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Remote Sensing from Unoccupied Aerial Systems: Opportunities to Enhance Arctic Plant Ecology in a Changing Climate

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Remote Sensing from Unoccupied Aerial Systems: Opportunities to Enhance Arctic Plant Ecology in a Changing Climate

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 timescales.

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; Fig. 1), where vegetation interacts with the environment at very fine scales from several centimeters to multiple meters (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 fulfill this need, small piloted airborne platforms have been used, which allows the collection of spatial datasets at sub-meter resolutions, over large landscapes, and away from road systems (Nolan et al., 2015; Heather et al., 2019; Cristóbal et al., 2021; 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 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 hours. 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 & 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 platforms to enable a broader-scale understanding of the Arctic (section 3.6; Fig. 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 (Fig. 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 analyzing vegetation distribution patterns across fine-scale environmental gradients, reducing the need for intensive field measurements. For instance, combining four years of UAS imagery with field surveys and time-series climate data, DelGreco et al. (2018) characterized vegetation composition in a low-Arctic mir and found high heterogeneity in 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 et al. (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; Wang & Gamon, 2019; Schweiger, 2018). 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 (Ustin and Gamon et al., 2010; Cavender-Bares et al., 2020). 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; Fig. 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 (Fig. 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 centimeters 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 (Fig. 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 aboveground biomass (AGB), another important structure parameter needed for carbon cycle modeling, 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 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 (Table 1 & 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; Fig. 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 (Fig. 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 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, i.e., those that work across a wide range of species and environments, is an ongoing area of research (e.g., Serbin et al., 2019; Yan et al., 2021; Wang et al., 2020; Schweiger et al., 2020), 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-catalyzed 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 & 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 Fig. 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 ºC) 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 belowground 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 modeling 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 (Scherrer & Körner, 2009; Lawrence & Swenson 2011; Bhatt et al. 2017; Aalto et al. 2018). 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, 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 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 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 (Nelson et al., 2022; Chapin et al., 2012), 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 & 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 (3m), 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 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 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 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, e.g., 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 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 minutes). 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 artifacts (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 is 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 down-stream 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, modeling, and prediction of arctic ecosystems.

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Conflicts 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.

Author Contributions

DY, SPS, BDM, KJD, and JL conceived the idea. All authors contributed to the writing of the manuscript.

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Figures and Tables:

Fig. 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.

