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Review

Recent trends and remaining challenges for optical remote sensing of Arctic tundra vegetation: A review and outlook

Alison Beamish[a,g,*], Martha K. Raynolds[b], Howard Epstein[c], Gerald V. Frost[d], Matthew J. Macander[d], Helena Bergstedt[e], Annett Bartsch[f,1], Stefan Kruse[g], Victoria Miles[h], Cemal Melih Tanis[i], Birgit Heim[g], Matthias Fuchs[a], Sabine Chabrillat[a], Iuliia Shevtsova[g], Mariana Verdonen[j], Johann Wagner[k]

[a] *Helmholtz-Zentrum Potsdam, German Centre for Geosciences (GFZ), Telegrafenberg A17, 14473 Potsdam, Germany*
[b] *Institute of Arctic Biology, University of Alaska Fairbanks, Irving, PO Box 757000, AK 99775-7000, United States of America*
[c] *Department of Geoinformatics – Z_GIS, University of Salzburg, Schillerstraße 30, 5020 Salzburg, Austria*
[d] *Alaska Biological Research, Inc, P.O. Box 80410, Fairbanks AK 99708, USA*
[e] *Department of Environmental Sciences, University of Virginia, 291 McCormick Road - Clark Hall, Charlottesville, VA 22904-4123, United States of America*
[f] *b.geos GmbH, Industriestrasse 1, 2100 Korneuburg, Austria*
[g] *Alfred Wegener Institute (AWI), Helmholtz Centre for Polar and Marine Research, Research Unit Potsdam, Telegrafenberg A43, 14773 Potsdam, Germany*
[h] *Nansen Environmental and Remote Sensing Centre/Bjerknes Centre for Climate Research, Thormøhlens Gate 47, N-5006 Bergen, Norway*
[i] *Finnish Meteorological Institute, Erik Palmenin Aukio 1, 00560 Helsinki, Finland*
[j] *Department of Geographical and Historical studies, University of Eastern Finland, P.O. Box 111, FI-80101 Joensuu, Finland*
[k] *Polar Knowledge Canada, 1 Uvajuq Road, Cambridge Bay, PO Box 2150, NU X0B 0C0, Canada*

ABSTRACT

A systematic review and inventory of recent research relating to optical remote sensing of Arctic vegetation was conducted, and thematic and geographical trends were summarized. Research was broadly categorized into four major themes of (1) time series, including NDVI trends and shrub expansion; (2) disturbance and recovery, including tundra fires, winter warming, herbivory, permafrost disturbance, and anthropogenic change; (3) vegetation properties, including biomass, primary productivity, seasonality, phenology, and pigments; and (4) classification and mapping. Remaining challenges associated with remote sensing of Arctic vegetation were divided into three categories and discussed. The first are issues related to environmental controls including disturbance, hydrology, plant functional types, phenology and the tundra-taiga ecotone, and understanding their influence on interpretation and validation of derived remote sensing trends. The second are issues of upscaling and extrapolation related to sensor physics and the comparability of data from multiple spatial, spectral, and temporal resolutions. The final category identifies more philosophical challenges surrounding the future of data accessibility, big data analysis, sharing and funding policies among major data providers such as national space agencies and private companies, as well as user groups in the public and private sectors. The review concludes that the best practices for the advancement of optical remote sensing of Arctic vegetation include (1) a continued effort to share and improve *in situ*-validated datasets using camera networks and small Unmanned Aerial Vehicles, (2) data fusion with non-optical data, (3) sensor continuity, consistency, and comparability, and (4) free availability and increased sharing of data. These efforts are necessary to generate high quality, temporally dense datasets for identifying trends in Arctic tundra vegetation.

1. Introduction

This review was undertaken to summarize the current state of optical remote sensing of Arctic vegetation. The goal was to provide an overview that would be useful for those developing the hardware and software tools to remotely sample tundra vegetation, and for researchers who are using the technology to address scientific questions. The last reviews of this type were conducted in the early 2000s (Laidler and Treitz, 2003; Stow et al., 2004), and remote sensing technologies have changed dramatically, especially with the increased use of unmanned aerial vehicles (UAVs).

Our focus area, the Arctic tundra biome has undergone extensive climatic and environmental changes in recent decades (IPCC, 2014). Resulting changes to terrestrial ecosystem structure and functioning include complex broad-scale shifts in primary productivity, vegetation species composition, and phenology as well as hydrological and disturbance regimes; collectively, these changes influence global climate via an array of feedback mechanisms (Chapin III et al., 2005; Elmendorf et al., 2012b; Post et al., 2009; Prevéy et al., 2017; Wrona et al., 2016). An extensive body of research detailing the importance of terrestrial

* Corresponding author.
E-mail address: alison.beamish@gfz-potsdam.de (A. Beamish).
[1] Austrian Polar Research Institute, Universitätsstraße 7, 1010 Vienna, Austria.

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Arctic tundra ecosystem functioning to global climate regulation and the Earth's energy and carbon balance has shifted the urgency of rapid Arctic change from a local to a global issue (ACIA, 2005).

Effective monitoring of vegetation change in this remote and logistically challenging biome is greatly supported by both well-established and emerging remote sensing technologies. Many tools exist to address pressing questions related to accelerated Arctic change at multiple spatial scales, from legacy platforms such as Landsat and the Advanced Very High Resolution Radiometer (AVHRR) from U.S. National Oceanic and Atmospheric Administration (NOAA) satellites to exciting new possibilities provided by UAVs and the explosion in Very High Spatial Resolution (VHSR) commercial satellite imagery. Since the last two major reviews by Laidler and Treitz, 2003 and Stow et al. (2004), the field of terrestrial Arctic remote sensing has seen great advancements in operational sensors as well as the temporal, spatial and spectral scales of available data. The last 15 years have also seen significant improvements in processing power including increased and freely available cloud computing services that have facilitated invaluable long-term, biome scale trend analyses (Beck et al., 2019; Bhatt et al., 2013; Walker et al., 2009) as well as the cross-over of memory-intensive methods such as machine learning from mathematics and physics to environmental remote sensing science (Ali et al., 2015; Belgiu and Drăguţ, 2016; Lary et al., 2016).

Despite the ever-increasing availability and accessibility of remote sensing data, challenges remain related to the unique characteristics of terrestrial Arctic ecosystems. The obvious challenges associated with optical remote sensing of Arctic vegetation arise from the combination of a short and rapidly progressing growing season, high cloud frequency, and low sun-angles (Stow et al., 2004). This can translate into few or no successful image acquisitions in an area of interest across a growing season. In turn, this makes intra- and inter-annual comparisons particularly difficult, where effective satellite revisit times are infrequent, or the logistics of airborne and field campaigns prohibit multiple acquisitions. Image time series often include different phenological or seasonal stages and differ in optical properties, not only due to vegetation but also the contribution and dominance of other ecosystem factors such as snow cover, surface water, soil moisture, illumination angle, and shadows (Beamish et al., 2017; Huemmrich et al., 2013). In addition, the scarcity and difficulty of obtaining high-quality validation datasets make cross-site comparisons and extrapolation to the biome scale challenging. A clear spatial bias in high quality ground-based validation datasets exists due to logistical and financial challenges of Arctic field campaigns. Despite these difficulties, a comprehensive and valuable body of research exists employing optical remote sensing to address questions of Arctic tundra vegetation change. Innovative new methods to overcome the limitations of optical remote sensing such as data fusion with non-optical and active sensor data (Greaves et al., 2016) as well as the supplementation of field-based measurements with UAVs and time-lapse imagery (i.e., Beamish et al., 2018; Riihimäki et al., 2019) are on the rise. The coming decade will see the development and application of legacy systems with a multi-decadal period of record (e.g., Landsat 9).

In the following review, recent trends in optical remote sensing of Arctic tundra vegetation spanning from the Tundra Taiga Ecotone (TTE) to the High Arctic are summarized into four major themes: time series, disturbance and recovery, vegetation properties, and classification and mapping. Identified remaining challenges are then broadly categorized into environmental controls on observed trends, upscaling and extrapolation, and philosophical challenges of data accessibility. Finally, an outlook and best practices are outlined with the intent of identifying knowledge gaps and informing current practices as well as future satellite mission planning.

2. Literature review

A systematic literature review from 2004 to 2019 was conducted using Google Scholar. This timeframe was selected for two reasons. First, it covers the time period since the last comprehensive reviews of remote sensing of terrestrial Arctic ecosystems by Laidler and Treitz, 2003 and Stow et al. (2004). Second, research in the field increased greatly after 2004. Keywords of "Arctic," "remote sensing," and "vegetation" were used and further filtering and searches were done to ensure remote sensing of vegetation was the main focus of each record. Records included in the review encompass ecosystems in the TTE, Low Arctic and High Arctic. These three subdivisions are defined respectively as follows for the purposes of this review; 1) the tundra taiga ecotone (TTE) is the transitional zone between tundra and the boreal forest, a spatially heterogeneous ecosystem with a discontinuous and non-uniform extent (Love, 1970; Ranson et al., 2011); 2) the Low Arctic includes ecosystems characterized by well-vegetated tundra communities dominated by low- and dwarf shrubs, sedges and other herbaceous species; (Subzones D and E of the Circumpolar Arctic Vegetation Map – CAVM, (Walker et al., 2005)) and 3) the High Arctic includes dwarf and prostrate shrub / sedge tundra and partially vegetated polar desert, or polar semi-desert ecosystems composed of mostly non-vascular species and herbaceous vascular plants (Subzones A, B, and C of the CAVM) (Bliss and Matveyeva, 1992). Over 200 records fitting these criteria were identified. Each record was assigned to nine different categories related to geographic region, theme, sensor, availability, spatial scale, ecosystem, and spectral resolution. The complete list of categories and number of entries for each category plus the inventory is provided in Supplementary Material (Table S1 and S2).

