Received: 25 February 2022 | Accepted: 5 July 2022

DOI: 10.1111/1365-2745.13976

Journal of Ecology | BRITISH ECOLOGICAL SOCIETY

REVIEW

Grime Review: What can remote sensing do for plant ecology?

Remote sensing from unoccupied aerial systems: Opportunities to enhance Arctic plant ecology in a changing climate

Dedi Yang[1,2] | Bailey D. Morrison[3] | Kenneth J. Davidson[1,2] | Julien Lamour[1] | Qianyu Li[1] | Peter R. Nelson[4] | Wouter Hantson[5] | Daniel J. Hayes[5] | Tyson L. Swetnam[6] | Andrew McMahon[1] | Jeremiah Anderson[1] | Kim S. Ely[1] | Alistair Rogers[1] | Shawn P. Serbin[1]

[1]Environmental and Climate Sciences Department, Brookhaven National Laboratory, Upton, New York, USA; [2]Department of Ecology and Evolution, Stony Brook University, Stony Brook, New York, USA; [3]Department of Civil and Environmental Engineering, University of California, Merced, California, USA; [4]Schoodic Institute at Acadia National Park, Winter Harbor, Maine, USA; [5]School of Forest Resources, University of Maine, Orono, Maine, USA and [6]BIO5 Institute, University of Arizona, Tucson, Arizona, USA

Correspondence
Dedi Yang
Email: dediyang@bnl.gov

Funding information
NASA's Arctic Boreal Vulnerability Experiment, Grant/Award Number: NNX15AU05A; Next-Generation Ecosystem Experiments (NGEE Arctic), Grant/Award Number: DE-SC0012704

Handling Editor: Anna K. Schweiger

Abstract

1. The Arctic is warming at a faster rate than any other biome on Earth, resulting in widespread changes in vegetation composition, structure and function that have important feedbacks to the global climate system. The heterogeneous nature of arctic landscapes creates challenges for monitoring and improving understanding of these ecosystems, as current efforts typically rely on ground, airborne or satellite-based observations that are limited in space, time or pixel resolution.
2. The use of remote sensing instruments on small unoccupied aerial systems (UASs) has emerged as an important tool to bridge the gap between detailed, but spatially limited ground-level measurements, and lower resolution, but spatially extensive high-altitude airborne and satellite observations. UASs allow researchers to view, describe and quantify vegetation dynamics at fine spatial scales (1–10 cm) over areas much larger than typical field plots. UASs can be deployed with a high degree of temporal flexibility, enabling observation across diurnal, seasonal and annual time-scales.
3. Here we review how established and emerging UAS remote sensing technologies can enhance arctic plant ecological research by quantifying fine-scale vegetation patterns and processes, and by enhancing the ability to link ground-based measurements with broader-scale information obtained from airborne and satellite platforms.
4. *Synthesis*. Improved ecological understanding and model representation of arctic vegetation is needed to forecast the fate of the Arctic in a rapidly changing climate. Observations from UASs provide an approach to address this need, however, the use of this technology in the Arctic currently remains limited. Here we share recommendations to better enable and encourage the use of UASs to improve the description, scaling and model representation of arctic vegetation.

KEYWORDS
Arctic, fine scale, landscape ecology, remote sensing, scaling, UAS, UAV, vegetation

1 | INTRODUCTION

The Arctic is warming faster than any other region on Earth, with associated changes in temperature, precipitation, surface albedo, sea ice and ocean circulation (IPCC, 2019). Tundra ecosystems of the Arctic are thus predicted to respond more rapidly to climate change than other terrestrial ecosystems (Chapin et al., 2005; Hinzman et al., 2005). Over the past 40 years, long-term ecological monitoring and satellite observations have indicated widespread changes in tundra vegetation composition, structure and function (Elmendorf et al., 2012; Pearson et al., 2013). Examples include a decadal 'greening' trend in satellite-derived vegetation indices observed across the Arctic concurrent with a widespread increase in shrub and tree cover (Elmendorf et al., 2012; Frost & Epstein, 2014; Ju & Masek, 2016; Myers-Smith et al., 2015; Sturm et al., 2001). These changes, coupled with permafrost thaw (Lawrence et al., 2008), more frequent tundra fires (Mack et al., 2011), and an altered hydrological cycle (Bring et al., 2016), are driving impacts on the energy balance and carbon budget of the Arctic (DeMarco et al., 2014; McGuire et al., 2018; Myers-Smith et al., 2011; Vowles & Björk, 2019).

The arctic tundra biome contains a high degree of spatial heterogeneity in vegetation distribution, land surface structure and environmental conditions (Myers-Smith et al., 2020; Virtanen & Ek, 2014; Figure 1), where vegetation interacts with the environment at very fine scales from several centimetres to multiple metres (Assmann et al., 2020; Davidson et al., 2016; Siewert & Olofsson, 2020). These fine-scale interactions result in strong patchiness in the direction and rate of vegetation changes across the Arctic that are currently missed by coarser-scale observations but could aggregate to meaningful impacts on ecosystem response to climate change (Bjorkman et al., 2018; Chen et al., 2020; Prevéy et al., 2018).

Traditional methods to characterize the variability in arctic vegetation involve intensive field surveys or experimental manipulations, which are often limited in their spatial and temporal coverage (Metcalfe et al., 2018; Schimel et al., 2015). Metcalfe et al. (2018) showed that the current pattern of ground sampling—focused on just a few intensively studied locations—may inaccurately portray large-scale tundra processes, hindering our ability to predict climate change impacts in the Arctic. In contrast, satellite and high-altitude airborne remote sensing platforms have been widely used to observe a range of key vegetation properties, dynamics and changes (Beamish et al., 2020). The use of these platforms has complemented traditional field measurements by providing wider spatial and temporal coverage (Shiklomanov et al., 2019).

However, the small stature of most arctic plants (typically <1 m) and wide spatial variation in their composition, structure and function creates a strong scale mismatch between the studied organisms and the satellite and airborne observations, typically collected at >5 m spatial resolution (Assmann et al., 2020; Siewert & Olofsson, 2020). This scale mismatch means that single pixels typically include a mixture of information from many plant species (Somers et al., 2011; Wu & Li, 2009) and often non-photosynthetic vegetation and other surface types including snow, surface water, bare soil, rock and dead plant materials, which makes the interpretation and 'unmixing' of the data difficult (Myers-Smith et al., 2020; Nelson et al., 2022). In addition, due to differences in calibration, resolution and revisit frequency, vegetation patterns and phenology derived from different satellite platforms can show large discrepancies between each other and with ground observations (Myers-Smith et al., 2020), introducing significant uncertainties in the understanding of arctic vegetation dynamics. Therefore, to enhance our understanding of tundra vegetation dynamics, measurements with a high spatial resolution and relatively broad scale are needed to bridge the gap between traditional fine-scale ground sampling and broad-scale, low-resolution satellite images (Myers-Smith et al., 2020).

To fulfil this need, small piloted airborne platforms have been used, which allows the collection of spatial datasets at sub-metre resolutions, over large landscapes and away from road systems (Cristóbal et al., 2021; Greaves et al., 2019; Nolan et al., 2015; Wainwright et al., 2021). However, piloted data collection is often expensive, involves certified flight crews and requires strategic flight planning (Chadwick et al., 2020). In addition, weather conditions (e.g. wind, cloud, and rain) can change rapidly during the course of a day in the Arctic, and conditions suitable for aircraft operation or remote sensing data collection oftentimes last only from several minutes to a couple of hours (Assmann et al., 2019), challenging the use of piloted airborne platforms.

The recent development and use of small unoccupied aerial systems (UASs; <25 kg) as a remote sensing platform has revolutionized the way that ecologists quantify vegetation status and dynamics (Anderson & Gaston, 2013; Assmann et al., 2019; Gaffey & Bhardwaj, 2020; Messina & Modica, 2020; Yao et al., 2019). The use of remote sensing instrumentation on UASs has many advantages over traditional field sampling or airborne/satellite platforms. For example, land surface observations can be easily obtained at a very high resolution (1–10 cm), allowing for characterization of fine-scale details in a manner that closely mirrors ground-based sampling but over larger spatial extents (Dainelli et al., 2021a, 2021b). Second, flight missions can be deployed at a flexible time frame that is optimized to research objectives, such as capturing the phenological cycle of target plants (D'Odorico et al., 2020) or repeatedly flying the same location over the course of a day to capture diurnal vegetation dynamics or solar-induced fluorescence (e.g. SIF; Wang et al., 2021). Third, aerosol and other atmospheric effects on remotely sensed imagery, that commonly occur from high-altitude airborne and satellite platforms, can be largely avoided by flying UASs at low altitude (Yao et al., 2019). Lastly, diverse types of remote sensing data are needed to describe the composition, structure and function of terrestrial vegetation; UASs can be used to collect these data using a variety

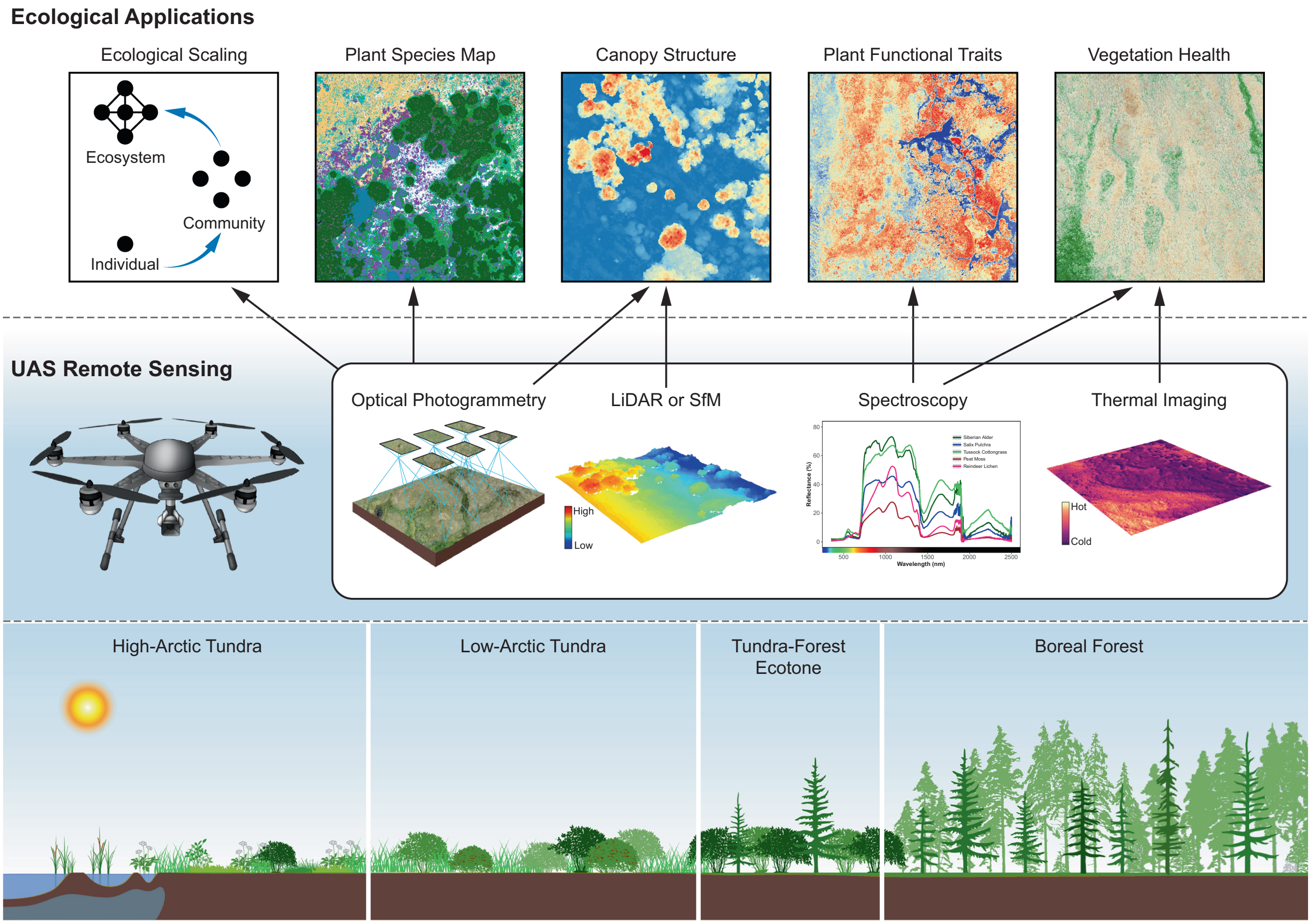


FIGURE 1 Illustration of arctic biomes (bottom panel), Unoccupied Aerial System (UAS) remote sensing technologies (middle panel) and the key applications of UAS remote sensing for plant research (top panel). The arrows between the elements of the middle and top panels indicate the connection between ecological applications and UAS remote sensing technologies. The arrows starting from the edge of the entire white box in the middle panel indicate that all available UAS technologies can be used for the specified ecological applications.

of sensors, such as optical red–green–blue (RGB) camera, multispectral and hyperspectral sensors, thermal infrared (TIR) camera and light detection and ranging (LiDAR, also commonly known as 'lidar') sensors. Recent studies have shown that vegetation data collected with UASs can have a similar fidelity as direct, in-situ measurements, demonstrating the potential of using UASs to characterize fine-scale vegetation patterns and processes (Chang et al., 2020; Lucieer et al., 2014; Thomson et al., 2021; Yang et al., 2020).

Thus far, the majority of UAS applications have focused on low-latitude ecosystems (Dainelli et al., 2021a, 2021b), but interest in using UASs in the Arctic has been steadily increasing. Some of the earlier examples include Tømmervik et al. (2014), Juszak et al. (2017) and Fraser et al. (2016), where optical and multispectral UASs were used to produce high-resolution maps of arctic plant species. Recently, other remote sensing technologies have also been used with UASs in the Arctic, including spectroscopy (Malenovský et al., 2017; Yang et al., 2020), TIR (Yang et al., 2020, 2021) and LiDAR (Collins et al., 2020), all of which offer exciting new opportunities to advance research. Here, we review how established and emerging approaches to UAS-based remote sensing can enhance arctic plant ecology research, increase understanding of the fine-scale vegetation composition and function and provide previously missing information at a resolution that bridges the gap between traditional, ground-based measurements and broad-scale, coarse-resolution airborne and satellite remote sensing. Specifically, we first summarize the remote sensing technologies that have been integrated with small UAS platforms and the key vegetation and surface data that can be obtained through this integration. We then highlight some of the most impactful applications of UAS-based remote sensing in plant ecology in the Arctic to date and provide examples of how these data can be used to address ecological questions. Finally, we provide perspectives on the remaining challenges that need to be addressed to extend and advance future UAS-based remote sensing in the Arctic.

2 | UAS REMOTE SENSING TECHNOLOGIES

2.1 | UAS platforms

The primary features that distinguish the variety of UASs available for use by the research community are physical size, the sophistication of pilot control aids (e.g. auto hover, obstacle avoidance) and automatic flight control systems (pre-planned, auto-piloted missions), and the power capacity (battery or fuel) which limits the payload, operating altitude and single flight duration (González-Jorge et al., 2017; Hardin et al., 2019). Typically, a large UAS (e.g. >25 kg) is more capable of carrying heavy instrumentation and covering large study areas, but their development and deployment is more expensive and requires complex ground operations, as well as more rigorous pilot certifications. Here, we focus on small UASs (either fixed-wing or copter) that can be easily transported and deployed in arctic environments and require simpler remote pilot certifications for operation (e.g. in the United States, the Federal Aviation Administration Part 107 certification). These small UASs usually have a flight duration of <2 h. Small UASs can fly safely at lower altitudes (<100 m above-ground level), enabling data collection at very high spatial resolutions (<10 cm).

2.2 | UAS sensors

In conjunction with the increased interest in their use for high-latitude research, there has been a similar increase in available sensors that can be deployed on small UAS platforms (Table 1). At present, the most common sensor type employed with UASs is the standard RGB camera. However, more recent research has started to utilize a range of other sensors, including multispectral cameras, imaging spectrometers, thermal cameras and LiDAR systems. Here, we refer interested readers to Colomina and Molina (2014) and Yao et al. (2019) for more details about these sensor types and their applications on UASs. The integration of these state-of-the-art sensors with UASs allows researchers to remotely observe terrestrial vegetation and land surfaces at very fine scales (<10 cm) and across the principal dimensions of plant biodiversity (e.g. taxonomic, spectral and structural; Dainelli et al., 2021a, 2021b).

A portfolio of vegetation and surface properties can be derived using the suite of instrumentation shown in Table 1. These properties include species identity and plant functional type (PFT), vegetation structure (e.g. canopy height and cover), plant traits and phenology, as well as many other parameters that are useful to depict vegetation distribution, energy balance, water cycling and carbon sequestration (Table 2). Note that this review focuses on vegetation applications; therefore, properties specific to other disciplines are not discussed. Table 2 also specifies how each property can be derived from different data products created using various remote sensing technologies. For example, high-density point clouds (a set of data points in three-dimensional space) can be created from two main technologies: direct laser scanning (i.e. LiDAR) and structure-from-motion (SfM) processing of optical RGB imagery (refer to Turner et al. (2012) and Westoby et al. (2012) for more details about SfM). In turn, point clouds can be used to derive a number of vegetation structure parameters, such as canopy height, cover and biomass (Table 2; Wallace et al., 2016).

3 | VEGETATION APPLICATIONS OF UAS-BASED REMOTE SENSING IN THE ARCTIC

The use of remote sensing instrumentation with UASs spans a wide range of applications in the Arctic. Here, we focus on two areas that can be particularly impactful for arctic ecology: (1) characterizing fine-scale patterns in vegetation composition, structure, traits and functions (Sections 3.1–3.5); and (2) scaling fine-scale vegetation patterns and processes to coarse-scale airborne or satellite

TABLE 1 Types of remote sensing sensors that have been implemented on UASs

Sensor Type	Description	References
Optical RGB camera	The most basic sensor type implemented with UAS, equipped with a standard complementary meta oxide semiconductor (CMOS) sensor through which red–blue–green coloured images are collected	Fraser et al. (2016); Yang et al. (2020)
Multispectral camera	Captures image data within specific wavelength ranges across the electromagnetic (EM) spectrum, commonly including blue, green, red, red-edge and near infrared	Assmann et al. (2019); Juszak et al. (2017)
Spectroradiometer	Measures the reflectance (or backward scattering) of solar radiation from an object or the emission (fluorescence) of the EM radiation from an object. A full range spectrometer covers the EM spectrum of visible to shortwave infrared (0.4–2.5 μm)	Chang et al. (2020); Malenovský et al. (2017); Lucieer et al. (2014)
Thermal camera	A device that detects infrared radiation of a surface. Infrared cameras are sensitive to wavelengths from about 1 um to 14 μm	Yang et al. (2020); Hoffmann et al. (2016); Hoffmann et al., 2016); Ellsäßer et al. (2020)
Light detection and ranging (LiDAR)	An active remote sensing technology that uses light in the form of a pulsed laser to measure ranges (variable distances) to the Earth, to generate three-dimensional information about surface characteristics	Lefsky et al. (2002); Collins et al. (2020)

TABLE 2 Key vegetation properties that can be derived from a UAS and the corresponding remote sensing techniques can produce each property. Note that spectral reflectance can be derived from two types of spectrometers: (1) point spectrometers, (2) imaging spectrometers. In this table, spectral reflectance indicate reflectance curves derived from both types of spectrometers, while hyperspectral imagery only indicates products from imaging spectrometers.

