ABoVE SCIENCE TEAM MEETING
ASTM 7
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VIRTUAL MEETING

An integrated CANAPANI and deep learning-based approach for mapping tall shrubs in Arctic tundra

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ABoVE Project Chopping-03: Changes in Shrub Abundance in Arctic Tundra and Impacts on Albedo

Overview

- Goal: to map changes in shrub cover from high resolution satellite imagery in Arctic tundra over a 10 to 15-year period and determine the impact of changing shrub cover on terrestrial albedo (+ve feedback: ↑surface temperature ➡ ↑shrubs ➡ ↓albedo ➡ ↑temperature)
- CANAPANI (Canopy Analysis with Panchromatic and NDVI Imagery)
  - CANAPI variant using NDVI to filter results.
  - Provides: Individual tall shrub locations (small shrub clusters in some cases), shrub number density; crown radius distribution; fractional shrub canopy cover.
  - Shrub heights are imprecise; shrubs in shadow in water tracks are not detectable.
  - Precision of canopy cover estimates impacts change metrics (imagery limitations; method limitations; user subjectivity).

Hybrid approach leveraging both CANAPANI and machine learning.

Impacts

Snow-shrub Interactions

Lowering of albedo

Fire

Response to slumping as permafrost thaws (invaders)

Changes to habitats

Uncertainty

…is not our friend. The precision of shrub cover estimates impacts change metrics importantly, including the sign. Error arises from limitations in:

1. The CANAPANI method;
2. The imagery (e.g., low dynamic range);
3. User subjectivity (WV02 image)

- CANAPAMI (LLS or ITER): variants that leverage the spectral bands
- Duchesne = experienced interpreter
- ChoppingT = rookie interpreter

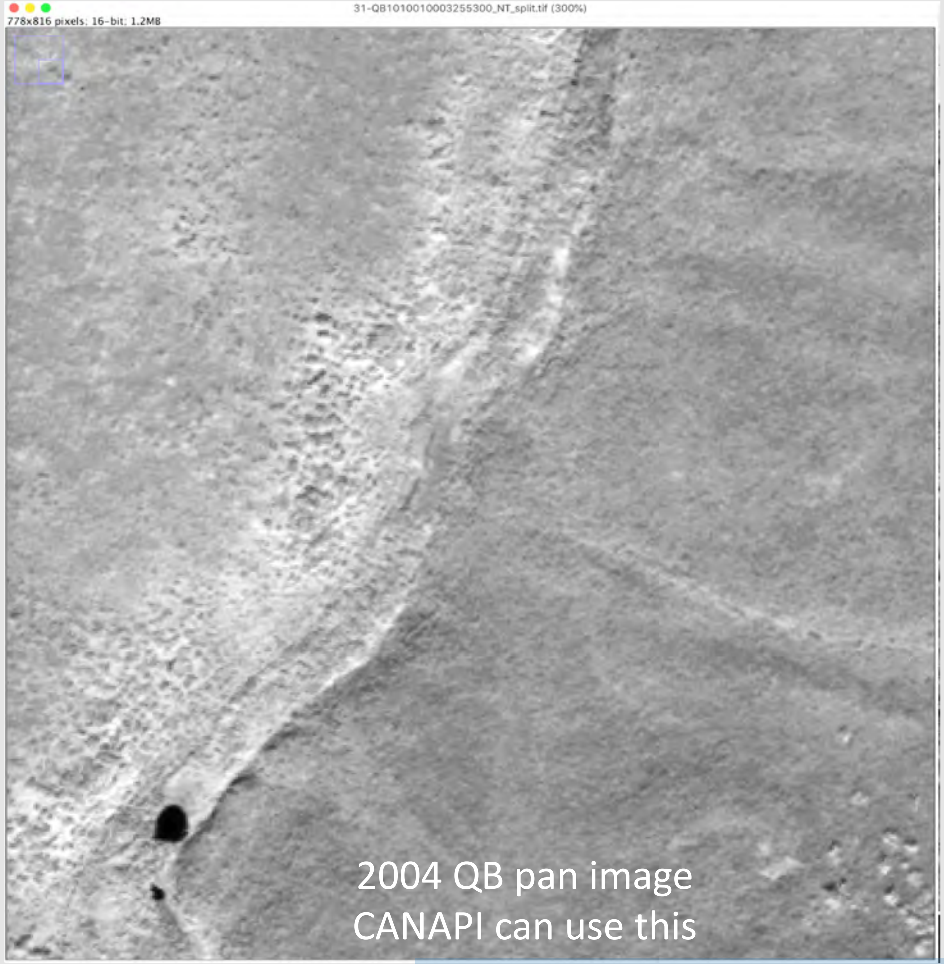
CANAPANI NDVI	# Valid Crowns	# Valid Heights	Heights: Crowns Ratio	Mean Crown Radius (m)	% Tall Shrub Cover	Mean height (m)
Duchesne	6128	5940	0.97	2.37	7.13	1.40
ChoppingM	8022	7686	0.96	2.39	9.33	1.32
Erb	8340	7865	0.94	2.30	8.63	1.42
Wang	9715	9103	0.94	2.37	11.11	1.47
ChoppingT	8013	7678	0.96	2.39	9.32	1.32
Mean	8043.60	7654.40	0.95	2.36	9.10	1.38
RMSE	1144.76	1008.32	0.01	0.03	1.28	0.06
Rel.Unc (%)	14.23	13.17	1.22	1.47	14.11	4.26