3. Recent trends in optical remote sensing of Arctic tundra vegetation

3.1. Time series analyses

Time series analysis was one of the most common themes among the inventoried research. The majority of these studies used the AVHRR-derived Normalized Difference Vegetation Index (NDVI) from NASA's Global Inventory Modeling and Mapping Studies (GIMMS) project, followed by Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat NDVI time series. Most recent change detection studies were time series analyses conducted in the Low Arctic or at the circumpolar scale, and the majority focused on NDVI trends also referred to as tundra greening/browning, productivity, or photosynthetic activity in some cases. Studies on shrub expansion, another common time series analysis, and how it relates to large-scale NDVI trends are also summarized.

3.1.1. NDVI trends

The publication and free availability of the GIMMS, MODIS, and Landsat datasets have contributed invaluably to optical remote sensing of Arctic vegetation resulting in long-term (> 20 years), biome-scale studies of tundra NDVI trends. Derived from multi-day NDVI composites, many early studies reported positive NDVI trends (greening) occurring extensively in tundra regions from the 1980s to the early 2000s, with some variability by vegetation cover type and density. Some of these studies used national boundaries to define their domains (Pouliot et al., 2008; Verbyla, 2008), others used a vegetation classification (Goetz et al., 2005), some used a latitudinal cut-off (e.g., > 50 °N for Bunn and Goetz (2006)), and some used the domain of the CAVM (CAVM Team, C, 2003; Walker et al., 2005) treeline delineation (Jia et al., 2003, 2009).

The continual maintenance and update of these time-series have resulted in corresponding updates of NDVI trends and more recent analyses revealed areas with strong declines in NDVI (often called browning, though visually the vegetation might just be less green) since 2000, in stark contrast to the previous 20 years (Bhatt et al., 2013). Complex spatial heterogeneity in NDVI trends and contrasting trends for different vegetation types emerged with analysis of the updated data, highlighting the non-linear nature of ecological change in the Arctic tundra biome. Anisimov et al. (2015) found that NDVI trends were positively correlated with temperature, and negatively with precipitation, in Arctic and Boreal Russia. Beck and Goetz (2011) found on a circumpolar scale the same trends as Verbyla (2008), with increases in NDVI in the Arctic, and declines in the boreal zone. Loranty et al. (2016) noted a matching contrast between areas of continuous vs. discontinuous permafrost, with increasing NDVI in areas of continuous permafrost (mostly Arctic) and decreasing NDVI in areas with discontinuous permafrost (mostly Boreal). Miles and Esau (2016) found similar latitudinal trends in West Siberia, with positive trends in more northern tundra and taiga (*Larix* forest) zones, and negative trends in more southern zones (*Picea* and *Pinus* forests). In analyzing the relationship between summer temperatures and NDVI trends, Reichle et al. (2018) found that relative temperature increases were strongest in the High Arctic, but NDVI increases were strongest in the Low Arctic. The annual correlation between the two variables was strongest in the mid-Arctic subzones, likely because plant biomass is typically very low in the High Arctic, and other climate variables such as precipitation become increasingly important in the Low Arctic.

In 2008 when the Landsat data became freely available, significantly higher spatial resolution time-series analyses of Arctic tundra became possible. With the increase in spatial resolution, some studies found discrepancies in the spatiotemporal patterns of previously reported GIMMS NDVI trends. For example, finer resolution data showed that increases in NDVI were not evenly distributed across the landscape and data provided by a different sensor changed the overall landscape trend (Raynolds et al., 2013). The Landsat data showed more extensive increases in NDVI in Quebec and Labrador, and less browning in boreal forests (Ju and Masek, 2016). In northwest Siberia, NDVI trends showed high interannual variability across and within different biomes and forest-land cover types, which influenced apparent decadal-scale trends (Miles et al., 2019).

These finding raised questions about the roles of spatial and temporal scale and land cover in observed tundra dynamics. None of the satellite records is perfect: AVHRR has a very long record but relatively coarse resolution (8 km) and is composed of intercalibrated data from a number of different sensors on different satellites (Pinzon et al., 2014). Landsat also has a long record but had poor retrieval over much of the Arctic in the 1990s, with many areas missing mid-summer cloud-free imagery in many years (Raynolds et al., 2013). Recent sensors such as Sentinel-2 lack the period-of-record necessary to reasonably estimate trends. This has prompted closer examination of land cover and *in situ* changes in tundra vegetation and surface properties to better understand the drivers of trends seen in satellite data. Researchers found similarly strong local and latitudinal variability in NDVI trends, which were well explained by vegetation type in Sub, Low and High Arctic sites (Bonney et al., 2018; Edwards and Treitz, 2017; Lara et al., 2018; McManus et al., 2012). Areas where divergent NDVI trends emerged depending on the sensor used, could be validated and resolved by *in situ* plant species data (Pattison et al., 2015). There is abundant evidence for the heterogeneous and divergent response of Arctic vegetation to climate change (Elmendorf et al., 2012a; Jorgenson et al., 2015; Miles et al., 2019), and recent tundra dynamics research emphasizes the importance of linking biome-scale and regional scale NDVI trends to vegetation changes on the ground.

The complexity of tundra NDVI trends were summarized in the most recent NOAA Arctic Report Card tundra greenness assessment (Frost et al., 2019) Fig. 1. Long-term trends continue to show an overall increase in Arctic NDVI over the satellite record, a trend expected to continue, as widespread and long-term indirect effects such as increased growing season length and active layer depths, in addition to the direct effects from a single warmer (or cooler) summer continue to drive tundra veg. Regional decreases and annual variations in tundra greenness were evident in the record; and 2018 was a particularly low NDVI year for North America, attributed to greater winter snow and below normal summer temperatures. Low NDVI values in Eurasia in 2015–2016 were attributed to extreme events such as winter warming, frost damage and drought, thermokarst (terrestrial features caused by selective permafrost thaw), and fire (Phoenix and Bjerke, 2016). Predicting and monitoring the events that drive decreasing NDVI signals with current optical remote sensing techniques represents a major challenge as they are sporadic in time and space, often occurring in winter with transient effects (Phoenix and Bjerke, 2016).

Some of the discrepancies in NDVI trends can in part be attributed to differences in the spectral response and spatial resolution of different sensors resulting in uncertainties (e.g., Pattison et al., 2015; Pouliot et al., 2008; Stow et al., 2007). For example, sources of uncertainty in AVHRR datasets arise from inconsistencies in the sensor bandpasses, orbital geometries, and imperfect cross-calibration across the many instruments that have contributed to the record. In addition, the spatial resolution of the GIMMS dataset is insufficient to reveal landscape-scale patterns of NDVI trend. In 2014, an updated GIMMS AVHRR-NDVI dataset (1981–2014) was released that used high quality, well-calibrated Sea-viewing Wide Field-of-view Sensor (SeaWiFS) data from 1997 to 2010 to cross calibrate among the AVHRR instruments (Pinzon et al., 2014). Guay et al. (2014) explicitly compared these widely used NDVI datasets including both versions of the legacy AVHRR GIMMS-NDVI datasets as well as more modern records of SeaWiFS, SPOT-VEGETATION, and MODIS. The authors found equally large areas of agreement (40%) and disagreement (40%) between the GIMMS datasets as well as with the more modern datasets. A similar comparison of the GIMMS datasets over North American high latitudes reported good agreement of NDVI trends observed by AVHRR and MODIS (Beck and Goetz, 2011). NASA is coordinating with the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) to continue the AVHRR record and has included an AVHRR sensor onboard the Metop-B and Metop-C satellites. Recent efforts have highlighted the importance of spectral agreement among sensors in Arctic ecosystems where acquisitions can be limited and conditions are often less than ideal (Runge and Grosse, 2019). Thus, time-series from concurrent and more modern systems, such as MODIS, Landsat, and Sentinel-2, are useful for corroborating AVHRR-observed trends, while also providing data at finer spatial scales necessary for comparison with ground data. We emphasize the value of datasets spanning a range of spatial and temporal resolutions for answering different questions regarding Arctic vegetation. AHVRR data continue to provide long-term, coarse circumpolar data. Medium and fine-resolution data are necessary for comparison with ground data with the longest period-of-record available. In addition, the MODIS record now encompasses 20 full growing seasons (2000–2019), which exceeds the period-of-record that was available from AVHRR seminal reports of high-latitude greening, which emerged in the late 1990s and early 2000s (e.g., Jia et al., 2003; Myneni et al., 1997). Continued effort is required to evaluate large-scale NDVI datasets against one another as well as against VHSR and *in situ* NDVI, aboveground biomass, community composition, and primary productivity in order to better understand the ecological processes driving environmental change in the Arctic biome.

