



University of New Hampshire



National Science Foundation

# B31F-0089: Use of high resolution UAS imagery to classify sub-arctic vegetation types

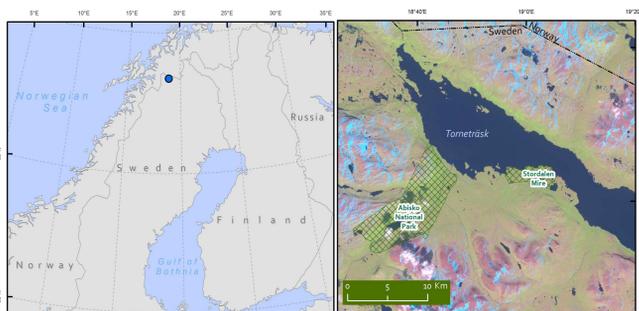
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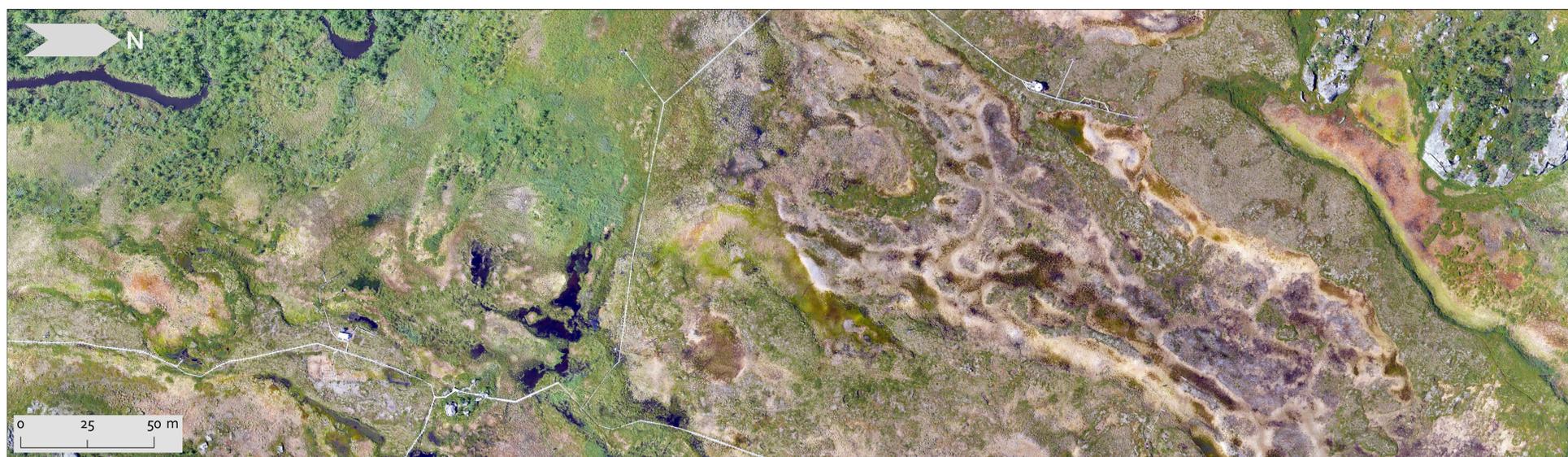
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**Overview** Sub-arctic permafrost regions are experiencing annual warming with a resulting thaw that induces changes to the vegetative landscape. This warming trend is directly correlated to increases in annual greenhouse gas emissions including methane (CH<sub>4</sub>). Vegetation species and composition are indirect indicators of CH<sub>4</sub> flux, and may serve as a proxy for estimating changes in CH<sub>4</sub> emission over time. A WorldView-2 image (WV-2, 2m<sup>2</sup> spatial resolution, 8 multispectral bands) was acquired in August 2014 over the Abisko region in northern Sweden. Aerial imagery was also collected in July 2014 over a 4km<sup>2</sup> area using a fixed wing unmanned aircraft system (UAS). To predict vegetation classes, spectral information from WV-2 was combined with texture analysis from the UAS imagery, and an unsupervised ISODATA clustering algorithm was conducted. Classification was compared with over 100 vegetation plots. Preliminary results are promising, thus supporting the use of UAS and high resolution satellite image collection to provide landscape level characterization of vegetation. Future work includes supervised classification in conjunction with regression trees & use of neural networks, as well as temporal analysis (2012 & 2013 imagery).

To study the annual change in vegetation composition, field analysis combined with aerial imagery was used. The use of unmanned aircraft systems (UAS) offers benefits that satellite imagery does not—the ability to obtain high spatial resolution (< 5cm) data with high temporal coverage (hourly, daily, etc) at a relatively low cost.



