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UAV Photogrammetry for Mapping Vegetation in the Low-Arctic

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Abstract: Plot-scale field measurements are necessary to monitor changes to tundra vegetation, which has a small stature and high spatial heterogeneity, while satellite remote sensing can be used to track coarser changes over larger regions. In this study we explored the potential of Unmanned Aerial Vehicle (UAV) photographic surveys to map low-Arctic vegetation at an intermediate scale. A multicopter was used to capture highly overlapping, sub-centimetre photographs over a 2 ha site near Tuktoyaktuk, NWT. Images were processed into ultra-dense 3D point clouds and 1 cm resolution orthomosaics and vegetation height models using Structure-from-Motion (SfM) methods. Shrub vegetation heights measured on the ground were accurately represented using SfM point cloud data ($r^2 = 0.96$, SE = 8 cm, n = 31) and a combination of spectral and height predictor variables yielded an 11-class classification with 82% overall accuracy. Differencing repeat UAV surveys before and after manually trimming shrub patches showed vegetation height decreases in trimmed areas (-6.5 cm, SD = 21 cm). Based on these findings, we conclude that UAV photogrammetry provides a promising, cost-efficient method for high-resolution mapping and monitoring of tundra vegetation that can be used to bridge the gap between plot and satellite remote sensing measurements.

Keywords: Unmanned Aerial Vehicle, UAV, UAS, Arctic, shrubs, vegetation, structure-from-motion, photogrammetry

Introduction

The most rapid, regional temperature increases in recent decades have occurred in the Arctic (ACIA 2004). This had led to widespread vegetation changes, especially in the form of increased vegetation productivity and shrub abundance (Myers-Smith et al. 2011). Local-scale disturbances from wildfire, thaw slumps, and human activity (e.g. seismic surveying and drilling sumps) have also promoted Arctic shrub growth by exposing and warming mineral soils (Johnstone and Kokelj 2008; Kemper and Macdonald 2009; Lantz et al. 2010). These vegetation changes can have impacts on carbon and radiation balance, snow depth, permafrost, infrastructure, and wildlife forage (Joly et al. 2009; Blok et al. 2010; Lantz et al. 2013; Gill et al. 2014). In order to assess these impacts, accurate and efficient methods are required to measure Arctic vegetation changes over a range of spatial and temporal scales. Maps depicting the current distribution of northern vegetation are also needed as input to terrestrial ecosystem models (Euskirchen et al. 2009) and permafrost models (Zhang et al. 2014).

The most detailed surveying and monitoring of Arctic tundra vegetation has been conducted using field plot measurements (Elmendorf et al. 2012), such as the point-frame method adopted by The International Tundra Experiment (Hudson and Henry 2009). Tundra vegetation composition can also be classified within plots by segmenting digital photographs taken vertically (Chen et al. 2010). Field plot methods provide an accurate means of quantifying changes in tundra vegetation composition and percent cover. However, these methods are also time consuming, and are constrained both spatially and temporally in the extents to which they can be practically applied.

Remote sensing provides a means of scaling up measurements of tundra vegetation over landscape to global scales (Stow et al. 2004). For example, analyses of both medium (McManus

et al. 2012; Fraser et al. 2014) and coarse resolution (Bhatt et al. 2010; Beck and Goetz 2011) optical satellite imagery used to calculate the Normalized Difference Vegetation Index ($NDVI = \frac{NIR - Red}{NIR + Red}$) has revealed that many Arctic regions have greened in recent decades due to increasing vegetation biomass. A limitation of these long-term satellite records is that they do not provide sufficient spatial resolution to precisely determine the nature of the vegetation changes in terms of composition, density, and height (Pattison et al. 2015; Moffat et al. In Review). Studies that have re-captured high resolution, historical photos have provided some of this detail (Tape et al. 2006; Myers-Smith et al. 2011; Fraser et al. 2014), but are ultimately constrained by the availability and spatial extent of archived imagery.

Airborne light detection and ranging (LiDAR) is an active remote sensing technology based on the measurement of laser echoes, which has been widely used to map forest vegetation structure (Wulder et al. 2012). Some studies have shown that airborne LiDAR can be an effective way to map shrub structure in temperate regions (Streutker and Glenn 2006; Riano et al. 2007). However, this application must account for the relatively low density of laser returns (typically 1-100 pts m⁻²) in relation to shrub size and crown heterogeneity. Terrestrial laser scanning, or ground-based LiDAR, has recently been used to generate much denser 3D point clouds in an Arctic tundra environment, which could be used to estimate both biomass and leaf area index of birch and willow shrub species with high accuracy (Greaves et al. 2015). One drawback with LiDAR-based methods is the high-cost of contracting airborne surveys or purchasing terrestrial LiDAR scanners, which can be more than \$100 000 USD for a high-end unit.

Advances in Structure-from-Motion (SfM) methods and software that combine computer vision and photogrammetry provide a relatively new and inexpensive means of generating

LiDAR-like point clouds and digital surface models (DSMs) from aerial photos (Westoby et al. 2012; Fonstad et al. 2013). An advantage of SfM over LiDAR is that SfM surface models can be used to simultaneously orthorectify air photos to create a precisely co-registered RGB orthomosaic of the surveyed area. SfM is similar to conventional photogrammetry in that both use triangulation of corresponding points in overlapping images to reconstruct a 3D scene. Unlike photogrammetry, SfM uses features that are automatically identified and matched between images using computer vision (Lowe 2004). SfM methods also do not require prior knowledge of either external camera calibration parameters (i.e. position and orientation) or internal parameters (i.e. lens properties) to perform bundle adjustment to reconstruct 3D scene structure. This makes SfM highly effective for mapping objects using a set of overlapping images where neither the location of scene features nor the camera positions are known (Snavely et al. 2007).

SfM techniques have been recently applied in a wide range of environmental mapping applications, including landslide dynamics (Turner et al. 2015), glacier movement (Ryan et al. 2015), snow depth (Nolan et al. 2015), river channel morphology (Dietrich 2016), and soil microtopography (Kaab et al. 2014; Nouwakpo et al. 2015). SfM point clouds and the elevation models derived from them have also been used to characterize the structure of vegetation, including trees (Dandois and Ellis 2014; Diaz-Varela et al. 2015; Puliti et al. 2015) and crops (Grenzdorffer 2014; Geipel et al. 2014). SfM modeling could potentially be used to characterize low-Arctic vegetation, but would have to address unique challenges related to the relatively small stature, high spatial heterogeneity, and structural complexity of the vegetation in this biome (Fig. 1).

Miniaturization and low production cost of unmanned aerial vehicle (UAV) components, including inertial measurement units and GPS, have led to rapid adoption of UAVs (or small unmanned aircraft systems; UAS) as flexible remote sensing platforms (Whitehead and Hugenholtz 2014). UAVs are being used increasingly as tools to collect very high resolution imagery for SfM processing (Lucieer et al. 2013; Dandois and Ellis 2014; Geipel et al. 2014; Turner et al. 2015). SfM is particularly suited for processing of UAV photos that are acquired using consumer grade, non-metric cameras with unstable lens calibration and where the camera orientation and position is not accurately measured. To our knowledge, only two published studies have used UAV-based imaging for high resolution mapping of Arctic vegetation. In one case, a fixed-wing UAV was used to acquire visible and infrared imagery to assess the separability of a range of Arctic plant communities in Svalbard based on RGB and NDVI images (Tommervik et al. 2014). In a nearby study area, Mora et al. (2015) fused UAV RGB imagery with visible and NIR imagery from manned aircraft to classify major vegetation types using four supervised classification methods. Both studies used spectral information only and did not examine the potential utility of height or structural information derived from SfM point clouds.

The purpose of this study is to investigate the use of UAV photographic surveys and SfM to characterize low-Arctic tundra vegetation. Specifically, we tested the potential to:

1. Map the height of shrub tundra vegetation;
2. Classify tundra vegetation at centimetre resolution; and
3. Detect changes in shrub vegetation height.

Methods

Study Area

This UAV mapping study was conducted at a site 10 km south of Tuktoyaktuk, Northwest Territories, Canada (Fig. 1a) within the Tuktoyaktuk Coastal Plain Ecoregion. This ecoregion is a low-relief, till plain covered by small lakes and wetlands and is underlain by continuous permafrost with a high ground ice content (Ecosystem Classification Group 2012). The climate of the Tuktoyaktuk Coastal Plain Ecoregion is cold and dry. The mean annual air temperature from 1971 to 2000 at Tuktoyaktuk was -10.2 C. Mean annual precipitation during this period averaged 139.3 mm, with 69.2 cm falling as snow (Environment Canada 2012). Mean annual permafrost temperatures near the Beaufort Sea coast can be below -6 C (Burn and Kokelj 2009).