Key surface or vegetation property	Data products that can be used to derive the vegetation property	Sensor type	References
Plant species, plant function type, composition and diversity	RGB imagery, Multispectral imagery, Hyperspectral imagery, Thermal infrared imagery, Canopy height model, Point clouds	Optical RGB camera, Multispectral camera, Imaging spectroradiometer, Thermal camera, LiDAR	Lucieer et al. (2014); Fraser et al. (2016); Juszak et al. (2017); Alonzo et al. (2018); Yang et al. (2020, 2021); Thomson et al. (2021)
Surface or vegetation albedo	Spectral reflectance, Multispectral imagery	Multispectral camera, Imaging or point spectroradiometer	Canisius et al. (2019); Xu et al. (2020)
Plant functional traits	Spectral reflectance, Thermal infrared imagery	Multispectral camera, Imaging or point spectroradiometer, Thermal camera	Shiklomanov et al. (2019); Thomson et al. (2021)
Water content	Thermal infrared imagery, Spectral reflectance	Thermal camera, Imaging or point spectroradiometer, Multispectral camera	Ellsäßer et al. (2020); Chan et al. (2021); Thomson et al. (2021)
Land-surface or canopy 'skin' temperature	Thermal infrared imagery	Thermal camera	Jones and Leinonen (2003); Costa et al. (2013); Yang et al. (2020); Still et al. (2019 & 2021)
Solar-induced fluorescence (SIF)	Very-fine spectral resolution reflectance	Imaging or point spectroradiometer	Chang et al. (2020)
Canopy height, cover, biomass	Point clouds	LiDAR, Optical RGB camera	Anderson and Gaston (2013); Alonzo et al. (2018, 2020); Cunliffe et al. (2020, 2021)
Digital Elevation Model (DEM)	Point clouds	LiDAR, Optical RGB camera	Fraser et al. (2016); Yang et al. (2020); Alonzo et al. (2020)
Seasonality and phenology	RGB imagery, Multispectral imagery, Hyperspectral imagery, Thermal infrared imagery	Optical RGB camera, Multispectral camera, Imaging spectroradiometer, Thermal camera	Assmann et al. (2020)

platforms to enable a broader-scale understanding of the Arctic (Section 3.6; Figure 1).

3.1 | Vegetation composition and diversity

Temperature increase in the Arctic is driving species distributions to shift northward and to higher elevations, altering historical biodiversity patterns that have strong links to ecosystem health and function (Wang & Gamon, 2019; Wasowicz et al., 2020). Being able to characterize the spatial patterns and drivers of change in arctic vegetation composition and diversity is important for forecasting how arctic ecosystems will respond to climate change. However, the scale mismatch between the small arctic plants and the coarse grain size of satellite or airborne observations (Davidson et al., 2016) results in significant biases in the characterization of vegetation composition and biodiversity (Figure 2; Gamon et al., 2019, 2020).

The primary advantage of using UAS-derived imagery for research into arctic vegetation composition and diversity is its fine grain size, which allows individual plants or species to be identified. Early applications that classify UAS optical RGB or multispectral imagery have proven useful for mapping a number of arctic plant species or PFTs. For example, Fraser et al. (2016) classified and mapped nine tundra vegetation types (i.e. willow, alder, birch, reindeer lichen, moss, sedge tussock, wet graminoid and mixed dwarf shrub heath) using RGB and height predictors. Recently, the use of imaging spectroscopy or the combined outputs of multi-sensor UASs showed the potential to identify more tundra species and improve mapping accuracy. For instance, Yang et al. (2021) used a combination of structural, spectral and thermal information to differentiate eight shrub species that are similar in spectral signatures but vary in canopy height and thermal properties. That study also demonstrated that the use of TIR imaging helps identify species with unique thermal characteristics, such as 'hot' canopy lichen species.

Together with high-resolution species or PFT maps, a number of key environmental parameters, including terrain features (e.g. elevation, thaw slumps, and solifluction), surface water distribution (e.g. rivers, drainages, thaw ponds), snow depth, soil moisture and active layer depth (e.g. using synthetic aperture radar) could be described at very high resolutions and across landscapes using UASs (Fraser et al., 2020; Gunn et al., 2021; Xu & Zhu, 2018). This diversity of data can assist in analysing vegetation distribution patterns across fine-scale environmental gradients, reducing the need for intensive field measurements. For instance, combining 4 years of UAS imagery with field surveys and time-series climate data, DelGreco (2018) characterized vegetation composition in a low-Arctic mir and found high heterogeneity in

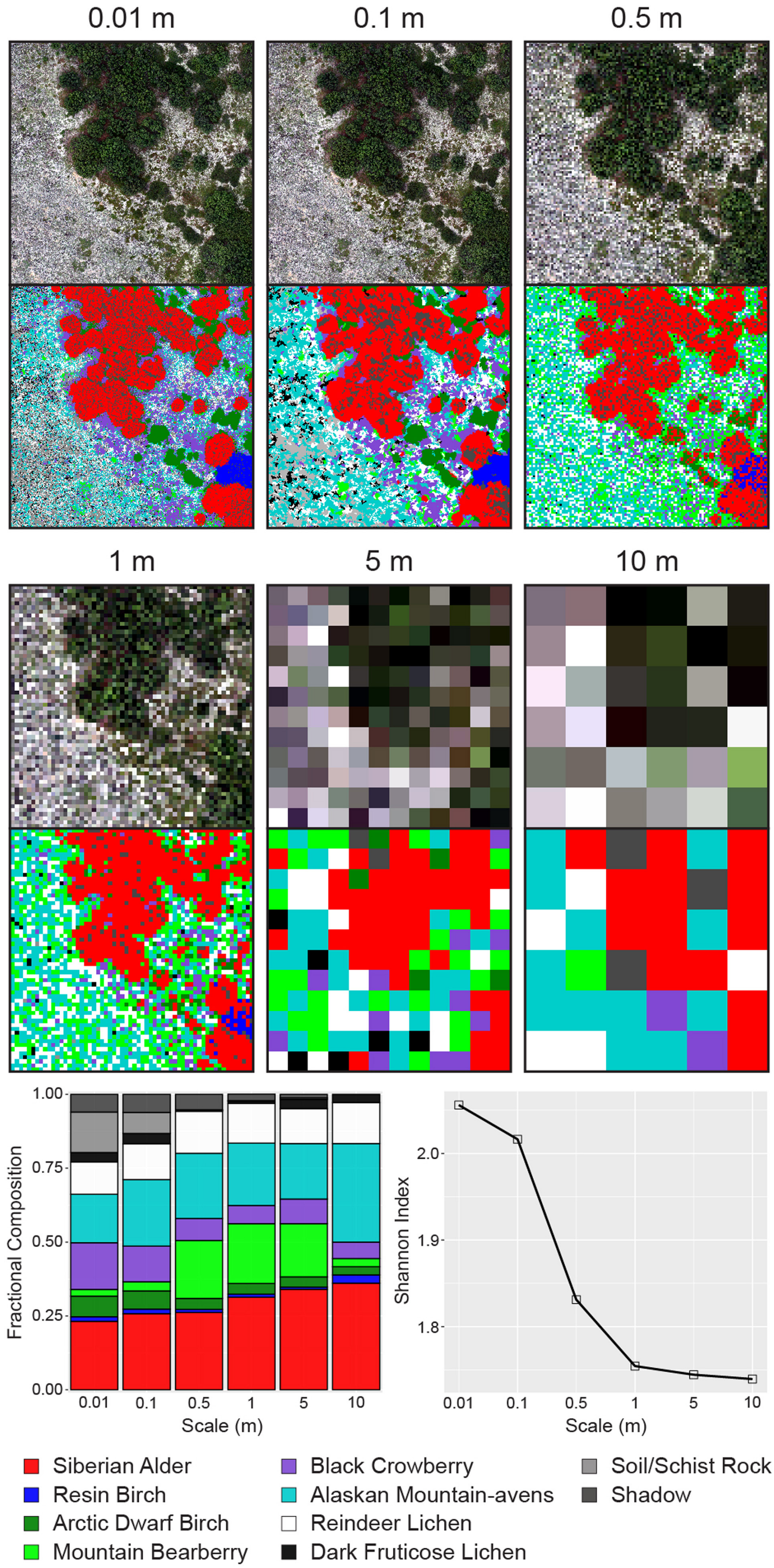


FIGURE 2 Scale effects on vegetation composition and diversity analysis in the Arctic. The top 6 panel pairs show remote sensing images acquired at different spatial resolutions (i.e. 0.01, 0.1, 0.5, 1, 5 and 10 m) in a shrub landscape and the species maps derived from these images using a random forest classification. The bottom 2 panels are vegetation composition and Shannon diversity index calculated using the species maps shown in the top 6 panel pairs. A fusion of UAS-derived RGB ortho-mosaic, canopy height model, and canopy temperature was used for the classification. Non-vegetation components were excluded for calculating the Shannon diversity. Noticeably, decreasing spatial resolution significantly confuses species classification, biases vegetation composition analysis and reduces Shannon diversity. Data used for this figure can be found in Serbin et al. (2021).

vegetation dynamics, driven by permafrost thaw and associated increases in soil wetness. With the diverse types of UAS data, specific species of interest (e.g. invasive species) can also be readily identified, which is essential to understand the emerging impacts of species distribution or changes on vegetation composition and diversity across arctic landscapes (Lucieer et al., 2014; Räsänen et al., 2020). Arctic vegetation dynamics and landscape changes are increasingly driven by more frequent and severe disturbances such as fire (French et al., 2015; McCarty et al., 2020) and rapid permafrost thaw or thermokarst (Jones et al., 2015; Turetsky et al., 2019). Before-and-after UAS surveys can be used to study the impacts of disturbances on arctic ecosystems and monitor post-disturbance vegetation recovery. Upscaling UAS data to link with time-series satellite records could then enable the mapping of vegetation composition and status over time (see Section 3.6). In a recent study by Siewert and Olofsson (2021), the utility of UASs to capture herbivore (vole and lemming) impacts on arctic vegetation composition and productivity was also investigated, which represents an exciting new area of UAS application in the Arctic.

In addition to maps of plant species or PFTs, vegetation composition and diversity patterns, including functional diversity, can also be inferred from analysis of spectral diversity using imaging spectroscopy sensors installed on UASs (Rocchini et al., 2010, 2018; Schweiger et al., 2018; Wang & Gamon, 2019). This approach assumes that genetic background and environment conditions result in differences in plant physiology, biochemistry and structure among individuals, species, lineages or PFTs that are readily expressed in spectral signatures (Cavender-Bares et al., 2020; Ustin & Gamon, 2010). The utility of this approach has been demonstrated in a variety of biomes with spectral data collected from UASs (Baldeck & Asner, 2013; Carlson et al., 2007), and has the potential to be as effective in the Arctic.

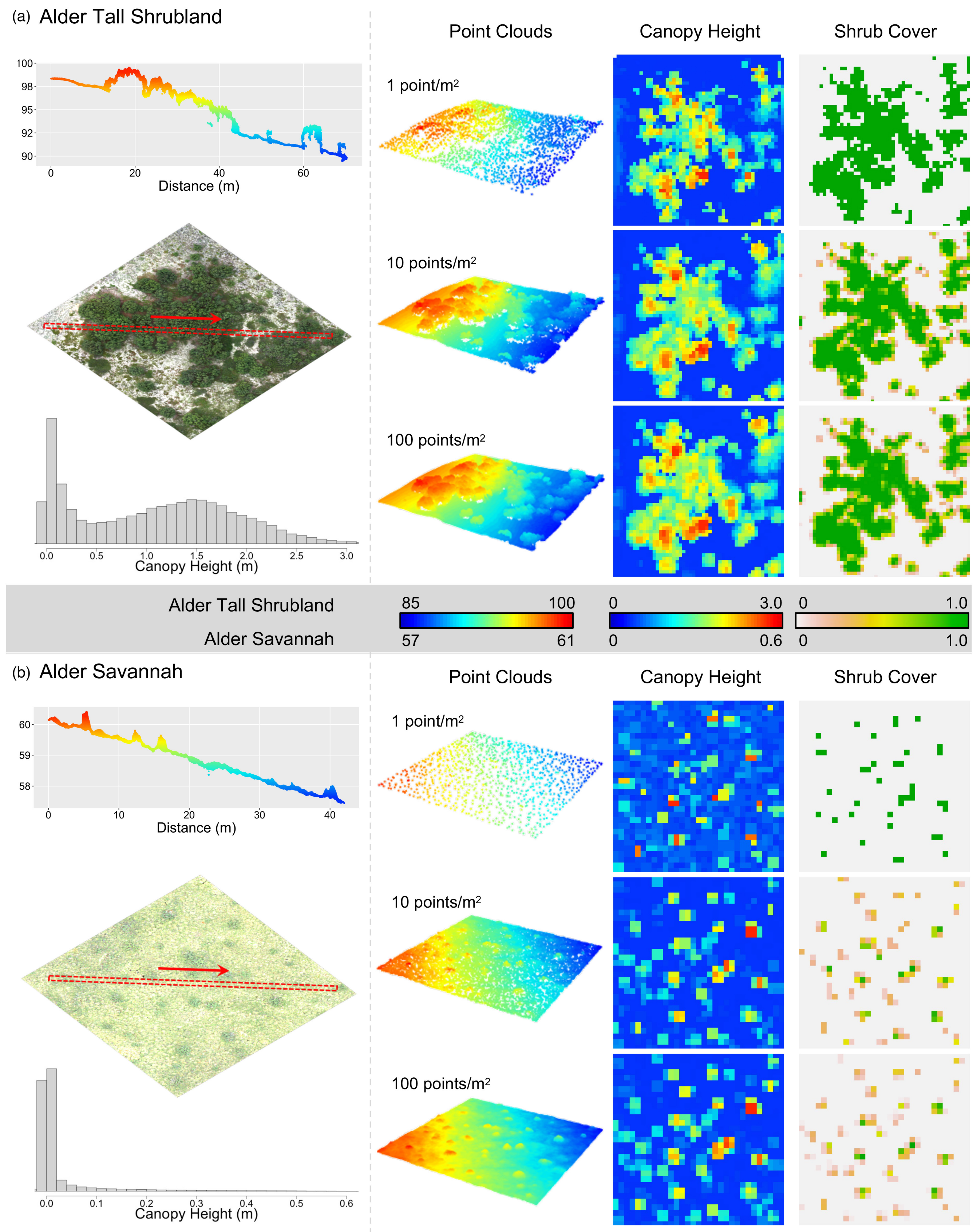
3.2 | Vegetation structure

There are a number of vegetation structural parameters that can be derived from UASs using point clouds generated by either LiDAR or SfM (Table 1, Bergen et al., 2009). Here, our illustration focuses on canopy height, vegetation cover and biomass estimates that are needed to investigate the shrubification of arctic ecosystems (Cunliffe et al., 2020; Greaves et al., 2015). Similar to high-resolution imaging, the main interest of using UASs to quantify arctic vegetation structure is that point clouds can be generated at ultra-high densities (>100 points/m^2), a requirement to capture open-canopy, sparsely distributed shrubs or to penetrate dense, closed canopies as is necessary for constructing a reliable baseline digital elevation model (DEM) and canopy height model (CHM; Figure 3; Alonzo et al., 2020). For example, using UAS SfM, Fraser et al. (2016) were able to obtain a point cloud density of ~30,000 points/m^2 at a low-arctic shrub tundra landscape. Collins et al. (2020) explored the efficacy of UAS LiDAR for scanning arctic vegetation and, while less dense than SfM, obtained point cloud densities of 300–500 points/m^2, which is more than 10 times as dense as typical airborne LiDAR point clouds (10–30 points/m^2; Alonzo et al., 2020).

To apply UAS LiDAR or SfM for quantifying vegetation height, a series of filters must be applied to detect data points returned from the bare ground surface (Andersen et al., 2003). Several methods exist for this process, including the improved progressive triangulated irregular network densification, but generally, they combine highly automated processes with some manual corrections (Kilian et al., 1996; Kraus & Pfeifer, 1998). The CHM is defined as the difference between the digital surface model (DSM) and a DEM interpolated from the 'ground return' data points (Figure 3). Fraser et al. (2016) and Yang et al. (2021) validated the accuracy of UAS SfM for deriving tundra vegetation height against ground measurements in high-Arctic (Tuktoyaktuk, Canada) and low-Arctic (Seward Peninsula, Alaska, USA) ecosystems, and reported a RMSE of <0.11 m and <0.14 m respectively. Alonzo et al. (2020) compared SfM-derived shrub height with LiDAR installed on Goddard's LiDAR, Hyperspectral & Thermal (G-LiHT) Imager and found excellent agreement between them (Pearson correlation coefficient = 0.89), indicating that both techniques are appropriate for measuring low-stature arctic plants. However, it should be noted that detecting 'ground' points in regions with dense graminoid cover (e.g. tussock tundra) could be challenging, as closed graminoid canopies that might be tens of centimetres deep can cover the true bare ground (Wang et al., 2016). In those regions, underestimations of shrub height may occur with either UAS LiDAR or SfM (Yang et al., 2021).