Overview of study region (left) & Abisko region (right, Landsat FCC); aerial image of study area in Stordalen mire acquired from UAS (far right)



## Methods

**Tall Shrub (TS)**  
ombrotrophic,  
found in dry areas

**Hummock (HM)**  
ombrotrophic, on  
permafrost

**Semi-Wet (SW)**  
Ombrotrophic or  
minerotrophic

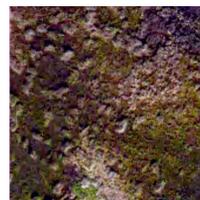
**Wet (WT)**  
Ombrotrophic

**Tall Graminoid (TG)**  
Wet minerotrophic

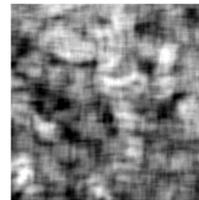
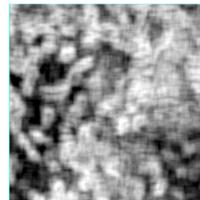
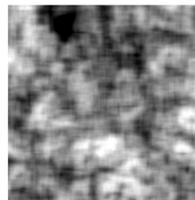
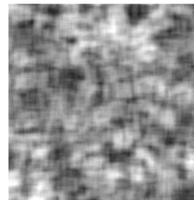
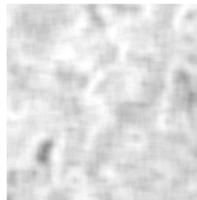
**Field Photos**  
From gridded plots as well as in-situ ancillary data, classes based largely on ecosystem & hydrology function.



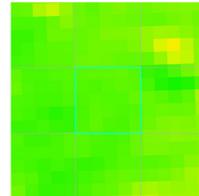
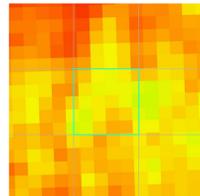
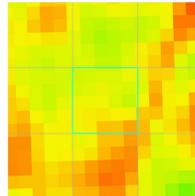
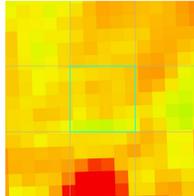
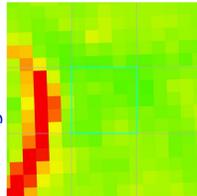
**UAS Aerial Imagery**  
2014/07/11, 3cm<sup>2</sup>, Panasonic Lumix (16MP) camera flown with a Robota Triton aircraft, flown at 70m



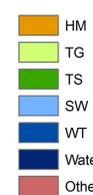
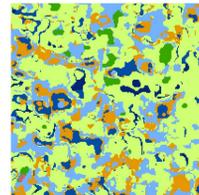
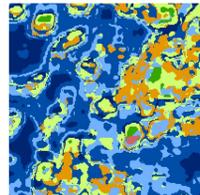
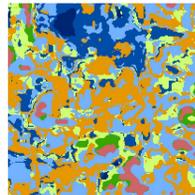
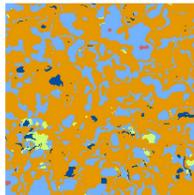
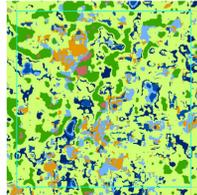
**Entropy (aerial)**  
50cm moving window, measure of the randomness of pixel gray levels



**WV-2**  
2014/08/08, 2m<sup>2</sup> multi, 50cm<sup>2</sup> pan, 8 spectral bands, 5 spectral indices (NDVI pictured right)



**Classification**  
Unsupervised ISODATA using 13 WV-2 bands & 3 texture bands



## Conclusions

Field plot design suited previous comparisons with 2m<sup>2</sup> WV-2 data alone. The addition of UAS imagery will require nested plots that reflect vegetation patterns and texture at various scales, as well as spectral reflectance.

Over 500 images were captured, & the highest quality images were mosaicked using Agisoft PhotoScan. Map-grade GPS data ( $\pm 50$ cm error) was not accurate enough for image georectification.

Results reflect general texture characteristics of vegetation. Smoother areas have a lower entropy. Use of mean and standard deviation of entropy for plots is currently being explored.

Spectral data provide additional leverage in classification efforts. Data that contributed most to classification were NDVI (pictured, left) & 1<sup>st</sup> principal component of 8 original bands. Data were resampled to 3cm to match aerial imagery.

Preliminary results show strengths & weaknesses. There was difficulty separating SW from HM & WT. HM & TG had good separation. HM seems to be over-classified.

## Future Work

Reorganization of vegetation classes to reflect ground cover instead of ecosystem function. Establishment of additional field plots.

Additional data collection planned for July 2015, possible inclusion of CIR camera or lidar sensor. Survey-grade GPS data ( $\pm 1$ cm) will also be collected.

Imagery flown at a lower altitude would yield finer spatial resolutions, enabling the detection of more subtle texture differences. Calculation of additional texture measures to aid in classification (variance, dissimilarity, lacunarity).

Further exploration of spectral characteristics as they contribute to more accurate classifications. Possible inclusion of 50cm panchromatic band.

A supervised classification via regression trees, boosted trees, or a similar data mining technique might improve results; also, a moving window clustering algorithm or object-based classification could be used.