Title: Drone data reveal heterogeneity in tundra greenness and phenology not captured by satellites

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Abstract:

Data across scales are required to monitor ecosystem responses to rapid warming in the Arctic and to interpret tundra greening trends. Here, we tested the correspondence among satellite- and drone-derived seasonal change in tundra greenness to identify optimal spatial scales for vegetation monitoring on Qikiqtaruk - Herschel Island in the Yukon Territory, Canada. Combining time-series of the Normalised Difference Vegetation Index (NDVI) from ultra-fine-grain multispectral drone imagery and satellite data (Sentinel-2 and MODIS) with ground-based observations for two growing seasons (2016 and 2017), we found high cross-dataset correspondence in peak season greenness (Spearman's $\rho > 0.77$) and cross-season greenness changes (drone-sentinel $R^2 = 0.69$) for eight one-hectare plots, with drones capturing lower NDVI values relative to Sentinel-2 satellites. We identified a plateau in the spatial variation of tundra greenness at distances of around half a metre in the plots, suggesting that these grain sizes are optimal for monitoring such variation in the two most common vegetation types on the island. We further observed a notable loss of seasonal variation in the spatial heterogeneity of landscape greenness (46.2 - 63.9%) when aggregating from ultra-fine-grain drone pixels (approx. 0.05 m) to the size of medium-grain satellite pixels (10 – 30 m). Finally, seasonal changes in drone-derived greenness were highly correlated with measurements of leaf-growth for focal deciduous species in the ground-validation plots (mean Spearman's $\rho = 0.68$). These findings indicate that multispectral drone measurements can capture temporal plant growth dynamics across tundra landscapes. Overall, our results demonstrate that novel technologies such as drone platforms and compact multispectral sensors allow us to study ecological systems at previously inaccessible scales and fill gaps in our understanding of tundra ecosystem processes. Capturing fine-scale variation across tundra landscapes will improve predictions of the ecological impacts and climate feedbacks of environmental change in the Arctic.

Keywords: Arctic tundra, vegetation monitoring, landscape phenology, satellite, drones, UAV and RPAS, NDVI, scale

Introduction

Identifying the scales at which ecological processes operate is a fundamental, yet often neglected element of ecological research (1–3). Cross-scale ecological information can inform our understanding of the causes and consequences of global change (2). In tundra ecosystems, vegetation responses triggered by rapid Arctic warming could influence ecosystem functions through altered carbon and nutrient cycles with potential feedbacks to the global climate system (4–8). Yet, challenging logistics have limited the extent of field-based observations in Arctic ecosystems (9–11). The grain sizes of global-extent satellite products (tens of meters to kilometres) are too coarse to capture the fine-scale dynamics of tundra plants (12–14) and to link vegetation change to key ecosystem functions (13). Thus by bridging this “scale-gap”, we can transform our understanding of pan-Arctic tundra vegetation change and associated global-scale climate feedbacks.

Satellites show greening of the tundra

Satellite observations indicate a ‘greening’ of tundra ecosystems (13,15–20) and shifts in growing season phenology over recent decades (13,21–24). Observations of increasing tundra greenness are often reported from surface-reflectance-derived Normalised Difference Vegetation Index (NDVI) (13,16,25,26). Satellite-observed tundra greening has been concurrent with ground-based observations of vegetation change in Arctic ecosystems (27) including increasing shrub cover (28–31) and taller community level plant height (32), as well as earlier leaf emergence and flowering at some (33–36), but not all tundra sites (37–39). However, mismatches between ground and satellite-based observations suggest the potential for an observational scale gap (13).

Arctic vegetation change and phenology have been linked to warming

Satellite-observed Arctic greening trends have been linked directly to warming air temperatures (13,19,20,40–46) and indirectly to sea-ice declines (17,47–51). Ground-based observations of tundra vegetation change correspond with warming (27,32,52) but do not always co-occur with satellite greening trends in the regions around the ecological monitoring sites (13,53). While satellite-based phenology observations from the Arctic have been mainly linked to temperature (22,54,55), *in situ* phenology in the tundra has been shown to be influenced by a suite of interacting factors including, but not limited to: snowmelt, temperature, day length, and the proximal influences of sea-ice on localised climate affect (34–36,38,56,57). Thus, ecological studies indicate greater complexity of drivers that analyses of satellite-derived greening trends to date.

Inconsistencies amongst satellite platforms and heterogenous greening trends

Greening trends and phenology measures derived from different satellite platforms do not always correspond (13,18) and greening trends vary at global (18), continental (42,58–60) and regional scales (46–48,61–64). Many areas of the Arctic show no trends in NDVI, with only around 20% of the Arctic spectrally greening and around 1 - 4% of the Arctic spectrally browning (13,62,65,66). Recent analyses suggest a slowdown of the Arctic-wide spectral greening trend over the past decade (43,67). Furthermore, despite NDVI being related to the photosynthetically active biomass in the tundra (14,68–70), geophysical, environmental and ecological factors, in addition to the non-linearity of NDVI-biomass relationships, complicate the interpretation of satellite-derived NDVI time-series at high-latitudes (13,71). The growing complexity highlighted in Arctic greening trends has led to repeated calls for ground validation of satellite observations (11,13,18,59,60,66,72,73).

