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Species Composition at the Sub-meter Level in Discontinuous Permafrost in Subarctic, Sweden

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Introduction

Northern latitudes are experiencing rapid warming. Wetlands underlain by permafrost are particularly vulnerable to warming which resulting in changes in vegetative cover. Species composition including diversity and richness has been associated with greenhouse gas emissions, therefore knowledge of species composition allows for the analysis of systematic change and quantification of emissions.

Species composition varies on the sub-meter scale based on topography and other microsite parameters. There are unknown factors with fine scale ground based remote sensing. By using this new methodology hopefully we can create an intermediate level of analyses to determine fine scale species composition. This complexity and the understanding of vegetation on the landscape level proves vital in our estimation of carbon dioxide (CO_2) and methane (CH_4) emissions and changes in these emissions over time.

Research Questions

- *What is the species composition at the sub-meter scale using remote sensing?*
- *Can we predict site type with the species composition? And can we predict species using ground based remote sensing?*

Methods

- Randomly selected 25 plots that were representative of five major cover types: Semi-wet, wet, hummock, tall graminoid, and tall shrub (Malmer *et al*. 2005). These 5 site types captured the majority of vegetation species that were present in the mire.
- Used 1mx1m quadrat with 64 equal subplots to measure percent cover for 26 species. This provided species richness and Shannon's evenness data.
- We collected ground based remote sensing (RS) at each plot to determine species composition using an ADC-lite (near infrared, red, green) and GoPro © (red, blue, green). With the remote sensing aspect we can now map our the mire with vegetation cover types and separate them according to site type.
- Each image was normalized using on a Teflon white chip. Textural analysis was conducted on each image for entropy, angular second momentum, and lacunarity. Lacunarity measures how fractal pattern fill empty space. It quantifies certain features and categorizes them accordingly. ASM is a measure of how rough or smooth an object is. Entropy measures the number of ways a system can be arranged and indicates the diversity as well as the spread of across possible pixel values.
- A logistic regression was developed to examine vegetation cover types and remote sensing parameters. We used a multiple linear regression using forwards stepwise variable selection

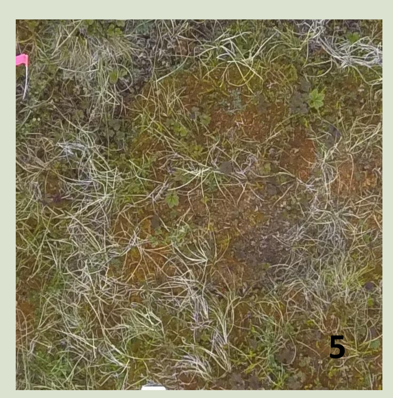


(Photo credit: Samantha Anderson. 1: *Empetrum nigrum* (crowberry) 2. *Andromeda polfolia* (bog rosemary) 3. Betula nana (Dwarf Birch)

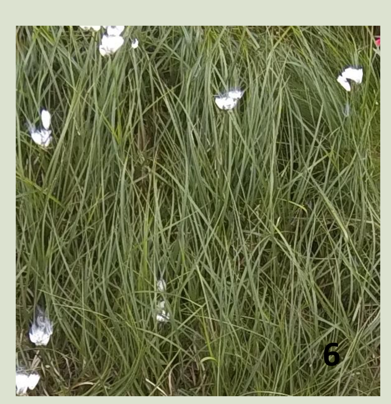
5 Site Types

We found that in areas where there were low species diversity one or two particular species dominated. As species diversity increased the plots became evenly distributed across different vegetative types.

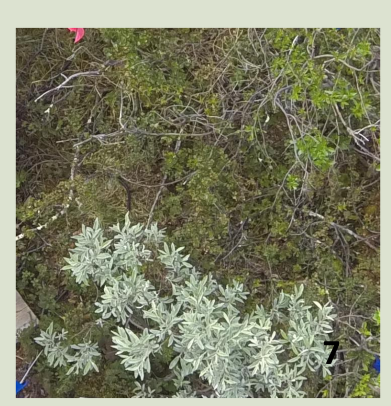
Wet
Species richness: 4
Shannon Index: 0.224



Semi-Wet
Species richness: 5
Shannon Index: 0.242



Tall Graminoid
Species richness: 4
Shannon Index: 0.139



Tall Shrub
Species richness: 9
Shannon Index: 0.387

Hummock
Species richness: 8
Shannon Index: 0.482

Results

Vegetation Parameters

We ran Tukey tests using the program JUMP to determine whether plant species were indicative of different vegetation types. This test provided us with statistically significant differences between site types according to which species was present within each category.