Estimates of vegetation cover can be made using the fraction of point clouds (either LiDAR or SfM based) returned from vegetation canopies, compared with non-vegetation returns (Lefsky et al., 2002; Nelson et al., 1984). In some cases, the cover of different vegetation layers (e.g. tree, shrub and grass layers) may be derived by segmenting the point clouds or CHM into height classes that correspond to different vegetation types. Similar to height, the detection of the ground surface (i.e. DEM) is an important aspect of cover determination. If the ground surface elevation is overestimated, vegetation cover will be underestimated, and vice versa. Point cloud density is another factor that influences cover determination. A low point density could lead to either omission of small shrub canopies or an overestimation of cover where gaps within dense shrub canopies cannot be detected (Figure 3). Vegetation maps derived from UASs can also be used to estimate the cover of total green vegetation (Riihimäki et al., 2019) or vegetation type of interest (e.g. lichen; Macander et al., 2020; also see *3.1*). This method is particularly useful in tundra regions where the land surface is covered by a single vegetation layer, or the top layer is of interest.

The mapping of vegetation height and cover extends to many ecological applications in the Arctic. For example, research into the impact of shrubification on tundra ecosystems involves a need for shrub height which importantly determines vegetation-mediated feedbacks to climate warming, such as snow depth, albedo, nutrient exchange, hydrology and energy flux (Léger et al., 2019; Mekonnen et al., 2021; Myers-Smith et al., 2011; Zhang et al., 2018). The estimate of vegetation cover, including lichens, is also useful to understand the distribution and habitat of arctic herbivores,



such as caribou (Joly et al., 2007, 2009). In a recent study, Cunliffe et al. (2020) showed that above-ground biomass (AGB), another important structure parameter needed for carbon cycle modelling, can be linearly estimated from canopy height (R^2 = 0.92), and outperformed normalized difference vegetation index (NDVI; $R^2 < 0.23$), a commonly used vegetation index for estimating AGB (Berner

FIGURE 3 Example application of UAS-derived point clouds for deriving canopy height and shrub cover in two representative arctic plant communities (a) Alder Tall Shrubland and (b) Alder Savanna. The effects of point cloud density (i.e. 1, 10, 100 points/m^2) on deriving canopy height and shrub cover are demonstrated in the right three columns (Point Clouds, Canopy Height and Shrub Cover). The height profiles (top-left panel in (a) and (b) respectively) correspond to the transects indicated by the dashed red lines shown in the RGB images. The histograms (bottom-left panel in (a) and (b) respectively) show the canopy height distribution of the entire landscapes indicated by the RGB images. The elevation of the point clouds and canopy height are both measured in metres. Data used for this figure can be found in Serbin et al. (2021).

et al., 2018; Raynolds et al., 2012). In fact, estimating AGB with LiDAR or SfM has drawn extra interest for arctic research, as destructive ground sampling and laboratory processing of AGB are extremely difficult in the remote Arctic (Cunliffe et al., 2020). In addition to canopy height, a variety of point cloud-derived metrics and their combinations have also been tested to map AGB (Alonzo et al., 2018, 2020). The performance of LiDAR and SfM was also compared by Alonzo et al. (2020), and both showed a strong ability to predict AGB (SfM: $R^2 > 0.75$, RMSE < 1.26 kg/m^2; LiDAR: $R^2 > 0.65$, RMSE < 1.48 kg/m^2).

One caveat to the use of UAS SfM is that SfM can only depict the outer surface of vegetation layers and thus contains little or no information on sub-canopy vegetation or terrain in areas with dense canopies (Lisein et al., 2013; Puliti et al., 2015). LiDAR can better penetrate dense canopies, but it often produces less dense point clouds than SfM, typically lacks multispectral information, and is also relatively expensive to collect (Collins et al., 2020). In addition, it is noted that plant species vary in their biomass allometry (Berner et al., 2015), which may bias structure-based AGB estimates. Integrating structure and spectral information into models has been shown promising for improving estimates of AGB (Alonzo et al., 2020), and suggests that collection of different UAS data types at the same locations may be needed to enhance the value of UAS remote sensing in the Arctic.

3.3 | Plant traits

Plant traits are key attributes of plant canopies or leaves that generalize the morphological, biochemical, phenological and physiological characteristics of an individual, a species or a PFT (Cornelissen et al., 2003; Violle et al., 2007). These attributes are one of the primary controls on the distribution and function of plants and therefore underpin many vegetation–climate interactions (Myers-Smith et al., 2018; Reich, 2014). For example, traits related to the uptake and allocation of resources, such as leaf mass per area, leaf longevity and foliar nutrient content, play a key role in the regulation of plant growth rate, primary productivity and decomposition rates (Cornwell et al., 2008; Diaz et al., 2004; Lavorel & Garnier, 2002). Similarly, canopy structural traits, such as leaf area and plant height, influence competition and light-harvesting potential, as well as surface albedo, and are strong determinants of plant biomass and snow dynamics that in turn, determine surface energy and water balance (Callaghan et al., 2004; Sturm, 2005).

Remote sensing, and spectroscopy in particular (Tables 1 and 2), has been shown to provide an effective method to remotely estimate a host of leaf and canopy traits across agricultural, grassland and forest ecosystems (Dahlin et al., 2013; Serbin & Townsend, 2020; Singh et al., 2015; Wang et al., 2019). This is because spectroradiometers can measure very-high-resolution spectral reflectance across a large number of narrow, near-contiguous wavebands (Gamon et al., 2019; Ustin et al., 2004) that allow for detection of the subtle absorption features of biochemical and structural properties in leaves and canopies (Curran, 1989; Kokaly et al., 2009; Figure 4). Typically, these mapping efforts based on imaging spectroscopy rely on direct connections between field plot sampling and remote sensing pixels (e.g. Singh et al., 2015). However, in the Arctic, this direct plot-to-pixel scaling is much more challenging. The integration of spectroscopic sensors with UASs is an ideal tool for this aim (Shiklomanov et al., 2019). By acquiring very-high-resolution, cloud-free hyperspectral imagery (Figure 4a) over landscapes, spectroscopic sensors on UASs allow for a more direct connection between the sampled vegetation and pixel reflectance, which can be used to develop trait scaling approaches and maps that can be used to train larger-scale trait models for airborne or satellite sensors (Thomson et al., 2021).

There are a number of approaches that can be used to predict traits from optical and hyperspectral UAS sensors. These methods range from relatively simple spectral vegetation indices (SVIs) which use the ratio of two or more spectral bands to infer plant stress, phenology, species diversity or pigment composition (Gamon et al., 1997; Goward & Huemmrich, 1992; Mänd et al., 2010; Schweiger, 2020), to more complex machine learning and latent variable methods, such as partial least squares regression (PLSR; Geladi & Kowalski, 1986; Wold et al., 2001), that are used to link pixel reflectance spectra with the underlying traits of interest (Burnett et al., 2021; Serbin & Townsend, 2020; Wang et al., 2021). It is noted that spectral data present a high level of collinearity among wavelengths (Chen et al., 2011); latent variable methods like PLSR are effective at handling this issue by projecting the large number of predictors (i.e. reflectance at different wavelengths) to a small number of latent variables and, at the same time, maximize the correlation between the response and latent variables. The inversion of radiative transfer models (RTMs), including PROSAIL (Jacquemoud et al., 2009), present another method to infer plant traits using spectral data (Féret et al., 2011) based on semi-mechanistic links between leaf properties, canopy structure, sun-sensor geometry and the resulting reflectance signature of leaves and canopies (Kuusk, 2018; Ollinger, 2011). Using imaging spectroscopy from UASs together with RTMs could allow for fine-scale retrieval of some key traits without requiring in-situ calibration data (Shiklomanov et al., 2019), as well as simulating

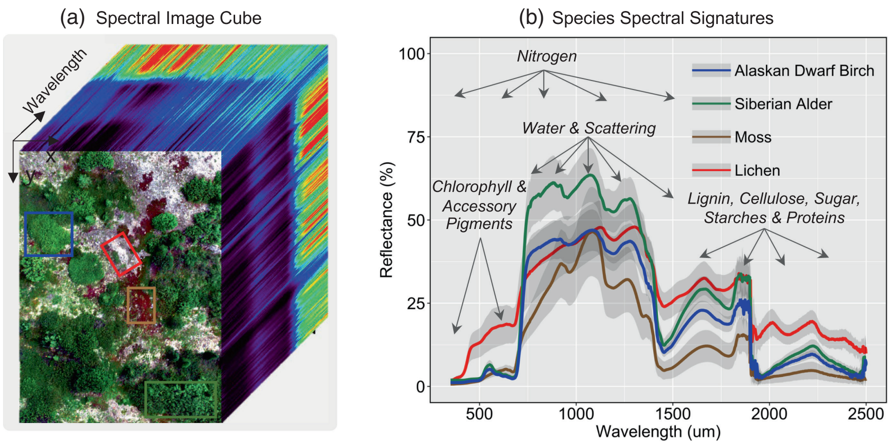


FIGURE 4 Example of hyperspectral UAS imagery from a shrub landscape (a) and spectral signatures of key arctic tundra plants identified from the UAS imagery (b). The spectral signatures sensitive to different leaf and canopy traits are illustrated in (b). The hyperspectral UAS imagery displayed in (a) is acquired at a 5 cm spatial resolution. Data used for this figure can be found at Nelson and Smith, (2022).

and testing retrievals across a range of sensor types (Shiklomanov et al., 2016).

In addition to spectroscopy, other technologies (e.g. LiDAR and TIR) can also be used to predict or improve the prediction of plant traits. For example, combining thermal data with spectroscopy can help better predict biochemical and physiological traits that affect or are affected by leaf temperature (Bishoyi & Sudhakar, 2017; Maimaitijiang et al., 2017). The integration of spectroscopy with point cloud-derived metrics (e.g. canopy height) is also useful to predict traits associated with vegetation structure (Ewald et al., 2018). Also, being able to simultaneously map vegetation traits, temperature and structure at a high spatial resolution can aid understanding of the response of plant traits to thermal changes among species and across tundra landscapes, as well as the vertical profile of plant traits within shrub or tree canopies.

However, it is noted that UAS-based remote sensing is not a 'silver bullet' for trait collection, given its limited spatial coverage. Trait models developed at a specific site with a particular set of species may not be readily extrapolated to other regions or different research objectives (Burnett et al., 2021). The development of generalized trait models, that is, those that work across a wide range of species and environments, is an ongoing area of research (e.g. Schweiger, 2020; Serbin et al., 2019; Wang, Chlus, et al., 2020; Yan et al., 2021), and such models could aid the application and iterative improvement of trait mapping in the Arctic using UASs. In addition, linking UAS data with hyperspectral data collected from airborne or satellite platforms to develop trait models and estimates at larger scales represents a unique opportunity to advance pan-Arctic retrieval of plant traits using remote sensing. This opportunity could substantially benefit from the ongoing and forthcoming spectroscopy missions, such as those associated with NASA's Arctic-Boreal Vulnerability Experiment (ABoVE) and Surface Biology and Geology (SBG) mission (Cawse-Nicholson et al., 2021).

3.4 | Vegetation stress and thermal function

Temperature is fundamentally important to a wide range of vegetation and ecosystem processes (Berry & Bjorkman, 1980; Chapin, 1983; Körner, 2006). The temperature of plant leaves (T_{leaf}) and canopies (T_{canopy}) directly influences a variety of processes, including the rate of enzyme-catalysed reactions, membrane fluidity and the diffusion and solubility of CO_2 and O_2, which together control the rate of photosynthesis and respiration and, subsequently, the short-term and chronic responses of plants to changes in their environment (Jones, 1992; Still et al., 2019, 2021). Therefore, characterizing T_{leaf} and T_{canopy} is particularly useful for investigating vegetation function and health, and quantifying terrestrial vegetation responses to climate change (Gersony et al., 2016; Krishna et al., 2021; Westermann et al., 2011; Yan et al., 2020). In terms of surface temperature variation, T_{canopy} is typically quantified with remote sensing platforms that retrieve land surface temperature (LST, Table 2) using a TIR sensor or camera (Table 1).

There is a rich history of using TIR imagery to quantify temperature variation across managed or natural ecosystems and to assess plant–environment interactions (Costa et al., 2013; Jones & Leinonen, 2003). We refer interested readers to Krishna et al. (2021) and Still et al. (2019, 2021) for a review of the theory and general applications of TIR. Here we focus on the use of TIR sensors on UASs for studying arctic ecology, plant function and ecological scaling. The heterogeneity of arctic ecosystems is mirrored by a large spatial variation in LST and energy balance properties (Dietrich & Körner, 2014; Scherrer & Körner, 2009; Yang et al., 2021). For example, in a ground-based study using a thermal camera, Scherrer and Körner (2009) detected a surface temperature variation of up to 20°C along a 100-m subarctic hillslope during clear-sky, mid-summer days. There is also a strong seasonality in LST and surface energy exchanges in the Arctic (Westermann et al., 2011) that has a strong control on regional to global climate feedback (Chae et al., 2015; Zhang et al., 2018).

The high degree of spatial and temporal variation in LST means that traditional remote sensing platforms (>60 m resolution, e.g. Landsat) may not adequately characterize the fine-scale variation in LST and its drivers across arctic landscapes, and thus leads to a mischaracterization of underlying surface biophysical changes in response to warming conditions (Soliman et al., 2012; Westermann et al., 2011). In particular, the mixing of different plant species and non-vegetation surfaces (e.g. rocks, soil, water, snow) in coarse-resolution satellite pixels makes it challenging to interpret the biological and environmental controls on LST (Cable et al., 2016). UAS-borne TIR could fill this gap by providing data at spatial resolutions that are high enough to capture LST variation across different surface components, but at the same time, can be repeated with a flexible time frame to capture LST dynamics (Simpson et al., 2021). In Figure 5, we show an example of UAS-collected LST at a low-arctic tundra site. Even in this small landscape of ~1 ha, a high degree of variation in T_{canopy} (~5–20°C) is observed, strongly tied to fine-scale patterns within and across plant community types (Breen et al., 2020). The description of these fine-scale details will allow researchers to link the variation in LST with surface and below-ground features (e.g. vegetation type, non-vegetation components, soil moisture, permafrost and disturbance gradients) to better understand the patterns and drivers of the spatiotemporal variation in LST (Yang et al., 2021), and to scale up or disaggregate coarse remote sensing signals to improve large-scale monitoring and modelling efforts in the Arctic (Lara et al., 2020).

In addition to characterizing fine-scale patterns and drivers of LST, linking UAS-collected LST with other observations could yield important new insights on the relationships between arctic ecosystem functioning and vegetation patterns. For example, quantifying the difference between T_{canopy} and T_{air} is useful for diagnosing spatial and/or temporal patterns in plant thermal regulation (Dietrich & Körner, 2014; Jin & Dickinson, 2010; Novick & Katul, 2020; Scherrer & Körner, 2009; Zhang et al., 2020). In the Arctic, considerable uncertainties remain in our understanding of thermal regulation, the role of plant stature and aerodynamics in energy cycling, and how future warming could impact plant function and fitness (Aalto et al., 2018; Bhatt et al., 2017; Lawrence & Swenson, 2011; Scherrer & Körner, 2009). In a recent study using a UAS-borne TIR, Yang et al. (2021) found strong spatial variation in thermal decoupling across shrub tundra landscapes that varied by PFT, patterns that have important implications for biodiversity, energy balance, permafrost thaw of arctic ecosystems (Myers-Smith et al., 2011; Zhang et al., 2018). For example, the T_{canopy} of deciduous tall shrubs was found to be significantly lower than other PFTs (e.g. moss, lichen, graminoid and low-lying shrubs) and typically below T_{air}, which leads to localized cooling during the growing season and exerts negative feedback to permafrost thaw (Blok et al., 2010; Frost et al., 2018) and plant diversity (Yang et al., 2021). Furthermore, using UAS-borne TIR in the footprint of eddy covariance towers could improve the characterization and scaling of surface energy exchanges and water cycling from site to ecosystem or biome scale (Ellsäßer et al., 2020; Hoffmann et al., 2016).

It is also worth mentioning that warmer and drier conditions in the Arctic are likely to increase plant stress, either directly through increased water stress or indirectly by prompting insect pest disturbances (Bjerke et al., 2014). Early detection of such stresses with satellite platforms is often complicated by an initial patchy landscape response, which signifies a potentially important and increasing role

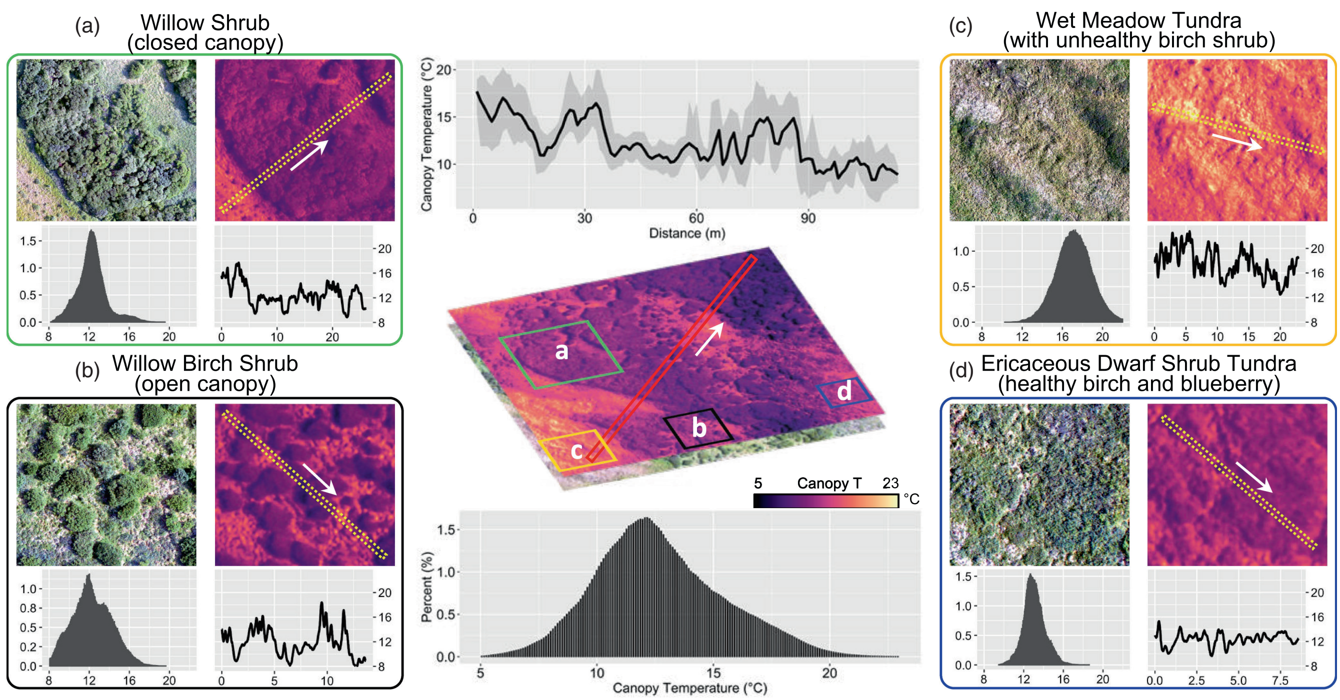


FIGURE 5 Example application of high-resolution UAS thermal imagery for depicting thermal variation across an arctic tundra landscape. The thermal profile and histogram of four representative plant communities are demonstrated in (a) Willow Shrub, (b) Willow Birch Shrub, (c) Wet Meadow Tundra, (d) Ericaceous Dwarf Shrub Tundra. The thermal profiles (line plots) in (a–d) correspond to the transects (1 m wide) indicated in each panel. The black line in the thermal profile plots represents the mean temperature every 1 m step along the transect, and the ribbon region indicates temperature standard deviation within each 1 m step. The arrows on the thermal images indicate the direction of the transects, from left to right, that correspond with the thermal profiles. The data used for this analysis are collected using a multi-sensor UAS developed by Yang et al. (2020). Data can be found in Serbin et al. (2021).

of UAS-borne TIR for identifying plant water or physiological stress in the Arctic (Still et al., 2019). In many other ecosystems (e.g. agriculture and forest), T_{canopy}, $T_{canopy} - T_{air}$ and thermal stress indices (e.g. canopy water stress index) derived from UASs have all been used to identify fine-scale water stress or insect pest outbreaks that create thermal anomalies in T_{canopy} (Costa et al., 2013; Jones & Leinonen, 2003; Krishna et al., 2021). The combination of spectroscopy with TIR may further improve the fidelity of this practice (Jones & Schofield, 2008; Krishna et al., 2021; Maimaitiyiming et al., 2020), aiding in the management of essential natural resources in the Arctic. For example, the retrieval of plant traits from spectroscopy may allow researchers to examine the impact of invasive insects on different plant species, especially where insect foraging preference is strongly determined by plant biochemical traits (Wang, Zhou, et al., 2020). In addition, research on arctic ecophysiology (e.g. photosynthetic and stomatal response to temperature) also requires knowledge of the thermal and reflectance characteristic of arctic plants (Chapin et al., 2012; Nelson et al., 2022), which can be simultaneously obtained from UASs.