The upper portion of the study site consists mainly of tall shrub tundra dominated by birch and willow, which slopes downward four meters to a high-centered, ice-wedge polygon complex where many of the ice wedges have degraded into water-filled troughs (Fig. 1b). The surveyed area is approximately 2 ha and contains several vegetation communities (upright shrub, sedge wetland, and tussock tundra) that are common in the Low Arctic (Ecosystem Classification Group 2012). The largest shrubs are birch (*Betula glandulosa* and *Betula nana*), willow (*Salix* spp.), and alder (*Alnus viridis ssp. fruticosa*). Shorter statured dwarf shrubs include bog blueberry (*Vaccinium uliginosum*), lingonberry (*Vaccinium vitis-idaea*), Labrador tea (*Rhododendron subarcticum*), crowberry (*Empetrum nigrum*), and bearberry (*Arctostaphylos rubra*). Common non-shrub vegetation includes cloudberry (*Rubus chamaemorus*), Lupin (*Lupinus arcticus*), tussock cottongrass (*Eriophorum vaginatum*), sedges (*Carex* spp.), mosses, and small patches of lichen (*Cladonia* and *Cladina* spp.).

UAV Photo Surveys

UAV photo surveys were conducted on August 2nd and 3rd, 2015 using a Spyder PX8 Plus 1000 octocopter by XPedition Robotics (Fig. 2). The PX8 uses the 3DR Pixhawk flight controller running ArduCopter v3.2.1 and dual 6S 6,600 mAh lipo batteries that provide a maximum flight time of about 18 minutes with the camera and gimbal. A 24 megapixel Sony a6000 mirrorless camera with Sony f/2.8 20mm pancake lens was mounted to the octocopter. Mission Planner v1.3 software was used to create autonomous 12-13 minute missions in a grid pattern with up to 90% forward overlap and 83% side photo overlap at 20-90 m height above ground (Table 1). This imaged each ground location with up to 60 photos at a 3-15 mm resolution. The camera was fixed at an angle approximately 10 degrees forward to minimize the potential for doming artifacts in the SfM height model that can result from incorrect radial camera calibration in a nadir-only camera orientation (James and Robson 2014). Photos in JPEG format were captured in shutter priority mode at a 1/1000 s interval, 250-400 ISO, and with focus fixed at infinity. GPS tags were added to the JPEG EXIF information using the log file from the onboard 3DR UBlox GPS that provided a 5 Hz update rate.

In the first two UAV surveys (Table 1), we specified 90% forward and 83% side overlap and high resolution (0.75 cm). This was done to achieve a detailed point cloud model to meet the SfM tundra mapping challenges discussed above. This approach also helped to facilitate successful reconstruction of shrub crowns, since their complex structure leads to large changes in the pattern of visible features with small changes in viewing perspective (Fig. 3). A high overlap should also better capture smaller ground patches within denser shrub vegetation where at least two observations are required for photo matching (Dandois et al. 2015). Survey #2 was a repeat of survey #1 following experimental shrub trimming conducted to examine the consistency of

shrub heights estimated using SfM processing. Survey #3 was conducted to acquire 0.33 cm resolution photos with less overlap for photo-interpretation of vegetation types. Survey #4 was conducted to test the sensitivity of the SfM modeling results to reduced photo resolution. In this survey, images were captured at 1.5 cm resolution by flying 90 m above ground. A second sensitivity test examined the impact of reducing photo overlap by re-processing survey #2 using every second photo and flight line. This yielded 80% forward and 70% side overlap, or 25% of the original photo density, which is more typical for SfM processing of air photos. All surveys were conducted under partly to mostly cloudy conditions with relatively low wind speeds for this region (9-10 km hr⁻¹).

UAV Photo Processing

Photos were processed using Agisoft PhotoScan v1.2.0 (build 2198) SfM software that applies proprietary algorithms in an automated workflow to generate dense 3D point clouds and orthomosaics. The point clouds generated from PhotoScan were edited and processed into DSMs and vegetation height models using CloudCompare v2.6.1 and ArcGIS v10.2 software. The overall data processing workflow is summarized in Figure 4 and detailed SfM software processing steps are described separately in the Supplementary Materials.

Modeling Shrub Heights

To characterize the vegetation in the study area, field surveys were conducted from August 5-10, 2015. At 28 survey points a tape measure was used to record the maximum height of the shrub patch and to measure heights of the six tallest branches to represent average height.

Sample shrubs included a range of maximum heights (19-202 cm), maximum crown diameters (40-398 cm) and species (birch, alder, and willow). Measurements of maximum height were also made for three conspicuous alders that were added for the shrub trimming experiment.

The x and y coordinates of each survey position were recorded using a Nikon Nivo 3.C total station positioned over a bench mark installed at the study site in 2014. Static survey data collected over this point using a Trimble R4 GNSS system was post-processed using Natural Resources Canada's Precise Point Positioning system to yield a benchmark with horizontal accuracy of ± 4 mm. To describe vegetation composition, we recorded the tallest species at 116 points and the dominant species in the area immediately surrounding each point, and also captured a vertical photo of the ground surface using a Nikon D7000 Camera. These points and photos aided in delineating training polygons for vegetation classification.

A vegetation height model was created by subtracting the raster bare earth model from the raster DSM. Vegetation height estimates were validated using regression analysis with the total station survey measurements. To assess the potential for measuring changes in shrub heights based on repeat UAV surveys, we used clippers to manually trim all the upper branches of (a) five alder shrubs by varying amounts of 10, 15, 20, or 30 cm, (b) one 3 m² patch of dense birch by ~15 cm, and (c) one 3 m² patch of dense willow by ~15 cm. Height changes were estimated by differencing the pre- and post-trimming DSMs from surveys 1 and 2 (Table 1). We also examined differences in the DSM in successive surveys within non-trimmed areas to determine the repeatability of height estimates.

Vegetation Type Classification

We also used the UAV orthomosaic and vegetation height model to map vegetation types at the study site. To accomplish this we created a classification legend that represented larger shrub species, major vegetation types, and other non-vegetation land cover types in the study area (Table 2). The thematic detail of the legend was guided by the level of discrimination thought to be possible using very high resolution RGB imagery and vegetation height models. Classes 1-3 (willow, alder, and birch) are composed of relatively dense, homogeneous patches of tall shrub species typically > 25 cm high. A mixed dwarf shrub / heath class (#10) was included to represent shorter-statured vegetation (< 25 cm) composed of heterogeneous mixtures of several classes. Test UAV photos with ~ 1 cm resolution captured over the study site in 2014 indicated that these mixtures could not be visually resolved.

To classify vegetation types we used the orthomosaic and vegetation height model derived from the repeat survey (#2), since this survey was conducted under more overcast conditions that minimized the intensity of shadowing. The 1 cm resolution RGB orthomosaic and vegetation height model were used to generate homogeneous clusters at multiple scales before classification using an image segmentation technique. Image segmentation is well-suited to classification applications that use high resolution images, including those from UAVs (Laliberte and Rango 2009; Knoth et al. 2013), where objects of interest are composed of several image pixels (Blaschke 2010). Additional contextual information (e.g. shape, texture) derived from the objects can also improve separability of classes in UAV imagery (Laliberte and Rango 2009; Knoth et al. 2013).

We used the multi-resolution segmentation algorithm in eCognition V8.8 software to create small Level-1 objects using only RGB information (Scale = 10, Shape = 0) and then created larger Level-2 objects (Scale = 20) by merging Level-1 objects stratified by heights ≤ 30

cm and > 30 cm. This ensured that the boundaries of shrubs taller than 30 cm were not merged with ground-level features within the scene. The small Scale factors were used to retain the smallest features of interest: patches of bright lichen. Objects with an area less than 10 pixels (10 cm^2) were merged into adjacent objects based on RGB values, yielding 1 176 817 objects over the study area with an average area of 127 cm^2 .

The exported image objects from eCognition were classified using the See5 decision tree algorithm implemented in R V3.2.2 software. Training data consisted of ~ 100 small polygons digitized for each class over the 1 cm orthomosaic using the 3 mm resolution UAV photo survey (Table 1) and the set of georeferenced ground photos as reference. eCognition objects that overlapped with training polygons were included in the reference dataset if they covered at least 10% of a digitized training polygon. Predictor features consisted of the mean and standard deviation of RGB brightness and height layers, spectral indices combining two or more RGB bands (Rasmussen et al. 2016), plus grey-level co-occurrence contrast texture, computed for each image segment (Table 3).

See5 decision trees were run using the default parameters of: 10 boosting iterations, a confidence factor of 0.25, and no winnowing. Feature selection was used to reduce the number of variables in the final model. To determine the features for the final model, decision trees were run initially using reference polygons with all features using 100 random splits of 75 % polygons for training and 25 % for testing. Attribute usage, expressed as a percentage of each model iteration, was summed for each variable across all 100 iterations to provide an overall ranking of variable importance. Variables were subsequently entered in a stepwise manner in the order of highest to lowest importance using the same 75 % training, 25 % testing polygon split and 100 iterations described previously. Accuracy was computed at each step and the subset of variables

that achieved an accuracy within 1 % of that obtained from all features was selected for the final model. The final map was obtained by applying a model trained on all reference polygons using the final set of selected features. The accuracy of each of the final 100 iterations was obtained using the polygons reserved as testing data. The final confusion matrix was obtained by summing the 100 matrices and calculating user's, producer's, overall accuracy, and kappa from the summed matrix.