3.1.2. Shrub expansion

One of the strongest vegetative changes associated with tundra greening is the well-documented phenomenon of shrub expansion. Shrub expansion has the potential to mitigate or exacerbate climate change making it a highly relevant topic in Arctic change research (Myers-Smith et al., 2011; Wookey et al., 2009). When historical imagery are included, remote sensing time series tracking shrub expansion can span up to 70 years (Fig. 2) (Stow et al., 2004; Sturm et al., 2001), and these datasets are essential for understanding current, and predicting future patterns of, shrub distribution at landscape scales (Myers-Smith et al., 2011).

The use of historical imagery and declassified satellite surveillance photographs has provided indisputable evidence for the expansion of

Fig. 1. Field observations at landscape patches that have experienced significant increases and decreases in NDVI reveal mechanisms of “greening” and “browning” on Alaska's Yukon-Kuskokwim Delta. At left, dense sedge meadows have developed in a lake basin that drained in the early 1990s, resulting in strong increases in NDVI. At right, coastal flooding during the 2000s induced patchy salt-kill of vegetation, evident as decreases in NDVI. Photos courtesy of G. V. Frost.

shrubs in the TTE and Low Arctic tundra in both Siberia and Alaska. The now seminal work by Sturm et al. (2001) and Tape et al. (2006) showcased the power of historical aerial imagery to visually detect this dramatic vegetative change across Alaska and initiated the extensive body of research that now exists on shrub expansion across the circumpolar Arctic. No equivalent aerial photography is available for the Russian Arctic, but Frost and Epstein (2014) quantitatively analyzed imagery from declassified, Cold War era surveillance satellites (1965–1972; ca. 75–200 cm) and modern IKONOS, QuickBird, GeoEYE-1 and WorldView-1 imagery (2002–2011; 50–80 cm) to evaluate tall shrub and tree expansion across northern Siberia.

Satellite-derived NDVI trends attributed to shrub expansion in the western Canadian Arctic and Siberia have been validated with *in situ* shrub growth datasets. Long-term NDVI greening trends (> 25 years) over Siberian tundra show strong linear correlations to dendrochronologies of willow (*Salix)* and alder (*Alnus)*, two dominant shrub genera with circumpolar distributions (Forbes et al., 2010; MacIas-Fauria et al., 2012). More spatially explicit approaches using detailed species fractional cover delineated from repeat aerial photography and VHSR data to directly link Landsat NDVI greening trends to expansions in shrub cover. Using visual assessment of aerial photo pairs (ca. 2 cm) from 1980 and 2013, Fraser et al., 2014b found an increase in shrub cover corresponding to widespread increases in Landsat NDVI over the same time period across the Tuktoyaktuk Coastal Plain in northwestern Canada. Using a similarly spatially explicit approach, Urban et al. (2014) applied an object-oriented supervised classification to historical Landsat MSS imagery (79 m) from 1973 and two RapidEye scenes (5 m) from 2012 and found an obvious increase in woody vegetation north of the treeline in northern Siberia.

In addition to validation of landscape NDVI greening trends, detailed, ground-based investigations have explored the relationships between structural characteristics of shrubs and seasonal NDVI values. Though providing only a snapshot, these studies aim to create a better understanding of the biophysical processes influencing observed large-scale NDVI trends as well as differentiation between increasing shrub size (e.g., height) and extent (e.g., cover), which can be modelled to investigate distinct implications for carbon cycling, surface albedo, radiative energy balance, and wildlife habitat (Boelman et al., 2011a; Juszak et al., 2014). Using simple linear regression, Boelman et al. (2011a) found that NDVI collected in an Alaskan Low Arctic tundra ecosystem prior to leaf-out gives good estimates of percent woody stem cover especially for larger shrubs which is more closely attributed to shrub height, while peak leaf is best suited for estimating deciduous canopy cover, more closely related to shrub extent. Juszak et al. (2014) used manipulation experiments to increase the variability of Siberian Low Arctic shrub canopies and determined *in situ* NDVI is most affected by leaf biomass and not plant area. However, in this study, phenological phase was not controlled for potentially influencing the results. Regardless, both of these field-based studies demonstrate the influence of vegetation biophysical characteristics such as leaf area and percent cover on NDVI values and highlight the importance of considering and constraining the phenological phase of satellite acquisitions for accurate retrieval and interpretation of landscape scale NDVI trends. Satellite and field spectrometer derived NDVI as well as high spatial resolution imagery effectively capture changes in Arctic shrub canopy extent and structure, providing valuable tools to monitor and predict the greatest vegetative change currently occurring in Arctic tundra ecosystems.

3.2. Disturbance and recovery

Optical remote sensing has also been used to effectively monitor disturbance and recovery of Arctic vegetation following tundra fires, winter warming, herbivory, permafrost disturbance, and anthropogenic activities across the circumpolar Arctic. Many of these disturbances can lead to decreased NDVI or tundra browning which can strongly

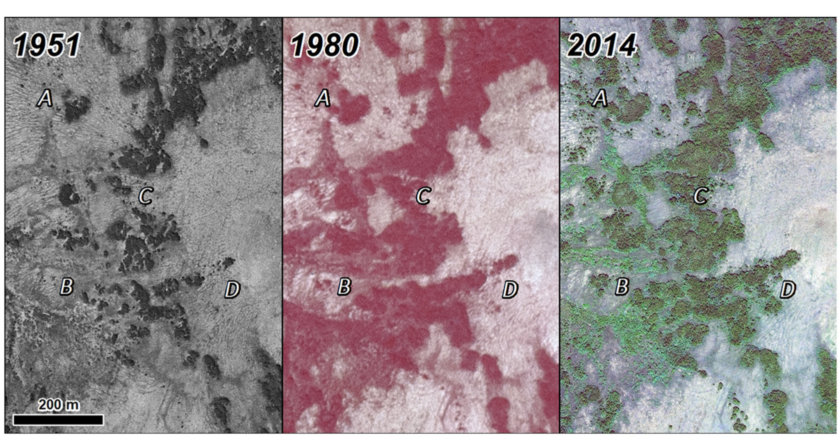

Fig. 2. A 63-year record of shrub expansion in Arctic Alaska using historical air photos and high-resolution satellite imagery. Letters indicate areas where significant changes in shrub cover and density have occurred. Photos courtesy of G. V. Frost.

influence surface energy balance and in turn permafrost stability (Jorgenson et al., 2010). However, rapid increases in vegetation productivity following disturbances have also been observed (Esau et al., 2016; Yu et al., 2015). Like time series analyses, the vast majority of these studies use satellite (red, green, blue (RGB), panchromatic, multispectral) -derived vegetation indices to infer disturbance to vegetation and subsequent recovery, and most occur in the Low Arctic. Given the local nature of disturbance, many of the studies use VHSR imagery and provide local, site-specific information.

3.2.1. Tundra fires

Historically, tundra fires were rarely reported, due to their remote locations and often small extents (Jones et al., 2013). However, recent tundra fire activity in Alaska—particularly the large Anaktuvuk River fire of 2007— has motivated numerous studies of tundra fire and increased recognition of its importance as an ecological disturbance agent in the Arctic (e.g., Bret-Harte et al., 2013; Higuera et al., 2008). The frequency of tundra fires is expected to increase, and the resilience of tundra to fire disturbance is expected to decrease with continued climate change (French et al., 2015; Hinzman et al., 2005). Remote sensing offers the best tool by which to monitor the extent and severity of tundra fires, and ecosystem recovery after fire.

Spectral indices typically applied to monitor wildfires in forest ecosystems, such as the Normalized Burn Ratio (NBR), have shown low correlations to burn severity in tundra ecosystems (Epting et al., 2005). In addition, the difficulty of acquiring appropriately timed pre- and post-fire imagery in the Arctic reduces the practicality of multi-temporal indices such as the differenced Normalized Burn Ratio (dNBR; Key and Benson, 2005). Studies of Alaskan tundra fires have shown that single-date, moderate resolution imagery from Landsat TM/ETM+ (30 m) and downsampled MODIS (30 m) imagery collected during the first post-fire growing season is sufficient to evaluate burn severity in Low Arctic tundra (Boelman et al., 2011b; Kolden and Rogan, 2013; Loboda et al., 2013). Boelman et al. (2011) found that the two-band Enhanced Vegetation Index (EVI2; (Barichivich et al., 2013)) was negatively correlated with burn severity, thereby reducing dependency on successful pre- and post-fire images. Loboda et al. (2013) found that multi-band spectral indices (e.g., Tasseled Cap Greenness), and single-band NIR observations from Landsat outperformed NBR in northwestern Alaskan tundra. Progress has also been made in applying contemporary very high resolution data for evaluating landscape-scale variability in fire severity, and legacy moderate resolution optical satellite datasets for evaluating the severity of historical fires. Chen et al. (2020) demonstrated the use of single-band NIR indices from both modern commercial satellite imagery (e.g., QuickBird-2), and Landsat Multi-Spectral Scanner (MSS) data for evaluating the severity of historical fires dating to the 1970s.

