# Mapping plant functional type distributions in Arctic ecosystems using WorldView-2 satellite imagery and unsupervised clustering

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**Introduction.** The Next-Generation Ecosystem Experiments (NGEE–Arctic) project seeks to improve the fidelity climate projections for high-latitude regions by quantifying the physical, chemical, and biological behavior of terrestrial ecosystems in Alaska. Arctic vegetation is particularly sensitive to warming conditions and likely to exhibit shifts in species composition, phenology and productivity under a changing climate.

**Objectives.** The objective of the this study was to characterize the landscape properties and develop high resolution maps of Plant Functional Type (*PFT*) distributions to provide representation of new Arctic vegetation types in the Community Land Model (*CLM*).

**Study Area.** A field campaign was conducted in Barrow, AK, during peak growing season in 2012 to collect vegetation harvests from 48 1 m × 1 m plots (Figure 1), which were then analyzed to estimate distributions of wet tundra graminoid, dry tundra sedge, bryophytes, forb, lichen, and shrub *PFTs* for use in modeling and analysis of other measurements.

**Approach.** Statistical relationships were developed between spectral (WorldView–2 multispectral data) and topographic (LiDAR) characteristics `[Predictors]` and *PFT* distributions `[Predictand]` at the vegetation plots. These derived relationships were employed to statistically upscale the observed *PFT* distributions for the larger landscape. By including multiple snapshots through the growing season, phenological behavior was included as a key property to distinguish among the *PFTs*.