Results

Processing of the photos from surveys 1 and 2 resulted in ultra-dense point clouds averaging more than 30 000 pts m⁻² (> 500 million points total over 1.5 ha), which is equivalent to an average horizontal point spacing smaller than 0.6 cm (Table 4). Figures 5 and 6 show a 0.75 cm resolution UAV photo, a dense point cloud, a vegetation height model, and a 1 cm orthomosaic for a portion of our study site. The final 1 cm orthomosaic shows few artifacts across rapid transitions in vegetation height (Fig. 5d, Fig. 6d), and appears similar in quality and detail to the original photos (Fig. 5a, Fig. 6a). The point cloud (Fig. 5b, Fig. 6b) and vegetation height model (Fig. 5c, Fig. 6c), created by subtracting a conservative bare earth model from the DSM, visually portray sparsely foliated, upper willow branches, the microtopography associated with sedge tussocks, and the shallow depressions within ice wedge polygons (Supplemental video 1). Visual comparisons of point clouds and ground photos show that the points effectively capture small branches forming the upper profile of shrubs (Fig. 7). We also observed alder crowns with denser clusters of leaves (Fig. 7 a-b) that were more completely represented in the point cloud data than willow crowns having fewer, smaller leaves (Fig. 7c).

A comparison of the maximum heights measured using UAV/SfM and the 31 shrubs measured in the field using a tape measure showed a strong association ($R^2 = 0.96$, S.E. = 8 cm, $p < 0.001$) (Fig. 8a). A linear regression line indicated a near 1:1 relationship with a slope of 0.91 and intercept of 6 cm. Average height computed from six representative upper branches was also estimated well based on the mean plus two standard deviations of the values from the vegetation height model within the shrub perimeters ($R^2=0.91$, S.E. = 11 cm, $p < 0.001$, $n=28$) (Fig. 8b). Note that this calculation also includes the lower branches and ground gaps within the crown perimeter. The maximum, measured extent of individual shrub crowns was also predicted using the extent of shrubs mapped as classes 1-3 in the vegetation classification ($R^2=0.93$, S.E. = 22 cm, $p < 0.001$, $n=28$).

Differencing the DSMs from survey 1 and 2 yielded a surface that accurately captured the extent of the shrub cutting experiment (Figure 9a). The DSM change product showed a mean 6.5 cm decrease (SD = 21 cm) within trimmed shrubs, which was significantly different from the mean 0 cm change (SD = 7.7 cm) within non-trimmed areas (t-test $p < 0.001$) (Supplementary video 2). The shrub patches were trimmed by varying amounts (10 cm, 15 cm, 20 cm, or 30 cm), and the degree of trimming showed a positive but non-significant relationship with the change in the DSMs ($R^2 = 0.41$, $p = 0.12$, $n = 7$). Note that the 6.5 cm average DSM change within the trimmed shrub canopies would be expected to be smaller than the amount trimmed because only upper branches were trimmed, while lower branches and gaps within the canopy extents (Fig. 3) were unaltered. High-frequency noise was observed in the DSM difference outside the area of shrub cutting owing to small differences in canopy reconstructions between the models. For example, figure 10 shows a close-up comparison of the two orthomosaics, two DSMs, and the resulting DSM difference. Although the DSMs appear generally similar, small offsets of 5-10

cm between branches or differences in the modeled surface elevation within shaded canopy gaps lead to noise in the change product. These differences may be caused by variability in lighting conditions and sun-camera-target geometries, small branch movements due to wind, or misregistration error between the two point clouds.

Sensitivity analyses showed that reducing either photo overlap or resolution lowered the accuracy of SfM-based height models. A 75% reduction in the density of photos led to an average point cloud density of 22 640 pts m⁻² compared to 35 953 pts m⁻² for the full set of photos (Table 4). Vegetation height predictions for the 31 measured shrubs were nearly as accurate (S.E. of 11.6 cm vs. 8.1 cm), but the reduced overlap point cloud contained frequent data gaps. Figure 11 shows a sample of dense point clouds derived from (a) the full set of photos from survey #2, (b) the 25% subset of photos from survey #2, and (c) the reduced resolution (1.5 cm) photos from survey #4. In the case of the 25% subset, gaps are present at the sides and interiors of shrub crowns and small gaps are present between crowns. These gaps can also be observed in a 20 cm wide transect sample of the point cloud (Fig. 11b, bottom). In the sensitivity analysis that used coarser resolution imagery (1.5 cm), point cloud density was reduced to 8 145 pts m⁻² and vegetation height predictions were poorer (S.E. = 23.2 cm, Table 3). While the point cloud distribution was relatively uniform (Figure 11c), it tended to truncate the heights of some shrubs, likely as a result of photos having insufficient resolution to capture smaller branches.

The final vegetation and land cover classification generated using a decision tree model contained 11 predictors, since additional features only marginally improved overall classification accuracy above 82% (Tables 3 and 5). Most of the variables selected in the final model were related to vegetation height and surface elevation (providing a proxy for landscape position), or

were spectral indices that combined two or more of the RGB channels (Table 3). Such normalized indices should at least partially control for brightness variation within photos (e.g. light shadows) or among photos (e.g. due to varying cloud cover) used to construct the orthomosaic. Separate decision tree classifications based only on the subset of spectral variables produced an overall accuracy of 72%, while the subset of only height variables produced an accuracy of 64%. The vegetation type classification and orthomosaic for a portion of the study area containing all cover types are shown in Figure 12, while Figure 13 shows the classification result for a single ice-wedge polygon surrounded by water. Table 5 presents a confusion matrix that provides for each class, the probability that the classified map is correct (user's accuracy corresponding to the rows) or that the training samples are correct (producer's accuracy corresponding to the columns). With the exception of sedge tussock (64% user's / 50% producer's) and wet graminoid (69% user's / 61% producer's), most classes show high accuracy (users and producers accuracy between 74-94%). The error matrix indicates that sedge tussock and wet graminoid are often confused with mixed dwarf shrub, which by definition contains vegetation mixtures that include sedge.

Discussion

The results of this study show that UAV photo surveys in Arctic tundra can be used to monitor changes in shrub growth and map fine-scale vegetation composition. The quality and detail of the derived point clouds are evidenced by accurate predictions of shrub heights and the ability to detect height changes in shrubs that were trimmed by 10-30 cm. Surveys with very high overlap also permit multiple observations of shadowed ground features within the gaps of individual shrub crowns (e.g. Fig. 3), enabling their reconstruction in the point cloud (Fig. 11a).

This indicates that SfM methods can be used to create accurate bare earth models in areas with dense shrub cover and fewer, smaller ground gaps.

Sensitivity analyses using reduced photo overlap and lower resolution suggest that photos with high resolution (0.75 cm) and overlap (90%) are needed to generate a point cloud that accurately represents shrub heights, shrub canopy gaps, and overall vegetation structure. In this study we only examined sensitivity tests exploring the impact of resolution and overlap. Since factors including: camera and lens characteristics, wind speed, cloud cover, GCP number and distribution, SfM algorithms and software settings, point cloud density, and method used for building bare earth models can affect SfM modeling results, more systematic study of these factors for mapping shrub tundra is needed. For example, Dandois et al. (2015) conducted a replicated set of UAV image acquisitions with treatments related to lighting, flight altitude, image overlap, and image processing.

The vegetation classification presented here shows that orthomosaic and height models derived from SfM processing can be accurately classified using image segmentation and decision trees (Table 5). Our classification results show that UAV imagery can be used to capture less frequent but important vegetation classes that are difficult to map using coarser satellite-based imagery. For example, patches of reindeer lichen have an average area of 84 cm² and cover only 1.6% of the study area, but were mapped with 86% accuracy. Lichen serves as an important source of winter caribou forage in our study region and has been declining in recent decades, likely as a result of shrub expansion driven by climate warming (Fraser et al. 2014; Moffat et al. In Review). Classification results indicate that the inclusion of structure and height variables increases accuracy (here by 10%) compared to using only RGB spectral variables. Spectral separability among cover types could likely be improved through the use of small multi-spectral

cameras (e.g. Tetracam or MicaSense). Unfortunately, increasing spectral resolution would compromise spatial resolution (i.e. 1 MP vs 24 MP) and likely make SfM modeling of shrub heights challenging. Another option is to explore the use of NIR converted cameras where the NIR blocking filter on a consumer camera is replaced, allowing for the generation of NDVI-like indices. However, it is not clear whether these converted cameras provide an improved ability to characterise vegetation compared to standard RGB cameras (Nijland et al. 2014; Rasmussen et al. 2016).

