Mapping retrogressive thaw slumps in Alaska North Slope from ArcticDEM and Planet CubeSat imagery using machine learning

University of Colorado Boulder

Lingcao Huang[1], Michael Willis[2], Kevin Schaefer[3], and Kristy Tiampo[2]

1. Earth Science & Observation Center, CIRES, University of Colorado Boulder.
2. Earth Science & Observation Center, CIRES & Geological Sciences, University of Colorado Boulder.
3. National Snow and Ice Data Center, CIRES, University of Colorado Boulder.

CIRES

Lingcao.Huang@colorado.edu

Abstract

Retrogressive thaw slumps (RTSs) are one of the most dynamic landforms resulting from the thawing of ice-rich permafrost. As reported by some local studies in Tibet and the Arctic, their occurrences and affected areas have increased dramatically in the past few decades. However, in most permafrost areas, their spatial distribution is still unknown due to the challenges of mapping them either from remote sensing data or in the field. Many RTSs, especially at their early developing stages, have small sizes in the area and only show up on very high-resolution (< 5 meters) imagery. Depending on the local environment, the appearance of RTSs may be very similar to the surroundings. To identify the RTSs in large areas and develop the corresponding automated pipeline, we choose Alaska North Slope (245,520 km^2) as our study area and apply machine learning algorithms including convolutional neural networks and quick shift image segmentation to a 2-m digital elevation model (i.e. ArcticDEM) and 3-m optical imagery acquired by Planet CubeSats. Our current experiments show promising results in several sub-regions, and we will scale up to the entire Alaska North Slope for compressive algorithm evaluation and mapping exercise. In this presentation, we present the technical details of our method and preliminary mapping results.

Motivation and *Objective*

- The RTS distribution and extents in permafrost regions are unknown except for a few local study areas.
- RTS distribution is essential for understanding the degradation of ice-rich permafrost and the corresponding impacts.
- High-resolution (<5 m) data enable us to detect and map many small and subtle RTSs, which may have been missed by previous studies.
- The deep-learning-based mapping method can automatically delineate small and obscure RTSs from remote sensing images (Huang et al., 2020).

