Complexity revealed in the greening of the Arctic

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Abstract

The "greening of the Arctic" is among the world's most significant large scale ecological responses to global climate change[1]. The Arctic has warmed at twice the rate of the rest of the planet on average in recent decades[2] and satellite-derived vegetation indices have indicated widespread increases in productivity (termed "greening") at high latitudes[3–8]. Greening trends have been attributed to *in situ* increases in vegetation biomass, cover and abundance[9–11] associated with warming trends[12]. Satellite observations allow for the quantification of vegetation change across northern biomes that are otherwise unevenly sampled by *in situ* ecological observations[13]. Satellite-derived data thus broadly inform predictions of large-scale climate feedbacks involving plant biomass, carbon storage, and surface energy budget[14,15]. Recently however, remotely-sensed Arctic greening trends have shown periods of slowing or even reversing in some regions (termed "Arctic browning")[16–19] sometimes arising from acute declines in productivity[18,20–23] seemingly at odds with earlier responses to long-term warming trends[24]. Research now indicates substantial diversity in ecological responses to changing climate regimes in the Arctic[25], but precise attribution of patterns and trends to ecological process remains a challenge due to conceptual and technical barriers in the analysis and combined interpretation of satellite and *in situ* observations[3,20,26,27]. An emerging consensus is that the underlying causes and future dynamics of Arctic greening and browning patterns and trends are complex, variable, and inherently scale dependent. Here, we review the complexities associated with observing and interpreting high-latitude greening to promote improved consensus, suggest a framework to focus future work, and identify these key research priorities that will advance applications of satellite and *in situ* observations to the study of past, present, and future Arctic vegetation change.

The greening of the Arctic

Over the past forty years, circum-Arctic measures of vegetation dynamics by satellites document widespread and long-term greening trends that are generally interpreted as signs of increased *in situ* biomass and productivity of Arctic terrestrial vegetation[3,5,6,12,23,28]. Slowing or reversal of these trends in recent years suggests a greater diversity of ecological responses to regional climate change than previously assumed[18,20,26,29,30] (Fig. 1). Terminology is mixed, but 'greening' is commonly used as shorthand for describing multi-decadal increases in remotely-sensed proxies of vegetation productivity thought to represent increased vegetation biomass *in situ*. Less frequently, greening is also used to describe advances in the seasonal timing of these vegetation proxies[29,31]. 'Browning' has been used in different ways in the literature, either representing a slowdown in the rate of greening, a switch in trend direction, or a decrease in greenness due to plant dieback from disturbances such as fires, insect outbreaks or extreme weather events[18]. In the most recent Intergovernmental Panel on Climate Change report, tundra vegetation change was identified as one of the clearest examples of terrestrial impacts, with reported high confidence in both the detection and attribution of responses to climate change with evidence for change detection including greening trends derived from satellite observations[1,16]. Recent efforts to synthesize vegetation change in Arctic ecosystems – including changes in plant productivity, biomass, cover, composition or phenology over time and in response to warming – suggest that vegetation change is concurrent with greening observed by satellites[9,32,33]. However, whether and how *in situ* changes in tundra productivity and phenology are directly related to the widespread changes in vegetation indices measured by satellites remains unclear.

Vegetation indices as proxies of vegetation productivity

Long-term trends in global vegetation dynamics are most commonly quantified from time-series of spectral vegetation indices derived from optical satellite imagery. These indices are designed to isolate signals of vegetation productivity from background variation by emphasizing reflectance signatures associated with plant structure or physiology in discrete regions of the radiometric spectrum[3,34–37]. Common vegetation indices include the Normalized Difference Vegetation Index (NDVI, Fig. 2), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), and Green Chromatic Coordinate index (GCC), among many others[38–40]. NDVI has been and continues to be the most widely used vegetation index, owing much to its simple ratio formula based on spectral bands monitored by early-generation earth observing satellites launched in the 1970s (Fig. 2). It is primarily for this historical continuity - rather than being best fit-to-purpose - that NDVI is the most commonly used index to quantify multidecadal Arctic greening. Most studies of long-term trends calculate annual measures of maximum NDVI to measure change over space and time, though time-integrated approaches are also used[35,41–43]. The longest-term freely-available NDVI datasets have been produced from several sensors with broad spatial coverages and different sampling frequencies, including primarily: 1) the Advanced Very-High-Resolution Radiometer (AVHRR – 1982 to present) on board NOAA satellites, 2) the Moderate-resolution Imaging Spectroradiometer (MODIS – 2000 to present) on board NASA satellites, and 3) NASA-USGS Landsat sensors (1972 to present). However, trends in NDVI data produced from different satellite datasets do not always correspond at a given location nor are dynamics of different greening metrics consistent across datasets[44] (Fig. 1). Thus, it can be challenging to distinguish ecological change from differences due to methods and sensor/platform-related issues when interpreting localized greening or browning signals (Table 1).

The ecology of greening and browning *in situ*

The biophysical and ecological processes that drive greening or browning patterns measured by satellites are diverse and may unfold across overlapping scales, extents and timeframes. In tundra ecosystems, vegetation changes linked to greening include for example: encroachment of vegetation on previously non-vegetated land surfaces[9], increasing biomass of previously existing vegetation[45], changes in community composition – such as tundra shrub expansion[9], and/or changes in plant traits such as height[32], leaf area, or phenology[46,47]. Tall shrub tundra typically has a higher NDVI than other tundra plant types[48–50], and bare ground[34] has a much lower NDVI than vegetated tundra (Fig. 2). Tundra without vascular plants, however, could have a substantial cover of biological soil crust communities consisting of lichens, cyanobacteria, mosses and green algae that may influence NDVI[51]. Thus, heterogeneity in plant communities, land cover and topography can influence the greenness of landscapes[52] and likely greening trends over time.

Not all areas of the Arctic are greening (Fig. 1), and in recent years heterogeneity in the direction and magnitude of vegetation change has become more pronounced[18–20,30]. Ecological explanations for vegetation browning include for example the sudden loss of living biomass due to extreme climatic events[21,53–55], biological interactions (e.g., disease or herbivore outbreaks)[56–58], permafrost degradation[19,59] (Fig. 1), increases in standing dead biomass[60], coastal erosion[61], salt inundation[62], altered surface water hydrology[63,64] or fire[6,65,66]. Additionally, decreased rates of vegetation greening could also be attributed to reduced productivity, not necessarily indicating browning vegetation, but rather a decrease in annual greenness due to more adverse growing season conditions, shorter growing seasons[20] or nutrient limitation[25]. Despite these changing dynamics, long-term greening trends remain far more pervasive than browning in tundra ecosystems (ratio of 20:1 in Park et al 2016). At circum-Arctic scales, the magnitude, spatial variability, and proximal drivers of patterns and trends of greening and browning are not well understood.