Post-fire changes in species composition and NDVI following fire have also been characterized using optical remote sensing to better understand post-fire succession (Barrett et al., 2012; Frost et al., 2020; Goetz et al., 2007; Jones et al., 2009; Rocha et al., 2012). *In situ* studies indicate that tundra vegetation typically recovers rapidly post-fire; changes in community composition are typically linked to fast-growing pioneer species and the proliferation of shrubs. These changes tend to result in rapid increases in NDVI within burns compared to surrounding undisturbed tundra (Rocha et al., 2012). Quantitative maps of the cover of tundra plant functional types (i.e., fuels for fire) derived from field datasets and Landsat imagery also provide valuable baseline datasets for monitoring fire impacts and post-fire succession in the future (He et al., 2019; Macander et al., 2017).

Monitoring tundra fire extent, severity, and post-fire succession is also crucial for understanding the consequences of fire on ecosystem function and the Arctic carbon balance. For context, the 1000 km^2 Anaktuvuk River Fire in 2007 released 2.1 Tg of carbon into the atmosphere, which was estimated to offset the annual carbon uptake by the entire biome (Mack et al., 2011). Given that 2019 was a record year with an unprecedented number of wildfires burning across boreal and tundra regions in Siberia, Greenland, and Alaska, optical remote sensing will play a critical role in quantifying fire impacts to the Arctic biome as a whole. However, non-optical remote sensing datasets, such as Synthetic Aperture Radar (SAR), are required for monitoring changes to permafrost conditions (Michaelides et al., 2019), which can strongly impact aboveground vegetation many years after the initial fire (Jones et al., 2015; Liu et al., 2014). Non-optical remote sensing data are also required for assessing soil thermal and hydrologic properties that require data collected in winter, when vegetation is snow-covered (Bartsch et al., 2020). Integration of *in situ* and disparate remote sensing datasets will be required to monitor and predict the changes to, and interactions between fire-affected vegetation and permafrost soils in a warmer Arctic.

3.2.2. Winter warming

Less well-documented but increasingly relevant vegetation disturbance in the Arctic are winter warming events where full or partial snowmelt exposes vegetation resulting in damage or death when normal winter conditions return causing decreases in NDVI during the growing season (Bokhorst et al., 2012a). Winter warming events have been identified as a major driver in recent landscape scale decreases in NDVI and a major challenge to constrain (Phoenix and Bjerke, 2016). Given that extreme weather events are increasing, the importance of winter warming and the role it plays in long-term NDVI trends is also increasing (AMAP, 2011).

These events often occur sporadically and have patchy extents due to the influence of topography and vegetation on snow depth and therefore vulnerability to snowmelt. Additionally, events occur during polar night and vegetation can recover in a few years making identification and study of the entire disturbance and recovery process challenging. From the limited literature available, events are identified and monitored opportunistically where detailed temperature and snow depth records exist or retroactively when damage is identified in the field (Phoenix and Bjerke, 2016).

Low Arctic and TTE vegetation disturbance and recovery as a result of warming events have been monitored using MODIS, Landsat, and SPOT-derived NDVI validated with *in situ* vegetation surveys (Bjerke et al., 2014; Bokhorst et al., 2012b, 2009). Bokhorst et al. (2009) concluded that the 16-day NDVI composites from MODIS are the most effective for landscape-scale monitoring of this disturbance given the acquisition restrictions, but only with prior knowledge of the event. *In situ* observations showed a reduction in summer growth of almost 90% of the dominant shrub species and an accompanying 26% reduction in July NDVI values from pre- to post-disturbance over an area of more than 1000 km^2. Snapshots provided by higher resolution satellites such as SPOT-5 reveal important local patterns of disturbance and facilitate more detailed characterizations of affected vegetation communities and species.

Plot and leaf-level optical remote sensing also revealed less obvious physiological damage to individuals not captured by vegetation surveys or landscape scale NDVI. Seemingly healthy individuals showed 16% reductions in leaf-level NDVI in the first growing season post-disturbance indicating physiological stress and changes to photosynthetic capacity and efficiency (Bokhorst et al., 2012b). These studies highlight how multi-scale remote sensing data can provide a more complete understanding of ecological impact of winter warming events complicating direct attribution of changes to only plant death; internal physiological damage may also contribute to observed landscape scale decreases in NDVI though direct linkages remains difficult.

Overall, multi-scale optical remote sensing is an effective tool for monitoring the biophysical effects of winter warming on vegetation, but ancillary data such as snow cover and temperature will be key to facilitating rapid identification and improved understanding of winter warming events. SAR data have great potential to contribute relevant snow cover data given its spatial and temporal scale, sensitivity to

Fig. 3. Extensive vegetation removal by a rapidly expanding Snow Goose Colony on the Alaskan North Slope. Photo: Brian Person, North Slope Borough Department of Wildlife Management.

dielectric properties (moisture) of the surface and independence to atmospheric conditions and polar night. SAR sensors are particularly sensitive to the presence of wet snow (Nagler and Rott, 2000), a precursor to snowmelt, due to the attenuation of the microwave signal by water and have been used to track snow melt in Arctic catchments (Stettner et al., 2018).

3.2.3. Herbivory

Though much of species conservation in animal ecology focuses on population declines, over-population can result in ecological impacts to wildlife habitat which can be monitored using optical remote sensing. Population growth of lesser snow geese (*Anser caerulescens caerulescens*), a keystone Arctic species, is attributed to ample forage from agricultural areas in overwintering grounds which has led to an overabundance in some areas (Ankney, 1996). This overabundance can result in excessive herbivory leading to significant reorganization of vegetation composition and in some cases the complete removal of vascular plant species, exposing the underlying peat in Arctic summering grounds (Kotanen and Jefferies, 1997) (Fig. 3).

Conkin and Alisauskas (2017) used two Landsat scenes acquired 23 years apart and supervised classification to quantify land cover change in the central Canadian Arctic as a result of snow goose abundance. The authors found a greater than fivefold increase in exposed peat and a significant decrease in preferred feeding and nesting habitats as a result of the growth of nearby nesting colonies.

Other keystone Artic species with fluctuating populations attributed in part to forage availability are barren ground caribou (*Rangifer tarandus groenlandica*) and migratory caribou (*Rangifer tarandus*) (Manseau et al., 1996). Unprecedented declines in population numbers of barren ground caribou herds have increased the urgency for a better understanding of the population cycles of these ecologically and culturally important species. Optical remote sensing archives such as AVHRR, MODIS, and Landsat offer powerful tools to examine regional, long-term habitat changes concurrently with herd size and more recently, herd movement (Rickbeil et al., 2017). Newton et al. (2014) found a negative relationship between Landsat-derived NDVI and caribou abundance (lagged by six years) between 1984 and 2010 in the Canadian Sub Arctic which is attributed to a decrease in forage quality due to overgrazing. Rickbeil et al. (2015) found a similar negative relationship between the fraction of photosynthetically active radiation (fPAR), a proxy of vegetation productivity derived from a combination of MODIS and AVHRR, and herd density between 1987 and 2013 in the western Canadian Low Arctic. More recent study found the same negative trends between AVHRR-NDVI and caribou herd density in the eastern Canadian Sub Arctic (Campeau et al., 2019). With the use of optical remote sensing, these studies support the ecosystem exploitation hypothesis, which states that vegetation is regulated by top-down herbivory in the absence of significant predation pressure (Fretwell and Barach, 1977). In contrast to this hypothesis, Fraser et al., 2014b attributed increasing NDVI trends to increased shrub abundance with concurrent decreases in caribou forage quality due to decreasing lichen abundance. This research highlights the complexity of tundra vegetation change and adds to our understanding of current and future caribou population dynamics.

3.2.4. Permafrost disturbance

Though permafrost disturbance is widespread across the Arctic, research explicitly investigating the impacts to Arctic vegetation properties using optical remote sensing is limited. Satellite derived vegetation indices have been used extensively to identify permafrost disturbance features such as active layer detachments, a downslope mass movement of soil and vegetation caused by rapidly thawing ice lenses at the base of the active layer, retrogressive thaw slumps, caused by thawing of exposed ground ice resulting in the formation of a steep headwall and near complete removal of vegetation, as well as drained lake basins and ground subsidence post-fire (Fraser et al., 2011; Jorgenson and Grosse, 2016; Nitze et al., 2017; Rudy et al., 2013). However, few studies have used vegetation indices to investigate pre- and post-disturbance vegetation dynamics likely due to a combination of detection limitation, particularly of small-scale disturbances, and relatively rapid vegetation recovery (Phoenix and Bjerke, 2016).

Fraser et al., 2014a found that retrogressive thaw slumps follow a similar recovery trajectory to tundra fires with vigorous vegetation growth once a slump stabilizes due to warm, nutrient-rich soil. Walker et al. (2009) also found that areas previously subjected to active layer detachments in Siberia had higher NDVI than surrounding undisturbed areas but noted the need for higher resolution imagery to fully evaluate the biophysical drivers behind the observed signals. Ground-based investigations show significant reorganization of vegetation communities following permafrost disturbance (Cray and Pollard, 2015; Khitun et al., 2015), with implications for primary productivity, biodiversity and aboveground biomass, warranting more detailed biophysical investigation with optical remote sensing data.