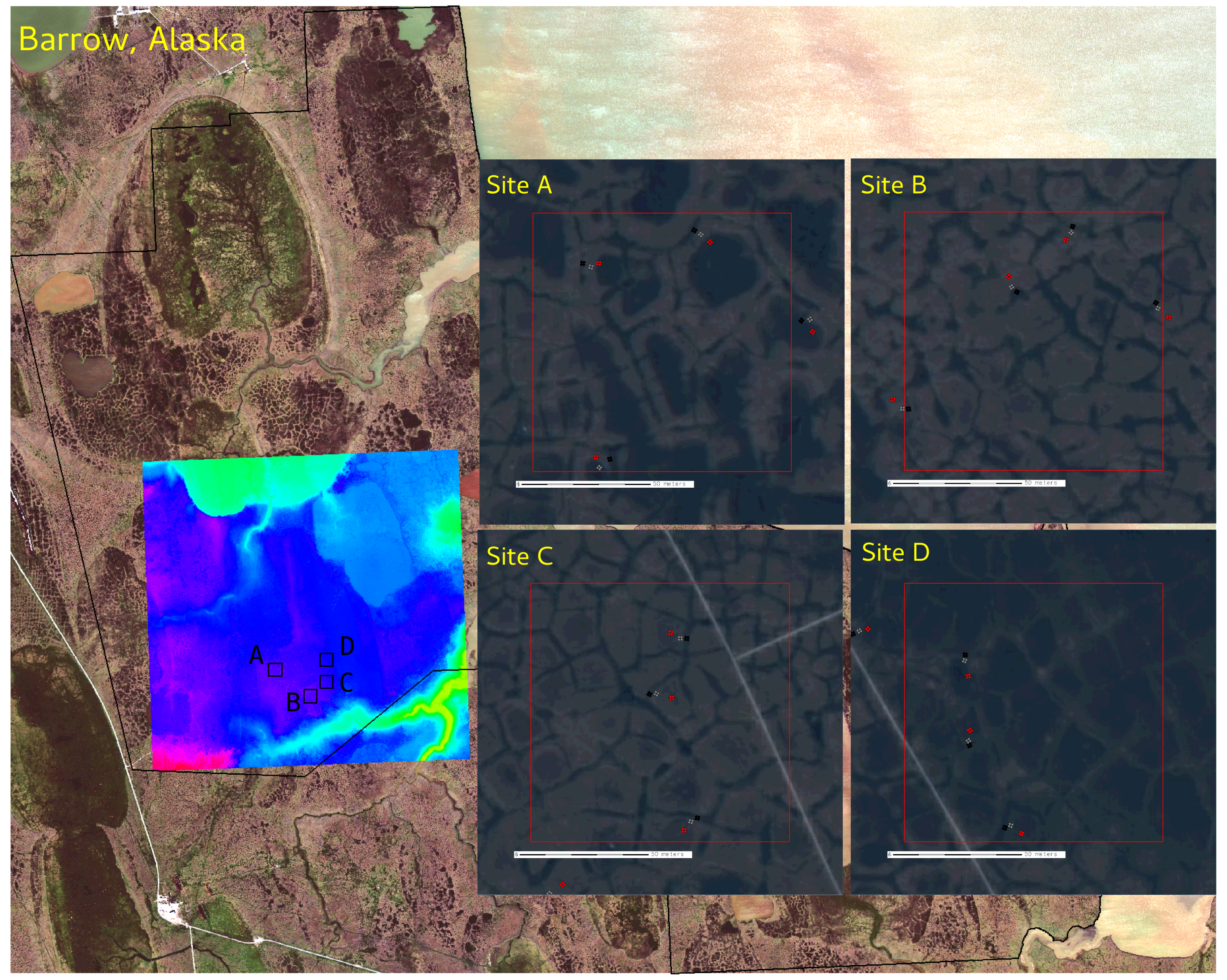


Figure 1: NGEE-Arctic sites at Barrow Environmental Observatory (BEO) span low, transitional, and high centered polygon-dominated tundra.

## Multivariate Spatiotemporal Statistics

**$K$–means Clustering.** A $k$-means algorithm was used to identify regions of similar characteristics based on times series (6 snapshots during the 2010 growing season, Figure 2) of WorldView–2 (*WV2*) multispectral imagery (Red, Green, Blue, Near Infrared bands), *WV2*-derived *NDVI* and LiDAR at 2 m resolution. Operating in a 31-dimensional data space, the method yields a classification of cells into $k$ classes based on their spectral and topographic properties.

**Vegetation Representativeness.** A representativeness metric described by Hargrove et al. (2003) and Hoffman et al. (2013) provides a unit-less, relative measure of the dissimilarity between any two pixels of interest (Figure 4). The 31–dimensional observational data, analyzed using this metric, provided a framework to quantify representativeness of field measurements collected during the 2012 field campaign. For ground-truthing of the *PFT* distribution products, 3 poorly and 3 well represented sites were selected at the A, B, C, and D sites (total of 24 points), and a second field campaign was conducted on July 29, 2014 (Figure 7).