- *to obtain the RTS distribution in Alaska North Slope.*

The study area

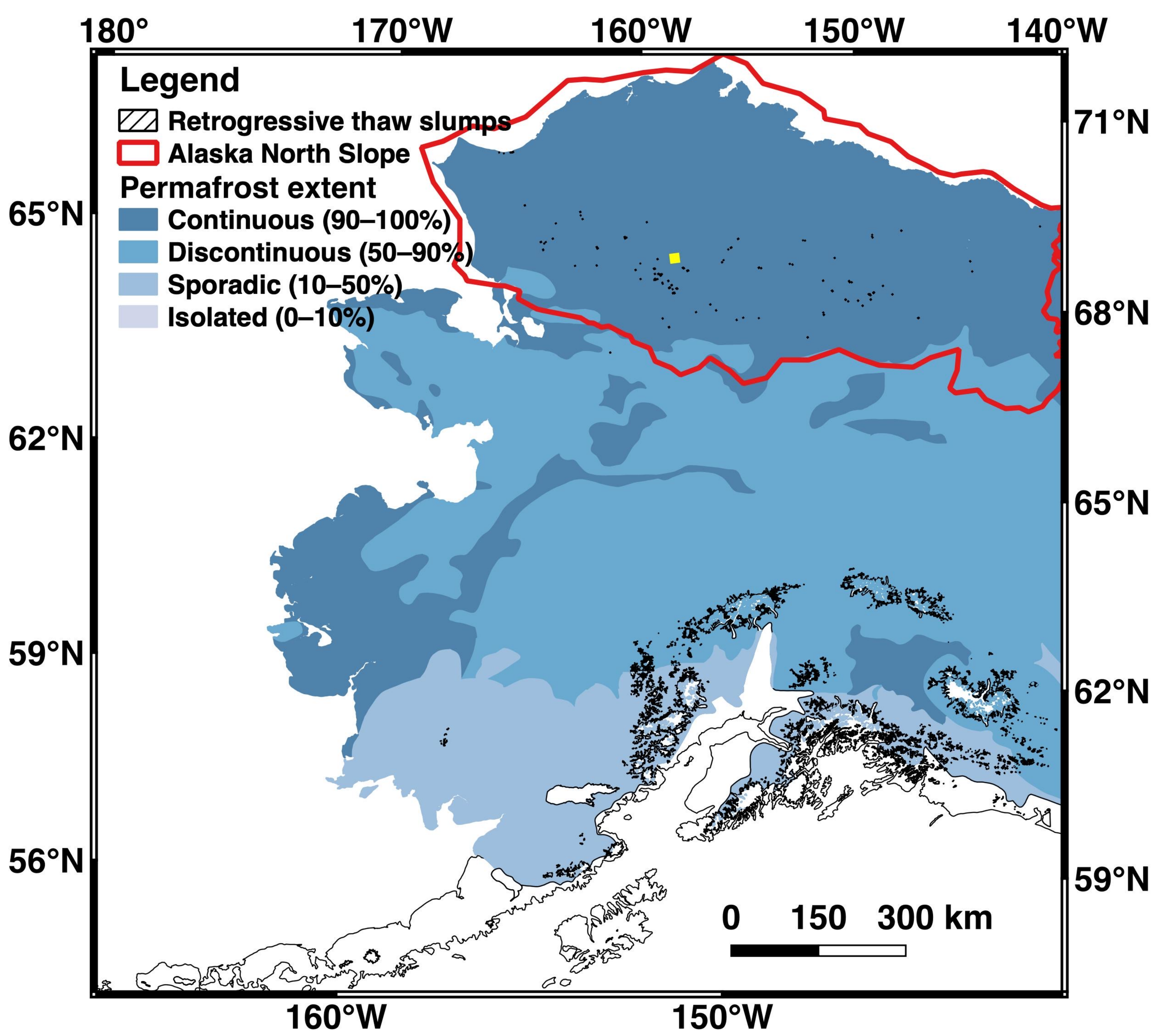

Figure 1. The red polygon outlines the extent of Alaska North Slope and most of which is underlain by continuous permafrost. Around 200 thaw slumps were identified using Landsat images as shown in the black dots (Nitze et al., 2018). The yellow point shows the location of an RTS in Figure 2.

