide leaf-on data and others only leaf-off (Appendix A Table A1). This can complicate the consistent calculation of habitat condition metrics with different LiDAR datasets, e.g., for measuring structural characteristics of herbaceous plants and understory vegetation below tree canopies. Collecting LiDAR point clouds and UAV imagery for both the growing (leaf-on) and non-growing (leaf-off) season or different phenological seasons (spring, summer) (Table 3) could, for instance, increase the accuracy of machine and deep learning algorithms from UAV LiDAR point clouds (Chen et al., 2022), improve the mapping of Natura 2000 habitats from UAV multispectral and RGB imagery (Šímová et al., 2023), and help quantify which collection scenario (leaf-on, leaf-off or both) for UAV LiDAR surveys is more suitable for the accurate derivation of terrain properties, plant biomass, vegetation structure, or other abiotic, biotic and landscape characteristics (Lin et al., 2021). Moreover, the level of detail in the provided point classification varies widely among different datasets (Fig. 3d). Two of the classes ('ground' and 'unclassified') are almost always provided (Fig. 3d) because most national and subnational LiDAR acquisition efforts are focused on the ground surface, with specifications and operations designed to provide an acceptable density of ground points suitable for terrain mapping, rather than for measuring vegetation. Other classes (e.g., vegetation, building, noise, and water points) are provided in only ~ 50 % of the datasets (Fig. 3d). Especially the classification of vegetation points varies widely, e.g., Finland categorizes vegetation into low, medium, and high; Estonia identifies tall vegetation; and Switzerland includes only a general vegetation class (Appendix A Table A1). Other countries do not provide any vegetation class at all (e.g., Scotland, Belgium, and the Netherlands; see Appendix A Table A1). When vegetation points are not provided in a separate class, they are typically included in the class 'unclassified'. 'Unclassified' can also contain points from other objects such as transmission towers, traffic signs, trucks, and cars (Fig. 3e), introducing potential uncertainties and biases that need quantifying when measuring vegetation structure with the 'unclassified' class (Kissling et al., 2023; Shi and Kissling, 2023). A consistent classification of vegetation in (sub)national LiDAR point clouds is therefore needed (Table 3). New methods are emerging, such as point-based deep learning methods for semantically labelling point clouds into vegetation classes such as grass, shrub, tree, or low/medium/high vegetation (Wen et al., 2021; Widyaningrum et al., 2021; Zhao et al., 2021a).

3.4. Robustness of metric calculations

The reliability of habitat condition indicators will depend on the robustness of features derived from UAV imagery and LiDAR point clouds. For instance, a large number of textural metrics (Eischeid et al., 2021; Park and Guldmann, 2020), vegetation indices and band ratios (Gonçalves et al., 2016; Xue and Su, 2017) and spectral heterogeneity metrics (Torresani et al., 2024) are derived from imagery captured by optical sensors (including RGB and NIR imagery from UAVs). UAV imagery (with structure-from-motion algorithms) and LiDAR point clouds from ALS surveys are also used to generate high spatial resolution DTMs and from these a range of topographical metrics such as topographic position, topographic wetness, terrain ruggedness, aspect, and slope (Assmann et al., 2022; Eischeid et al., 2021; Ikkala et al., 2022; Jiménez-Jiménez et al., 2021). The robustness and sensitivity of such features can be influenced by decisions during UAV imagery capture and pre-processing (Fig. 4a–c). For instance, when using UAV RGB imagery to map peatland microforms such as wet hollows and dry hummocks or plant functional types such as peat moss, shrubs, and lichens (Steenvoorden et al., 2023; Steenvoorden and Limpens, 2023; Steenvoorden et al., 2022), the metrics used as classification input variables can strongly dependent on parameters such as minimum ortho-mosaic segment size (Steenvoorden et al., 2023), UAV image resampling resolution (Steenvoorden and Limpens, 2023), or the window size for detrending DTMs (Steenvoorden et al., 2024). Assessing the sensitivity and robustness of metrics to various pre-processing steps is thus needed (Table 3) and essential for achieving consistent accurate vegetation mapping (Steenvoorden and Limpens, 2023) and reliable habitat condition indicators (Steenvoorden et al., 2024; Steenvoorden et al., 2022).

Like processing UAV imagery, various characteristics of LiDAR point clouds derived from ALS surveys can influence the consistent and robust calculation of habitat condition metrics. One of the most important factors is the variation in point cloud density which varies widely in publicly available LiDAR datasets (e.g., ranging from 1 to 30 points/m^2, Fig. 3a) due to differences in ALS flight parameters, scanning geometry, utilized sensor hardware, and season of data acquisition (leaf-on or leaf-off). Since laser scanner technology is rapidly improving, point densities also vary between ALS surveys from different time periods in the same country (i.e., higher scanning frequencies resulting in higher point densities). This can potentially affect the calculation of biotic, abiotic and landscape characteristics and the monitoring of habitat condition over time. To demonstrate the effect of varying point densities, we calculated 25 LiDAR vegetation metrics in selected Natura 2000 sites in the Netherlands (i.e., woodlands with Natura 2000 habitat codes N16, N17, N19 and N20) using the original point density of the Dutch AHN4 dataset (20–30 points/m^2) as well as six systematically down-sampled point clouds, i.e., keeping 5 %, 10 %, 20 %, 40 %, 60 % and 80 % of the points in the original point clouds (see details of methodology in Appendix B). Since the volume geometry used for metric calculation (e.g., grid cell spatial resolution) can also influence metric robustness (Meijer et al., 2020), we performed this analysis for 1×1 m, 2×2 m, 5×5 m, and 10×10 m grid cells (see Appendix B Fig. B4–B7). Our analysis revealed that metrics of canopy height (e.g., Hp95) and vegetation openness (e.g., PPR) are largely robust to varying point densities, even when calculated with strongly down-sampled point densities of $<$ 10 points/m^2 (Fig. 5). However, other metrics such as understory density are less robust and tend to become more variable at finer spatial resolutions (i.e., 1×1 m, 2×2 m and 5×5 m), i.e., when point densities are $<$ 20 vegetation points/m^2 (see BR_2_3 in Fig. 5). Moreover, vertical variability metrics such as the Shannon index (a measure of foliage height diversity) can strongly vary with changing point densities at all grid cell spatial resolutions (Fig. 5). These examples from Natura 2000 woodlands show that comprehensively testing the robustness of LiDAR metrics is essential to ensure that measuring and monitoring habitat condition with ALS point clouds is consistent across time and space.

3.5. Generalizability and transferability of models

Since in-situ data collection is often limited to a few locations and small areas, it is common in the Earth sciences to apply upscaling algorithms to predict geospatial information over a large spatial extent (Ge et al., 2019). This typically involves models (e.g., regression, machine learning, geostatistical methods) that combine in-situ measurements (e.g., of biotic, abiotic and landscape characteristics, Table 1) with auxiliary information (e.g., remotely sensed data from satellites, UAVs and crewed aircraft). Among the most widely used approaches are machine learning methods such as Random Forest (RF) and support vector machines (SVMs) which are, for instance, applied with airborne LiDAR data and imagery from UAVs or crewed aircraft to map invasive plant species (Hantson et al., 2012; Singh et al., 2024), ground cover (Eischeid et al., 2021), condition of wetland habitats such as reedbeds and peatlands (Dronova et al., 2021; Koma et al., 2021b; Steenvoorden et al., 2024), or woody plant encroachment in grasslands and heathlands (Gonçalves et al., 2016; Olariu et al., 2022). Most recently, deep learning models such as Convolutional Neural Networks (CNNs) have emerged as a transformative machine learning method for data-driven Earth Science (Diab et al., 2022; Reichstein et al., 2019; Yun et al., 2024). While a large variety of different types of deep learning models can be applied to