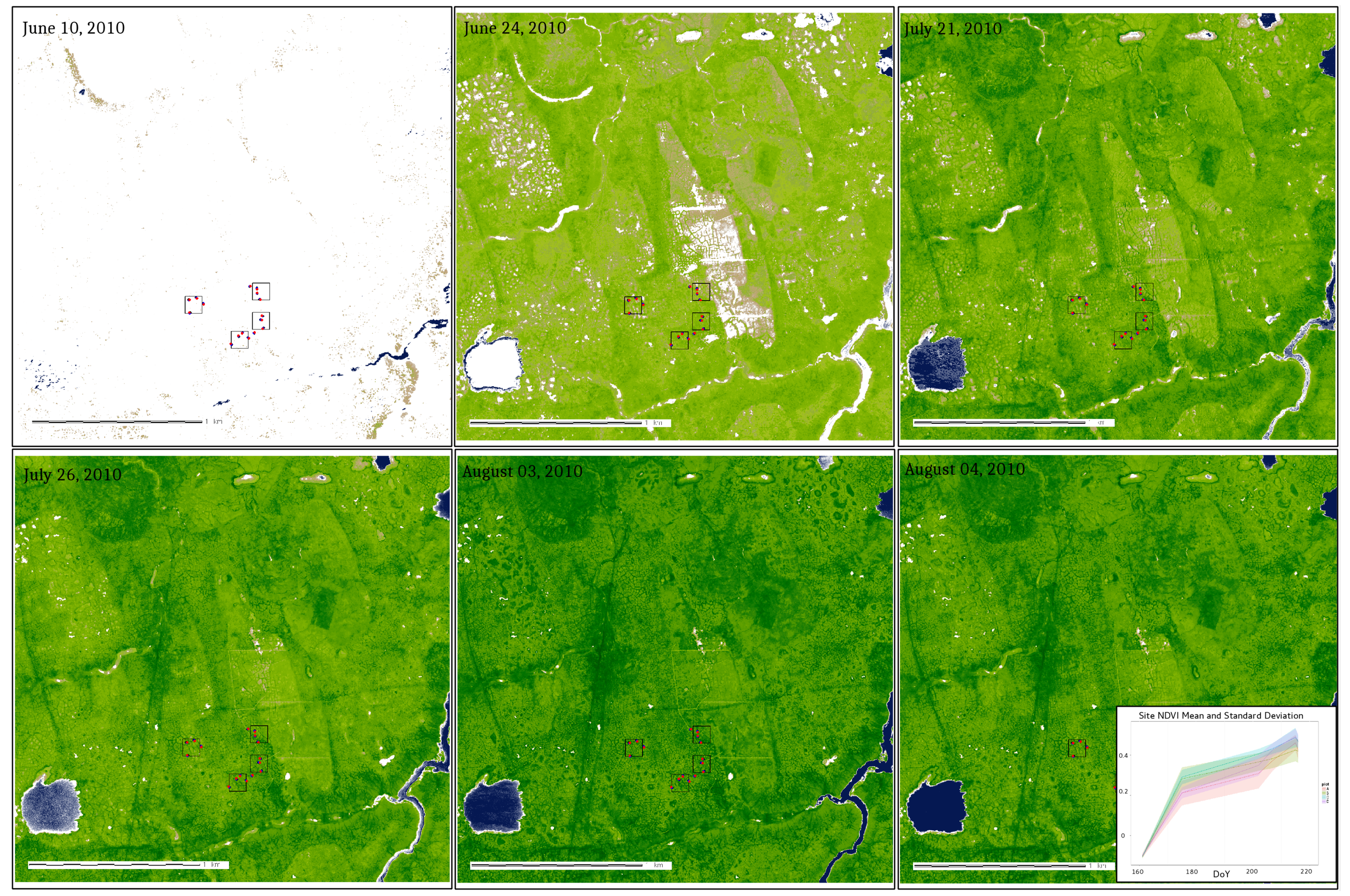


Figure 2: WorldView-2-derived *NDVI*-based phenology during the 2010 growing season (June–August) permitted the cluster analysis to further distinguish vegetation groupings by the timing of green-up.