Remote sensing images and ArcticDEM

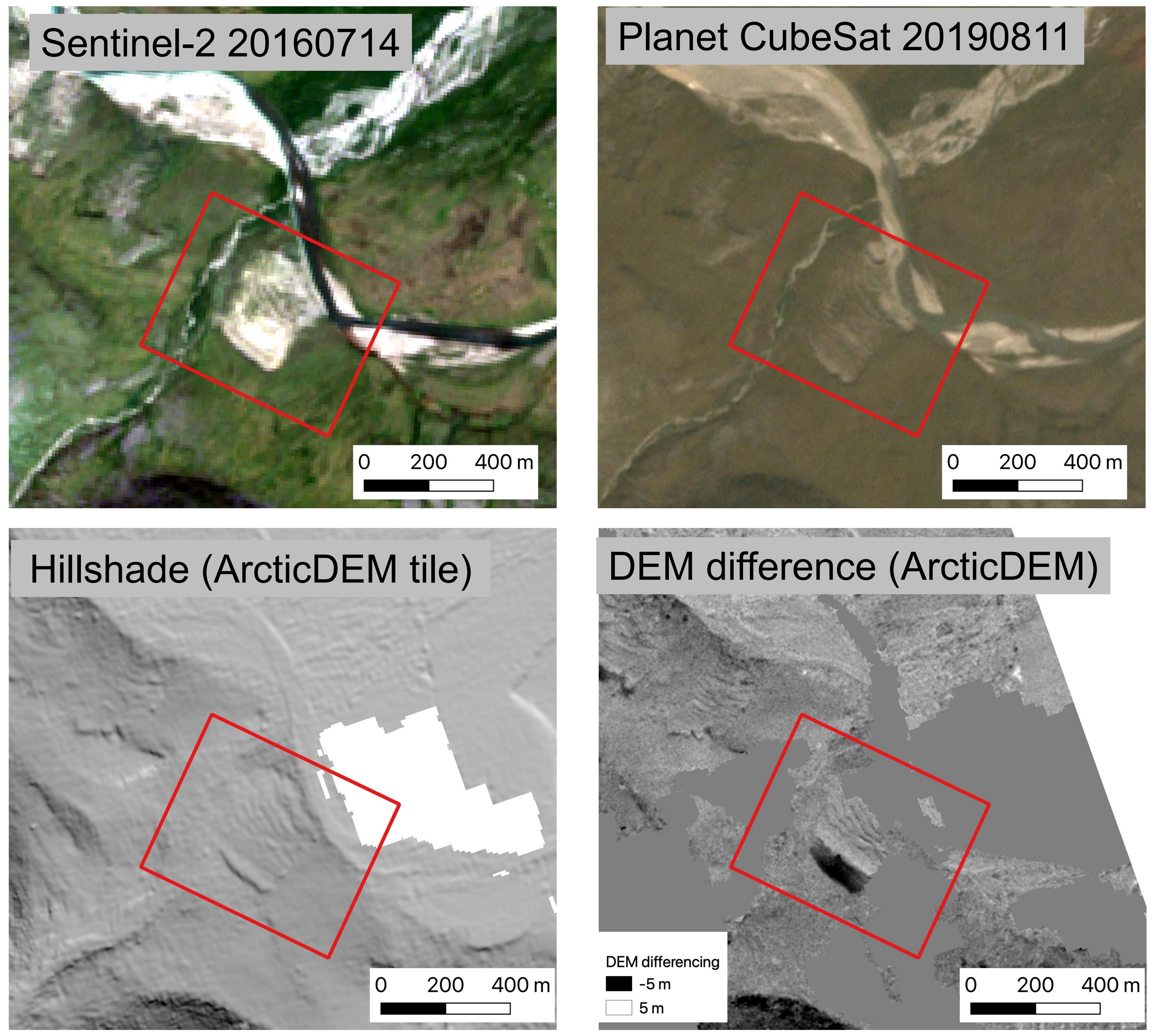

Figure 2. Images of an RTS in Alaska North slope, including RGB (red, green, and blue) bands from Sentinel-2 and Planet CubeSats, hillshade and elevation difference (oldest - newest) derived from ArcticDEM. An RTS is marked by the red box.