The scale discrepancy problem in Arctic greening

A major problem in linking satellite-derived trends of tundra spectral greenness and phenology to *in situ* observations of ecological processes is the discrepancy in observational scales (13,29,61,72,74). Satellite datasets with long-term records are limited by their moderate- to coarse-grain sizes, ranging from 30 m (Landsat) to 250 m (MODIS) and 8 km (AVHRR-GIMMS3g). *In situ* ecological monitoring in the Arctic is logistically challenging and therefore restricted in extent to a limited number of sites and often metre-squared plots (10,75). Only a few studies have linked on-the-ground vegetation or phenology change to satellite trends in NDVI in Arctic tundra (13,14,47,48,53,76–78). However, drones equipped with compact sensors now allow for the collection of ultra-fine-grain multispectral imagery at landscape extents that can potentially bridge the scale-gap between satellite and ground-based observations (14,79–82).

Novel drone data to study variation in greenness

Here, we set out to test whether drones can be used to identify the key ecological scales for studying tundra greenness on Qikiqtaruk by bridging the scale gap between satellite and *in situ* data. First, we tested whether satellite- and drone-derived measures of mean landscape-scale greenness (NDVI) agree across two growing seasons while controlling for the potentially confounding effects of topography and land cover. Second, we identified the key spatial scales for ecological variation in landscape greenness within the two most common vegetation types at our study site using variograms. Third, we tested how the magnitude of seasonal variation in tundra greenness scales across grain sizes from fine-resolution drone imagery to medium-grain satellite imagery. Finally, we assessed whether drone-derived NDVI corresponds with on-the-ground measures of within growing season change in plant growth frequently measured by long-term field-based monitoring networks. Thus, in our analysis we validated satellite-derived landscape estimates of vegetation greenness with ultra-fine-grain drone data and described spatial and temporal variation in tundra productivity at grain sizes and extents that were not previously accessible.

Methods

Site description: Qikiqtaruk - Herschel Island

Qikiqtaruk (69.57 N, 138.91 W) is located in the Beaufort Sea along the coastline of the North Slope of the Yukon Territory, Canada. The vegetation is characteristic moist acidic shrub tundra (83) found in the Western Arctic regions of North America that has experienced strong spectral greening in recent decades (13). The two most common plant communities on the island are the tussock sedge ("Herschel") and Dryas-vetch ("Komakuk") vegetation types (84,85). We established four study areas on the east end of the island, each with two co-located one-hectare plots in the two key vegetation cover types (Figure 1, Table S1). We selected plots with homogenous terrain and land cover to represent the two key vegetation types and to control for the potentially confounding effects of terrain and cover heterogeneity.

Multispectral drone time-series

We analysed 62 drone surveys across four research areas with one-hectare plots in the two vegetation types at the site (Table S3). We collected multispectral drone imagery using Parrot Sequoia (Paris, France) compact multispectral sensors mounted on multi-rotor drone platforms in June to August in 2016 and 2017. We used three different drone platforms: a Tarot 680 Pro hexacopter with camera sensor stabilisation in 2016, and a 3DR Iris+ and a DJI Phantom 4 Pro without sensor stabilisation in 2017. Surveys were flown in a lawn-mower flight pattern at an altitude of ca. 50 m, giving ground-sampling distances of 0.04 m to 0.06 m. Images were acquired with 75% front- and side-lap as close as possible to solar noon (mean absolute difference to solar noon 2.16 h, maximum 6-7 h). See Table S3 for further details.

We processed the Sequoia imagery using Pix4D Mapper v4.0.21 (Lausanne, Switzerland) with the *agMultispectral* template and the 'merge map tiles' option set to true to generate co-registered single-band surface reflectance maps. Radiometric calibration was carried out in Pix4D Mapper using pre- or post-flight imagery of calibrated reflectance panels; in 2016 we used a MicaSense (Seattle, USA) panel and in 2017 a SphereOptics (Herrsching, Germany) Zenith Lite panel. We measured panel reflectance pre- and post- season and used the mean values for radiometric calibration. We also calibrated for sensor properties and sun irradiance measured by the incident light sensor. We used four to six ground control points per survey to geolocate the imagery in Pix4D Mapper with an estimated accuracy of 1-2 pixels between bands and 2-6 pixels between surveys (81). We calculated the Sequoia NDVI as the normalised difference between the near-infrared (770 nm – 810 nm) and red (640 nm – 680 nm) bands of sensor.

Satellite time-series

We obtained MODIS NDVI values for the time period between May and September 2016 and 2017 for all 250 m MODIS pixels that contained the survey plots. NDVI values were retrieved from the 16-day MOD13Q1 v6 Terra product (86) using the Google Earth Engine (87). We discarded all values with a 'Summary QA' score of -1 (no data) or 3 (cloudy). Table S4 lists the resulting MODIS-pixel-date pairs. The MODIS NDVI is calculated as the normalised difference between bands 1 (841 nm – 876 nm) and band 2 (620 nm – 670 nm).

For the Sentinel-2 time-series, we gathered all Sentinel-2 MSI L1C scenes containing the tile covering Qikiqtaruk (T07WET) that were available on the Copernicus Open Access Hub (https://scihub.copernicus.eu/) for the same time period as the MODIS pixels. We processed all scenes to L2A using Sen2Cor 2.4.0 (88), retained all bands with 10 m resolution (2-4 & 8), applied the cloud mask and generated a true-colour image. We inspected all scenes visually and discarded all imagery with cloud contamination over the study area (78% of scenes for 2016 and 74% of scenes for 2017). The resulting set contained nine cloud-free Sentinel-2 L2A scenes of the study area from 2016 and fifteen scenes from 2017 (Table S5). Finally, the Sentinel NDVI was calculated as the normalised difference between band 8 (784.5 nm - 899.5 nm) and band 4 (650 nm - 680 nm).