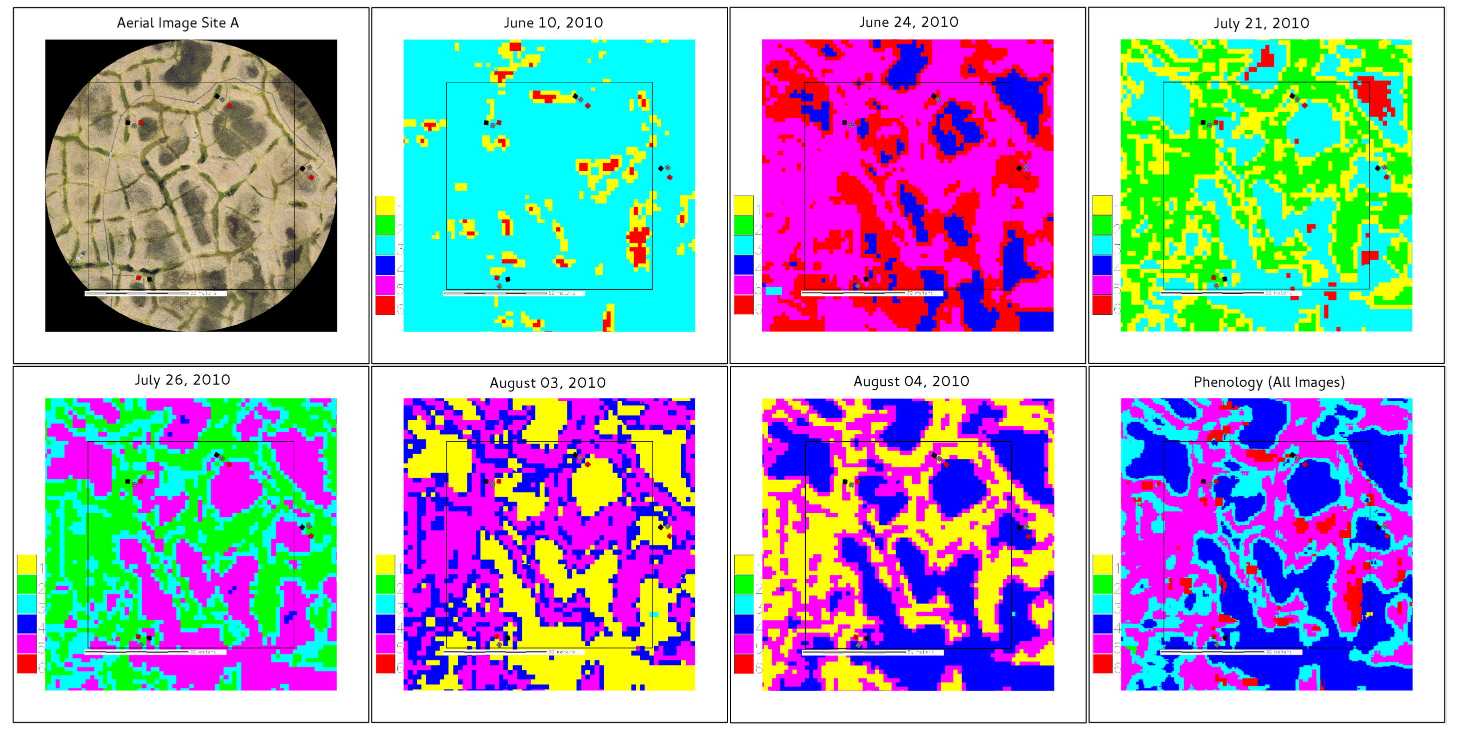


Figure 3: (Top Left) Aerial image (∼10 cm) for Site A. Individual $k = 6$ classifications during the 2010 growing season (June–August). (Bottom Right) Unified cluster analysis with phenology, using all 2010 snapshots.

