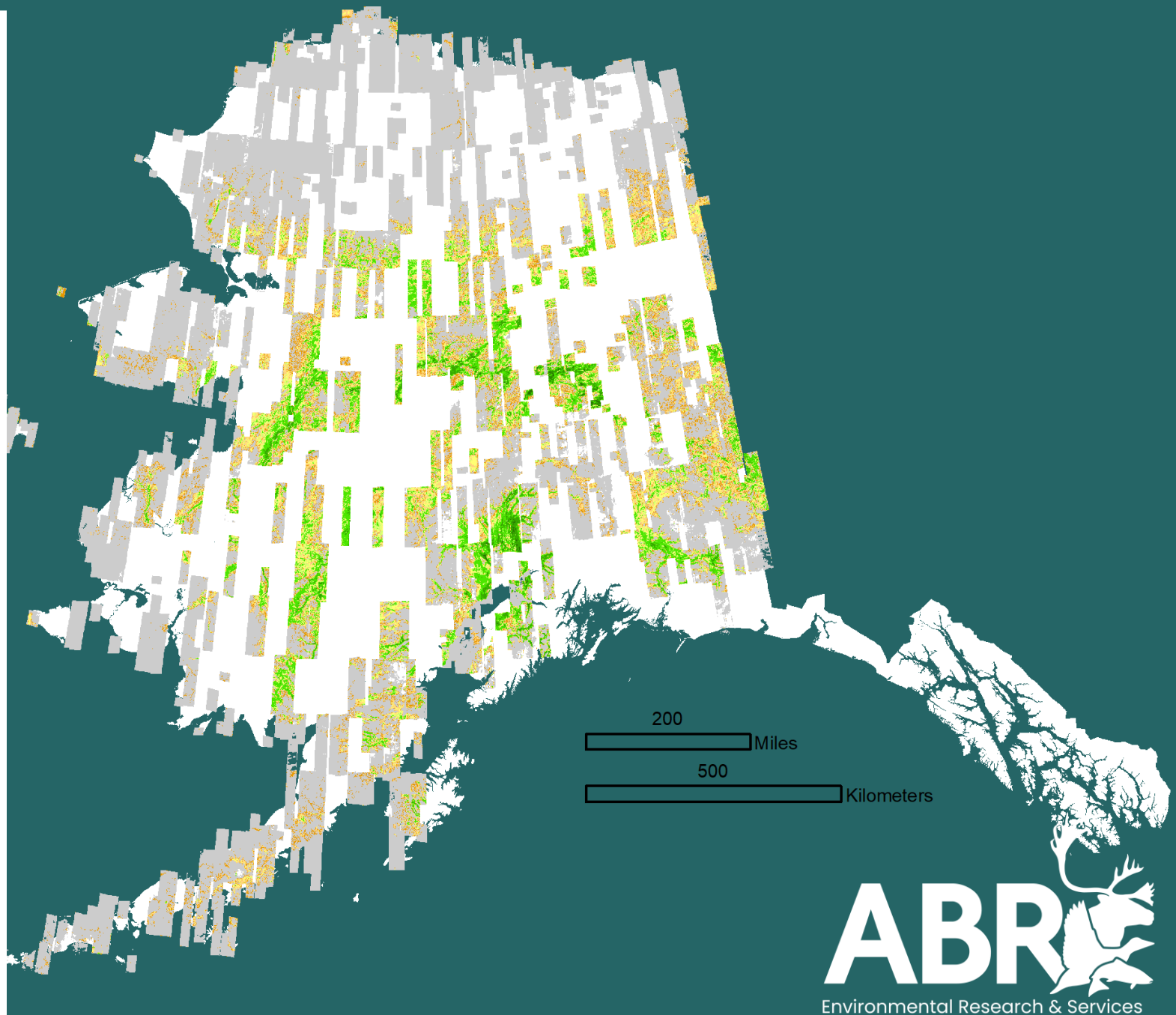


GeoAI for Environmental Understanding in Alaska

Matt Macander

mmacander@abrinc.com



Modeling Vegetation
Canopy Height

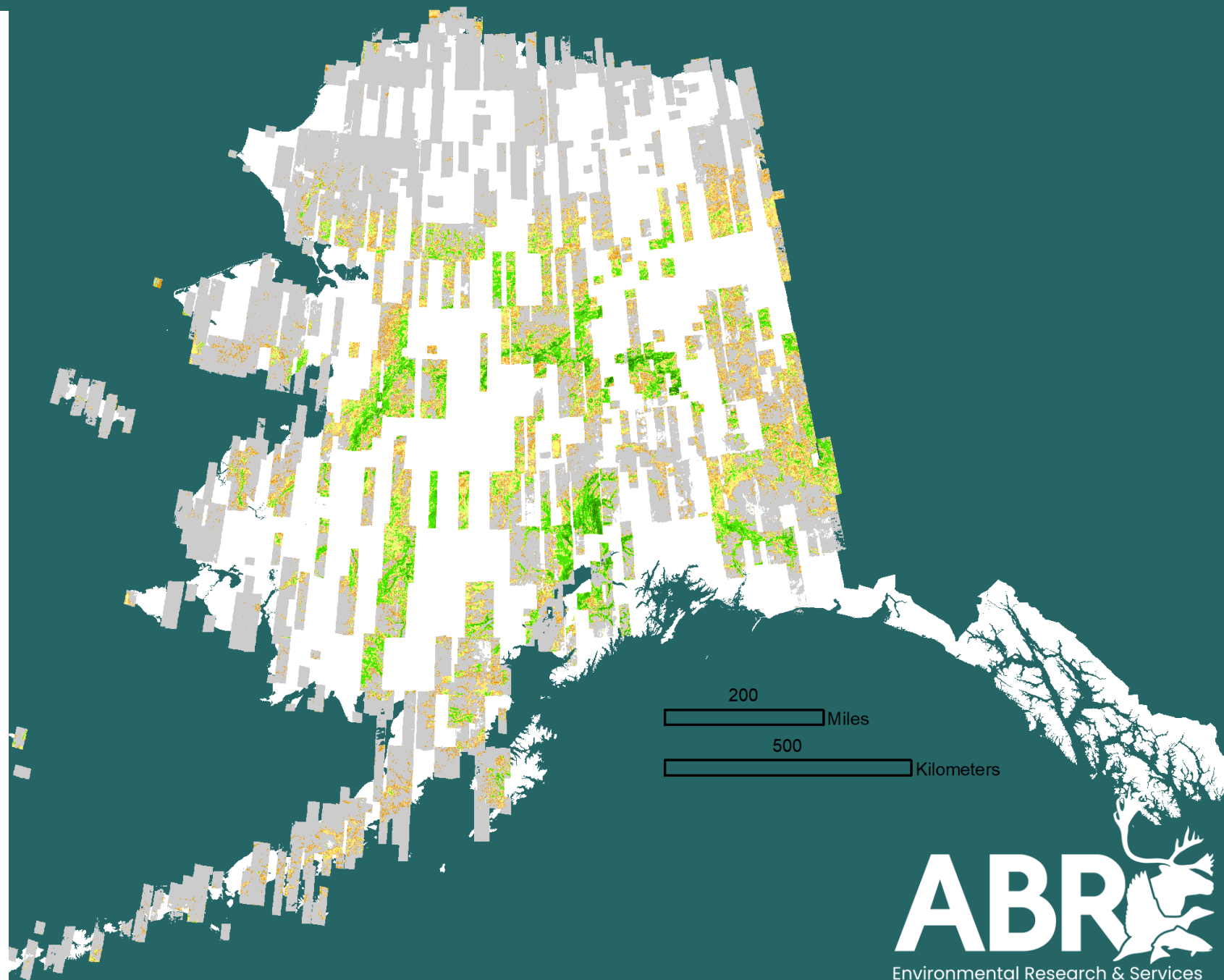
Statewide Soils

Tracking Annual Insect
Damage

Annual Snow Goose
(Nest) Counts

Brant Nest Occupancy

Dall's Sheep
Demography at Salt Licks



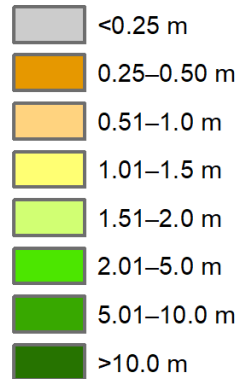
Deep learning vegetation height prediction from commercial multi-spectral VHR surface reflectance

2 types of deep learning architectures:

1. Custom UNet for regression.
2. Fine-tuning an existing Vision Transformer model (ViT DINOv2) for remote sensing data of boreal vegetation:
 - a. Embedding the NIR band (and any other band; e.g. DTM)
 - b. Using boreal forest/shrub specific training data
 - c. Unfreezing ViT encoder and decoder

**Canopy Height Model
2-m Strips
Trained on DGGs and GLiHT Lidar
and IFSAR CHM
2010–2021**

Canopy Height

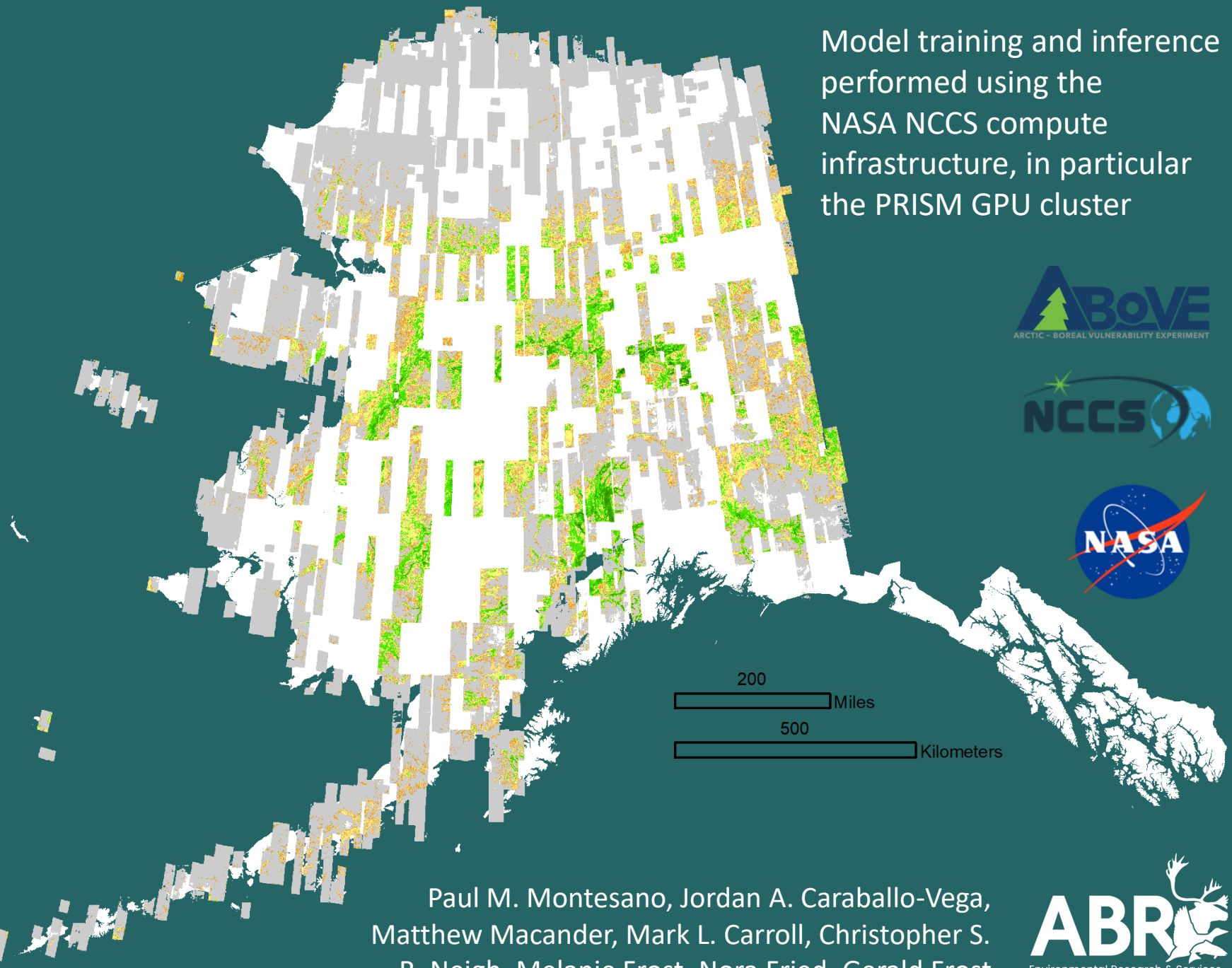
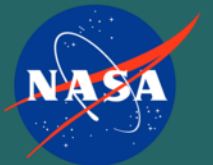


UNET Convolutional Neural Network
Predictors July and August
Blue/Green/Red/NIR
Normalized Reflectance
2 m resolution

Trained using 128 m chips
218k Lidar CHM
255k IFSAR CHM

Preliminary Validation
Mean Absolute Error = 1.02 m
R-squared = 0.714

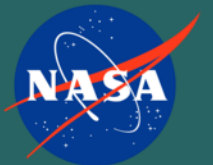
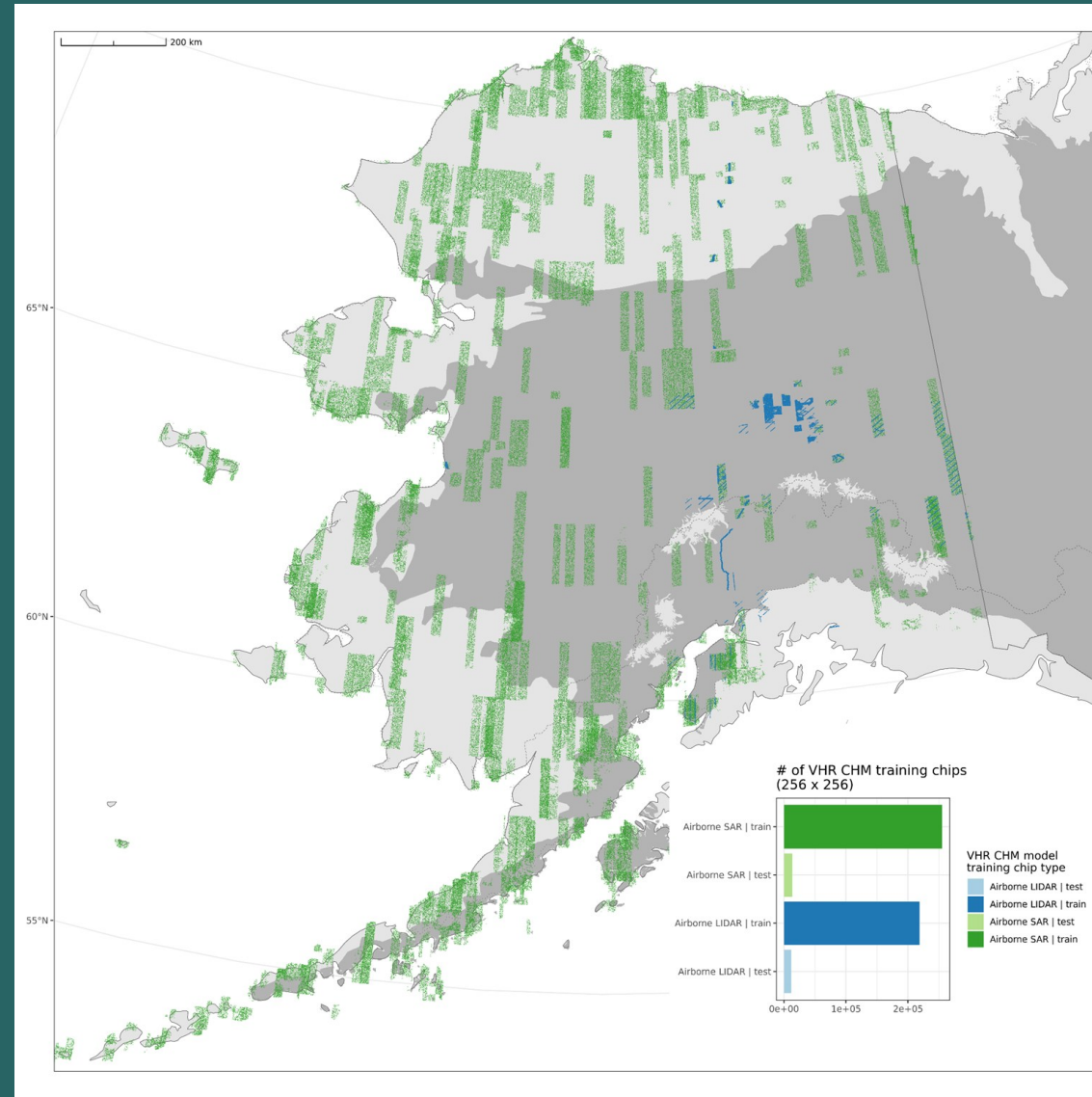
Model training and inference
performed using the
NASA NCCS compute
infrastructure, in particular
the PRISM GPU cluster