- *Rubus chamemorus* (Cloudberry) and *Empetrum nigrum* (Crowberry) were found to be statistically significant in the tall shrub and hummock sites compared to the "wetter" sites.
- *Betula nana* (Dwarf Birch) and *Carex* were on the opposite sides of the spectrum were *Betula nana* was prevalent in the tall shrub areas and *Carex* was prevalent in the tall graminoid areas.

(Figure 1. Image was taking from a remotely operated vehicle (ROV) using an ACD Lite camera . Images were captured every 5 seconds then stitched together to map out the mire. The green square represents one of our hummock plots. Created by Michael Palace.)

Remote Sensing Parameters

Lacunarity, angular second moment (ASM) and entropy were three factors that we measured (Table 2a). Forward stepwise regression was conducted to determine which remote sensing(RS) parameter was the best predictor of a given species. This process answered the question can remote sensing predict species? Depending on which parameter you are looking at vegetation can be predicted with a p-value of 0.05 or less. A satellite image was used to see spatial variability of the plots and to conduct GIS based networking analysis. The networking analysis was done to provide an image that distinguished between different site types (Figure 2). Each category is represented in different colors to model what was ground truthed in the field.

Can remote sensing predict species?

Table 2a.

	Remote Sensing Parameters							
Species	Intercept	entropy_incell	eveness_incell	eveness_whole	asm_incell	asm_whole	FD	TI
Empetrum nigrum (Crowberry)	***4.137***						***-2.185***	
Eriophorum vaginatum	**-0.269**							***0.066***
Sphagnum spp.	***75.388***				***-90.408***		***7.698***	
Salix lapponum (Downy Willow)	-0.144	***-1.255***	***7.146***					
Betula nana (Dwarf Birch)	1.475	***-1.169***		8.928		***2.404***	**-2.238**	5.37E-02
Andromeda polifolia (Bog Rosemary)	***5.222***				**-5**			
Rubus chamemorus (Cloudberry)	***11.280***				***-5.261***		***-6.409***	***0.127***
p>0.05, **p<0.05, *p<0.01***								

(Table 2a: Forward stepwise regression estimates of remote sensing parameters predicting species. Entropy whole was not included due to the fact that it did not come up as a parameter for identifying species.)

Table 2b.

Species	p-value	r^2	RMSE
Empetrum nigrum (Crowberry)	0.0003	0.23	0.097
Eriophorum vaginatum	0.0013	0.20	0.125
Sphagnum	<.0001	0.59	0.185
Salix lapponum (Downy Willow)	<.0001	0.33	0.058
Betula nana (Dwarf Birch)	<.0001	0.48	0.046
Andromeda polifolia (Bog Rosemary)	0.0015	0.19	0.025
Rubus chamemorus (Cloudberry)	<.0001	0.47	0.067

(Table 2b: Forward stepwise regression results showing p-values, r-squared and root mean square values to determine whether remote sensing parameters is a good predictor of species.. [Root mean square error (RMSE) is sample standard deviation of the differences between predicted values and observed values or a measure of how accurate your data is])