Ground-based plant phenology measurements

We carried out ground-based phenology monitoring in eight 2 m x 2 m plots (Table S2), one adjacent to each one-hectare plot (mean distance = 23 m, max distance = 52 m). Within these plots we monitored six individual plants from the most common species: *E. vaginatum*, *D. integrifolia*, *S. pulchra* and *A. latifolia* in tussock sedge tundra; *D. integrifolia*, *S. arctica* and *A. latifolia* in Dryas-vetch tundra. We measured the length of the longest leaf on each individual on the survey date to the nearest millimetre. This approach is widely used in field-based phenology monitoring protocols (89), and will allow for NDVI to be directly related to phenological changes in plant traits. The majority of ground-based phenology surveys were carried out on the same day as the drone surveys (mean difference = 0.3 days, maximum difference = 3 days, Table S6).

Cross-sensor correspondence

To test cross-sensor correspondence, we first plotted the mean NDVI for all plots, time-points and sensors available (MODIS = single pixel) across both growing seasons. We then calculated the mean difference and Spearman's rank correlation of the peak-season NDVI for 2017 amongst the sensors (mean 20 July - 10 August). We matched all drone and Sentinel-2 scenes that were less than two days apart, resampled the drone bands to the Sentinel-2 grid, calculated the NDVI and tested the predictive relationship between the resampled drone and sentinel NDVI pixel-pairs for a random sub sample (10% of total, n = 700) with Bayesian linear models (Table S9 and S10) from the MCMCglmm v.2.29 package (Hadfield 2010).

Spatial autocorrelation

To assess the spatial autocorrelation of variation in tundra greenness within the eight plots, we sampled variograms and fitted variogram models using the gstat v. 2.0-5 package (Pebesma 2004, Gräler et al 2016). All variograms were sampled with a bin width of 0.15 m from 0 to 15 m and a bin width of 3 m from 0 to 45 m.

Grain size and phenology

We tested the influence of grain-size on observations of tundra greenness phenology by fitting simplified growing season curves to the raster stacks for each plot and season. We first resampled the drone bands for all time-points to grids with grain sizes of 0.5, 1, 5, 10, 20 and 33.33 m. We then calculated the NDVI and fitted simple quadratic models to each pixel in the growing season stacks (y = ax2 + bx + c, where x is the day of year and y the pixel NDVI, a the quadratic coefficient, b the linear coefficient and c the constant term). We found a strong negative correlation between the quadratic and linear coefficients of the models (Figure S5), we selected only the quadratic coefficient for further analysis.

Ground validation

To test the correspondence between our ground-based phenology measurements and the drone observations, we derived time-series of the mean longest leaf length and greenness for each 2 m x 2 m ground-based monitoring plot. For each drone survey, we calculated the mean-NDVI of the 2 m x 2 m monitoring plot and matched this with the mean longest leaf length values derived from the corresponding ground-based surveys (Table S6). We then calculated the Spearman's rank correlation between mean-NDVI and mean longest feaf length for each plot and season.

Statistical analyses

We conducted statistical analyses using R v. 3.6.0 (90). We used the ‘resample’ function of the raster package in R for resampling from finer to coarser resolutions (91). See extended methods for further information.

Results

Landscape greenness corresponded among sensors

Landscape greenness corresponded among drone, Sentinel-2 and MODIS across both the 2016 and 2017 growing seasons. Growing season curves of the plot mean NDVI were similar (Figure 1) and peak-season plot mean NDVI values for 2017 were highly correlated across sensors (Spearman’s $\rho > 0.77$, Table S7). However, we observed an offset between drone and satellite plot-mean NDVI of around 0.08 absolute NDVI that was consistent for both MODIS and Sentinel platforms (Table S8). Resampled 10 m drone pixels and the corresponding spatially co-located Sentinel-2 pixels were highly correlated (marginal $R^2 = 0.69$, see Figure 2 and Table S9). We found that vegetation type, the specific Sentinel platform (Sentinel-2A / Sentinel-2B), and the time-difference between Sentinel scene and drone data acquisition influenced the relationship between Sentinel-2 pixel NDVI and drone-derived NDVI (marginal $R^2 = 0.87$, Table S10).

Spatial variation in landscape greenness peaked at approx. 0.5 m

We observed a peak in spatial variation in the NDVI values of pixel pairs for distances below 0.5 meter (mean range 0.46 m) during the peak-season of 2017 (26-28 July) and little additional spatial variation was found between pixel pairs for distances of up to 45 m thereafter (Figure 3). This pattern was consistent across vegetation types in seven out of our eight plots (Figure 3, S2 and S3). The only exception is the Dryas-vetch plot in Area 3, which showed the same patterns for distance below 10 m, but thereafter spatial variation steadily increased (Figure S3).

Seasonal-variation was lost when aggregating to medium grain sizes

We observed a notable loss in the amount of seasonal variation in tundra greenness when aggregating grain size from ultra-fine-grain drone to medium-grain satellite data. The loss was particularly pronounced at grain-sizes above 10 m – the grain size of Sentinel-2 MSI pixels (46.2 - 63.9%) (Figure 4). The variation in the quadratic coefficient of the simple growing season curves (Figure 4b and S6) decayed logarithmically with grain size (Figure 4a), while no change occurred in the mean tendency of the coefficient (Figure S4). The quadratic and linear coefficients of the growing season curves were strongly correlated (Spearman’s ρ = -0.999), thus the same pattern holds true for the linear component of the curve fit (Figure S5).