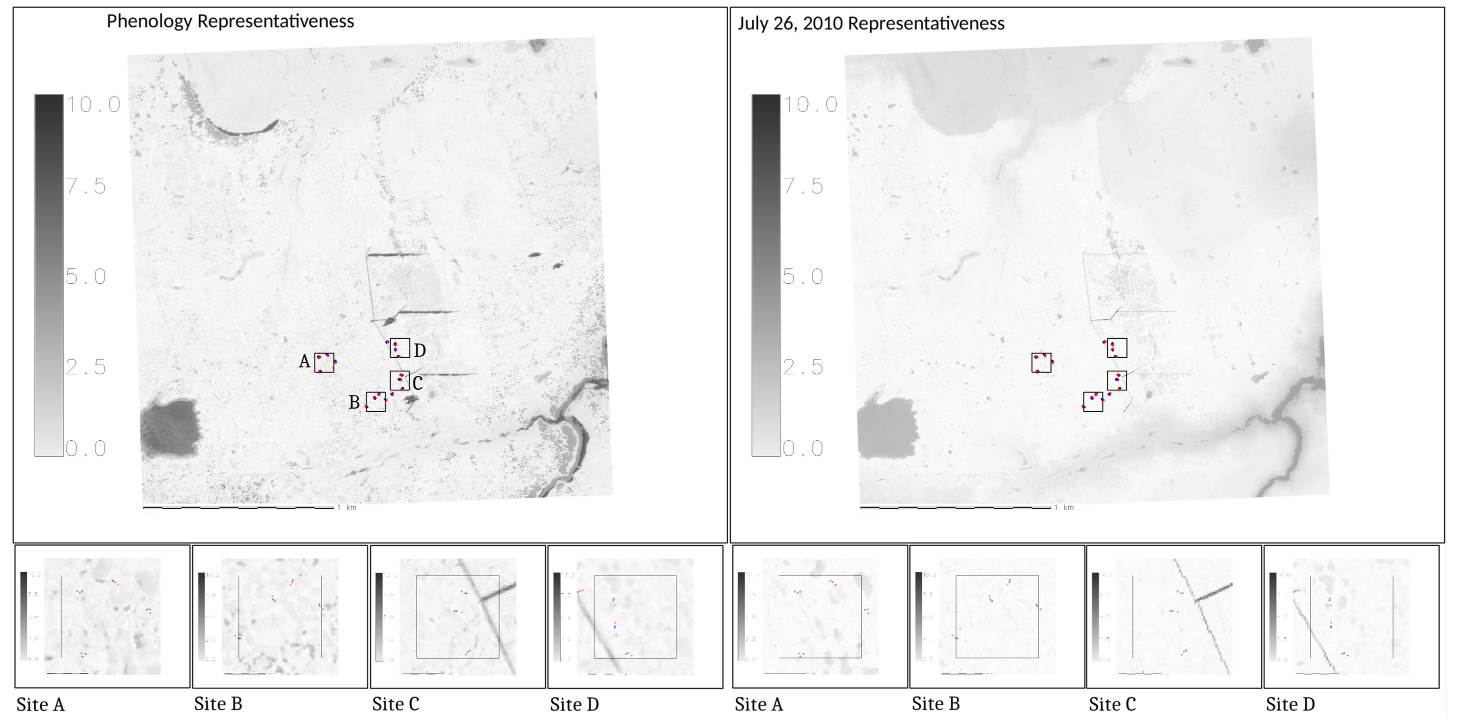


Figure 4: Representativeness with phenology (left) and without (right) based on vegetation sampling locations. Darker colors indicate poorly represented areas and lighter colors indicate well represented areas.

## Plant Functional Type Distribution Estimates

**Upscaling Algorithm.** We applied an Inverse Distance Weighting (*IDW*) interpolation algorithm that accepts sparse, irregularly scattered data over a multidimensional domain to upscale vegetation measurements. In *IDW*, the interpolating function is expressed as a weighted average of the data values, where the weights are inverse functions of the distances from the data sites in a multi-dimensional data space. *IDW* was performed on each $k$–value (Figure 5), and was compared against the single image and phenology-included estimations Figure 8. Figure 6 shows the estimated distribution of *PFTs* for Site A.

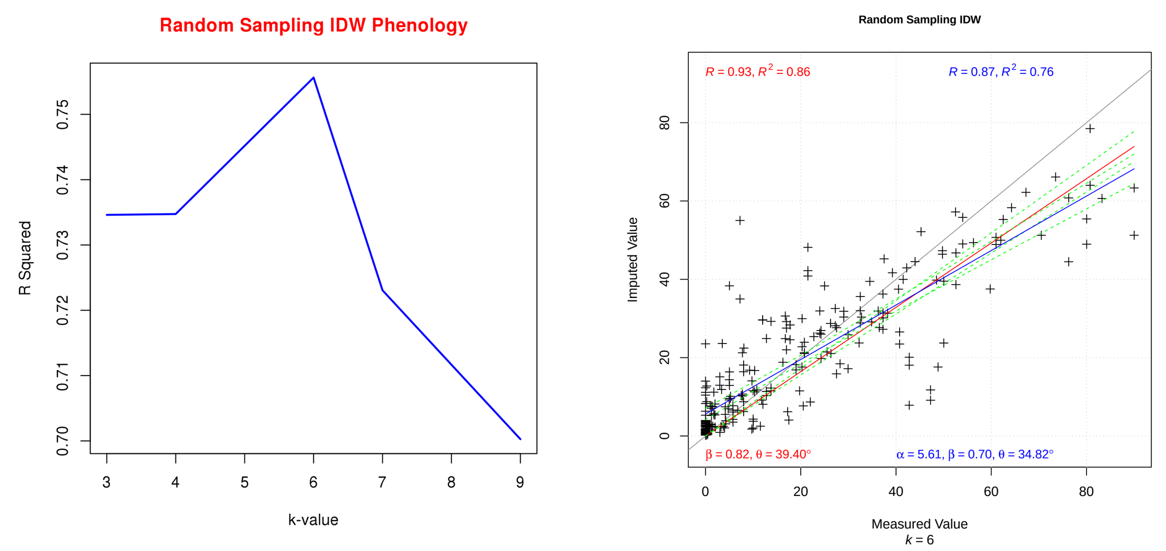


Figure 5: (Left) Random sampling for $k$–values. (Right) Random sampling for $k = 6$.