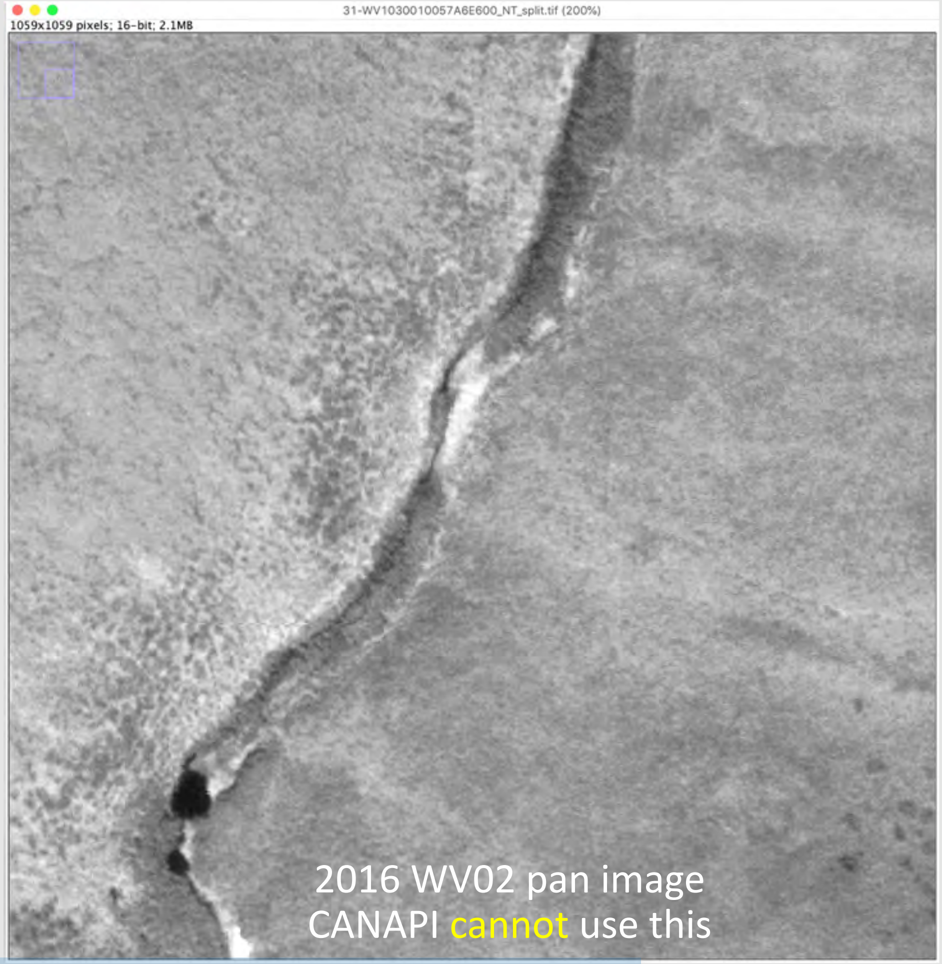
CANAPAMI (LLS)	# Valid Crowns	# Valid Heights	Heights: Crowns Ratio	Mean Crown Radius (m)	% Tall Shrub Cover	Mean height (m)
Duchesne	3002	2564	0.85	2.28	3.21	1.40
ChoppingM	8252	7411	0.90	2.39	9.65	1.27
Erb	6862	6194	0.90	2.37	7.70	1.29
Wang	4323	3879	0.90	2.46	5.36	1.30
ChoppingT	7880	7063	0.90	2.40	9.27	1.28
Mean	6063.80	5422.20	0.89	2.38	7.04	1.31
RMSE	2055.67	1886.48	0.02	0.06	2.44	0.05
Rel.Unc (%)	33.90	34.79	2.02	2.48	34.66	3.59

CANAPAMI (ITER)	# Valid Crowns	# Valid Heights	Heights: Crowns Ratio	Mean Crown Radius (m)	% Tall Shrub Cover	Mean height (m)
Duchesne	3009	2588	0.86	2.27	3.20	1.40
ChoppingM	8206	7367	0.90	2.40	9.61	1.28
Erb	6905	6365	0.92	2.32	7.42	1.28
Wang	9955	8403	0.84	2.37	11.42	1.32
ChoppingT	7432	6650	0.89	2.41	8.83	1.28
Mean	7101.40	6274.60	0.88	2.35	8.10	1.31
RMSE	2291.67	1972.99	0.03	0.05	2.77	0.05
Rel.Unc (%)	32.27	31.44	3.16	2.23	34.19	3.53

Issues with imagery: low dynamic range

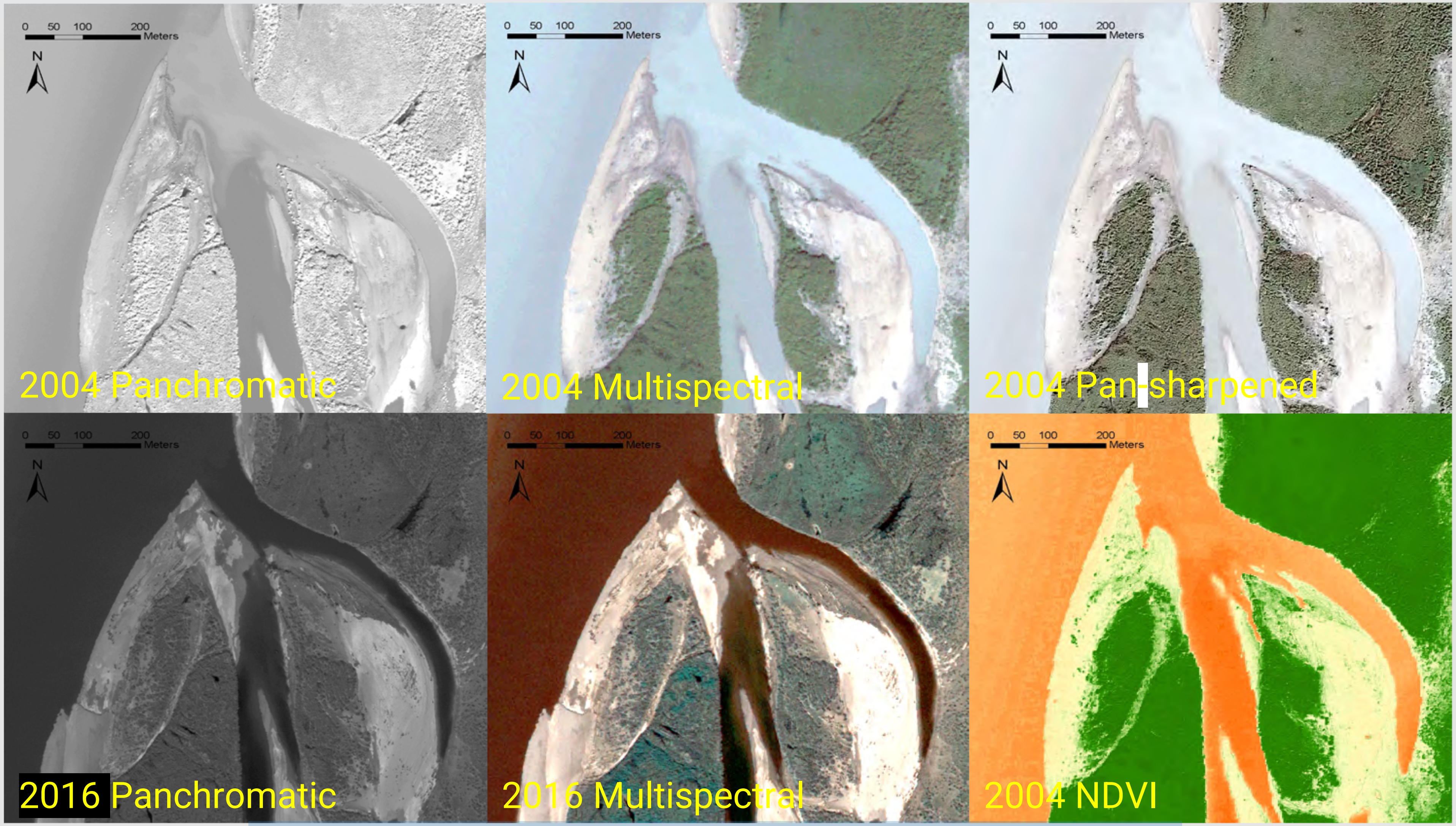
CANAPI (and variants) exploit specular reflection from sunlit shrub crowns