Drone-derived spectral greenness correlated well with leaf measurements

Drone-derived spectral greenness correlated well (mean ρ = 0.66 - 0.71) with ground-based measurements of cross-season phenology for graminoids and deciduous plants (Figure 5). The mean Spearman’s correlation coefficient of the measured mean leaf length and the mean NDVI values in the ground-based phenology plots was 0.68 across all species and time-series (Table S11 and Figure 5a). The graminoids and deciduous shrub species followed this mean tendency well across all time-series, while the partially-evergreen *D. integrifolia* showed mixed responses between plots and years (mean ρ = 0.22, Figure 5a). The drone-based greenness time-series of the 2 m x 2 m ground-phenology plots highlight fine-scale differences in phenology such as the continuous greening of tussocks that was visible at the tussock sedge tundra plot in Area 2 (Figure 5c).

Discussion

Our analysis of cross-scale time-series of landscape greenness on Qikiqtaruk highlights four main findings: 1) Measures of mean tendency in landscape greenness were consistent, but slightly offset with drones capturing lower NDVI values than Sentinel-2 and MODIS satellites (Figures 1 and 2). 2) The majority of variation in landscape greenness was contained at scales of around half-a-metre, and thus not captured by medium-grain satellites such as Sentinel-2 (Figure 3). 3) When aggregating growing season curves from ultra-fine-grain drone to medium-grain satellite pixel sizes, a notable amount (46.2 - 63.9%) of variation in greeness phenology was lost (Figure 4). 4) Drone-based measures of landscape greenness correlated well with ground-based measurements of leaf length (Figure 5). Taken together, our results highlight that drone platforms and compact multispectral sensors can capture key ecological processes such as vegetation phenology and bridge the existing scale gap between satellite and ground-based monitoring in tundra ecosystems.

Our study indicates cross-platform agreement, yet a positive offset, in mean landscape greenness. The correspondence between drone and satellite-derived NDVI has yet to be tested across Arctic sites (13,14). Some studies of natural or agricultural systems have reported similar or higher levels of agreement between multispectral reflectance products from drones and satellites (14,92,93), while others reported mixed or poor agreement (94–96). As in Franzini et al. (2019), we observed a positive offset between drone and satellite NDVI (Figure 2a and Table S8) that warrants further investigation. Possible ecological interpretations of this offset are that drone data better capture low NDVI values. Possible technical explanations for this offset include: differences in viewing geometries between drones (highly variable) and satellites (relatively consistent), distinct sensor properties of drone and satellite sensors, influences of the atmosphere between the sensor and the land surface and a variety of other factors influencing the estimated reflectance. Siewert and Olofson (2020) do not report this offset in the more heterogenous tundra of Arctic Sweden, raising the possibility that within-landscape variation in land cover or topography may influence correspondence between vegetation greenness across scales. The homogeneity of the landscape within our survey plots likely contributes to the strong correlation between drone- and satellite-derived NDVI that we have observed (13). Additional research is needed to evaluate how other scale-varying landscape characteristics like land cover (including non-vegetative surfaces like water, rocks, snow, etc.) and topography affect drone and satellite correspondence across the diverse and structurally complex tundra biome.

In our study, ecological information was lost when upscaling from ultra-fine-grain (~ 0.05 m) drone to moderate grain (~ 10 – 30m) satellite resolutions. Even the most recent generation of freely-available multispectral satellite products can be limited in their ability to capture fine-grain ecological processes of tundra vegetation change (13). Information transfer during upscaling leads to the loss of more information in tundra ecosystems compared to other biomes (14,97) as land cover and vegetation structure are fragmented at finer scales (98). However, exactly how spatial aggregation influences the loss in observed ecological variability across the diversity of Arctic landscapes remains poorly quantified (11,13). Yet, this variability is critical to understanding climate-driven changes in vegetation phenology (35,36,99), plant-pollinator interactions (100), and trophic interactions (101). With drone-based monitoring, we observed a decrease in magnitude of the spatial variability in landscape-level phenology throughout the growing season (Figures 4 and Figure S2), while aggregation to moderate satellite grains obscured both the magnitude and timing of phenological heterogeneity (Figures 4 and S6). Thus, time-series of fine-grain remotely-sensed observations will be critical for answering key research questions about tundra ecosystem functioning in a warming Arctic (102).

Our results indicate that drone-based greenness time-series captured variation in plot-level leaf-growth of deciduous tundra plant species. We demonstrate how drones can be used to measure variation in tundra plant phenology of metre-scale patches at landscape extents. Drones have been successfully used to monitor phenology of individual plants (trees) in temperate forest ecosystems (103–105), and our study indicates that individual plant-level phenology monitoring of sub-decimeter variability from drones could also be carried out in tundra ecosystems. Future studies that quantify plant growth or phenology events such as leaf emergence and flowering across the landscape could provide key information on resource availability for plant-consumer interactions (100,101). Our findings also highlight known limitations of NDVI to track phenology in evergreens or other non-deciduous taxa (*D. integrifolia*, Figure 5), suggesting that tests of alternative vegetation index - plant growth relationships (105) are needed to capture cross-season variation in tundra evergreen and moss species. Combining drone-based time-series with observations from phenocams, satellite and ground-based study plots has the potential to revolutionise our understanding of landscape-scale phenology (13) by moving beyond the previously small samples of individuals monitored in the Arctic tundra (36,37,39,106).