Paul M. Montesano, Jordan A. Caraballo-Vega,
Matthew Macander, Mark L. Carroll, Christopher S.
R. Neigh, Melanie Frost, Nora Fried, Gerald Frost



- Training observations of vegetation height from airborne P-band SAR (IFSAR) & small-footprint lidar (GLiHT, 3DEP, legacy)
- Matched with July & August VHR image strips
- Final training set: 24,454 tiles (256 x 256 @ 2 m)



Paul M. Montesano, Jordan A. Caraballo-Vega,
Matthew Macander, Mark L. Carroll, Christopher S.
R. Neigh, Melanie Frost, Nora Fried, Gerald Frost



Collecting reference field and UAV obs. of vegetation height along transects in western AK

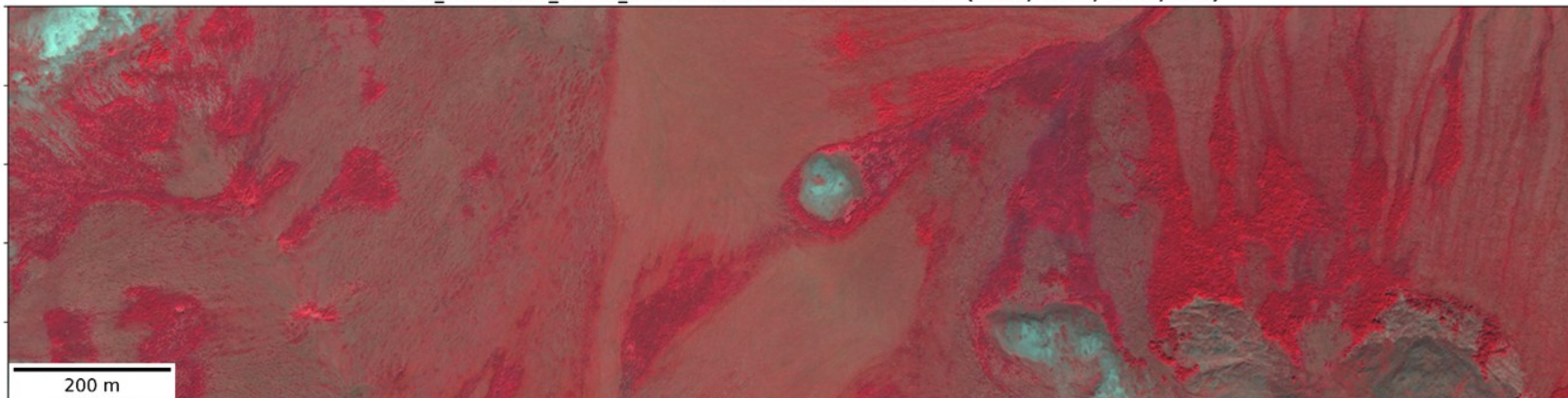
- Point-intercept design along transects coincident with ICESat-2 (provides independent spaceborne vegetation height estimate)
- $n=1040$ points at 2-m intervals along $n=10$ transects
- Spanning gradient from tall shrubs (~5m) to tundra



Collecting reference field and UAV obs. of vegetation height along transects in western AK

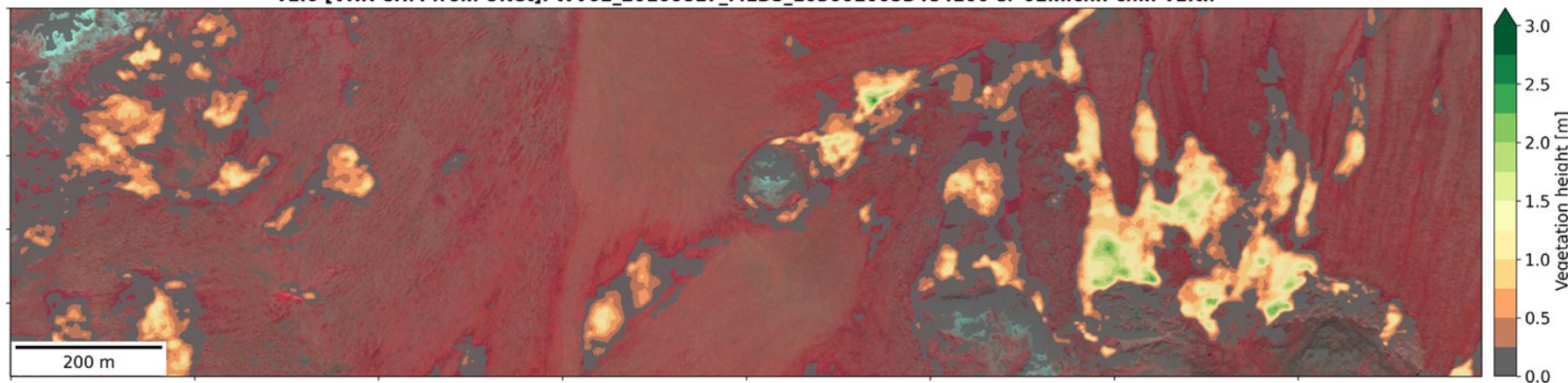


WV02_20160817_M1BS_103001005B484100-sr-02m.tif: (7000, 2200, 2000, 500)



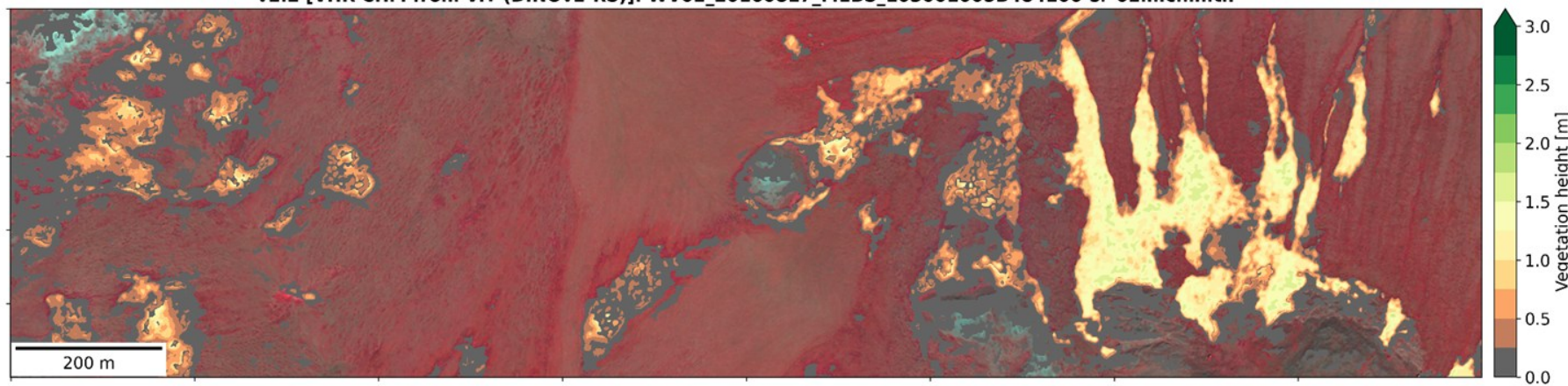
2-m Maxar Imagery

v1.0 [VHR CHM from UNet]: WV02_20160817_M1BS_103001005B484100-sr-02m.cnn-chm-v1.tif



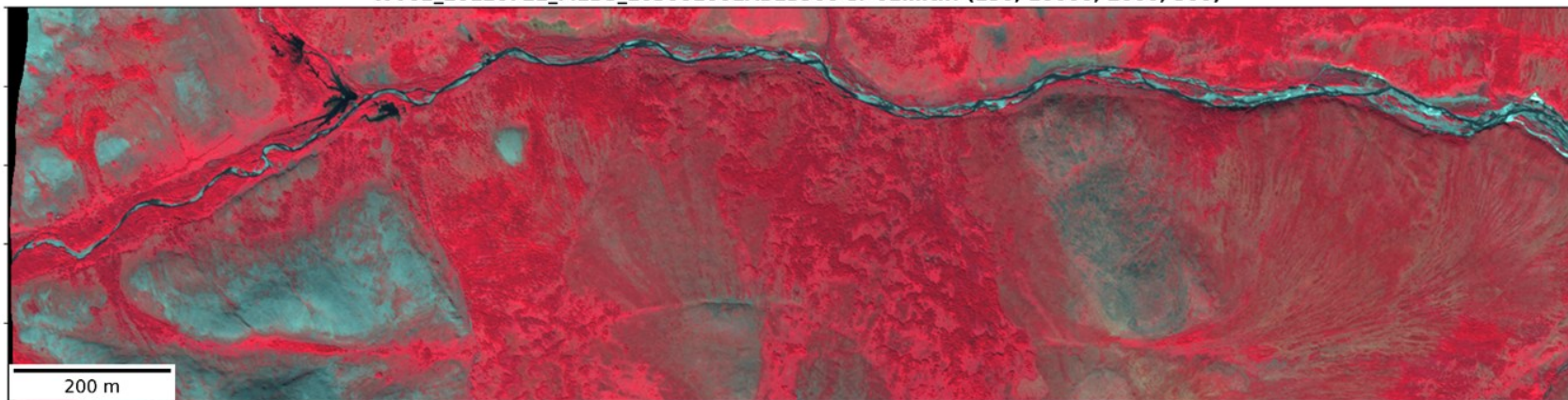
UNET Canopy
Height Model
(transparent = zero height)

v2.2 [VHR CHM from ViT (DINOv2-RS)]: WV02_20160817_M1BS_103001005B484100-sr-02m.chm.tif



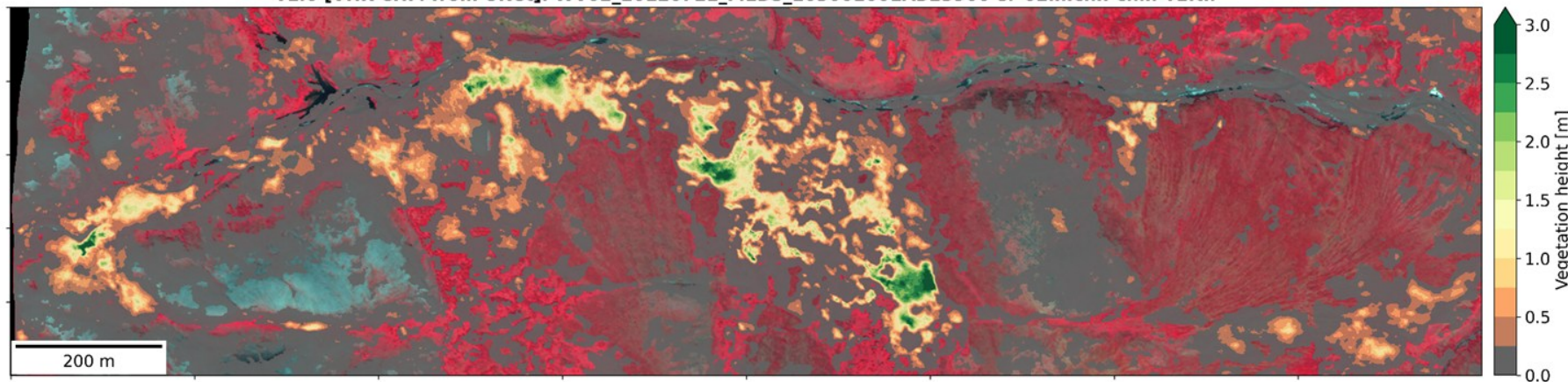
Vision Transformer
Canopy
Height Model
(transparent = zero height)

WV02_20120721_M1BS_103001001AB23900-sr-02m.tif: (150, 10000, 2000, 500)



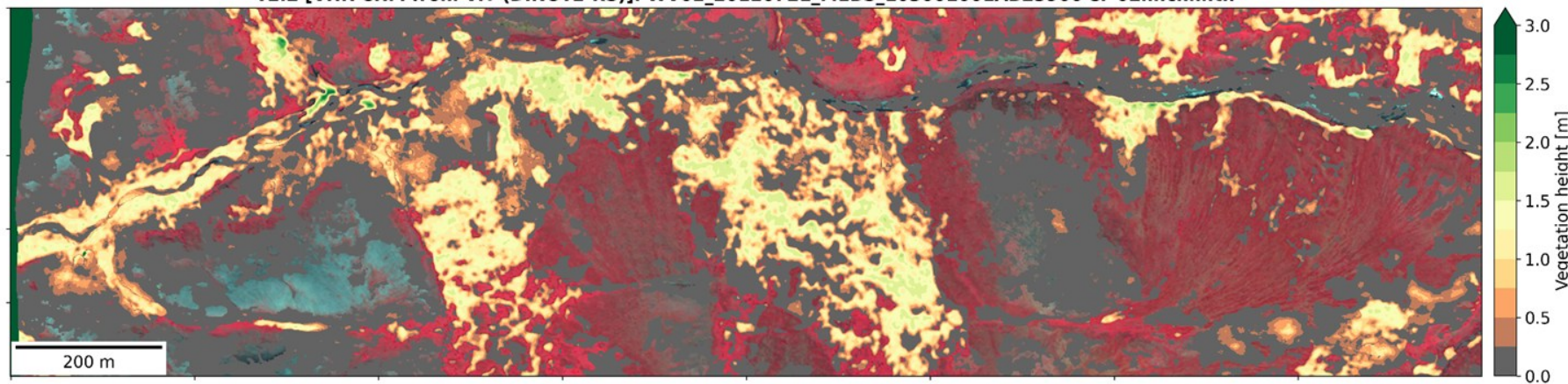
2-m Maxar Imagery

v1.0 [VHR CHM from UNet]: WV02_20120721_M1BS_103001001AB23900-sr-02m.cnn-chm-v1.tif