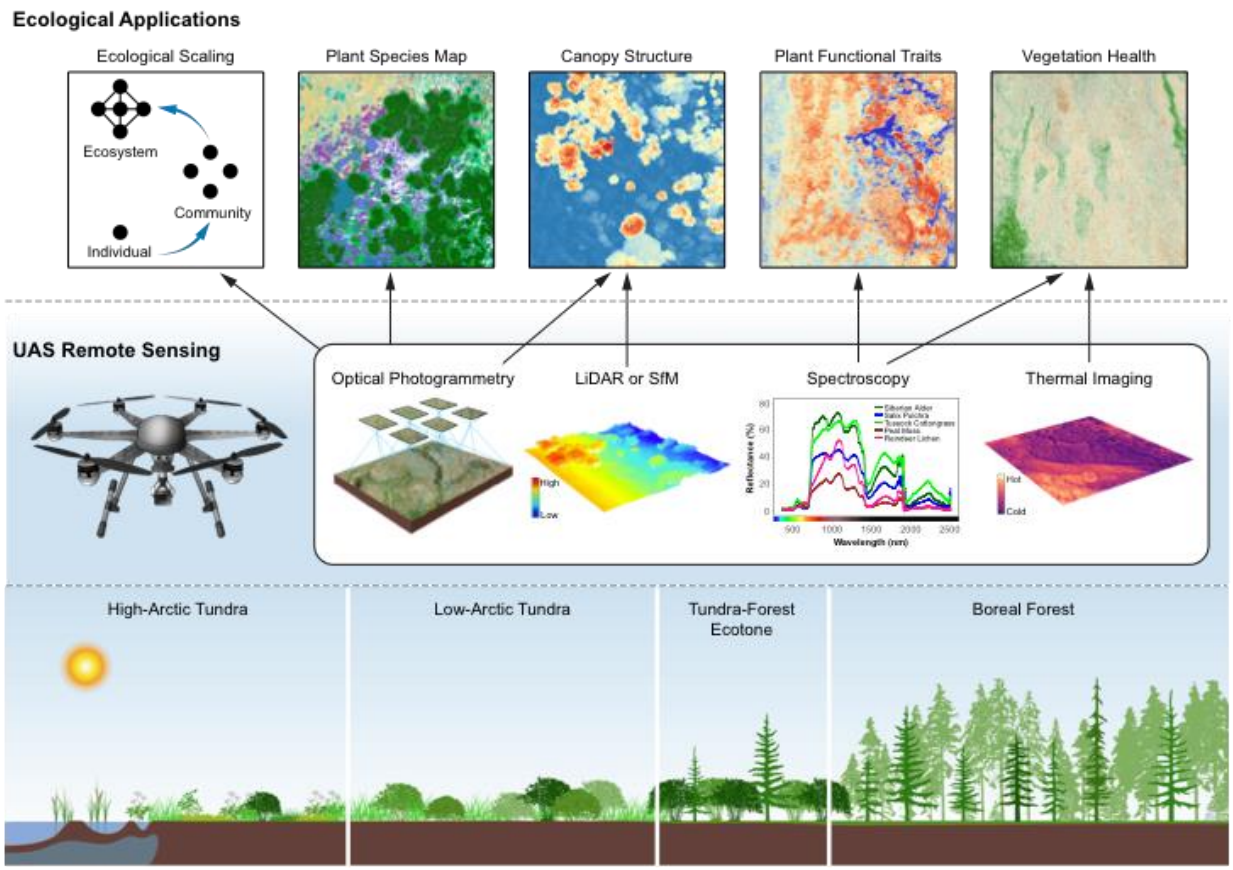


Fig. 2: Scale effects on vegetation composition and diversity analysis in the Arctic. The top 6 panel pairs show remote sensing images acquired at different spatial resolutions (i.e., 0.01, 0.1, 0.5, 1, 5, and 10 m) in a shrub landscape and the species maps derived from these images using a random forest 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).

