UAS for Forest Inventory Traits: A Review

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Abstract

Traits are notoriously challenging to measure at a desirably large spatial extent with traditional field methods, which limits the discoveries that forest ecologists can make with these data. There is a ripe opportunity for uncrewed aerial systems (UAS) to contribute to ecology through forest inventory trait mapping. UAS can help overcome the challenge of scale by collecting data at a larger spatial extent with comparable resolution. With the proliferation of large-scale spatially explicit analyses, using UAS for forest trait mapping is synergistic with the direction that the field of forest ecology is headed, and thus an essential method for forest ecology toolkits. Here we provide evidence that forest traits are increasingly used as the metrics of focus in forest ecology, review what forest inventory traits and attributes can be derived from UAS-based data, and dive into a case example of how researchers derive a particular trait, carbon stock, from UAS-based data. Our results highlight the underutilization and infancy of UAS in forest ecology. From our review of the carbon stock literature, we found a different method of calculating carbon stock from UAS data in every paper, each with their own hurdles and caveats in estimating plant-based carbon stock. UAS can push forest ecology and the concomitant field

of spatial ecology into a future with better temporal and spatial resolution of data collected on an evermore affordable budget.

Keywords

Unmanned aerial systems; Uncrewed aerial systems; UAS; Forest traits; Functional traits; Functional biogeography; Forest inventory; Forest ecology; Vegetation index; Forest structure

Introduction

The use of small-scale data can limit discovery in the field of forest ecology. Researchers make inferences at the population-, community-, or ecosystem-level from forest inventory datasets; however, data collection is often constrained spatially and temporally by traditional field survey methods. Major technological innovations, like open source programming languages and computers with high processing power, enabled the development of cutting-edge statistical and theoretical methods to maximize return on messy or incomplete datasets (Knuth, 2003), (Maltenfort, 2015). Remote sensing technologies offer more comprehensive data collection and have recently been modernized through miniaturization of cameras and sensors, though this innovation has yet to realize its potential in forest ecology. Advances in uncrewed aerial systems (UAS) allow users to gather data at relevant spatial and temporal resolutions and with unprecedented efficiency compared to using traditional field-based methods with comparable effort and resources. UAS collect data with fine enough spatial resolution to measure trees at a scale relevant to their biology, while simultaneously covering a spatial extent large enough to measure landscapes. These spatially explicit data from UAS will push spatial ecology forward (Anderson & Gaston, 2013) (Box 1).

There are ripe opportunities for UAS to contribute to ecology through forest inventory trait mapping. Measuring forest traits allows for continuous comparison across ecosystems and for appropriate incorporation of forest dynamics into Earth system models (e.g., global climate models) (Scheiter et al. 2013, van Bodegom et al. 2014, Reich et al. 2014). However, traits are notoriously challenging to measure at a large enough spatial scale with traditional field methods (Violle et al., 2014), a challenge that UAS can help overcome by collecting data at a larger spatial extent with comparable resolution. UAS act as a link between field collections and airborne- and satellite-based imagery by scaling up ground measurements of traits to larger landscapes and by unmixing spatially coarse airborne- and satellite-based imagery for more accurate trait mapping to regional and global scales (Box 1). As anthropogenic influences continue to alter forests, flexible and efficient technologies like UAS are needed to track success in management practices and changes in forest ecosystem stability (Mori et al., 2017). With the proliferation of large-scale spatially explicit analyses, using UAS for forest trait mapping is synergistic with the direction the field of forest ecology is headed, and thus an essential method for forest ecology toolkits.

Here we provide evidence that forest traits are increasingly used as metrics of focus in forest ecology, review what forest inventory traits and attributes can be derived from UAS-based data, and dive into a case example of how researchers derive a particular trait, carbon stock, from UAS-based data. In this venture, we provide examples of and spur ideas for the multitude of ways that UAS can be used to estimate forest inventory traits. While the up-front expense of and expertise required to collect and process UAS data hold back many forest ecologists from using UAS, we aspire to lower the barrier of entry for such researchers who may lack a community of support for using UAS (Box 2).

Why is measuring plant traits important?

Forest ecologists measure traits and attributes of trees to characterize their habitats and understand change through time. A trait is a morphological, anatomical, biochemical, physiological, or phenological feature of individuals or their component organs or tissues (Violle et al., 2007), like aboveground biomass (AGB), diameter at breast height (DBH), or absorbed photosynthetically active radiation (PAR). An attribute is similar to or a proxy for a trait, but not a trait itself, like count of individuals, which is an attribute of a population, or a vegetation index (VI) like normalized difference vegetation index (NDVI), which is a spectral indicator of healthy vegetation. A challenge ecologists face today is collecting sufficient data to enable forecasting of ecosystem-level responses to environmental changes and to compare these changes across the globe (Violle et al., 2014). For example, an understanding of how fine-scale spatial variation in plant traits correlates with environmental variables that have high spatial turnover or correlates even with landscape-scale factors (e.g., elevation, slope, moisture gradients) would open the door to ecologists asking new questions with actionable inferences for policy.

Since traits and attributes (hereafter, referred to simply as traits, for brevity) can be measured continuously across ecosystems, they can better predict ecosystem functioning and create a more robust theoretical baseline than species-level parameters which are limited to each specific geography (Cornelissen et al. 2003, Cadotte et al. 2011, Pérez-Harguindeguy et al. 2013, Violle et al. 2014). Scientists collecting UAS-based trait data can promote open and reusable science by sharing their data on public plant trait databases such as TRY, which integrates plant trait data from several hundreds of trait datasets in one consistent format (Kattge et al., 2011). In a classic example of trait-based remote sensing in conservation, Asner et al. (2017) derived a set of non-correlated, functional traits of rainforest canopies using instrumentation on a crewed aircraft, which were directly useful for conservation in Peru (Kapos, 2017). This exemplifies a recent paradigm shift to functional biogeography, which relates the functional structure of ecosystems to ecosystem features. The shift from species-based to functional biogeography in forest ecology calls for tools like UAS to collect spectral and structural forest properties for measurement of small-scale plant traits continuously across regions (Violle et al., 2014, Schneider et al. 2017).

Why UAS over other forms of data collection for measuring forest traits?

The fine spatial resolution, moderate spatial extent, and temporal flexibility of UAS surveys set UAS apart from other methods of ecological survey (Box 1). Anderson and Gaston (2013) review the benefits that UAS bring to ecology, including making scale-appropriate measurements of forests that enable ecologists to relate structure to function. The fine detail of UAS-based measurements allow detection of textural heterogeneity that aid in estimating forest traits, like leaf area index (LAI), chlorophyll content, and functional group (Laliberte & Rango 2009, Lu et al. 2018). Forest traits used as parameters in dynamic global vegetation models (DGVMs), like biomass, leaf mass per area, stem-specific density, and seed mass, are important components of climate change models (Scheiter et al. 2013, van Bodegom et al. 2014, Reich et al. 2014). Stahl et al. (2014) used seed mass, woody density, and plant height to predict tree species range shifts in a changing climate. Such traits can be more accurately estimated with UAS than with other remote sensing sources due to the fine spatial resolution of UAS imagery (Houborg et al., 2015).

Biodiversity is commonly described as a driver of ecosystem function; however, forest structure, which UAS can measure precisely and accurately, has been considered a better predictor of ecosystem function than even biodiversity (LaRue et al., 2019). For example, forest gap shape metrics were used to identify a strong dependency between disturbance patterns and understory plant diversity in light-limited forests (Getzin et al., 2012). UAS can measure fine spatial detail of forest canopy structure, like canopy height models (CHMs), gap sizes, or understory composition, which can lead to better estimates of ecosystem function over a larger spatial scale than traditional field surveys can capture with equal effort.