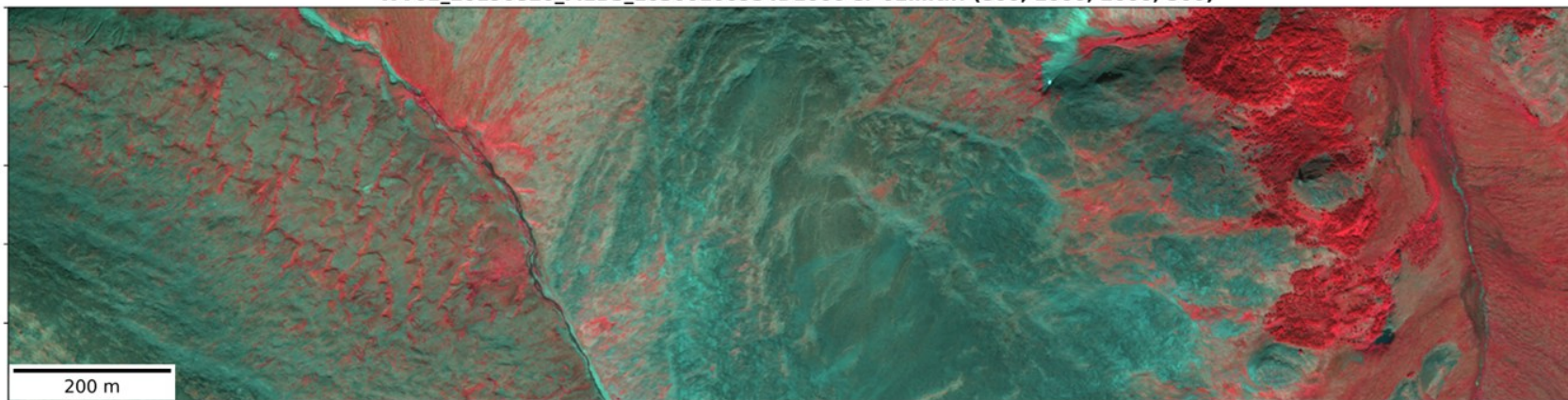
UNET Canopy
Height Model
(transparent = zero height)

v2.2 [VHR CHM from ViT (DINOv2-RS)]: WV02_20120721_M1BS_103001001AB23900-sr-02m.chm.tif



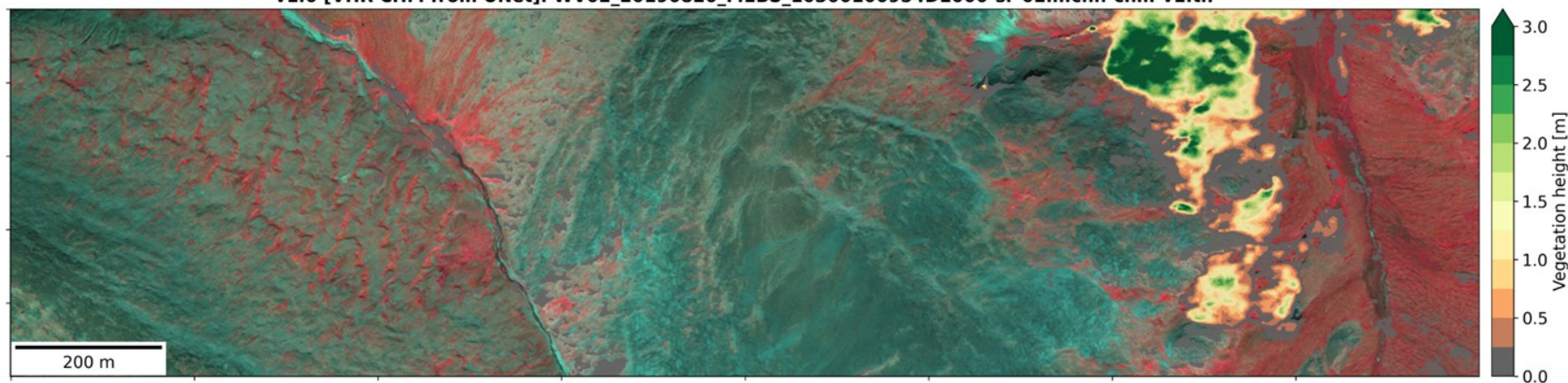
Vision Transformer
Canopy
Height Model
(transparent = zero height)

WV02_20190820_M1BS_10300100954DE000-sr-02m.tif: (800, 1000, 2000, 500)



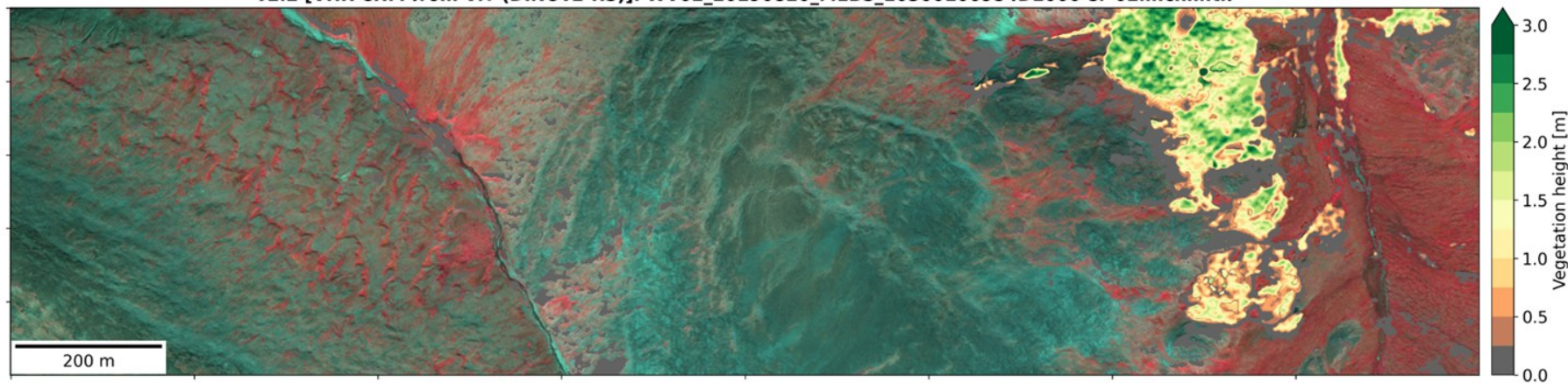
2-m Maxar Imagery

v1.0 [VHR CHM from UNet]: WV02_20190820_M1BS_10300100954DE000-sr-02m.cnn-chm-v1.tif



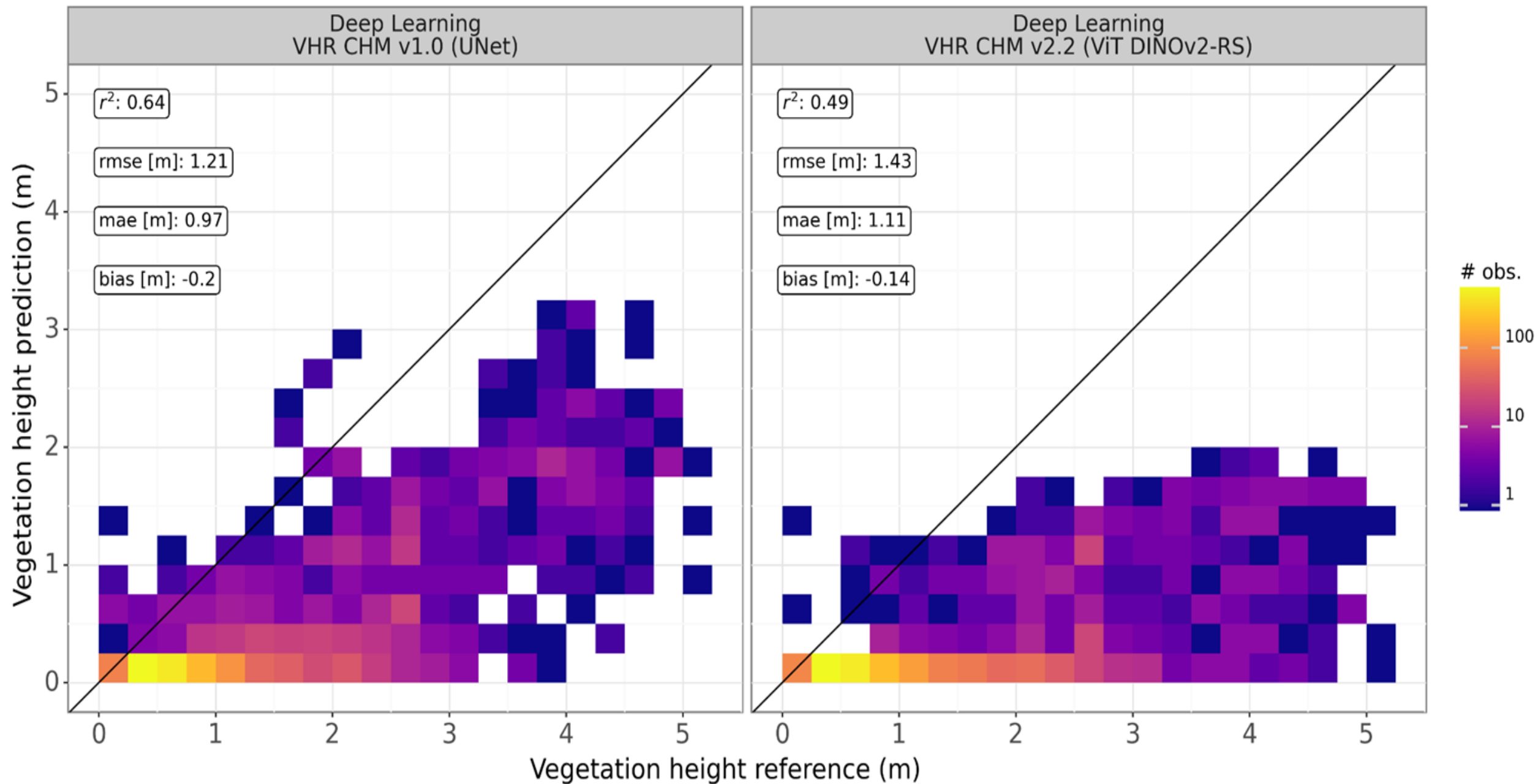
UNET Canopy
Height Model
(transparent = zero height)

v2.2 [VHR CHM from ViT (DINOv2-RS)]: WV02_20190820_M1BS_10300100954DE000-sr-02m.chm.tif



Vision Transformer
Canopy
Height Model
(transparent = zero height)

Fine-tuned deep learning predictions of VHR CHMs
transitional vegetation height validation (Seward Peninsula, Alaska)



Alaska Soil Data Bank: Prediction of Soil Properties/Classes (10m)



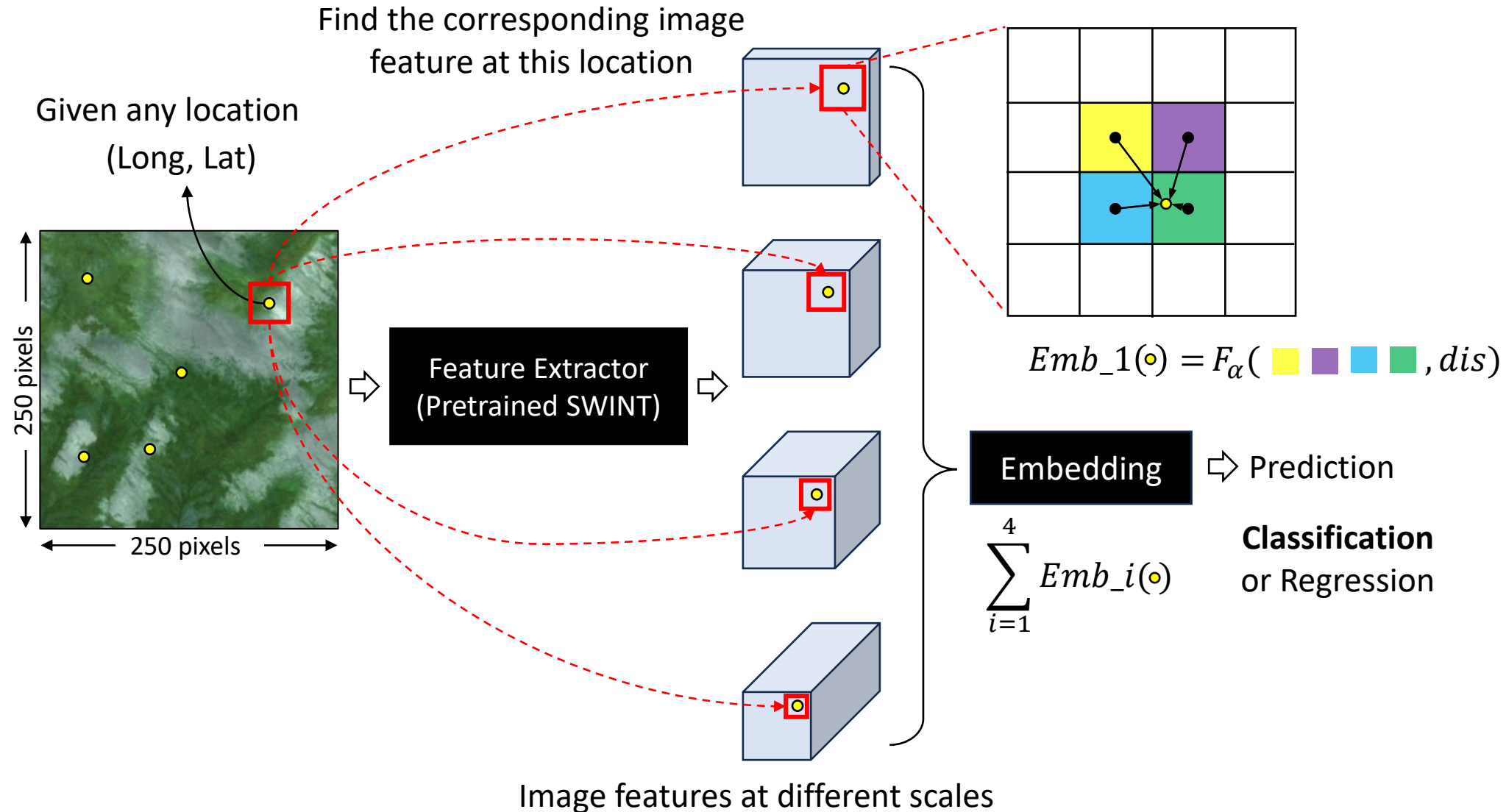
Nic Jelinski, University of Minnesota and many, many other

- **Models:**
 - Random forest w/ gradient boosting (less computationally intensive)
 - SATlas pre-trained Foundation models (more computationally intensive, esp. inference)
- **Point Dataset;** > 40,000 points statewide, consolidated and harmonized from USDA-NRCS NASIS, NPS, Jorgenson Permafrost Database, ABR, USFS, BLM, DOE, and many others. This synthesis and harmonization work is supported by the “Alaska Soil Data Bank” project, funded by USDA-NRCS.
- **Target Variables:**
 - Near-surface permafrost presence/absence probability
 - Soil classes (orders)
 - In progress:
 - Continuous soil properties: pH
 - Class-based soil properties: texture classes