Nitze et al. (2018) provided an extensive inventory of permafrost disturbances using Landsat stacks throughout the circumpolar Arctic but also noted the limitations of 30 *m* resolution data in identifying local disturbances such as active layer detachments and small retrogressive thaw slumps which have the most significant impact on vegetation. Retrogressive thaw slumps often occur in clusters due to climate, geology, ground-ice conditions and topography, information that could inform focused research efforts (Nitze et al., 2018). Closer collaborations between Arctic geomorphologists and vegetation scientists through the identification of disturbance hotspots using a combination of passive optical as well active sensors such as SAR and Light Detection and Ranging (LiDAR), which are independent of atmospheric conditions and would improve timely identification and understanding of vegetation dynamics following thermokarst phenomena.

3.2.5. Anthropogenic activities

Past and current industrial development, which exists in the most remote corners of the Arctic, results in direct, long-lasting disturbance to tundra vegetation (Forbes et al., 2001). Research on the ecological impacts of hydrocarbon development in Siberia demonstrate how essential multi-resolution remote sensing data are to effectively monitor vegetative disturbance and recovery at scales relevant to nomadic and semi-nomadic reindeer herders (Kumpula et al., 2010, 2011, 2012; Walker et al., 2009). Studies highlight how VHSR imagery is necessary in combination with lower resolution imagery to assess the impact on reindeer habitat quality given the local and linear nature of many features (Kumpula et al., 2012; Yu et al., 2015). The Prudhoe Bay Oilfield of Alaska is the oldest and most extensive industrial complex in the Arctic and is situated on extremely sensitive ice-rich permafrost making it an excellent case study. A high resolution 62-year aerial photograph time-series revealed extensive disturbance to vegetation and surface hydrological regimes by thermokarst activity, caused by selective thawing of permafrost, with implications for wildlife habitat, local residents, and industry (Raynolds et al., 2014). Further, Raynolds and Walker (2016) highlighted how increased thermokarst increased surface wetness confounding NDVI signals and in turn regional trends in tundra greening.

Esau et al. (2016) found fragmented patterns of vegetation change around urban areas in western Siberia. Changes to vegetation are time-dependent with new development decreasing NDVI, while older development sites show strong increases in NDVI due to a re-population of microsites with woody vegetation. Similar increasing greenness and wetness trends due to revegetation of abandoned mine sites and seismic lines in the Canadian Low Arctic can be observed using Landsat Tasseled Cap transformation trends (Fraser et al., 2014a). In addition to the impacts of infrastructure and transportation, optical remote sensing has also been used to quantify the ecological impact of a major oil spill in the Usa Basin, Siberia in 1994 which found profound changes in vegetation community composition and corresponding changes in Landsat- NDVI (Walker et al., 2006). Given the continued rapid increase in hydrocarbon infrastructure and likely a concurrent rise in urban infrastructure development as well as possible increase in the number of oil spill accidents, particularly in western Siberia, a better inventory and understanding of the impacts on ecosystem functioning using high spatial resolution satellite imagery is necessary.

3.3. *Vegetation properties*

Recent optical remote sensing research to model or estimate Arctic vegetation properties, which includes biophysical and biochemical variables as well as phenology and primary productivity, is largely dependent on inferred relationships with vegetation indices. The extensive evidence that increased tundra NDVI is due to shrub growth and other plant compositional changes (Goetz et al., 2005; Jia et al., 2006) indicate that vegetative change is indeed occurring. However, evidence directly linking trends to changes of vegetation properties is sparse due to a limited number of high-quality validation datasets as a result of the logistical challenges associated with Arctic fieldwork. This review identifies near-field remote sensing systems such as time-lapse cameras as a promising tool for validation of vegetative changes in remote Arctic ecosystems.

3.3.1. *Aboveground biomass and Leaf Area Index (LAI)*

The majority of recent studies on vegetation properties have focused on estimations of aboveground biomass using field data and satellite-derived vegetation indices at multiple spatial scales (e.g., Chen et al., 2009; Kushida et al., 2009, 2015; Räsänen et al., 2019; Raynolds et al., 2012; Riedel et al., 2005Liu and Treitz, 2018). The most extensive examination of the relationship between aboveground biomass and satellite derived NDVI was conducted by Raynolds et al. (2012) across the North American and Eurasian Arctic transects. This unique dataset found that total aboveground biomass measured by destructive sampling was strongly related to peak summer, maximum NDVI at the 1 km AVHRR scale. This relationship was then used to look at 30 years of aboveground biomass dynamics across the Arctic biome, which showed the greatest changes in the Low Arctic, but with high spatial variability (Epstein et al., 2012). Research at the 30-m Landsat and VHSR scale in both Low and High Arctic sites has also found strong relationships of destructively sampled aboveground biomass and vegetation cover with peak summer NDVI (Berner et al., 2018; Laidler et al., 2009). However, additional research using VHSR from multiple circumpolar sites suggests that biomass-NDVI relationships derived from vegetation height and cover are site- and scale-dependent, and models cannot be applied universally (Atkinson and Treitz, 2013; Räsänen et al., 2019). In the increasingly relevant field of imaging spectroscopy (i.e., high spectral resolution optical data), Liu et al. (2017) provided a summary of how the unique characteristics of Arctic vegetation influences optical properties and reiterated recent findings that narrowband vegetation indices provide more accurate estimations of phytomass, biomass, and leaf area index (LAI) than broadband indices (e.g Bratsch et al., 2017; Buchhorn et al., 2013). These findings are important in the context of current and upcoming spaceborne imaging spectroscopy missions such as the German EnMAP satellite (Guanter et al., 2015) and the Italian PRISMA satellite (Loizzo et al., 2018), which could greatly improve estimates of Arctic biomass.

In contrast to biomass, Williams et al. (2008) found that Leaf Area Index (LAI) and field-based NDVI had a scale invariant relationship, and when LAI was extrapolated to the Landsat scale, the error magnitude was comparable to Landsat NDVI calibration errors. These results are similar to ground-based investigations by both Goswami et al. (2015) and Riedel et al. (2005) who found strong correlations between LAI and NDVI. These studies also found that this relationship tends to saturate at LAI values between 2 and 3 (m^2m^{-2}) making upscaling in highly vegetated areas prone to underestimations. *In situ* measurements and extrapolation of LAI to satellite scales in ecosystems with low-stature vegetation remains challenging with no standardized methods (Bréda, 2003). Methods to accurately measure and extrapolate LAI in erect-shrub Arctic ecosystems uses a combination of light fraction penetration through the canopy, and surface canopy reflectance (e.g., NDVI) (Van Wijk and Williams, 2005). In prostrate communities where measuring light penetration is not possible given low canopy height, destructive sampling and digital photography have been used to generate LAI estimates (Goswami et al., 2015). Overall, LAI remains a challenging biophysical variable to model with optical remote sensing given the absence of consistent and accurate *in situ* measurements and validation in some Arctic ecosystems.

3.3.2. *Vegetation seasonality, phenology, and primary productivity*

In addition to greening, NDVI datasets have also been used to look at changes in the seasonality, phenology, and primary productivity of tundra vegetation related to the period, timing, and magnitude of annual photosynthetic activity and carbon exchange (e.g., Bhatt et al., 2017; Gamon et al., 2013; Shaver et al., 2013; Tagesson et al., 2010; Xu et al., 2013; Zeng et al., 2013). In the literature, seasonality is generally defined as the length and timing of photosynthetic activity and is derived from temporal patterns of NDVI, while vegetation phenology is related to specific plant developmental stages and is often defined by NDVI thresholds. The two terms are often used interchangeably, and while intrinsically linked, they represent two distinct ecological processes. To date there are very few studies that directly link optical remote sensing signals to specific *in situ* phenological stages such as leaf-out or flowering (e.g., Beamish et al., 2016; Beck et al., 2007).

As with other variables inferred from optical remote sensing, changes in vegetation seasonality and phenology show non-linear trends over time with strong scale and geographic dependence. At continental scales, seasonality derived from AVHRR and MODIS-NDVI suggests a lengthening and intensification of the growing season at northern latitudes due to earlier onset of spring, resulting in greater CO_2 uptake and a prolonged period of photosynthetic activity (Barichivich et al., 2013; Zeng et al., 2011). However, the timeframe, density of datasets, and extent of the studied area greatly influence observed trends. For example over a 30-year period Eurasia ($> 50°$) showed greater increases in growing season length than North America (Barichivich et al., 2013), while on shorter, more recent time scales (2000–2010), North America ($> 60°$) had far greater advances in the start of the growing season (Zeng et al., 2011). A recent circumpolar analysis of tundra vegetation seasonality found decreasing springtime AVHRR-NDVI, suggesting a shortening of the growing season, likely a result of complex ecological phenomena including increased standing water, delayed spring snowmelt, winter thaw, and re-freezing events (Bhatt et al., 2017). Field-based investigations into the changing seasonality found that vegetation productivity (field-based NDVI) did not increase despite earlier snowmelt in a Low Arctic coastal wet sedge tundra, and corresponding satellite data were unable to identify differences in timing of snowmelt and NDVI (Gamon et al., 2013). The onset of Arctic vegetation activity and phenology have been shown to be highly correlated with satellite derived snowmelt at the satellite scale (Zeng and Jia, 2013), but this ground-based investigation once again highlights the heterogeneity and scale dependence of processes and the importance of *in situ* measurements to provide detail not available from satellite observations. Anderson et al. (2016) used ordinary digital cameras to successfully monitor phenology of dominant High Arctic species highlighting the utility of near remote sensing systems reducing the dependence on intensive *in situ* observations.