3.5 | Vegetation seasonality and phenology

In a recent review, Myers-Smith et al. (2020) discussed the extraordinary complexity of capturing plant seasonality and phenology (e.g. leaf emergence, development, senescence and abscission; Schwartz, 2013) in the Arctic, involving spatial heterogeneity, scaling processes and data availability, and highlighted persistent challenges to addressing this complexity with traditional remote sensing. Particularly, the low revisit frequency (>8 days) and the strong cloud and fog contamination (Tjernström et al., 2015) curtails the acquisition of a suitable amount of clear-sky satellite imagery needed to establish a robust time-series observation for the curve fitting or thresholding used to derive phenometrics (Gu et al., 2009). Not surprisingly, seasonal phenological patterns and decadal trends derived from different satellite platforms often do not align with each other (Myers-Smith et al., 2020).

The utility of UASs for studying vegetation seasonality and phenology lies in the ability that flight missions can be easily repeated with a flexible time frame with revisit time optimized to the phenological cycle of target species (Anderson & Gaston, 2013; Getzin et al., 2012). This flexibility is particularly useful in the context of arctic environments, as frequent revisits can be made in spring and autumn (key phenological stages) to counter the influence of cloud and fog on data availability. In a recent study, Assmann et al. (2020) explored the use of a multispectral sensor on a UAS for capturing seasonal dynamics in NDVI and revealed high spatial heterogeneity in tundra greenness and phenology not captured by satellites. In particular, a notable loss in the seasonal variation of NDVI was observed when grain size increased from ultra-fine UAS (5 cm) to medium-size satellite pixels (30 m), highlighting a need to investigate spatiotemporal scaling processes in arctic plant seasonality and phenology.

Notably, the collection of reliable time-series UAS observations could face practical challenges in the Arctic. Site access can be limited in early spring due to snow coverage. Optimal imaging conditions also are rarely present with fluctuating cloud cover, rain and wind conditions within a day and throughout the year, all of which require careful calibration among UAS flights (Assmann et al., 2020). Thus far, limited work has been done with UAS remote sensing of plant seasonality and phenology in the Arctic. Nevertheless, as arctic researchers begin to use UASs (e.g. the High-Latitude Drone Ecology Network, HiLDEN), time-series observations will be more readily available. Moreover, given the various types of instrumentation that can be mounted on a UAS, repeated observations provide an opportunity to expand seasonality and phenology studies beyond simple vegetation indices which have shown limitations in tracking arctic phenology (Assmann et al., 2020; Myers-Smith et al., 2020; Wang et al., 2018). For example, the seasonal changes in leaf pigments, functional traits, canopy structure and thermal properties can all be potentially explored with UAS spectroscopy, LiDAR and thermal imaging (D'Odorico et al., 2020; Keenan et al., 2014; Liu et al., 2015; Still et al., 2019). Furthermore, given the high resolution of UAS data, phenological diversity across key plant species and environmental gradients can be investigated. This is important for predicting the range dynamics of arctic vegetation under future climate change, as plant phenology importantly controls plant survival (Chuine, 2010) while being highly sensitive to micro-climate and varying strongly across plant species (Andresen et al., 2018; Collins et al., 2021; Prevéy et al., 2018).

3.6 | Ecological scaling

Typically, airborne and satellite platforms provide excellent seasonal and long-term monitoring of ecosystems, but they are limited in the ability to identify underlying surface processes (Anderson, 2018; Lechner et al., 2012). In contrast, ground-based measurements provide detailed information on vegetation structure, composition and dynamics, but are limited in spatial extent given most observations are point or plot measurements and come from only a few specific regions (Metcalfe et al., 2018; Schimel et al., 2015; Siewert & Olofsson, 2020). This mismatch between the scales (both spatial resolution and extent) of in-situ and airborne/satellite observations, plus current sampling biases, makes it challenging to scale, map and describe broad-scale vegetation changes in the heterogeneous Arctic (Assmann et al., 2020; Myers-Smith et al., 2020; Siewert & Olofsson, 2020; Yang et al., 2021).

UAS remote sensing offers unique opportunities to bridge this scale gap (Siewert & Olofsson, 2020). In Sections 3.1–3.5, we illustrated that UAS data can capture many sources of vegetation and surface heterogeneity that are present in arctic ecosystems, providing a tool to depict fine-scale vegetation patterns and processes, similar to traditional ground surveys but over larger spatial extents. These fine-scale details enable an easy connection with in-situ vegetation surveys to extrapolate ground observations over larger areas, which in turn facilitates landscape-scale understanding of vegetation dynamics in the Arctic. For example, Siewert and Olofsson (2020) showed that NDVI derived from ground measurements in the northern Arctic agrees better with estimates derived from UAS imagery with a 12 cm resolution (R^2 = 0.89) than satellite imagery at 10 m, 30 m and 250 m resolutions (R^2 = 0.2, 0.16, 0.01 respectively). This scale dependency is propagated to strongly influence the estimation of AGB and GPP (gross primary productivity) using NDVI (e.g. % bias of estimated AGB: 17.0% 30 m, 21.0% 75 m).

The integration of ground observations with UAS data can expand the spatial extent of ecological studies, but UASs are not intended nor expected to collect observations over the large areas needed for monitoring vegetation changes across the Arctic (Myers-Smith et al., 2020). However, UAS data can be a useful proxy of ground measurements to further calibrate models built with airborne or spaceborne observations to assess larger-scale ecological patterns, which represents an exciting future research opportunity in the Arctic (Myers-Smith et al., 2020). For example, Thomson et al. (2021) explored the feasibility of using trait maps developed with a multispectral UAS to upscale plant water content to the wider landscape using Sentinel-2A imagery (10 m). Similarly, Riihimäki et al. (2019) used UAS maps as training data and built SVI-based models to estimate green vegetation cover from Planet Cubesat (3 m), Sentinel-2A (10 m) and Landsat 8 OLI (30 m).

Integrating UAS data with satellite and airborne imagery can also help improve our mechanistic understanding of the links between fine-scale vegetation dynamics and broader-scale ecological patterns and trends (Myers-Smith et al., 2020). For example, using datasets collected with a multi-sensor UAS, Yang et al. (2021) showed that landscape-scale variation in vegetation thermoregulation and canopy structure is largely driven by PFT composition, as well as trait variation within each PFT. By linking vegetation properties with UAS data at different scales, the scale at which dynamic processes occur and the drivers of large-scale variation can also be determined (Assmann et al., 2020; Siewert & Olofsson, 2020). For example, Assmann et al. (2020) captured plant growth dynamics across tundra landscapes by investigating the seasonal change in tundra NDVI with a multispectral UAS. They identified that a resolution of ~50 cm is the optimal grain size for monitoring arctic greening in dryas-vetch and tussock-sedge communities and showed a loss of seasonal variation in the spatial heterogeneity of landscape greenness when aggregating from UAS pixels (50 cm) to medium-grained satellite pixels (10–30 m). These types of applications present new opportunities to identify how fine-scale vegetation and surface heterogeneity influences the spatiotemporal patterns of coarse remote sensing signals, improving our ability to interpret and describe remotely sensed changes across the Arctic (Myers-Smith et al., 2020).

4 | FROM DESCRIBING VEGETATION TO ANSWERING ECOLOGICAL QUESTIONS

How does UAS data can be used to improve ecological approaches and address fundamental ecological questions pertinent to the Arctic? Ecologists seek to understand how organisms (i.e. plants in this Review) interact with each other and their abiotic environment (Sutherland et al., 2013; Tansley, 1935). In the Arctic, this objective is typified by the need to quantify, understand and predict how vegetation is responding to a changing climate and the impact of these changes on the larger arctic biome. However, presently, our ability to address this objective has been limited by significant data and knowledge gaps that hinder our ecological understanding of the Arctic and increases model uncertainty associated with predicting the fate of the Arctic (Fisher, Hayes, et al., 2018; Fisher, Koven, et al., 2018; Metcalfe et al., 2018).

In Table 3, we summarize some of the most pressing ecological questions that could be potentially addressed through the use of UASs. These questions span five key research areas, including fine-scale vegetation and surface heterogeneity, shrubification, arctic 'greening', disturbance and process model uncertainty (Fisher, Hayes, et al., 2018; Fisher, Koven, et al., 2018; Mekonnen et al., 2021; Myers-Smith et al., 2011; Rogers et al., 2022). For each ecological question, we specify the measurement need to address the question and how UASs can fill this need by using the technologies or data presented in Section 3.

One key aspect of arctic ecology research that UAS remote sensing could revolutionize is the parameterization and benchmarking of process models used to simulate arctic vegetation. These are key steps to reducing model uncertainty and are required for robust prediction of change in the Arctic (Fisher et al., 2014; Fisher, Hayes, et al., 2018; Fisher, Koven, et al., 2018). In process models, the diversity of plant species and their traits are typically binned into PFTs. However, the current classification of tundra PFTs has focused on a few primary classes, for example, evergreen and deciduous shrubs, graminoids, forbs, moss and lichen (Wullschleger et al., 2014). The parameterization of these PFTs also largely relies on scant ground measurements or assumptions from temperate species (Rogers et al., 2017, 2019), which leads to significantly higher model uncertainties in the Arctic than other biomes. Here, we expect that as its applications extend in the Arctic, measurements from UASs could play an important role in filling this gap. For example, the detailed identification and mapping of PFTs with UASs that consider functional and structural differences across plants can be directly used to inform landscape-scale models; these fine-scale classifications can also be scaled up to create vegetation composition maps using airborne or satellite platforms to inform regional or biome-scale models. Similarly, the diverse and species-specific structure, traits and function that can be derived from UASs provide a relatively easy avenue to parameterize PFTs, given sufficient UAS data are collected in key locations in the Arctic or methods are developed to connect UAS information to broad-scale remote sensing data (e.g. Thomson et al., 2021).

5 | PERSPECTIVES, CHALLENGES AND FUTURE DIRECTIONS

In an era of unprecedented change in the Arctic, understanding plant responses to novel environmental conditions at local, watershed and larger scales is essential for our capacity to forecast the fate of

TABLE 3 Key arctic ecological questions or knowledge gaps that UAS can help or partially help with.

Research area	Key ecological questions or knowledge gaps	Measurement needs	Role of UAS platforms
Vegetation distribution and surface heterogeneity	How does the distribution of Arctic vegetation vary among species and locations in the Arctic?	Species-specific vegetation maps across Arctic landscapes	Provide data to improve identification and mapping of plant species (3.1) at fine scales and provide training data for larger mapping efforts
	How do plant biophysical properties differ among vegetation types in the same locality?	Species-specific or fine-scale estimates of plant biophysical properties	Very high-resolution maps of vegetation structure, traits and function (3.2–3.5)
	What is the connection between fine-scale vegetation and surface patterns with larger ecosystem processes?	Detailed information on vegetation composition, structure, and function as it relates to fine-scale surface features (e.g. topography, moisture and disturbance events).	Linking UAS measurements of vegetation and surface properties with ecosystem-scale measurements from flux towers or satellites can help explain the drivers of variation in ecosystem properties (3.1–3.6)
Shrubification	What controls Arctic shrubification?	High-fidelity shrub cover and type maps linked with environmental gradients and disturbance history	Fine-scale characterization of shrub species, traits, biophysical properties. Connect fine-scale variation with landscape features (e.g. topography, water and disturbances) to identify abiotic and disturbance controls on shrub distribution (3.1–3.5)
	How does shrubification affect plant biodiversity?	Accurate vegetation composition and diversity maps together with shrub fractional cover information	High-resolution maps of vegetation fractional cover that can be used to train regional mapping efforts (3.1)
	How does shrubification interact with snow accumulation and permafrost thaw?	Spatially detailed snow depth and thaw measurements in relation to shrub distribution, cover and structure	Create high-resolution maps of shrub structure, distribution and cover to link with other remotely sensed (SAR, LiDAR) or field survey measurements of snow and thaw depth data (3.1 and 3.2)
	How does shrubification affect surface energy and water exchange?	Accurate characterization of shrub LAI, albedo and surface 'skin' temperature across shrub types and environmental gradients	A fine-scale understanding of the influence of shrubs on landscape vegetation dynamics and sensible heat exchanges, to inform broader scaling, mapping and modelling efforts (3.2 and 3.4)
Arctic greening	What are the landscape controls on the rate of 'Arctic greening'? How does scale (both spatial and temporal) affect our understanding of greening in the Arctic?	Improved understanding of the local-scale drivers of the larger regional variability in Arctic greening and its connection with changes in vegetation and abiotic environments	Collection of UAS data for select areas can help resolve fine-scale drivers (e.g. shrubification, sub-pixel disturbance, changes in species composition) of the larger-scale greening signal in coarse-resolution satellite data. Collection of UAS data at key phenophases can be used to explore how vegetation seasonality influences greenness. UAS observations can also be used to parameterize radiative transfer models to simulate how different landscape features influence the emergent reflectance patterns at coarse resolution (3.1–3.3 and 3.5–3.6)
Disturbance	How do the effects of disturbance type and extent vary across different vegetation and ecosystem types?	High-resolution disturbance area mapping in relation to pre-disturbance vegetation type, topography and soil conditions	Paired UAS flights before and after disturbance can be used to investigate patterns of change in relation to disturbance extent (3.1)
	How does disturbance severity control recovery patterns of tundra vegetation? After permafrost thaw, what is the successional trajectory of the vegetation?	Time-series and high-resolution vegetation composition and status mapping before and after disturbance (fire, permafrost thaw or pest outbreaks)	Repeat UAS flights to train larger upscaling methods to enable time-series monitoring of vegetation composition and status during recovery (3.1 and 3.6)

(Continues)

TABLE 3 (Continued)

Research area	Key ecological questions or knowledge gaps	Measurement needs	Role of UAS platforms
Model uncertainty	What PFTs currently populate the Arctic?	Improved estimates of fractional cover of PFTs	High-resolution and detailed PFT mapping and upscaling to satellite platforms (3.1)
	What is the current structure and stand biomass in the Arctic?	Better estimates of standing biomass and canopy structure and in relation to disturbance and land-use history	Characterize standing vegetation height, structure and biomass properties (3.2). Validation of larger biomass mapping efforts (3.3)
	How do we improve the parameterization of terrestrial biosphere models in the Arctic?	Measure key parameters currently in models but poorly represented and characterize their variation along climatic gradients	UAS platforms can be used to develop fine-scale maps of plant traits and then link the variation in traits with environmental and climatic gradients in the Arctic (3.3)
	Vegetation phenology is not driven by biology or abiotic conditions but is prescribed	Monitoring of vegetation seasonality at a fine-resolution at landscape scales	Repeat flights can be used to define phenological timing. Fine-scale maps of surface topography and snow distribution from UASs can be connected with phenological observations to study how abiotic features regulate vegetation seasonality (3.3)
	Green leaves do not always equate with full photosynthetic capacity When are Arctic plants photosynthesizing? How consistent is photosynthetic temperature response across the landscape?	Improved understanding of the controls on photosynthetic capacity and stress tolerance including abiotic drivers, and biotic and temporal variation	Imaging spectroscopy with UASs will enable high-resolution mapping of photosynthetic traits and linking with surface and environmental gradients (3.3). Thermal imaging and SIF from UAS allows for the characterization of photosynthetic activity at the scale of individual plants
	What is the impact of scale on model predictions?	Multi-scale characterization of vegetation and environmental measurements	Fill the scaling gap between leaf/individual scale measurements of traits and other airborne and spaceborne remote sensing platforms

these ecosystems (Fisher et al., 2014; Mekonnen et al., 2021; Rogers et al., 2022). In Sections 3 and 4, we highlighted some of the most impactful applications of UASs in the Arctic, and below we lay out the next key steps, as well as the persistent challenges facing widespread use of UASs in the Arctic.

5.1 | Challenges and caveats of flying UASs in the Arctic

The short growing season, typically characterized by weather that is unsuitable for UAS operations, means that flying a UAS in the Arctic is particularly challenging. To minimize variation in solar angle, flying around solar noon is usually suggested (Assmann et al., 2019). However, in some areas, windy conditions can hamper effective flight control, increase battery usage, delay or ground UAS flights. On par with these logistics challenges, technical issues, such as aircraft material failure, compass issues and software failure, are also not uncommon in the Arctic—all of which significantly increase time and cost while challenging UAS flight planning and operation (Assmann et al., 2019).