Satlas Foundation Models for Soil Mapping

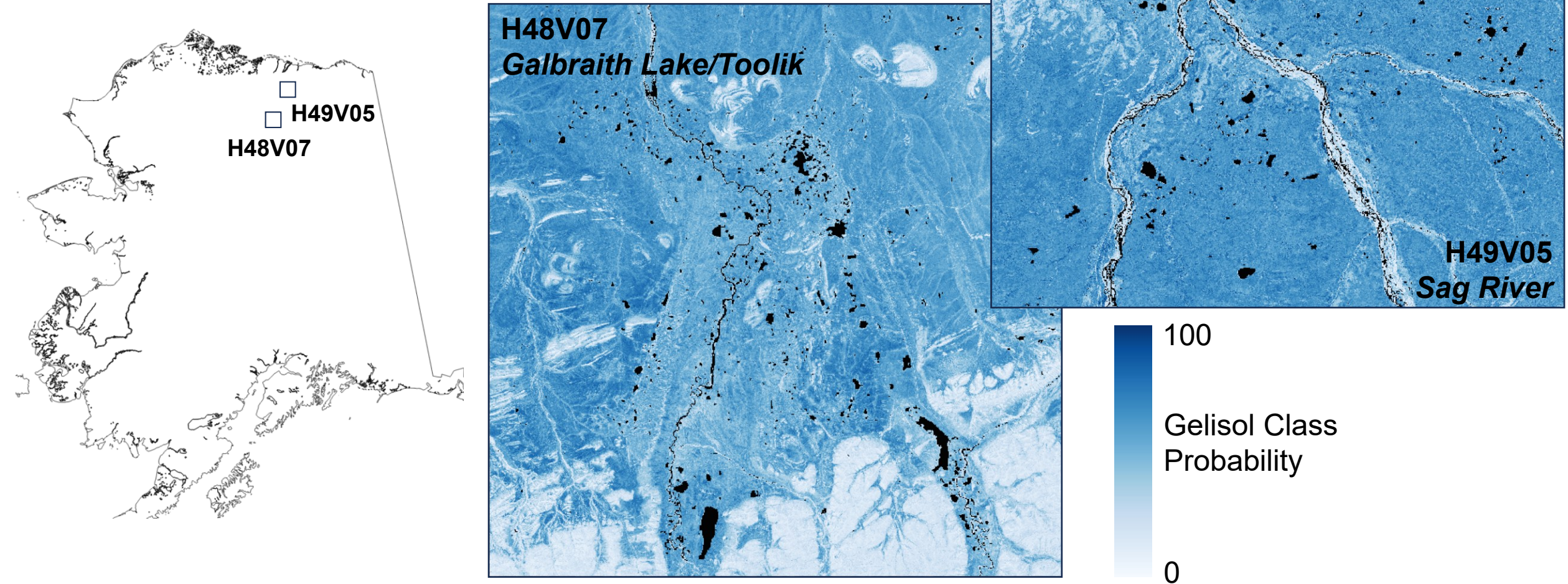
Utilizing non-aligned/different resolution covariates. Inference can be done at fine scales and mean outputs at various resolutions.



Example Results

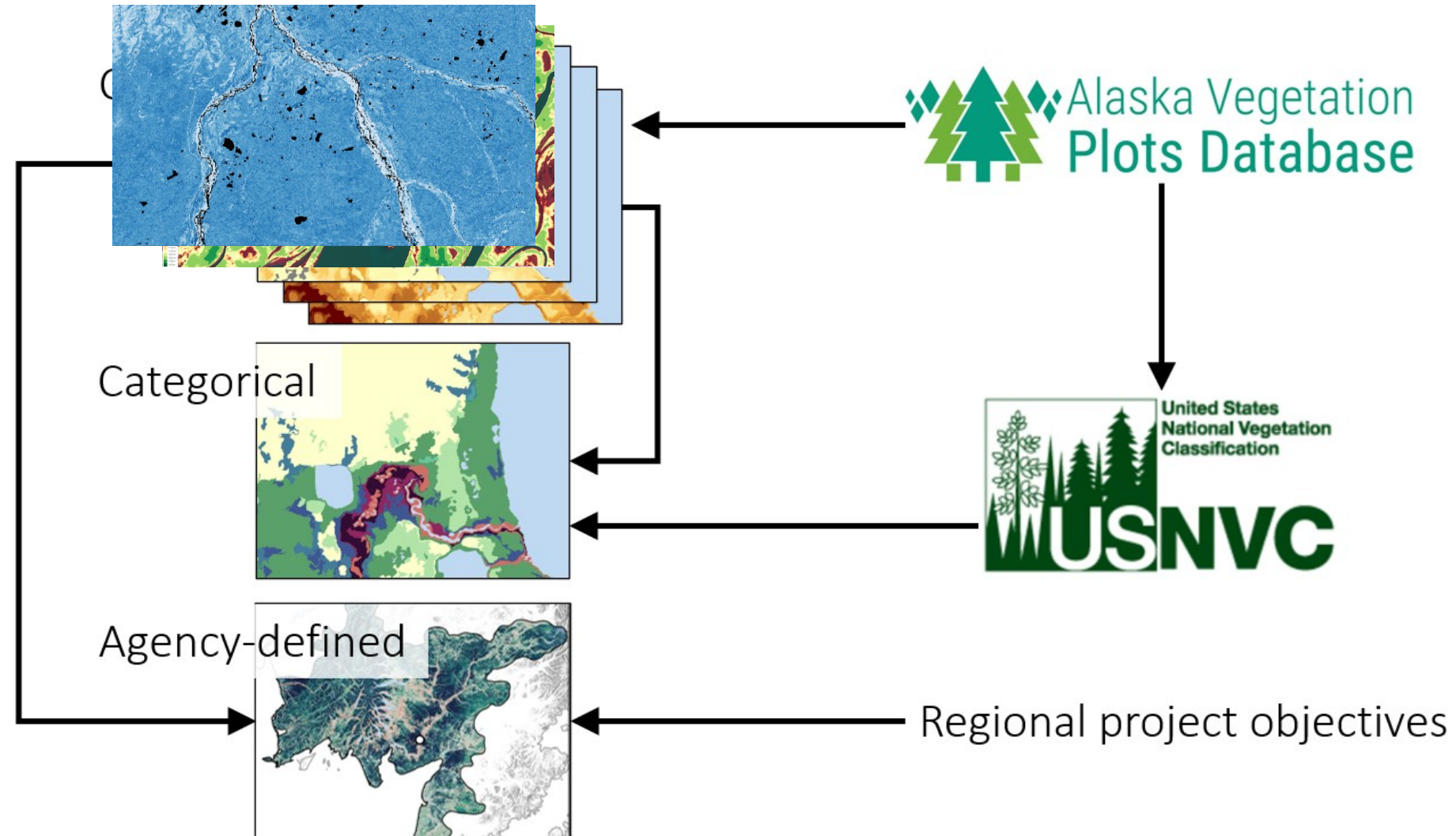
Gelisol Class Probability

Random Forest (10m)



Statewide Vegetation Map Components

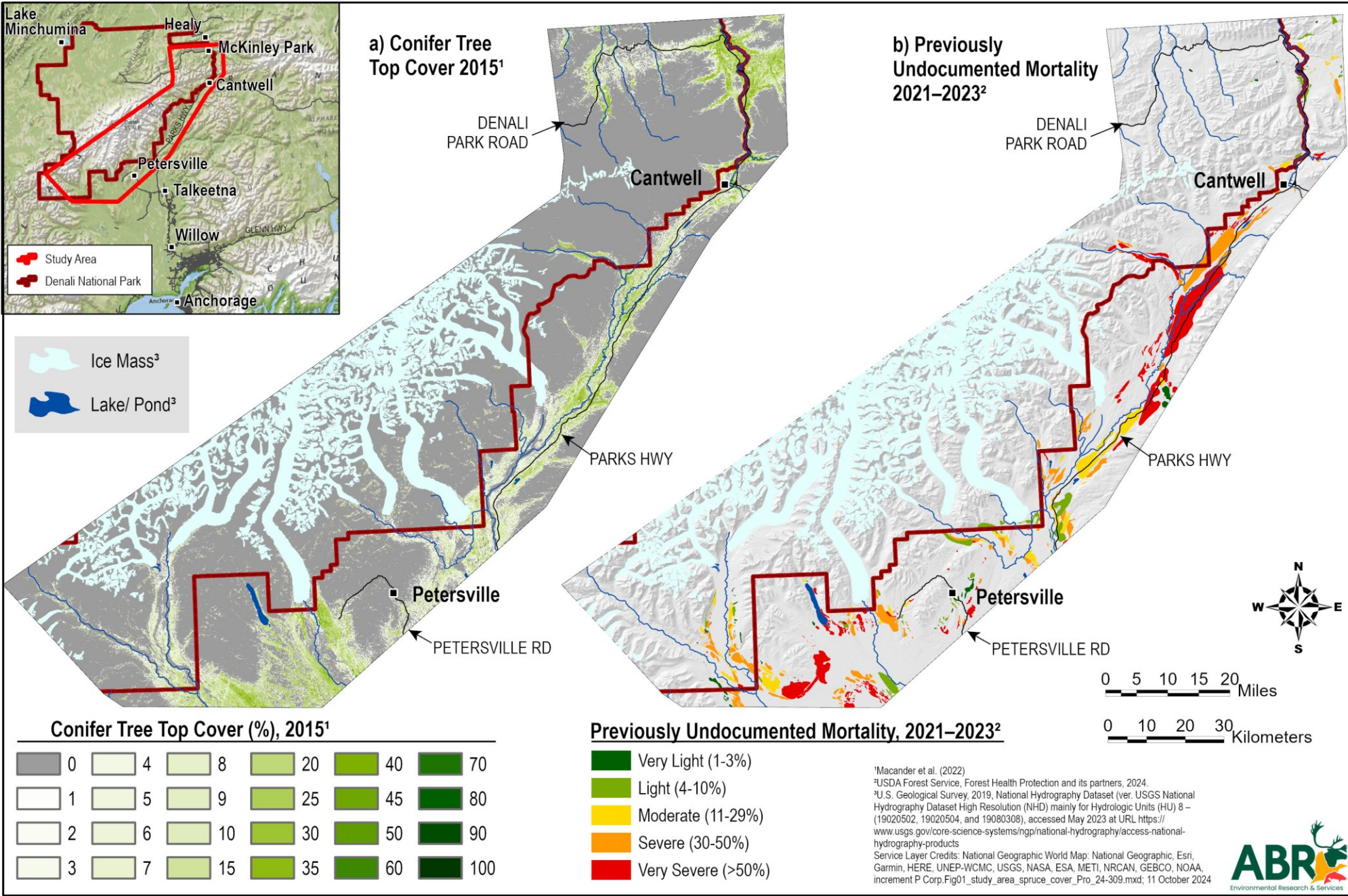
- Maintain current statewide/regional vegetation, fuels, and habitat maps (AKVEG Map)



Tracking Annual Insect Damage

Matt Macander, ABR
Carl Roland, NPS

EROS Earth
Foundation Model
prototype results
shared by Neal Pastick,
USGS



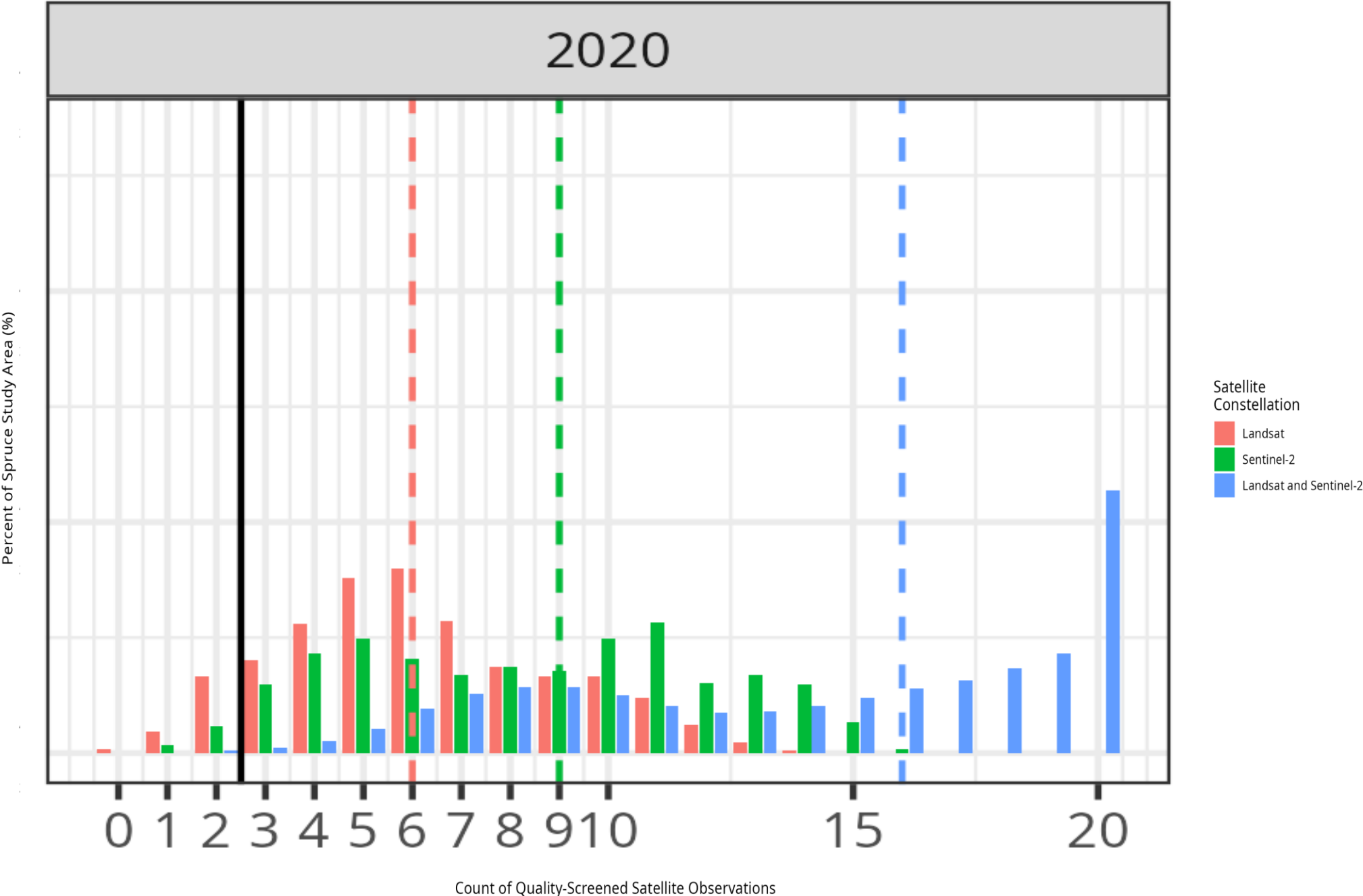
Tracking Annual Insect Damage

Counts of annual July and August satellite observations.

≥3 observations, median resistant to outliers (cloud, shadow, haze).

Annual observations often insufficient prior to launch of Sentinel 2 constellation starting in 2016.