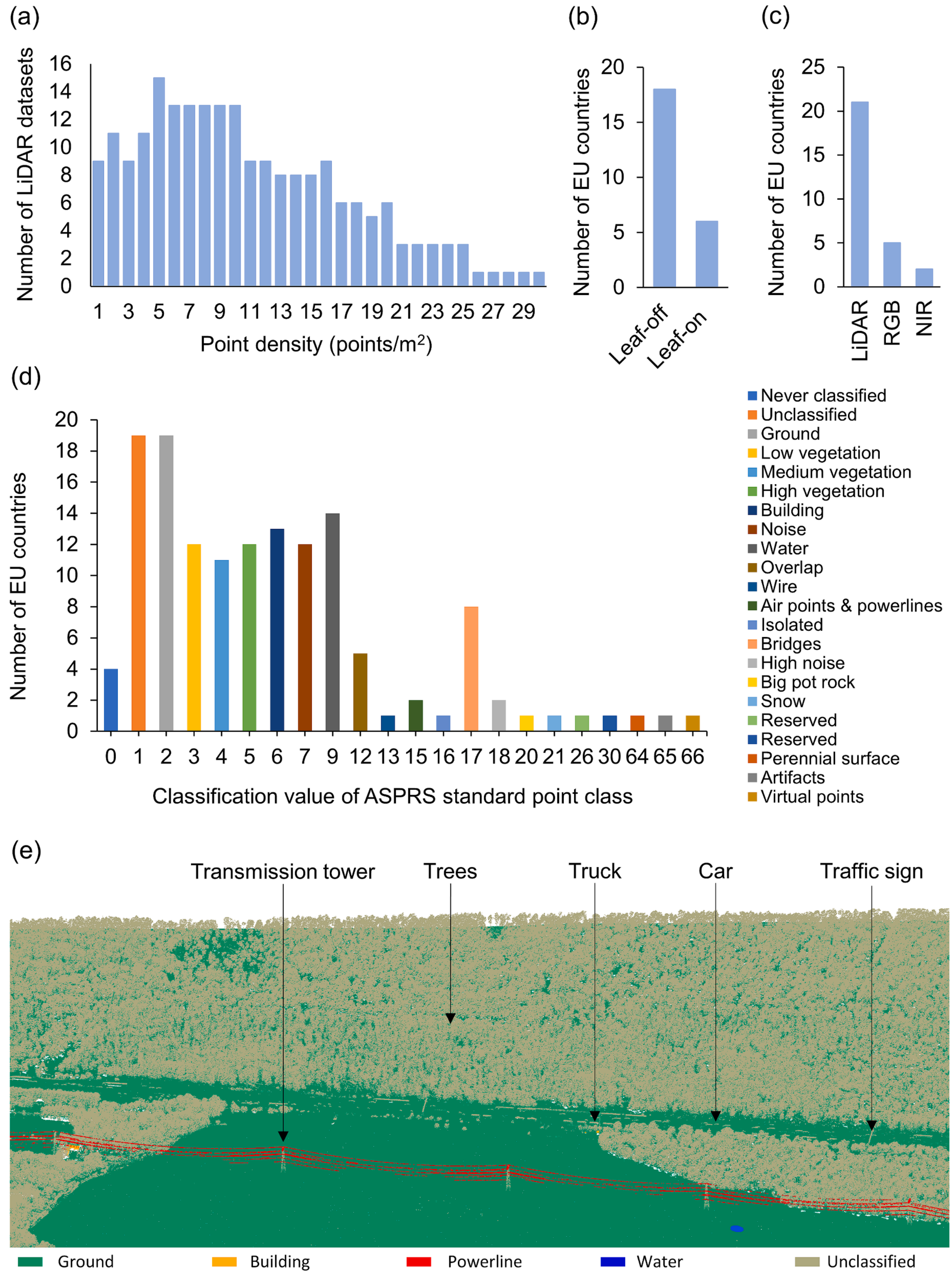

Fig. 3. Variation in characteristics of LiDAR point clouds collected through (sub)national ALS surveys in Europe (see details in Appendix A Table A1). (a) Range of available point densities; (b) Season of data acquisition (leaf-on vs. leaf-off); (c) Available information on LiDAR and simultaneously collected imagery in the Red, Green and Blue (RGB) and Near-Infrared (NIR) spectrum; (d) Available point classifications following the ASPRS standard point classes. (e) Example of a LiDAR point cloud (AHN4 dataset from the Netherlands) in which vegetation and non-vegetation objects (e.g., trees, transmission towers, traffic signs, trucks, and cars) are included in the same class ('unclassified', olive). The 'ground' class (green) includes ground points (i.e., terrain), but also short-stature vegetation (e.g., grasses). White areas indicate areas with no data (e.g., building fronts, below trees). The image depicts an area in the southwest of the 'De Veluwe' (Natura 2000 site code NL9801023) which is in the center of the Netherlands (52.0875278 N, 5.9507778 E). The nature reserve is mainly composed of heath and scrubs (Natura 2000 habitat code N08) and coniferous and mixed woodlands (Natura 2000 habitat codes N17 and N19), but highways and an overhead powerline are crossing.