The relationship between primary productivity and NDVI in Arctic tundra is highly variable. Direct comparison of carbon fluxes to NDVI or biophysical variables modelled from NDVI such as Light Use Efficiency (LUE) or LAI, suggest that optical remote sensing can be used to predict primary productivity with relative certainty in highly vegetated communities such as wet sedge meadows, fens, and shrub-dominated tundra (Emmerton et al., 2016; Street et al., 2007; Tagesson et al., 2010, 2012; Ueyama et al., 2013). Sparsely vegetated polar semi-deserts remain challenging to predict due to low plant growth (Emmerton et al., 2016). Westergaard-Nielsen et al. (2013, 2017) demonstrated that near-field remote sensing systems of time lapse digital cameras are also capable of monitoring gross primary productivity in Low and High Arctic ecosystems with a high degree of certainty. Seasonal estimates across different vegetation communities and phenological phases have proven highly variable (La Puma et al., 2007). The relationship between optical remote sensing signals and primary productivity is not linear, and vegetation community type, phenological phase, as well as climate variables such as growing degree-days, must be taken into consideration when scaling to regions and the tundra biome.

3.3.3. Vegetation pigments and nutrients

Photosynthetic pigment and foliar nutrient content are perhaps the least-well characterized tundra vegetation properties, despite being key indicators of vegetation health and activity. This is again the result of limitations in validation datasets due to difficulties in sample conservation and processing in remote Arctic sites. The use of image spectroscopy and spectral indices as proxies is well established across many other biomes (Asner, 1998; Asner and Martin, 2008; Carlson et al., 2007; Clevers and Gitelson, 2013; Sims and Gamon, 2002). Within the timeframe of this review, only two studies examining the direct relationship between optical remote sensing signals and photosynthetic pigment content in the Arctic were identified. Zagajewski et al. (2018) assessed the feasibility of *in situ* hyperspectral remote sensing to monitor High Arctic vegetation vitality and found strong correlations between narrowband, pigment-driven spectral indices and pigment content. The second study by Beamish et al. (2018) examined the relationships among narrowband indices, camera-derived greenness, and pigment content and found that simple green indices are sufficient to track seasonal pigment driven changes in Low Arctic vegetation. The relationship between optical remote sensing and foliar nutrients was notably missing from our review, highlighting the need for focused research into this area. Van Wijk et al. (2005) found a tight coupling between canopy fraction measured LAI and foliar nitrogen, suggesting this relationship could exist with spectrally derived LAI, though further investigation is needed.

3.3.4. Solar-induced chlorophyll fluorescence

An emerging trend in optical remote sensing of Arctic tundra vegetation involves acquisitions of passive solar-induced chlorophyll fluorescence (SIF). SIF, a by-product of light absorption by the chlorophyll complex during photosynthesis, is a more direct proxy for photosynthetic activity than vegetation indices and can be quantified by both ground and satellite observations (Frankenberg et al., 2014; Porcar-Castell et al., 2014). The two most common satellite sensors used in SIF applications are NASA's Orbiting Carbon Observatory-2 (OCO-2) and the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT)/European Space Agency (ESA)'s Global Ozone Monitoring Experiment 2 (GOME-2). The GOME-2 collects data at a 40 x 40 km scale, while OCO-2 has a spatial resolution of 1.29 x 2.25 km with sparse and spatially discontinuous coverage, and these are used to infer regional and biome-scale trends in ozone and CO_2, respectively. In 2017, ESA launched the TROPOspheric Monitoring Instrument (TROMPOMI) with an improved spatiotemporal resolution (7 km × 3.5 km, daily spatially continuous global coverage) but a broad viewing angle requiring cautious interpretation.

The use of SIF data for terrestrial applications in the Arctic is in its infancy but initial studies suggest that in comparison to vegetation indices such as EVI, SIF is less susceptible to confounding signals from non-vegetated surfaces, which is a great advantage in patchy and discontinuous Arctic ecosystems (Luus et al., 2017). Luus et al. (2017) compared airborne and tower measurements of CO_2 fluxes to EVI and SIF over Alaskan tundra and found that SIF-based estimates provide more realistic models of seasonal tundra photosynthesis with green-up occurring nine days later than EVI-based estimates. A further study from Walther et al. (2018) found disagreements between pan-Arctic tundra productivity estimated by vegetation indices (greenness) and SIF, with VI-derived greenness peaking later than SIF. A recent study using downscaled GOME-2 SIF (ca. 5 km) to examine recent circumpolar greening trends once again found disagreement between long-term NDVI trends (2003–2013) with a clearer tundra browning signal in the SIF data compared to spatially and temporally heterogeneous NDVI greening trends.

Though SIF data are less susceptible to confounding signals from non-vegetated surfaces and providing a potentially more realistic estimate of photosynthetic activity, it is susceptible to high noise levels. This is due to the very large footprint and integration time of the sensors, as well as the generally weak signals from prostrate Arctic vegetation, and overall low photosynthetic rates and low illumination conditions. There is a need for more detailed *in situ* studies at finer spatial scales and a greater understanding of the technical limitations and inherent uncertainties to fully understand the relationship between SIF and photosynthetic activity of Arctic tundra vegetation, yet the recent research demonstrates the potential for this technique to improve our understanding of vegetation change in the Arctic.

3.4. Classification and mapping

The creation of ecosystem maps is foundational for interdisciplinary research and long-term monitoring in the Arctic, however circumpolar scale maps with consistent nomenclature are limited (Macander et al., 2017).To date, the only circumpolar-scale Arctic land cover map with consistent nomenclature is the CAVM (Circumpolar Arctic Vegetation Map, (CAVM Team, C, 2003)). The CAVM provides a hierarchical classification of the tundra biome using physiognomic units with accompanying detailed vegetation descriptions derived from a combination of AVHRR spectral information and manual delineation by regional experts. The original map has a 14 km resolution but a 1-km resolution raster CAVM has recently been developed which greatly improves the spatial resolution and detail (Raynolds et al., 2019). This map, while highly valuable for its circumpolar extent, is limited to areas north of the treeline and is still coarse in scale for some applications. Other regional and local classification and mapping efforts have focused on integrative ecological classifications similar to the CAVM that combine vegetation information with other environmental variables such as geology and climate, as well as efforts to map plant communities, plant functional types, and percent vegetation cover which are reviewed in the following sections.

3.4.1. Ecological classification

The majority of recent mapping efforts using optical remote sensing data provide rasterized ecological classifications across the circumpolar Arctic at local and regional scales. These maps are generally produced through a combination of semi-automated supervised and unsupervised classifications of satellite spectral reflectance data with the inclusion of ancillary data, such as terrain attributes, percent vegetation cover, aboveground biomass, and soil moisture (Johansen et al., 2012). Classification schemes are essential for accurate modeling of ecosystem processes such as carbon exchange (Atkinson and Treitz, 2012), methane emissions (Schneider et al., 2009), and for long-term ecological monitoring in remote national parks (Fraser et al., 2012). Ancillary data are required for ecological mapping due to the heterogeneous and patchy nature of Arctic tundra vegetation, which makes spectral separation of distinct ecological classes difficult. Recently Langford et al. (2019) investigated vegetation mapping using artificial neural networks and highlighted emerging supervised and unsupervised classification methods that could improve classification of heterogeneous Arctic vegetation.

3.4.2. Community composition, plant functional types, and percent vegetation cover

Recent quantitative fractional vegetation mapping efforts by Macander et al. (2017) successfully mapped plant functional types in Arctic Alaska using spectral predictors from Landsat data. Best results were found for canopy-forming species such as deciduous shrubs, and the methodology allows for periodic updates. Ottlé et al. (2013) conducted a similar mapping exercise at a 1-km scale across Siberia using a variety of land cover products and noted the importance of such efforts for accurate climate modelling. Bartsch et al. (2016) identified the need for a separate but compatible plant functional type (PFT) classification for ecosystems from the Sub to High Arctic that includes robust classification of shrubs, as well as mosses and lichens in communities where they are not the dominant functional group. Better resolution of the presence and abundance of additional vascular plant types such as graminoids and forbs is also needed across the TTE to High Arctic latitudinal gradient. Landsat and Sentinel-2 imagery were identified as having great potential to fill this gap in land cover mapping, providing improved spatial and spectral resolutions (Olthof et al., 2009). Further conclusions by Bartsch et al. (2016) suggest that existing shrub classifications from global land cover products could be extended to Arctic ecosystems, as they can be easily validated with existing *in situ* data. In addition, land cover classes of mosses and lichens, such as those created by Langford et al. (2016) using WorldView data for the Alaskan Arctic Coastal Plain, should be modified to use lower spatial resolution data such as Landsat or Sentinel-2 to facilitate circumpolar-scale mapping.