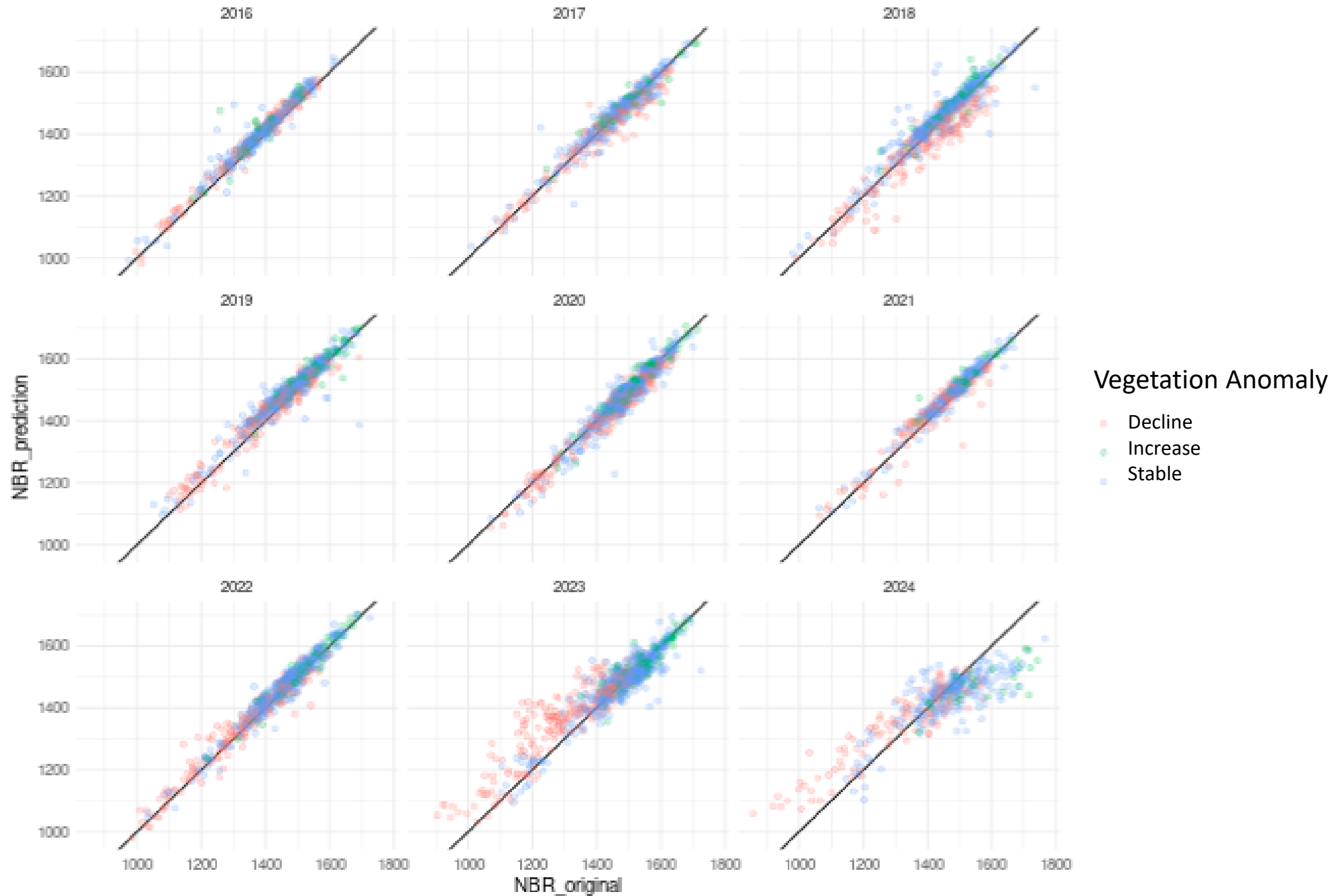
Substantial phenological variation in Arctic and Subarctic even with July/August constraint



Tracking Annual Insect Damage

Explored predictions of July and August using 'forecast' head.

Normalized Burn Ratio (NBR) higher for health vegetation, lowers after burns or other disturbance.



Tracking Annual Insect Damage

Spruce Bark Beetle outbreak annual history mapped at 30-m resolution.

Earliest Year of Detectable Decline

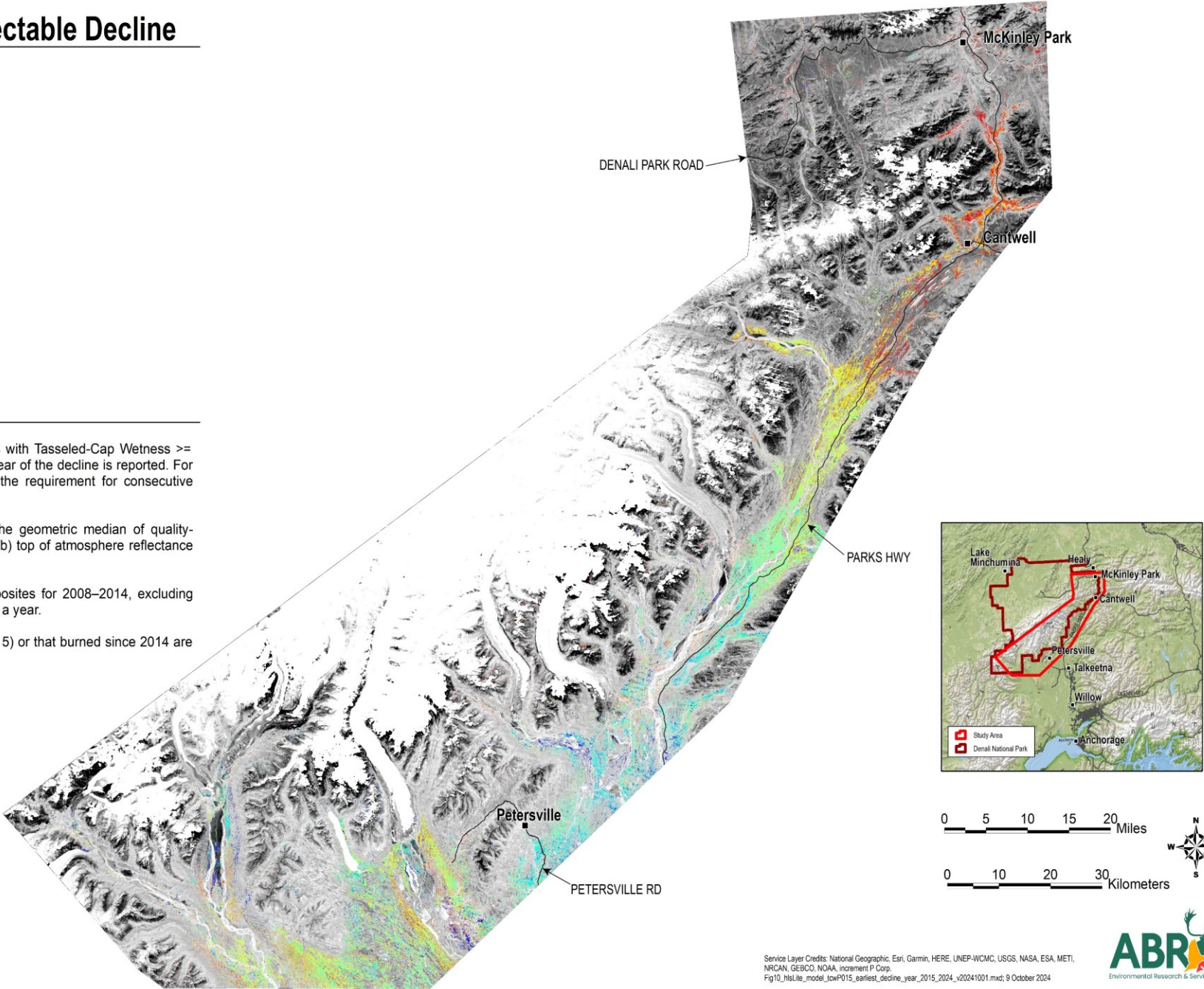
- 2015
- 2016
- 2017
- 2018
- 2019
- 2020
- 2021
- 2022
- 2023 (2 consecutive years)
- 2024 (1 year)

Notes:
Decline is defined as 3 consecutive years with Tasseled-Cap Wetness ≥ 0.015 below baseline value. The earliest year of the decline is reported. For the end of time-series (2023 and 2024) the requirement for consecutive years is relaxed.

Annual composites are calculated from the geometric median of quality-masked Landsat (7/8/9) and Sentinel 2 (a/b) top of atmosphere reflectance from July and August imagery each year.

Baseline value is median of annual composites for 2008–2014, excluding years when there were <3 observations for a year.

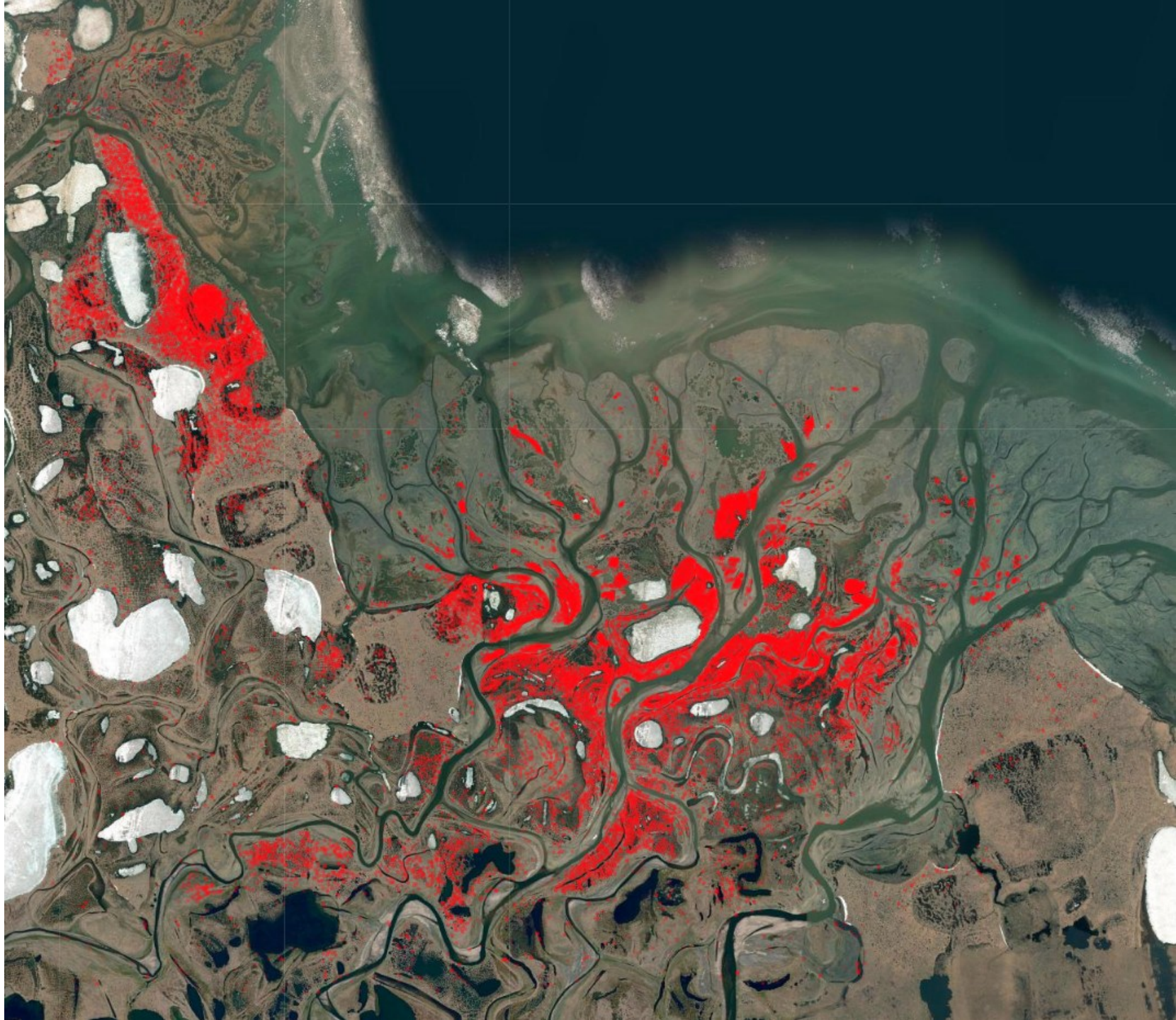
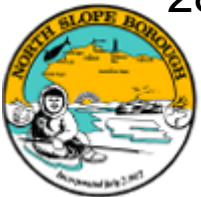
Pixels with 0% Conifer Tree top cover (2015) or that burned since 2014 are masked.



Ikpikpuk Delta Snow Geese Nesting Pair Photo Census

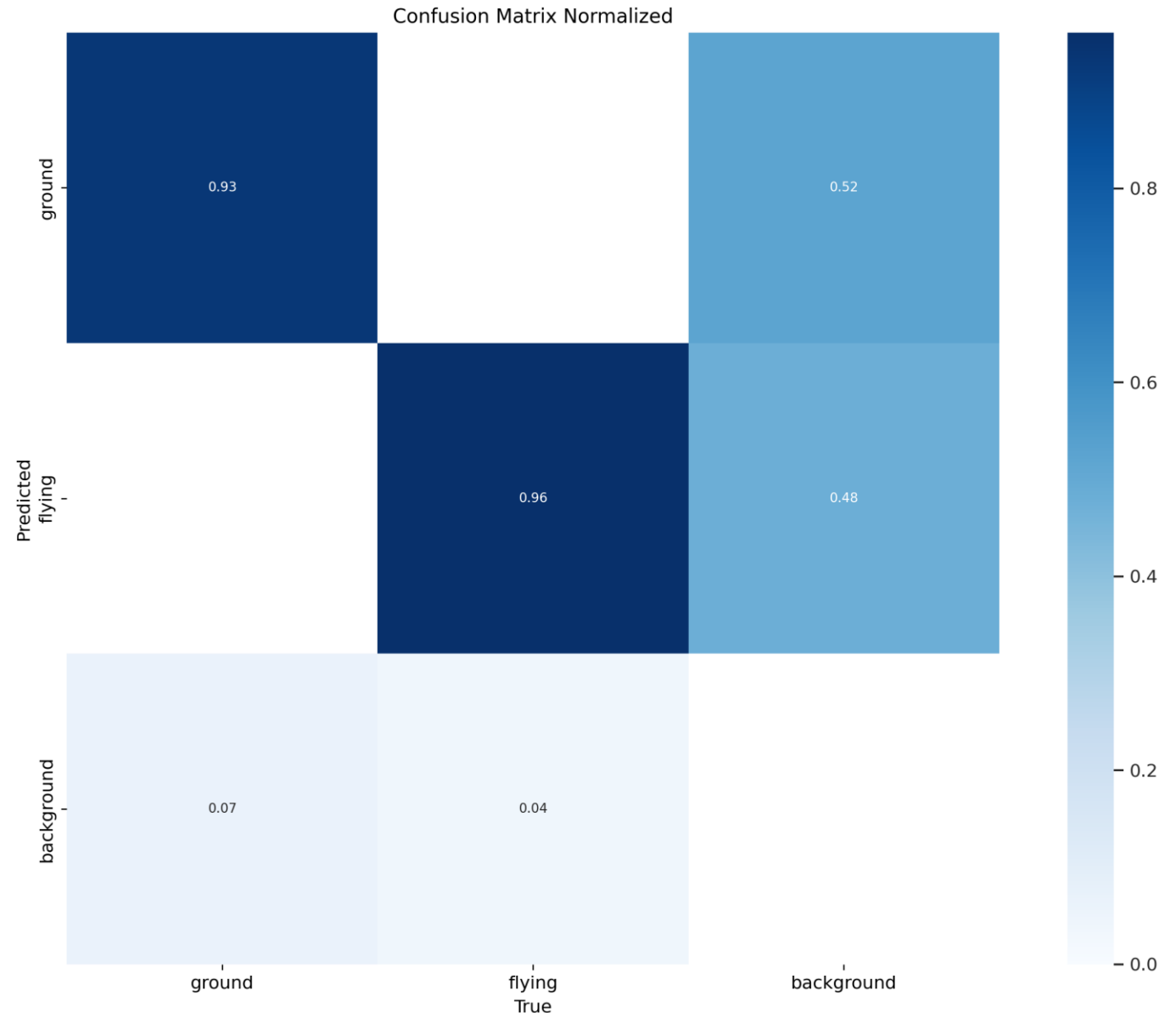
North Slope Borough
Wildlife Management

- Flown 11 June 2023
- 5,600 geotagged 45 megapixel images
- Mosaic 5 cm resolution
- Ran YOLOv5 model trained on subset of 2022 data
- ~44,500 detections
- Provided nest density stratification data needed for field work, analysis complete 28 June