Correspondence between satellite and ground-based observations

Evidence for correspondence among *in situ* vegetation change and changes in satellite-derived vegetation indices is mixed[67–70]. NDVI trends across satellite datasets do not necessarily directly correspond with one another[3,6], nor does any one sensor or vegetation index combination correspond directly with *in situ* vegetation composition change[69]. For example, AVHRR NDVI greening trends did not correspond with the lack of change observed with Landsat NDVI data and *in situ* plant composition between 1984 and 2009 in North Eastern Alaska[69]. NDVI has been related to interannual variation in radial shrub growth[7,10,71], yet how radial growth links to change in leaf area or aboveground biomass is not always clear[72–74], let alone how it influences landscape measures of productivity (Fig. 4).

Making direct comparisons of productivity changes from vegetation cover estimates[9,33], biomass harvests[48] or shrub growth[75] is complicated by the lack of annual-resolution data and low sampling replication across the landscape.

In addition to productivity analyses, growing season length[17,76,77] and plant phenology advance over time[76,78–82] have been quantified using both satellite and ground-based datasets, though paired comparisons do not always correspond (Fig. 5). Measures of longer growing seasons have been attributed to earlier snowmelt and/or earlier leaf emergence in spring[83], and longer periods of photosynthetic activity or later snowfall in autumn[84]. However, the few studies that have monitored both localised leaf emergence and senescence of tundra plants have not found evidence for an increasing growing period at specific sites[76,77]. In addition, community-level analyses indicate shorter flowering season lengths at sites around the tundra biome[85]. Plant phenology changes with warming[85,86] could also be linked to changing species composition or diversity[9,32,33], thus influencing the phenological diversity across the landscape[87,88]. However, for satellite observations may not capture whether photosynthetic activity begins earlier in the spring and/or continues later into the autumn in tundra ecosystems where deciduous vascular plants make up only a portion of the vegetated land cover. Taken together, whether circum-Arctic satellite observations across high latitudes represent either a longer snow-free period uncoupled from vegetation response or an actual realized longer growing season of plants remains uncertain[76,89–91].

Explaining the lack of correspondence between *in situ* and satellite-derived measures of tundra vegetation change and greening is fraught with complexities of terminology, challenges of interpretation of spectral vegetation indices at high latitudes, and scaling issues (Fig. 4).

Challenge 1: Terminology

Although the terms ‘greening’ and ‘browning’ were first popularized in the context of boreal forest change[8] they have been adopted to describe widespread changes throughout all terrestrial Arctic systems[4,5,7,20]. Greening and browning trends refer to decadal phenomena that may operate at any spatial scale, from localized patches, to landscapes or even biome extents, while greening and browning events occur more rapidly (i.e., are short term) and, due to their mechanistic drivers, will often be restricted from patch to regional scales (the impacts of volcanic eruptions, such as Mount Pinatubo in 1991, are an exception[92]). Therefore, greening or browning events might be embedded within overall greening or browning trends without necessarily driving them (Fig. 6). In turn, greening or browning trends and events may also result in threshold changes where productivity does not return to the longer-term baseline (Fig. 6; e.g., pulse in recruitment at treeline[93] or shrubline[94] or a large fire[66]). The baseline to which we compare productivity change will influence our interpretation of trends[95]. In both satellite datasets and field observations, the baseline conditions are often constrained by the limitations of data availability rather than any ecologically meaningful starting point[3]. For these reasons, substantial uncertainty associated with ecological attribution of greening and browning could be reduced by more comprehensive descriptions of these time series beyond simply the direction of trends (Fig. 6).

With a baseline and trend direction established, examining the trend magnitude and variance around the fit over time can aid ecological interpretation (Fig. 6). To distinguish greening and browning events from the longer-term trends, we propose defining events as “outliers in NDVI (or other spectral vegetation indices) that occur relative to the long-term mean or trend” using a Theil-Sen estimator or similar statistical test for robust trend analyses of satellite data[35,96]. Here, we define a *greening trend* as an increase in NDVI or other greenness-related indices over decadal time scales. When attributed to *in situ* vegetation change, we interpret this pattern as improved conditions for photosynthesis, reduced resource limitation, or responses to disturbance in plant communities, resulting in greater aboveground biomass, leaf area, productivity or successional change. We define a *browning trend* as a decrease in NDVI or other greenness-related indices over decadal time scales. Browning trends may correspond with an *in situ* change in vegetation productivity due to plant dieback or loss of vegetation cover through biotic or abiotic disturbances.

We suggest avoiding definitions of browning that refer to a slowdown of positive greening trends because the relationship between vegetation indices and on-the-ground measures of vegetation productivity is non-linear and variable (Fig. 2 and 6). A slowdown in a positive vegetation index time series trend could therefore relate to a decline, no change, or even an increase in vegetation productivity on the ground purely due to statistical rather than ecological factors. To some degree any definition of greening or browning is arbitrary, but the purpose of the definitions we propose here is to draw a distinction between slower acting climatic or biotic drivers of greening or browning trends versus event-driven changes caused by weather, biotic pulses, or other regional events such as fire. Beyond advocating for clearly defined terms, challenges persist in the interpretation of physiologically meaningful parameters from the available long-term optical satellite data, and in overcoming the mismatch between observations and their potential drivers that operate across different spatial and temporal scales.