A promising application of UAV photogrammetry in the Arctic is low-cost, non-destructive vegetation monitoring at local scales. Over short time intervals, repeat surveys could be used to document the progression of spectral changes and phenology during a growing season (Dandois and Ellis 2013). Over multi-year intervals, UAV surveys could be used to detect gradual changes in the composition, cover, and height of tundra vegetation as it responds to climate or disturbance. Chen et al. (2009) demonstrated that biomass and leaf area of Arctic shrubs could be estimated through non-destructive measurements of percent cover and mean height, both of which could be estimated from UAV photogrammetry. Arctic shrub biomass has also been estimated using volumetric surface differencing and voxel-counting approaches based on terrestrial laser scanning point clouds (Greaves et al. 2015). These approaches could be tested for measuring shrub biomass and leaf area using dense point clouds, vegetation height models, and vegetation classifications derived from UAV imagery.

Our results suggest that UAV photogrammetry offers the potential to help bridge the spatial gap between Arctic field measurements and high or medium resolution satellite imagery. Plot data are required to accurately capture the fine-scale heterogeneity in vegetation cover present in Arctic regions. In order to extrapolate this plot-level information to larger regions, a

large jump in spatial scale is necessary when training or calibrating satellite remote sensing algorithms using field plot data (Chen et al. 2009; Reynolds et al. 2012). The high resolutions (1-5 cm) and multi-hectare coverage provided by UAV photogrammetry could help fill this gap and make upscaling more robust. Similarly, this form of near-surface remote sensing could be used to interpret and validate time-series products derived from moderate resolution satellite sensors by allowing frequent temporal sampling (Hufkens et al. 2012).

Environmental characteristics that can either alter, or be altered by vegetation could also be monitored concurrently through repeat UAV surveys. For example snow depth, which increases ground temperature and nutrient mineralization for shrub growth, yet is also modified by shrub vegetation (Sturm et al. 2005), is amenable to mapping using SfM methods (Nolan et al. 2015). Thermokarst processes related to degradation of ground ice could also be investigated by measuring both elevation and spectral changes caused by ground subsidence and the formation of small melt ponds and troughs over ice wedges (Reynolds et al. 2014; Jones et al. 2015; Steedman et al. 2015). Fine-scale topographic characteristics can also be quantified using SfM processing of UAV surveys to model hydrological flow-paths and areas of concentrated flow (Lucieer et al. 2013). These characteristics have an important control on tundra vegetation distribution and growth (Naito and Cairns 2011; Cameron and Lantz 2016).

Challenges

There are several limitations inherent in the UAV-SfM tundra mapping application presented in this paper that should be highlighted. First, the spatial extents that can be mapped using a consumer grade multicopter UAV are limited by battery flight time. For example, a

custom multicopter with a 30 minute flight time could cover a maximum of about 15 ha when capturing 1 cm resolution images with high overlap (85% forward / 70% side). Although small, fixed-wing UAVs can provide 45-90 minute flight times and cover larger areas, at present, almost all UAV operations in North America are required to be conducted within visual line of sight (VLOS). VLOS extends to about 300-1 000 m depending on the size and type of UAV and weather conditions. One strategy to increase the extent of SfM-based tundra vegetation mapping would be to use cameras mounted on low-level manned aircraft with survey grade GNSS systems (e.g. Nolan and DesLauriers 2015). However, the flight altitude and speed would have to be capable of capturing ~ 1 cm imagery with small motion blur and sufficient overlap to effectively model shrub vegetation.

The computer processing time required to build ultra-dense point clouds using highly overlapping photos also limits the area that can be covered using this approach. Photo sets from surveys in this study took up to 10 days to process using a mid-level workstation (dual 2.0 GHz Xeon processors with 32 cores, 80 GB RAM, Quadro K4000 GPU). This could likely be reduced to about 2-3 days by using a latest-generation workstation and GPU, or by reducing the point cloud density setting from ultra to high, which produces a point cloud with only a small loss of detail. The time spent in the field surveying GCP targets and then locating them in imagery during SfM processing could also be reduced by using a survey-grade GNSS receiver on the UAV to provide direct georeferencing of imagery to about 5 cm accuracy (Mian et al. 2015).

Considering the limitations related to flight duration and processing time, fine resolution (~ 1cm) UAV mapping of tundra vegetation may be best suited for relatively small areas for: (1) creating highly detailed maps of land cover or biophysical parameters that can be used as training data to classify fine resolution satellite imagery over larger areas; or (2) quantifying

vegetation cover and height changes over sample areas that are representative of regional-scale change processes (e.g. Fraser et al. 2014).

The need to conduct missions in optimal weather conditions to capture photos that can yield high-quality point clouds and orthomosaics is another factor that could limit this application in the Arctic. For example, coastal Arctic areas with strong winds are problematic because winds can shift the location of shrub branches between photos and make features difficult to match. Our surveys appeared to be minimally impacted by $\sim 10 \text{ km hr}^{-1}$ winds, but these were only half the average summer wind speed within the study area. We observed that the highest quality orthomosaic was produced from a survey conducted under light overcast conditions near the time of solar noon, which produced smaller and lighter vegetation shadows. To yield comparable photographs and point clouds that can be used for change detection, repeat surveys should use the same camera positions and be taken at the same time of day to recreate these favourable conditions.

Conclusions

This study demonstrates that highly overlapping, sub-centimetre resolution photos captured using a consumer-grade camera and multicopter UAV can be processed using SfM software to characterize low-Arctic shrub vegetation by:

1. Accurately measuring the height of tundra shrubs using a vegetation height model derived from a dense point cloud;
2. Measuring changes to shrub heights by differencing digital surface models;

3. Mapping a range of vegetation and land cover types using image segmentation and a decision tree classifier that uses both RGB spectral and height-based features; and
4. Representing the crown diameter of shrub patches based on a vegetation classification.

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References

- ACIA. 2004. Impacts of a Warming Arctic: Arctic Climate Impact Assessment. Cambridge University Press, Cambridge.
- Axelsson, P. 2000. DEM generation from laser scanner data using adaptive TIN models. *International Archives of Photogrammetry and Remote Sensing*, XXXIII **33**.
- Beck, P.S.A., and Goetz, S.J. 2011. Satellite observations of high northern latitude vegetation productivity changes between 1982 and 2008: ecological variability and regional differences. *Environmental Research Letters* **6**(4): 045501. doi:10.1088/1748-9326/6/4/045501.
- Bhatt, U.S., Walker, D.A., Raynolds, M.K., Comiso, J.C., Epstein, H.E., Jia, G., Gens, R., Pinzon, J.E., Tucker, C.J., Tweedie, C.E., and Webber, P.J. 2010. Circumpolar Arctic Tundra Vegetation Change Is Linked to Sea Ice Decline. *Earth Interactions* **14**(8): 1–20. doi:10.1175/2010EI315.1.
- Blaschke, T. 2010. Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing* **65**(1): 2–16. doi:10.1016/j.isprsjprs.2009.06.004.

- Blok, D., Heijmans, M.M.P.D., Schaepman-Strub, G., Kononov, A.V., Maximov, T.C., and Berendse, F. 2010. Shrub expansion may reduce summer permafrost thaw in Siberian tundra. *Global Change Biology* **16**(4): 1296–1305. doi:10.1111/j.1365-2486.2009.02110.x.
- Burn, C.R., and Kokelj, S.V. 2009. The environment and permafrost of the Mackenzie Delta area. *Permafrost and Periglacial Processes* **20**(2): 83–105. doi:10.1002/ppp.655.
- Cameron, E.A., and Lantz, T.C. 2016. Drivers of tall shrub proliferation adjacent to the Dempster Highway, Northwest Territories, Canada. *Environmental Research Letters* **11**(4):045006. doi:10.1088/1748-9326/11/4/045006.
- Chen, W., Blain, D., Li, J., Koehler, K., Fraser, R., Zhang, Y., Leblanc, S., Olthof, I., Wang, J., and McGovern, M. 2009. Biomass measurements and relationships with Landsat-7/ETM+ and JERS-1/SAR data over Canada's western sub-Arctic and low Arctic. *International Journal of Remote Sensing* **30**(9): 2355–2376. doi:10.1080/01431160802549401.
- Chen, W., Li, J., Zhang, Y., Zhou, F., Koehler, K., LeBlanc, S., Fraser, R., Olthof, I., Zhang, Y., and Wang, J. 2009. Relating Biomass and Leaf Area Index to Non-destructive Measurements in Order to Monitor Changes in Arctic Vegetation. *ARCTIC* **62**(3): 281–294. doi:10.14430/arctic148.
- Chen, Z., Chen, W., Leblanc, S.G., and Henry, G.H.R. 2010. Digital Photograph Analysis for Measuring Percent Plant Cover in the Arctic. *ARCTIC* **63**(3): 315–326. doi:10.14430/arctic1495.
- Dandois, J.P., and Ellis, E.C. 2013. High spatial resolution three-dimensional mapping of vegetation spectral dynamics using computer vision. *Remote Sensing of Environment* **136**: 259–276. doi:10.1016/j.rse.2013.04.005.
- Dandois, J.P., Olano, M., and Ellis, E.C. 2015. Optimal Altitude, Overlap, and Weather Conditions for Computer Vision UAV Estimates of Forest Structure. *Remote Sensing* **7**(10): 13895–13920. doi:10.3390/rs71013895.
- Díaz-Varela, R.A., de la Rosa, R., León, L., and Zarco-Tejada, P.J. 2015. High-Resolution Airborne UAV Imagery to Assess Olive Tree Crown Parameters Using 3D Photo Reconstruction: Application in Breeding Trials. *Remote Sensing* **7**(4): 4213–4232. doi:10.3390/rs70404213.
- Dietrich, J.T. 2016. Riverscape mapping with helicopter-based Structure-from-Motion photogrammetry. *Geomorphology* **252**: 144–157. doi:10.1016/j.geomorph.2015.05.008.
- Ecosystem Classification Group. 2012. Ecological Regions of the Northwest Territories – Southern Arctic. Department of Environment and Natural Resources, Government of the Northwest Territories, Yellowknife, NT, Canada. 170 pp.