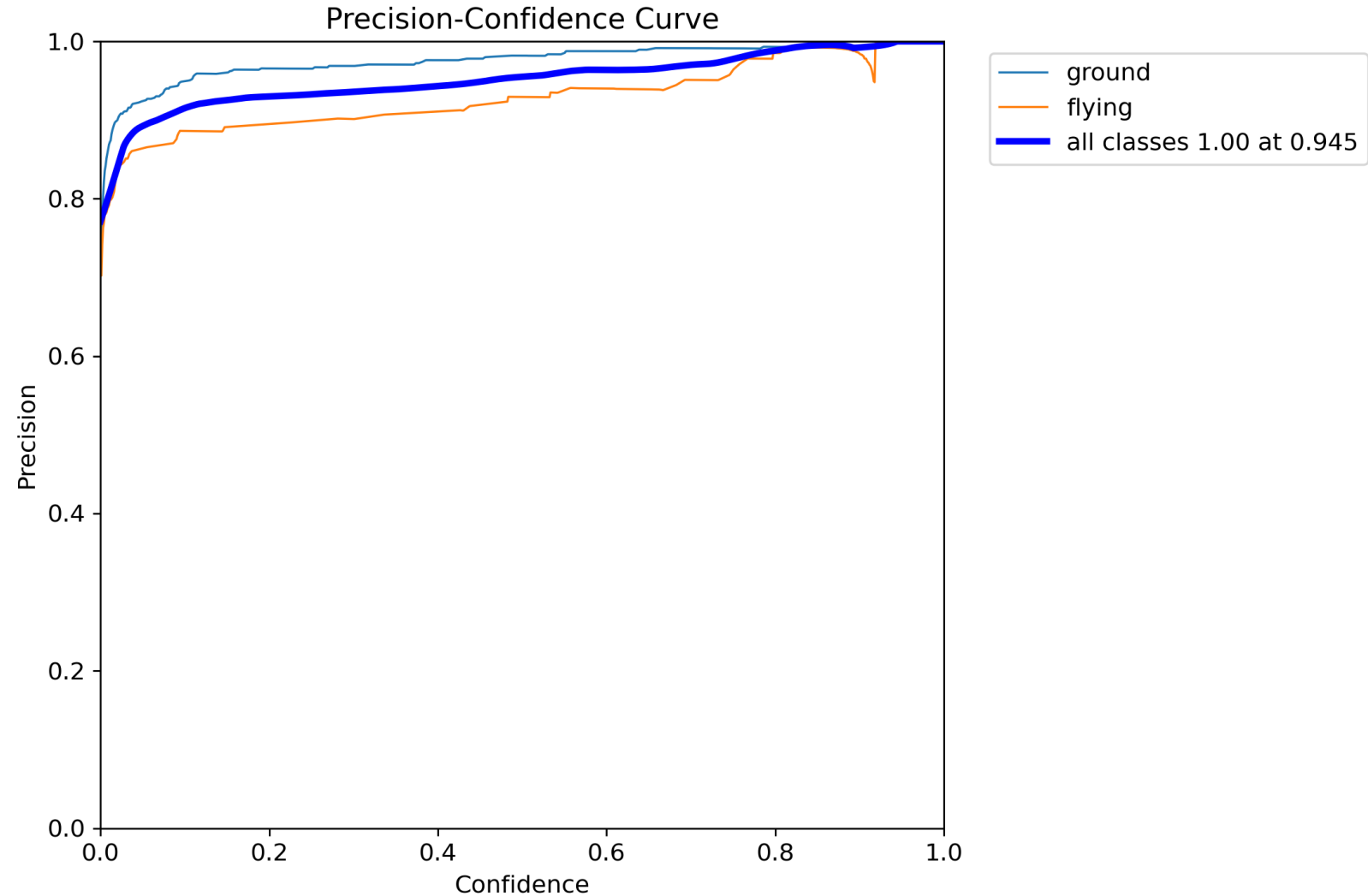
Ikpikpuk Delta Snow Geese Nesting Pair Photo Census 2022–2023

- Additional training / validation data collected from 2022 and 2023 mosaics emphasizing flying birds and images with sparse bird density
- Retrained models using Python / YOLOV8



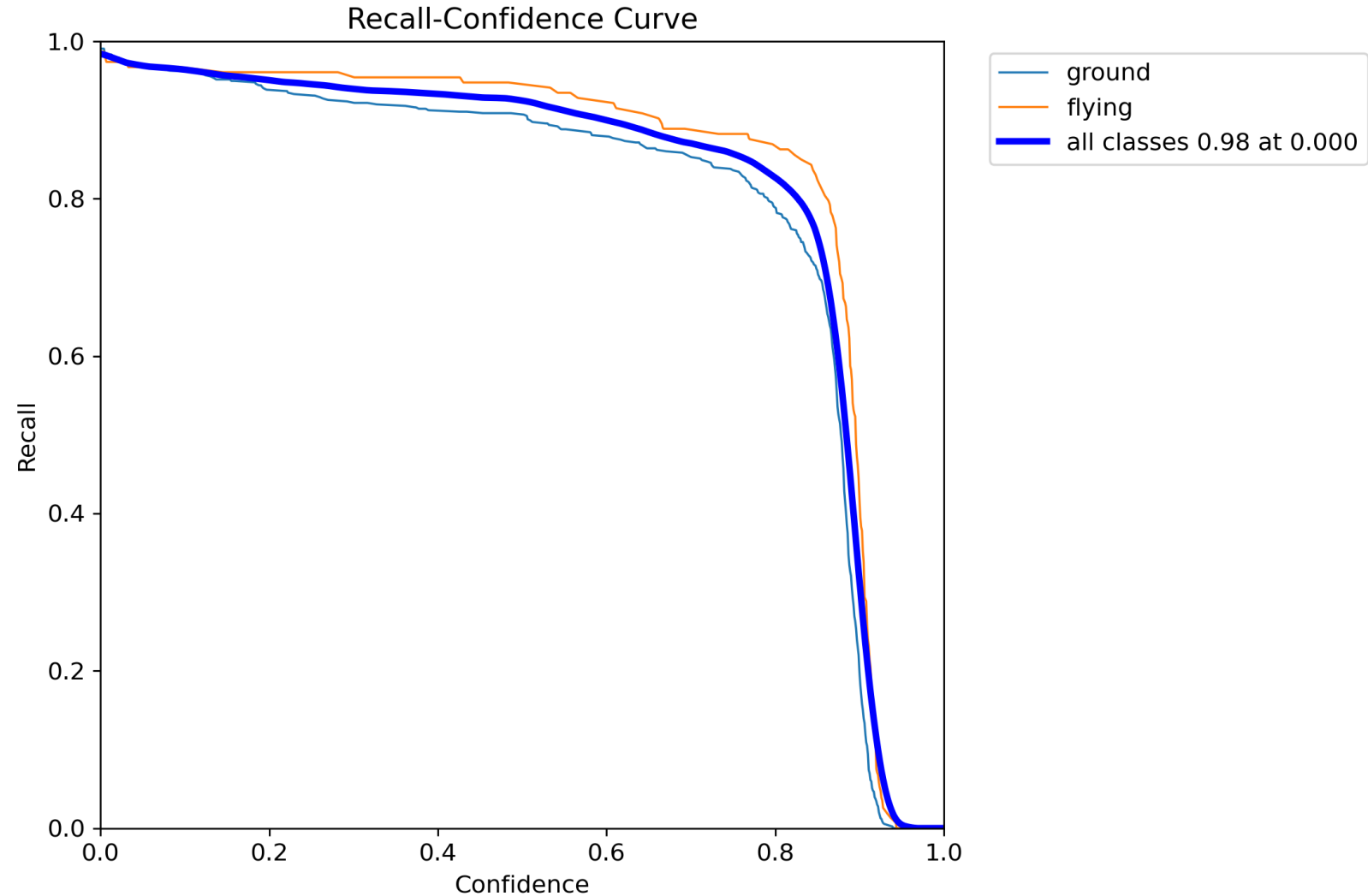
Ikpikpuk Delta Snow Geese Nesting Pair Photo Census 2022–2023

- Additional training / validation data collected from 2022 and 2023 mosaics emphasizing flying birds and images with sparse bird density
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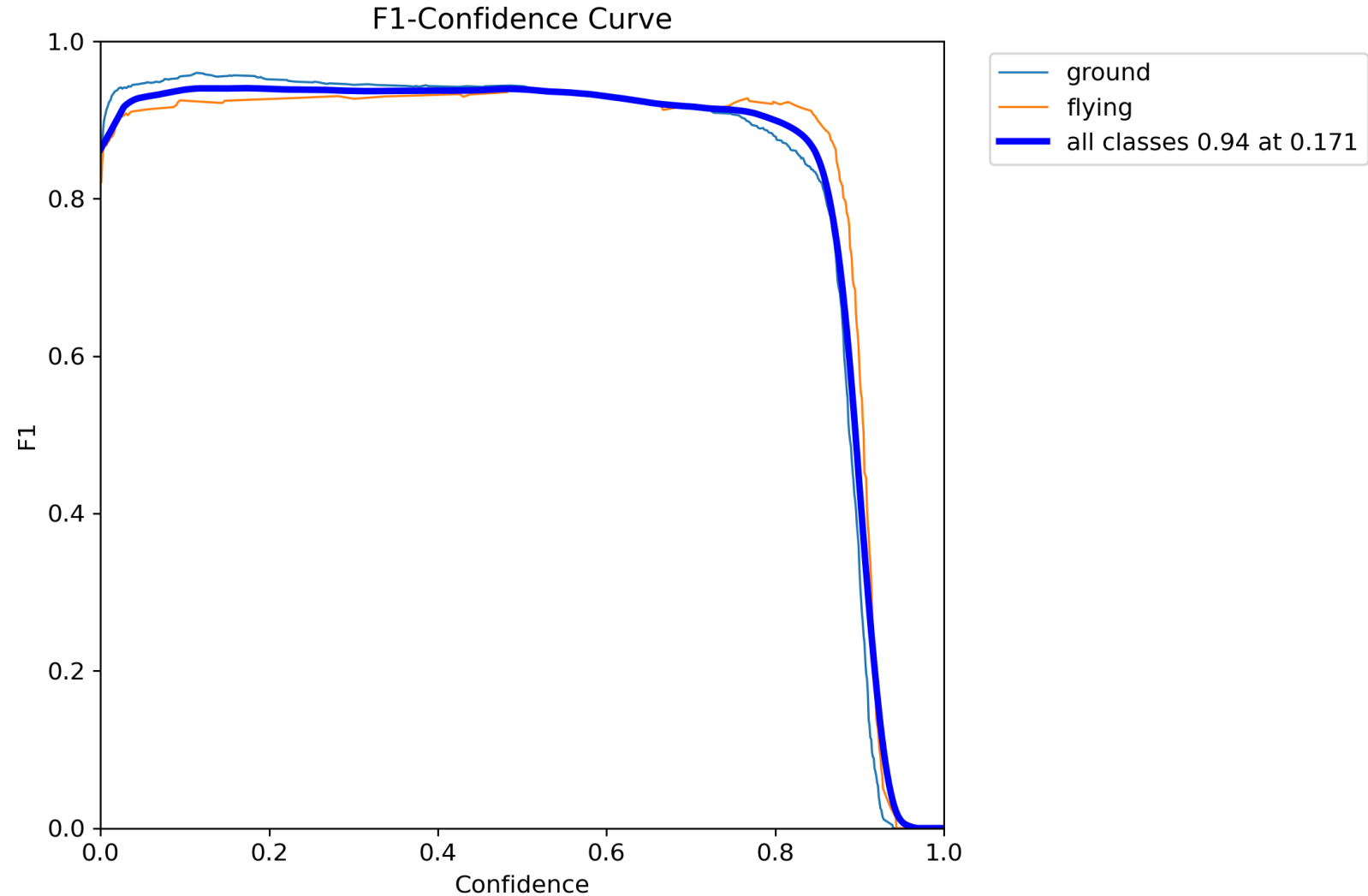
Ikpikpak Delta Snow Geese Nesting Pair Photo Census 2022–2023

- Additional training / validation data collected from 2022 and 2023 mosaics emphasizing flying birds and images with sparse bird density
- Retrained models using Python / YOLOV8

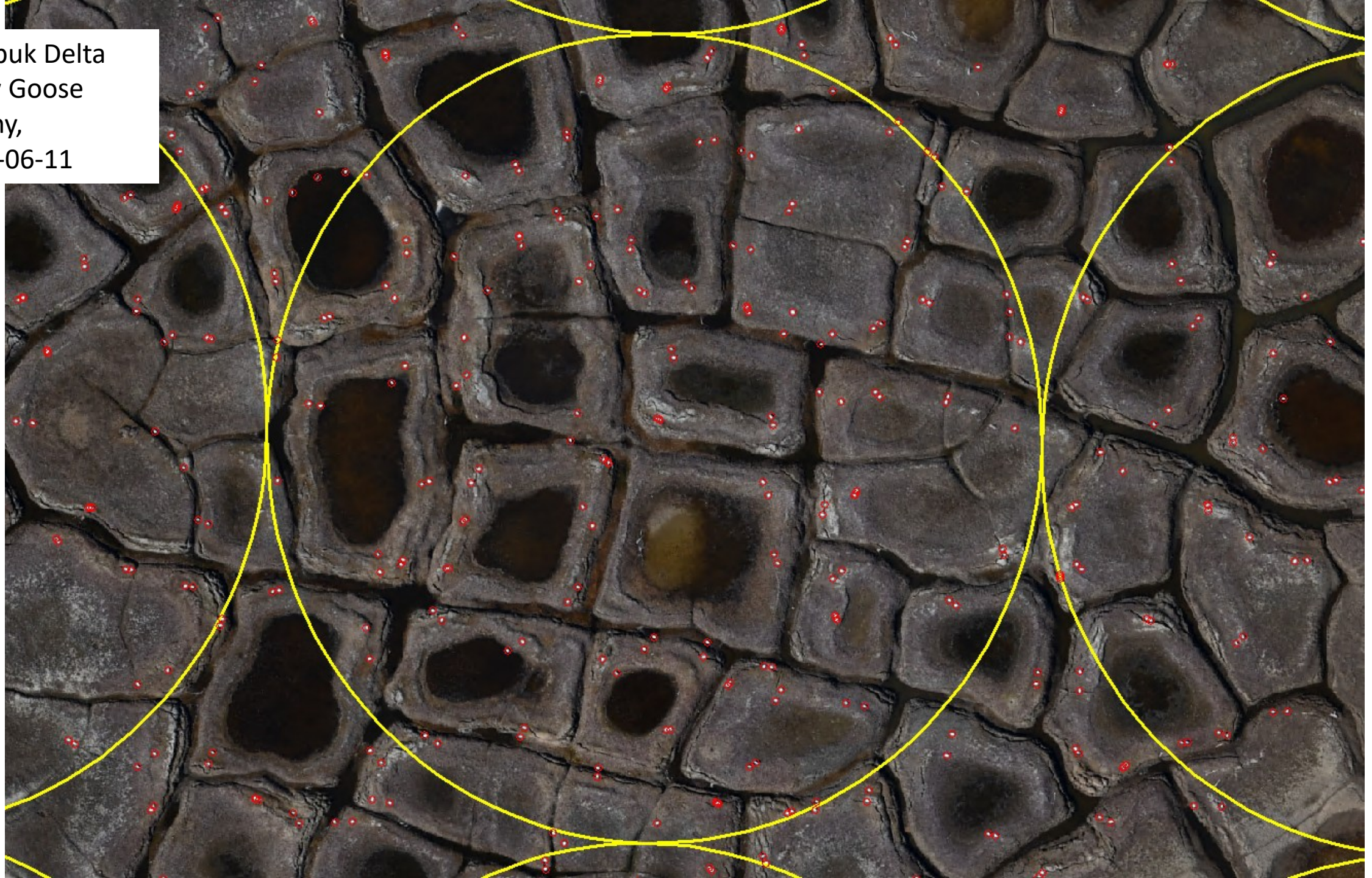


Ikpikpak Delta Snow Geese Nesting Pair Photo Census 2022–2023

- Additional training / validation data collected from 2022 and 2023 mosaics emphasizing flying birds and images with sparse bird density
- Retrained models using Python / YOLOV8