To maximize UAS data coverage and impact on larger-scale research, it is important to optimize flight plans and operations. In practice, this can be challenging as small UASs tend to have short flight times (usually 15–20 min). In order to cover a large study site, successive flights are often needed, which rely on consistent weather conditions and multiple battery sets. The general lack of accessible power at remote locations means that most researchers will either need a large number of batteries, a generator for on-site recharge, or both. In the future, these challenges may be mitigated by new battery technology, more efficient electric motors and controllers, as well as new platform designs or options (e.g. fixed-wing vs. copter) that may be able to extend flight times for specific mapping missions. The increased development and use of multi-sensor UASs would also largely reduce the complexity of obtaining multiple data types by facilitating simultaneous collection (Yang et al., 2020).

Another key consideration when leveraging UASs for ecological applications is the high spatial resolution of the data. While this is a primary benefit of UAS observations, it also raises challenges for image analysis. Raw UAS imagery may suffer from 'salt-and-pepper' noise artefacts (an impulse type of noise that commonly exists in high-resolution images, especially when the pixel size is smaller than the studied object; Azzeh et al., 2018). Given this, most studies exploring ecological patterns and processes should use object-based methods, like species mapping which requires the consideration of object size (Yang et al., 2020, 2021). When stitching multiple flights together is required to cover a large study area, it is also important to conduct calibration or standardization to ensure consistency across different times of day, illumination conditions or changes unrelated to changes in the surface properties being observed (Hakala et al., 2018). The use of ground control points may also be needed to connect datasets from multiple flights and confirm correct geolocation.

5.2 | Challenges and next steps for UAS data processing and sharing

The spatial resolution of UAS imagery creates significant challenges related to data volume and processing. At high resolutions (<10 cm), even flights over small areas (e.g. 200 × 300 m) using a standard RGB camera can generate data in excess of tens of gigabytes (Wyngaard et al., 2019). UAS flights are often conducted as successive overlapping missions to cover a study area (Gillan et al., 2021), and in some cases will include data collected from multiple instruments simultaneously (e.g. Yang et al., 2020). To store, process and use these data, large local or cloud storage, fast disc access and high-performance computers are usually needed.

Different UAS platforms and sensors may also require different software and workflows to post-process data. For basic SfM processing, commercial software packages are commonly used, and while these software packages have rapidly evolved to provide reasonably efficient processing, the memory and storage requirements may still exceed standard end-user computers, and these software can be expensive. Alternatively, open-source platforms for SfM processing have become more common, including OpenDroneMap (https://www.opendronemap.org/), which can be run using a web interface, where processing jobs can be submitted to local or remote compute clusters. The capacity to set up ad-hoc, on-demand UAS data processing frameworks using open-source tools such as OpenDroneMap represents an important direction in the development of regular UAS monitoring of critical ecosystems.

For other instrumentation, post-processing may have other challenges. For example, the processing of LiDAR may require linking flight data with ground calibration targets and the interpolation of ground return points to get accurate vegetation height information (Lefsky et al., 2002). For TIR, the use of a calibration constant or in-image standard to generate absolute temperature retrievals is required, and ambient conditions and other aspects related to sun-sensor geometry should be considered during processing (Messina & Modica, 2020). Similarly, the processing of UAS-borne imaging spectroscopy may require the collection of calibration targets and atmospheric corrections to retrieve at-surface reflectance (Adão et al., 2017).

UAS data are usually stored onboard the platform and downloaded after a flight. This can raise data provenance challenges, as it is important that the integrated UAS and flight control systems correctly link the key metadata for each measurement that is necessary to establish data quality assurance and control, and for spatial referencing during post-processing. Managing in-flight metadata (flight planning, mission logs, atmospheric optical conditions) is also important for downstream remote sensing normalization and for atmospheric correction of multi- and hyper-spectral data into surface reflectance data products.

Long-term data preservation is also an important and often overlooked aspect of UAS research. Community adoption of common data and metadata reporting formats is necessary to aid in the interoperability of UAS data products. Currently, there are no dedicated archives for UAS data storage, nor are there common standards for baseline metadata to ensure long-term data preservation. The increased use of UASs for arctic research will require new means for data archiving, sharing and access in order to facilitate wider use and allow larger synthesis activities (Cunliffe et al., 2021). Traditional data sharing approaches (e.g. static data archiving) are insufficient for effective storage, discovery and sharing of large datasets, like UAS data.

UAS data should be accessible through an external, well-documented application programmer interface (API) that can be coupled with open-source tools for data discovery, subsetting and extraction directly within data analysis workflows. New or expanded investments in open-source, cloud-based, secure and version-controlled data storage platforms that have hierarchical storage capabilities should facilitate ease of discovery and use of UAS data. A notable example is the CyVerse Open Science Workspace (https://cyverse.org/), which supports hierarchical data storage, includes file and archive version control, provides digital object identifiers (DOIs) for data and uses an API for data search, discovery and retrieval (Gillan et al., 2019, 2021; Swetnam et al., 2017). Platforms like CyVerse also provide cloud computation and analysis support, facilitating a fully cloud-based data processing, storage and publishing workflow (e.g. Gillan et al., 2021). UAS data products can also be hosted over internet protocols such as HTTP(S), cloud storage buckets (Amazon S3 and Google Cloud Services) and image collections in the Google Earth Engine (GEE). Similarly, UAS datasets stored in the cloud benefit from a simple additional step to store these files as Cloud Optimized GeoTIFFs which are optimized for data storage, subsetting and processing in the cloud without any additional server software requirements (https://www.cogeo.org/). Using these tools and repositories can then facilitate rapid integration into other cloud-based tools, including GEE, as well as popular extensions of these tools into R and Python, allowing for fully cloud-based analyses. For example, by storing UAS data in a Google Cloud bucket, it is possible to share images and image collections through GEE, thus making it easier for the broader use of datasets in scripted workflows that leverage other spatial datasets.

5.3 | Future directions of UAS remote sensing in the Arctic

The expanded use of UASs is an important next step to improve our understanding of the fine-scale patterns and drivers of plant composition, structure, function and change in the Arctic. By combining these platforms with traditional field surveys and plant ecology research, as well as integrating with other airborne and satellite data, we will be able to develop the new techniques and methods necessary to better monitor and model this globally important and climatically sensitive region (Cunliffe et al., 2020; Siewert & Olofsson, 2020; Yang et al., 2021). Therefore, we strongly advocate for the increased use of optical RGB and multispectral UASs, but also encourage efforts to use other sensors, such as thermal cameras, imaging spectrometers, LiDAR and SIF sensors. In particular, SIF sensors on UASs have already been shown to be especially useful for capturing photosynthesis-related vegetation properties and functions, like GPP, in low-latitude ecosystems (Chang et al., 2020; Wang et al., 2021). The widespread use of a greater range of sensors will accelerate our ability to understand fine-scale variation in the form and function of arctic plants and bridge the gap between ground and satellite observations.

Using UASs to investigate fine-scale vegetation patterns and foster ecological scaling represents their major applications in the Arctic, but the collection of UAS data also extends to many other ecological applications or different disciplines that are not included in this review (Gaffey & Bhardwaj, 2020). For example, the construction of a reliable DEM is important to hydrological studies that capture or model surface or soil water across arctic landscapes (Vélez-Nicolás et al., 2021). In addition, by flying UASs both prior to and after snowmelt, snow depth can also be mapped, which is important to understand shrub–snow interactions in the Arctic (Lawrence & Swenson, 2011). Further exploring the use of UASs in different areas, and synthesizing them with vegetation applications, will be valuable to understanding the patterns, drivers of change and impacts of vegetation dynamics in the Arctic.

In light of the practical challenges of working in the Arctic, new strategies can be used to increase the spatial and temporal coverage of UAS data. In the past decade, citizen science has grown immensely and is regarded as an important tool for studies in ecology (Dickinson et al., 2010; McKinley et al., 2017). With the advent of low-price UASs and sensors, citizen science holds a great potential to increase site accessibility and foster long-term ecosystem monitoring of arctic ecosystems with UASs.

To sum up, with the fastest warming on Earth, widespread vegetation and land surface change is occurring in the Arctic. In order to accurately assess these changes and project their impacts on arctic ecosystems, we must address the challenge pertinent to this region—a high degree of spatial heterogeneity in vegetation distribution, land surface structure and environmental conditions. The deployment and use of new technologies, like UASs, is an important part of the solution to address this challenge. Through this review, we hope to shed light on the research opportunities provided by UASs and facilitate a broader use of this technology to improve our description, understanding, modelling and prediction of arctic ecosystems.

AUTHOR CONTRIBUTIONS

Dedi Yang, Shawn P. Serbin, Bailey D. Morrison, Kenneth J. Davidson and Julien Lamour conceived the idea. All authors contributed to the writing of the manuscript.

ACKNOWLEDGEMENTS

This work was supported by the Next-Generation Ecosystem Experiments (NGEE Arctic) project that is supported by the Office of Biological and Environmental Research in the United States Department of Energy, Office of Science, and through the Department of Energy contract No. DE-SC0012704 to Brookhaven National Laboratory. PRN was supported by NASA's Arctic Boreal Vulnerability Experiment (ABoVE) Grant NNX15AU05A. We thank Editor Jason Fridley, Editor Emily Lines and Editor Tommaso Jucker for their encouragement to write this review and the great comments on the proposal and the draft of this manuscript.

CONFLICT OF 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 manuscript.

DATA AVAILABILITY STATEMENT

All data used in this manuscript are publicly available. Data for Figures 2, 3 and 5 are cited in figure captions with details from Serbin et al. (2020). Data for Figure 4 are cited in figure caption with details from Nelson and Smith (2022).

ORCID

Dedi Yang https://orcid.org/0000-0003-1705-7823
Bailey D. Morrison https://orcid.org/0000-0001-5824-8605
Kenneth J. Davidson https://orcid.org/0000-0001-5745-9689
Julien Lamour https://orcid.org/0000-0002-4410-507X
Qianyu Li https://orcid.org/0000-0002-0627-039X
Peter R. Nelson https://orcid.org/0000-0001-5539-4914
Wouter Hantson https://orcid.org/0000-0002-2882-6897
Daniel J. Hayes https://orcid.org/0000-0002-3011-7934
Tyson L. Swetnam https://orcid.org/0000-0002-6639-7181
Jeremiah Anderson https://orcid.org/0000-0001-8925-5226
Kim S. Ely https://orcid.org/0000-0002-3915-001X
Alistair Rogers https://orcid.org/0000-0001-9262-7430
Shawn P. Serbin https://orcid.org/0000-0003-4136-8971

REFERENCES

Aalto, J., Scherrer, D., Lenoir, J., Guisan, A., & Luoto, M. (2018). Biogeophysical controls on soil-atmosphere thermal differences: Implications on warming Arctic ecosystems. *Environmental Research Letters*, *13*(7), 074003.

Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R., & Sousa, J. J. (2017). Hyperspectral imaging: A review on UAV-based sensors, data processing and applications for agriculture and forestry. *Remote Sensing*, *9*(11), 1110.

Alonzo, M., Andersen, H.-E., Morton, D. C., & Cook, B. D. (2018). Quantifying boreal forest structure and composition using UAV structure from motion. *Forests*, *Trees and Livelihoods*, *9*(3), 119.

Alonzo, M., Dial, R. J., Schulz, B. K., Andersen, H.-E., Lewis-Clark, E., Cook, B. D., & Morton, D. C. (2020). Mapping tall shrub biomass in Alaska at landscape scale using structure-from-motion photogrammetry and lidar. *Remote Sensing of Environment*, *245*, 111841.

Andersen, H.-E., Foster, J. R., & Reutebuch, S. E. (2003). Estimating forest structure parameters within Fort Lewis Military Reservation using airborne laser scanner (LIDAR) data. In *Proceedings*, *2nd inter-national precision forestry symposium* (pp. 45–53). University of Washington, College of Forest Resources.

Anderson, C. B. (2018). Biodiversity monitoring, earth observations and the ecology of scale. *Ecology Letters*, *21*(10), 1572–1585.

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

Andresen, C. G., Tweedie, C. E., & Lougheed, V. L. (2018). Climate and nutrient effects on Arctic wetland plant phenology observed from phenocams. *Remote Sensing of Environment*, *205*, 46–55.

Assmann, J. J., Kerby, J. T., Cunliffe, A. M., & Myers-Smith, I. H. (2019). Vegetation monitoring using multispectral sensors – Best practices and lessons learned from high latitudes. *Journal of Unmanned Vehicle Systems*, *7*(1), 54–75.

Assmann, J. J., Myers-Smith, I. H., Kerby, J. T., Cunliffe, A. M., & Daskalova, G. N. (2020). Drone data reveal heterogeneity in tundra greenness and phenology not captured by satellites. *Environmental Research Letters*, *15*(12), 125002.

Azzeh, J., Zahran, B., & Alqadi, Z. (2018). Salt and pepper noise: Effects and removal. *JOIV: International Journal on Informatics Visualization*, *2*(4), 252–256.

Baldeck, C., & Asner, G. (2013). Estimating vegetation beta diversity from airborne imaging spectroscopy and unsupervised clustering. *Remote Sensing*, *5*(5), 2057–2071.

Beamish, A., Raynolds, M. K., Epstein, H., Frost, G. V., Macander, M. J., Bergstedt, H., Bartsch, A., Kruse, S., Miles, V., Tanis, C. M., Heim, B., Fuchs, M., Chabrillat, S., Shevtsova, I., Verdonen, M., & Wagner, J. (2020). Recent trends and remaining challenges for optical remote sensing of Arctic tundra vegetation: A review and outlook. *Remote Sensing of Environment*, *246*, 111872.

Bergen, K. M., Goetz, S. J., Dubayah, R. O., Henebry, G. M., Hunsaker, C. T., Imhoff, M. L., Nelson, R. F., Parker, G. G., & Radeloff, V. C. (2009). Remote sensing of vegetation 3-D structure for biodiversity and habitat: Review and implications for lidar and radar spaceborne missions. *Journal of Geophysical Research*, *114*, G00E06. https://doi.org/10.1029/2008JG000883

Berner, L. T., Alexander, H. D., Loranty, M. M., Ganzlin, P., Mack, M. C., Davydov, S. P., & Goetz, S. J. (2015). Biomass allometry for alder, dwarf birch, and willow in boreal forest and tundra ecosystems of far northeastern Siberia and north-central Alaska. *Forest Ecology and Management*, *337*, 110–118.

Berner, L. T., Jantz, P., Tape, K. D., & Goetz, S. J. (2018). Tundra plant above-ground biomass and shrub dominance mapped across the North Slope of Alaska. *Environmental Research Letters*, *13*(3), 035002.

Berry, J., & Bjorkman, O. (1980). Photosynthetic response and adaptation to temperature in higher plants. *Annual Review of Plant Physiology*, *31*(1), 491–543.

Bhatt, U. S., Walker, D. A., Raynolds, M. K., Bieniek, P. A., Epstein, H. E., Comiso, J. C., Pinzon, J. E., Tucker, C. J., Steele, M., Ermold, W., & Zhang, J. (2017). Changing seasonality of panarctic tundra vegetation in relationship to climatic variables. *Environmental Research Letters*, *12*(5), 055003.

Bishoyi, D., & Sudhakar, K. (2017). Modeling and performance simulation of 100 MW PTC based solar thermal power plant in Udaipur India. *Case Studies in Thermal Engineering*, *10*, 216–226.

Bjerke, J. W., Karlsen, S. R., Høgda, K. A., Malnes, E., Jepsen, J. U., Lovibond, S., Vikhamar-Schuler, D., & Tømmervik, H. (2014). Record-low primary productivity and high plant damage in the Nordic Arctic Region in 2012 caused by multiple weather events and pest outbreaks. *Environmental Research Letters*, *9*(8), 084006.

Bjorkman, A. D., Myers-Smith, I. H., Elmendorf, S. C., Normand, S., Rüger, N., Beck, P. S. A., Blach-Overgaard, A., Blok, D., Cornelissen, J. H. C., Forbes, B. C., Georges, D., Goetz, S. J., Guay, K. C., Henry, G. H. R., HilleRisLambers, J., Hollister, R. D., Karger, D. N., Kattge, J., Manning, P., … Weiher, E. (2018). Plant functional trait change across a warming tundra biome. *Nature*, *562*(7725), 57–62.

Blok, D., Heijmans, M. M. P. D., Schaepman-Strub, G., Kononov, A. V., Maximov, T. C., & Berendse, F. (2010). Shrub expansion may reduce summer permafrost thaw in Siberian tundra. *Global Change Biology*, *16*(4), 1296–1305.

Breen, A., Iversen, C., Salmon, V., VanderStel, H., Busey, B., & Wullschleger, S. (2020). *NGEE Arctic Plant Traits: Plant community composition*, *Kougarok Road Mile Marker 64*, *Seward Peninsula*, *Alaska*, *2016*. Next Generation Ecosystem Experiments Arctic Data Collection, Oak Ridge National Laboratory, U.S. Department of Energy. https://doi.org/10.5440/1465967

Bring, A., Fedorova, I., Dibike, Y., Hinzman, L., Mård, J., Mernild, S. H., Prowse, T., Semenova, O., Stuefer, S. L., & Woo, M. -K. (2016). Arctic terrestrial hydrology: A synthesis of processes, regional effects, and research challenges. *Journal of Geophysical Research: Biogeosciences*, *121*(3), 621–649.

Burnett, A. C., Anderson, J., Davidson, K. J., Ely, K. S., Lamour, J., Li, Q., Morrison, B. D., Yang, D., Rogers, A., & Serbin, S. P. (2021). A best-practice guide to predicting plant traits from leaf-level hyperspectral data using partial least squares regression. *Journal of Experimental Botany*, *72*(18), 6175–6189.

Cable, W. L., Romanovsky, V. E., & Jorgenson, M. T. (2016). Scaling-up permafrost thermal measurements in western Alaska using an ecotype approach. *The Cryosphere*, *10*(5), 2517–2532. https://doi.org/10.5194/tc-10-2517-2016

Callaghan, T. V., Björn, L. O., Chernov, Y., Chapin, T., Christensen, T. R., Huntley, B., Ims, R. A., Johansson, M., Jolly, D., Jonasson, S., Matveyeva, N., Panikov, N., Oechel, W., & Shaver, G. (2004). Effects on the function of Arctic ecosystems in the short- and long-term perspectives. *Ambio*, *33*(7), 448–458.

