Mapping Arctic Representativeness and Vegetation using Data Mining and Machine Learning Techniques **SECONAR RIDGE** TENNESSEE

National Laboratory

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Introduction

The Arctic ecosystem is a large permafrost-dominated region with regional climate, ecohydrology and geomorphology that drive a diverse and heterogeneous distribution of vegetation on the landscape. Using a coordinated modeling and field/laboratory observations approach, NGEE–Arctic is working to improve our understanding of Arctic ecosystems and how they may evolve in the future.

• While resource and logistical constraints limit the extent and frequency of measurements, we developed and employed a systematic sampling strategy to objectively represent environmental variability at appropriate spatial and temporal scales.

• Using machine learning techniques we combined high resolution satellite data with field observations to develop high resolution maps of Arctic vegetation.

While core field observation campaigns within NGEE-Arctic are focused at a set of cores sites in Alaska, leveraging the work being conducted by other research groups across the broader Pan-Arctic region allows scaling of observations and models to the larger landscape.



Arctic Vegetation Mapping at Seward Peninsula

Availability of high resolution remote sensing data in the Arctic is often limited due to frequent cloud cover and polar darkness. However, many satellites collect data using different sensor types, at different resolutions and return frequencies. We developed a multi-sensor data fusion approach to combine the information content from a range of sensor types and resolutions available at the Seward Peninsula for improved mapping of vegetation at high resolution.

 Table 2: Spectral and topographic variables used in multi-sensor fusion based
vegetation classifications

S	ensor Group	Predictor Variable	Unit	Date
A	LOS-1	HH	γ^0	29 August 2007
P	ALSAR	HV	γ^0	
S	POT-5	Green, Red, NIR (0.5–0.9 µm)	DN	June-September 2009 – 2012
lf	SAR	Elevation	m	July 2012
E	0-1	198 spectral bands (0.4 to 2.5 μ m)	DN	24 June 2015
Lá	andsat 8	9 spectral bands (0.4 – 2.29 µm)	DN	17 August 2016

Representativeness-based Design of Observation Network

NGEE-Arctic Sampling Network Design in Alaska

Our analysis using a suite of 37 climate, edaphic and permafrost characteristics for the present and projected future conditions (from downscaled GCMs) delineates key ecoregions in Alaska, and also suggests a northward shift in the environmental conditions under various climate change scenarios.



With a combination of a northern site at Barrow, Alaska, and a set of southern sites at Seward Peninsula, Alaska, NGEE–Arctic is employing a space-for-time approach to sample the regions to best understand the current status of vegetation and implications of a warming climate on these sensitive ecosystems.

(c) Sites measuring CH₄ (52)

(d) Sites operational in winter (53)

Figure 4: Representativeness of Pan-Arctic network of flux measurement sites

Understanding the inventory of observations available through international partner networks in the Arctic enables development of new synthesis data products and models.

Mapping PFT Distributions at BEO



Different satellite sensors are sensitive to different aspects of diverse vegetation on the landscape, and when combined provides a wealth of information.





(a) Landsat, SPOT-5, PALSAR, DEM

Figure 7: Response of various sensors to vegetation characteristics

We developed Deep Neural Network models and trained them with existing vegetation maps and field based vegetation community data for accurate high resolution maps of vegetation.



(b) Council Site Representativeness (a) Barrow Site Representativeness Figure 2: Quantifying representativeness of observations collected at NGEE-Arctic cores sites in the context of the broader landscape

Our representativeness analysis allows for quantitative assessment of the optimality of the observations and samples being conducted and provides a statistical scaling framework for extrapolation of these observations to the larger landscape.

Hoffman, F. M., J. Kumar, R. T. Mills, and W. W. Hargrove (2013), Representativeness-based Sampling Network Design for the State of Alaska, Landscape Ecol., 28(8):1567–1586, doi:10.1007/s10980-013-9902-0.

Scaling Understanding to the Pan-Arctic Region



Figure 5: Vegetation community and distribution show wide variations across polygonal tundra microtopography

Microtopography in continuous permafrost polygonal tundra at the Barrow Environmental Observatory govern the surface and subsurface hydrology and regulate soil moisture and soil temperature, which has direct implications for the vegetation community and distributions at sub-meter scales.

Table 1: Remote sensing data used for vegetation mapping with and without phenology.

	Number of Variables	
Variables	(without phenology, with phenology)	Platform
Elevation	1, 1	Lidar
TOA Red Band	1, 6	WorldView-2
TOA Blue Band	1, 6	WorldView-2
TOA Green Band	1, 6	WorldView-2
TOA NIR Band	1, 6	WorldView-2
NDVI	1, 6	WorldView-2

We employed high resolution spectral remote sensing and digital elevation models to develop machine learning models using vegetation community data and develop high resolution maps of vegetation community distribution. Capturing vegetation phenology using repeat imagery exploits variations in the timing of green up for different vegetation types, allowing improved accuracy in resulting data products.



Figure 8: Deep learning-based multi-sensor fusion approach for vegetation mapping



Vegetation Classes Alder Willow Shrubs Dryas/Lichen Dwarf Shrub Tundra Mixed Shrub Sedge Tussock Tundra Bog

Figure 3: Distributed network of flux observation sites (131) across the Arctic provides potential for scaling our observations and modeling studies to understand the broader Pan-Arctic region.



Figure 6: High resolution vegetation maps captures vegetation community and distribution across polygon types

Langford, Z. L., J. Kumar, F. M. Hoffman, R. J. Norby, S. D. Wullschleger, V. L. Sloan, and C. M. Iversen (2016), Mapping Arctic Plant Functional Type Distributions in the Barrow Environmental Observatory Using WorldView-2 and LiDAR Datasets, *Remote Sens.*, 8(9):733, doi:10.3390/rs8090733.

Figure 9: Deep learning-based vegetation map for Kougarok Watershed at Seward Peninsula

Langford, Z. L., J. Kumar, and F. M. Hoffman (2017), Convolutional Neural Network Approach for Mapping Arctic Vegetation using Multi-Sensor Remote Sensing Fusion, Proceedings of the 2017 IEEE International Conference on Data Mining Workshops (ICDMW 2017), Institute of Electrical and Electronics Engineers (IEEE), Conference Publishing Services (CPS), doi:10.1109/ICDMW.2017.48, data doi:10.5440/1418854.

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