Challenge 2: Understanding spectral vegetation indices

Vegetation indices are proxies of photosynthetic activity rather than direct measurements of biological productivity[38,97,98]. The statistical relationship between a vegetation index and biomass, phenology, or any other measures of productivity can vary due to a suite of intrinsic (e.g., sensor design, quality flagging algorithms) and extrinsic (e.g., atmospheric conditions, sun angle) factors[3,99] (Table 1). For example, the centre wavelength and width of red or near-infrared or other spectral bands used to generate vegetation indices were designed for different purposes in different sensors (Fig. 2). While the formula for NDVI may be the same, the covered spectral wavelength ranges differ between different satellite datasets[100](Fig. 2B), and may be more or less sensitive to specific non-vegetative influences, such as atmospheric scattering or the magnitude of spectral mixing associated with non-vegetated surfaces. Widespread non-vegetative changes in high-latitude ecosystems could confound and decouple vegetation index time series from changes in plant productivity (Table 1). For example, changes in the extent of summer snow patches[101], surface water[102] or surface soil moisture[103] that are often associated with landscape-scale topographic variation could influence greening patterns and trends. In addition, satellite data signal processing varies across available products. Thus, strong caution is warranted when comparing products or even versions of the same product with different atmospheric corrections, quality assessments, and spatial/temporal compositing approaches. The influences of non-vegetative geophysical and signal processing factors on NDVI are actively studied by the remote-sensing community (Table 1), but could be better accounted for or quantified in Arctic greening studies.

The potential for non-linear relationships between vegetation indices and measures of Arctic vegetation productivity presents further conceptual challenges in trend interpretation (Fig. 2). These arise from comparing a normalized ratio against a continuous productivity measure of interest, such as biomass changes or shrub ring width (Fig. 4). A linear trend in an NDVI time series (Fig. 1) does not necessarily mean linear changes in vegetation productivity[34,104] (Fig. 2). Because greening and browning terminology are tied to changes in vegetation proxies, such as NDVI, rather than direct measures of biological change, mismatches could occur between remotely-sensed vegetation proxies and *in situ* vegetation change (Fig. 3, 4 and 5). These potential mismatches exemplify why caution should be used when interpreting linear trends in ratio-defined (i.e., potentially nonlinear) proxies.

Measuring landscape phenology with satellite data (phenometrics), especially at high latitudes, presents additional challenges to simple ecological interpretation that are associated with methodologies and seasonal variations in data quality (Table 1). For example, vegetation metrics from early spring are much more likely to be influenced by snow, standing water or low sun angle than those closer to peak biomass in mid- to late-summer[5,49,103], yet these are critical periods for establishing a baseline for curve fitting or thresholding used to derive phenometrics. Seasonal variation in cloud or fog cover, highly variable and sensitive to changing sea ice conditions[105], further influences both data availability and image compositing approaches in many phenology products[46]. Use of time-integrated vegetation indices can reduce some of these signal to noise issues[17,106], but ultimately no phenometric is best suited to all Arctic environments. Snow regimes and land cover variability differ annually and regionally and thus phenometrics using coarse-grain imagery can integrate different abiotic and biotic signals at different points in space and time[107]. Phenological differences of days to weeks or even months[108] can result from analyses using different methods and metrics for the same datasets at the same location, , such relative differences are of substantial ecological importance given the short growing seasons of the Arctic[17,107]. Circum-Arctic analyses of vegetation indices generally agree that phenological shifts in the greenness of the landsurface are widespread[17,109,110], but caution is warranted for local-scale comparisons or mechanistic interpretations of biome-scale trends.

Challenge 3: Scaling issues

Scale, and its influence on pattern, presents a longstanding challenge in the interpretation of remotely-sensed vegetation proxies[111–113]. All long-term vegetation proxy time series (Landsat, MODIS, AVHRR) spatially aggregate spectral data to pixels (i.e. grains) that span hundreds of square metres to tens of square kilometres, reducing the spectral signatures of a substantial number of individual plants and non-vegetative features in a landscape to a single numerical value. The loss of variability within pixels masks information useful for the attribution of greening signals to ecological processes (Table 1, Fig. 4). For example, within a single AVHRR GIMMS3g pixel (where a sub-selection of 1 km x 1 km pixels are upscaled to 8 x 8 km[37]), greening signals, such as increased shrub cover on south-facing slopes or re-vegetation of drained lake beds, may be mixed with browning signals, from disturbances such as retrogressive thaw slumps or vegetation trampling by herbivores. The emergent time series from such a pixel describes no single vegetation dynamic, but rather their integrated spectral responses (Fig. 4). Broad-scale patterns of spatial variability in greening and browning across pixels are also influenced by grain size[113] (Figure 1). However, the extent to which the sometimes-contradictory greening and browning signals found across different datasets can be attributed to the influence of scale of measurement on pattern formation is poorly understood. Both spatial and temporal patterns in coarse-grained vegetation proxies capture signals of changing phytomass[10,34,50,69,104], but lacking additional context, they are generally insufficient for the attribution of trends to specific ecological mechanisms of *in situ* vegetation change.

The low temporal sampling frequency of a few days to a few weeks of many remote-sensing datasets also introduces temporal scale-dependent effects that may be magnified in Arctic systems (Table 1). At high latitudes, optical satellite sensors are only effective for a short annual window due to prolonged polar night, with further data quality issues associated with low sun angle, and persistent cloud cover (Table 1). For example, comparisons of phenology across latitudes can be less reliable at higher versus lower latitudes due to shorter growing seasons and therefore fewer satellite data collection points for use in change detection analyses[114]. Metrics based on the annual maximum NDVI of a given pixel are also more likely to be influenced by temporal sampling artefacts at high latitudes than those that integrate productivity estimates through time, such as the growing season integrated NDVI (GSINDVI)[41], time-integrated NDVI (TiNDVI)[42] or early growing season integrated NDVI indices[43]. The magnitude and extent of spatial and temporal scaling issues in high-latitude ecosystems warrant further consideration and research, both from remote sensing and field-based projects[112].

Emerging tools and observation networks

Many factors need careful consideration in comparisons between *in situ* changes in plant biomass and coarse-grained satellite measures of productivity and phenology. Existing *in situ* observations from long-term ecological monitoring[9,18,33,76,115], historical imagery[116,117], phenocam networks[118] and high-resolution imagery such as from aircraft, flux towers, and drones[119,120] are not spatially or temporally comprehensive, yet provide invaluable context to the interpretation and modelling of ecological dynamics captured by existing decadal satellite observations. Recent and ongoing release of satellite datasets to the research community such as the privately owned Digital Globe and Planet constellations or the European Union funded Sentinel missions will provide higher spatial (2-10 m) and temporal resolution (1-5 days) across the Arctic with spectral bands designed for the calculation of both widely-used and newly developed vegetation indices[121–123]. Reanalysis of existing datasets with improved atmospheric corrections, such as MODIS MAIAC[124], will improve understanding of past changes. Data collection campaigns equipped with improved sensors, such as those that can measure solar-induced chlorophyll fluorescence (SIF) at high resolution[125,126], and the increasingly widespread adoption of proximal remote-sensing platforms such as aircraft, drones and phenocam networks using standardized protocols will be required to better test the links between *in situ* vegetation dynamics and broader remotely sensed patterns and trends. In addition, data integration modelling approaches will be necessary to mechanistically link remote sensing observations with ecological change in high-latitude ecosystems[14,19,127].