Methods

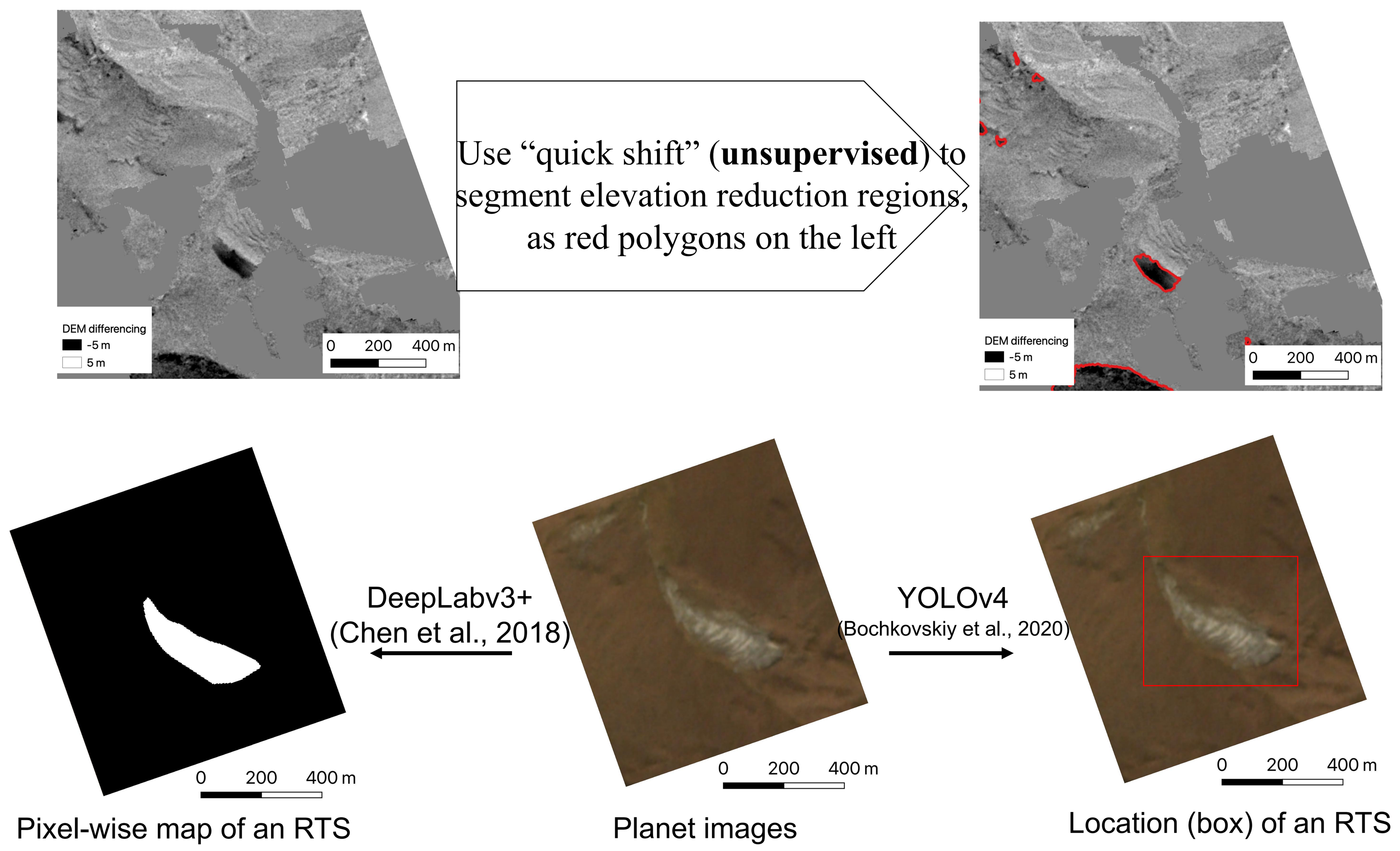

Figure 3. Input and output of different machine learning algorithms.

1. Produce elevation difference from the strip version of ArcticDEM, then use an unsupervised algorithm to segment elevation reduction areas.
2. Use a semantic segmentation algorithm (DeepLabv3+) to get the accurate RTS boundaries on images.
3. Use an object detection algorithm (YOLOv4) to identify RTS locations, which runs much faster than other similar algorithms.
4. Combine the output from different data and algorithms and produce the map of RTS occurrences based on predefined rules.