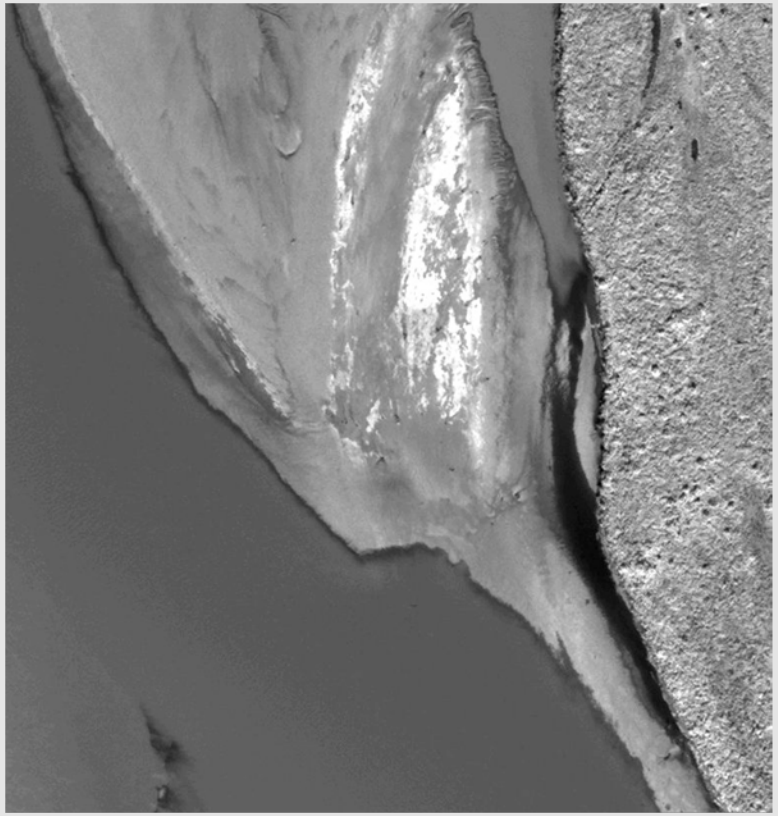
Example

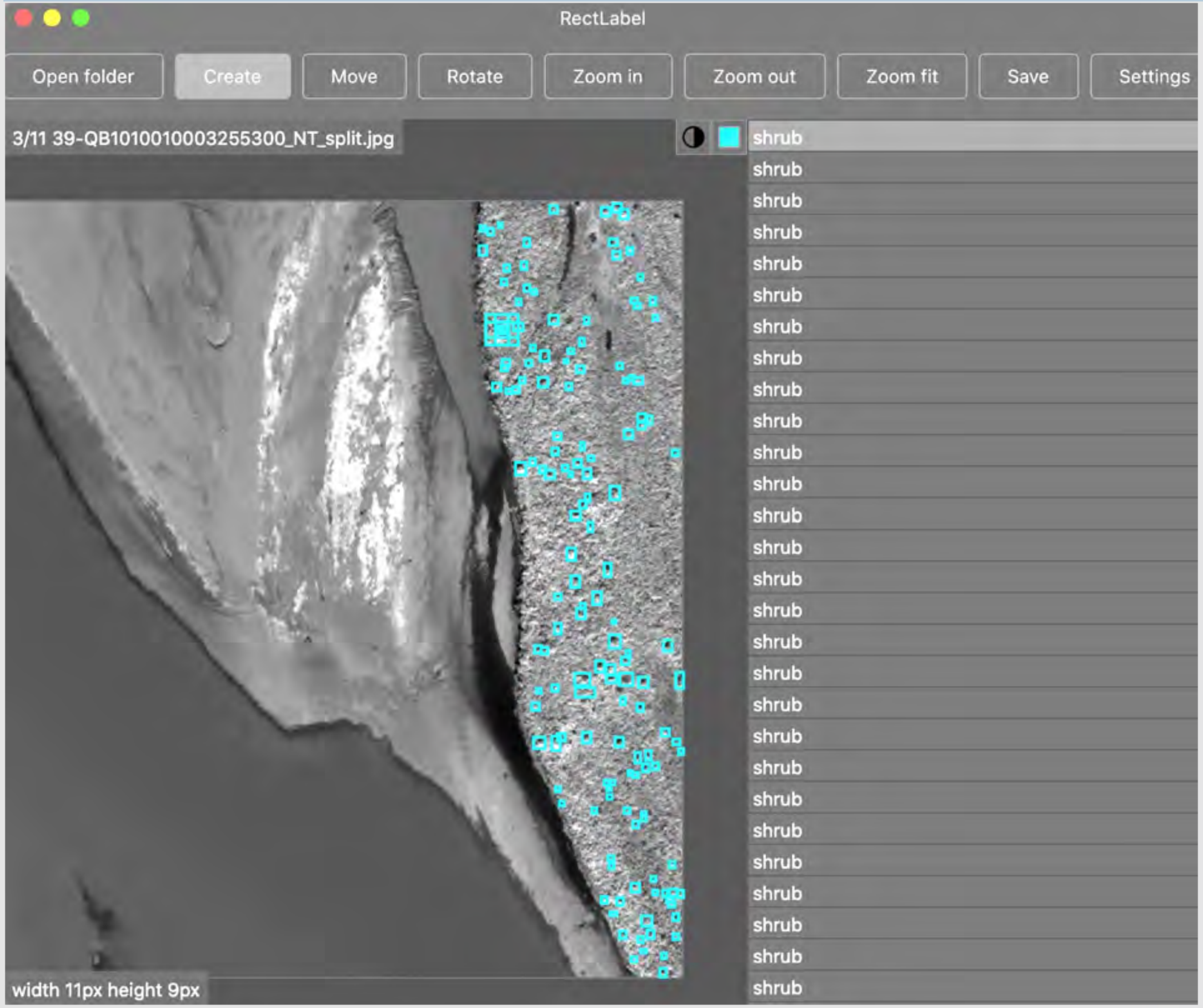
Pan-sharpening aids digitizing of shrubs for production of training datasets