Future research priorities

We have identified three future areas for fundamental advances in our understanding of greening and browning dynamics at high latitudes, these include:

1. **Validation of existing observations –** Where are we confident in observed greening and browning trends? Where do we have less confidence in the interpretation of

patterns and trends in vegetation indices? How can local-scale information (e.g., topographic and/or land-cover heterogeneity) inform the validation of existing observations?

2. **Integrated interpretations of change –** Can scaling issues be surmounted to find common signals of change across different observations? How can this information from various sources and scales (e.g., satellites, airborne, drone, phenocam and *in situ* records) be integrated to inform deeper ecological understanding of the drivers of greening and browning patterns and trends?
3. **Mechanistic understanding of observations –** Can we mechanistically test, model and hind cast patterns of vegetation proxy change? How can greening and browning observations be integrated into dynamic vegetation and Earth system models to improve our understanding of global climate feedbacks at high latitudes (e.g., carbon cycling and surface energy budget feedbacks)?

Conclusions

Recent research has highlighted the complexity in observed Arctic greening and browning trends and patterns. Although satellite data have been used to detect and attribute global change impacts and resulting climate feedbacks in Arctic ecosystems[1,15], substantial questions and uncertainties remain. The three major challenges in resolving these uncertainties are: 1) improving the clarity of the definitions of widely used terminology associated with greening and browning phenomena, 2) promoting the understanding of the strengths and limitations of vegetation indices when making ecological interpretations and, 3) better incorporating and accounting for different scales of observations and observation error into analyses of changing tundra productivity and phenology. New sensors and better access to legacy data are promising developments, but new data alone will not provide solutions to many of these longstanding conceptual and technical challenges. The complexity of Arctic greening patterns will only be fully understood through multidisciplinary efforts spanning the fields of ecology, remote sensing, climate science, Earth science and computer science that look towards contemporary and future change, but also backwards by conducting re-analyses of historical data. Ultimately, we urgently need a deeper understanding of the relationships between patterns and processes in greening and browning dynamics to improve estimates of the globally-significant climate change feedbacks in high-latitude ecosystems[1].

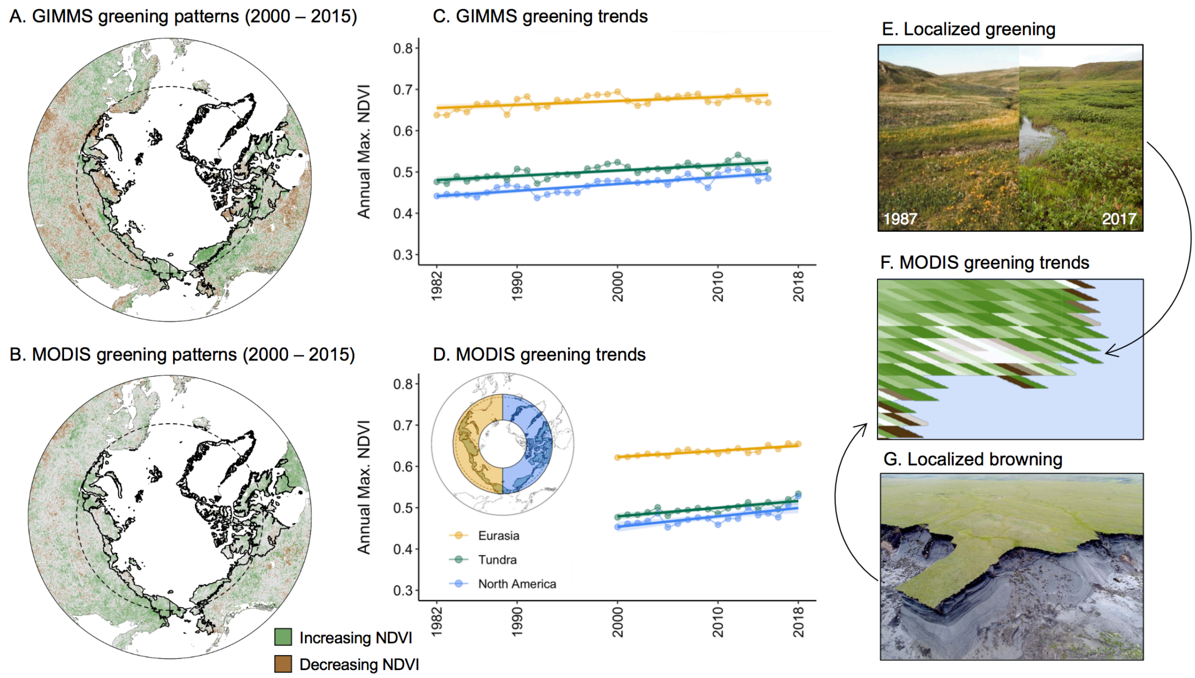

Figure 1. Arctic greening patterns vary across space and time and among satellite datasets likely driven in part by actual *in situ* change and in part by challenges of satellite data interpretation and integration. Trends in maximum NDVI are spatiotemporally variable across the circum-polar North (A and B, data subsetted to temporally overlapping years), and maximum NDVI varies by geographic region (C and D, full time series), expressed by localized greening - for example shrub encroachment (E) - and browning such as this retrogressive thaw slump (G) occurring at the pixel scale on Qikiqtaruk - Herschel Island in the Canadian Arctic (F). NDVI trends were calculated using robust regression (Theil-Sen estimator) in the Google Earth Engine for the GIMMS3gv1 (1982 to 2015) and MODIS MOD13A1v6 (2000 to 2018) NDVI products. Dashed line indicates the Arctic Circle and the black outlined polygon indicates the Arctic tundra region from the Circum-Arctic Vegetation Map (www.geobotany.uaf.edu/cavm/).