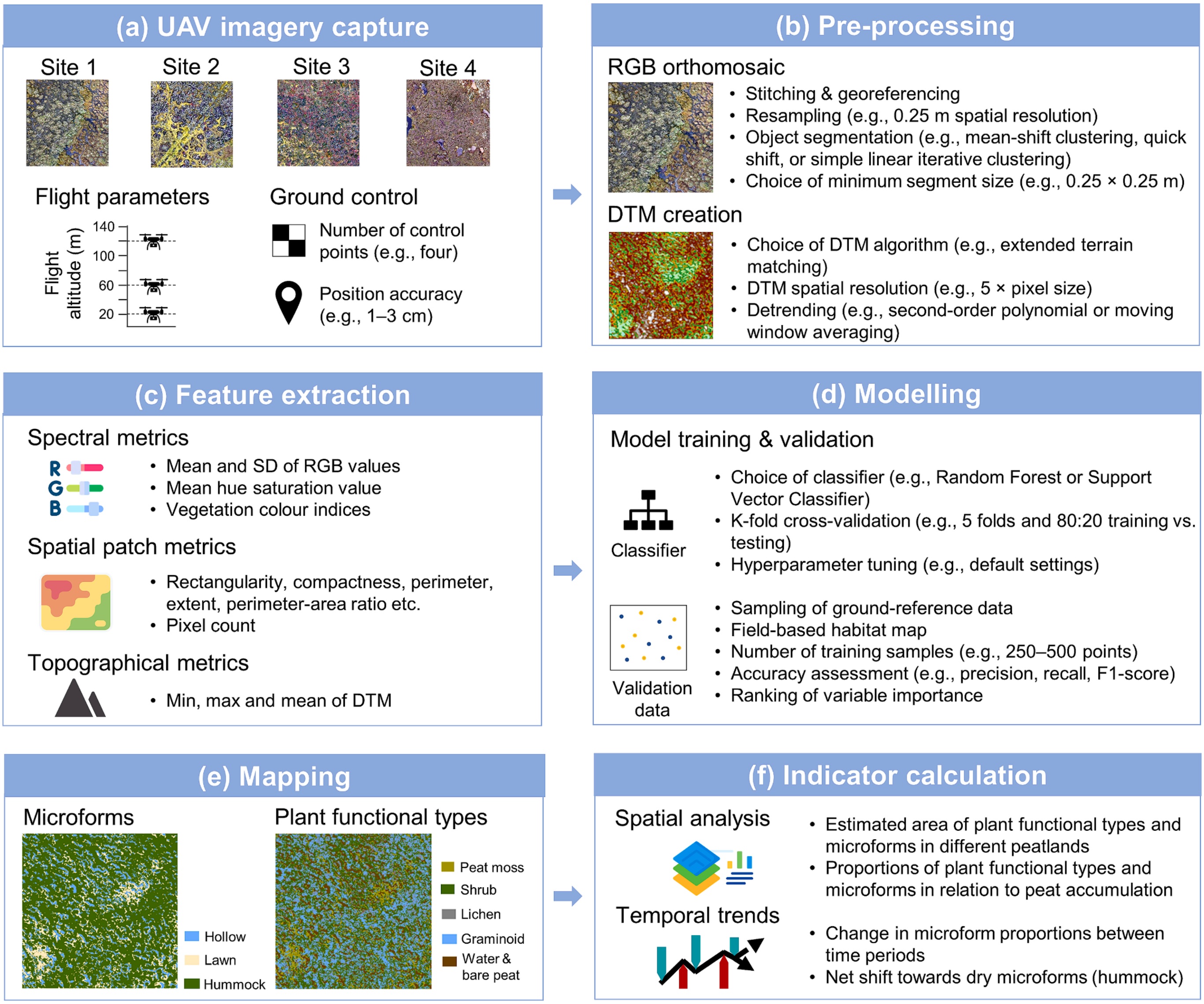

Fig. 4. Example of a workflow for processing UAV imagery into indicators of habitat condition. (a,b) Details and decisions during data collection and pre-processing, (c,d) examples of feature extraction and modelling, and (e,f) mapping of vegetation and indicator calculation. The figure synthesizes details of a workflow that has been applied to the monitoring and mapping of peatlands in Ireland (Steenvoorden et al., 2023; Steenvoorden et al., 2024; Steenvoorden and Limpens, 2023; Steenvoorden et al., 2022). These peatlands especially represent blanket bogs (Natura 2000 habitat code: 7130) and active raised bogs (Natura 2000 habitat code: 7110).

LiDAR point clouds and UAV imagery (Diab et al., 2022; Yun et al., 2024), CNNs in particular have revolutionized the field of object detection, useful for measuring various aspects of habitat condition. Good examples already exist from forest studies (Yun et al., 2024), e.g., tree species mapping from 2D RGB imagery and classification and individual tree mapping from 3D LiDAR point cloud segmentation (Table 4). Other examples of deep learning applications with UAV imagery include mapping of plant communities and individual plant species in grasslands (Pöttker et al., 2023; Zhang et al., 2020), monitoring flower abundance and invasive plant species in urban and agricultural areas (Singh et al., 2024; Sookhan et al., 2024), and classifying vegetation cover types in peatlands (Palace et al., 2018). However, the transferability of machine learning models across multiple sites and national, regional, or continental extents is often limited because large amounts of data for model training and evaluation are not available or not easily (or openly) accessible.

The transferability of machine learning models to other sites can be impaired if the vegetation structural or habitat and terrain conditions of unmeasured sites are not sufficiently captured in the training and ground reference samples (Fekety et al., 2018; Steenvoorden et al., 2024; Steenvoorden and Limpens, 2023; Yun et al., 2024). Classical machine learning methods such as RF and SVMs perform well with small to moderately sized datasets and are generally quicker to train, but their capacity to capture deep or complex relationships is limited. This can limit the spatial transferability of UAV-based vegetation mapping across multiple sites, e.g., if the size, shape and configuration of vegetation characteristics varies among sites (Steenvoorden and Limpens, 2023) or if the ground-reference data are too coarse or imprecise (Steenvoorden et al., 2024). Vegetation mapping and indicator calculation can also be influenced by various decisions during the training and validation of machine learning methods, e.g., the choice of the classifier, the ratio of training/testing samples, the number of folds for cross-validation, values for hyperparameters, the choice of accuracy metrics etc. (Fig. 4d–f). In contrast to RF and SVMs, deep learning models such as CNNs consist of numerous layers and a vast number of parameters (weights), and are thus highly flexible, capable of modelling intricate relationships and

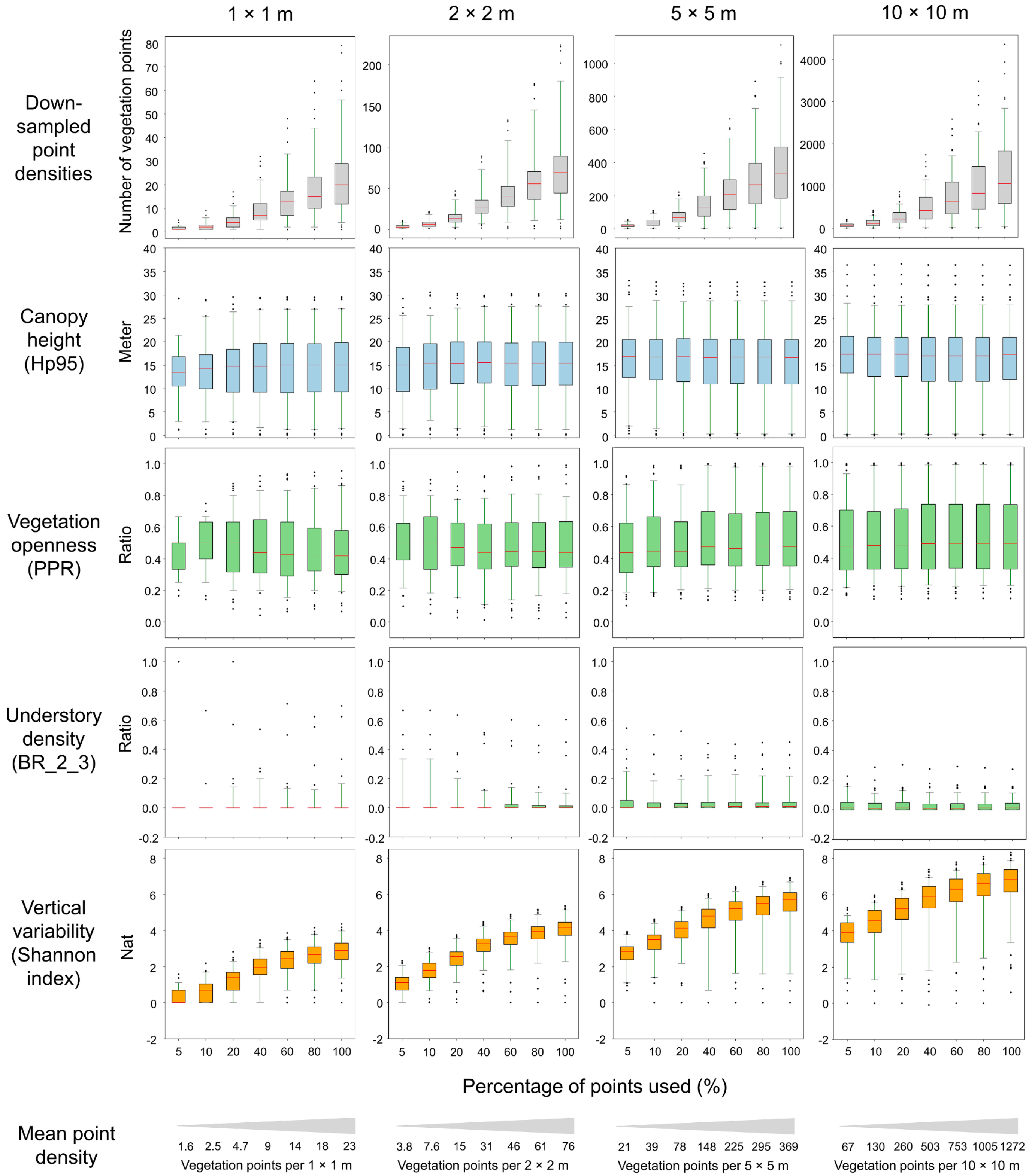

Fig. 5. The effect of grid cell spatial resolution and varying point densities on the robustness of LiDAR vegetation metrics derived from airborne ALS point clouds. LiDAR vegetation metrics were calculated at four spatial resolutions (i.e., 1 × 1 m, 2 × 2 m, 5 × 5 m and 10 × 10 m) with six systematically down-sampled point clouds (i.e., keeping 5 %, 10 %, 20 %, 40 %, 60 % and 80 % of the points from the original Dutch AHN4 dataset '100 %'). Mean point densities are given for each percentage of points used. Metrics were calculated using randomly located woodland plots in the Netherlands ($n = 94$). See Appendix B for methodological details, Appendix Fig. B4–B7 for additional metrics, and Appendix B Table B1 for metric abbreviations and definitions.