Training datasets

= a lot of work



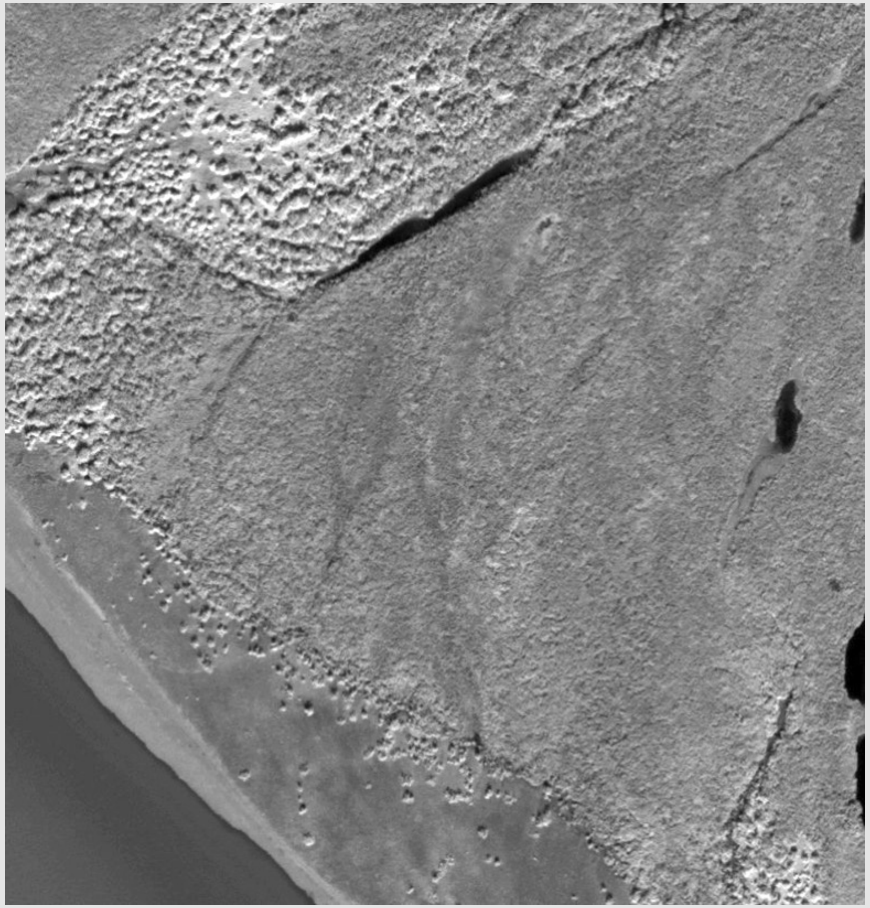


Outputs from RectLabel or VIA OpenSource are JSON files with shrub annotations

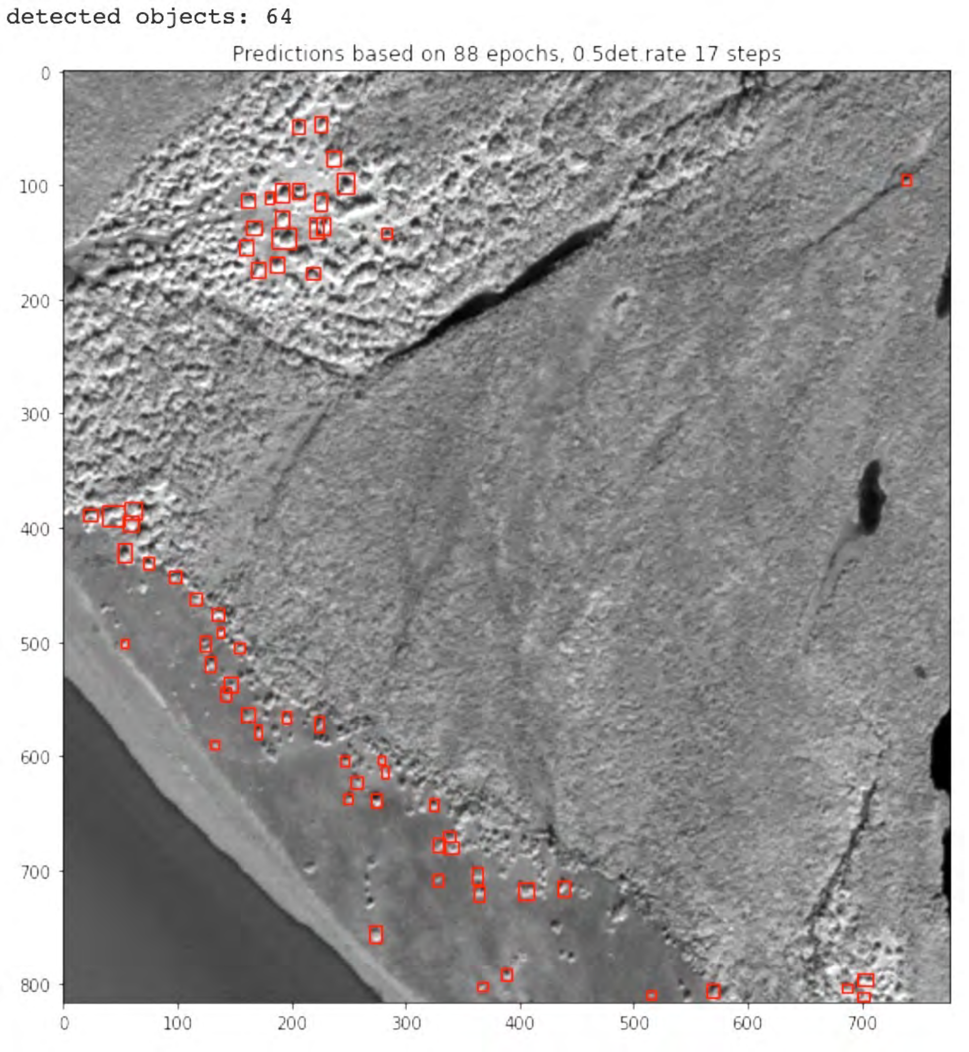
Initial ML Results