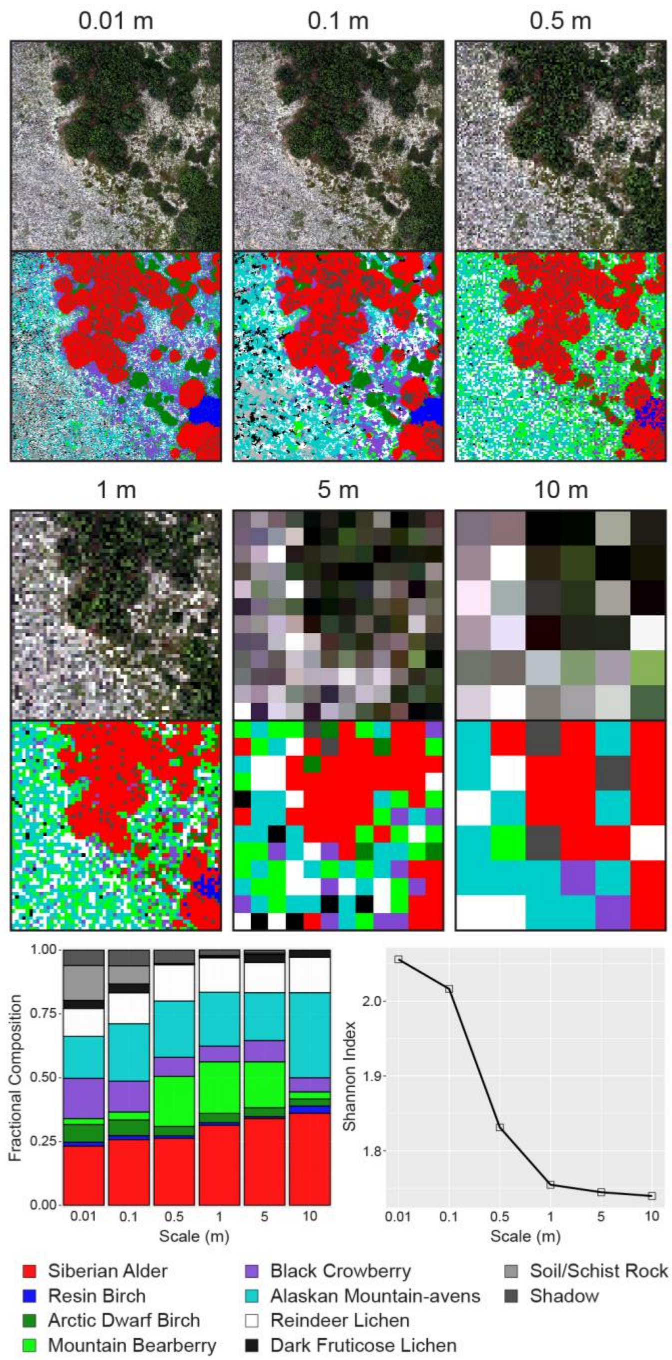
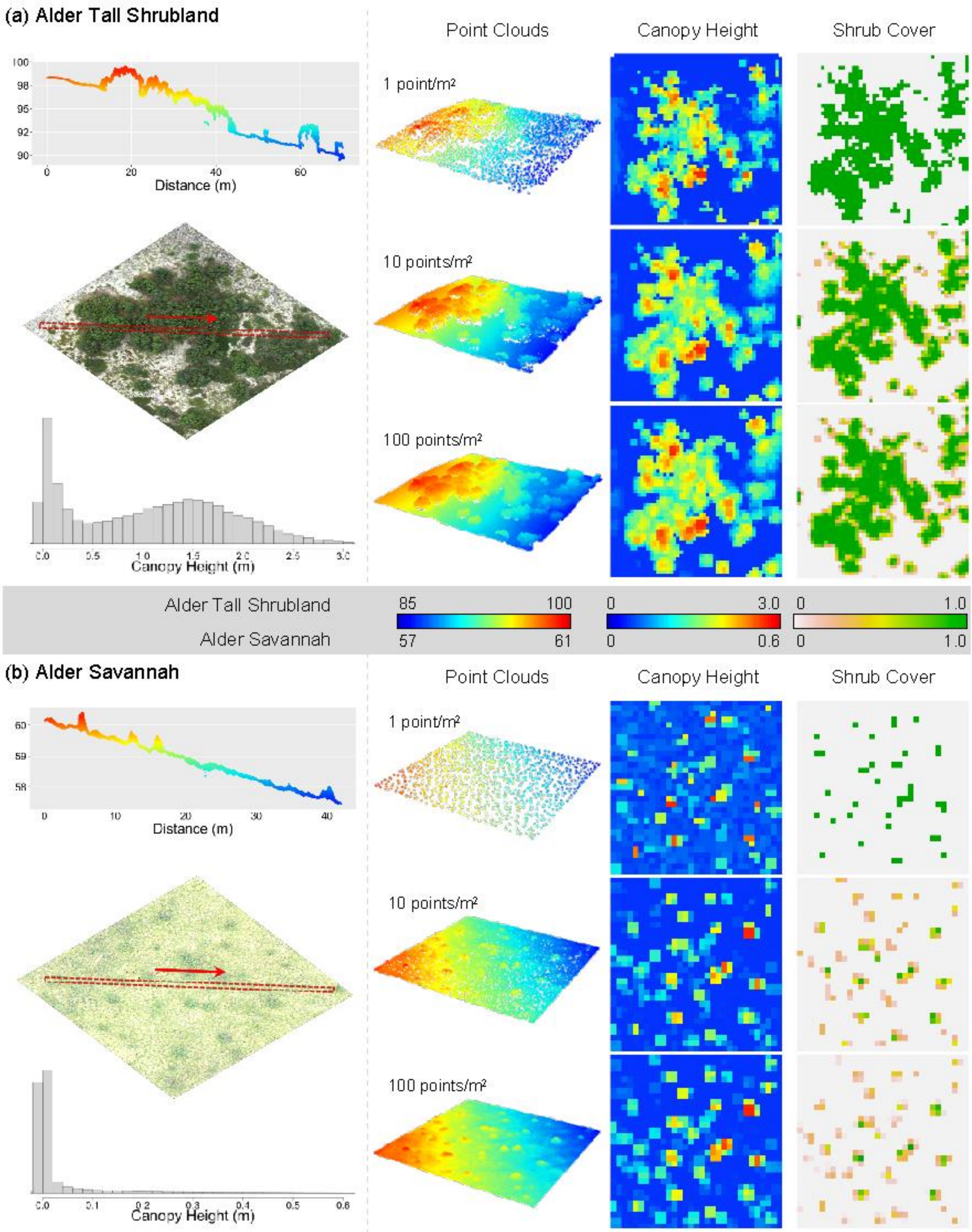