Table 4
Examples from forestry showing deep learning algorithms applied to LiDAR point clouds and Red, Green and Blue (RGB) imagery obtained from UAVs and crewed aircraft. Most of the studies have been conducted in production forests, plantations or urban environments, and not in Natura 2000 sites or other types of nature reserves. A more comprehensive review of deep learning applications in forestry studies, including satellite remote sensing and mobile or ground-based terrestrial laser scanning, is provided in Yun et al. (2024).

Deep learning algorithm	Application	Reference
LiDAR point clouds		
LayerNet	Classification and 3D segmentation of individual birch and larch trees	Liu et al. (2021)
PointCNN	Classification and 3D segmentation of four tree classes (coniferous, deciduous, standing dead tree with crown, and snag)	Hell et al. (2022)
ForAINet	3D segmentation of trees and automated retrieval of tree parameters (height, crown diameter, crown volume, DBH, and location) and stand structure (digital terrain model and stand density)	Xiang et al. (2024)
Point Transformer	Individual tree segmentation in conifer and mixed forest	Zhang et al. (2023)
FR-GCNet	Point cloud classification (semantic labelling of tree, grass, soil, and other points)	Zhao et al. (2021a)
Silvi-Net	Classification of individual pine, birch, alder, and dead trees	Briechle et al. (2021)
YOLO	2D mapping of individual tree crowns	Sun et al. (2022)
UAV/aircraft RGB imagery		
U-Net	2D mapping of herbaceous vegetation communities, a shrub species, and a tree species	Kattenborn et al. (2019)
DeepLab	2D mapping of individual tree crowns of three Amazonian palm species	Ferreira et al. (2020)
ResNet	2D mapping of woody vegetation distribution	Cheng et al. (2023)
DenseNet	2D mapping of five species of trees	Wang et al. (2023)
GoogLeNet	2D mapping of dead pine trees	Tao et al. (2020)
YOLO	Detection of tree crown locations	Wu et al. (2022)
Faster-RCNN	Detection of planted pine seedlings	Pearse et al. (2020)

hierarchies within the data. However, to effectively train such complex models without overfitting, substantial computational resources and a large amount of diverse data are necessary. Consequently, most deep learning applications for mapping habitat characteristics have so far been done at single sites or with single datasets (e.g., examples in Table 4), and only few models have been trained and evaluated with datasets from multiple sites or across large spatial extents (e.g., Xiang et al., 2024). The generalizability of deep learning models can be further influenced by the specific properties of the implemented method, e.g., whether multilayer perceptrons, graph neural networks, or multi-view neural networks are used (Yun et al., 2024). Moreover, data acquired with different sensor platforms —such as airborne, mobile, terrestrial or UAV laser scanners— have very different point of views and differ in data properties (e.g., point densities, level of details captured from trees) and acquisition time. Deep learning models trained with LiDAR data from one sensor platform (e.g., ALS) may thus not necessarily be transferable to data obtained from another sensor platform (e.g., terrestrial or UAV laser scanners). However, using different combinations of input training data may even allow to train sensor-agnostic deep learning models that can handle diverse laser scanning data (Wielgosz et al., 2024).

A major difference among deep learning models for applications to LiDAR point clouds is whether they can handle 2D or 3D data (Fig. 6). Point-based models (e.g., PointCNN, LayerNet or FR-GCNet) can directly use the 3D point clouds, but they need large amounts of manually labelled training and testing points. This requires open-access training and validation datasets for benchmarking and testing model performance (e.g., Diab et al., 2022; Singer and Asari, 2021; Varney et al., 2020). Currently available LiDAR benchmarking datasets are mainly suited for point classification or object segmentation and thus not necessarily applicable to habitat condition mapping. Moreover, publicly available datasets for deep learning applications often represent urban environments, parks and plantations (Yun et al., 2024), but data from protected areas and nature reserves, relevant for habitat condition monitoring, are lacking. In contrast to point-based models, the projection-based models are computationally less demanding but need to project the 3D data onto a 2D plane (e.g., Silvi-Net, Deep CNN, Faster R-CNN or YOLO) or into voxels (e.g., VoxelNet). The LiDAR data must therefore be regularized by projecting the 3D point cloud into 2D pixels, voxels, or side-view images (Fig. 6). Projection-based models lose spatial and geometry information from the 3D point cloud (Diab et al., 2022; Yun et al., 2024), and the choice of the pixel or voxel size (which depends on available point densities) can affect the accuracy of the deep learning models when applied to other datasets (Xi et al., 2020). Hybrid methods that integrate both 2D grid-based and 3D point-based methods (Shi and Kissling, 2023) or the fusion of deep learning and machine learning concepts (Yun et al., 2024) are alternatives that can be computationally efficient. Hybrid methods are also an option for integrating UAV data with other remotely sensed data, for example, using 2D or 3D UAV data (RGB, multispectral, thermal, LiDAR etc.) to train, validate and calibrate coarser resolution aerial and satellite imagery (e.g., Landsat imagery, radar from Sentinel-1, or optical imagery from Sentinel-2). Example applications are invasive plant species mapping (Singh et al., 2024) or estimating biomass and tree densities in wetlands (Dronova et al., 2021).

3.6. Big data computing

Deriving biotic, abiotic and landscape characteristics over large spatial extents from airborne and UAV data involves processing massive datasets. UAV data volumes from single sites vary widely depending on camera resolution, flight altitude, sensor type, area covered, image overlap, and data compression formats. As an example, the 45 UAV datasets available from OpenDroneMap (https://www.opendronemap.org/odm/datasets/, accessed 10 October 2024) have on average 392 ± 1,042 images (range: 16–7,169 images) with a volume of 1,907 ± 4,195 MB (range: 14–28,434 MB). Resampling UAV imagery to a coarser spatial resolution (e.g., from 2–3 cm to 0.25–0.5 m) can help reduce data volumes and processing times without impacting site-level mapping accuracies (Steenvoorden and Limpens, 2023). However, establishing which resampling resolution has minimum impact on classification accuracy is key and this can vary substantially among sites and vegetation classes, even within the same habitat type (e.g., peatlands; Steenvoorden and Limpens, 2023).