* we now have better ways to visualize these results

Too few shrubs detected



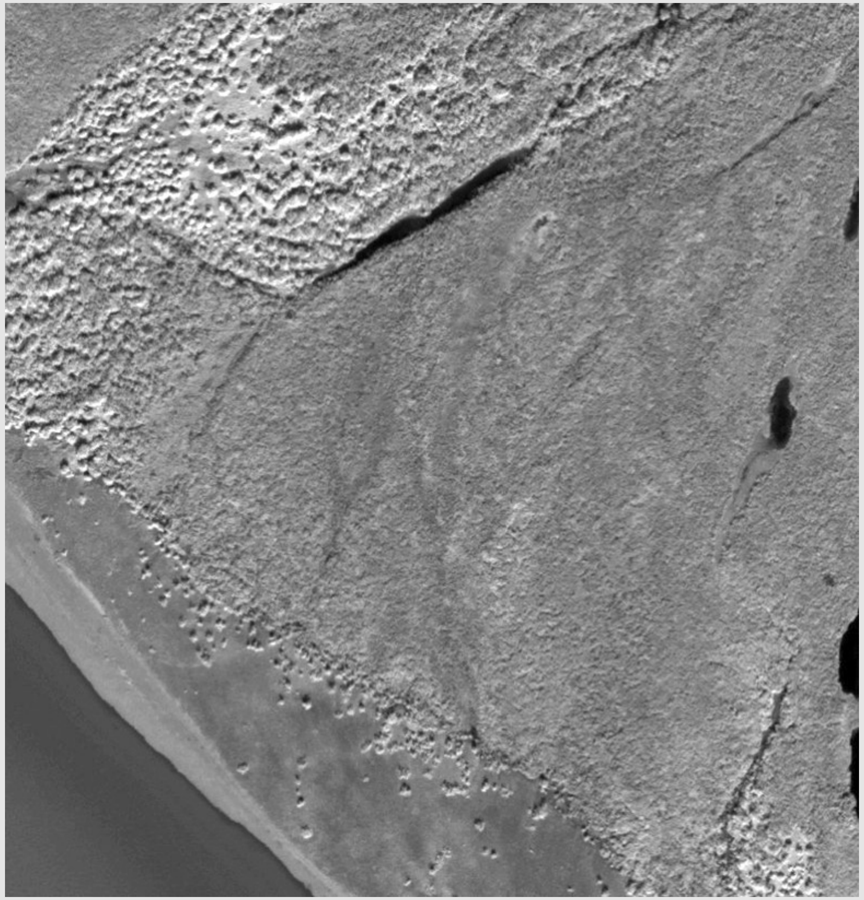
Quickbird 1010010003255300 (500 x 500 m)



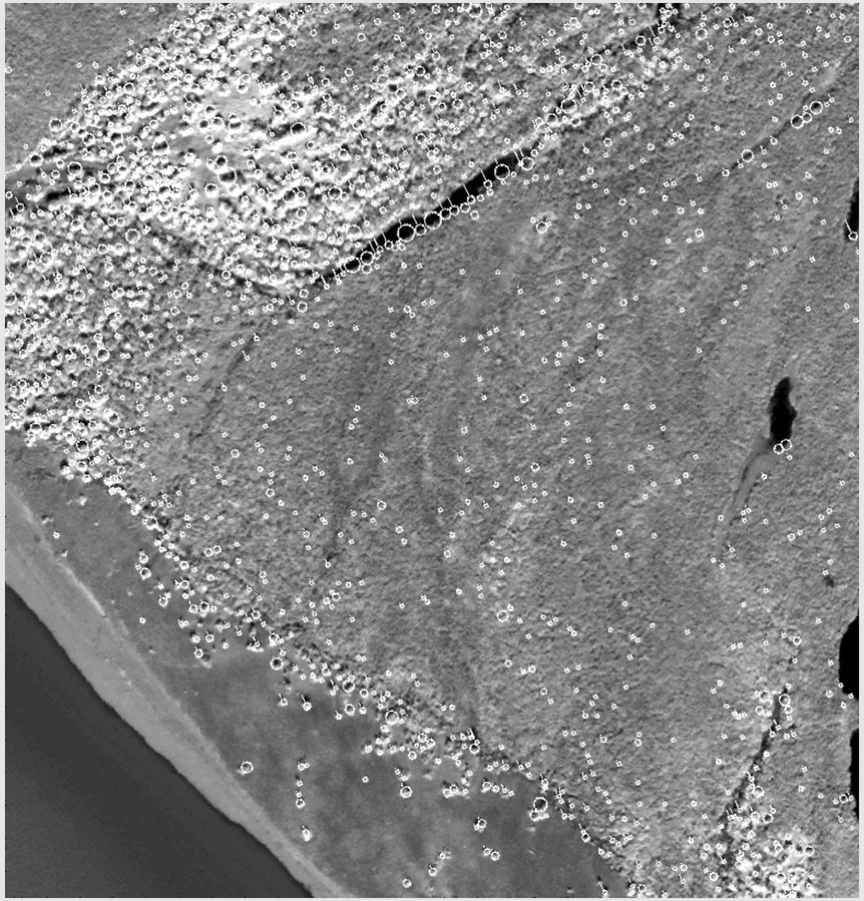
How does CANAPANI do?