UAS-based measurements can supplement field measurements (Mohan et al., 2017) (Box 1). Camera sensors on UAS collect spectral information that can be used to calculate VIs that are proxies for the chemical composition of vegetation (Anderson & Gaston, 2013) (Box 2). Minimal field sampling spanning the variance of data can be used to calibrate accurate estimates of canopy foliar chemical traits using airborne remote sensing (Asner et al. 2015). Saarinen et al. (2018) derived biodiversity indicators in boreal forests using spectral and structural features from UAS-based imagery. They found that dead wood biomass and species richness were underestimated whereas structural variability indicators were the most accurately estimated, the latter which is challenging to measure using traditional field measurements and relatively straight-forward to measure with UAS (Box 3). Conclusions drawn using traditional field data are limited in scale relative to those made with remote sensing data while efforts for the research team are comparable.

UAS remote sensing fills a critical gap between field-based inventories and airborne or satellite remote sensing of forests, linking scales rather than competing (Pádua et al., 2017). Although open source airborne and satellite imagery has revolutionized our understanding of global natural phenomena, it has coarse spatial and temporal resolution, is altered by the atmosphere and, in most cases, is dependent on perfect weather. On the other end of the spectrum, traditional field-based methods of mapping plant traits are essential for ground-truthing and are important for familiarizing oneself with their study system, but can be money-, time-, and labor-intensive. By capturing intermediate spectral and structural heterogeneity across a landscape repeatedly and reliably, UAS act as a complementary link between these scales (Box 1). The fine spatial resolution, moderate spatial extent, and collection regularity offered by UAS surveys have already made UAS an important part of forest inventory monitoring (Wallace et al., 2016). Goodbody et al. (2017) describe a helpful case study in which they estimated tree height and volume derived from airborne lidar data and UAS RGB imagery (Box 3) and find that measurements from UAS RGB imagery, the less common of the two collection methods for forest surveys, generate accurate forest inventory measurements for sustainable forest management. UAS can accelerate findings in forest ecology by measuring functional traits in areas where land-use history or field surveys exist in order to measure human impacts on ecosystems and to better relate biodiversity to ecosystem functioning (Kapos 2017, Schneider et al. 2017). In such cases, ground-based data calibrate stand-level models from UAS, which can be scaled up to satellite or airborne imagery to make predictions at regional levels, allowing traits to be more accurately predicted across a continuous spatial extent. This need for UAS to extend field-collected data is part of the impetus for this review. In this work, we describe how forest ecologists can use UAS to measure traits in their study systems in novel ways.

Forest Inventory Trait Review

Here, we illustrate which traits have been derived from UAS data. We queried Web of Science (WoS) for plant traits measured by UAS (Supporting Information). The aim of our search was to identify which forest inventory traits are already being measured by UAS and for how long. First, we did a broad search to compile a list of which forest inventory traits have been quantified in the literature. Next, we searched each forest inventory trait individually for studies that described the trait as being estimated from UAS data. We expanded each of these queries from just UAS to adding ‘remote sensing’ generally to contextualize how recent and underutilized UAS are in remote sensing of forest traits. The UAS search results are a subset of the results from the UAS and remote sensing search. The reader must keep in mind that the query results summarized in Figure 1 contain papers with matching forest trait terms, but a subset of the returned papers may have theses less relevant to this review than others. We next describe a deep dive into one trait, carbon stock, for which we rigorously filtered the Web of Science results to consider only papers which quantify carbon stock estimates.

Forest inventory traits that can be derived from UAS data - our bread ‘n butter

Our results highlight the underutilization and infancy of UAS in forest ecology. This presents a need for illustrating the utility of this novel and growing field, which this review demonstrates. For the query containing terms related only to UAS, we found an average of only 58 papers per forest inventory trait, compared to 1395 papers in the search containing remote sensing terms (Figure 1). No forest inventory trait had more publications for the UAS search compared to the remote sensing search. The most recent forest inventory trait to enter the remote sensing literature was plant magnesium content in 2004, whereas traits continued to be published for the first time up to the year that this review was done in 2019 (e.g. photosynthetic pigments). The average publication year for the UAS-only search was 2011, compared to 1990 in the search containing remote sensing terms (Figure 1). Photosynthetic pigments and plant calcium had only one result under the UAS search (Figure 1), which points to ample opportunities to measure certain forest traits that are under-studied with UAS. Since UAS are a new technology, it makes sense that there are fewer and more recent studies of forest traits using UAS, but when we compare the average rate of publication since the first year published for each trait, we find 5 papers per year for UAS searches compared to 39 for remote sensing. These summary statistics point out that there continues to be a slow rate of uptake for UAS-based studies in the remote sensing literature, which demonstrates that there is room to push UAS surveys of forest inventory traits along to catch up to other types of remote sensing. However, we see that a new forest inventory trait has been published using UAS methods nearly every year for the last two decades, which demonstrates a solid record of innovation for UAS in forest ecology.

The kinds of forest inventory traits gathered from the literature were varied. To help interpret the WoS results, we organized the forest inventory traits into the following categories (count of traits in parentheses): biochemical (6), biodiversity (1), morphological (12), phenological (3), physiological (8), and population (1) (Figure 1, Supporting Information). The singular traits in a category are species richness in biodiversity and count of individuals in population. Some of the earliest traits surveyed by UAS were physiological, namely absorbed PAR, NDVI, stomatal conductance, water content/stress, leaf chlorophyll, and water use, which were published in the 2000's. Similarly, physiological traits were published early on in the remote sensing literature, too, with the five named traits being published by 1992. Biochemical traits are more recent in the UAS publication record, with plant potassium, phosphorous, magnesium, and calcium published for the first time in the last five years. Plant nitrogen (2008) and the earliest published UAS trait, carbon stock (1998), are exceptions. Physiological and morphological traits are among the most bountifully published trait categories both UAS and general remote sensing literature. Land cover classification is far and away the most published in the remote sensing literature with 10170 results, ahead of NDVI in second with 5976 results. The traits with over 100 publications in the UAS search include land cover classification (154) and NDVI (237 - the most published for UAS), as well as others that yielded 2000 results in the remote sensing: include canopy height (203 UAS, 2053 remote sensing), water content/stress (170, 2706), LAI (212, 3478), leaf chlorophyll (175, 5281), and carbon stock (118, 5501). The traits which had the fewest references returned in the UAS-only search were: plant magnesium (2), plant photosynthetic efficiency (2), photosynthetic pigments (1), and plant calcium (1); whereas the traits with the fewest references in the remote sensing search were: forest gap size (46), leaf mass per area (46), budburst (31), plant calcium (28), and plant magnesium (16). Phenological traits were among the least published for both searches, which includes budburst, leaf flushing, and senescence. Web of Science queries and select references for papers where UAS measured forest inventory traits in Figure 1 are listed in the supplementary section (Supporting Information).

Carbon deep dive

Here we take a deep dive into an example of a single trait, carbon stock, that researchers estimate from UAS data for forest trait mapping. By exploring one trait more thoroughly, we can get a better idea of the various approaches and challenges there are in quantifying a forest trait from UAS data. We selected this trait for our focus because it has the longest publication record in UAS literature.