- Elmendorf, S.C., Henry, G.H.R., Hollister, R.D., Björk, R.G., Bjorkman, A.D., Callaghan, T.V., Collier, L.S., Cooper, E.J., Cornelissen, J.H.C., Day, T.A., Fosaa, A.M., Gould, W.A., Grétarsdóttir, J., Harte, J., Hermanutz, L., Hik, D.S., Hofgaard, A., Jarrad, F., Jónsdóttir, I.S., Keuper, F., Klanderud, K., Klein, J.A., Koh, S., Kudo, G., Lang, S.I., Loewen, V., May, J.L., Mercado, J., Michelsen, A., Molau, U., Myers-Smith, I.H., Oberbauer, S.F., Pieper, S., Post, E., Rixen, C., Robinson, C.H., Schmidt, N.M., Shaver, G.R., Stenström, A., Tolvanen, A., Totland, Ø., Troxler, T., Wahren, C.-H., Webber, P.J., Welker, J.M., and Wookey, P.A. 2012. Global assessment of experimental climate warming on tundra vegetation: heterogeneity over space and time: Warming effects on tundra vegetation. *Ecology Letters* **15**(2): 164–175. doi:10.1111/j.1461-0248.2011.01716.x.
- Environment Canada. 2012. National climate data and information archive. Ottawa: Environment Canada.
<http://climate.weather.gc.ca/>.
- Euskirchen, E.S., McGuire, A.D., Chapin, F.S., Yi, S., and Thompson, C.C. 2009. Changes in vegetation in northern Alaska under scenarios of climate change, 2003–2100: implications for climate feedbacks. *Ecological Applications* **19**(4): 1022–1043. doi:10.1890/08-0806.1.
- Fonstad, M.A., Dietrich, J.T., Courville, B.C., Jensen, J.L., and Carbonneau, P.E. 2013. Topographic structure from motion: a new development in photogrammetric measurement. *Earth Surf. Process. Landforms* **38**(4): 421–430. doi:10.1002/esp.3366.
- Fraser, R.H., Lantz, T.C., Olthof, I., Kokelj, S.V., and Sims, R.A. 2014. Warming-Induced Shrub Expansion and Lichen Decline in the Western Canadian Arctic. *Ecosystems* **17**(7): 1151–1168. doi:10.1007/s10021-014-9783-3.
- Geipel, J., Link, J., and Claupein, W. 2014. Combined Spectral and Spatial Modeling of Corn Yield Based on Aerial Images and Crop Surface Models Acquired with an Unmanned Aircraft System. *Remote Sensing* **6**(11): 10335–10355. doi:10.3390/rs61110335.
- Gill, H.K., Lantz, T.C., O'Neill, B., and Kokelj, S.V. 2014. Cumulative Impacts and Feedbacks of a Gravel Road on Shrub Tundra Ecosystems in the Peel Plateau, Northwest Territories, Canada. *Arctic, Antarctic, and Alpine Research* **46**(4): 947–961. doi:10.1657/1938-4246-46.4.947.
- Greaves, H.E., Vierling, L.A., Eitel, J.U.H., Boelman, N.T., Magney, T.S., Prager, C.M., and Griffin, K.L. 2015. Estimating aboveground biomass and leaf area of low-stature Arctic shrubs with terrestrial LiDAR. *Remote Sensing of Environment* **164**: 26–35. doi:10.1016/j.rse.2015.02.023.

- Grenzdörffer, G.J. 2014. Crop height determination with UAS point clouds. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* **1**: 135–140. doi:10.5194/isprsarchives-XL-1-135-2014.
- Hudson, J.M.G., and Henry, G.H.R. 2009. Increased plant biomass in a High Arctic heath community from 1981 to 2008. *Ecology* **90**(10): 2657–2663. doi:10.1890/09-0102.1.
- Hufkens, K., Friedl, M., Sonnentag, O., Braswell, B.H., Milliman, T., and Richardson, A.D. 2012. Linking near-surface and satellite remote sensing measurements of deciduous broadleaf forest phenology. *Remote Sensing of Environment* **117**: 307–321. doi:10.1016/j.rse.2011.10.006.
- James, M.R., and Robson, S. 2014. Mitigating systematic error in topographic models derived from UAV and ground-based image networks. *Earth Surf. Process. Landforms* **39**(10): 1413–1420. doi:10.1002/esp.3609.
- Johnstone, J.F., and Kokelj, S.V. 2008. Environmental Conditions and Vegetation Recovery at Abandoned Drilling Mud Sumps in the Mackenzie Delta Region, Northwest Territories, Canada. *ARCTIC* **61**(2): 199–211.
- Jones, B.M., Grosse, G., Arp, C.D., Miller, E., Liu, L., Hayes, D.J., and Larsen, C.F. 2015. Recent Arctic tundra fire initiates widespread thermokarst development. *Scientific Reports* **5**: 15865. doi:10.1038/srep15865.
- Kääb, A., Girod, L., and Berthling, I. 2014. Surface kinematics of periglacial sorted circles using structure-from-motion technology. *The Cryosphere* **8**(3): 1041–1056. doi:10.5194/tc-8-1041-2014.
- Kemper, J.T., and Macdonald, S.E. 2009. Directional change in upland tundra plant communities 20–30 years after seismic exploration in the Canadian low-arctic. *Journal of Vegetation Science* **20**(3): 557–567. doi:10.1111/j.1654-1103.2009.01069.x.
- Knoth, C., Klein, B., Prinz, T., and Kleinebecker, T. 2013. Unmanned aerial vehicles as innovative remote sensing platforms for high-resolution infrared imagery to support restoration monitoring in cut-over bogs. *Appl Veg Sci* **16**(3): 509–517. doi:10.1111/avsc.12024.
- Laliberte, A.S., and Rango, A. 2009. Texture and Scale in Object-Based Analysis of Subdecimeter Resolution Unmanned Aerial Vehicle (UAV) Imagery. *IEEE Transactions on Geoscience and Remote Sensing* **47**(3): 761–770. doi:10.1109/TGRS.2008.2009355.
- Lantz, T.C., Gergel, S.E., and Henry, G.H.R. 2010. Response of green alder (*Alnus viridis* subsp. *fruticosa*) patch dynamics and plant community composition to fire and regional temperature in north-western Canada: Response of vegetation to fire and regional climate. *Journal of Biogeography*: no–no. doi:10.1111/j.1365-2699.2010.02317.x.