Our study highlights limitations and challenges associated with the collection of multispectral drone time-series in Arctic ecosystems. Recent studies have discussed challenges associated with the use of compact multispectral drone sensors including radiometric consistency and repeatability (81,107,108). Due to logistic constraints, we were not able to always conduct surveys under optimal conditions due to sun angle or cloud cover nor as frequently as planned due to wind or precipitation (Table S3), which likely introduced bias and/or noise into our drone data (e.g., Figure 4b). Access limitations meant that we could not capture spring and autumn on Qikiqtaruk. As an early-generation multispectral drone sensor, the Parrot Sequoia was tailored for deriving the NDVI, which despite being the legacy workhorse of tundra remote-sensing has limitations (11,13). In particular, NDVI can be confounded by moisture and surface water (11,13,73,109), complicating interpretation in wet tundra and particularly in fine-grain size data. However, the rapid technological development of drones and sensors, as well as further consolidation and standardisation of methods (110), will allow for pan-Arctic syntheses of fine-grain data to resolve the uncertainty and complexity of Arctic greening patterns trends (13,14,81) (see also the High Latitude Drone Ecology Network - https://arcticdrones.org/).

Our study demonstrates that drones can fill the scale-gap between satellite and field studies in the observation of terrestrial Arctic vegetation change (13,111). Rather than investigating and explaining patterns at scales pre-defined by satellite datasets or field-based networks, researchers can use drones to identify scale-domains that are most closely associated with ecological processes of interest. Field ecologists can now use scaling theory provided by the remote sensing community (74,112–115) at scales and temporal intervals that will allow for hypothesis testing about what mechanisms are driving landscape-level ecological change. Drone imagery will also allow the remote sensing community to track the effects of sub-pixel heterogeneity on satellite products down to the grain of individual plants and communities (14) that have been long studied by field-based monitoring networks, like the International Tundra Experiment (75). Only by improving our understanding of how ecologically important information is captured across grain sizes can we reduce uncertainties in the medium- and coarse-grain satellite observation that feed into Earth system models and shape their predictions (4,8). Fine-scale remote sensing from drones and aircraft provides key tools for disentangling the drivers behind the greening of the Arctic (13,14,79,102).

Conclusions

Novel remote-sensing technologies such as drones now allow us to study ecological variation in landscapes continuously across scales. Fine-grain ecological observation is of particular importance where variation in plant growth happens at very small spatial scales such as in tundra ecosystems (13,71). Our finding of a peak in spatial variation found at distances of ~0.5 m in the plots on Qikiqtaruk shows the grain size at which phenological information within the plant communities is best captured at this site. We demonstrate that key ecological information is lost when observing the tundra at even decimeter or coarser scales, such as those of medium grain satellites (~ 10 – 30m). Despite the methodological challenges of collecting multispectral drone imagery in remote environments (81), our time-series of vegetation greenness correlated well with ground-based measurements of leaf growth in the validation plots. Drones now enable cross-scale studies that fill scale gaps between satellite and ground-based observations facilitating the identification of key drivers of vegetation change to inform projections of climate change impacts and feedbacks in the tundra biome.

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Author Contributions

JJA and IMS conceived the study with input from JTK and AMC. JJA carried out data processing and analysis. JJA and IMS led the drone and ground-validation field work in

2016. AMC led the drone field surveys with input from JTK and GD led the ground-validation for 2017 with input from JTK. JJA, IMS and JTK wrote the manuscript with input from AMC and GD. IMS supervised and acquired funding for the research.

Data availability

All processed drone and Sentinel imagery is available via a data repository on Zenodo (embargoed till publication of this manuscript).
Should the reviewers wish to access the data prior publication, a mirror of the Zenodo repository can be accessed via this confidential link:
[redacted]

All code used to conduct the analysis, produce figures ands as well as summary data outputs and MODIS pixel values can be found on this GitHub repository (already openly available):
https://github.com/jakobjassmann/qhi_phen_ts

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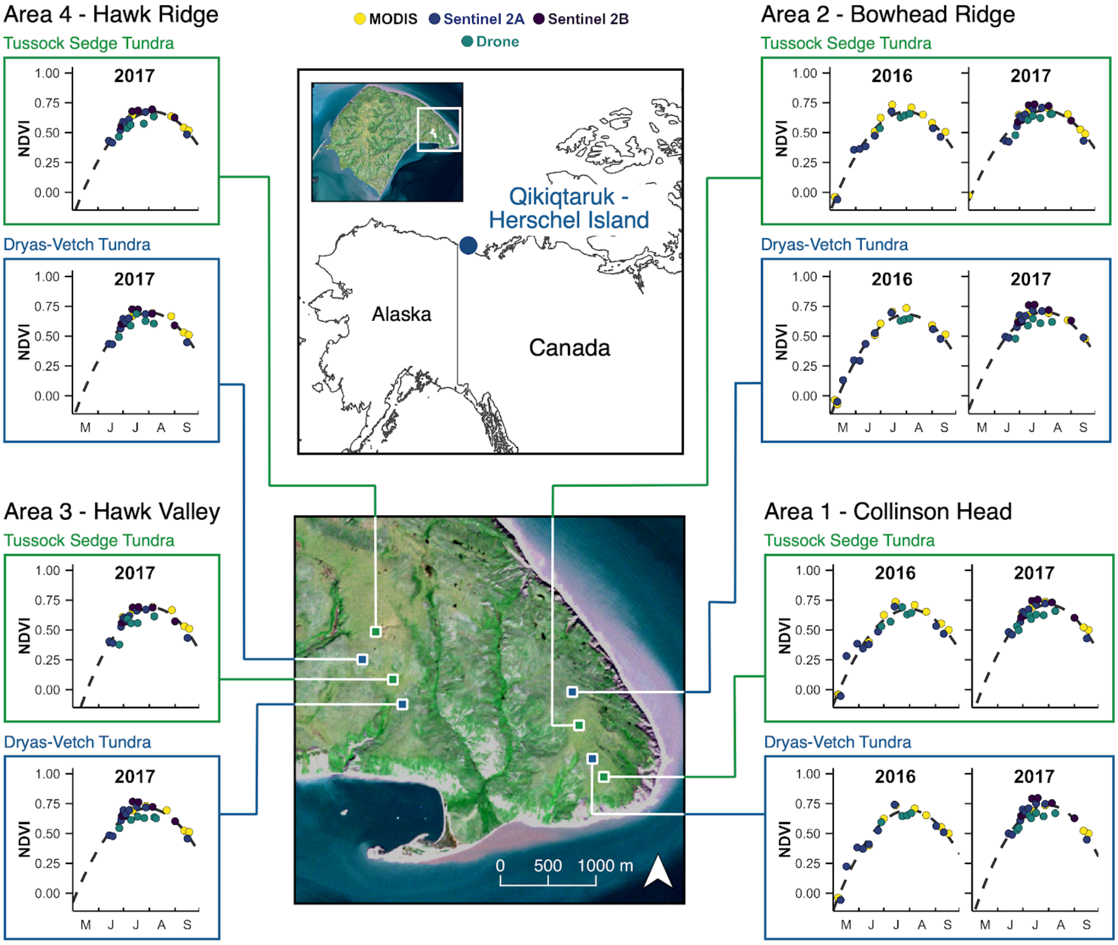