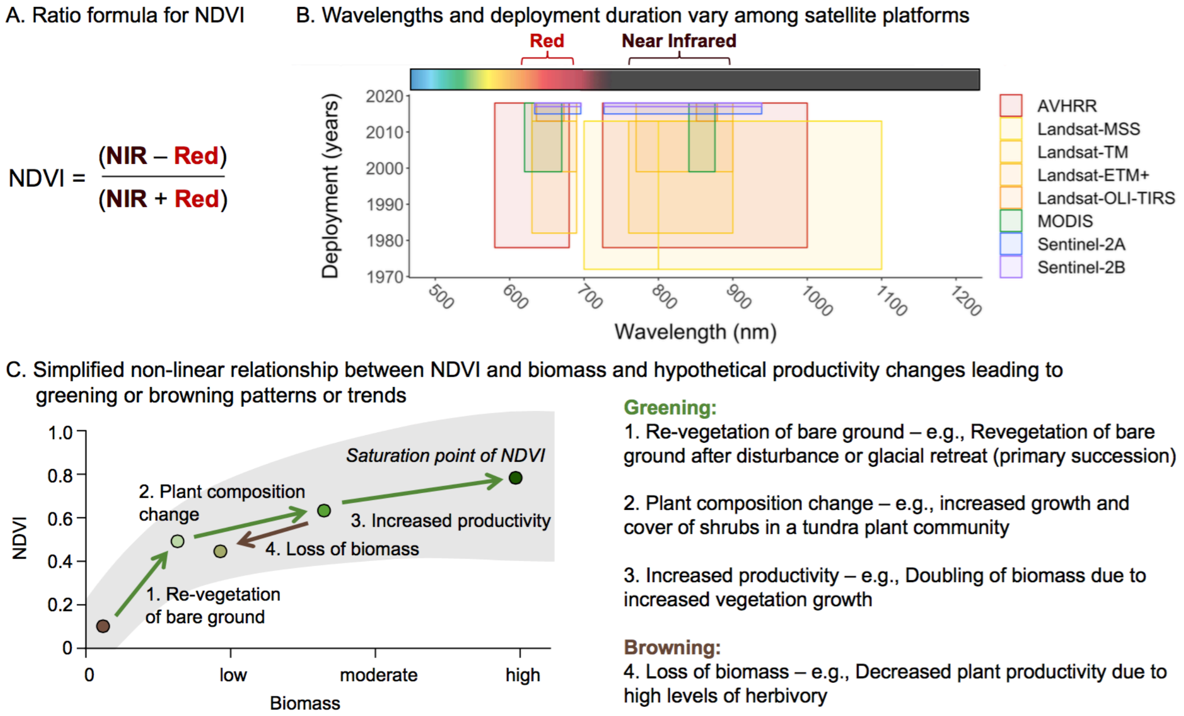

Figure 2. The Normalized Difference Vegetation Index (NDVI is calculated by a simple ratio formula of the red and near infrared bands (A). Different satellite sensors produce bands that are nominally called 'Red' or 'NIR' (among others) but they can span substantially different spectral widths even if they share a similar centre wavelength (B). Time series of high-latitude NDVI greenness from different satellite datasets or changing sensors on the same satellite platform may differentially respond to changes captured in these spectra. Different satellite datasets have been deployed for longer or shorter durations introducing challenges to cross sensor comparisons when also capturing longer-term vegetation change (Fig. 1) even among intercalibrations of the same sensor type on different generations of satellite platforms. The relationship between biomass and NDVI is non-linear (C). Thus, different ecological mechanisms (hypothetical here) could lead to very different magnitudes of greening and browning change depending on the initial and final biomass of the changing vegetation.