Having fine-scale measurements of forest traits like carbon stock is imperative for building accurate climate models or DGVMs, tools necessary for proper forest conservation and policy decision-making. Historically, forest conservation planning has often been based on individual species distributions or estimates of ecosystem services (Kapos, 2017). Planning for conservation programs, like countries' efforts to reduce emissions from deforestation and forest degradation (REDD+) and other climate mitigation programs, can benefit greatly from accurate and spatially continuous mapping of forest traits, like carbon stock, for land-use planning (Kapos

2017). UAS-based mapping can capture parameters that go into carbon stock calculation like canopy height, LAI, canopy cover, and species identification, and improve such measurements influencing policy by creating more highly resolved maps of functional traits, continuous across space. The work of Asner et al. (2017) in measuring traits of Peruvian forest canopy using airborne remote sensing had direct policy impact on Peru's conservation plans. Forest conservation planning from UAS measurements is a natural next step. While UAS cannot reach the spatial extent of airborne remote sensing, UAS can provide more precise measurements that can be scaled-up to coarser resolution remote sensing. This scaling can inform regional or global models, while providing a tractable approach for collecting remote sensing data for end users for which airborne collection would be out of scope. Quantifying carbon stock is important for a number of ecological and economic applications: identifying ecological carbon sinks and sources through time, tracking carbon emissions, studying impacts of land use change, and measuring agricultural productivity. Carbon stock is the second most published forest inventory trait in remote sensing and one of the most published using UAS (Figure 1). It has the third longest publication record in remote sensing and the longest using UAS (Figure 1).

We queried the Web of Science, searching for studies that measured carbon stock with UAS. We combed through the roughly 150 results and found only nine where carbon stock volume was actually estimated from UAS-derived data (Table 1). Most of the papers alluded to the utility of estimating carbon stock with their UAS data, as a future direction perhaps, but did not complete this task. Due to this small number, we did not limit the studies to forest inventories and allowed for other vegetation types like lucerne, dryland vegetation, and bog (Table 1).

The nine studies measuring carbon stock spanned four continents. Eight studies surveyed diverse, naturally occurring communities, while one of the nine studied a planted monoculture

(Wehrhan et al., 2016). Only one study used lidar (McClelland II et al., 2018), while the rest used RGB or multispectral imagery, which exemplifies the hurdle of monetary cost for drone-based lidar (Deering & Stoker, 2014).

Measuring carbon stock directly is challenging and requires chemical analysis and an understanding of the distribution of carbon stored throughout a plant. When using remote sensing methods like UAS to estimate carbon stock, calculating biomass is a common first step. All articles but one followed this method, calculating carbon stock using allometric equations from biomass estimates (Table 1). The divergent study estimated carbon loss by comparing the digital elevation models (DEM) pre- and post-degradation (gully formation) of peatland and using a cited carbon density at the site as a reference (Scholefield et al., 2019).

Methodological approaches for estimating carbon stock range from simple to sophisticated. Cunliffe et al. (2016) and Wehrhan et al. (2016) simply used a linear coefficient derived from the literature to convert biomass to carbon and used no validation method (Table 1). Dandois & Ellis (2013) assessed accuracy of AGB estimation, but not of carbon estimation. Messinger et al. (2016) and Swinfield et al. (2019) calculated RMSE by comparing drone-based SfM estimations of carbon to those of airborne- and drone-based LiDAR measurements, respectively. McClelland II et al. (2018) reported 24.07 Mg CO_2 RMSE for their above ground carbon estimation. On the more sophisticated end of the spectrum were Jayathunga et al. (2018) and Li et al. (2019). Jayathunga et al. (2018) used GLMMs to calculate carbon stock, integrating species-specific factors like wood density and biomass expansion for the conversion of volume. Their carbon estimations had 17.4% rRMSE for UAV-SfM estimates considering canopy cover and 18.9% without considering canopy cover. Li et al. (2019) derived VI's texture features, height metrics, and species classifications from their RGB imagery used these as predictors in three regression models (i.e., random forest, artificial neural network, and support vector regression). The random forest model yielded the most accurate results with 0.81 R2, 20.46 Mg C ha^{-1}, and 20% rRMSE (Table 1). These methods for calculating carbon stock from UAS-based measurements are still being refined.

Discussion

The literature reviewed covers a variety of forest inventory traits, both spectrally- and structurally-derived. Of the categories we organized the forest inventory traits into, morphological and physiological traits make up most of the earliest traits studied using UAS-derived data. Carbon stock, land cover, LAI, absorbed PAR, and NDVI are common forest traits and proxies used to understand stand-level productivity, structure, and function. Such traits are useful in studying biodiversity and ecosystem function in forests. The most recent traits studied using UAS-derived data are largely biochemical (e.g., plant potassium, magnesium, and phosphorus), which are challenging to quantify due to the labor and expense of ground-truthing measurements in a laboratory, and are not as commonly used in understanding community dynamics. Other recent appearances in the literature include traits that require measurement of fluorescence (e.g. photosynthetic efficiency) or that can be challenging for a UAS to view (e.g. forest canopy can occlude stem basal area). However, there are still traits that have been measured elsewhere in the remote sensing literature, but yet barely by UAS, such as photosynthetic pigments and plant calcium. These traits present opportunities for scientists to borrow methods from the remote sensing literature to estimate those traits with UAS data. Still, some forest traits have yet to be measured by remote sensing at all. For example, understanding how much carbon trees store below-ground is also important for a holistic understanding of how much carbon a forest stores, but UAS are not yet able to measure this, albeit below-ground carbon is challenging to measure even with more hands-on field methods. Our results reported that the average rate of publication since the first year of publication for each trait was 5 papers per year for UAS searches compared to 39 for remote sensing. This may be explained by a lag in adoption of using UAS in forest ecology research, inconsistency in terminology as UAS has gained traction, and/or the lack of UAS data standardization and public availability.

While more traits are being measured by UAS, we also see expansion of new ways to measure a given trait from UAS-based data. Given the number of sensors to choose from, the variety of flight parameters to select in flying a mission, and various ways to post-process the data, there are many ways to arrive at a trait estimation. We see a variety of traits can be measured using different sensors, but even the same trait can be measured in different ways depending on the scientific question at-hand. In Table 2, we highlight a few citations from our review of forest inventory traits to illustrate which sensors that can be used and combined in measuring forest traits to address a variety of scientific objectives. For forest researchers with agroforestry applications, (Pádua et al., 2017) review contemporary UAS methods and advise users in on UAS selection for their work. From our review of the carbon stock literature, we found a different method of calculating carbon stock in every paper, each with their own hurdles and caveats in estimating plant-based carbon stock (Table 1). For example, one paper used segmentation to delineate individual trees (Li et al., 2019), while most used an area-based (e.g. stand-level) approach. We also recognize that there is not yet an agreement for the most appropriate statistical approaches in deriving a trait from UAS data and cross-validating these estimations, even though such a relation is important in comparing studies that estimate the same trait. One recommendation is to test the estimation accuracy of various statistical approaches in order to justify the best one to use in measuring traits (Capolupo et al., 2015). If more forest researchers followed a single model in quantifying forest carbon stock, results across studies could be more easily compared and these results could more simply be used to inform global climate models. This calls for forest ecologists to be transparent with the choices they make in collecting and processing the data so that benchmark comparisons can be made between methods (Capolupo et al. 2015, Hoffmann et al. 2015, Wallace et al. 2016, Yue, et al. 2018a, Yue et al. 2018b). There needs to be a conversation comparing and refining various forest trait estimation methods from UAS data to amplify their existing utility.

Problems & Challenges

While UAS are becoming a tool to revolutionize spatial ecology, challenges in equipment and licensing maintenance, data quality control and replication, and workflow standardization are still being refined in forest ecology (Anderson & Gaston, 2013). In order to fly a drone, a user must understand local regulations (e.g., U.S. Federal Aviation Administration's (FAA) airspace restrictions) and UAS licensing rules. Once licensing and legalities are figured out, technicalities for data quality assurance and quality control must be addressed (Box 2). Researchers face camera calibration and data replication challenges.(Dandois & Ellis, 2013) summarize factors that influence data quality obtained by post-processing remote sensing data. Flight parameters like altitude, speed, and image overlap are often not reported with UAS-based results, but determine data quality and influence interpretation of results (Baxter & Hamilton, 2018). Sensor calibration techniques are inconsistent across applications, but light exposure on a given day strongly influences image classification accuracy (Lehmann et al. 2015). Changing light conditions also cast shadows and interfere with contrast between trees, which can cover up important species-specific information (Nevalainen et al., 2017). Thus, it is recommended to fly at local solar noon in sunny conditions or during overcast conditions (Lehmann et al. 2015). Since shadow pixels deteriorate the average spectra of vegetation, (Näsi et al., 2015)) avoid this by selecting the 6 brightest pixels within a tree boundary and achieve proper separation of crown color classes to identify tree health.