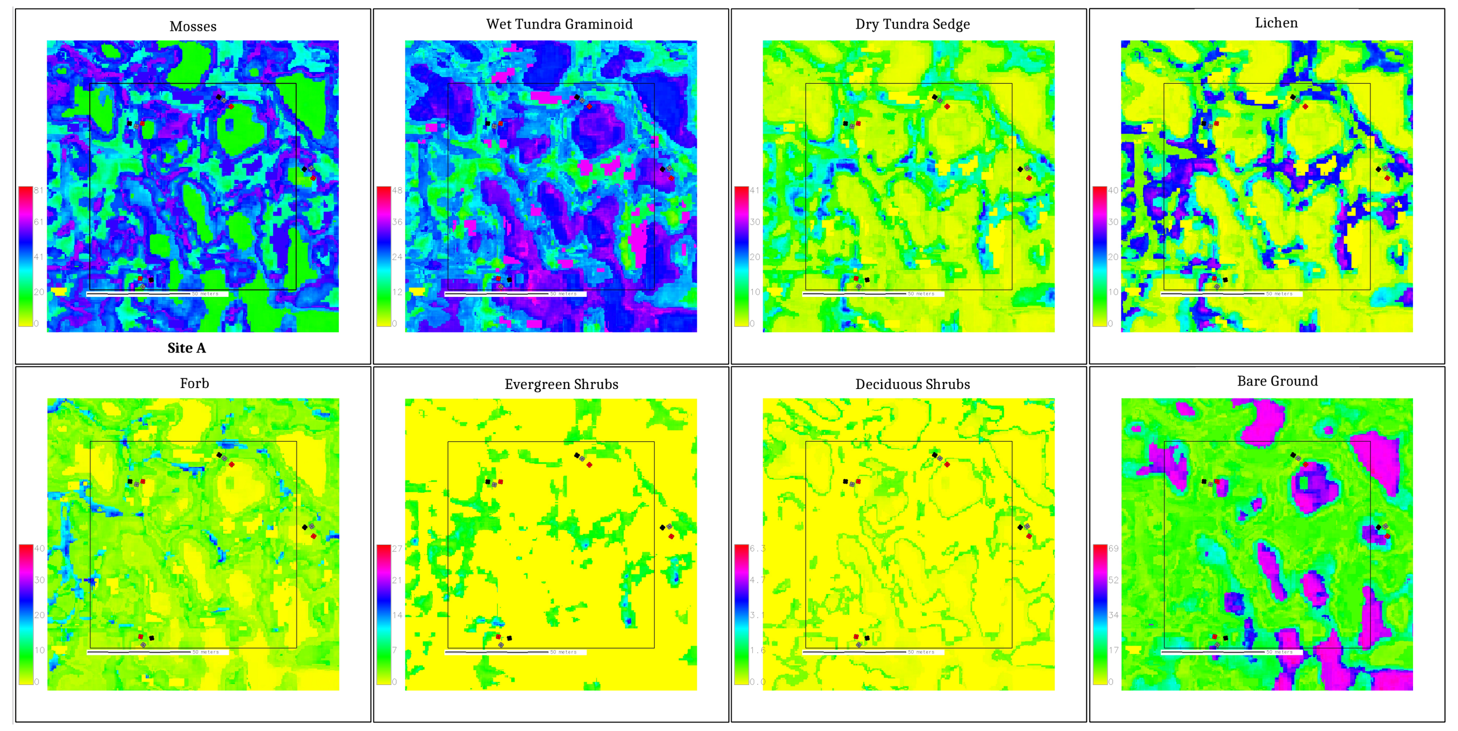


Figure 6: *PFT* proportional distribution estimates produced from the *IDW* algorithm.