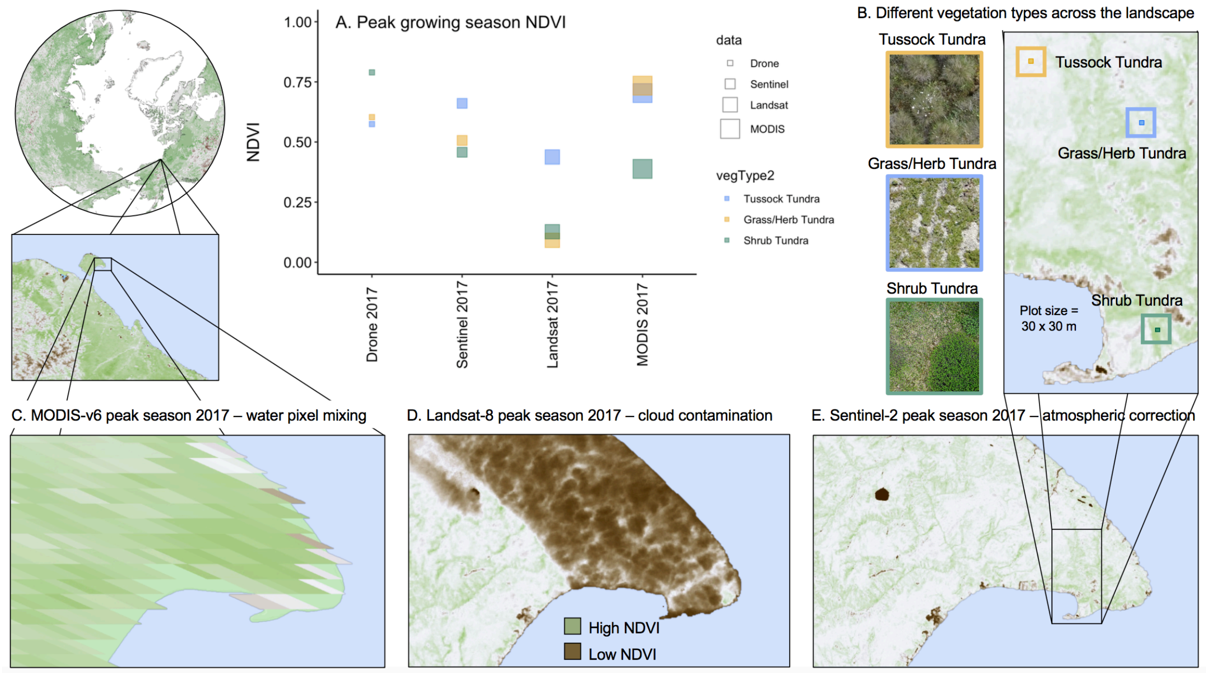

Figure 3. Localized interpretations and comparisons of NDVI ‘greenness’ are challenging to make across data collected across different spatial scales (including grain sizes and extents), landscape contexts, and periods within the growing season (A – E, Table 1). Here, we plot NDVI patterns for peak season (derived from available cloud-free data between 13th July to 4th August in 2017, but note in B that there were no cloud-/fog-free Landsat data available). We purposefully present data with quality and processing issues above to highlight the challenges in isolating scaling factors (e.g., timing of image acquisition and grain size of imagery), data quality (e.g., cloud contamination and lack of atmospheric corrections) from differences in ecological context (e.g., vegetation type) in quantifying NDVI in regional to global studies where data quality issues maybe spatially or temporally variable among locations. On Qikiqtaruk – Herschel Island in the Canadian Arctic during the period of 2017 peak biomass, NDVI values from commonly available satellite data products and drone datasets (A) differed substantially across products and across 30 m x 30 m plots of three different vegetation types (B). Here, factors such as sub-pixel mixing (C), cloud or fog contamination (D), lack of atmospheric correction (E), different plot grain sizes of data in more or less heterogeneous vegetation cover and timing of data collection could have all influenced NDVI values. Data were analysed and extracted for 30 x 30 m plots using the

Google Earth Engine for the MODIS MYD13A1v6 (pixel size = 500 m x 500 m) and Landsat 8 (pixel size = 30 m x 30 m) NDVI product, and the top-of-atmosphere Sentinel-2 NDVI product without atmospheric corrections (pixel size = 10 m x 10 m) NDVI, and Pix4D-processed drone data collected using a radiometrically calibrated four-band multispectral sensor (Sequoia, pixel size = 12 cm x 12 cm) on an FX-61 fixed-wing platform with the High-latitude Drone Ecology Network protocols[128] (arcticdrones.org).

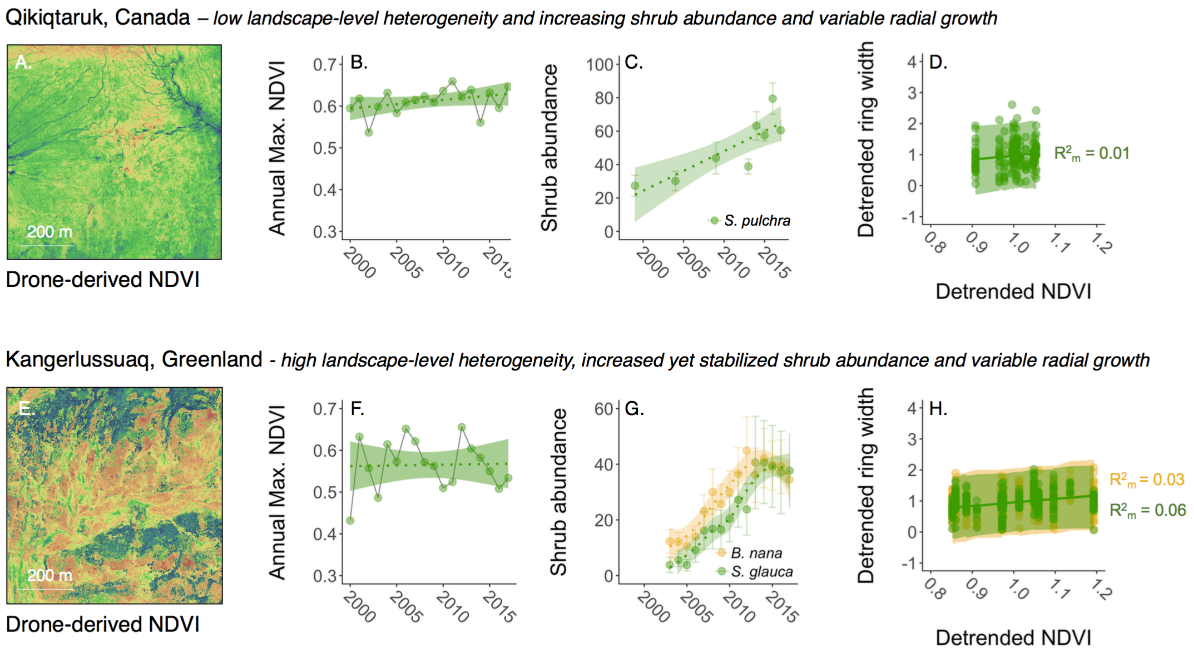

Figure 4. Sub-pixel spatial heterogeneity in greening and browning (A, E) can influence the observed signal at coarser grains (B, F) and may or may not represent *in situ* observations of vegetation change such as increases in shrub abundance (C, G) and interannual variability in shrub growth (D, H, sample sizes: Yukon *Salix pulchra* = 21[76,129], Greenland *Betula nana* = 42[73,130], *Salix glauca* = 32[73,131]). Error bars (C, G) are standard error around mean values of shrub abundance derived from point framing in 12 1-m^2 plots at the Qikiqtaruk site[76,129] and 13 0.25-m^2 plots at the Kangerlussuaq site[132,133]. Models error (D, H) are credible intervals for a Bayesian hierarchical models of the relationship between annual growth rings and NDVI with shrub individual and year as random effects. Detrending is using a spline fit from the dplR package in R. Credible intervals for model slopes overlapped with

zero indicating that the relationships in D and H are not statistically significant. Marginal R^2 values indicate the variance in detrended ring widths explained by detrended NDVI (D, H). Low heterogeneity (i.e. relatively homogenous land cover) sites might be more likely to express clear greening (A) trends versus high-heterogeneity sites (with a variety of land-cover types, each potentially responding differently) that might be more likely to have variable NDVI among years (B). Landscape NDVI patterns (A and F) were measured using a Parrot Sequoia and FX-61 fixed wing platform according to High-latitude Drone Ecology Network protocols in the summer of 2017 (arcticdrones.org) and analysed using the Pix4D software. Coarser-grain NDVI time series (MODIS MOD13A1v6, 500m pixels) were calculated using Google Earth Engine and the Phenex package in R.