Figure 1: Drone-data captured the temporal variation in satellite data across vegetation communities, areas and years. This figure showcases variation in landscape greenness (NDVI) across the one-hectare sampling plots on Qikiqtaruk and outlines cross-season agreement amongst drone, Sentinel-2 and MODIS sensors. Map sources: North America (116,117) and Qikiqtaruk, Copernicus Sentinel-2 true colour image July 2017.

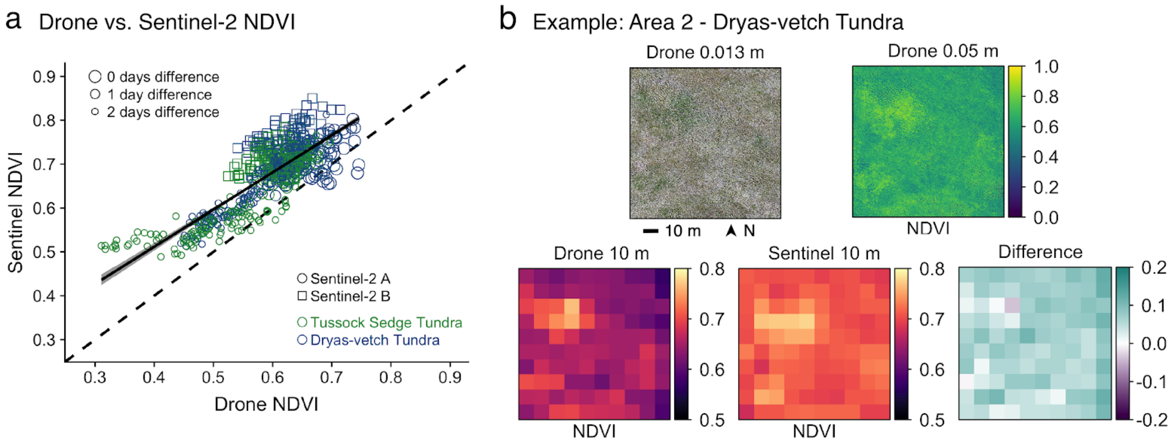

Figure 2: Drone-data better captured spatial heterogeneity in NDVI relative to Sentinel-2 MSI. a) Pixel by pixel correlations between 10 m aggregated drone NDVI and native 10 m Sentinel-2 NDVI for a random sample of pixels (10% of total pixels, n = 700) across all drone-sentinel image pairs for the 2017 growing season. b) Example visualisations from the Dryas-vetch tundra at Area 2 - Bowhead Ridge showing ultra-fine-grain 0.013 m true colour RGB imagery, 0.05 m native-scale drone NDVI, 10 m resampled drone NDVI, 10 m native Sentinel-2 NDVI and the absolute difference between resampled drone and Sentinel-2 NDVI.