Fig. 3: Example application of UAS-derived point clouds for deriving canopy height and shrub cover in two representative arctic plant communities (a) Alder Tall Shrubland and (b) Alder Savannah. The effects of point cloud density (i.e., 1, 10, 100 points/m^2) on deriving canopy height and shrub cover 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 meters. Data used for this figure can be found in Serbin et al., (2021).



(a) Alder Tall Shrubland
Point Clouds
Canopy Height
Shrub Cover
1 point/m²
10 points/m²
100 points/m²
Distance (m)
Canopy Height (m)
Alder Tall Shrubland
Alder Savannah
85
100
57
61
0
3.0
0
0.6
0
1.0
(b) Alder Savannah
Point Clouds
Canopy Height
Shrub Cover
1 point/m²
10 points/m²
100 points/m²
Distance (m)
Canopy Height (m)

Fig. 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: https://github.com/nelsopet/lecospec.

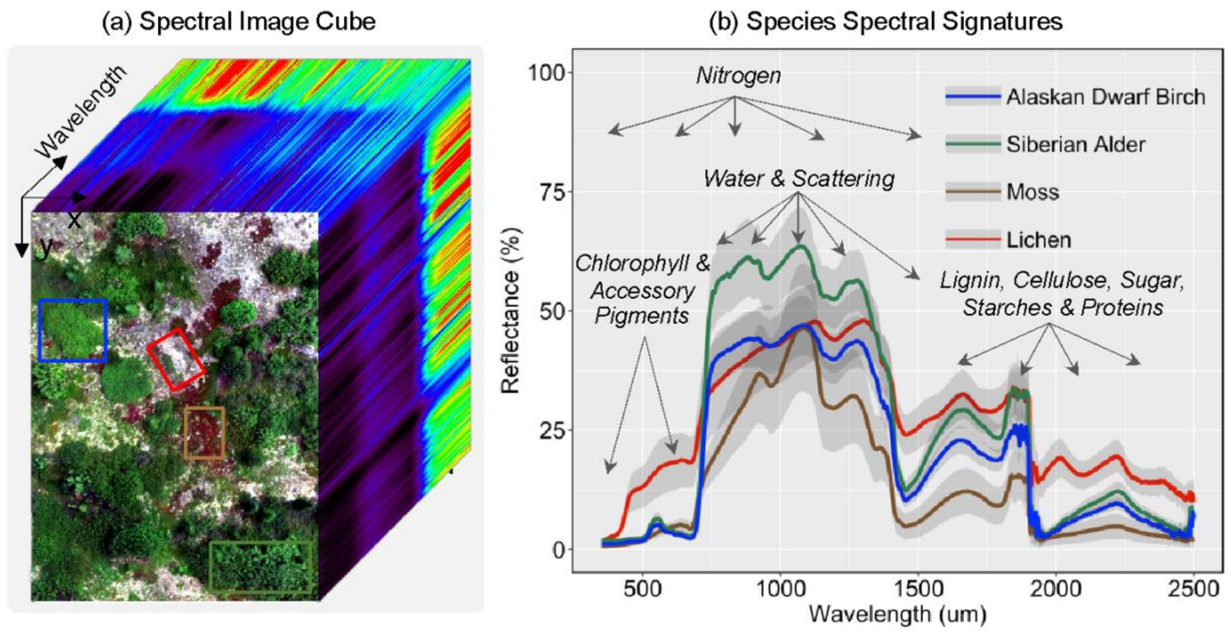


Fig. 5: Example application of high-resolution UAS thermal imagery for depicting thermal variation across an arctic tundra landscape. The thermal profile and histogram of four representative plant communities are demonstrated in (a) Willow Shrub, (b) Willow Birch Shrub, (c) Wet Meadow Tundra, (d) Ericaceous 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).