Canisius, F., Wang, S., Croft, H., Leblanc, S. G., Russell, H. A. J., Chen, J., & Wang, R. (2019). A UAV-based sensor system for measuring land surface albedo: Tested over a Boreal Peatland Ecosystem. *Drones*, *3*, 27.

Carlson, K. M., Asner, G. P., Hughes, R. F., Ostertag, R., & Martin, R. E. (2007). Hyperspectral remote sensing of canopy biodiversity in Hawaiian lowland rainforests. *Ecosystems*, *10*(4), 536–549.

Cavender-Bares, J., Gamon, J. A., & Townsend, P. A. (2020). *Remote sensing of plant biodiversity* (pp. 1–12). Springer.

Cawse-Nicholson, K., Townsend, P. A., Schimel, D., Assiri, A. M., Blake, P. L., Buongiorno, M. F., Campbell, P., Carmon, N., Casey, K. A., Correa-Pabón, R. E., Dahlin, K. M., Dashti, H., Dennison, P. E., Dierssen, H., Erickson, A., Fisher, J. B., Frouin, R., Gatebe, C. K., Gholizadeh, H., … Zhang, Q. (2021). NASA's surface biology and geology designated observable: A perspective on surface imaging algorithms. *Remote Sensing of Environment*, *257*, 112349.

Chadwick, K. D., Brodrick, P. G., Grant, K., Goulden, T., Henderson, A., Falco, N., Wainwright, H., Williams, K. H., Bill, M., Breckheimer, I., Brodie, E. L., Steltzer, H., Williams, C. F. R., Blonder, B., Chen, J., Dafflon, B., Damerow, J., Hancher, M., Khurram, A., & Maher, K. (2020). Integrating airborne remote sensing and field campaigns for ecology and Earth system science. *Methods in Ecology and Evolution*, *11*(11), 1492–1508.

Chae, Y., Kang, S. M., Jeong, S.-J., Kim, B., & Frierson, D. M. W. (2015). Arctic greening can cause earlier seasonality of Arctic amplification. *Geophysical Research Letters*, *42*(2), 536–541.

Chan, C., Nelson, P. R., Hayes, D. J., Zhang, Y.-J., & Hall, B. (2021). Predicting water stress in wild blueberry fields using airborne visible and near infrared imaging spectroscopy. *Remote Sensing*, *13*(8), 1425.

Chang, C. Y., Zhou, R., Kira, O., Marri, S., Skovira, J., Gu, L., & Sun, Y. (2020). An Unmanned Aerial System (UAS) for concurrent measurements of solar-induced chlorophyll fluorescence and hyperspectral reflectance toward improving crop monitoring. *Agricultural and Forest Meteorology*, *294*, 108145.

Chapin, F. S. (1983). Direct and indirect effects of temperature on arctic plants. *Polar Biology*, *2*(1), 47–52.

Chapin, F. S., Jefferies, R. L., Reynolds, J. F., Shaver, G. R., Svoboda, J., & Chu, E. W. (2012). *Arctic ecosystems in a changing climate: An ecophysiological perspective*. Academic Press.

Chapin, F. S., Sturm, M., Serreze, M. C., McFadden, J. P., Key, J. R., Lloyd, A. H., McGuire, A. D., Rupp, T. S., Lynch, A. H., Schimel, J. P., Beringer, J., Chapman, W. L., Epstein, H. E., Euskirchen, E. S., Hinzman, L. D., Jia, G., Ping, C.-L., Tape, K. D., Thompson, C. D. C., … Welker, J. M. (2005). Role of land-surface changes in Arctic summer warming. *Science*, *310*(5748), 657–660.

Chen, W., Tape, K. D., Euskirchen, E. S., Liang, S., Matos, A., Greenberg, J., & Fraterrigo, J. M. (2020). Impacts of Arctic shrubs on root traits and belowground nutrient cycles across a Northern Alaskan climate gradient. *Frontiers in Plant Science*, *11*, 588098.

Chen, X., Chen, J., Jia, X., Somers, B., Wu, J., & Coppin, P. (2011). A quantitative analysis of virtual endmembers' increased impact on the collinearity effect in spectral unmixing. *IEEE Transactions on Geoscience and Remote Sensing*, *49*(8), 2945–2956.

Chuine, I. (2010). Why does phenology drive species distribution? *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *365*(1555), 3149–3160.

Collins, A. D., Andresen, C. G., Charsley-Groffman, L. M., Cochran, T., Dann, J., Lathrop, E., Riemersma, G. J., Swanson, E. M., Tapadinhas, A., & Wilson, C. J. (2020). UAS LIDAR mapping of an Arctic tundra watershed: Challenges and opportunities. ISPRS – International Archives of the Photogrammetry Remote Sensing and Spatial Information Sciences, XLIV-M-2-2020, 1–8.

Collins, C. G., Elmendorf, S. C., Hollister, R. D., Henry, G. H. R., Clark, K., Bjorkman, A. D., Myers-Smith, I. H., Prevéy, J. S., Ashton, I. W., Assmann, J. J., Alatalo, J. M., Carbognani, M., Chisholm, C., Cooper, E. J., Forrester, C., Jónsdóttir, I. S., Klanderud, K., Kopp, C. W., Livensperger, C., … Suding, K. N. (2021). Experimental warming differentially affects vegetative and reproductive phenology of tundra plants. *Nature Communications*, *12*(1), 3442.

Colomina, I., & Molina, P. (2014). Unmanned aerial systems for photogrammetry and remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *92*, 79–97.

Cornelissen, J. H. C., Lavorel, S., Garnier, E., Díaz, S., Buchmann, N., Gurvich, D. E., Reich, P. B., Steege, H. T., Morgan, H. D., Van Der Heijden, M. G. A., Pausas, J. G., & Poorter, H. (2003). A handbook of protocols for standardized and easy measurement of plant functional traits worldwide. *Australian Journal of Botany*, *51*(4), 335.

Cornwell, W. K., Cornelissen, J. H. C., Amatangelo, K., Dorrepaal, E., Eviner, V. T., Godoy, O., Hobbie, S. E., Hoorens, B., Kurokawa, H., Pérez-Harguindeguy, N., Quested, H. M., Santiago, L. S., Wardle, D. A., Wright, I. J., Aerts, R., Allison, S. D., van Bodegom, P., Brovkin, V., Chatain, A., … Westoby, M. (2008). Plant species traits are the predominant control on litter decomposition rates within biomes worldwide. *Ecology Letters*, *11*(10), 1065–1071.

Costa, J. M., Grant, O. M., & Chaves, M. M. (2013). Thermography to explore plant–environment interactions. *Journal of Experimental Botany*, *64*(13), 3937–3949.

Cristóbal, J., Graham, P., Prakash, A., Buchhorn, M., Gens, R., Guldager, N., & Bertram, M. (2021). Airborne hyperspectral data acquisition and processing in the Arctic: A pilot study using the hyspex imaging spectrometer for wetland mapping. *Remote Sensing*, *13*(6), 1178. https://doi.org/10.3390/rs13061178

Cunliffe, A., Anderson, K., Boschetti, F., Brazier, R., Graham, H., Myers-Smith, I., Astor, T., Boer, M., Calvo, L., Clark, P., Cramer, M., Encinas-Lara, M., Escarzaga, S., Fernández-Guisuraga, J., Fisher, A., Gdulová, K., Gillespie, B., Griebel, A., Hanan, N., & Wojcikiewicz, R. (2021). Global application of an unoccupied aerial vehicle photogrammetry protocol for predicting aboveground biomass in non-forest ecosystems. *Remote Sensing in Ecology and Conservation*, *8*(1), 57–71.

Cunliffe, A. M., Assmann, J. J., Daskalova, G. N., Kerby, J. T., & Myers-Smith, I. H. (2020). Aboveground biomass corresponds strongly with drone-derived canopy height but weakly with greenness (NDVI) in a shrub tundra landscape. *Environmental Research Letters*, *15*(12), 125004.

Curran, P. J. (1989). Remote sensing of foliar chemistry. *Remote Sensing of Environment*, *30*(3), 271–278.

Dahlin, K. M., Asner, G. P., & Field, C. B. (2013). Environmental and community controls on plant canopy chemistry in a Mediterranean-type ecosystem. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(17), 6895–6900.

Dainelli, R., Toscano, P., Di Gennaro, S. F., & Matese, A. (2021a). Recent advances in unmanned aerial vehicle forest remote sensing – A systematic review. Part I: A general framework. *Forests*, *12*(3), 327.

Dainelli, R., Toscano, P., Di Gennaro, S. F., & Matese, A. (2021b). Recent advances in unmanned aerial vehicles forest remote sensing – A systematic review. Part II: Research applications. *Forests*, *12*(4), 397.

Davidson, S., Santos, M., Sloan, V., Watts, J., Phoenix, G., Oechel, W., & Zona, D. (2016). Mapping Arctic tundra vegetation communities using field spectroscopy and multispectral satellite data in North Alaska, USA. *Remote Sensing*, *8*(12), 978.

DelGreco, J. L. (2018). *Four years of unmanned aerial system imagery reveals vegetation change in a sub-arctic mire due to permafrost thaw*. University of New Hampshire. https://search.proquest.com/openview/eeb612484b1d5948a6cedb8b7094b99e/1?pq-origsite=gscholar&cbl=18750

DeMarco, J., Mack, M. C., & Bret-Harte, M. S. (2014). Effects of arctic shrub expansion on biophysical vs. biogeochemical drivers of litter decomposition. *Ecology*, *95*(7), 1861–1875.

Diaz, S., Hodgson, J. G., Thompson, K., Cabido, M., Cornelissen, J. H. C., Jalili, A., Montserrat-Martí, G., Grime, J. P., Zarrinkamar, F., Asri, Y., Band, S. R., Basconcelo, S., Castro-Díez, P., Funes, G., Hamzehee, B., Khoshnevi, M., Pérez-Harguindeguy, N., Pérez-Rontomé, M. C., Shirvany, F. A., … Zak, M. R. (2004). The plant traits that drive ecosystems: Evidence from three continents. *Journal of Vegetation Science*, *15*(3), 295–304.

Dickinson, J. L., Zuckerberg, B., & Bonter, D. N. (2010). Citizen science as an ecological research tool: challenges and benefits. *Annual Review of Ecology, Evolution, and Systematics*, *41*(1), 149–172.

Dietrich, L., & Körner, C. (2014). Thermal imaging reveals massive heat accumulation in flowers across a broad spectrum of alpine taxa. *Alpine Botany*, *124*(1), 27–35.

D'Odorico, P., Besik, A., Wong, C. Y. S., Isabel, N., & Ensminger, I. (2020). High-throughput drone-based remote sensing reliably tracks phenology in thousands of conifer seedlings. *The New Phytologist*, *226*(6), 1667–1681.

Ellsäßer, F., Stiegler, C., Röll, A., June, T., Knohl, A., & Hölscher, D. (2020). Predicting evapotranspiration from drone-based thermography – A method comparison in a tropical oil palm plantation. *Biogeosciences*, *2020*, 1–37.

Elmendorf, S. C., Henry, G. H. R., Hollister, R. D., Björk, R. G., Boulanger-Lapointe, N., Cooper, E. J., Cornelissen, J. H. C., Day, T. A., Dorrepaal, E., Elumeeva, T. G., Gill, M., Gould, W. A., Harte, J., Hik, D. S., Hofgaard, A., Johnson, D. R., Johnstone, J. F., Jónsdóttir, I. S., Jorgenson, J. C., … Wipf, S. (2012). Plot-scale evidence of tundra vegetation change and links to recent summer warming. *Nature Climate Change*, *2*(6), 453–457.

Ewald, M., Aerts, R., Lenoir, J., Fassnacht, F. E., Nicolas, M., Skowronek, S., Piat, J., Honnay, O., Garzón-López, C. X., Feilhauer, H., Van De Kerchove, R., Somers, B., Hattab, T., Rocchini, D., & Schmidtlein, S. (2018). LiDAR derived forest structure data improves predictions of canopy N and P concentrations from imaging spectroscopy. *Remote Sensing of Environment*, *211*, 13–25.

Féret, J.-B., François, C., Gitelson, A., Asner, G. P., Barry, K. M., Panigada, C., Richardson, A. D., & Jacquemoud, S. (2011). Optimizing spectral indices and chemometric analysis of leaf chemical properties using radiative transfer modeling. *Remote Sensing of Environment*, *115*(10), 2742–2750.

Fisher, J. B., Hayes, D. J., Schwalm, C. R., Huntzinger, D. N., Stofferahn, E., Schaefer, K., Luo, Y., Wullschleger, S. D., Goetz, S., Miller, C. E., Griffith, P., Chadburn, S., Chatterjee, A., Ciais, P., Douglas, T. A., Genet, H., Ito, A., Neigh, C. S. R., Poulter, B., … Zhang, Z. (2018). Missing pieces to modeling the Arctic-Boreal puzzle. *Environmental Research Letters*, *13*(2), 020202.

Fisher, J. B., Sikka, M., Oechel, W. C., Huntzinger, D. N., Melton, J. R., Koven, C. D., Ahlström, A., Arain, A. M., Baker, I., Chen, J. M., Ciais, P., Davidson, C., Dietze, M., El-Masri, B., Hayes, D., Huntingford, C., Jain, A., Levy, P. E., Lomas, M. R., … Miller, C. E. (2014). Carbon cycle uncertainty in the Alaskan Arctic. *Biogeosciences Discussions*, *11*(2), 2887–2932.

Fisher, R. A., Koven, C. D., Anderegg, W. R. L., Christoffersen, B. O., Dietze, M. C., Farrior, C. E., Holm, J. A., Hurtt, G. C., Knox, R. G., Lawrence, P. J., Lichstein, J. W., Longo, M., Matheny, A. M., Medvigy, D., Muller-Landau, H. C., Powell, T. L., Serbin, S. P., Sato, H., Shuman, J. K., … Moorcroft, P. R. (2018). Vegetation demographics in Earth System Models: A review of progress and priorities. *Global Change Biology*, *24*(1), 35–54.

Fraser, R. H., Lantz, T. C., McFarlane-Winchester, M., van der Sluijs, J., & Prévost, C. (2020). *Testing the potential of UAV photogrammetry for deriving bare earth models in Arctic shrublands*. Natural Resources Canada.

Fraser, R. H., Olthof, I., Lantz, T. C., & Schmitt, C. (2016). UAV photogrammetry for mapping vegetation in the low-Arctic. *Arctic Science*, *2*(3), 79–102.

French, N. H. F., Jenkins, L. K., Loboda, T. V., Flannigan, M., Jandt, R., Bourgeau-Chavez, L. L., & Whitley, M. (2015). Fire in arctic tundra of Alaska: Past fire activity, future fire potential, and significance for land management and ecology. *International Journal of Wildland Fire*, *24*(8), 1045–1061.

Frost, G. V., & Epstein, H. E. (2014). Tall shrub and tree expansion in Siberian tundra ecotones since the 1960s. *Global Change Biology*, *20*(4), 1264–1277.

Frost, G. V., Epstein, H. E., Walker, D. A., Matyshak, G., & Ermokhina, K. (2018). Seasonal and long-term changes to active-layer temperatures after tall shrubland expansion and succession in Arctic tundra. *Ecosystems*, *21*(3), 507–520.

Gaffey, C., & Bhardwaj, A. (2020). Applications of unmanned aerial vehicles in cryosphere: Latest advances and prospects. *Remote Sensing*, *12*(6), 948.

Gamon, J. A., Serrano, L., & Surfus, J. S. (1997). The photochemical reflectance index: An optical indicator of photosynthetic radiation use efficiency across species, functional types, and nutrient levels. *Oecologia*, *112*(4), 492–501.

Gamon, J. A., Somers, B., Malenovský, Z., Middleton, E. M., Rascher, U., & Schaepman, M. E. (2019). Assessing vegetation function with imaging spectroscopy. *Surveys in Geophysics*, *40*(3), 489–513.

Gamon, J. A., Wang, R., Gholizadeh, H., Zutta, B., Townsend, P. A., & Cavender-Bares, J. (2020). Consideration of scale in remote sensing of biodiversity. In *Remote sensing of plant biodiversity* (pp. 425–447). Springer, Cham.

Geladi, P., & Kowalski, B. R. (1986). Partial least-squares regression: A tutorial. *Analytica Chimica Acta*, *185*, 1–17.

Gersony, J. T., Prager, C. M., Boelman, N. T., Eitel, J. U. H., Gough, L., Greaves, H. E., Griffin, K. L., Magney, T. S., Sweet, S. K., Vierling, L. A., & Naeem, S. (2016). Scaling thermal properties from the leaf to the canopy in the Alaskan Arctic tundra. *Arctic, Antarctic, and Alpine Research*, *48*(4), 739–754.

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.

Gillan, J. K., McClaran, M. P., Swetnam, T. L., & Heilman, P. (2019). Estimating forage utilization with drone-based photogrammetric point clouds. *Rangeland Ecology & Management*, *72*(4), 575–585.

Gillan, J. K., Ponce-Campos, G. E., Swetnam, T. L., Gorlier, A., Heilman, P., & McClaran, M. P. (2021). Innovations to expand drone data collection and analysis for rangeland monitoring. *Ecosphere*, *12*(7), e03649.

González-Jorge, H., Martínez-Sánchez, J., Bueno, M., & Arias, A. P. (2017). Unmanned aerial systems for civil applications: A review. *Drones*, *1*(1), 2.

Goward, S. N., & Huemmrich, K. F. (1992). Vegetation canopy PAR absorptance and the normalized difference vegetation index: An assessment using the SAIL model. *Remote Sensing of Environment*, *39*(2), 119–140.

Greaves, H. E., Eitel, J. U. H., Vierling, L. A., Boelman, N. T., Griffin, K. L., Magney, T. S., & Prager, C. M. (2019). 20 cm resolution mapping of tundra vegetation communities provides an ecological baseline for important research areas in a changing Arctic environment. *Environmental Research Communications*, *1*(10), 105004.

Greaves, H. E., Vierling, L. A., Eitel, J. U. H., Boelman, N. T., Magney, T. S., Prager, C. M., & Griffin, K. L. (2015). Estimating aboveground biomass and leaf area of low-stature Arctic shrubs with terrestrial LiDAR. *Remote Sensing of Environment*, *164*, 26–35.