Processing LiDAR point clouds from country-wide ALS surveys involves handling much larger data volumes, typically > 5 TB (Appendix A Table A1). Consequently, processing is computationally demanding (Assmann et al., 2022; Kissling et al., 2023) and may require collaborations with software engineers to implement parallel and distributed processing (Meijer et al., 2020). For example, processing the country-wide LiDAR data (AHN3) of the Netherlands (>33,000 km^2 land area) involved ~16 TB of data containing ~700 billion points (Kissling et al., 2022). Processing this dataset into 25 vegetation structure metrics at 10 m resolution across the whole Netherlands took 294 days of total central processing unit (CPU) time (i.e., 14 days total wall-time), using a high-throughput workflow on a cluster of virtual machines (VMs) with fast CPUs and high memory nodes within the Dutch national IT infrastructure 'SURF' (Kissling et al., 2022). Such processing can be reduced if the area of interest is smaller than a whole country. For instance, focusing only on all Dutch Natura 2000 sites, the total data volume from the latest country-wide LiDAR survey (AHN4) amounts to < 0.8 TB (115 billion points). For a single 56 km^2 large Natura 2000 site in the Netherlands —i.e., the Oostvaardersplassen nature reserve (Natura 2000 site code

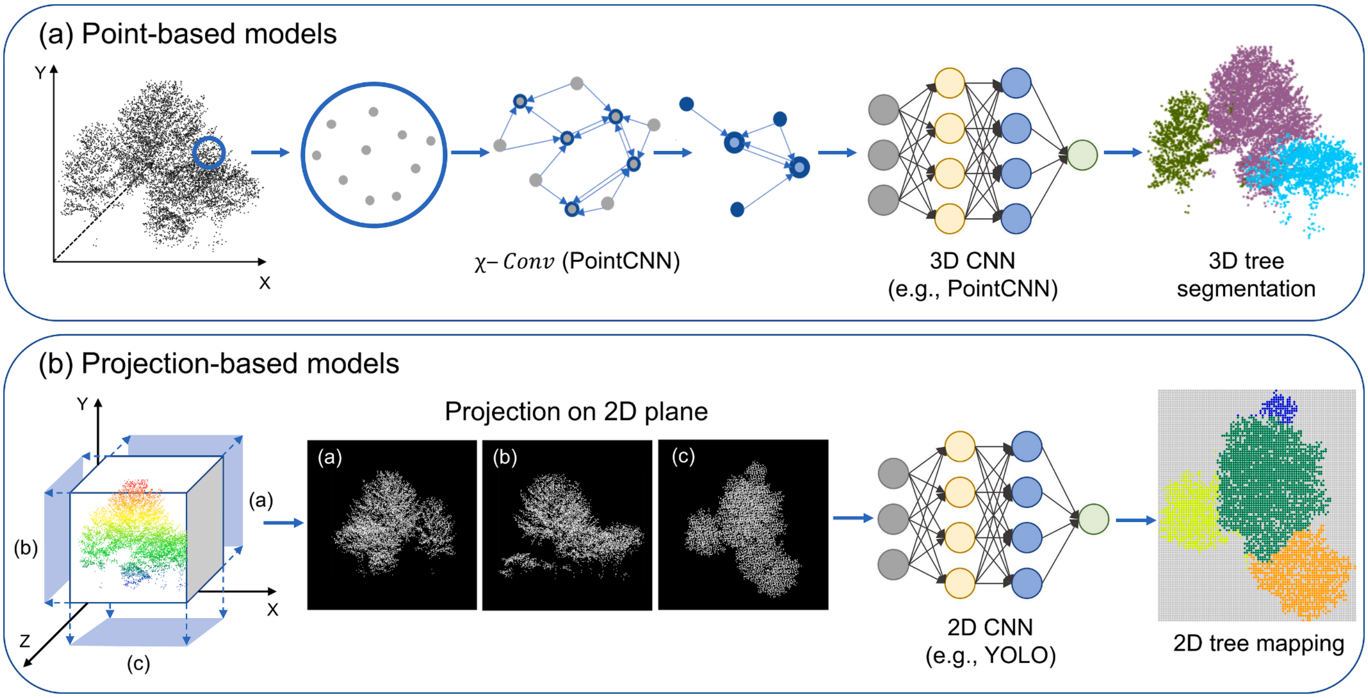

Fig. 6. Two major types of deep learning models that can be useful for habitat condition applications, exemplified with Convolutional Neural Networks (CNNs). (a) Point-based models can directly manage 3D data. (b) Projection-based models first need to project point clouds of 3D objects onto multiple view planes.

NL9802054) which is dominated by marshes (Natura 2000 habitat code N07) and dry and humid grasslands (Natura 2000 habitat codes N09 and N10)— the data volume is 2.6 GB (~0.55 billion points) and 9.3 GB (~1.4 billion points) for the AHN3 and AHN4 surveys, respectively.

The consistent monitoring of habitat condition would benefit from reproducible, scalable, and distributed, open-source workflows that can handle the efficient processing of massive amounts of data across multiple sites (Table 3). For example, workflows for LiDAR point cloud processing require various compute-intensive steps, such as re-tiling, normalization, feature extraction and rasterization (Fig. 7). To perform an efficient processing, the raw point clouds (usually hundreds to thousands of LAZ files with an individual data volume of up to several gigabytes) first have to be downloaded from national repositories and then split and re-tiled into ten thousands of tiles with smaller size (e.g., 1 km × 1 km) (Kissling et al., 2022). This requires IT-infrastructures with big data storage, sufficient computing and engineering resources, the scheduling of virtual machines, and parallelization and distribution of tasks (Kissling et al., 2022; Meijer et al., 2020; Wang et al., 2022). A challenge is that specialized knowledge of input data, workflow implementation, and remote infrastructure scheduling is usually needed. For instance, deploying a LiDAR processing workflow with a cluster of VMs on a national IT-infrastructure requires defining how the tasks are distributed among workers of the cluster (Kissling et al., 2022). When deploying the same workflow on a remote cloud infrastructure, additional functionality such as splitter and a merger modules might be needed to avoid performance bottlenecks (Wang et al., 2022; Zhao et al., 2022). Different IT-infrastructures will also provide different computing capacity and resources, for instance in terms of number of workers/VMs, available cores per worker/VM, and memory capacity. Configuration adjustments must be made based on the input data (e.g., volume), required output (e.g., spatial resolution, number of metrics), and the availability of computing resources within a given IT infrastructure. Implementing high-throughput workflows for habitat condition assessments would therefore benefit from remote cloud infrastructures, services for big data storage, and easy-to-use tools for data and workflow management.

4. Towards a cloud-based virtual research environment

The above synthesis summarizes challenges and potential solutions for consistently measuring habitat condition from LiDAR point clouds and UAV imagery over large spatial extents. We suggest that many of the potential solutions (summarized in Table 3) could be addressed and supported by developing a collaborative cloud VRE for habitat condition research and monitoring using airborne LiDAR and UAV remote sensing data (Fig. 8). Such a VRE would include tools for the discovery, access, management, and standardization of data and processing workflows (Zhao et al., 2022) and thus enable a more consistent data processing and metric retrieval for habitat condition information. Below we discuss the VRE components in more detail with a specific focus on LiDAR point clouds and UAV imagery.