Occluded or understory trees and overlapping crowns also make tree identification or crown segmentation harder. (Wallace et al., 2016) found that UAV-based lidar and SfM overestimated tree height compared to field measurements in a broadleaf eucalyptus forest, but LiDAR had better canopy penetration than SfM in complex forest structure. Identifying individual coniferous trees usually involves finding the local maxima in a CHM, whereas identifying individual deciduous trees in the same way can lead to different branches on a tree being identified separately (Baena et al., 2017). As images are collected during the UAS flight, higher overlap between subsequent images leads to more comprehensive forest mapping during post-processing. (Michez et al., 2018) found more accurate biomass predictions from a model that used images from two UAV flights at different times within a season compared to a model that used images from a single UAV flight. Even aligning high-resolution spectral data with field validation data requires some expert knowledge and additional inquiry. For example, (Scholl et al., 2020) use airborne data to explore how different methods of delineating the crown polygon from which to sample spectra affects tree species classification.

While great strides have been made in troubleshooting UAS methods to measure more forest traits or to measure them more accurately, there is still more to accomplish. Forest inventory traits we cannot or currently have trouble measuring include belowground biomass, wood density, and tree age, as well as distinguishing vertical distribution of various traits, like chemical composition. Estimating measurement error for remote sensing methods requires ground-truthed data, like GCPs in estimating spatial error or leaf tissue samples for chemical analysis for estimating chlorophyll content from multispectral imagery. Despite the broad reaches of UAS spatially, it can take many days for a multirotor UAS to survey a forest stand in entirety with high image overlap. Launching coordinated fleets of UAS to survey a forest could address this shortcoming in spatial extent (Merino et al., 2012).

Frontier & future directions

Using UAS to study forest inventory traits is still a wild west, in which forest ecologists are continually discovering the capabilities of UAS-derived data. Integrating remotely sensed plant functional traits, environmental databases, and DGVMs will help elucidate mechanisms behind functional diversity and ecosystem function (Schneider et al., 2017). Another frontier in studying forest inventory traits is combining UAS flights and autonomous ground vehicles equipped with lidar to better explore the top and bottom of a forest canopy (Jaakkola et al., 2017). Despite the promise of using UAS in forest ecology, considerations must be made in using these new methods. The use of UAS are best applied by supplementing existing aerial-, space-, and ground-based technologies rather than replacing them (Dash et al., 2017). Sensors on UAVs will need continual innovations to expand their spectral range and specificity to better monitor forest activities such as insect infestations (Näsi et al. 2015, Dash et al., 2017), hydrological traits (Anderegg et al., 2018), and biotic and abiotic causes of tree dieback (Lehmann et al. 2015).

There is a need for community-level knowledge-sharing to push UAS-based ecology to being more accessible. For example, there are not standard metadata required to publish with UAS surveys, but certain metadata are needed in order to make a study reproducible. Many of the most usable post-processing photogrammetry software still are proprietary. There is not yet a commonly agreed-upon storage service that has abilities appropriate to the size of UAS data and their associated data products to save UAS data openly for public access. Getting started incorporating UAS methods into the study of forest inventory traits can be as simple as getting plugged into similar groups developing their own drone ecology programs. The High Latitude Drone Ecology Network and Intermountain Drone Ecology Network are examples of such grassroots groups looking to share and refine UAS protocol within a community. The Index DataBase is a useful online resource for matching remote sensing spectral indices to forest inventory traits.

UAS can push forest ecology and the concomitant field of spatial ecology into a future with better temporal and spatial resolution of data collected on an evermore affordable budget. Bringing UAS into the toolkits of forest ecologists is a big break from the traditional methods of forest inventories, but essential for collecting measurements at a scale appropriate for questions regarding ecosystem-level processes or community-level dynamics. Beyond forest applications, UAS imagery is a goldmine for extracting various traits, making them invaluable records for long-term ecological studies that can be revisited for future scientific questions. With the expansion of UAS use in ecology, global trait mapping will be possible at centimeter scales, pushing ecological forecasting and global climate models to be more accurate and reliable.

Data archive

All data and code for this article are available via GitHub:
https://github.com/annaspiers/uas_foresttraits_review

Declarations

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References

Anderegg, W. R. L., Konings, A. G., Trugman, A. T., Yu, K., Bowling, D. R., Gabbitas, R., Karp, D. S., Pacala, S., Sperry, J. S., Sulman, B. N., & Zenes, N. (2018). Hydraulic diversity of forests regulates ecosystem resilience during drought. *Nature*, *561*(7724). https://doi.org/10.1038/s41586-018-0539-7

Anderson, K., & Gaston, K. J. (2013). Lightweight unmanned aerial vehicles will revolutionize spatial ecology. *Frontiers in Ecology and the Environment*, *11*(3), 138–146. https://doi.org/10.1890/120150

Asner, G. P., Martin, R. E., Knapp, D. E., Tupayachi, R., Anderson, C. B., Sinca, F., Vaughn, N. R., & Llactayo, W. (2017). Airborne laser-guided imaging spectroscopy to map forest trait diversity and guide conservation. *Science*, *355*(6323), 385. https://doi.org/10.1126/science.aaj1987

Asner, Gregory P., Martin, R. E., Anderson, C. B., & Knapp, D. E. (2015). Quantifying forest canopy traits: Imaging spectroscopy versus field survey. *Remote Sensing of Environment*, *158*, 15–27. https://doi.org/10.1016/j.rse.2014.11.011

Baena, S., Moat, J., Whaley, O., & Boyd, D. S. (2017). Identifying species from the air: UAVs and the very high resolution challenge for plant conservation. *PLOS ONE*, *12*(11), e0188714. https://doi.org/10.1371/journal.pone.0188714

Baxter, P. W. J., & Hamilton, G. (2018). Learning to fly: Integrating spatial ecology with unmanned aerial vehicle surveys. *Ecosphere*, *9*(4), e02194. https://doi.org/10.1002/ecs2.2194

Cadotte, M. W., Carscadden, K., & Mirotchnick, N. (2011). Beyond species: Functional diversity and the maintenance of ecological processes and services. *Journal of Applied Ecology*, *48*(5), 1079–1087. https://doi.org/10.1111/j.1365-2664.2011.02048.x

Capolupo, A., Kooistra, L., Berendonk, C., Boccia, L., & Suomalainen, J. (2015). Estimating Plant Traits of Grasslands from UAV-Acquired Hyperspectral Images: A Comparison of Statistical Approaches. *ISPRS International Journal of Geo-Information*, *4*(4), 2792–2820. https://doi.org/10.3390/ijgi4042792

Cornelissen, J., Lavorel, S., Garnier, E. B., Diaz, S., Buchmann, N., Gurvich, D., Reich, P., ter

Steege, H., Morgan, H. D. G., Van der Heijden, M., Pausas, J. G. H., & Poorter, H. (2003). Handbook of protocols for standardised and easy measurement of plant functional traits worldwide. *Australian Journal of Botany, v.51, 335-380 (2003)*, *51*. https://doi.org/10.1071/BT02124

Cunliffe, A. M., Brazier, R. E., & Anderson, K. (2016). Ultra-fine grain landscape-scale quantification of dryland vegetation structure with drone-acquired structure-from-motion photogrammetry. *Remote Sensing of Environment*, *183*, 129–143. https://doi.org/10.1016/j.rse.2016.05.019

Dandois, J. P., & Ellis, E. C. (2013). High spatial resolution three-dimensional mapping of vegetation spectral dynamics using computer vision. *Remote Sensing of Environment*, *136*, 259–276. https://doi.org/10.1016/j.rse.2013.04.005

Dash, J. P., Watt, M. S., Pearse, G. D., Heaphy, M., & Dungey, H. S. (2017). Assessing very high resolution UAV imagery for monitoring forest health during a simulated disease outbreak. *ISPRS Journal of Photogrammetry and Remote Sensing*, *131*, 1–14. https://doi.org/10.1016/j.isprsjprs.2017.07.007

Deering, C. A., & Stoker, J. M. (2014). Casing of LiDAR. *LiDAR News Magazine*, *4*(6), 4.