Ikpikpuk Delta
Snow Goose
Colony,
2023-06-11



Development of an Automated Nest Camera Analysis Pipeline for Brant Nest Occupancy Metrics

Tawna Morgan and Julie Parrett, ABR

Vijay Patil, USGS



NOLO 0.88 LO 0.83



Brant 0.88



Brant 0.91



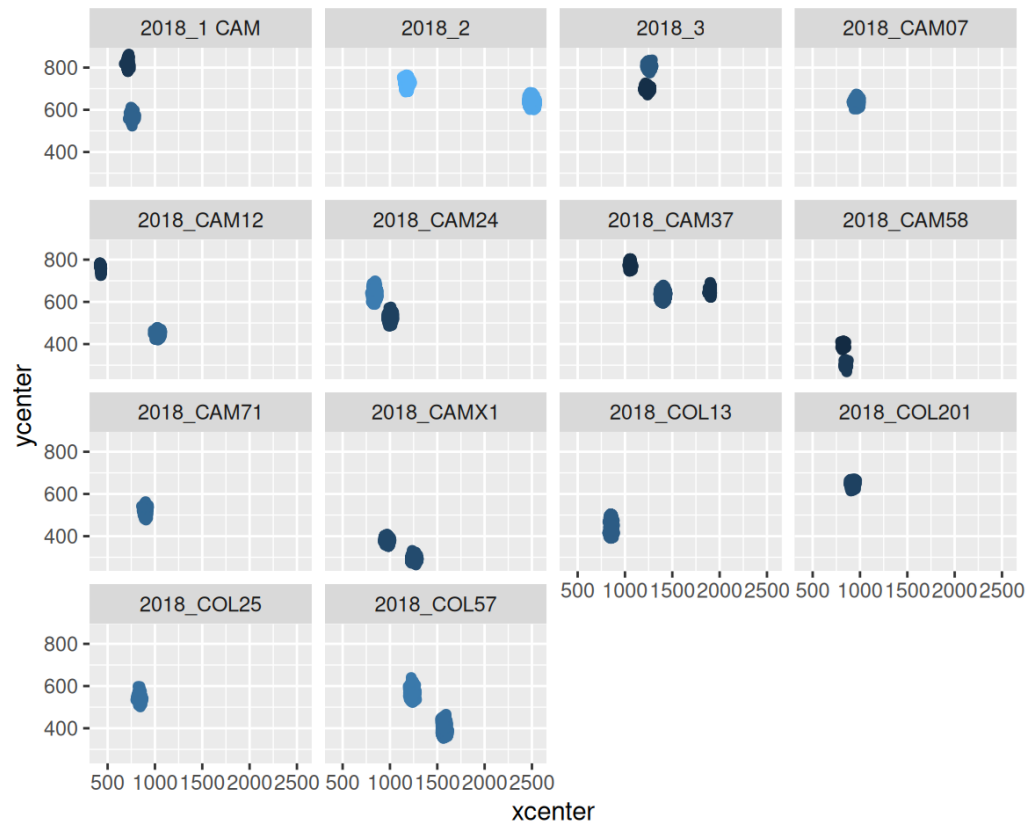


NOLO 0.88 LO 0.83

Brant 0.88

Brant 0.91

- Images collected every 5 minutes from stationary camera.
- Megadetector model frozen at layer 12 and trained to identify Brant.
- We didn't care about other species so everything was lumped into a NOLO category.

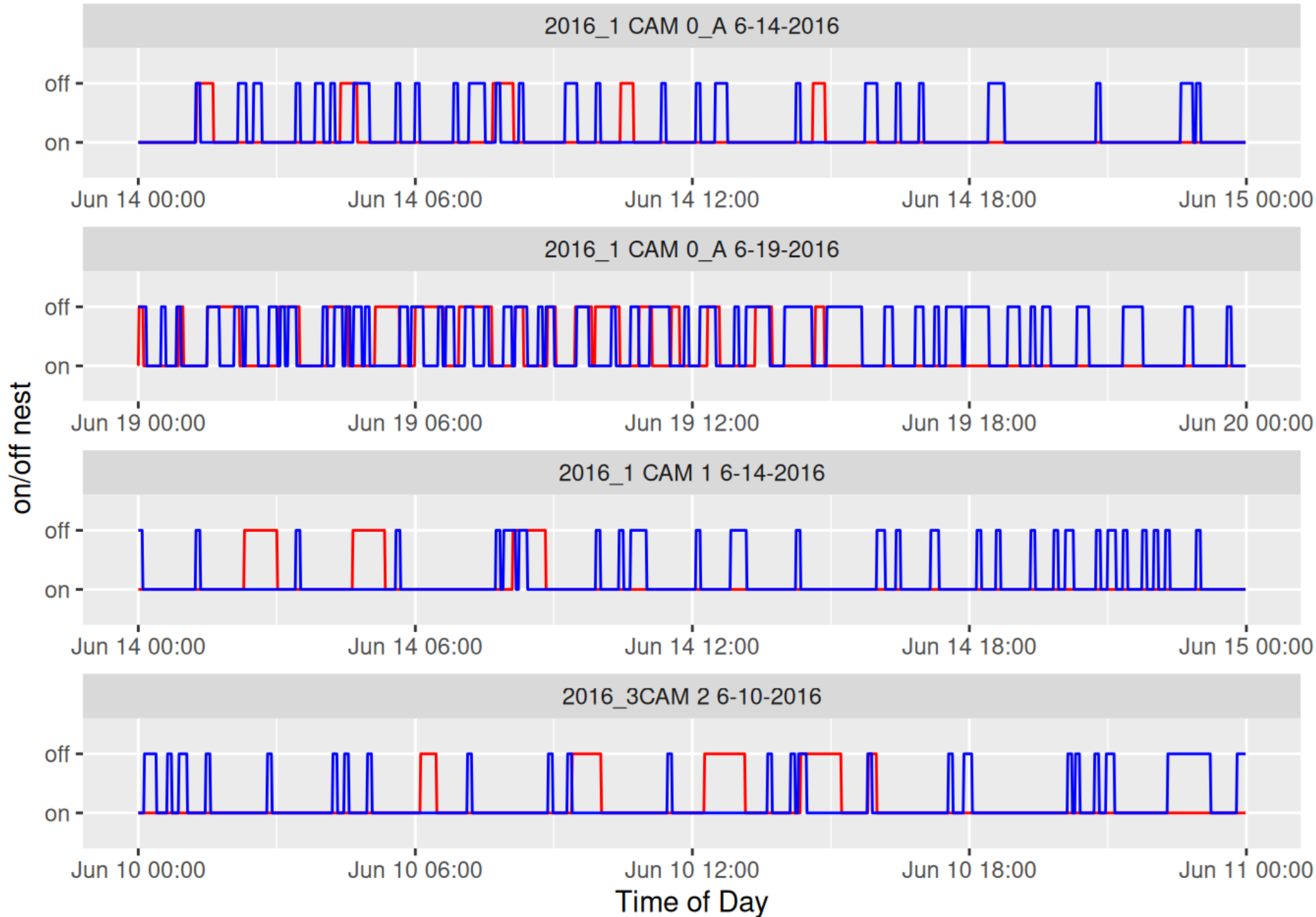


Incubation metrics calculated for multiple nests per image. Target nest was the one closest to the center of an image.

Probably the same nest, but camera shifted location

1. Initial spatial clustering of detection location revealed likely nest locations.
2. Further filtering on the spatial range covered by a cluster and the median time between detections determined actual nest locations.





Sample of 24 hours indicating whether or not a bird was detected within the determined nest cluster for each 5 minute interval.

Blue is AI model.
Red is human.

Next: Improve regions that don't align between human and AI



Nest no longer active. Failure?
Success?

Incubating

Based on the on/off nest determination we could calculate daily nest constancy (total minutes off the nest and frequency of trips from the nest).

Next: Can we determine nest success/failure or nest timing from constancy information.

Dalton Highway Dall's Sheep Lick Cameras



Erin Julianus, BLM
Christopher Swingley, ABR

- Camera traps placed at 15 Dall's sheep mineral lick sites in Dalton Highway corridor, 2015–2023
- Time-lapse photos every 15–60 minutes plus additional motion-triggered bursts of 5 frames
- > 2 million photos total



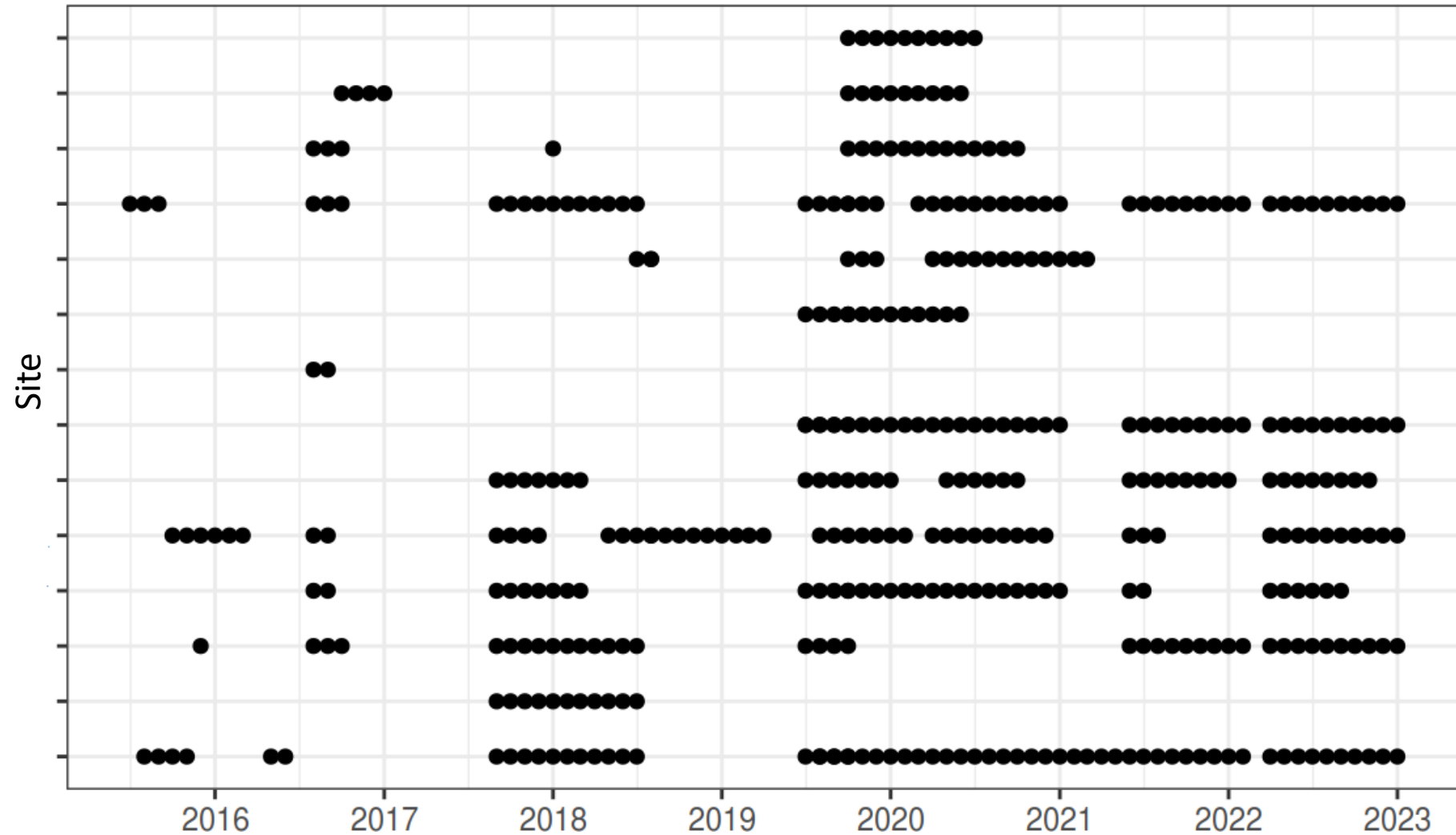
Dalton Highway Dall's Sheep Lick Cameras