4.1. Data management

An important step for developing a more consistent habitat condition monitoring is to make existing LiDAR point clouds and UAV imagery and related training and validation data easier to find and access. This requires improved data repositories, data exchange APIs, and metadata catalogues (Fig. 8). At a global scale, a network for ALS data has recently been established to collect metadata from data providers (Stereńczak et al., 2020). However, this is far from being extensive, and a large amount of ALS data is not yet captured. For Europe, a recent European Commission report listed the available ALS LiDAR point clouds and DTMs (Kakoulaki et al., 2021). However, since its publication, more flight campaigns have been conducted and more countries published their (sub)national datasets (see overview in Appendix A Table A1). Also, there is currently no central data repository in place for LiDAR point clouds. Instead, all national datasets are stored on separate geoportals and websites, usually without machine-readable access to their interfaces, i.e., no standardized communication protocols such as REST-APIs (Representational State Transfer Application Programming Interfaces) can be used. National websites are usually in the local language and poorly documented which generates additional barriers for data reuse in a European context. There are also only few domain-specific

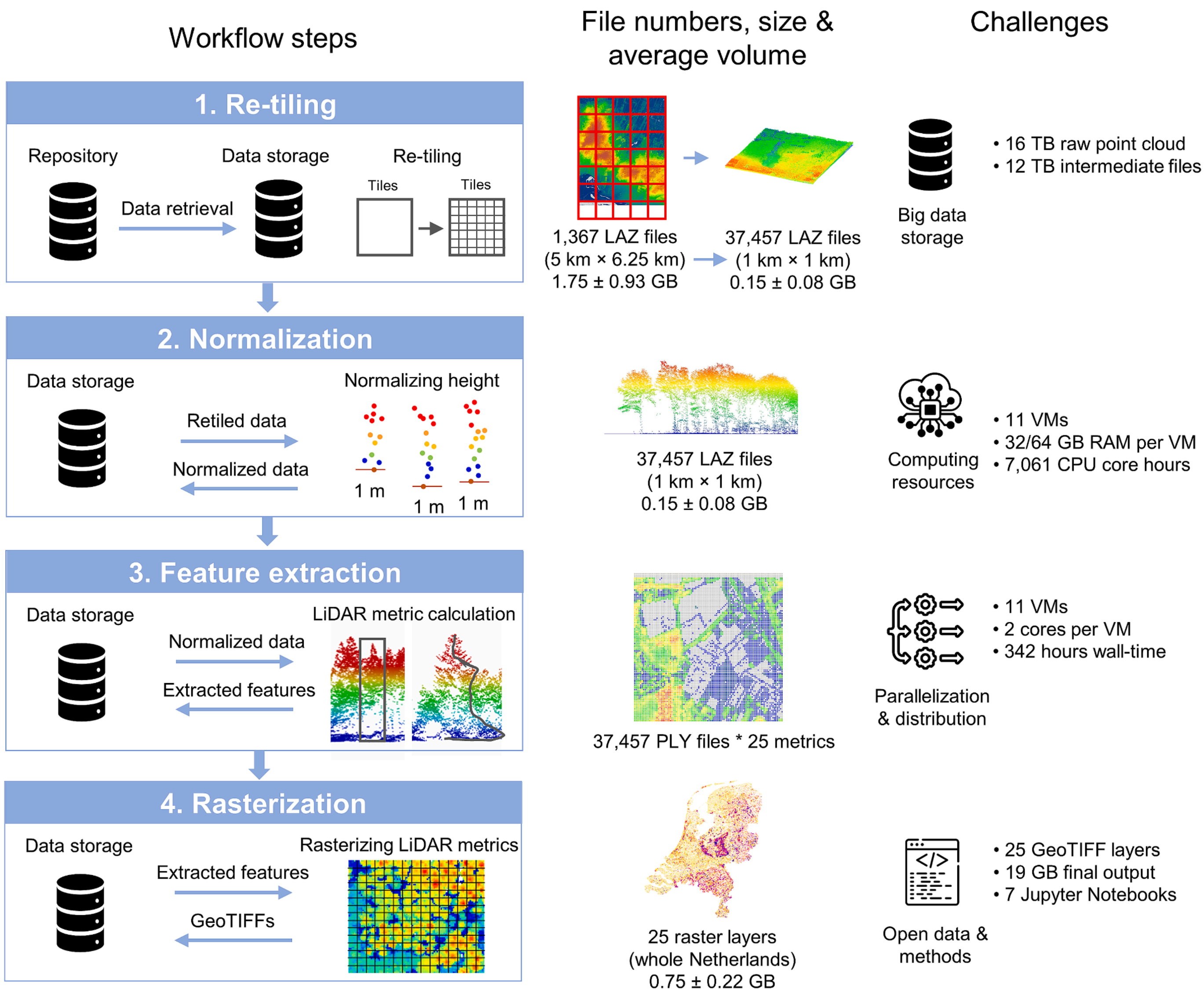

Fig. 7. Example of a high-throughput LiDAR workflow for generating geospatial data products of vegetation structure from national ALS point clouds. Handling the number, sizes and volumes of files creates various challenges in terms of big data storage, computing resources, parallel and distributed processing, and open data and methods. The example illustrates the processing of a country-wide ALS dataset of the Netherlands. See details in Kissling et al. (2022).

repositories available (national or global) for sharing raw and pre-processed UAV imagery. One example is OpenAerialMap (https://openaerialmap.org/) which provides access to openly licensed imagery. Much UAV data, however, are only available in generalist open repositories such as Zenodo (https://zenodo.org/) and therefore often hard to find. More broadly, there is currently no overview or inventory of UAV datasets and their ground-reference data available for habitat condition monitoring.

A metadata catalogue with human- and machine-readable metadata is needed to improve the provisioning of FAIR data, i.e., to increase findability and accessibility (Hardisty et al., 2019; Wilkinson et al., 2016). A range of metadata catalogue technologies are already available for organizing, discovering, and managing geospatial and environmental data. The SpatioTemporal Asset Catalogs (STAC) is promising as it is optimized for geospatial indexing, retrieval, and metadata representation of massive remote sensing data (https://stacspec.org/). It therefore offers several key advantages over other cataloguing systems (e.g., CKAN, Dataverse, and GeoNetwork) when dealing with LiDAR point clouds, drone imagery, and satellite data (Schindler et al., 2023; Zhao et al., 2021b). STAC allows a fast and efficient search using bounding boxes, geometries, and date ranges, is optimized for cloud-native storage, and makes it easy to discover specific data types such as spectral bands in UAV imagery. When describing metadata in a catalogue, existing standards should be used and extended to capture key information on the datasets (e.g., general info, geographic and temporal information, flight information), how data are stored (databases, single files, file formats, etc.), and how they can be accessed (e.g., via open data platforms, institutional repositories or websites). The LAS/LAZ format (ASPRS, 2019) already provides a good basis for the standardized description of LiDAR raw data (e.g., point clouds from national ALS surveys), but it currently does not capture flight attributes (e.g., field-of-view, swath overlap, pulse rate, scan rate, and flight speeds). Once LiDAR point clouds are processed, the derived LiDAR metrics are typically made available as geospatial raster files (Assmann et al., 2022; Kissling et al., 2022; Roussel et al., 2020) for which metadata can be described using standards such as INSPIRE, ISO, and EML (Hardisty et al., 2019). For datasets captured with UAVs, there is currently no standardized way of describing the metadata, but the development of a Minimum Information Framework (MIF) has been suggested to describe UAV platforms and flight plans (Barbieri et al., 2023), including best practice protocols for campaign flying and data pre-processing.