#valid crowns : 1628
#valid heights : 1568
heights:crowns ratio : 0.96
mean crown radius (m): 2.15

Not too shabby



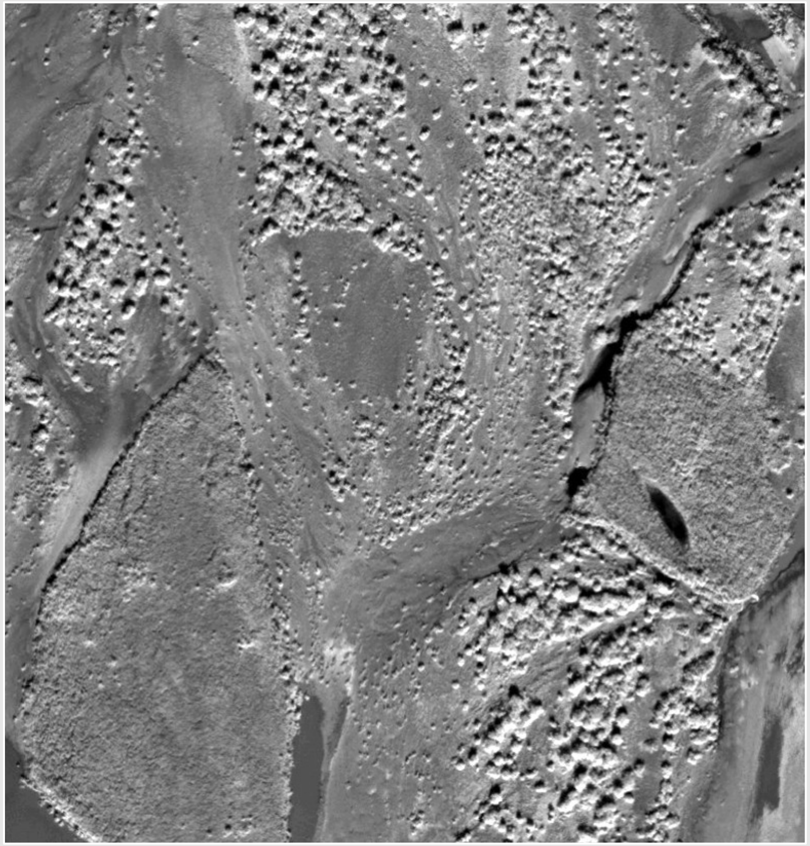
Quickbird 1010010003255300 (500 x 500 m)

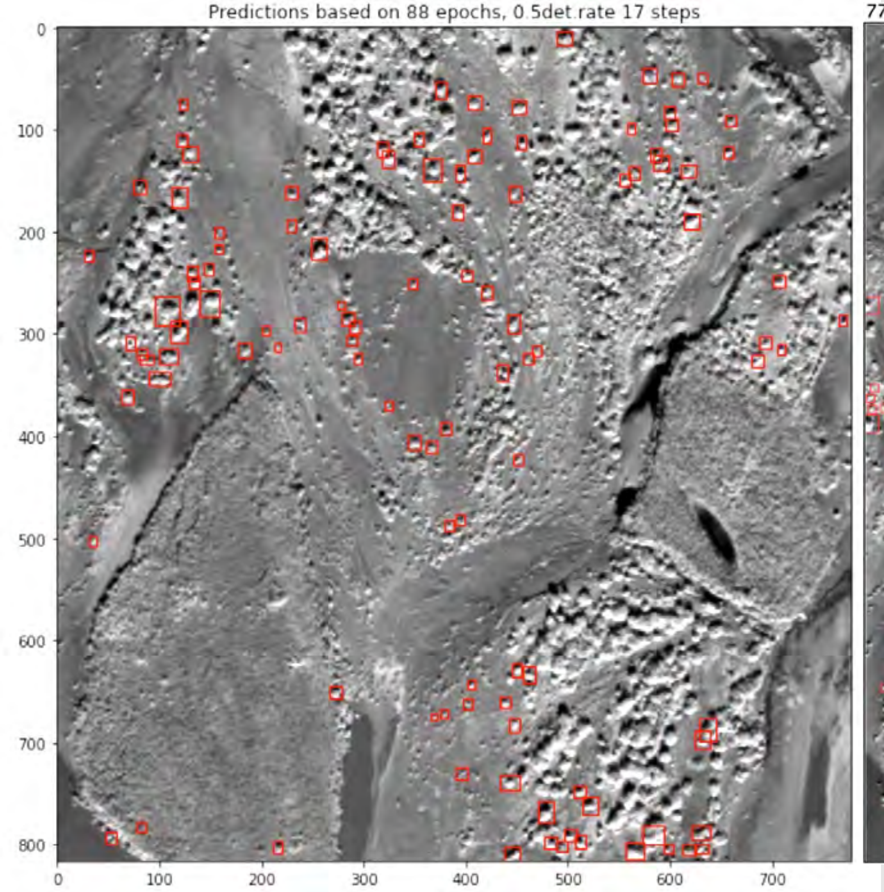


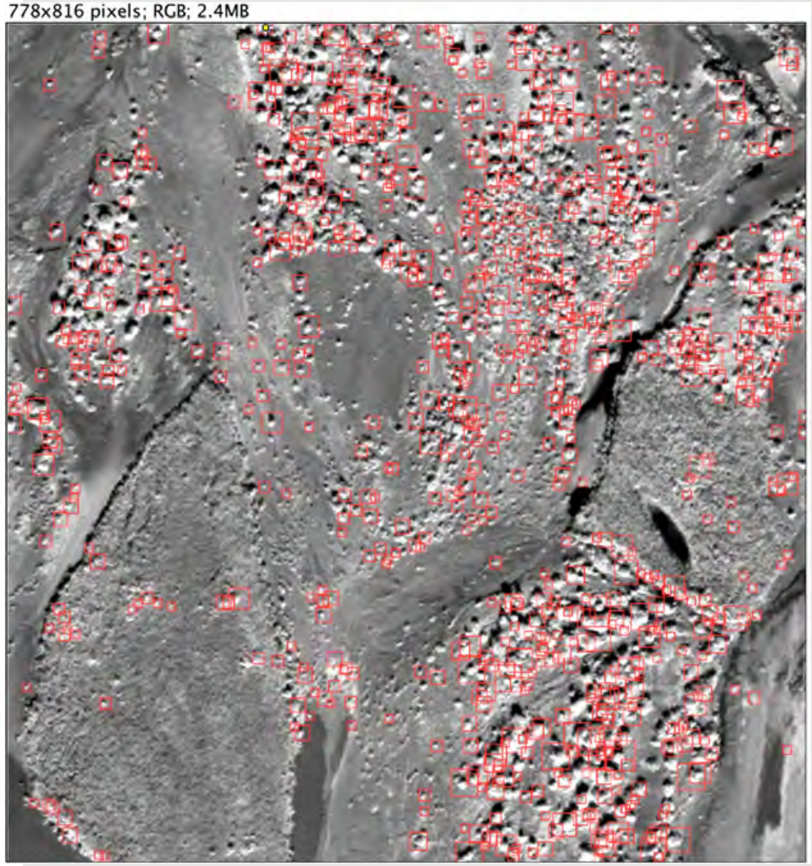
CANAPI (CANAPANI w/no NDVI filter)