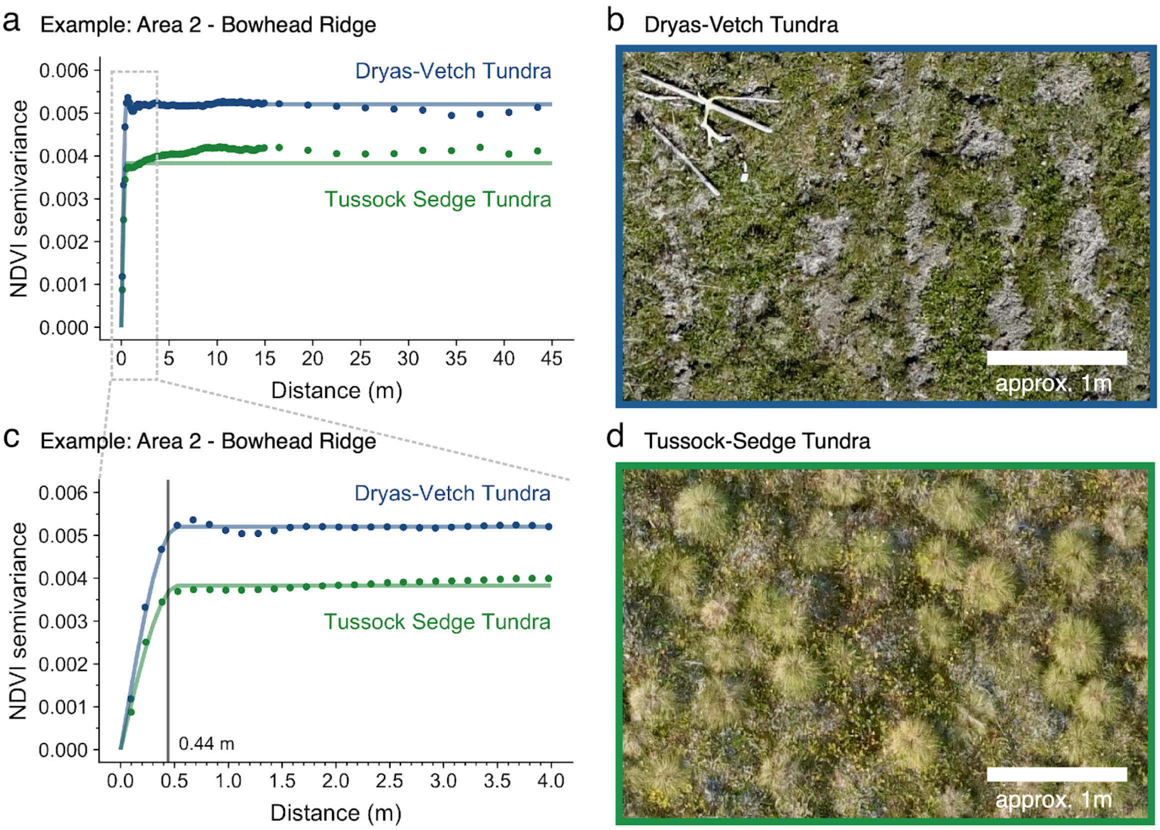

Figure 3: Spatial variation of vegetation greenness peaked at distances of ~0.5 m in both studied vegetation types, with little or no increase in the spatial dependence of greenness at distances above ~0.5 m. Figure shows example variograms. Overall spatial variation in greenness is higher in the Dryas-Vetch Tundra when compared to the Tussock-Sedge Tundra (a and c). Left panels: variograms for the Dryas-vetch and tussock sedge tundra plots in Area 2 for distances up to 5 m (a) and 45 m (c) at peak season in 2017. The dark grey line in (c) indicates the mean range estimated from the variogram models of both vegetation types from Areas 1, 2, and 4 during peak-season (26 and 28 July) in 2017 (see also Figure S1). Right panels: Dryas-vetch tundra with bare ground patches caused by cryoturbation and solifluction (c) and tussocks sedge tundra with distinctive patterns of tussocks interspersed by patches of willows and herbs (d).