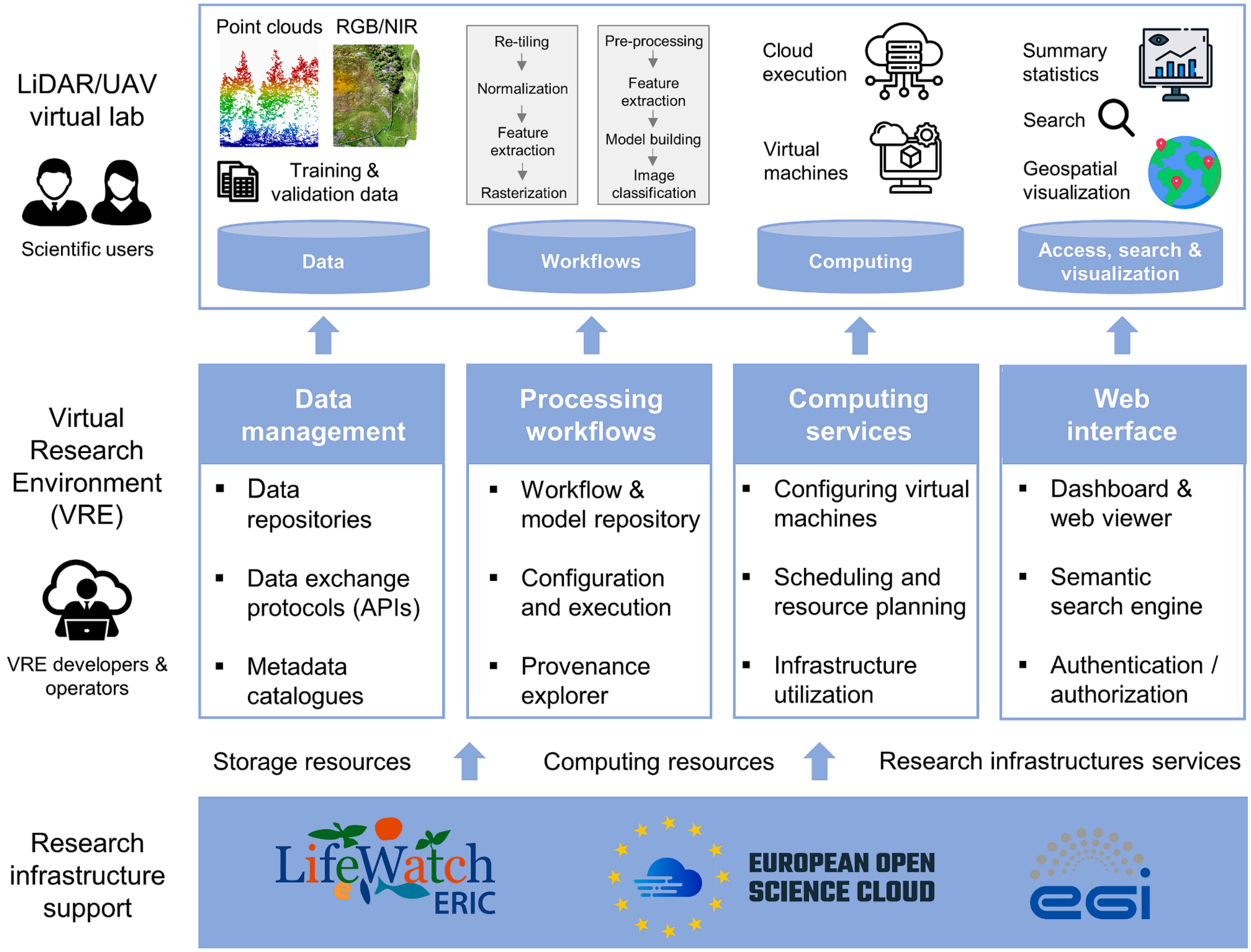

Fig. 8. A simplified illustration of a virtual research environment that enables the creation of application-specific virtual labs for habitat condition research and monitoring. This includes data management, processing workflows, computing and web services for processing airborne LiDAR or UAV remote sensing data to extract biotic, abiotic and landscape characteristics of habitats. Existing research infrastructures (with examples from the EU) can provide services, storage, and computing resources.

4.2. Processing workflows

Like for data, existing processing workflows and scripts for habitat condition research and monitoring are not easy to find and access. Nevertheless, several general workflow registries and repositories exist. For instance, WorkflowHub (https://workflowhub.eu/) is a workflow registry that aims to facilitate discovery and re-use of workflows in an accessible and interoperable way. Similarly, machine learning models can be stored and shared on open-source platforms such as Hugging Face (https://huggingface.co/). These registries and repositories are domain-agnostic, and no workflows or machine learning models for habitat condition metrics from LiDAR and UAV imagery are so far included. Generalist repositories such as Zenodo can also store processing workflows, but those are hard to find as they are not documented in a standardized way. For software that has been developed in the Python programming language, the Python Package Index (PyPI) provides a software repository. The workflow management in a VRE should therefore provide a workflow and model repository or APIs to harvest metadata from existing workflow registries and model repositories (Fig. 8). This should include relevant R and Python scripts and other open-source software tools for processing LiDAR point clouds and UAV imagery, e.g., for pre-processing and feature extraction of UAV imagery (Fig. 4) or for re-tiling, normalization, feature extraction and rasterization of ALS point clouds (Fig. 7). Reproducible and FAIR workflows for training and validating machine learning models should be made available. This would enhance and facilitate the re-use of code for the consistent calculation of habitat condition metrics from airborne LiDAR and UAV data.

In addition to a workflow and model repository, a VRE could provide additional services for workflow management (Fig. 8). For instance, the workflow management system of the VRE would help to design new application-specific workflows, to configure specific parameters in workflows (as well as input and output), and to execute the processing (Zhao et al., 2022). A provenance explorer can provide an interface for more technically oriented users to monitor the progress of the whole process, to interactively explore the system logs and workflow processing history, and to identify anomalies and reproduce workflows or problems when scheduled in the cloud (Zhao et al., 2022). When developing the workflow management system of the VRE, notebook environments (e.g., R-Studio and Jupyter) and popular programming languages (e.g., Python, R, C++ and Julia) should be considered to ensure the ease of use and friendliness of the system (Zhao et al., 2022). Also, a range of free and open-source software tools for LiDAR and UAV image processing are already available and should be considered. For UAV imagery, this includes open-source software such as OpenDroneMap (https://www.opendronemap.org/) and QGIS with its UAV Toolbox and Orfeo Toolbox plugins (https://www.qgis.org/) which support RGB, multispectral and thermal images, georeferencing, DTM generation, orthomosaic creation, and geospatial data analysis. Other examples include Meshroom (https://alicevision.org/) which is a free, open-source 3D reconstruction software that provides photogrammetry pipelines for structure-from-motion, and various other open source hardware and software tools for UAVs (Pereyra Irujo et al., 2023). For data obtained with LiDAR, open-source software for 3D point cloud processing such as CloudCompare (https://www.danielgm.net/cc/), the Point Data Abstraction Library (PDAL, https://pdal.io/en/2.6.0/), the Geospatial Data Abstraction Library (GDAL, https://gdal.org/), the R package LidR (Roussel et al., 2020), the Python tool Laserchicken (Meijer et al., 2020), and Jupyter Notebooks of the high-throughput Laserfarm workflow (Kissling et al., 2022) is available. For less-programming oriented users, simplified and user-friendly interfaces should be available for workflow execution, e.g., by encapsulating different workflow steps as dockerized services with file-based input and output (Zhao et al., 2022).

4.3. Computing services

Running workflows with UAV images and LiDAR point clouds in a cloud-based VRE offers several advantages over personal computers, particularly for processing, storage, and collaboration. For instance, cloud-based VREs can automatically scale resources (compute, memory, storage), allow to adjust processing power based on workload, and can dramatically reduce the overall processing time by facilitating distributed computing (with advanced computational clusters, often equipped with GPUs) and parallel processing (splitting larger datasets into smaller chunks and process them in parallel). They also allow users to access data and workflows from anywhere with an internet connection, making collaboration between geographically distributed teams easy. However, this also requires various computing services (Fig. 8), such as tools for cloud automation that enable the execution of workflows on remote infrastructures, including planning, automation and configuration of VMs and computing clusters, and the scheduling of workflow execution (Zhao et al., 2022). With such computing services, users can flexibly adjust the configurations of the cloud environment (e.g., the number of VMs, the number of cores per VM, the scheduled wall-time etc.), based on the input data characteristics, data volume and the deployed workflow. This allows using computing resources in an efficient way.