Getzin, S., Wiegand, K., & Schöning, I. (2012). Assessing biodiversity in forests using very high-resolution images and unmanned aerial vehicles. *Methods in Ecology and Evolution*, *3*(2), 397–404. https://doi.org/10.1111/j.2041-210X.2011.00158.x

Goodbody, T. R., Coops, N. C., Marshall, P. L., Tompalski, P., & Crawford, P. (2017). Unmanned aerial systems for precision forest inventory purposes: A review and case study. *The Forestry Chronicle*, *93*(1), 71–81.

Hoffmann, H., Nieto, H., Jensen, R., Guzinski, R., Zarco-Tejada, P., & Friborg, T. (2015). *Estimating evapotranspiration with thermal UAV data and two source energy balance models* (Vol. 20). https://doi.org/10.5194/hessd-12-7469-2015

Houborg, R., Fisher, J. B., & Skidmore, A. K. (2015). Advances in remote sensing of vegetation function and traits. *International Journal of Applied Earth Observation and Geoinformation*, *43*, 1–6. https://doi.org/10.1016/j.jag.2015.06.001

Jaakkola, A., Hyyppä, J., Yu, X., Kukko, A., Kaartinen, H., Liang, X., Hyyppä, H., & Wang, Y. (2017). Autonomous Collection of Forest Field Reference—The Outlook and a First Step with UAV Laser Scanning. *Remote Sensing*, *9*(8), 785. https://doi.org/10.3390/rs9080785

Jayathunga, S., Owari, T., & Tsuyuki, S. (2018). Evaluating the Performance of Photogrammetric Products Using Fixed-Wing UAV Imagery over a Mixed Conifer–Broadleaf Forest: Comparison with Airborne Laser Scanning. *Remote Sensing*, *10*(2), 187. https://doi.org/10.3390/rs10020187

Kapos, V. (2017). Seeing the forest through the trees. *Science*, *355*(6323), 347–349. https://doi.org/10.1126/science.aal5120

Kattge, J., Díaz, S., Lavorel, S., Prentice, I. C., Leadley, P., Bönisch, G., Garnier, E., Westoby, M., Reich, P. B., Wright, I. J., Cornelissen, J. H. C., Violle, C., Harrison, S. P., Bodegom, P. M. V., Reichstein, M., Enquist, B. J., Soudzilovskaia, N. A., Ackerly, D. D., Anand, M., … Wirth, C. (2011). TRY – a global database of plant traits. *Global Change Biology*, *17*(9), 2905–2935. https://doi.org/10.1111/j.1365-2486.2011.02451.x

Knuth, K. H. (2003). *Intelligent machines in the twenty-first century: Foundations of inference and inquiry*. https://royalsocietypublishing.org/doi/10.1098/rsta.2003.1268

Laliberte, A. S., & Rango, A. (2009). Texture and Scale in Object-Based Analysis of Subdecimeter Resolution Unmanned Aerial Vehicle (UAV) Imagery. *IEEE Transactions on Geoscience and Remote Sensing*, *47*(3), 761–770. https://doi.org/10.1109/TGRS.2008.2009355

LaRue, E. A., Hardiman, B. S., Elliott, J. M., & Fei, S. (2019). Structural diversity as a predictor of ecosystem function. *Environmental Research Letters*, *14*(11), 114011. https://doi.org/10.1088/1748-9326/ab49bb

Lehmann, J., Nieberding, F., Prinz, T., & Knoth, C. (2015). Analysis of Unmanned Aerial System-Based CIR Images in Forestry—A New Perspective to Monitor Pest Infestation Levels. *Forests*, *6*(12), 594–612. https://doi.org/10.3390/f6030594

Li, Z., Zan, Q., Yang, Q., Zhu, D., Chen, Y., & Yu, S. (2019). Remote Estimation of Mangrove Aboveground Carbon Stock at the Species Level Using a Low-Cost Unmanned Aerial Vehicle System. *Remote Sensing*, *11*(9), 1018. https://doi.org/10.3390/rs11091018

Lu, B., He, Y., & Liu, H. H. T. (2018). Mapping vegetation biophysical and biochemical properties using unmanned aerial vehicles-acquired imagery. *International Journal of Remote Sensing*, *39*(15–16), 5265–5287. https://doi.org/10.1080/01431161.2017.1363441

Maltenfort, M. G. (2015). Understanding Bayesian Statistics. *Clinical Spine Surgery*, *28*(8), 294. https://doi.org/10.1097/BSD.0000000000000320

McClelland II, M. P., Hale, D. S., & Aardt, J. van. (2018). A comparison of manned and unmanned aerial Lidar systems in the context of sustainable forest management. *Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping III*, *10664*, 106640S. https://doi.org/10.1117/12.2304850

Merino, L., Caballero, F., Martínez-de-Dios, J. R., Maza, I., & Ollero, A. (2012). An Unmanned Aircraft System for Automatic Forest Fire Monitoring and Measurement. *Journal of Intelligent & Robotic Systems*, *65*(1), 533–548. https://doi.org/10.1007/s10846-011-9560-x

Messinger, M., Asner, G., & Silman, M. (2016). Rapid Assessments of Amazon Forest Structure and Biomass Using Small Unmanned Aerial Systems. *Remote Sensing*, *8*(8), 615. https://doi.org/10.3390/rs8080615

Michez, A., Bauwens, S., Brostaux, Y., Hiel, M.-P., Garré, S., Lejeune, P., & Dumont, B. (2018). How Far Can Consumer-Grade UAV RGB Imagery Describe Crop Production? A 3D and Multitemporal Modeling Approach Applied to Zea mays. *Remote Sensing*, *10*(11), 1798. https://doi.org/10.3390/rs10111798

Mohan, M., Silva, C., Klauberg, C., Jat, P., Catts, G., Cardil, A., Hudak, A., & Dia, M. (2017). Individual Tree Detection from Unmanned Aerial Vehicle (UAV) Derived Canopy Height Model in an Open Canopy Mixed Conifer Forest. *Forests*, *8*(9), 340. https://doi.org/10.3390/f8090340

Mori, A. S., Lertzman, K. P., & Gustafsson, L. (2017). Biodiversity and ecosystem services in forest ecosystems: A research agenda for applied forest ecology. *Journal of Applied Ecology*, *54*(1), 12–27. https://doi.org/10.1111/1365-2664.12669

Näsi, R., Honkavaara, E., Lyytikäinen-Saarenmaa, P., Blomqvist, M., Litkey, P., Hakala, T., Viljanen, N., Kantola, T., Tanhuanpää, T., & Holopainen, M. (2015). Using UAV-Based Photogrammetry and Hyperspectral Imaging for Mapping Bark Beetle Damage at Tree-Level. *Remote Sensing*, *7*(12), 15467–15493. https://doi.org/10.3390/rs71115467