How does CANAPANI do?

* we now have better ways to visualize these results







Quickbird 1010010003255300 (500x500 m)

ML: Epoch 210; Steps per Epoch: 17; Detection Minimum Confidence: 0.5 → ~133 shrubs

CANAPI (CANAPANI w/no NDVI filter)

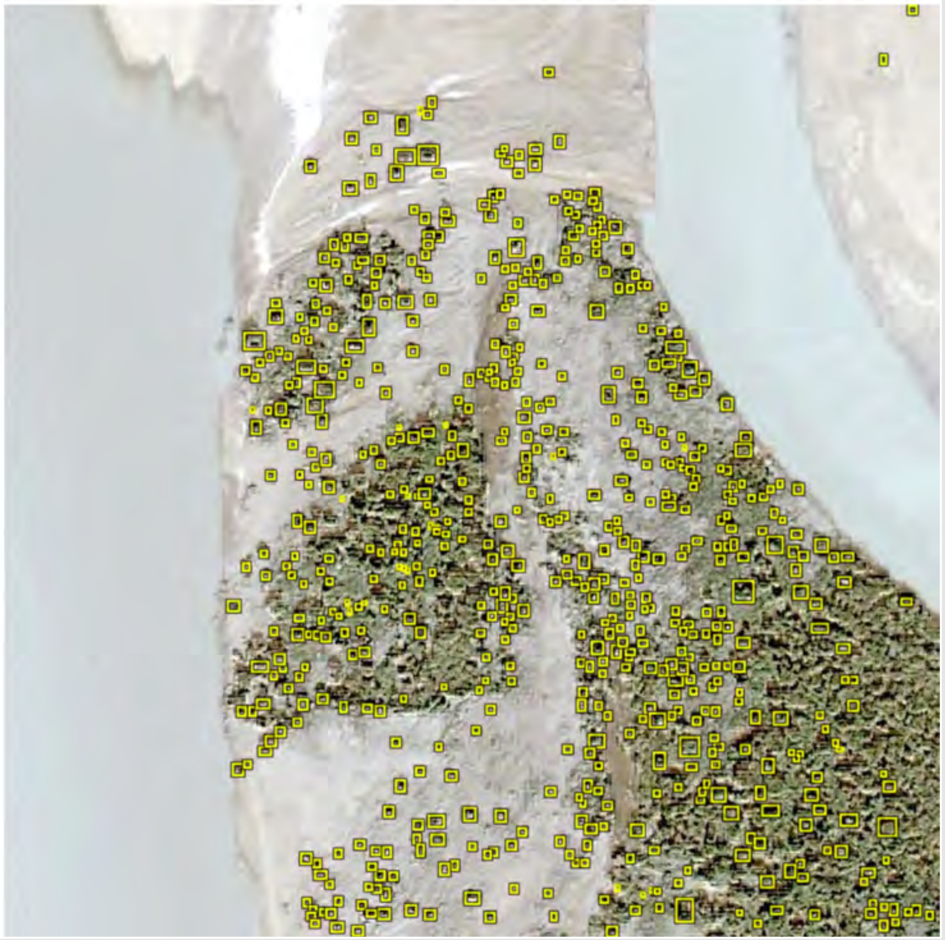
#valid crowns: 2085 #valid heights: 2018
heights:crowns: 0.97 mean crown radius: 2.32m

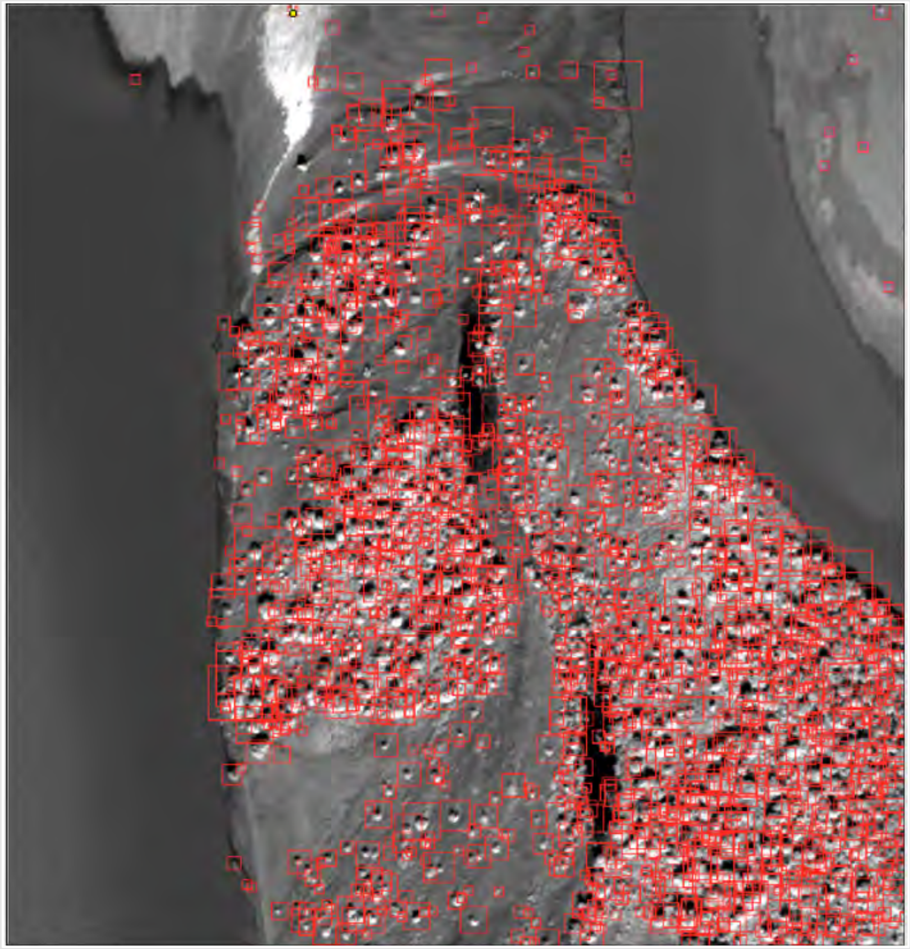
A hybrid approach: the best of both worlds?