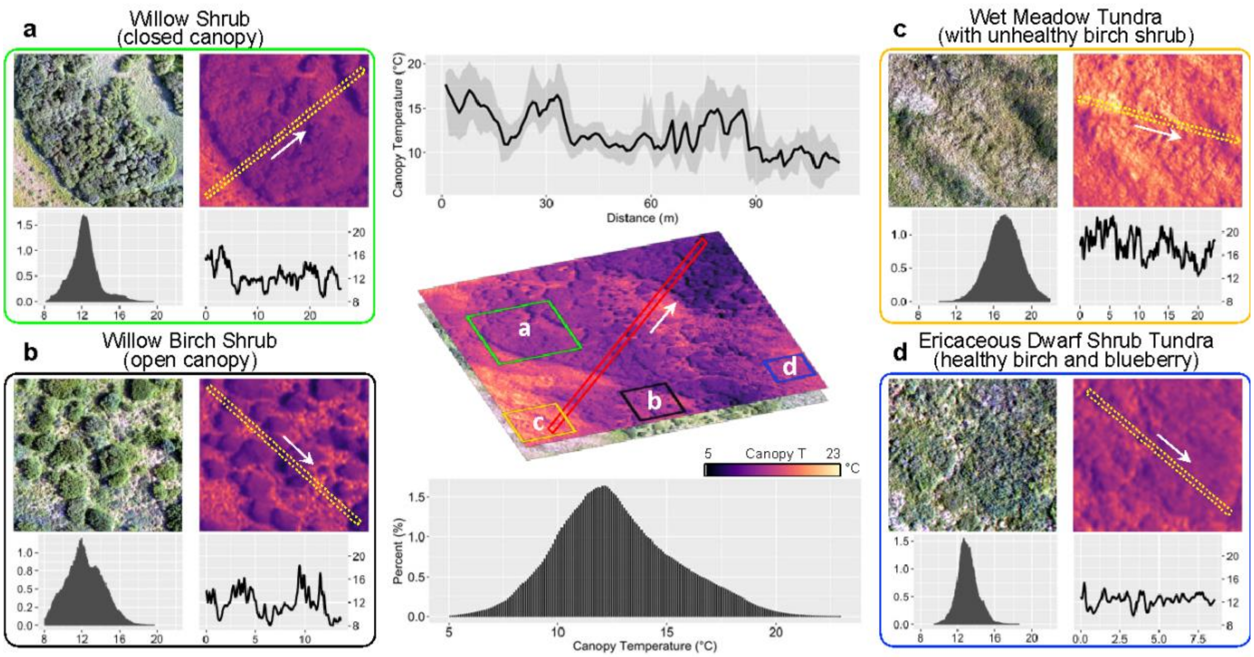


Table 1: Types of remote sensing sensors that have been implemented on UASs

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 colored 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); Malenovsky 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 - 14 μm.	Yang et al. (2020); Hoffmann et al. (2016); Hoffmann et al. 2016); Ellsäßer, (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. (2016); 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	Ellsaber et al. (2020); Chan et al. (2021); Thomson et al. (2021)
Land-surface or canopy "skin" temperature	Thermal infrared imagery	Thermal camera	Jones et al. (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	Andersen & Gaston (2003); Alonzo et al. (2016 & 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)

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 & 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 modeling efforts (3.2 & 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 & 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 & 3.6)
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.	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.
	When are Arctic plants photosynthesizing?		
	How consistent is photosynthetic temperature response across the landscape?		
	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