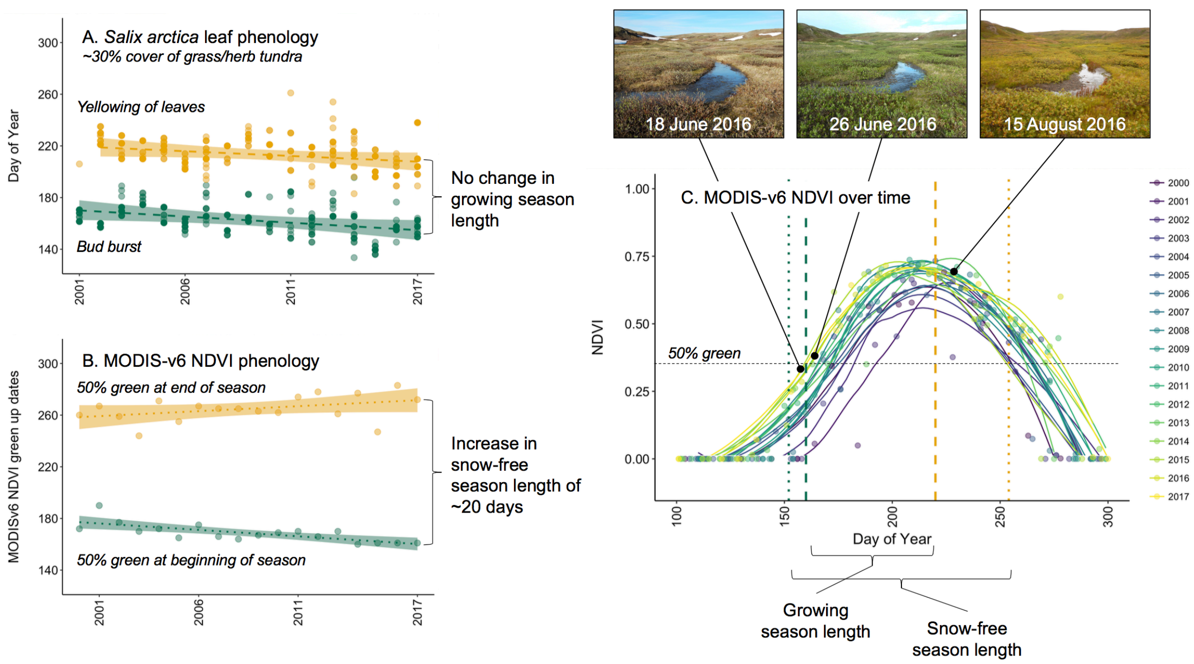

Figure 5. Satellite observed snow-free season length of the land surface (B and C) might not directly correspond to the growing season of plants in tundra ecosystems (A). Plant phenology data are from 20 monitored plots on Qikiqtaruk-Herschel Island for the species *Salix arctica,* which makes up approximately 30% of the cover in the grass- and forb-dominated vegetation type (Fig. 3), indicate that both leaf emergence and senescence have become earlier, resulting in no change in realized growing season length despite substantial

increases in the snow-free period of the land surface[76] (A – C). Plant phenology data are from the Qikiqtaruk Ecological Monitoring program[129] (A), and satellite data are MODIS MOD13A1v6 extracted for the pixel containing the phenology transects with the Google Earth Engine and interpolated and smoothed using the Phenex library in the programming language R (B and C).

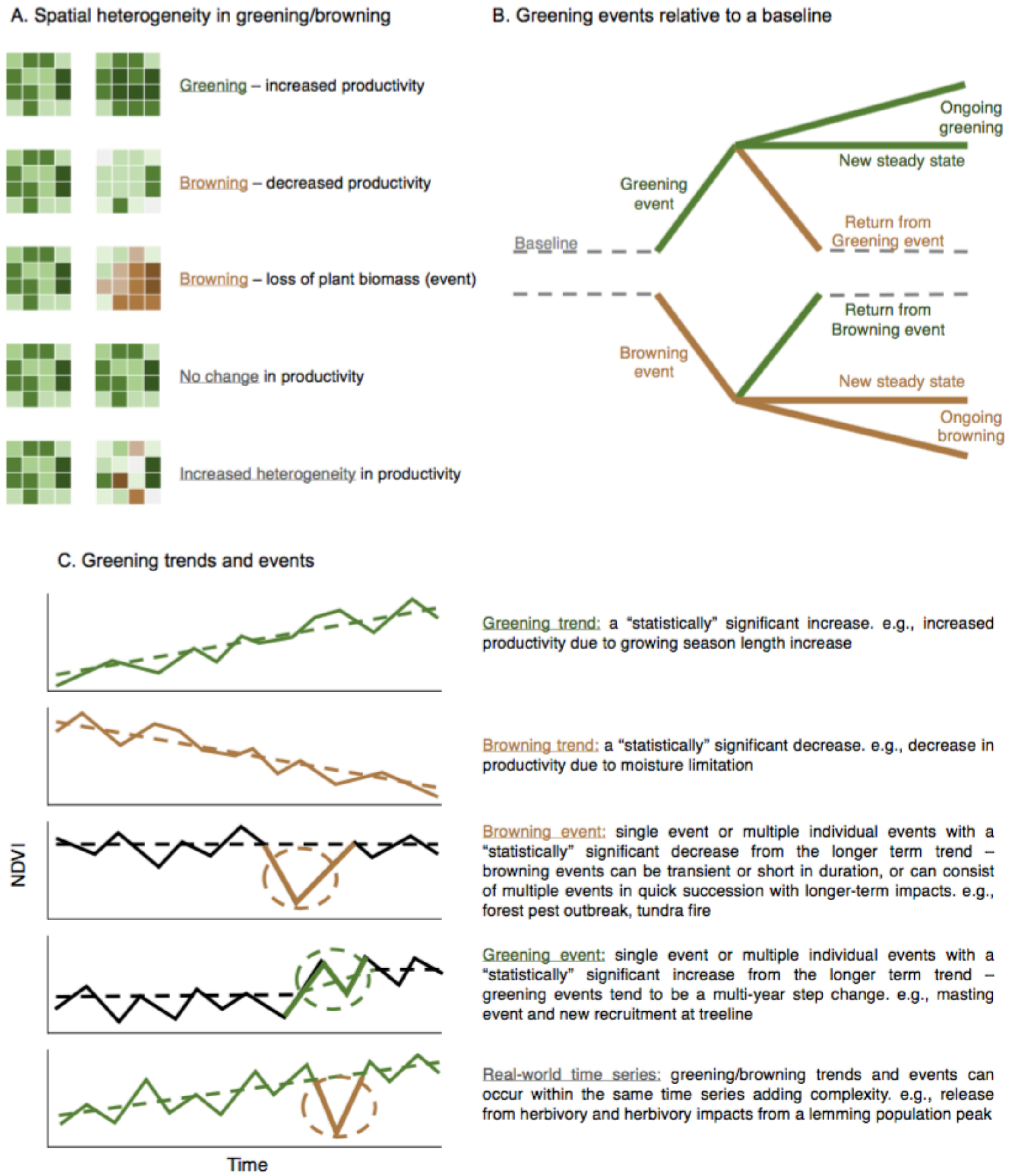

Figure 6. Conceptual diagrams and definitions of greening/browning trends versus greening/browning events. Five examples of local scale (smaller sub-units within a single conceptual 'pixel') changes in plant productivity show how the combination of