4. Remaining challenges for optical remote sensing of Arctic tundra vegetation

4.1. Environmental controls on observed NDVI trends

In addition to technical challenges associated with the identification of ecological phenomena using remote sensing data, a better understanding of the environmental and climatic controls on these phenomena is necessary to validate and better understand observed trends. This is no easy task given mismatching spatial and temporal scales of available data as well as the complex interactions and feedback mechanisms among variables. Environmental and climatic data such as soil moisture, precipitation, snow depth, air and surface temperature as well as sea ice are generally interpolated from a limited number of meteorological stations or are averaged over large spatial scales from satellite data making attribution to observed NDVI trends challenging (Comiso, 2003; Raynolds et al., 2008).

Bhatt et al. (2010, 2013, 2017) have published several foundational papers examining NDVI productivity trends in relation to near-coastal sea ice cover and land surface temperatures. Initial examinations of these trends suggest decreasing sea ice and increasing summer temperatures correspond to observed increases in productivity in both Low and High Arctic ecosystems (Bhatt et al., 2010). More recently, decreases in early season NDVI in Eurasia were concurrent with decreased sea ice cover and increasing evapotranspiration leading to cloudier skies and colder temperatures (Bhatt et al., 2013). Phenomena such as increased standing water, delayed snow melt, winter warming events, and increased surface moisture have all been identified as decreasing NDVI at the local scale but do not explain large scale circumpolar trends (Bhatt et al., 2017; Bieniek et al., 2015; Phoenix and Bjerke, 2016; Raynolds and Walker, 2016).

Despite identification and discussion of potential drivers in the last decade of terrestrial Arctic remote sensing research, robustly attributing climate and environmental drivers to changing Arctic productivity is, and will continue to be, challenging given the uncertainties and complex feedbacks inherent in these data. Myers-Smith et al. (2020) outlines how interdisciplinary research that includes remote sensing, ecology, Earth-system science and computer science in combination with re-analysis of historical data is necessary to begin to fully understand the complexity of Arctic NDVI trends.

4.2. Upscaling and extrapolation

The usual trade-offs among spectral, spatial, and temporal resolutions are magnified by the challenges of data acquisition in the Arctic, including frequent cloud cover, long dark winters, and low sun angles. To address the challenges identified in this review, a better understanding of the differences among sensors in terms of spectral and radiometric sensitivity, viewing geometry, and geometric resolution is needed to develop standardized, high latitude-specific methods to allow the fusion of data from multiple sensors. An additional consideration to upscaling and extrapolation is the inherent spatial biases in much of the *in situ* data collection that occurs in the Arctic. Given the cost and logistics of data collection outside of established research areas, the limited high-quality data come from highly localized areas which should be taken into account when performing upscaling exercises. In the following sections the ecological factors leading to uncertainties when upscaling and extrapolating optical remote sensing data in terrestrial Arctic ecosystems are outlined.

4.2.1. Unmanned aerial vehicles

UAV technologies have been identified as highly valuable tools for improving the spatial coverage and scale of remote sensing of Arctic ecosystems. Recent studies show the promise of UAV-derived imagery and photogrammetry as an accurate and cost-effective tool for mapping Low Arctic vegetation cover and height at an intermediate scale (Fraser et al., 2016; Riihimäki et al., 2019). However, the relatively new technology of UAVs has the potential to be “cutting edge” as well as “bleeding edge” (high expense, low reliability), and coordinated efforts such as those being championed by the High Latitude Drone Ecology Network (HiLDEN; arcticdrones.org) are required. Assmann et al. (2018) provide a thorough outline of their best practices and lessons learned from three years of data collection in the Canadian Arctic. They identified the following four key components for ensuring high quality data: flight planning and overlap, weather and sun, geolocation and ground control points, and radiometric calibration. They concluded that with a standardized workflow that carefully considers the above factors, UAV acquisitions can produce multispectral or hyperspectral data that are comparable across study regions, plots, sensors, and time.

4.2.2. Disturbance and hydrology

A further issue associated with scaling and extrapolation of data and observed trends is the incorporation of scale-variant features such as disturbances and surface hydrology dynamics (e.g., extent of lakes and ponds). At high spatial resolutions, permafrost disturbances and tundra wetlands, lakes, and ponds are easily identifiable, but sub-pixel changes in surface water extent can confound observed trends in vegetation change using coarser datasets (e.g., Landsat, MODIS) (see Raynolds and Walker, 2016). A circumpolar-scale inventory of disturbances and surface hydrological features, such as efforts by Nitze et al. (2017), would greatly benefit the extraction and interpretation of observed trends of Arctic vegetation change. Modern, multi-polarization synthetic aperture radar (SAR) platforms were identified as necessary for mapping Arctic water bodies, given the highly dynamic extent of these features over short time periods (Barrett et al., 2012; Bartsch et al., 2012). Pixel-based trend analyses using the Landsat archive, such as those developed by Nitze and Grosse (2016) and Pastick et al. (2019), are a promising development for inventorying permafrost disturbance hotspots, which in turn can be validated with high resolution and *in situ* data where available.

4.2.3. Plant functional types

The identification of PFTs also remains a challenge in regional and biome scale Arctic vegetation remote sensing given varying scales of data used, as well as a lack of standard circumpolar nomenclature. Previous studies have found that spectral differentiation of PFTs is possible (see Macander et al., 2017) but these data have mostly included ground-based hyperspectral measurements (Beamish et al., 2017; Bratsch et al., 2016; Buchhorn et al., 2013; Huemmrich et al., 2013). As highlighted previously, the identification of mosses and lichens, and the standardization of these functional types in terms of definition and spectral properties, are key requirements for improving vegetation remote sensing in the Arctic, and high spectral resolution data is needed. Improved representation of lichens and mosses is also highly desirable for understanding subsurface properties of Arctic landscapes, given the importance of these PFTs in maintaining the ground temperature regime. However, this is a highly complex task and one that cannot be fully addressed using only multispectral data. For example, reflectance spectroscopy values of moss species are highly dependent on their moisture content, which can change very rapidly but do not always reflect actual changes in primary productivity (May et al., 2018). As part of the NASAs Arctic and Boreal Vulnerability Experiment (ABoVE), a concerted effort is being made to understand the relationships between ground-based and airborne spectral reflectance and PFTs. This research will greatly improve the use of data from the Italian PRISMA hyperspectral satellite and the upcoming launch of the German EnMAP hyperspectral satellite, which will provide additional and highly valuable data to address the important nonvascular component of Arctic vegetation on a much larger extent than is currently possible.

Another approach to measuring plant diversity using remote sensing, aside from established methods (e.g., PFTs), is to evaluate functional diversity (i.e., the range and values of defined spectral indices related to ecosystem function) as a potentially more informative and straightforward measure of ecosystem functioning (Alcaraz-Segura et al., 2013; Villarreal et al., 2018; Virtanen et al., 2013) based on field, airborne, and satellite data. This approach may present a more logical way to link carbon, water, and energy cycling, as well as herbivore activity and movement, to diversity of ecosystem functioning.

4.2.4. Vegetation phenology

Monitoring vegetation at different phenological stages can be seen as both a challenge and an opportunity. Given the rapidly lengthening growing season and the high percentage of senesced vegetation present in many Arctic vegetation communities, accurately monitoring phenology with remote sensing data at high temporal frequency is difficult. Archives such as AVHRR and Landsat provide the opportunity for large-scale monitoring of vegetation phenology (Stow et al., 2004), however the fine-scale heterogeneous nature of Arctic vegetation, and therefore vegetation phenology, cannot be captured at such coarse scales. The incorporation of time-lapse digital cameras and an increase in camera networks and data sharing offer promising ways to increase phenological measurements and validate remote sensing products (Anderson et al., 2016; Beamish et al., 2016). Remote sensing data from different phenological phases could provide new possibilities for classification of spectrally similar communities. Beamish et al. (2017) and Bratsch et al. (2016) found that the differentiation of spectrally similar Alaskan tundra vegetation communities increased in the late season owing to a relative increase in among-community variability in spectral reflectance. Macander et al. (2017) also found an improvement in classification of PFTs in Alaskan tundra using multi-seasonal composites. These results highlight the need to incorporate non-peak season remote sensing data into Arctic vegetation monitoring and mapping.

4.2.5. Tundra-taiga ecotone

A final challenge in upscaling and extrapolation is the TTE. This dynamic transitional ecosystem includes the unique components of Low Arctic vegetation communities and sparse, isolated trees. The position, composition, and abruptness of the TTE varies greatly across the circumpolar Arctic-boreal region (Callaghan et al., 2002). Previous research has identified that monitoring and characterizing the TTE using remote sensing techniques has large uncertainties and requires fine-scale, site-based data (Callaghan et al., 2002; Danby, 2011). Due to the highly variable ecosystem structure, both coarse and fine-scale remote sensing often contain measurement errors greater than the vegetation or vegetation change signal (Montesano et al., 2014). Increased ground-based measurements of vegetation are needed to better characterize uncertainties at coarse and fine remote sensing scales. This is particularly true for vegetation structure changes that are most closely linked to changes in climate (Montesano, 2015). Montesano et al. (2014) outlined how the integration of spaceborne Light Detection and Ranging (LiDAR) data with high resolution spaceborne stereo imagery to model canopy height could vastly improve our understanding of the uncertainties and therefore dynamics associated with monitoring TTE changes. The authors also highlight the potential of the upcoming spaceborne LiDAR ICESat-2 satellite from NASA to extract vegetation height data at the circumpolar scale.