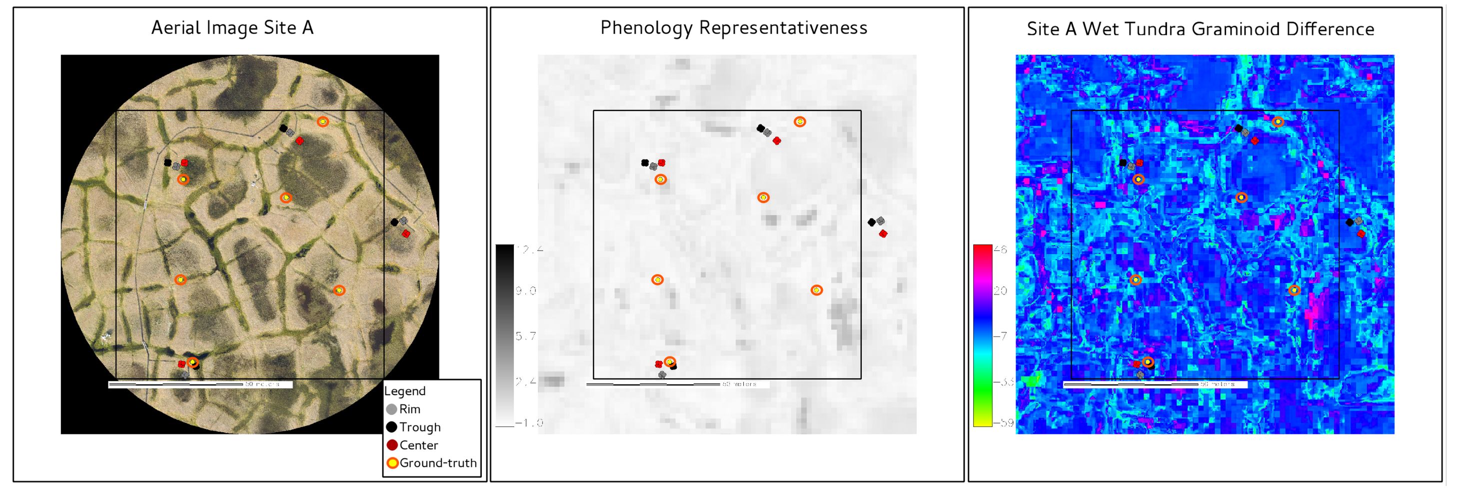


Figure 7: Ground-truthing locations for Site A. (Left) Aerial image, (Middle) phenology representativeness, (Right) representativeness differences between the phenology included data and the single snapshot.