- Lantz, T.C., Marsh, P., and Kokelj, S.V. 2012. Recent Shrub Proliferation in the Mackenzie Delta Uplands and Microclimatic Implications. *Ecosystems* **16**(1): 47–59. doi:10.1007/s10021-012-9595-2.
- Lucieer, A., Turner, D., King, D.H., and Robinson, S.A. 2014. Using an Unmanned Aerial Vehicle (UAV) to capture micro-topography of Antarctic moss beds. *International Journal of Applied Earth Observation and Geoinformation* **27, Part A**: 53–62. doi:10.1016/j.jag.2013.05.011.
- Lucieer, A., Turner, D., King, D.H., and Robinson, S.A. 2014. Using an Unmanned Aerial Vehicle (UAV) to capture micro-topography of Antarctic moss beds. *International Journal of Applied Earth Observation and Geoinformation* **27, Part A**: 53–62. doi:10.1016/j.jag.2013.05.011.
- McManus, Kelly M., Morton, D.C., Masek, J.G., Wang, D., Sexton, J.O., Nagol, J.R., Ropars, P., and Boudreau, S. 2012. Satellite-based evidence for shrub and graminoid tundra expansion in northern Quebec from 1986 to 2010. *Global Change Biology* **18**(7): 2313–2323. doi:10.1111/j.1365-2486.2012.02708.x.
- Mian, O., Lutes, J., Lipa, G., Hutton, J.J., Gavelle, E., and Borghini, S. 2015. Direct georeferencing on small unmanned aerial platforms for improved reliability and accuracy of mapping without the need for ground control points. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* **XL-1/W4**: 397–402. doi:10.5194/isprsarchives-XL-1-W4-397-2015.
- Moffat, N., Lantz, T.C., Fraser, R.H., and Olthof, I. In Review. Recent vegetation change (1980- 2013) in the tundra ecosystems of the Tuktoyaktuk Coastlands, NWT, Canada.
- Mora, C., Vieira, G., Pina, P., Lousada, M., and Christiansen, H.H. 2015. Land Cover Classification Using High-Resolution Aerial Photography in Adventdalen, Svalbard. *Geografiska Annaler: Series A, Physical Geography* **97**(3): 473–488. doi:10.1111/geoa.12088.
- Myers-Smith, I.H., Forbes, B.C., Wilking, M., Hallinger, M., Lantz, T., Blok, D., Tape, K.D., Macias-Fauria, M., Sass-Klaassen, U., Lévesque, E., Boudreau, S., Ropars, P., Hermanutz, L., Trant, A., Collier, L.S., Weijers, S., Rozema, J., Rayback, S.A., Schmidt, N.M., Schaepman-Strub, G., Wipf, S., Rixen, C., Ménard, C.B., Venn, S., Goetz, S., Andreu-Hayles, L., Elmendorf, S., Ravolainen, V., Welker, J., Grogan, P., Epstein, H.E., and Hik, D.S. 2011. Shrub expansion in tundra ecosystems: dynamics, impacts and research priorities. *Environmental Research Letters* **6**(4): 045509. doi:10.1088/1748-9326/6/4/045509.

- Myers-Smith, I.H., Hik, D.S., Kennedy, C., Cooley, D., Johnstone, J.F., Kenney, A.J., and Krebs, C.J. 2011. Expansion of Canopy-Forming Willows Over the Twentieth Century on Herschel Island, Yukon Territory, Canada. *AMBIO* **40**(6): 610–623. doi:10.1007/s13280-011-0168-y.
- Naito, A.T., and Cairns, D.M. 2011. Relationships between Arctic shrub dynamics and topographically derived hydrologic characteristics. *Environmental Research Letters* **6**(4): 045506. doi:10.1088/1748-9326/6/4/045506.
- Nijland, W., de Jong, R., de Jong, S.M., Wulder, M.A., Bater, C.W., and Coops, N.C. 2014. Monitoring plant condition and phenology using infrared sensitive consumer grade digital cameras. *Agricultural and Forest Meteorology* **184**: 98–106. doi:10.1016/j.agrformet.2013.09.007.
- Nolan, M., and DesLauriers, K. 2015. Which are the highest peaks in the US Arctic? Fodar settles the debate. *The Cryosphere Discussions* **9**(6): 6871–6907. doi:10.5194/tcd-9-6871-2015.
- Nolan, M., Larsen, C.F., and Sturm, M. 2015. Mapping snow-depth from manned-aircraft on landscape scales at centimetre resolution using Structure-from-Motion photogrammetry. *The Cryosphere Discussions* **9**: 333–381. doi:10.5194/tcd-9-333-2015.
- Nouwakpo, S.K., Weltz, M.A., and McGwire, K. 2015. Assessing the performance of structure-from-motion photogrammetry and terrestrial LiDAR for reconstructing soil surface microtopography of naturally vegetated plots. *Earth Surf. Process. Landforms*: n/a–n/a. doi:10.1002/esp.3787.
- Pattison, R.R., Jorgenson, J.C., Raynolds, M.K., and Welker, J.M. 2015. Trends in NDVI and Tundra Community Composition in the Arctic of NE Alaska Between 1984 and 2009. *Ecosystems* **18**(4): 707–719. doi:10.1007/s10021-015-9858-9.
- Puliti, S., Ørka, H.O., Gobakken, T., and Næsset, E. 2015. Inventory of Small Forest Areas Using an Unmanned Aerial System. *Remote Sensing* **7**(8): 9632–9654. doi:10.3390/rs70809632.
- Rasmussen, J., Ntakos, G., Nielsen, J., Svensgaard, J., Poulsen, R.N., and Christensen, S. 2016. Are vegetation indices derived from consumer-grade cameras mounted on UAVs sufficiently reliable for assessing experimental plots? *European Journal of Agronomy* **74**: 75–92. doi:10.1016/j.eja.2015.11.026.
- Raynolds, M.K., Walker, D.A., Epstein, H.E., Pinzon, J.E., and Tucker, C.J. 2012. A new estimate of tundra-biome phytomass from trans-Arctic field data and AVHRR NDVI. *Remote Sensing Letters* **3**(5): 403–411. doi:10.1080/01431161.2011.609188.

- Riaño, D., Chuvieco, E., Ustin, S.L., Salas, J., Rodríguez-Pérez, J.R., Ribeiro, L.M., Viegas, D.X., Moreno, J.M., and Fernández, H. 2007. Estimation of shrub height for fuel-type mapping combining airborne LiDAR and simultaneous color infrared ortho imaging. *Int. J. Wildland Fire* **16**(3): 341–348.
- Ryan, J.C., Hubbard, A.L., Box, J.E., Todd, J., Christoffersen, P., Carr, J.R., Holt, T.O., and Snooke, N. 2015. UAV photogrammetry and structure from motion to assess calving dynamics at Store Glacier, a large outlet draining the Greenland ice sheet. *The Cryosphere* **9**: 1–11. doi:10.5194/tc-9-1-2015.
- Snavely, N., Seitz, S.M., and Szeliski, R. 2007. Modeling the World from Internet Photo Collections. *Int J Comput Vis* **80**(2): 189–210. doi:10.1007/s11263-007-0107-3.
- Steedman, A.E., Lantz, T.C., and Kokelj, S.V. 2016. Spatio-Temporal Variation in High-Centre Polygons and Ice-Wedge Melt Ponds, Tuktoyaktuk Coastlands, Northwest Territories. *Permafrost and Periglac. Process.*: Early View Paper. doi:10.1002/ppp.1880.
- Stow, D.A., Hope, A., McGuire, D., Verbyla, D., Gamon, J., Huemmrich, F., Houston, S., Racine, C., Sturm, M., Tape, K., Hinzman, L., Yoshikawa, K., Tweedie, C., Noyle, B., Silapaswan, C., Douglas, D., Griffith, B., Jia, G., Epstein, H., Walker, D., Daeschner, S., Petersen, A., Zhou, L., and Myneni, R. 2004. Remote sensing of vegetation and land-cover change in Arctic Tundra Ecosystems. *Remote Sensing of Environment* **89**(3): 281–308. doi:10.1016/j.rse.2003.10.018.
- Streutker, D.R., and Glenn, N.F. 2006. LiDAR measurement of sagebrush steppe vegetation heights. *Remote Sensing of Environment* **102**(1–2): 135–145. doi:10.1016/j.rse.2006.02.011.
- Sturm, M., Schimel, J., Michaelson, G., Welker, J.M., Oberbauer, S.F., Liston, G.E., Fahnestock, J., and Romanovsky, V.E. 2005. Winter Biological Processes Could Help Convert Arctic Tundra to Shrubland. *BioScience* **55**(1): 17–26. doi:10.1641/0006-3568(2005)055[0017:WPCHC]2.0.CO;2.
- Tape, K., Sturm, M., and Racine, C. 2006. The evidence for shrub expansion in Northern Alaska and the Pan-Arctic. *Global Change Biology* **12**(4): 686–702. doi:10.1111/j.1365-2486.2006.01128.x.
- Tømmervik, H., Karlsen, S-R., Nilsen, L., Johansen, B., Storvold, R., Zmarz, A., Beck, P.S., Johansen, K-S., Høgda, K-A., Goetz, S., Park, T., Zagajewski, B., Myneni, R.B., and Bjerke, J.W. 2014. Use of unmanned aircraft systems (UAS) in a multi-scale vegetation index study of arctic plant communities in Adventdalen on Svalbard. *EARSeL eProceedings*, 13(S1), 47-52.

- Turner, D., Lucieer, A., and de Jong, S.M. 2015. Time Series Analysis of Landslide Dynamics Using an Unmanned Aerial Vehicle (UAV). *Remote Sensing* **7**(2): 1736–1757. doi:10.3390/rs70201736.
- Westoby, M.J., Brasington, J., Glasser, N.F., Hambrey, M.J., and Reynolds, J.M. 2012. “Structure-from-Motion” photogrammetry: A low-cost, effective tool for geoscience applications. *Geomorphology* **179**: 300–314. doi:10.1016/j.geomorph.2012.08.021.
- Whitehead, K., and Hugenholtz, C.H. 2014. Remote sensing of the environment with small unmanned aircraft systems (UASs), part 1: a review of progress and challenges. *J. Unmanned Veh. Sys.* **02**(03): 69–85. doi:10.1139/juvs-2014-0006.
- Wulder, M.A., White, J.C., Nelson, R.F., Næsset, E., Ørka, H.O., Coops, N.C., Hilker, T., Bater, C.W., and Gobakken, T. 2012. Lidar sampling for large-area forest characterization: A review. *Remote Sensing of Environment* **121**: 196–209. doi:10.1016/j.rse.2012.02.001.
- Zhang, Y., Olthof, I., Fraser, R., and Wolfe, S.A. 2014. A new approach to mapping permafrost and change incorporating uncertainties in ground conditions and climate projections. *The Cryosphere* **8**(6): 2177–2194. doi:10.5194/tc-8-2177-2014.