In addition to better quantification of forest structure, an effort is underway for the development of a unified Circum-Boreal Vegetation Map (CBVM) similar to the CAVM that will include detailed classification of the TTE. This effort is coordinated under the Conservation of Arctic Flora and Fauna (CAFF), an initiative of the Arctic Council to cooperate on species biodiversity and habitat management and research. As with the CAVM, the CBVM will have applications for many stakeholders and will provide a much-needed common baseline for monitoring environmental change, wildlife habitat, and natural resource activities.

4.3. Data processing and sharing

With the introduction of platforms such as Google Earth Engine (GEE), the capabilities of a powerful cloud computing environment are accessible and readily available to the research community (Gorelick et al., 2017). Next to providing a wide range of remote sensing imagery and data products, GEE creates the possibility of long time-series analyses and continental or global scale analyses. These new capabilities have allowed scientists to address new questions and have enabled monitoring efforts that were previously infeasible. While improving data accessibility and processing power, GEE is by no means a perfect solution, and working at the circumpolar scale is challenging. In addition, as it is a commercial platform, it raises concerns regarding, among others, continued free access and availability of the platform, as well as privacy and copyright issues. Other platforms, such as EarthServer, Docker and the Coupled Model Intercomparison Project (CMIP) which provide cloud-based virtual services have also emerged, and gained prominence and acceptance within the research community (Baumann et al., 2016; Eyring et al., 2016). Different services provided by the Copernicus program, such as the Copernicus Sentinel Hub, also provide open access to vast amounts of Earth observation data. However, these services mostly charge a fee for download or cloud computing capabilities, with expansion into capabilities for processing and analysing being planned (Sudmanns et al., 2019).

A relatively untapped resource is camera networks from different organizations which provide data through various protocols and platforms, e.g., Phenocam, FTP, HTTP, web page request, Zenodo, Pangaea. At the moment, one needs to search for the camera networks and the data availability separately. It is possible to fetch image data through common platforms or software that are able to use different protocols (Tanis et al., 2018). A camera network portal to gather different camera networks in one place, providing information on the data and how to access it, would be beneficial to the research community. This portal would also have an interactive webpage where institutes and researchers could collaborate to gather, share, and maintain the information and processing procedures (e.g., Confluence, Wiki). In addition to the data, the portal could have a section for algorithms for processing image data for vegetation, snow, and ice phenology, along with the software, if available. Adding a section for projects and publications, the portal would attract researchers, academics, entrepreneurs, and innovators.

While these platforms certainly show immense progress by the Earth-observation community over recent years, none of them are specifically created for issues concerning Arctic landscapes. In the case of GEE, the datasets provided are largely created with a focus on lower latitudes, which can cause problems, including lower quality data, for Arctic regions.

5. Best practices and outlook of optical remote sensing of Arctic tundra vegetation

5.1. Importance of continuity of satellite sensors, products, and free availability

Continuity of sensors is critical for monitoring changes on the Earth's surface, however, improving technology results in changes to successive space missions. Improvements, such as more numerous and narrower spectral bandwidths, provide higher quality data, but often make them difficult to analyze long-term trends. For example, NDVI data from the Landsat 8 OLI sensor are not equivalent to the data from Landsat 5 and 7 (Roy et al., 2016), and transformation functions may have to be developed for individual applications. Recent efforts have provided spectral corrections to allow for direct comparison and the creation of dense time series of Sentinel-2 and Landsat 8 OLI data over Eastern Siberia (Runge and Grosse, 2019). Similarly, MODIS data have been used in conjunction with the AVHRR data record, but these data are not directly analogous (Fensholt et al., 2009). Space agencies are working to make new sensors compatible and encourage research on best practices to translate or merge new sensor data with old records to create the longest possible databases.

In concert with sensor continuity, the terrestrial Arctic remote sensing community recognizes the importance of continuity in the products created and distributed via data portals by various space agencies. The geo-registered, orthorectified images (Level 1 processing) and surface parameters calibrated (Level 2) are the primary products used by the remote sensing community. Processing technology also changes, but improvements in satellite orbit correction, and resulting geo-registration and sensor calibration, as well as corrections such as Bidirectional Reflectance Distribution Function (BRDF) (Buchhorn et al., 2016), can often be applied retroactively to a whole data series (e.g., MODIS Version 6 Vegetation Products), and have been less disruptive than changes in sensor technology.

The privatization of Landsat data in the 1980s resulted in high costs, low quality products, low usage, and large temporal gaps (Wulder et al., 2012), clearly demonstrating the inadvisability of this approach. User fees cannot support the cost of sensor deployment, so any fee reduces the data utility to society in general. With free availability of Landsat data, the number of scenes downloaded jumped from less than 50,000 per year to over five million in 2013 (Turner et al., 2015). A large majority of Arctic vegetation research is based on freely available data, including Landsat, MODIS, Sentinel-2, TerraSAR-X and TandemX (limited availability), and other SAR data. Some researchers used free access to high-resolution data from WorldView and QuickBird, available as part of their US-funded research. The free availability of satellite data supports a wide range of studies and applications by students and early career researchers that would not otherwise be possible. The exploration of big data sets, such as through Google Earth Engine, would be most affected by any pricing of satellite data. Consistent, free data availability is of great importance to the community.

5.2. Sensor advancements and data fusion

The addition of spaceborne imaging spectrometers, i.e., hyperspectral satellites, could address some of the identified issues related to the unique optical characteristics of Arctic tundra vegetation. In this context, current studies for further operational hyperspectral missions such as the SBG (NASA) (Green, 2018) and CHIME (ESA) (Rast et al., 2019), which are presently in phases A/B, are particularly relevant. These missions are designed to provide global coverage, unlike EnMAP and PRISMA which are target missions that acquire a limited number of data acquisitions per day but are valuable for advancing research and retrieval algorithms, as well as the identification of future potential changes. Imaging spectroscopy shows great potential to refine and expand our understanding of Arctic vegetation change.

The field of data fusion is also recognized as highly promising for Arctic applications given the relative scarcity and limitations of optical datasets. The inclusion of Light Detection and Ranging (LiDAR) and Synthetic Aperture Radar (SAR) have been shown to improve estimates of shrub extent, PFTs, and aboveground biomass (Chen et al., 2009; Greaves et al., 2016; Langford et al., 2016; Riihimäki et al., 2017). These data represent an especially promising tool in Arctic land surface remote sensing given the independence from atmospheric distortions (e.g., clouds) and illumination.

5.3. In situ validation

A concerted effort to collect and share high quality validated *in situ* datasets is the best way to overcome sensor, scale, and geographic uncertainties in optical remote sensing of Arctic vegetation. Improved metadata standards will be crucial to accomplish this. An inventory of all available Arctic databases is provided in the Supplementary Material (Table S2). Methods such as those by Dafflon et al. (2017), who provide a comprehensive examination of environmental controls by concurrent above- and below-ground monitoring of permafrost, soil, and vegetation optical properties, would be highly valuable to extend to multiple sites. Time-lapse and repeat digital photography should also be aggregated and expanded through the creation of an Arctic camera network. This simple, cost-effective method can greatly increase the frequency and extent of *in situ* validation data. Carefully collected UAV image time-series can fill a similar role, documenting vegetation distribution and structure at a level of detail equivalent to many traditional *in situ* observations. Continued efforts to standardize data collection through protocol sharing and collaboration would also greatly improve cross-site comparisons and extrapolation.

5.4. Outlook

Overall there is broad consensus that remote sensing is an indispensable tool in monitoring Arctic vegetation change. However, the use of remote sensing data in Arctic ecosystems would benefit from a coordinated sharing of lessons learned and best practices among both remote sensing scientists and plant ecologists. The unique optical properties of terrestrial Arctic ecosystems, as well as the relative scarcity of both remote sensing and field-based environmental data, require collaborative efforts to further the field of Arctic vegetation science. In particular, the inclusion of *in situ* environmental control data to validate observed remote sensing trends at multiple spatial scales is needed. As freely available databases increase, metadata standards will improve, leading to greater consistency of data products. Detection of soil moisture dynamics, water bodies, and disturbances by remote sensing has received recent attention, and as a result the utility of incorporating non-optical and active sensor data was highlighted. Data fusion with SAR and LiDAR shows high potential in monitoring land surface and vegetation change. The identification and extrapolation of the ecologically important plant functional types (PFTs) remain a challenge, but new approaches targeting functional diversity rather than traditional diversity measures may create a more ecologically relevant classification scheme in terrestrial Arctic tundra ecosystems. Monitoring Arctic vegetation phenology also requires the incorporation of additional data sources such as time-lapse imagery, which can be used to validate remote sensing trends. With an increased emphasis on data sharing and availability as well as the advent of technologies such as the Google Earth Engine, the identified challenges associated with Arctic vegetation remote sensing at multiple scales can surely be addressed.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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