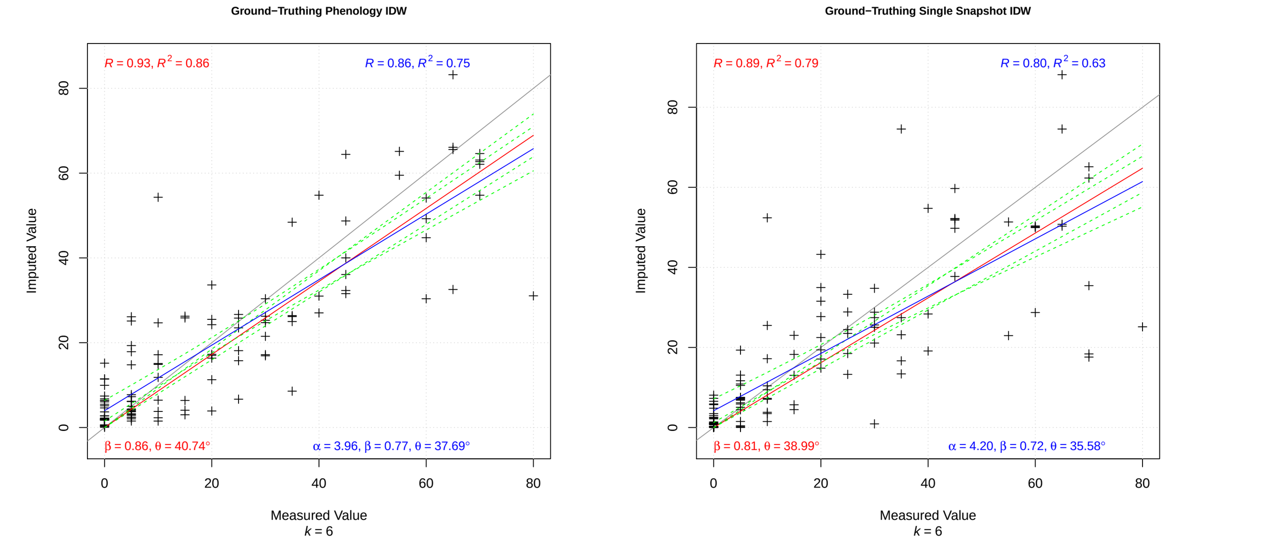


Figure 8: Validation with ground-truth points for all *PFTs*, including phenology (Left) and single image (Right).

**Improving Representativeness.** An additional field campaign was performed on August 29, 2014, which included the same poor and well represented sites from July 29, 2014. The *IDW* algorithm was updated using the data collected on July 29, 2014 (Figure 9, Right) and compared against the original algorithm (Figure 9, Left).

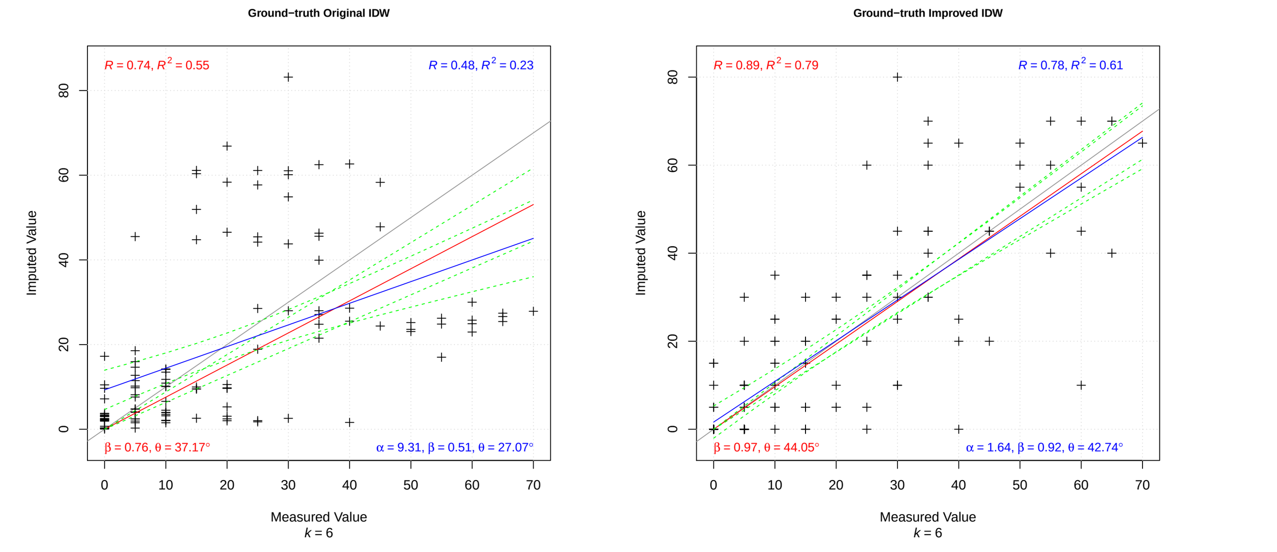


Figure 9: Validation with ground-truth points for the original (Left) and the improved upscaling (Right).

## Conclusions.

- High resolution *PFT* distribution estimates were developed and are being used to parameterize *CLM* for Arctic ecosystems.
- The representativeness analysis provides identification of sampling gaps and informs site selection.
- Growing season phenology significantly improved the accuracy of *PFT* distribution estimates.

**References:**

- W. W. Hargrove, F. M. Hoffman and B. E. Law (2003), New analysis reveals representativeness of the AmeriFlux network. *Eos Trans. AGU* 84(48):529–535.
- F. M. Hoffman, 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.

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