Figure Captions

Fig. 1. (a) Study location just south of Tuktoyaktuk, NWT, Canada; (b) photo of study area taken from a helicopter with orange experimental snow fences visible (the white dashed line shows UAV surveyed area); (c) ground photo taken in August 2015 of the lower portion of the study area where denser upright shrub transitions to dwarf shrub and graminoid tundra in an area of high-centered polygonal terrain.

Fig. 2. Spyder PX8 Plus 1000 octocopter by XPedition Robotics with Sony a6000 24 MP mirrorless camera used for UAV surveys.

Fig. 3. Three UAV photograph subsets of an alder shrub showing the effect that degree of forward overlap has on the consistency of visible features that can be used for SfM feature matching. The image on the left was extracted from a photo having 90% overlap with the middle image, while the image of the right was extracted from a photo having 70% overlap with the middle image. Forward overlap here corresponds to the top-bottom direction of the photos.

Fig. 4. Flowchart showing overall UAV image processing steps to generate vegetation classification.

Fig. 5. Area of study site showing (a) 0.75 cm resolution UAV photo, (b) oblique view of the ultra-dense point cloud, (c) vegetation height model, and (d) 1 cm orthomosaic.

Fig. 6. Area containing the two alder shrubs shown in the inset of Figure 5 providing a more detailed view of (a) 0.75 cm resolution UAV photo, (b) oblique view of the ultra-dense point cloud, (c) vegetation height model, and (d) 1 cm orthomosaic.

Fig. 7. Comparisons of ultra-dense point cloud with ground photos taken of alder shrubs (a-b) and a willow shrub (c). Modeled and measured maximum shrub heights are indicated in the upper-left corners.

Fig. 8. (a) Relationship between maximum canopy heights from the UAV-based model with maximum canopy heights measured in the field. (b) Relationship between mean + two standard deviations of canopy heights from the UAV-based model with average canopy heights based on six field measurements. On both figures the solid line shows the results of the least squares regression and the dashed line shows the 1:1 line.

Fig. 9. Estimated height change based on differencing pre- and post-cutting DSMs for the sub-area containing the trimmed shrubs (outlined in black with trimming amounts indicated). Shrubs 1-5 were alders, area 6 was dominated by willow, and area 7 was dominated by birch. Close-up views of DSM differences for four of the trimmed alders are shown at the bottom. The rectangular inset on the upper panel shows the uncut area shown enlarged in Figure 10.

Fig. 10. Close-up view of orthomosaics and DSMs from the repeat surveys in an unmodified area containing low willow and birch shrubs. The image at the bottom-right shows the DSM difference between the two surveys. A 50 cm interval grid is overlaid to provide scale.

Fig. 11. A sample of dense point clouds derived from (a) the full set of photos from survey #2, (b) the 25% subset of photos from survey #2, and (c) the reduced resolution (1.5 cm) photos from survey #4. The red areas indicate gaps containing no point cloud data. The graphs at the bottom show the heights of all points contained within 20 cm wide transect moving up the slope.

Fig. 12. Colour orthomosaic (top) and vegetation type classification (bottom) for a portion of the study area that includes all cover types.

Fig. 13. Colour orthomosaic (top) and vegetation type classification (bottom) covering a single ice-wedge polygon surrounded by water.

Supplementary video 1. Ultra-dense point cloud animation showing a portion of the lower slope within the study area. The animation was created by importing the Agisoft Photoscan dense point cloud into Pix4dmapper Discovery software.

Supplementary video 2. Animation of pre- and post-trimming ultra-dense point clouds showing height changes in two of the trimmed alder shrubs.

Draft

Supplementary Material – UAV Photo Software Processing Steps

Specific software settings and options are italicized in parentheses.

- (1) Identify and remove any blurry photos (about 1% of photos) using the PixelPeeper v1.0 tool (<http://www.textures.com/pixelPeeper>) and import remaining geotagged photos into Agisoft PhotoScan.
- (2) Identify and then match thousands of scale-invariant features (or keypoints) in overlapping photos using a computer vision approach similar to one described in Lowe (2004) (*PhotoScan Align Photos settings: Accuracy=High, Pair preselection=Reference*).
- (3) Solve for the 3D location of each keypoint and calibration parameters for each camera (location/pose, focal length, etc.) using a photogrammetric technique called bundle adjustment, which results in a sparse cloud of 3D points. In our work flow the camera calibration and 1-3 m accuracy UAV georeferencing were optimized at this step using three GCP ground targets (red Frisbees with a painted yellow cross) located to within 2 cm using post-differential GPS correction to a nearby base station. (*Accomplished using Align Photos in PhotoScan as above*).
- (4) Generate an ultra-dense point cloud of coloured 3D points using multi-view stereo image matching (*PhotoScan Build Dense Cloud settings: Quality=Ultra-High+High+Medium, Depth filtering=Mild*). Ultra-High quality matches photos at full resolution and was found to best capture small, isolated clumps of leaves on upper shrub branches that are visible in ground photos. Photos were also processed in additional PhotoScan “chunks” to generate dense point clouds at High and Medium Quality

settings, which downscales the photos by a factor of 2 and 4. These additional point clouds, which increase the number of points by $\sim 20\%$ and can fill gaps in some areas of the Ultra-High quality cloud, were then merged with the Ultra-High quality cloud to form a final, multi-scale point cloud.

- (5) Remove 3D points in the dense cloud representing water, since image matching performs poorly over featureless, opaque water and produces significant noise that can impact subsequent terrain modeling (*PhotoScan select point by photo mask tool*).
- (6) Generate an orthomosaic by orthorectifying each photo to conform to a digital surface model and then mosaicking them (*Agisoft Build Orthomosaic settings: Surface=DEM, Blending mode=Mosaic, Pixel size=0.01 m*).
- (7) Export the orthomosaic as a 1 cm resolution geoTIFF file and the dense point cloud as tiled .las files, both in UTM zone 8 projection. At this stage in our workflow the outputs from all surveys were clipped to a smaller common analysis area covering 1.5 ha (Fig. 1b).
- (8) Import and edit .las files in CloudCompare to remove remaining water points at the shoreline that were not captured in the PhotoScan water masks. In our analysis CloudCompare was used to mask out any points lying below the shoreline elevation.
- (9) Generate an ArcGIS LAS dataset (*ArcGIS Create LAS Dataset Tool*).
- (10) Create a raster height model (DSM) representing the upper surface formed by the 3D points by selecting the point with largest z value in each 1 cm cell (*ArcGIS LAS Dataset to Raster Tool*).
- (11) Create a 1 cm raster height model representing the ground surface below vegetation (bare earth model). This step is challenging since, unlike LiDAR laser pulses that can

fully penetrate vegetation canopies, only the ground gaps between canopies are normally visible in overlapping photos and represented in SfM point clouds (Dandois and Ellis 2013). Furthermore, most areas between low shrub canopies are covered by shorter dwarf shrubs (e.g. heaths), making true ground patches infrequent. In our workflow a bare earth model was created by selecting minimum height points on a 2 m grid spacing and triangulating these to model local changes in surface topography before being rasterized (ArcGIS LAS Dataset to Raster Tool: Linear Triangulation option). This bottom-up approach is similar to that of Axelsson (2000), except that only one iteration of ground point selection is conducted to produce a conservative TIN surface from the lowest points.

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Table 1. Summary of the four UAV surveys conducted within the study area. Solar noon, when the sun was at its highest elevation, occurred at 2:58 PM local time. AGL is flying height above ground level and Res is resolution or pixel size.

ID	Date / Local Time	Speed (m s ⁻¹)	AGL (m)	Res. (cm)	Area (ha)	Photos (#)	Overlap forward / side (%)	Notes
1	07-30-2015 5:27 PM	4	45	0.75	1.9	542	90/83	Baseline survey
2	07-31-2015 4:42 PM	4	45	0.75	1.9	599	90/83	Repeat of #1 after trimming sample of shrubs
3	07-31-2015 5:02 PM	4	20	0.33	2.1	468	60/25	Reference photos for visual interpretation of vegetation
4	07-31-2015 10:04 AM	10	90	1.5	9.2	691	85/83	To test effect of decreasing resolution

Table 2. Vegetation / land cover legend used for the decision tree classification.