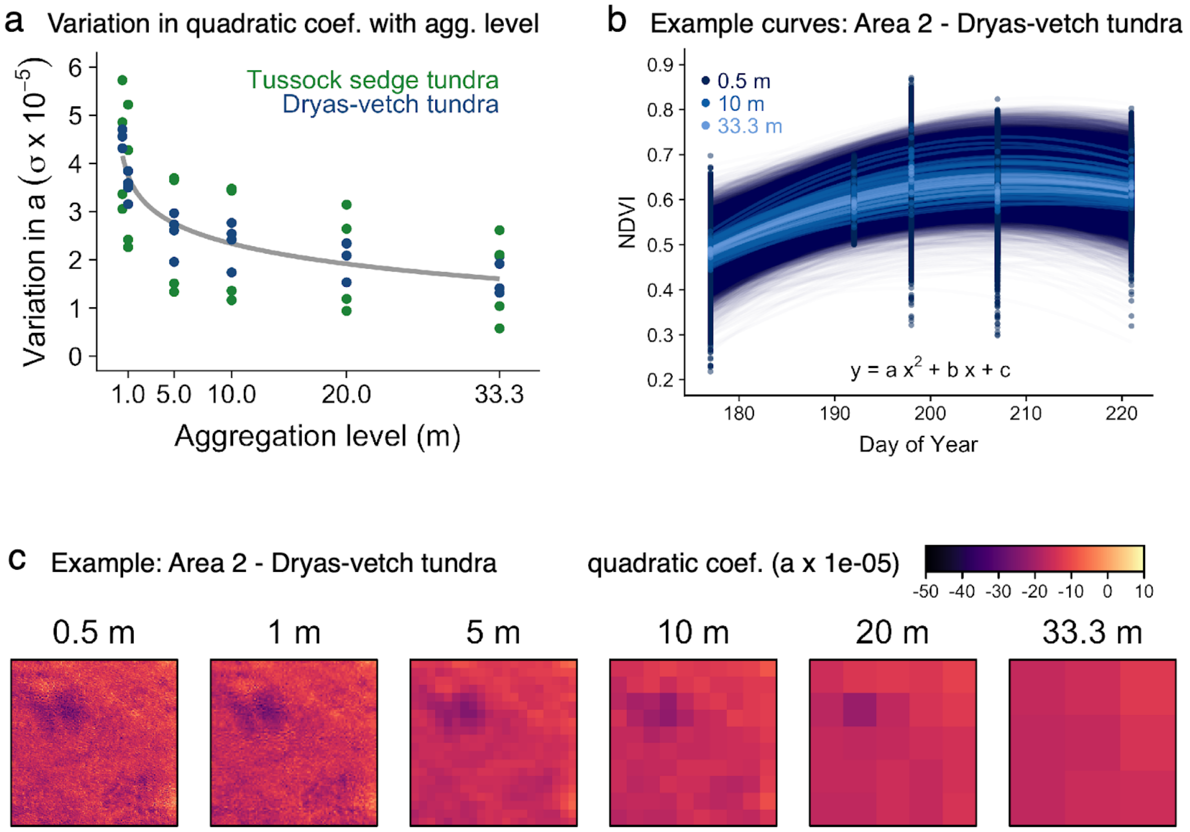

Figure 4: Fine-scale variation representing key ecological heterogeneity in tundra phenology was lost when aggregating from ultra-fine-grain drone to medium-grain satellite pixel sizes. When aggregating the drone data across grain sizes, we observed a logarithmic decay in variation (standard deviation) in the quadratic coefficient (shown in a) of simple growing season curves fitted to the eight vegetation plots in the 2017 season. As examples we visualise all curve-fits for the dryas-vetch tundra plot in Area 2 fitted to the time-series of the minimum, central and maximum grain-sizes tested (0.5 m, 10 m and 33.3 m) in (b) and show the spatial distribution of the quadratic coefficient for each grain size for dryas-vetch tundra plot in Area 2 in panel c), similar patterns are found across all areas (a). See Figure S7 for example curves from the dryas vetch tundra plot in Area 2 from all tested grain sizes.

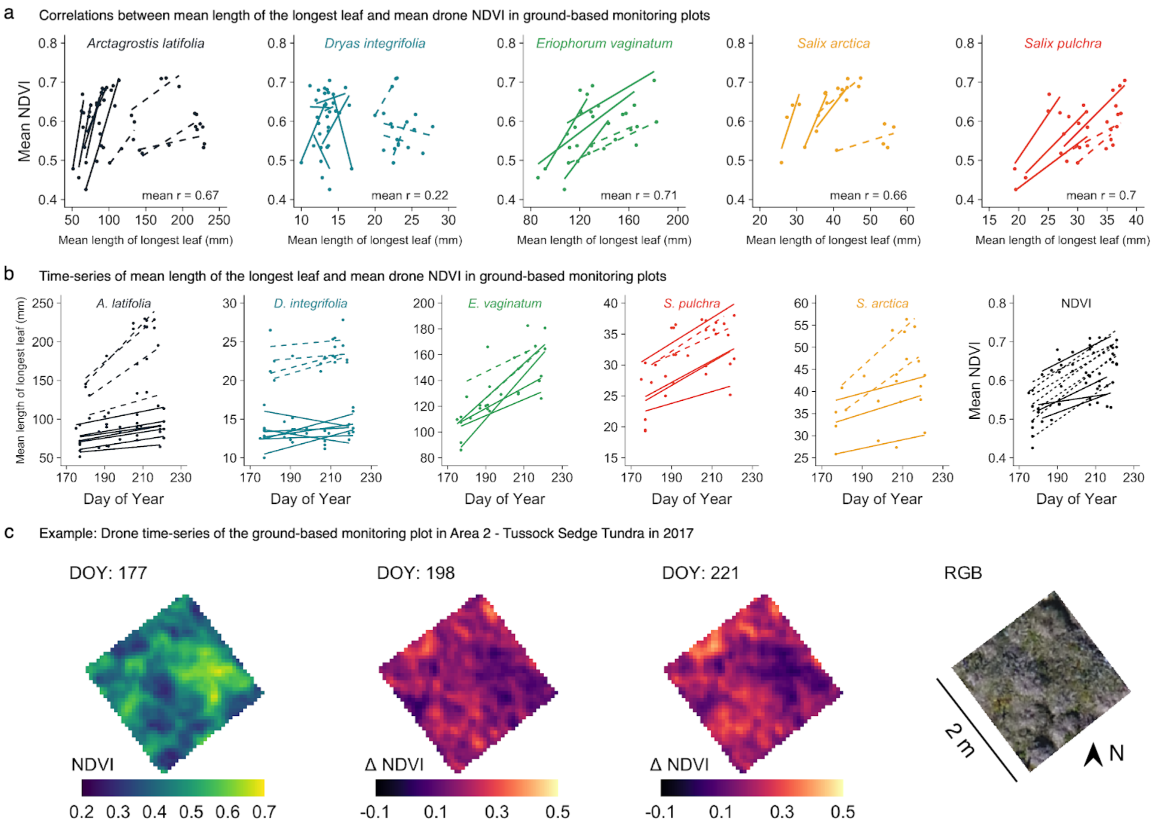

Figure 5: Time-series of ground-based leaf length measurements correlated with drone-derived mean NDVI across four of five dominant plant species on Qikiqtaruk. Correlation between mean longest leaf length and NDVI in each 2 m x 2 m ground-phenology plot across all species, areas and seasons (a) and the corresponding time-series (b). Dashed lines indicate time-series from 2016 and solid lines indicate time-series from 2017. Lines represent least-square regressions to illustrate the relationships of longest-leaf length and NDVI (a), as well as day of year (DOY) and the time-series variable (b) for each plot and year combination. Uneven numbers of time-series between species result as the set of species monitored varied between vegetation types. (c) As an example, we illustrate the drone-based NDVI observations by showing the start, midpoint and end of the timeseries for the 2 m x 2 m ground-validation plot in the tussock sedge tundra of Area 2 in 2017. The first time-point in (c) represents the greenness in the plot at the beginning of the time-series, the two subsequent plots show the relative difference in greenness to this first observation at the given DOY, and the final plot shows a true-colour image of the plot taken by drone on the 17 July 2017 (DOY 198).