Gu, L., Post, W. M., Baldocchi, D. D., Black, T. A., Suyker, A. E., Verma, S. B., Vesala, T., & Wofsy, S. C. (2009). Characterizing the seasonal dynamics of plant community photosynthesis across a range of vegetation types. In A. Noormets (Ed.), *Phenology of ecosystem processes: Applications in global change research* (pp. 35–58). Springer New York.

Gunn, G. E., Jones, B. M., & Rangel, R. C. (2021). Unpiloted aerial vehicle retrieval of snow depth over freshwater lake ice using structure from motion. *Frontiers in Remote Sensing*, *2*, 675846.

Hakala, T., Markelin, L., Honkavaara, E., Scott, B., Theocharous, T., Nevalainen, O., Näsi, R., Suomalainen, J., Viljanen, N., Greenwell, C., & Fox, N. (2018). Direct reflectance measurements from drones: Sensor absolute radiometric calibration and system tests for forest reflectance characterization. *Sensors*, *18*(5), 1417.

Hardin, P. J., Lulla, V., Jensen, R. R., & Jensen, J. R. (2019). Small Unmanned Aerial Systems (sUAS) for environmental remote sensing: Challenges and opportunities revisited. *GIScience and Remote Sensing*, *56*(2), 309–322.

Hinzman, L. D., Bettez, N. D., Bolton, W. R., Chapin, F. S., Dyurgerov, M. B., Fastie, C. L., Griffith, B., Hollister, R. D., Hope, A., Huntington, H. P., Jensen, A. M., Jia, G. J., Jorgenson, T., Kane, D. L., Klein, D. R., Kofinas, G., Lynch, A. H., Lloyd, A. H., McGuire, A. D., … Yoshikawa, K. (2005). Evidence and implications of recent climate change in northern Alaska and other Arctic regions. *Climatic Change*, *72*(3), 251–298.

Hoffmann, H., Nieto, H., Jensen, R., Guzinski, R., Zarco-Tejada, P., & Friborg, T. (2016). Estimating evaporation with thermal UAV data and two-source energy balance models. *Hydrology and Earth System Sciences*, *20*(2), 697–713.

IPCC. (2019). *Special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems: Summary for policymakers*. Intergovernmental Panel on Climate Change.

Jacquemoud, S., Verhoef, W., Baret, F., Bacour, C., Zarco-Tejada, P. J., Asner, G. P., François, C., & Ustin, S. L. (2009). PROSPECT+SAIL models: A review of use for vegetation characterization. *Remote Sensing of the Environment*, *113*, S56–S66.

Jin, M., & Dickinson, R. E. (2010). Land surface skin temperature climatology: Benefitting from the strengths of satellite observations. *Environmental Research Letters*, *5*(4), 044004.

Joly, K., Jandt, R. R., & Klein, D. R. (2009). Decrease of lichens in Arctic ecosystems: The role of wildfire, caribou, reindeer, competition and climate in north-western Alaska. *Polar Research*, *28*(3), 433–442.

Joly, K., Jeanie Cole, M., & Jandt, R. R. (2007). Diets of overwintering caribou, *Rangifer tarandus*, track decadal changes in arctic tundra vegetation. *The Canadian Field-Naturalist*, *121*(4), 379–383.

Jones, B. M., Grosse, G., Arp, C. D., Miller, E., Liu, L., Hayes, D. J., & Larsen, C. F. (2015). Recent Arctic tundra fire initiates widespread thermokarst development. *Scientific Reports*, *5*(1), 15865.

Jones, H. G. (1992). *Plants and microclimate: A quantitative approach to environmental plant physiology*. Cambridge University Press.

Jones, H. G., & Leinonen, I. (2003). Thermal imaging for the study of plant water relations. *Journal of Agricultural Meteorology*, *59*(3), 205–217.

Jones, H. G., & Schofield, P. (2008). Thermal and other remote sensing of plant stress. *General and Applied Plant Physiology*, *34*(1-2), 19–32.

Ju, J., & Masek, J. G. (2016). The vegetation greenness trend in Canada and US Alaska from 1984–2012 Landsat data. *Remote Sensing of Environment*, *176*, 1–16.

Juszak, I., Iturrate-Garcia, M., Gastellu-Etchegorry, J.-P., Schaepman, M. E., Maximov, T. C., & Schaepman-Strub, G. (2017). Drivers of shortwave radiation fluxes in Arctic tundra across scales. *Remote Sensing of Environment*, *193*, 86–102.

Keenan, T. F., Darby, B., Felts, E., Sonnentag, O., Friedl, M. A., Hufkens, K., O'Keef, J., Klosterman, S., Munger, J. W., Toome, M., & Richardson, A. D. (2014). Tracking forest phenology and seasonal physiology using digital repeat photography: A critical assessment. *Ecological Applications*, *24*(6), 1478–1489.

Kilian, J., Haala, N., & Englich, M. (1996). Capture and evaluation of airborne laser scanner data. *International Archives of Photogrammetry and Remote Sensing*, *31*, 383–388.

Kokaly, R. F., Asner, G. P., Ollinger, S. V., Martin, M. E., & Wessman, C. A. (2009). Characterizing canopy biochemistry from imaging spectroscopy and its application to ecosystem studies. *Remote Sensing of Environment*, *113*, S78–S91.

Körner, C. (2006). Significance of temperature in plant life. In *Plant growth and climate change* (pp. 48–69). Wiley.

Kraus, K., & Pfeifer, N. (1998). Determination of terrain models in wooded areas with airborne laser scanner data. *ISPRS Journal of Photogrammetry and Remote Sensing*, *53*(4), 193–203.

Krishna, G., Sahoo, R. N., Singh, P., Patra, H., Bajpai, V., Das, B., Kumar, S., Dhandapani, R., Vishwakarma, C., Pal, M., & Chinnusamy, V. (2021). Application of thermal imaging and hyperspectral remote sensing for crop water deficit stress monitoring. *Geocarto International*, *36*(5), 481–498.

Kuusk, A. (2018). 3.03 – Canopy radiative transfer modeling. In S. Liang (Ed.), *Comprehensive remote sensing* (pp. 9–22). Elsevier.

Lara, M. J., McGuire, A. D., Euskirchen, E. S., Genet, H., Yi, S., Rutter, R., Iversen, C., Sloan, V., & Wullschleger, S. D. (2020). Local-scale Arctic tundra heterogeneity affects regional-scale carbon dynamics. *Nature Communications*, *11*(1), 4925.

Lavorel, S., & Garnier, E. (2002). Predicting changes in community composition and ecosystem functioning from plant traits: Revisiting the Holy Grail. *Functional Ecology*, *16*(5), 545–556.

Lawrence, D. M., Slater, A. G., Tomas, R. A., Holland, M. M., & Deser, C. (2008). Accelerated Arctic land warming and permafrost degradation during rapid sea ice loss. *Geophysical Research Letters*, *35*(11), L11506.

Lawrence, D. M., & Swenson, S. C. (2011). Permafrost response to increasing Arctic shrub abundance depends on the relative influence of shrubs on local soil cooling versus large-scale climate warming. *Environmental Research Letters*, *6*(4), 045504.

Lechner, A. M., Langford, W. T., Bekessy, S. A., & Jones, S. D. (2012). Scale and error in remote sensing: Are landscape ecologists addressing these issues? *Landscape Ecology*, *27*(9), 1249–1260.

Lefsky, M. A., Cohen, W. B., Parker, G. G., & Harding, D. J. (2002). Lidar Remote Sensing for Ecosystem Studies: Lidar, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes and should be of particular interest to forest, landscape, and global ecologists. *Bioscience*, *52*(1), 19–30.

Léger, E., Dafflon, B., Robert, Y., Ulrich, C., Peterson, J. E., Biraud, S. C., Romanovsky, V. E., & Hubbard, S. S. (2019). A distributed temperature profiling method for assessing spatial variability in ground temperatures in a discontinuous permafrost region of Alaska. *The Cryosphere*, *13*(11), 2853–2867.

Lisein, J., Pierrot-Deseilligny, M., Bonnet, S., & Lejeune, P. (2013). A photogrammetric workflow for the creation of a forest canopy height model from small unmanned aerial system imagery. *Forests*, *Trees and Livelihoods*, *4*(4), 922–944.

Liu, Z., Hu, H., Yu, H., Yang, X., Yang, H., Ruan, C., Wang, Y., & Tang, J. (2015). Relationship between leaf physiologic traits and canopy color indices during the leaf expansion period in an oak forest. *Ecosphere*, *6*(12), art259.

Lucieer, A., Malenovský, Z., Veness, T., & Wallace, L. (2014). HyperUAS-imaging spectroscopy from a multirotor unmanned aircraft system. *Journal of Field Robotics*, *31*(4), 571–590.

Macander, M. J., Palm, E. C., Frost, G. V., Herriges, J. D., Nelson, P. R., Roland, C., Russell, K. L. M., Suitor, M. J., Bentzen, T. W., Joly, K., Goetz, S. J., & Hebblewhite, M. (2020). Lichen cover mapping for caribou ranges in interior Alaska and Yukon. *Environmental Research Letters*, *15*(5), 055001.

Mack, M. C., Bret-Harte, M. S., Hollingsworth, T. N., Jandt, R. R., Schuur, E. A. G., Shaver, G. R., & Verbyla, D. L. (2011). Carbon loss from an unprecedented Arctic tundra wildfire. *Nature*, *475*(7357), 489–492.

Maimaitijiang, M., Ghulam, A., Sidike, P., Hartling, S., Maimaitiyiming, M., Peterson, K., Shavers, E., Fishman, J., Peterson, J., Kadam, S., Burken, J., & Fritschi, F. (2017). Unmanned Aerial System (UAS)-based phenotyping of soybean using multi-sensor data fusion and extreme learning machine. *ISPRS Journal of Photogrammetry and Remote Sensing*, *134*, 43–58.

Maimaitiyiming, M., Sagan, V., Sidike, P., Maimaitijiang, M., Miller, A. J., & Kwasniewski, M. (2020). Leveraging very-high spatial resolution hyperspectral and thermal UAV imageries for characterizing diurnal indicators of grapevine physiology. *Remote Sensing*, *12*(19), 3216.

Malenovský, Z., Lucieer, A., King, D. H., Turnbull, J. D., & Robinson, S. A. (2017). Unmanned aircraft system advances health mapping of fragile polar vegetation. *Methods in Ecology and Evolution/British Ecological Society*, *8*(12), 1842–1857.

Mänd, P., Hallik, L., Peñuelas, J., Nilson, T., Duce, P., Emmett, B. A., Beier, C., Estiarte, M., Garadnai, J., Kalapos, T., Schmidt, I. K., Kovács-Láng, E., Prieto, P., Tietema, A., Westerveld, J. W., & Kull, O. (2010). Responses of the reflectance indices PRI and NDVI to experimental warming and drought in European shrublands along a north–south climatic gradient. *Remote Sensing of Environment*, *114*(3), 626–636.

McCarty, J. L., Smith, T. E. L., & Turetsky, M. R. (2020). Arctic fires re-emerging. *Nature Geoscience*, *13*(10), 658–660.

McGuire, A. D., Lawrence, D. M., Koven, C., Clein, J. S., Burke, E., Chen, G., Jafarov, E., MacDougall, A. H., Marchenko, S., Nicolsky, D., Peng, S., Rinke, A., Ciais, P., Gouttevin, I., Hayes, D. J., Ji, D., Krinner, G., Moore, J. C., Romanovsky, V., … Zhuang, Q. (2018). Dependence of the evolution of carbon dynamics in the northern permafrost region on the trajectory of climate change. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(15), 3882–3887.

McKinley, D. C., Miller-Rushing, A. J., Ballard, H. L., Bonney, R., Brown, H., Cook-Patton, S. C., Evans, D. M., French, R. A., Parrish, J. K., Phillips, T. B., Ryan, S. F., Shanley, L. A., Shirk, J. L., Stepenuck, K. F., Weltzin, J. F., Wiggins, A., Boyle, O. D., Briggs, R. D., Chapin, S. F., & Soukup, M. A. (2017). Citizen science can improve conservation science, natural resource management, and environmental protection. *Biological Conservation*, *208*, 15–28.

Mekonnen, Z. A., Riley, W. J., Berner, L. T., Bouskill, N. J., Torn, M. S., Iwahana, G., Breen, A. L., Myers-Smith, I. H., Criado, M. G., Liu, Y., Euskirchen, E. S., Goetz, S. J., Mack, M. C., & Grant, R. F. (2021). Arctic tundra shrubification: A review of mechanisms and impacts on ecosystem carbon balance. *Environmental Research Letters*, *16*(5), 053001.

Messina, G., & Modica, G. (2020). Applications of UAV thermal imagery in precision agriculture: State of the art and future research outlook. *Remote Sensing*, *12*(9), 1491.

Metcalfe, D. B., Hermans, T. D. G., Ahlstrand, J., Becker, M., Berggren, M., Björk, R. G., Björkman, M. P., Blok, D., Chaudhary, N., Chisholm, C., Classen, A. T., Hasselquist, N. J., Jonsson, M., Kristensen, J. A., Kumordzi, B. B., Lee, H., Mayor, J. R., Prevéy, J., Pantazatou, K., & Abdi, A. M. (2018). Patchy field sampling biases understanding of climate change impacts across the Arctic. *Nature Ecology & Evolution*, *2*(9), 1443–1448.

Myers-Smith, I. H., Elmendorf, S. C., Beck, P. S. A., Wilmking, M., Hallinger, M., Blok, D., Tape, K. D., Rayback, S. A., Macias-Fauria, M., Forbes, B. C., Speed, J. D. M., Boulanger-Lapointe, N., Rixen, C., Lévesque, E., Schmidt, N. M., Baittinger, C., Trant, A. J., Hermanutz, L., Collier, L. S., & Vellend, M. (2015). Climate sensitivity of shrub growth across the tundra biome. *Nature Climate Change*, *5*(9), 887–891.

Myers-Smith, I. H., Forbes, B. C., Wilmking, M., Hallinger, M., Lantz, T., Blok, D., Tape, K. D., Macias-Fauria, M., Sass-Klaassen, U., Lévesque, E., Boudreau, S., Ropars, P., Hermanutz, L., Trant, A., Collier, L. S., Weijers, S., Rozema, J., Rayback, S. A., Schmidt, N. M., & Hik, D. S. (2011). Shrub expansion in tundra ecosystems: Dynamics, impacts and research priorities. *Environmental Research Letters*, *6*(4), 045509.

Myers-Smith, I. H., Kerby, J. T., Phoenix, G. K., Bjerke, J. W., Epstein, H. E., Assmann, J. J., John, C., Andreu-Hayles, L., Angers-Blondin, S., Beck, P. S. A., Berner, L. T., Bhatt, U. S., Bjorkman, A. D., Blok, D., Bryn, A., Christiansen, C. T., Cornelissen, J. H. C., Cunliffe, A. M., Elmendorf, S. C., & Wipf, S. (2020). Complexity revealed in the greening of the Arctic. *Nature Climate Change*, *10*(2), 106–117.

Myers-Smith, I. H., Thomas, H. J. D., & Bjorkman, A. D. (2018). Plant traits inform predictions of tundra responses to global change. *The New Phytologist*, *221*(4), 1742–1748.

Nelson, P. R., Maguire, A. J., Pierrat, Z., Orcutt, E. L., Yang, D., Serbin, S., Frost, G. V., Macander, M. J., Magney, T. S., Thompson, D. R., Wang, J. A., Oberbauer, S. F., Zesati, S. V., Davidson, S. J., Epstein, H. E., Unger, S., Campbell, P. K. E., Carmon, N., Velez-Reyes, M., & Huemmrich, K. F. (2022). Remote sensing of tundra ecosystems using high spectral resolution reflectance: Opportunities and challenges. *Journal of Geophysical Research*, *127*(2), e2021JG006697.

Nelson, P. R., & Smith, K. (2022). *ABoVE: UAV and ground-based VNIR/SWIR spectroscopy data of plant functional types*. ORNL DAAC. https://doi.org/10.3334/ORNLDAAC/1980

Nelson, R., Krabill, W., & MacLean, G. (1984). Determining forest canopy characteristics using airborne laser data. *Remote Sensing of Environment*, *15*(3), 201–212.

Nolan, M., Larsen, C., & Sturm, M. (2015). Mapping snow depth from manned aircraft on landscape scales at centimeter resolution using structure-from-motion photogrammetry. *The Cryosphere*, *9*(4), 1445–1463.

Novick, K. A., & Katul, G. G. (2020). The duality of reforestation impacts on surface and air temperature. *Journal of Geophysical Research: Biogeosciences*, *125*(4), e2019JG005543.

Ollinger, S. V. (2011). Sources of variability in canopy reflectance and the convergent properties of plants. *The New Phytologist*, *189*(2), 375–394.

Pearson, R. G., Phillips, S. J., Loranty, M. M., Beck, P. S. A., Damoulas, T., Knight, S. J., & Goetz, S. J. (2013). Shifts in Arctic vegetation and associated feedbacks under climate change. *Nature Climate Change*, *3*(7), 673–677.

Prevéy, J. S., Rixen, C., Rüger, N., Høye, T. T., Bjorkman, A. D., Myers-Smith, I. H., Elmendorf, S. C., Ashton, I. W., Cannone, N., Chisholm, C. L., Clark, K., Cooper, E. J., Elberling, B., Fosaa, A. M., Henry, G. H. R., Hollister, R. D., Jónsdóttir, I. S., Klanderud, K., Kopp, C. W., … Wipf, S. (2018). Warming shortens flowering seasons of tundra plant communities. *Nature Ecology & Evolution*, *3*(1), 45–52.

Puliti, S., Ørka, H. O., Gobakken, T., & Næsset, E. (2015). Inventory of small forest areas using an unmanned aerial system. *Remote Sensing*, *7*(8), 9632–9654.

Räsänen, A., Aurela, M., Juutinen, S., Kumpula, T., Lohila, A., Penttilä, T., & Virtanen, T. (2020). Detecting northern peatland vegetation patterns at ultra-high spatial resolution. *Remote Sensing in Ecology and Conservation*, *6*(4), 457–471.

Raynolds, M. K., Walker, D. A., Epstein, H. E., Pinzon, J. E., & Tucker, C. J. (2012). A new estimate of tundra-biome phytomass from trans-Arctic field data and AVHRR NDVI. *Remote Sensing Letters*, *3*(5), 403–411.

Reich, P. B. (2014). The world-wide 'fast-slow' plant economics spectrum: A traits manifesto. *The Journal of Ecology*, *102*(2), 275–301.