Class ID	Class Name	Description
1	Willow	<i>Salix pulchra</i> and <i>Salix glauca</i> . Often overtops birch shrub
2	Alder	Tallest shrubs up to 2m, most common at the base of the slope (<i>Alnus viridis ssp. fruticosa</i>)
3	Birch	Most common low shrub (<i>Betula glandulosa</i> and <i>Betula nana</i>)
4	Reindeer lichen	Mostly occurs in small patches
5	Moss	
6	Sedge tussock	Most common at slope base (<i>Eriophorum vaginatum</i>)
7	Soil and dark cryptogams	
8	Wet graminoid	<i>Carex spp.</i> common in wet troughs between ice-wedge polygons and at wet, flat sites
9	Water	In degraded ice-wedge troughs.
10	Mixed dwarf shrub heath	Heterogeneous mixtures of short-statured (<25 cm) vegetation consisting of heath shrubs, forbs, and classes 3-6 (includes <i>Rhododendron</i> , <i>Vaccinium</i> , <i>Arctostaphylos</i> , <i>Empetrum</i> , <i>Rubus</i> , <i>Carex</i>)
11	Shrub shadow	Dark shadows cast by classes 1-3 (represents class 10 in most cases)

Table 3. List of predictor variables (features) computed for each eCognition image segment and used for See5 decision tree classification. Variables are listed by the cumulative improvement in overall classification accuracy provided. A subset of 11 variables (above the dashed line) was selected for the final classification model. R, G, and B correspond to the red, green, and blue bands.

Variable	Description	Cumulative Accuracy (%)
vh_max	Maximum vegetation height	
NDGB	Normalised Difference of G&B = $G-B / G+B$	58.6
NDGR	Normalized Difference of G&R = $G-R / G+R$	69.6
vh_mean	Mean vegetation height	70.6
dsm_mean	Mean DSM elevation	77.2
dsm_max	Maximum DSM elevation	78
dsm_sd	Standard deviation of DSM	78.9
max_diff	(Maximum difference of mean R,G,B) / (brightness)	80.4
RB_ratio	R / B	80.8
ExG	Excess greenness $(2G-B-R)/(2G+B+R)$	81
tex_mean	Mean grey level co-occurrence 5-by-5 texture	82
red_mean	Mean red channel value	81.7
green_mean	Mean green channel value	81.7
greyness	Brightness similarity in R,G,B	81.8
vh_sd	Standard deviation of vegetation height	82
red_max	Maximum red channel value	82.2
tex_max	Maximum grey level co-occurrence 5-by-5 texture	82.1
green_sd	Standard deviation of green channel	82.3
blue_mean	Mean blue channel value	82.3
brightness	Sum of mean R,G,B values	82.1
green_max	Maximum green channel value	82.4
blue_max	Maximum blue channel value	82.3
blue_sd	Standard deviation of blue channel	82.3
red_sd	Standard deviation of red channel	82.4

tex_sd	Standard deviation of texture	82.4
compactness	Object (length × width) / area	82.6

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Table 4. Point cloud density and vegetation height model performance based on 31 samples for four SfM processing trials.

Survey / Trial	Point Cloud Density (pts/m ²)	Height Model R ²	Standard Error (cm)
Survey 1 – 45 m, 0.75 cm res.	31 033	0.96	8.1
Survey 2 – 45 m, 0.75 cm res.	35 953	N/A	N/A
Survey 2 – reduced photo overlap (25% density)	22 640	0.92	11.6
Survey 4 – 90 m, 1.5 cm res.	8 145	0.70	23.2

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Table 5. Confusion matrix indicating the probability that the classified map is correct (user’s accuracy corresponding to the rows) or that the training samples are correct (producer’s accuracy corresponding to the columns) for each class. The table also includes: the overall accuracy, overall kappa accuracy that compensates for agreement due to random chance, overall accuracy based on a classifier using only spectral RGB variables, and overall accuracy based on a classifier using only height variables derived from the DSM and vegetation height model. Wet Gram is wet graminoid.

	Willow	Alder	Birch	Lichen	Moss	Tussock	Soil	Wet Gram.	Water	Dwarf Shrub	Shadow	User's Accuracy (%)
Willow	5233	282	198	89	0	30	30	23	0	84	4	88
Alder	469	10446	211	0	0	0	10	5	8	4	0	94
Birch	449	306	15294	0	0	283	13	374	0	653	79	88
Lichen	57	1	3	2578	0	102	40	98	14	101	0	86
Moss	0	0	0	0	2281	27	28	112	0	178	0	87
Sedge Tussock	27	0	139	73	4	3782	37	396	1	1452	0	64
Soil	2	10	0	44	1	0	3629	67	96	40	0	93
Wet Graminoid	3	0	233	54	74	480	52	5240	46	1391	0	69
Water	0	3	0	1	0	0	126	43	2992	6	0	94
Dwarf Shrub	140	14	812	143	439	2920	151	2246	27	20661	52	75
Shrub Shadow	0	0	52	0	0	0	44	24	0	1	369	75
Producer's Accuracy (%)	82	94	90	86	81	50	87	61	94	84	73	
Overall accuracy:	82%											
Overall kappa accuracy:	78%											
Spectral only:	72%											
Height only:	64%

Fig. 1. (a) Study location just south of Tuktoyaktuk, NWT, Canada; (b) photo of study area taken from a helicopter with orange experimental snow fences visible (the white dashed line shows UAV surveyed area); (c) ground photo taken in August 2015 of the lower portion of the study area where denser upright shrub transitions to dwarf shrub and graminoid tundra in an area of high-centered polygonal terrain.
115x102mm (300 x 300 DPI)

Fig. 2. Spyder PX8 Plus 1000 octocopter by XPedition Robotics with Sony a6000 24 MP mirrorless camera used for UAV surveys.
85x50mm (300 x 300 DPI)

Fig. 3. Three UAV photograph subsets of an alder shrub showing the effect that degree of forward overlap has on the consistency of visible features that can be used for SfM feature matching. The image on the left was extracted from a photo having 90% overlap with the middle image, while the image of the right was extracted from a photo having 70% overlap with the middle image. Forward overlap here corresponds to the top-bottom direction of the photos.

135x74mm (300 x 300 DPI)

Fig. 4. Flowchart showing overall UAV image processing steps to generate vegetation classification.
57x100mm (300 x 300 DPI)

Fig. 5. Area of study site showing (a) 0.75 cm resolution UAV photo, (b) oblique view of the ultra-dense point cloud, (c) vegetation height model, and (d) 1 cm orthomosaic.
118x98mm (300 x 300 DPI)

Fig. 6. Area containing the two alder shrubs shown in the inset of Figure 5 providing a more detailed view of (a) 0.75 cm resolution UAV photo, (b) oblique view of the ultra-dense point cloud, (c) vegetation height model, and (d) 1 cm orthomosaic.
118x93mm (300 x 300 DPI)

Fig. 7. Comparisons of ultra-dense point cloud with ground photos taken of alder shrubs (a-b) and a willow shrub (c). Modeled and measured maximum shrub heights are indicated in the upper-left corners.
105x169mm (300 x 300 DPI)

Fig. 8. (a) Relationship between maximum canopy heights from the UAV-based model with maximum canopy heights measured in the field. (b) Relationship between mean + two standard deviations of canopy heights from the UAV-based model with average canopy heights based on six field measurements. On both figures the solid line shows the results of the least squares regression and the dashed line shows the 1:1 line.

73x102mm (300 x 300 DPI)

Fig. 9. Estimated height change based on differencing pre- and post-cutting DSMs for the sub-area containing the trimmed shrubs (outlined in black with trimming amounts indicated). Shrubs 1-5 were alders, area 6 was dominated by willow, and area 7 was dominated by birch. Close-up views of DSM differences for four of the trimmed alders are shown at the bottom. The rectangular inset on the upper panel shows the uncut area shown enlarged in Figure 10.
112x99mm (300 x 300 DPI)

Fig. 10. Close-up view of orthomosaics and DSMs from the repeat surveys in an unmodified area containing low willow and birch shrubs. The image at the bottom-right shows the DSM difference between the two surveys. A 50 cm interval grid is overlaid to provide scale.
124x99mm (300 x 300 DPI)

Fig. 11. A sample of dense point clouds derived from (a) the full set of photos from survey #2, (b) the 25% subset of photos from survey #2, and (c) the reduced resolution (1.5 cm) photos from survey #4. The red areas indicate gaps containing no point cloud data. The graphs at the bottom show the heights of all points contained within 20 cm wide transect moving up the slope.
137x88mm (300 x 300 DPI)

Fig. 12. Colour orthomosaic (top) and vegetation type classification (bottom) for a portion of the study area that includes all cover types.
91x111mm (300 x 300 DPI)

Fig. 13. Colour orthomosaic (top) and vegetation type classification (bottom) covering a single ice-wedge polygon surrounded by water.
140x62mm (300 x 300 DPI)

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