greening/browning events/trends within a pixel can be reduced to a higher-level greening/browning pattern as their effects are scaled up (A). The ecological processes that comprise greening and browning trends include a combination of events, such as a pulse of plant recruitment, a dieback of plants due to an extreme winter climate event, herbivore or disease outbreak or other disturbance and the subsequent recovery, or longer-term change such as increasing shrub cover or progression of permafrost disturbances and periglacial processes (B and C). A combination of high-/low-frequency and high-/low-intensity events can result in, for example, a browning trend over time (see also[18]).

Table 1. A variety of factors can influence the magnitude and direction of change in vegetation indices. These effects can be more or less important in coarse-grain imagery and can be particularly problematic at high latitudes. The effects include: 1) radiometric effects - differences among satellite datasets include band widths, atmospheric effects, cloud-screening algorithms, sensor degradation, orbital shift and bidirectional reflectance distribution functions originating from differences in field of view and sun geometries[30,99,134]; 2) spectral mixing - the reflectance of sub-pixel spatial heterogeneity that can influence the overall pixel signal (Fig. 3); and, 3) adjacency effects - the reflectance of surrounding pixels that can influence the signal of a given pixel (Fig. 3).

Factors influencing vegetation indices	Specific effects	Influence on greening patterns and trends
Low sun angle	Radiometric effects	At high latitudes, low sun angles and cloud shadows can have a greater influence on vegetation indices relative to lower latitudes[106]. Low sun angle reduces NDVI, an effect magnified in spring and autumn. Shadows also reduce NDVI and may be difficult to detect in coarse grained imagery[43].
Cloud cover	Radiometric effects, Spectral mixing, Adjacency effects	Thin cloud, fog and smoke can influence imagery, reducing NDVI. Particularly problematic in coastal regions, cloud and fog can vary greatly between image acquisitions[135]. Cloud-screening algorithms differ among satellite datasets (partly as a function of available spectral bands), and partly cloudy or hazy conditions are particularly difficult for screening algorithms to detect consistently across different satellite products. The fogginess of Arctic locations can vary throughout time due to changing sea ice conditions[105] or increasing temperatures[43].
Standing water	Spectral mixing, Adjacency effects	Standing water[102] can influence comparisons of vegetation indices across space and may not be detectable in coarse-grained imagery, despite influencing spectral signatures. NDVI values of water are generally low, however shallow water or standing water intermixed with vegetation or algal growth may not be identified as water by quality filters and may have higher NDVI. Water within a pixel may lead to artificially low NDVI values and can influence estimates of NDVI change over time. This is especially relevant to the Arctic during the spring and summer as snow melts and turns into numerous ephemeral ponds and lakes whose spectral signatures will be mixed with nearby vegetation. Changes in standing water over time associated with changing precipitation, permafrost conditions, and/or warming could drive NDVI signals rather than any changes in the plant biomass[101,102,136,137].
Snow patches	Spectral mixing, Adjacency effects	Sub-pixel sized snow patches[101] will decrease the NDVI for a given tundra area. NDVI values of snow are strongly negative. Earlier snow loss may drive a strong positive trend in NDVI.

		Longer persistence of snow on the landscape in patches may not be filtered by quality algorithms, but still lead to lower NDVI values.
Soil moisture	Spectral mixing	Soil moisture can influence the reflectance of vegetated tundra surfaces[103,138,139]. NDVI values are sensitive to soil moisture, which may or may not covary with vegetation changes. Furthermore, NDVI is relatively insensitive to changes in very sparsely vegetated (e.g., the High Arctic[140]) and very densely vegetated (e.g., forest or shrubland[141]) environments.
Short growing season	Timing of image acquisition	Trends in NDVI metrics and growing season length can be influenced by data acquisition and not only vegetation change. To compare spatial patterns in vegetation indices among sites, images are required from the same time within the growing season and the same time points within the day[137]. However, the short growing seasons at high latitudes make image acquisition a particularly important issue in these settings. Different datasets have different temporal frequencies for overpasses thus influencing comparisons. Growing season length decreases with higher latitudes, thus the impact of missing data is of a greater magnitude as latitude increases.
Rapid plant phenology	Chosen phenometric	The specific metrics used to quantify greening or browning will influence the resulting patterns observed[108]. Combining datasets with different spatial and temporal resolutions and/or using different phenometrics can limit comparisons when methodological signals overwhelm vegetation signals (Fig. 3). Variation in phenology metrics due to curve-fitting methods can exceed variation in measured phenology signals. Thus, using the same phenological functions across large geographic and ecological gradients, such as across the high latitudes, may introduce biases and/or errors.

Author Contributions

IHM-S and JTK conducted the analyses and wrote the manuscript with contributions from all authors. GKP, JWB and HE contributed substantially to early versions of the manuscript. IHM-S, JTK, JJA, AMC, CJ, SA-B, HJDT and ESP collected drone and *in situ* data. This paper results from two collaborations: the sTundra working group led by IHM-S, SCE and ADB and the 'Event Drivers of Arctic Browning Workshop' at the University of Sheffield led by GKP.

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Data and code availability

Data come from publicly available remote sensing and ecological datasets including: MODIS (modis.gsfc.nasa.gov/), GIMMS 3g.v1 (nex.nasa.gov/nex/projects/1349/), the High Latitude Drone Ecology Network (arcticdrones.org/), shrub abundance[129,132], annual growth ring[129–131] and phenology datasets[129]. Code is available in a GitHub repository (github.com/ShrubHub/GreeningHub).

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