Preliminary results

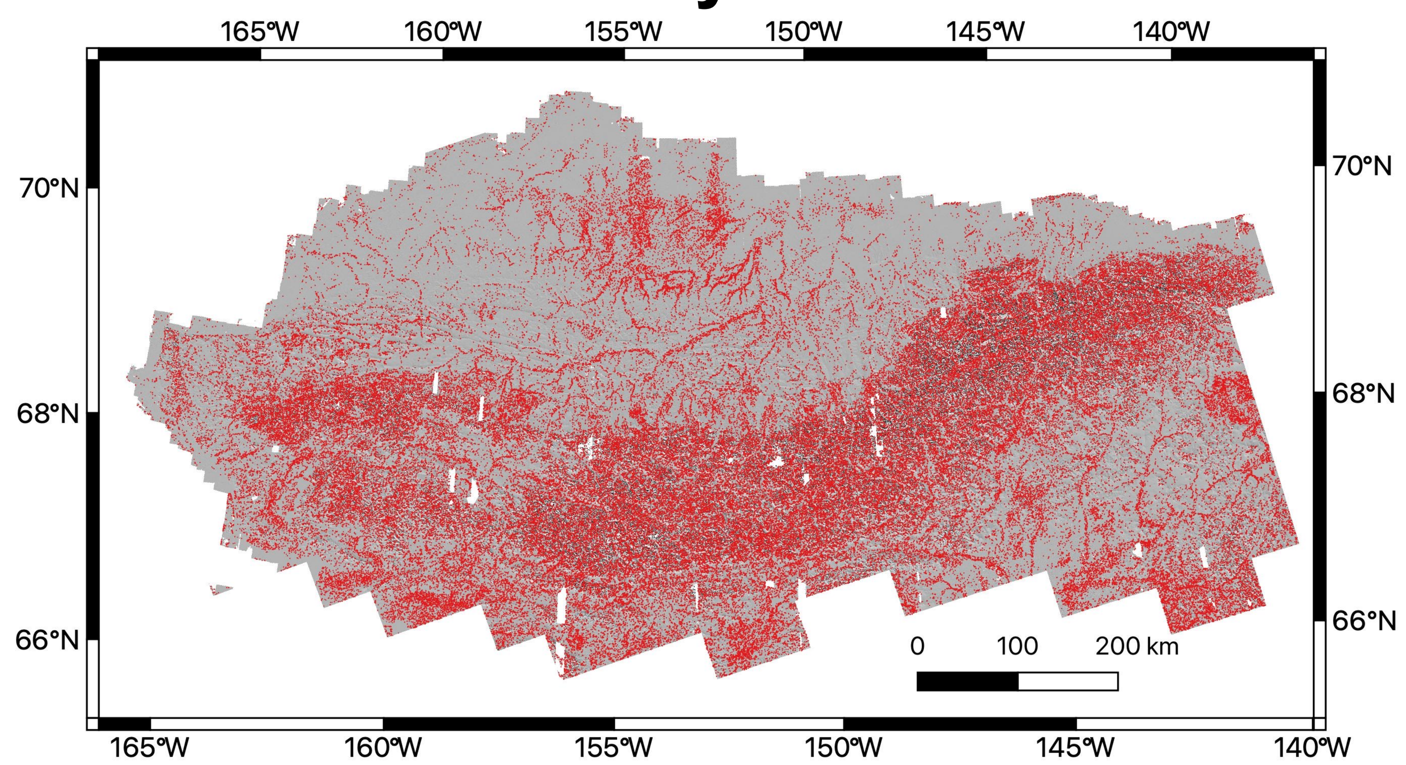

Figure 4. Overview of boxes output by applying YOLOv4 to hillshade derived from ArcticDEM.

- Too many false positives (>50,000) because we have very limited training data for hillshade.
- The prediction step of YOLOv4 took around one hour for Alaska North Slope, much faster than other algorithms.
- We are updating the results by including more data to suppress the false positives. New results will be posted at the following link:

https://docs.google.com/document/d/1e0OAv25YkgKOjXV8JV07Yv3Nxm7V6cZfOszGLKjfJI0/edit?usp=sharing

Summary

- We combine multi-sources of high-resolution data and take advantage of different machine learning algorithms, aiming to obtain the distribution of retrogressive thaw slumps in the Alaska North Slope.
- The main issue is that too many false positives are in the results.

Future work

- *Include more data such as coverage of snow cover and water bodies for removing some false positives.*
- *Combine outputs from different automated pipeline to obtain an accurate map of RTSs in Alaska North Slope.*
- *Investigate the temporal changes of these RTSs and understanding the controlling factors.*

References

- Huang, L., Luo, J., Lin, Z., Niu, F., & Liu, L. (2020). Using deep learning to map retrogressive thaw slumps in the Beiluhe region (Tibetan Plateau) from CubeSat images. Remote Sensing of Environment, 237, 111534.
- Nitze, I., Grosse, G., Jones, B. M., Romanovsky, V. E., & Boike, J. (2018). Remote sensing quantifies widespread abundance of permafrost region disturbances across the Arctic and Subarctic. Nature communications, 9(1), 1-11.
- Chen, L. C., Zhu, Y., Papandreou, G., Schroff, F., & Adam, H. (2018). Encoder-decoder with atrous separable convolution for semantic image segmentation. In Proceedings of the European conference on computer vision (ECCV) (pp. 801-818).
- Bochkovskiy, A., Wang, C. Y., & Liao, H. Y. M. (2020). Yolov4: Optimal speed and accuracy of object detection. arXiv preprint arXiv:2004.10934.

Acknowledgments

- This work utilized resources from the University of Colorado Boulder Research Computing Group, which is supported by the National Science Foundation (awards ACI-1532235 and ACI-1532236), the University of Colorado Boulder, and Colorado State University.