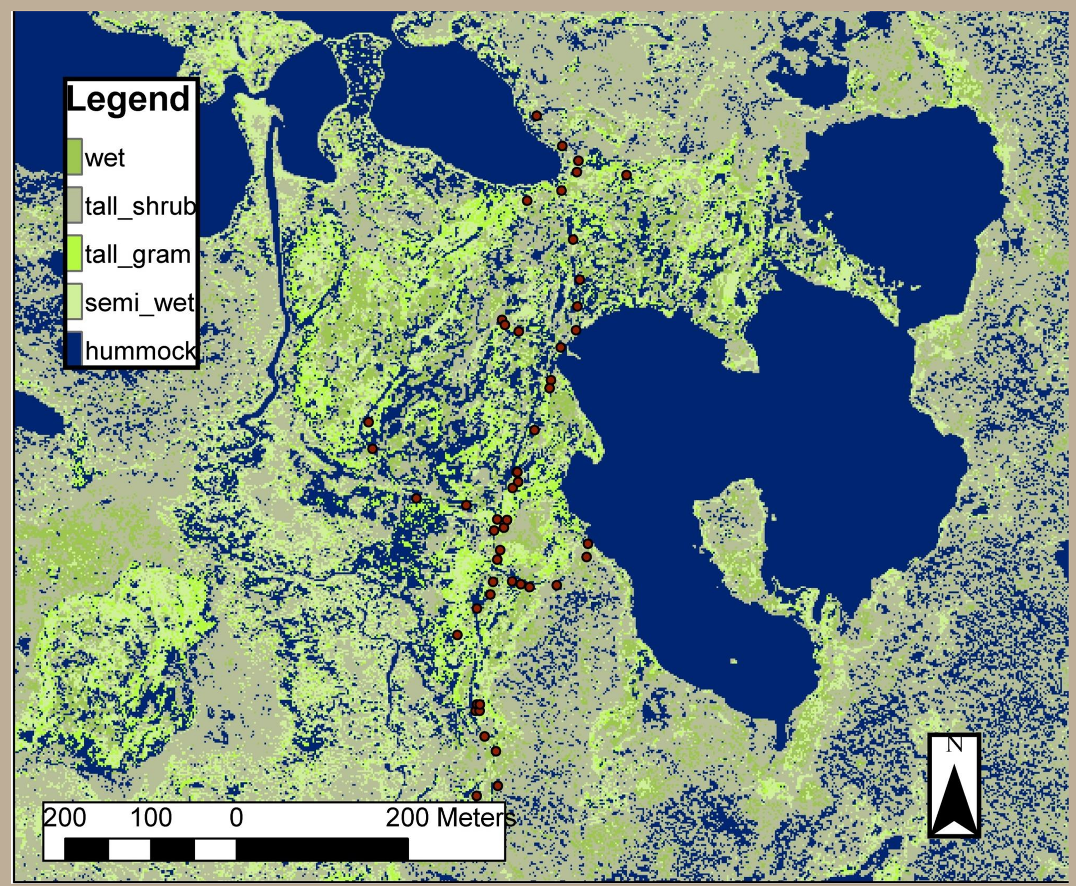
Eriophorum angustifolium runs along the boardwalk in Stordalen Mire in Abisko, Sweden. Photo credit: Samantha Anderson.[9]

Can we predict site type with species?

Table 1.

	Site Type Parameters	
Species	R^2	Prob>ChiSq
Vaccinium vitis-idaea (Lingonberry)	0.51	<.0001
Empetrum nigrum (Crowberry)	0.57	<.0001
Eriophorum vaginatum	0.22	0.0006
Sphagnum spp.	0.73	<.0001
Carex spp.	0.54	<.0001
Betula nana (Dwarf Birch)	0.52	<.0001
Andromeda polifolia (Bog Rosemary)	0.41	<.0001
Rubus chamemorus (Cloudberry)	0.77	<.0001

(Table 1: Multiple regression analysis determining species through site type. Some species were found in certain site types indicating a higher correlation coefficient . *Eriophorum vaginatum* was found throughout all site types resulting in a lower correlation coefficient.)



(Figure 2. The 50 sampled plots are indicated by the red dots and the large aggregate blue areas are lakes. Photo created by Michael Palace.)


On the left: Michael Layne and Samantha Anderson capture a tall graminoid plot with a 1m by 1m quadrat using a GoPro©[10] . On the right: Advisor Dr. Michael Palace sets up ground based remote sensing equipment in Stordalen mire[11] . (Photo credit: Samantha Anderson[10] and Ashley Lang[11] .

Conclusion

We found that there were significantly different species composition within each vegetation cover type and also determined which species were indicative for cover type. Our logistical regression was able to significantly classify vegetation cover types based on RS parameters. Our multiple regression analysis indicated Betula nana (Dwarf Birch) (p=<0.0001) and Sphagnum (p=<0.0001) were statistically significant with respect to RS parameters. By measuring species composition and predicting site type through imaging we have a better understanding of where greenhouse gases flux. In future this data could enhance predictability for local GHG flux hot spots. A higher resolution camera would better the chance of identifying fine detailed plant species like those in an open field or mire ecosystem. We suggest that ground based remote sensing methods may provide a unique and efficient method to quantify vegetation across the landscape in northern latitude wetlands.

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