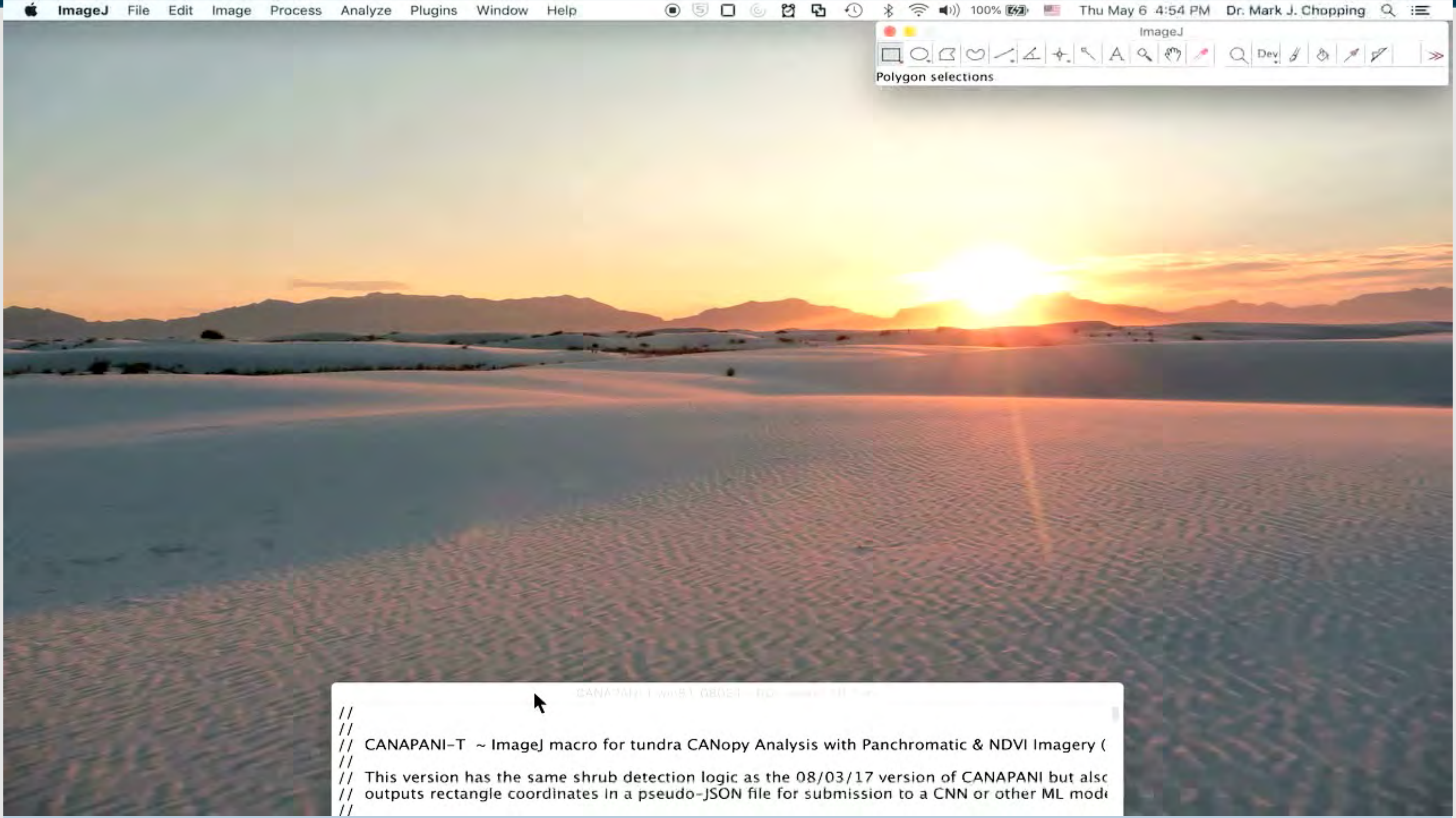
- The CANAPI approach exploits a physical signal (specular reflection) to detect tall shrubs, while ML models are empirical (they learn to recognize patterns).
- We can train the ML model using all available image information (panchromatic + multispectral), with improved training datasets obtained using CANAPANI-based shrub detection. This:
  - Provides much larger training datasets – and very quickly.
  - Allows gathering of training data for a wider range of conditions & landscape types.
  - False positives are generally a small fraction of the total but filtering can easily be implemented with post-run human intervention.

Obtaining training data

Manual digitizing *vs* CANAPANI: similar results but a large difference in the time required (see next)







 Shrub map, canopy statistics, and JSON file derived using DigitalGlobe WorldView-2 imagery.

The road ahead

1. Create larger and better training datasets using CANAPANI, with and without human filtering.
2. Train the ML model in PRISM on ADAPT and test.
3. If the results are satisfactory, apply with large number of sites across the Alaskan and Canadian Arctic tundra, for locations with tall shrubs.
4. Apply with training datasets for low shrub cover as well.
5. Repeat 3 & 4 to map changes in both tall and low shrubs.
6. Assess the relationship between shrub cover and surface albedo from MODIS and MISR at these sites.

Acknowledgements

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The CANAPANI codes are available on request from Mark Chopping (mark.chopping@montclair.edu)

The ML work is being performed mainly by Darko Radakovic (radakovicd1@montclair.edu)