Mapping Retrogressive Thaw Slumps from Satellite Data Using Deep Learning

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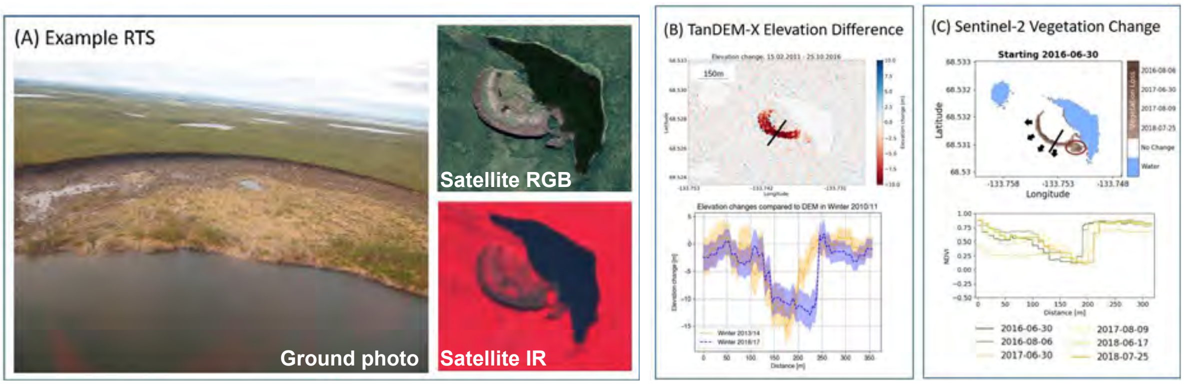

Figure 1: Example thaw slump in the Mackenzie River Delta. In (A) an image taken from a Helicopter in 2018 (left), an optical satellite image from WorldView from summer 2017 (top right), and a Sentinel-2 False-Color image from summer 2017 (bottom left) is shown. (B) shows the measured elevation changes between two TanDEM-X observations in 2011 and 2016. The image on the bottom shows a transect through the headwall. (C) shows the temporal evolution of the slump based on the vegetation change obtained by Sentinel-2 imagery covering the timespan from summer 2016 to 2018. On the bottom image the same transect as for the elevation difference is shown but with the NDVI change (a vegetation indicator) on the y-axis. The red circle shows the location of a newly formed second RTS in 2017.

Project description

Context and motivation The Arctic permafrost zone is expected to exhibit large changes caused by rising temperatures. Due to the storage of large amounts of carbon in the soil, the Arctic permafrost regions are expected to become a substantial carbon source to the atmosphere, known as the permafrost-carbon feedback. This effect is considered to be one of the tipping points in the Earth-climate system that can lead to a runaway effect of rising temperatures. Permafrost underlies approximately 15% of the landmass in the Northern Hemisphere and when ice-rich permafrost thaws it can alter the surface characteristics of a landscape which is commonly referred to as thermokarst. Among the most rapid and dramatic changes are retrogressive thaw slumps (RTS). RTS have major impacts by changing ecosystem and hydrological equilibria and furthermore impact the earth system on a global scale by reinforcing climate change with the additional mobilization of organic carbon that was previously stored in the frozen soil.

RTSs occur in ice-rich permafrost regions and are characterized by a steep headwall and a scar zone where the thawed material from the headwall is transported downslope into streams and rivers (Fig. 1A). RTSs evolve by the retreat of the headwall with rates of up to several tens of meters per year. To detect and map RTS using satellite systems, two approaches are currently possible, a direct approach using the induced volumetric changes by differencing digital elevation models (DEMs) generated at different times (DEM differencing, Fig. 1B) and an indirect tracing by classifying RTS characteristics in optical and infrared satellite images, where RTS can be related to land surface characteristics induced by the retreating headwall and the sediment transport downslope (Fig. 1C).

Gaps and challenges Recent computer vision systems relying on deep learning, specifically convolutional neural networks, have shown huge advances in extracting information from geospatial images at large. Specifically, tasks such as object detection or semantic and instance segmentation can be achieved with high accuracy and unprecedented generalization accuracy. However, the sheer size of the available data (think about imaging the whole planet at 10m spatial resolution, with few days of revisit time) make most of these applications hard to operationalize. In general, object detection and identification in unrestricted geospatial data is a complex task, where the huge amount of data and the very large visual ambiguity result in infeasible computing time and large amounts of false positives. In this MSc project, we aim at tackling some of these open research gaps with a clear and well-defined application in mind. Ideally such systems can be reused and generalized to other tasks but these aspects will not be part of the project. The final goal is to develop a retrieval scheme for outlining areas that experience elevation loss due to RTS activity.