Riihimäki, H., Luoto, M., & Heiskanen, J. (2019). Estimating fractional cover of tundra vegetation at multiple scales using unmanned aerial systems and optical satellite data. *Remote Sensing of Environment*, *224*, 119–132.

Rocchini, D., Balkenhol, N., Carter, G. A., Foody, G. M., Gillespie, T. W., He, K. S., Kark, S., Levin, N., Lucas, K., Luoto, M., Nagendra, H., Oldeland, J., Ricotta, C., Southworth, J., & Neteler, M. (2010). Remotely sensed spectral heterogeneity as a proxy of species diversity: Recent advances and open challenges. *Ecological Informatics*, *5*(5), 318–329.

Rocchini, D., Luque, S., Pettorelli, N., Bastin, L., Doktor, D., Faedi, N., Feilhauer, H., Féret, J.-B., Foody, G. M., Gavish, Y., Godinho, S., Kunin, W. E., Lausch, A., Leitão, P. J., Marcantonio, M., Neteler, M., Ricotta, C., Schmidtlein, S., Vihervaara, P., … Nagendra, H. (2018). Measuring β-diversity by remote sensing: A challenge for biodiversity monitoring. *Methods in Ecology and Evolution*, *9*(8), 1787–1798.

Rogers, A., Serbin, S. P., Ely, K. S., Sloan, V. L., & Wullschleger, S. D. (2017). Terrestrial biosphere models underestimate photosynthetic capacity and CO_2 assimilation in the Arctic. *The New Phytologist*, *216*(4), 1090–1103.

Rogers, A., Serbin, S. P., Ely, K. S., & Wullschleger, S. D. (2019). Terrestrial biosphere models may overestimate Arctic CO_2 assimilation if they do not account for decreased quantum yield and convexity at low temperature. *The New Phytologist*, *223*(1), 167–179.

Rogers, A., Serbin, S. P., & Way, D. A. (2022). Reducing model uncertainty of climate change impacts on high latitude carbon assimilation. *Global Change Biology*, *28*(4), 1222–1247.

Scherrer, D., & Körner, C. (2009). Infra-red thermometry of alpine landscapes challenges climatic warming projections. *Global Change Biology*, *16*(9), 2602–2613.

Schimel, D., Pavlick, R., Fisher, J. B., Asner, G. P., Saatchi, S., Townsend, P., Miller, C., Frankenberg, C., Hibbard, K., & Cox, P. (2015). Observing terrestrial ecosystems and the carbon cycle from space. *Global Change Biology*, *21*(5), 1762–1776.

Schwartz, M. D. (2013). *Phenology: An integrative environmental science*. Springer.

Schweiger, A. K. (2020). Spectral field campaigns: Planning and data collection. In *Remote sensing of plant biodiversity* (pp. 385–423). Springer, Cham.

Schweiger, A. K., Cavender-Bares, J., Townsend, P. A., Hobbie, S. E., Madritch, M. D., Wang, R., Tilman, D., & Gamon, J. A. (2018). Plant spectral diversity integrates functional and phylogenetic components of biodiversity and predicts ecosystem function. *Nature Ecology & Evolution*, *2*(6), 976–982.

Serbin, S., Yang, D., & McMahon, A. (2021). *Landscape-scale characterization of arctic tundra vegetation composition, structure, and function with a multi-sensor unoccupied aerial system: Supporting data*. Next Generation Ecosystem Experiments Arctic Data Collection, Oak Ridge National Laboratory, U.S. Department of Energy. https://doi.org/10.5440/1778212

Serbin, S. P., & Townsend, P. A. (2020). In J. Cavender-Bares, J. A. Gamon, & P. A. Townsend (Eds.), *Remote sensing of plant biodiversity* (pp. 43–82). Springer, Cham.

Serbin, S. P., Wu, J., Ely, K. S., Kruger, E. L., Townsend, P. A., Meng, R., Wolfe, B. T., Chlus, A., Wang, Z., & Rogers, A. (2019). From the Arctic to the tropics: Multibiome prediction of leaf mass per area using leaf reflectance. *The New Phytologist*, *224*(4), 1557–1568.

Shiklomanov, A. N., Bradley, B. A., Dahlin, K. M., M Fox, A., Gough, C. M., Hoffman, F. M., M Middleton, E., Serbin, S. P., Smallman, L., & Smith, W. K. (2019). Enhancing global change experiments through integration of remote-sensing techniques. *Frontiers in Ecology and the Environment*, *17*(4), 215–224.

Shiklomanov, A. N., Dietze, M. C., Viskari, T., Townsend, P. A., & Serbin, S. P. (2016). Quantifying the influences of spectral resolution on uncertainty in leaf trait estimates through a Bayesian approach to RTM inversion. *Remote Sensing of Environment*, *183*, 226–238.

Siewert, M. B., & Olofsson, J. (2020). Scale-dependency of Arctic ecosystem properties revealed by UAV. *Environmental Research Letters*, *15*(9), 094030.

Siewert, M. B., & Olofsson, J. (2021). UAV reveals substantial but heterogeneous effects of herbivores on Arctic vegetation. *Scientific Reports*, *11*(1), 19468.

Simpson, J. E., Holman, F., Nieto, H., Voelksch, I., Mauder, M., Klatt, J., Fiener, P., & Kaplan, J. O. (2021). High spatial and temporal resolution energy flux mapping of different land covers using an off-the-shelf unmanned aerial system. *Remote Sensing*, *13*(7), 1286.

Singh, A., Serbin, S. P., McNeil, B. E., Kingdon, C. C., & Townsend, P. A. (2015). Imaging spectroscopy algorithms for mapping canopy foliar chemical and morphological traits and their uncertainties. *Ecological Applications*, *25*(8), 2180–2197.

Soliman, A., Duguay, C., Saunders, W., & Hachem, S. (2012). Pan-Arctic land surface temperature from MODIS and AATSR: Product development and intercomparison. *Remote Sensing*, *4*(12), 3833–3856.

Somers, B., Asner, G. P., Tits, L., & Coppin, P. (2011). Endmember variability in spectral mixture analysis: A review. *Remote Sensing of Environment*, *115*(7), 1603–1616.

Still, C., Powell, R., Aubrecht, D., Kim, Y., Helliker, B., Roberts, D., Richardson, A. D., & Goulden, M. (2019). Thermal imaging in plant and ecosystem ecology: Applications and challenges. *Ecosphere*, *10*(6), e02768.

Still, C. J., Rastogi, B., Page, G. F. M., Griffith, D. M., Sibley, A., Schulze, M., Hawkins, L., Pau, S., Detto, M., & Helliker, B. R. (2021). Imaging canopy temperature: Shedding (thermal) light on ecosystem processes. *New Phytologist*, *230*(5), 1746–1753.

Sturm, M. (2005). Changing snow and shrub conditions affect albedo with global implications. *Journal of Geophysical Research*, *110*(G1), G01004.

Sturm, M., Racine, C., & Tape, K. (2001). Increasing shrub abundance in the Arctic. *Nature*, *411*(6837), 546–547.

Sutherland, W. J., Freckleton, R. P., Godfray, H. C. J., Beissinger, S. R., Benton, T., Cameron, D. D., Carmel, Y., Coomes, D. A., Coulson, T., Emmerson, M. C., Hails, R. S., Hays, G. C., Hodgson, D. J., Hutchings, M. J., Johnson, D., Jones, J. P. G., Keeling, M. J., Kokko, H., Kunin, W. E., … Wiegand, T. (2013). Identification of 100 fundamental ecological questions. *The Journal of Ecology*, *101*(1), 58–67.

Swetnam, T. L., Brooks, P. D., Barnard, H. R., Harpold, A. A., & Gallo, E. L. (2017). Topographically driven differences in energy and water constrain climatic control on forest carbon sequestration. *Ecosphere*, *8*(4), e01797.

Tansley, A. G. (1935). The Use and Abuse of Vegetational Concepts and Terms. *Ecology*, *16*(3), 284–307.

Thomson, E. R., Spiegel, M. P., Althuizen, I. H. J., Bass, P., Chen, S., Chmurzynski, A., Halbritter, A. H., Henn, J. J., Jónsdóttir, I. S., Klanderud, K., Li, Y., Maitner, B. S., Michaletz, S. T., Niittynen, P., Roos, R. E., Telford, R. J., Enquist, B. J., Vandvik, V., Macias-Fauria, M., & Malhi, Y. (2021). Multiscale mapping of plant functional groups and plant traits in the High Arctic using field spectroscopy, UAV imagery and Sentinel-2A data. *Environmental Research Letters*, *16*(5), 055006.

Tjernström, M., Shupe, M. D., Brooks, I. M., Persson, P. O. G., Prytherch, J., Salisbury, D. J., Sedlar, J., Achtert, P., Brooks, B. J., Johnston, P. E., Sotiropoulou, G., & Wolfe, D. (2015). Warm-air advection, air mass transformation and fog causes rapid ice melt. *Geophysical Research Letters*, *42*(13), 5594–5602.

Tømmervik, H., Karlsen, S.-R., Nilsen, L., Johansen, B., Storvold, R., Zmarz, A., Beck, P. S., Høgda, K. A., Goetz, S., Park, T., & Zagajewski, B. (2014). *Use of unmanned aircraft systems (UAS) in a multi-scale vegetation index study of Arctic plant communities in Adventdalen on Svalbard*. EARSeL eProceedings, Special Issue: 34th EARSeL Symposium. European Association of Remote Sensing Laboratories.

Turetsky, M. R., Abbott, B. W., Jones, M. C., Walter Anthony, K., Olefeldt, D., Schuur, E. A. G., Koven, C., McGuire, A. D., Grosse, G., Kuhry, P., Hugelius, G., Lawrence, D. M., Gibson, C., & Sannel, A. B. K. (2019). Permafrost collapse is accelerating carbon release. *Nature*, *569*(7754), 32–34.

Turner, D., Lucieer, A., & Watson, C. (2012). An automated technique for generating georectified mosaics from ultra-high resolution Unmanned Aerial Vehicle (UAV) imagery, based on Structure from Motion (SfM) point clouds. *Remote Sensing*, *4*(5), 1392–1410.

Ustin, S. L., & Gamon, J. A. (2010). Remote sensing of plant functional types. *The New Phytologist*, *186*(4), 795–816. https://doi.org/10.1111/j.1469-8137.2010.03284.x

Ustin, S. L., Roberts, D. A., Gamon, J. A., Asner, G. P., & Green, R. O. (2004). Using imaging spectroscopy to study ecosystem processes and properties. *Bioscience*, *54*(6), 523–534.

Vélez-Nicolás, M., García-López, S., Barbero, L., Ruiz-Ortiz, V., & Sánchez-Bellón, Á. (2021). Applications of Unmanned Aerial Systems (UASs) in hydrology: A review. *Remote Sensing*, *13*(7), 1359.

Violle, C., Navas, M., Vile, D., Kazakou, E., Fortunel, C., Hummel, I., & Garnier, E. (2007). Let the concept of trait be functional! *Oikos*, *116*(5), 882–892.

Virtanen, T., & Ek, M. (2014). The fragmented nature of tundra landscape. *International Journal of Applied Earth Observation and Geoinformation*, *27*, 4–12.

Vowles, T., & Björk, R. G. (2019). Implications of evergreen shrub expansion in the Arctic. *The Journal of Ecology*, *107*(2), 650–655.

Wainwright, H. M., Oktem, R., Dafflon, B., Dengel, S., Curtis, J. B., Torn, M. S., Cherry, J., & Hubbard, S. S. (2021). High-resolution spatiotemporal estimation of net ecosystem exchange in ice-wedge polygon tundra using in situ sensors and remote sensing data. *Land*, *10*(7), 722.

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, Trees and Livelihoods*, *7*(3), 62.

Wang, D., Zhou, L., Wang, Q., & Ding, J. (2020). Plant chemistry determines host preference and performance of an invasive insect. *Frontiers in Plant Science*, *11*, 594663.

Wang, N., Suomalainen, J., Bartholomeus, H., Kooistra, L., Masiliūnas, D., & Clevers, J. G. P. W. (2021). Diurnal variation of sun-induced chlorophyll fluorescence of agricultural crops observed from a point-based spectrometer on a UAV. *International Journal of Applied Earth Observation and Geoinformation*, *96*, 102276.

Wang, P., Mommer, L., van Ruijven, J., Berendse, F., Maximov, T. C., & Heijmans, M. M. P. D. (2016). Seasonal changes and vertical distribution of root standing biomass of graminoids and shrubs at a Siberian tundra site. *Plant and Soil*, *407*(1), 55–65.

Wang, R., & Gamon, J. A. (2019). Remote sensing of terrestrial plant biodiversity. *Remote Sensing of Environment*, *231*, 111218.

Wang, S., Lu, X., Cheng, X., Li, X., Peichl, M., & Mammarella, I. (2018). Limitations and challenges of MODIS-derived phenological metrics across different landscapes in Pan-Arctic regions. *Remote Sensing*, *10*(11), 1784.

Wang, Z., Chlus, A., Geygan, R., Ye, Z., Zheng, T., Singh, A., Couture, J. J., Cavender-Bares, J., Kruger, E. L., & Townsend, P. A. (2020). Foliar functional traits from imaging spectroscopy across biomes in eastern North America. *The New Phytologist*, *228*(2), 494–511.

Wang, Z., Townsend, P. A., Schweiger, A. K., Couture, J. J., Singh, A., Hobbie, S. E., & Cavender-Bares, J. (2019). Mapping foliar functional traits and their uncertainties across three years in a grassland experiment. *Remote Sensing of Environment*, *221*, 405–416.

Wasowicz, P., Sennikov, A. N., Westergaard, K. B., Spellman, K., Carlson, M., Gillespie, L. J., Saarela, J. M., Seefeldt, S. S., Bennett, B., Bay, C., Ickert-Bond, S., & Väre, H. (2020). Non-native vascular flora of the Arctic: Taxonomic richness, distribution and pathways. *Ambio*, *49*(3), 693–703.

Westermann, S., Langer, M., & Boike, J. (2011). Spatial and temporal variations of summer surface temperatures of high-arctic tundra on Svalbard – Implications for MODIS LST based permafrost monitoring. *Remote Sensing of Environment*, *115*(3), 908–922.

Westoby, M. J., Brasington, J., Glasser, N. F., Hambrey, M. J., & Reynolds, J. M. (2012). 'Structure-from-Motion' photogrammetry: A low-cost, effective tool for geoscience applications. *Geomorphology*, *179*, 300–314.

Wold, S., Sjöström, M., & Eriksson, L. (2001). PLS-regression: A basic tool of chemometrics. *Chemometrics and Intelligent Laboratory Systems*, *58*(2), 109–130.

Wu, H., & Li, Z.-L. (2009). Scale issues in remote sensing: A review on analysis, processing and modeling. *Sensors*, *9*(3), 1768–1793.

Wullschleger, S. D., Epstein, H. E., Box, E. O., Euskirchen, E. S., Goswami, S., Iversen, C. M., Kattge, J., Norby, R. J., van Bodegom, P. M., & Xu, X. (2014). Plant functional types in Earth system models: Past experiences and future directions for application of dynamic vegetation models in high-latitude ecosystems. *Annals of Botany*, *114*(1), 1–16.

Wyngaard, J., Barbieri, L., Thomer, A., Adams, J., Sullivan, D., Crosby, C., Parr, C., Klump, J., Raj Shrestha, S., & Bell, T. (2019). Emergent challenges for science sUAS data management: Fairness through community engagement and best practices development. *Remote Sensing*, *11*(15), 1797.

Xu, X., Asawa, T., & Kobayashi, H. (2020). Narrow-to-broadband conversion for albedo estimation on urban surfaces by UAV-based multi-spectral camera. *Remote Sensing*, *12*(14), 2214.

Xu, Z., & Zhu, D. (2018). High-resolution miniature UAV SAR imaging based on GPU Architecture. *Journal of Physics. Conference Series*, *1074*(1), 012122.

Yan, Y., Mao, K., Shi, J., Piao, S., Shen, X., Dozier, J., Liu, Y., Ren, H.-L., & Bao, Q. (2020). Driving forces of land surface temperature anomalous changes in North America in 2002–2018. *Scientific Reports*, *10*(1), 6931.

Yan, Z., Guo, Z., Serbin, S. P., Song, G., Zhao, Y., Chen, Y., Wu, S., Wang, J., Wang, X., Li, J., Wang, B., Wu, Y., Su, Y., Wang, H., Rogers, A., Liu, L., & Wu, J. (2021). Spectroscopy outperforms leaf trait relationships for predicting photosynthetic capacity across different forest types. *The New Phytologist*, *232*(1), 134–147.

Yang, D., Meng, R., Morrison, B. D., McMahon, A., Hantson, W., Hayes, D. J., Breen, A. L., Salmon, V. G., & Serbin, S. P. (2020). A multi-sensor unoccupied aerial system improves characterization of vegetation composition and canopy properties in the Arctic Tundra. *Remote Sensing*, *12*(16), 2638.

Yang, D., Morrison, B. D., Hantson, W., Breen, A. L., McMahon, A., Li, Q., Salmon, V. G., Hayes, D. J., & Serbin, S. P. (2021). Landscape-scale characterization of Arctic tundra vegetation composition, structure, and function with a multi-sensor unoccupied aerial system. *Environmental Research Letters*, *16*, 085005.

Yao, H., Qin, R., & Chen, X. (2019). Unmanned aerial vehicle for remote sensing applications – A review. *Remote Sensing*, *11*(12), 1443.

Zhang, Q., Barnes, M., Benson, M., Burakowski, E., Oishi, A. C., Ouimette, A., Sanders-DeMott, R., Stoy, P. C., Wenzel, M., Xiong, L., Yi, K., & Novick, K. A. (2020). Reforestation and surface cooling in temperate zones: Mechanisms and implications. *Global Change Biology*, *26*(6), 3384–3401.

Zhang, W., Miller, P. A., Jansson, C., Samuelsson, P., Mao, J., & Smith, B. (2018). Self-amplifying feedbacks accelerate greening and warming of the arctic. *Geophysical Research Letters*, *45*(14), 7102–7111.

How to cite this article: Yang, D., Morrison, B. D., Davidson, K. J., Lamour, J., Li, Q., Nelson, P. R., Hantson, W., Hayes, D. J., Swetnam, T. L., McMahon, A., Anderson, J., Ely, K. S., Rogers, A., & Serbin, S. P. (2022). Remote sensing from unoccupied aerial systems: Opportunities to enhance Arctic plant ecology in a changing climate. *Journal of Ecology*, *110*, 2812–2835. https://doi.org/10.1111/1365-2745.13976