The computing services in the VRE should utilize services and resources from existing research infrastructures (Fig. 8). For instance, in the case of Europe, LifeWatch ERIC is an e-Science European infrastructure for biodiversity and ecosystem research, which provides various ICT tools and services, including functionalities for VREs (https://www.lifewatch.eu/). The European Open Science Cloud (EOSC) is a virtual environment for hosting and processing research data to support EU open science, e.g., with open and seamless services for storage, management, analysis and re-use of research data (https://eosc.eu/). The European Grid Infrastructure (EGI) provides access to high-throughput computing resources across Europe using grid computing techniques, including high-throughput and cloud computing, storage, and data management (https://www.egi.eu/). Other cloud-based hosting and processing solutions such as public clouds (Amazon, Microsoft Azure, Google cloud etc.) can also be considered. Hence, basic IT services could come from existing research infrastructures whereas the specific services of a VRE supporting habitat condition monitoring would have to be developed, taking already existing tools into account.

4.4. Web services

A VRE needs to be supported by an interactive, engaging, and user-friendly web interface that gives users access to data, processing workflows, models, available training and validation datasets, and other relevant tools and services (Fig. 8). This requires various digital tools for the secure sharing and dissemination of knowledge, such as online dashboards, web viewers, a semantic search engine, authentication and authorization procedures for federated and distributed systems, and automatic translation functions for different languages. Online dashboards and web viewers would visualize the key information of the assets (e.g., data, models, processing workflows), show the progress of workflow execution, and provide a view on geospatial data (e.g., via a map viewer), graphics, and summary statistics. A semantic search engine could provide a web interface to search internal and external catalogues (e.g., for LiDAR point clouds, UAV imagery, derived geospatial data products, training data, workflows, scripts etc.), and also an API for the application to invoke via Jupyter (Zhao et al., 2022). A knowledgebase in the VRE could also include best practice guidelines (e.g., how to design UAV surveys and which metadata to record), suggestions and templates for metadata standards and formats, and tutorials for data management education. Finally, users from different institutions should be able to securely access information that is distributed on different web servers, e.g. through an authentication and authorization infrastructure (AAI) that address the requirements of federated and distributed systems (e.g., EOSC-hub AAI in the European Union).

4.5. Research, collaboration and funding

First steps, developing some of the VRE components, have already been made. For instance, the creation of a RDA interest group (Berman and Crosas, 2020) with focus on ‘Small Unmanned Aircraft Systems’ Data’ will help to discuss and develop UAV data collection standards, and a minimum information framework for collecting metadata for UAV datasets has been described (Barbieri et al., 2023). Moreover, an efficient, scalable and distributed high-throughput workflow for processing multi-terabyte LiDAR point clouds on remote infrastructures has been developed (Kissling et al., 2022) and a notebook-based cloud VRE in the Jupyter environment has been implemented on the LifeWatch infrastructure (Zhao et al., 2022). However, a much larger effort is needed to develop a VRE that can supporting habitat condition monitoring in the EU (Høye et al., 2023). A crucial aspect is to have support from research infrastructures such as LifeWatch ERIC for VRE development and maintenance and sustainable long-term funding that goes beyond the budgets of short-term research projects. VRE development further requires interdisciplinary collaborations between potential scientific users of the virtual labs (i.e., domain scientist with expertise in ecology, remote sensing, and geoprocessing) and computer scientists who develop the VRE (e.g., data scientists, machine learning engineers, and software developers). Scientific users of the VRE should also collaborate closely with monitoring practitioners and nature conservation agencies to ensure that the derived knowledge facilitates policy-supporting applications such as the implementation of the EU Habitats Directive and the Natura 2000 network (Vanden Borre et al., 2011). For instance, interactions with governmental agencies, community initiatives, farmers, private landowners, environmental consultancies, and UAV and LiDAR survey service providers are required to better understand which LiDAR and UAV remote sensing data and tools are most relevant for a cost-effective habitat condition monitoring. This input is key to identify relevant habitat condition metrics that require upscaling and to develop user friendly survey protocols, metadata tools and protocols, workflows, and cloud-based data storage and processing services dedicated to a standardized LiDAR and UAV data acquisition and processing. These interactions and collaborations require an improved coordination, an increase in financial resources, and enhanced capacity building and stakeholder engagement (Moersberger et al., 2024). Support from existing European research infrastructures (e.g., LifeWatch, EOSC, EGI) together with funding from the European Commission and the establishment of a European Biodiversity Observation Coordinating Centre (EBOCC) could help to achieve these goals (Høye et al., 2024; Liquete et al., 2024). A close collaboration with the European Environment Agency (EEA) is also crucial, especially to provide FAIR (meta)data through their SDI geospatial data catalogue (https://sdi.eea.europa.eu/), to include the European Environment Information and Observation Network (Eionet) representing member and cooperating countries (https://www.eionet.europa.eu/), and to interact with the European

Topic Centre on Biodiversity and Ecosystems (ETC BE) with its thematic expertise for the implementation of EU directives, including ecosystem assessments (https://www.eionet.europa.eu/etcs/etc-be).

5. Conclusions

In this *viewpoint* article, we synthesized the challenges and potential solutions for consistently measuring and monitoring habitat condition from airborne LiDAR and UAV remote sensing over large spatial extents. We propose the development of a VRE to enhance data discovery, sharing, access, and standardization, as well as workflow reproducibility and model transferability. This will require the application of open standards and best practices for data collection and pre-processing, the compilation of standardized, richly described and machine-actionable metadata, the development of free and open-source software and FAIR geospatial processing workflows, targeted investments and sustainable long-term funding. The adoption of open science principles (open data, open source, and open methods) and FAIR guiding principles, together with close collaborations with monitoring practitioners, nature conservation agencies, and national and EU bodies, and the uptake of new data, workflows, models, and tools will substantially improve indicator calculation and the tracking of progress towards conservation targets and policy goals. This will ultimately help to reverse the degradation and unsustainable use of natural resources.

CRediT authorship contribution statement

W. Daniel Kissling: Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Yifang Shi:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis. **Jinhu Wang:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Agata Walicka:** Writing – review & editing, Writing – original draft. **Charles George:** Writing – review & editing, Writing – original draft. **Jesper E. Moeslund:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition. **France Gerard:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition.

Funding

This research was funded by the European Commission through the MAMBO project (grant agreement number 101060639). WDK also acknowledges funding for the EuropaBON project from the European Union's Horizon 2020 research and innovation programme (grant agreement number 101003553). Views and opinions expressed are those of the authors only and do not necessarily reflect those of the European Union or the European Commission. Neither the EU nor the EC can be held responsible for them.

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.

Acknowledgements

We thank Jasper Steenvoorden, Vítězslav Moudrý and an anonymous reviewer for their constructive and inspiring comments. We also acknowledge comments on an earlier manuscript version by six anonymous reviewers with expertise in UAVs, LiDAR, deep learning, and forestry. We thank Christophe Dominik (Helmholtz-Centre for Environmental Research - UFZ) and Alexis Joly (INRIA) for comments and feedback on the MAMBO deliverable, Zhiming Zhao (University of Amsterdam) for discussions about cloud-based virtual research environments, and João Gonçalves for permission to use a map from his research in Fig. 1.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2024.112970.

Data availability

The data and analysis scripts created for this study are openly available in Zenodo at https://zenodo.org/records/13619387. The scripts are also accessible on the GitHub repository (https://github.com/Jinhu-Wang/Testing-the-robustness-of-LiDAR-vegetation-metrics-to-varying-point-densities).

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