Erin Julianus, BLM and Christopher Swingley, ABR

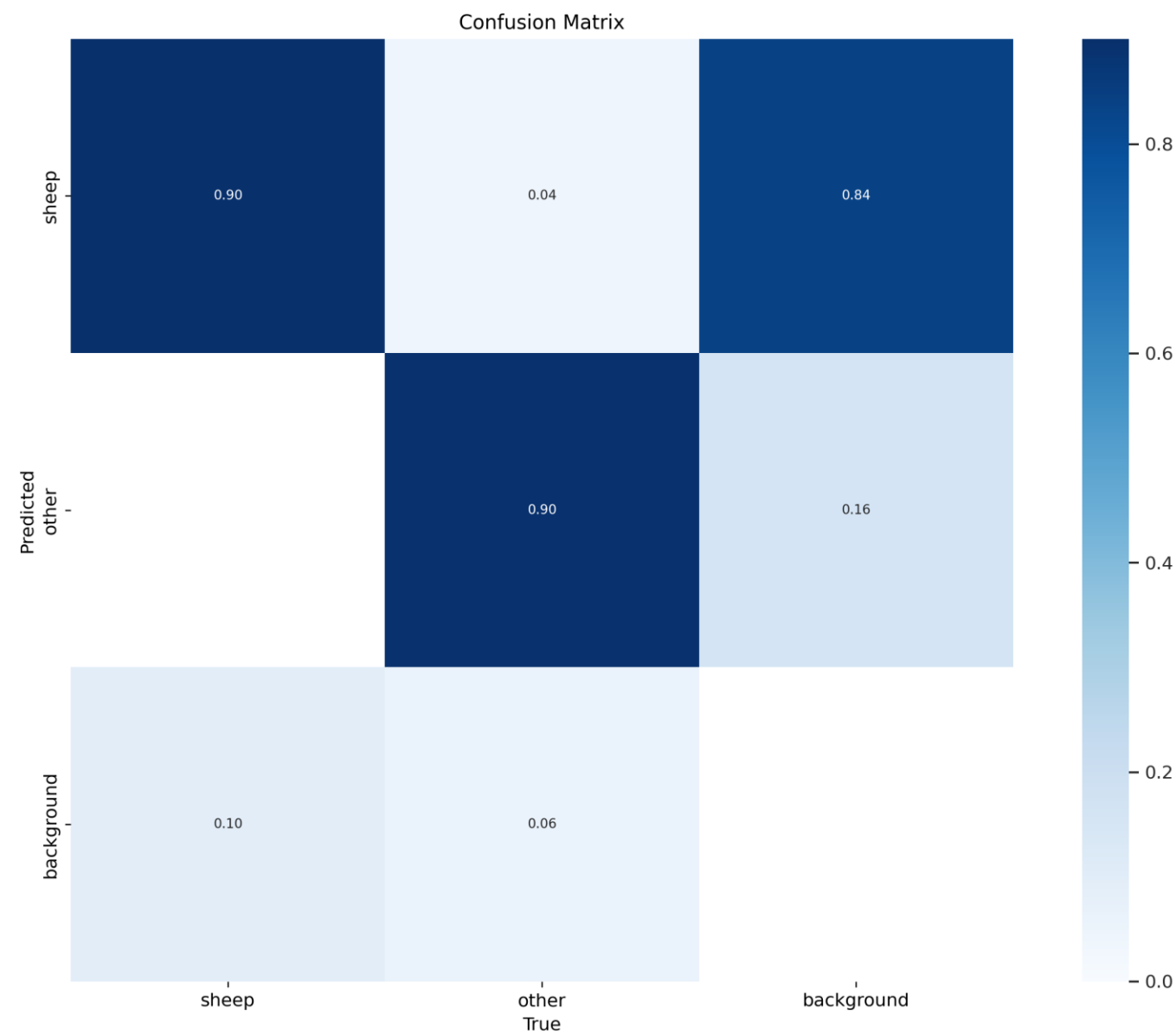
- Transition from 100% manual review to AI-assisted review with human identification of sheep age class / sex
- Automated pipeline following Celis et al. 2024
 - Resnet model to classify good vs. bad (obscured) photos
 - Megadetector to identify animals in photos and a resnet model to classify the animals to species (sheep vs. other)
 - Human review of all sheep detections to classify to age class / sex

Celis, G., Ungar, P., Sokolov, A., Sokolova, N., Böhner, H., Liu, D., Gilg, O., Fufachev, I., Pokrovskaya, O., Ims, R.A. and Zhou, W., 2024. A versatile, semi-automated image analysis workflow for time-lapse camera trap image classification. *Ecological Informatics*, 81, p.102578.

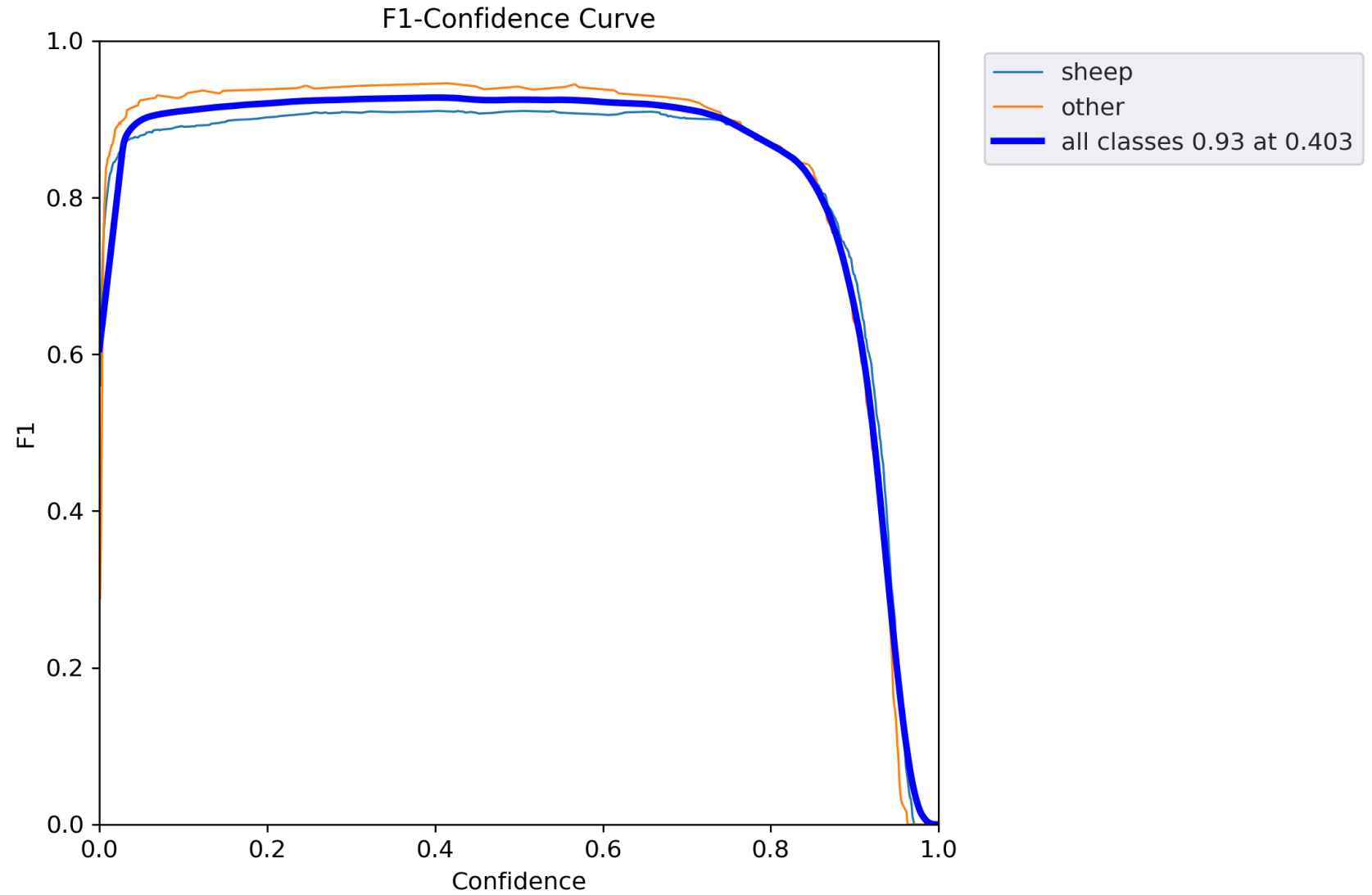
Camera deployments by site



Dalton Highway Dall's Sheep

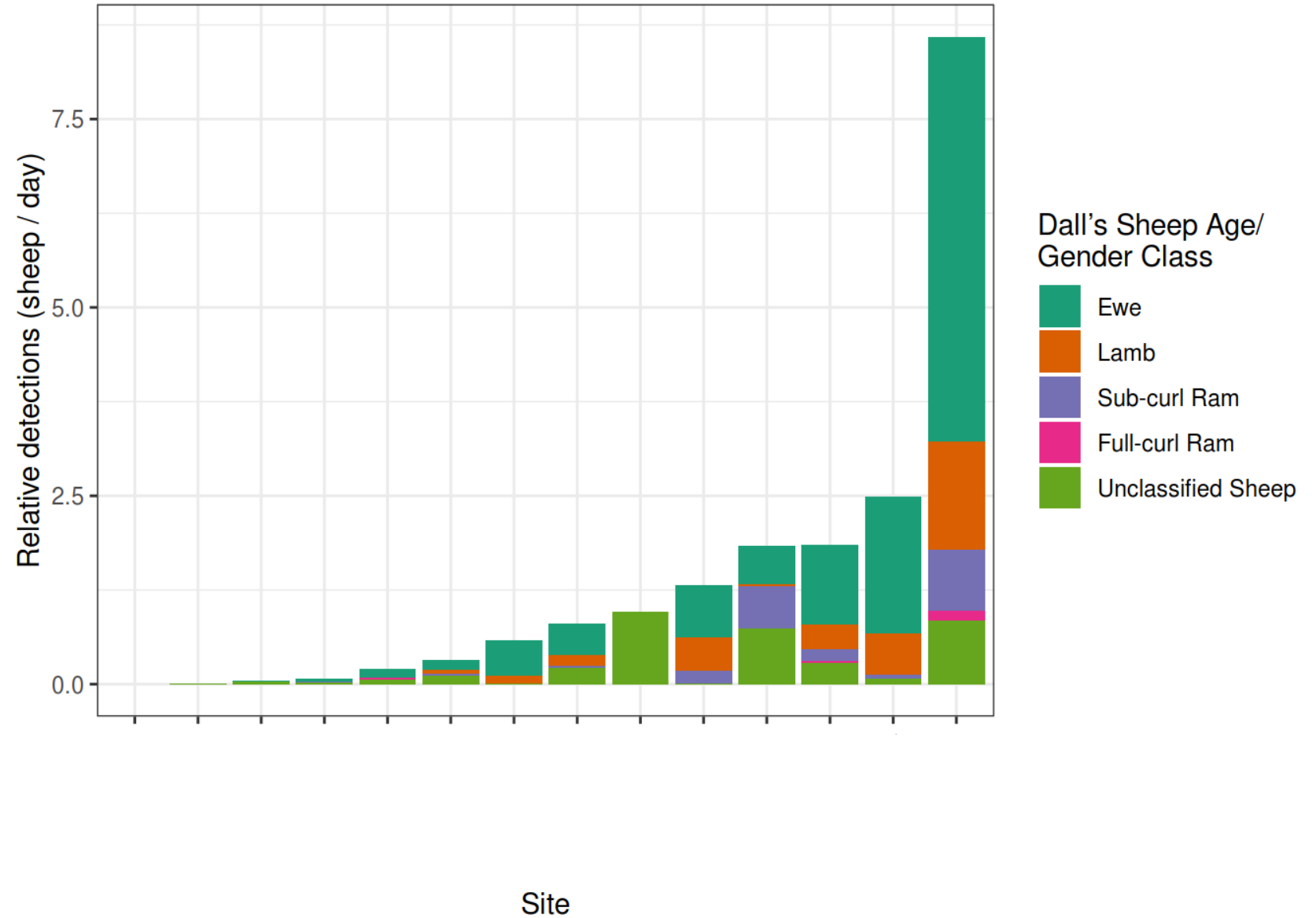


Dalton Highway Dall's Sheep



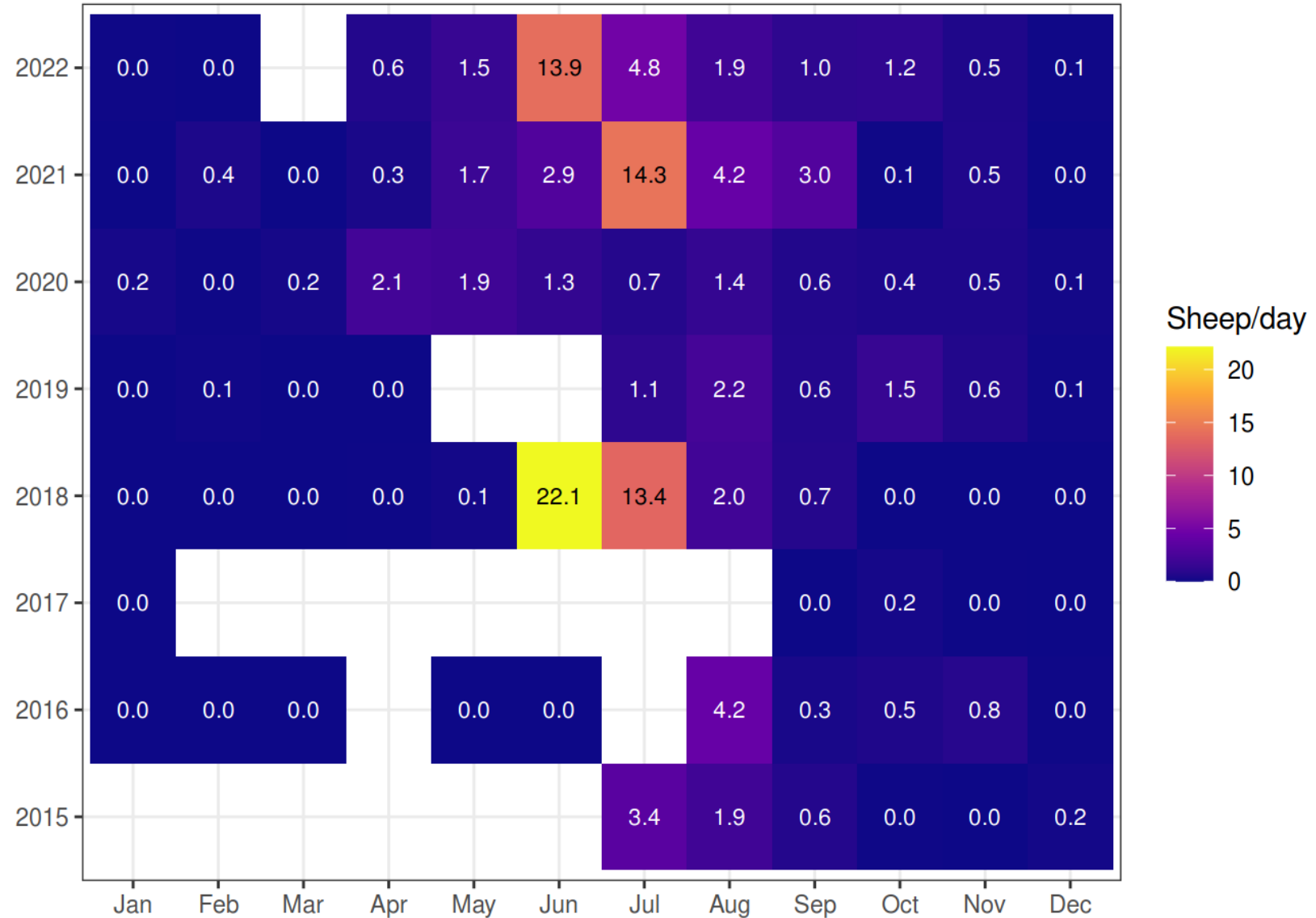
Dalton Highway Dall's Sheep

Sheep / day by age
class, sex, and site



Dalton Highway Dall's Sheep

Sheep / day by
month and year



Dalton
Highway
Dall's
Sheep
Lick
Camera
Traps



HF2 PRO COVERT



Dalton
Highway
Dall's
Sheep
Lick
Camera
Traps



2022-07-05 21:39:12 M 1/5

66°F

HF2 PRO COVERT



Dalton
Highway
Dall's
Sheep
Lick
Camera
Traps



Dalton
Highway
Dall's
Sheep
Lick
Camera
Traps



Dalton
Highway
Dall's
Sheep
Lick
Camera
Traps



Dalton Highway Dall's Sheep Lick Camera Traps



Dalton
Highway
Dall's
Sheep
Lick
Camera
Traps



Dalton
Highway
Dall's
Sheep
Lick
Camera
Traps



Thank
You!

mmacander@abrinc.com