Nevalainen, O., Honkavaara, E., Tuominen, S., Viljanen, N., Hakala, T., Yu, X., Hyyppä, J., Saari, H., Pölönen, I., Imai, N., & Tommaselli, A. (2017). Individual Tree Detection and Classification with UAV-Based Photogrammetric Point Clouds and Hyperspectral Imaging. *Remote Sensing*, *9*(3), 185. https://doi.org/10.3390/rs9030185

Pádua, L., Vanko, J., Hruška, J., Adão, T., Sousa, J. J., Peres, E., & Morais, R. (2017). UAS, sensors, and data processing in agroforestry: A review towards practical applications. *International Journal of Remote Sensing*, 1–43. https://doi.org/10.1080/01431161.2017.1297548

Pérez-Harguindeguy, N., Díaz, S., Garnier, E., Lavorel, S., Poorter, H., Jaureguiberry, P., Bret-Harte, M. S., Cornwell, W. K., Craine, J. M., Gurvich, D. E., Urcelay, C., Veneklaas, E. J., Reich, P. B., Poorter, L., Wright, I. J., Ray, P., Enrico, L., Pausas, J. G., de Vos, A. C., … Cornelissen, J. H. C. (2013). *New handbook for standardised measurement of plant functional traits worldwide*. https://doi.org/10.1071/BT12225

Reich, P. B., Luo, Y., Bradford, J. B., Poorter, H., Perry, C. H., & Oleksyn, J. (2014). Temperature drives global patterns in forest biomass distribution in leaves, stems, and roots. *Proceedings of the National Academy of Sciences*, *111*(38), 13721–13726. https://doi.org/10.1073/pnas.1216053111

Saarinen, N., Vastaranta, M., Näsi, R., Rosnell, T., Hakala, T., Honkavaara, E., Wulder, M. A., Luoma, V., Tommaselli, A. M. G., Imai, N. N., Ribeiro, E. A. W., Guimarães, R. B., Holopainen, M., & Hyyppä, J. (2018). Assessing Biodiversity in Boreal Forests with UAV-Based Photogrammetric Point Clouds and Hyperspectral Imaging. *Remote Sensing*, *10*(2), 338. https://doi.org/10.3390/rs10020338

Scheiter, S., Langan, L., & Higgins, S. I. (2013). Next-generation dynamic global vegetation models: Learning from community ecology. *New Phytologist*, *198*(3), 957–969. https://doi.org/10.1111/nph.12210

Schneider, F. D., Morsdorf, F., Schmid, B., Petchey, O. L., Hueni, A., Schimel, D. S., & Schaepman, M. E. (2017). Mapping functional diversity from remotely sensed morphological and physiological forest traits. *Nature Communications*, *8*(1), 1–12. https://doi.org/10.1038/s41467-017-01530-3

Scholefield, P., Morton, D., McShane, G., Carrasco, L., Whitfield, M. G., Rowland, C., Rose, R., Wood, C., Tebbs, E., Dodd, B., & Monteith, D. (2019). Estimating habitat extent and carbon loss from an eroded northern blanket bog using UAV derived imagery and topography. *Progress in Physical Geography: Earth and Environment*, *43*(2), 282–298. https://doi.org/10.1177/0309133319841300

Scholl, V. M., Cattau, M. E., Joseph, M. B., & Balch, J. K. (2020). Integrating National Ecological Observatory Network (NEON) Airborne Remote Sensing and In-Situ Data for Optimal Tree Species Classification. *Remote Sensing*, *12*(9), 1414. https://doi.org/10.3390/rs12091414

Stahl, U., Reu, B., & Wirth, C. (2014). Predicting species' range limits from functional traits for the tree flora of North America. *Proceedings of the National Academy of Sciences*, *111*(38), 13739–13744. https://doi.org/10.1073/pnas.1300673111

Swinfield, T., Lindsell, J. A., Williams, J. V., Harrison, R. D., Agustiono, Habibi, Gemita, E., Schönlieb, C. B., & Coomes, D. A. (2019). Accurate Measurement of Tropical Forest Canopy Heights and Aboveground Carbon Using Structure From Motion. *Remote Sensing*, *11*(8), 928. https://doi.org/10.3390/rs11080928

Thorp, K. R., Thompson, A. L., Harders, S. J., French, A. N., & Ward, R. W. (2018). High-Throughput Phenotyping of Crop Water Use Efficiency via Multispectral Drone Imagery and a Daily Soil Water Balance Model. *Remote Sensing*, *10*(11), 1682. https://doi.org/10.3390/rs10111682

van Bodegom, P. M., Douma, J. C., & Verheijen, L. M. (2014). A fully traits-based approach to modeling global vegetation distribution. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(38), 13733–13738. https://doi.org/10.1073/pnas.1304551110

Violle, C., Navas, M.-L., Vile, D., Kazakou, E., Fortunel, C., Hummel, I., & Garnier, E. (2007). Let the concept of trait be functional! *Oikos*, *116*(5), 882–892. https://doi.org/10.1111/j.0030-1299.2007.15559.x

Violle, C., Reich, P. B., Pacala, S. W., Enquist, B. J., & Kattge, J. (2014). The emergence and promise of functional biogeography. *Proceedings of the National Academy of Sciences*, *111*(38), 13690–13696. https://doi.org/10.1073/pnas.1415442111

Wallace, L., Lucieer, A., Malenovský, Z., Turner, D., & Vopěnka, P. (2016). Assessment of Forest Structure Using Two UAV Techniques: A Comparison of Airborne Laser Scanning and Structure from Motion (SfM) Point Clouds. *Forests*, *7*(3), 62. https://doi.org/10.3390/f7030062

Wan, L., Li, Y., Cen, H., Zhu, J., Yin, W., Wu, W., Zhu, H., Sun, D., Zhou, W., & He, Y. (2018). Combining UAV-Based Vegetation Indices and Image Classification to Estimate Flower Number in Oilseed Rape. *Remote Sensing*, *10*(9), 1484. https://doi.org/10.3390/rs10091484

Wehrhan, M., Rauneker, P., & Sommer, M. (2016). UAV-Based Estimation of Carbon Exports from Heterogeneous Soil Landscapes—A Case Study from the CarboZALF Experimental Area. *Sensors (Basel, Switzerland)*, *16*(2), 255. https://doi.org/10.3390/s16020255

Yue, J., Feng, H., Jin, X., Yuan, H., Li, Z., Zhou, C., Yang, G., & Tian, Q. (2018). A Comparison of Crop Parameters Estimation Using Images from UAV-Mounted Snapshot Hyperspectral Sensor and High-Definition Digital Camera. *Remote Sensing*, *10*(7), 1138. https://doi.org/10.3390/rs10071138

Yue, J., Feng, H., Yang, G., & Li, Z. (2018). A Comparison of Regression Techniques for Estimation of Above-Ground Winter Wheat Biomass Using Near-Surface Spectroscopy. *Remote Sensing*, *10*(1), 66. https://doi.org/10.3390/rs10010066

Box 1. The myriad benefits of UAS

The benefits of UAS are abundant and together make them a valuable ecological surveying tool for forest monitoring. UAS are affordable; can link across data scales; allow for frequent monitoring across large spatial extents; are not constrained by cloud cover; and help eliminate sampling bias.