Research scope and methods We aim at developing a machine learning system that is trained on both DEMs and optical images. The project will explore the two data sources as either inputs for a supervised object detection / instance segmentation model based on convolutional neural networks; or if the different data sources will be processed independently. Earth observation data is usually very large, and evaluating the model at all possible spatial locations at a different range of spatial scales (e.g. from few dozens to hundreds of meters) is infeasible and often just impractical.

A possible strategy to develop such a generic object detection system able to provide inference over large areas could be to use elevation differences as a prior distribution over spatial locations at which the classification method will be applied, as DEMs differences can be calculated efficiently. Alternatively, methods based on self-supervised learning over pairs of temporal images, where patches not containing RTS are used to learn bi-temporal representations and can be used to pretrain instance segmentation models. Again, DEMs differencing can be used as a spatial prior to sample locations for evaluation.

Data In this project the goal is to detect RTSs by identifying changes in elevation and visual appearance of land cover over time. To this end, DEMs generated from the TanDEM-X satellites are provided for selected Arctic permafrost regions. The spatial resolution of the generated DEMs is about 10 meters and vertical accuracies are about 2 to 3 meters depending on specific observations properties. The temporal resolution is variable and depends on the specific regions; On the pan-Arctic scale observations in the years 2011/12, 2016/17 as well as 2020/21 are available. Additional optical/infrared data is available from the Sentinel-2 satellite and will be used as additional data sources. For several regions across the Arctic permafrost zone polygons (see Fig. 2) outlining significant elevation changes due to RTSs activity are available and will be used for training models and assessing generalization capabilities of different machine learning models.

An example pair of Sentinel-2 optical/infrared images can be browsed in at these two links. Images are shown in False Color (Vegetation is shown as red color) on the Taymyr Peninsula where a heatwave initiated many RTSs. Examples can be seen here in the Sentinel-Hub browser: Summer 2019 and Summer 2022

Example Data (see Readme) can be obtained here: POLYBOX link.

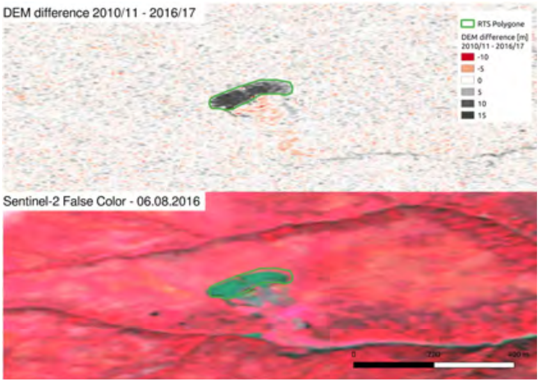

Figure 2: Example of RTS polygones in the Peel study region located at N67.26 W-135.27. Top: DEM difference image between winter 2010/11 and 2016/17. Bottom: False color Sentinel-2 image taken on 06.08.2016.

Additional information

We expect the student to conduct rigorous research and come up with original solutions to a difficult problem, and to identify relevant baselines to which compare developed models. A successful project characterized by original models and good results, if the supervising team agrees, will be considered for submission in specialized domain science scientific journals.

The supervising team is composed of applied ML scientists from the Swiss Data Science Center (Dr. Michele Volpi, Prof. Fernando Perez-Cruz) and scientists from the Chair of Earth Observation and Remote Sensing (Dr. Philipp Bernhard, Kathrin Maier, Prof. Irena Hajnsek). The team covers all the aspects of this challenging project.

- **Difficulty of the project**: Challenging, but the supervising team is top!
- **You will learn and get your hands dirty** with different deep learning flavors and computer vision tools. You will learn good scientific research practices, literature research, PyTorch.
- **Requirements**: Machine Learning fundamentals, computer vision fundamentals, good Python skills, experience with git, motivation
- **Evaluated and expected deliverables**: Thesis manuscript detailing the research, motivation, approach and original solution; according to d-INFK guidelines. Versioned and commented code, runnable, able to reproduce all the analysis (hosted on SDSC platform renkulab.io).
- **Media**: Project framework on ETHZ news, 2022
- **Some starting points**: SOLOv2, Mask R-CNN,
- **Main supervisors and persons of contact**: Dr. Michele Volpi (michele.volpi@sdsc.ethz.ch), Dr. Philipp Bernhard (bernhard@ethz.ch)

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