- **UAS save money and time**. UAS platforms are cheaper than launching a satellite into space, renting an aircraft and pilot, or employing a team of expert technicians to do a forest inventory. Goodbody et al. (2017) point out that collecting airborne data is economically inefficient for small areas, making it unusable for operational forest inventory surveying. Their ease of use and large spatial coverage allow UAS to be deployed quickly and with automated missions which facilitates updating inventories regularly, as Marques et al. (2019) leveraged in monitoring chestnut trees. This feature make it optimal for phenological studies, where measuring plants multiple times within a growing season is necessary for the scientific question (Dandois & Ellis 2013).
- **UAS operate as a critical link across scales**. Their spatial resolution is small enough for ground data to effectively validate UAS measurements, and their spatial extent is large enough to scale-up to coarser aircraft and space-based measurements. By linking across scales, UAS allow a better comparison of error across scales and more accurate trait predictions across landscapes. UAS sensors gather higher point density than airborne or space-based sensors, which is important for capturing centimeter- or millimeter-scale detail, with multi-/hyperspectral and RGB imagery, respectively (Näsi et al. 2015, Lehmann et al. 2015, Wallace 2016). In forestry, this means UAS can measure traits of individual trees or stands and even branch-level detail. Due to poor prediction accuracy of species-specific diameter distributions, enabling tree-level modeling allows more accurate inventories of forest growth (Nevalainen et al. 2017).
- **UAS are opening doors to measure sites that have been challenging to access or disregarded otherwise**. Whereas satellite and airborne images need to undergo a quality control step to mask out cloud cover, UAS can fly at low altitude below cloud cover. This is particularly important in areas where overcast conditions are normal (Koh & Wich 2012, Dash 2017). Nonetheless, UAS images must be corrected for radiometric non-uniformity due to unstable illumination throughout a mission just like in other types of image-based remote sensing (Näsi 2015). There is a bias in ecological surveys towards species and biota that are accessible, so the integration of UAS is issuing in an era of more comprehensive global mapping, which is important for accurate ecological forecasting. (Schneider 2017). Due to their ease of navigation and ability to fly autonomously, UAS can survey difficult-to-access areas where sampling has not been possible (e.g. avalanche-prone mountainsides).

Box 2. Overview of Nuts & Bolts of Forest Trait Mapping

Many decisions go into selecting what UAS and associated software are best for your scientific questions. Here, we will touch on some specific considerations for mapping forest traits.

- **Licensing.** Legal and logistical restrictions on UAS flight vary highly across countries and localities**.** In the United States, one may fly a drone as a hobbyist with minimal training and documentation, though there are certain benefits of becoming licensed. See the FAA's website for current licensing regulation. Some academic institutions, like the University of Colorado Boulder, maintain an FAA certificate of waiver or authorization (COA) that researchers may be licensed under, in addition to being covered by university insurance.
- **UAS sensors & platforms.** Reviews of UAS sensors and platforms exist already that can help orient a researcher starting to use UAS (Tang and Shao 2015, Pajares 2015, Goodbody et al. 2017). Multi-rotor drones are useful in surveying forests given their fine maneuverability to fly through canopy gaps and given their ability to fly slow, which is important for photogrammetry.
- **Flight planning.** For forest surveying, an automated flight plan should be followed rather than flying manually, in order to collect evenly-spaced images over a pre-planned AOI. Most autopilot software programs work only with certain UAS platforms. Examples include: ArduPilot, Pixhawk, DIY Drones, MapPilot. Take into consideration radiometric and geometric corrections you plan to make in post-processing for correcting image distortions and georeferencing (Näsi et al. 2015, Adão et al. 2017). The vertical structure of forests can interfere with signal when collecting GNSS coordinates from the ground.
- **Post-processing.** Spectral and structural data products extracted from UAS imagery include reflectance, point cloud, orthomosaic, digital terrain model (DTM), and canopy height model (CHM). Open source processing tools like CloudCompare, LAStools, and the lidR R package allow users to manipulate and edit point clouds.
- **Deriving forest traits from UAS data.**
    - Data fusion: UAS data combined with other data sources to derive plant traits. Non-forest examples include: crop water use efficiency (Thorp et al., 2018), crop LAI and biomass (Yue, Feng, Yang, et al., 2018), and oilseed rape flower number (Wan et al., 2018).
    - Crown segmentation: Delineating trees is more challenging in forests than for a stand-alone tree.
    - Machine learning: Random forests can predict traits such as DBH, basal area, AGB, crown height, crown perimeter, and more (Jaakkola et al., 2017).
    - Vegetation indices: Spectral transformation of bands can quantify tree health traits. For example, pine beetle infestations increase near-infrared light and decrease visible light compared to reflectance of healthy pine trees, which is quantified as NDVI (Näsi et al., 2015).

Box 3. lidar versus SfM

Forest structural traits are derived from lidar point clouds or from high resolution structure-from-motion (SfM) point clouds. Lidar gathers the vertical profile of vegetation by shooting laser beams into the canopy and measuring the number and strength of returns. Lidar provides accurate estimates of forest vertical structure with similar precision to ground-based measurements over a larger range, better than SfM can provide (Wallace 2016, Goodbody et al. 2017). However, building SfM point clouds is more affordable than lidar because it requires only an RGB camera and post-processing photogrammetric software. First, digital images are taken over the area of interest (AOI) with high overlap, then SfM computer vision algorithms stitch the images together to create a 3D point cloud of the AOI. Deriving canopies from RGB images affordably is one of the greatest features of UAS that make them an amazing ecological tool. Furukawa & Hernández (2015) describe what goes on under the hood of algorithms used in SfM and stereo reconstruction workflows and software. Examples of SfM software programs include: Ecosynth (Dandois & Ellis, 2013), OpenDroneMap, IMAGINE Photogrammetry, Pix4Dmapper, and Agisoft MetaShape. The US Geologic Survey (USGS) National UAS Project Office has a detailed post-processing workflow for generating a point cloud using SfM (USGS National UAS Project Office, n.d.).

While lidar and SfM have been found to be comparable methods for measuring structural traits, there are trade-offs. Capturing understory structure is challenging in dense forests using SfM (Wolf 2000, Wallace 2016, Jayathunga 2018). This introduces error into ground and topography estimates, so an external digital terrain model (DTM) or digital elevation model (DEM) is necessary to calculate accurate canopy traits (Dandois and Ellis 2013, Näsi et al. 2015, Ota et al. 2015, Wallace et al. 2016, Goodbody et al. 2017, Jayathunga et al. 2018). Wallace (2016) found that lidar also captured greater canopy cover than SfM due to there being less overlap in images at the canopy edge and thus having sparser point density. On the other hand, SfM provides higher point density and has a wider field of view (FOV) so can provide wider spatial coverage than airborne lidar (White et al. 2013), although higher point density comes with a higher computational cost in post-processing (Wallace et al., 2016).

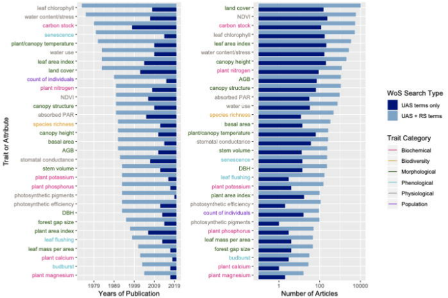

Figure 1. Left, earliest year of publication for papers reported in Web of Science (WoS) query. Right, number of articles reported in WoS search. Colors indicate results from searches for forest inventory traits using (i) UAS terms only (dark blue) and (ii) UAS and remote sensing (RS) terms (light blue). WoS query from May 2019.

Table 1. Metadata extracted from the nine studies we found that estimated carbon stock from UAS-derived data. Swinfield et al. 2019 compared measurements from two kinds of UAS, so occupy two rows. AGB = aboveground biomass, DBH = diameter at breast height, C = carbon, ACD = aboveground carbon density, BA = basal area, V = volume, ρ = wood density, H = tree height

Paper	**Spatial extent (ha)**	**Location**	**Coordinate system**	**Sensor type**	**Sensor model**	**UAV type**	**UAV model**	**Monoculture vs. Diverse**	**GSD (cm)**	**Ground control software**	**Flying height AGL (m)**	**Image overlap (with/across)**	**Flight pattern**	**Terrain following?**	**Photogrammetric software**	**Segmentation?**	**Allometric equation used to calculate carbon**	**Validation methods**	**Trait estimation accuracy (RMSE or SD)**
Dandois & Ellis 2013	18.75	USA (Maryland)	WGS84 UTM Zone 18N horizontal	RGB	Canon SD4000	multirotor	HiSystems GmbH Mikrokopter Hexakopter	Diverse (deciduous forest)	NA	NA	350	NA	NA	NA	Agisoft PhotoScan (v0. 8.4 build 1289)	No	AGB = exp(-2.0127 + 2.4342 * ln(DBH)) carbon density = 0.5 * AGB	Comparison to field measurements	Carbon estimation accuracy not assessed directly. AGB estimation accuracy 94-112 (Mg ha− 1) RMSE
Wehrhan et al. 2016	6	Germany	ETRS 89 UTM 33	Multispectral	Tetracam Mini-MCA 12	fixed-wing	Carolo P360	Monoculture (lucerne)	10	Ground control software: MAVCDesk	163	50%/60%	lawnmower	NA	Agisoft PhotoScan (v1.2)	No	C export = .44 * (linear relationship between fresh and dry phytomass)	NA	NA
Messinger et al. 2016	516	Peruvian Amazon	NA	RGB	Canon S110	fixed-wing	Linn Aerospace Kestrel	Diverse (tropical rainforest)	6.2 – 7.7	3DRobotics Pixhawk	200-250	75-85%/50%	grid	NA	Agisoft PhotoScan Professional	No	EACD = aTCHb1 * BAb2 * ρBAb3 where EACD is Estimated Aboveground Carbon Density, top-of-canopy height (TCH) is top of canopy height, BA is the regional average basal area, ρBA is the regional average basal area-weighted wood density, and α, b1, b2, and b3 are coefficients estimated from the data	Comparison to airborne LiDAR measurments	At 0.5 ha grain size, the mean ACD for the area flown was 78.64 ± 10.52 Mg·C·ha−1 with SFM and 78.86 ± 9.26 Mg·C·ha−1 using LiDAR (**R2** = 0.80, 4.8 Mg·C·ha−1 RMSE)
Cunliffe et al. 2016	3.5	USA (New Mexico)	NA	RGB	Canon S110	multirotor	3D Robotics Y6 hexacopter	Diverse (dryland vegetation)	0.4 - 0.7	Open Source Mission Planner (V1.3)	15-20	NA	grid	NA	Agisoft PhotoScan (v1. 1.0)	No	Biomass to carbon volume conversion coefficients taken from other sources grass C = 0.45 * (grass biomass) shrub C = 0.48 * (shrub biomass) juniper C = 0.50 * (juniper biomass)	NA	NA
McClelland et al. 2018	1.12	USA (Virginia, North Carolina)	NA	LiDAR	Velodyne VLP-16	multirotor	DJI Matrice M-600 Pro	Diverse (deciduous forest)	NA	NA	60-90	NA	grid	Yes	none	No	AGLC = -112.15 + 4.87*Ht25ile + 0.0087*Int70ile where AGLC is aboveground live carbon, Ht25ile is the 25th percentile of height, and lnt70ile is the 70th percentile of intensity, etc.	Comparison to field measurements	RMSE = 24.07 Mg CO2 RSE = 27.12% R2 = 0.72 Adj. R2 = 0.68
Jayathunga et al. 2018	33.75	Japan	JGD2000 Japan–19 zone XII	RGB	Sony NEX–5 16.1	fixed-wing	Trimble UX5	Diverse (pan–mixed conifer–broadleaf forest)	14.1	NA	500	95%/80%	NA	NA	Agisoft PhotoScan Professional (v1. 3.2)	No	CST = SIGMA_j ([V_j x D_j x BEF_j] x (1+R_j) x CF) where CST is the carbon stock in living biomass (Mg C ha–1); V is the merchantable volume (m3 ha–1); D is the wood density (t–d.m. m–3); BEF is the biomass expansion factor for the conversion of volume; R is the root–to–shoot ratio; CF is the carbon fraction of dry matter (Mg C t–d.m.–1); and j is the tree species	Comparison to field measurements	R2 = 0.72 = 14.3 Mg C ha–1 RMSE rRMSE = 17.4%

Scholefield et al. 2019	0.24	England	OSGB 36	RGB	Panasonic Lumix DMC-LX7	fixed-wing	QuestUAV 300™	Diverse (bog)	4.5	Skycircuits	122	NA	NA	NA	Agisoft PhotoScan Professional (v1. 4.2)	No	Using a cut–fill, hypsometric model of the eroded gully, carbon loss was calculated using carbon density measurements	No validation data collected	NA	
Li et al. 2019	320	China	NA	RGB	Sony RX1RM2	multirotor	ZR-66B	Diverse (mangrove forest)	2	Misson Planner	100	74%/65%	NA	NA	Pix4Dmapper	Yes	log(stem biomass) = a*log (DBH2H) + b where a and b are species-specific values (see table 1 for values). Allometric eqns calculated for stem, branch, and leaf	A 10-fold cross-validation was used to compare machine learning algorithm's estimations of AGC.	best model (random forest) yielded: R2 = 0.81 RMSE = 20.46 Mg C ha−1 relative RMSE (rRMSE) = 0.20 MAE = 14.82 Mg C ha−1 relative MAE (rMAE) = 0.14	
Swinfield et al. 2019	82	Indonesia (Kapas)	NA	RGB	Canon S110	multirotor	Tarot Ironman 650	Diverse (tropical rainforest)	NA	NA	140	NA	NA	NA	Agisoft PhotoScan (v1. 2.4)	No	ACD = 0.567 * H^0.554 * A1. 081 * ρ0.186 where ACD is aboveground carbon density, ρ is the wood density, calculated as ρ=0. 385H0.097, and A is the basal area, calculated as A=1.12H	drone-based LiDAR assumed as unbiased benchmark	27.2 tonnes/ha RMSE between LiDAR and SfM ACD estimates	
Swinfield et al. 2019	48	Indonesia (Bato)	NA	Multispectral	Parrot Sequoia	(same as above)	3DR Solo	(same as above)	NA	NA	120	NA	NA	NA	(same as above)	(same as above)	(same as above)	drone-based SfM compared to drone-based LiDAR measurements	(same as above)	

Table 2. Selection of papers from forest inventory trait review to demonstrate the variety of traits that may be measured by sensor(s) to address different scientific objectives.

Scientific objective	Citation	Trait(s) measured	RGB	Multispectral	Hyperspectral	Thermal	LiDAR	Comments
Identify relationships between disturbance and diversity	Getzin et al. (2012)	understory floristic diversity						Surveyed biodiversity through canopy gaps. Deciduous⁄Coniferous forests in Germany.
Identify correlations between phenology and spectral and structural traits	Klosterman and Richardson (2017)	green chromatic coordinate, red chromatic coordinate, and several other VI's						Deciduous forest in Massachusetts, USA
Assess pruning effects on tree structure and texture	Johansen et al. (2018)	crown delineation, crown shape metrics, several VI's						Lychee orchard in Australia.
Map leaf traits that influence primary productivity and nutrient cycling	Thomson et al. (2018)	Leaf economic spectrum: a composite trait of leaf nitrogen, leaf phosphorus, and leaf mass per area						Tropical forest in West Africa.
Methods comparison for measuring forest structural metrics	Wallace et al. (2016)	terrain height, canopy horizontal/vertical distrubutions, stem location, crown area						Comparison between airborne LiDAR and UAS-based RGB imagery (Box 3). Eucalyptus forest in Australia.
Use forest traits to map genetic variation	Blonder et al. (2020)	ploidy level						Quaking apen forest in Colorado, USA.
	Santini et al. (2019)	canopy temperature, vegetation cover, and several VIs						The first study of its kind to screen for genetic variation in functional traits of a mature forest. *Pinus halepensis* common garden in Spain.