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Toward the use of deep learning and high-resolution digital elevation models for extracting geological landforms: an example for eskers.

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Summary

Canada Centre for Mapping and Earth Observation (CCMEO) has a long track record in the offer of topographic information of Canada's territory. In 2015, CCMEO's team launched the National Elevation Data Strategy, which aims to provide an accurate and up-to-date 3D representation of the territory. As of winter 2019, elevation datasets covering more than 3.2 million km² of the Canadian landmass have been made available freely for Canadians under the product name *High-Resolution Digital Elevation Models* (HRDEM). This huge amount of new data represents a mine of cartographic and geological information. In order to automate extraction information from that data, CCMEO's team leveraged the recent developments in deep learning, more specifically Convolutional Neural Networks. A first application using deep learning and high-resolution optical satellite imagery has shown promising results for automatic feature extraction of roads, buildings and waterbodies (Proulx-Bourque and Turgeon-Pelchat, 2018). A similar methodology applied to multiple resolution elevation data was also shown to be promising (Turgeon-Pelchat et al., 2019). In a more geoscience perspective, CCMEO recently began evaluating the synergy of both fully convolutional networks and the HRDEM product for extracting eskers in Northern Canada. It is well-known that machine learning technologies offer immense opportunities in geoscience (Karpatne et al., 2017). The study area for this project consists of 42 500 km² of elevation data spread across Northern Canada. Training and validation data were created in order to train multiple models. Once trained, models were tested on other areas and the performance of the models were compared to ground truth in order to fully analyze the potential and to bring out ideas for future works. Results of this experiment will be available in the course of winter 2019 and will be presented at GeoConvention 2019.

Theory / Method / Workflow

Introduction

For decades, the Canada Centre for Mapping and Earth Observation (CCMEO), Natural Resources Canada (NRCan), has been offering authoritative geospatial data of the country. One of the most popular datasets is the elevation data, which consists in a 3D representation of the territory. In the recent years, users have shown more and more interest for accurate, detailed and up-to-date elevation data. As part of the National Elevation Data Strategy that was deployed in 2015, CCMEO aims to respond to this need by offering a new generation of Digital Elevation Models (DEM). Up to now, ~3.2 million km² of highly accurate data was made freely available for Canadians through a product named *High-Resolution Digital Elevation Model* (HRDEM). The area covered by HRDEM keeps growing: by summer 2019, 1.1 million km² of data will be added, including a complete coverage of the Canadian Arctic. In the South, HRDEM is derived from highly accurate LiDAR data, whereas in the North, CCMEO is leveraging the data from the ArcticDEM initiative (Porter et al., 2018) and provides a corrected version of it in the HRDEM product. This new dataset represents a rich source of information for a variety of domains such as geology, floodplain mitigation, climate change monitoring, forestry and mining.

From a cartographic perspective, this new dataset is detailed enough to extract multiple topographic elements, such as buildings and hydrography, as well as geological structures. The challenge of this task lies in the sheer volume and processing of this data. As an innovation-driven organization, CCMEO has always been seeking for leading-edge technologies in order to provide state-of-the-art geospatial data for Canadians. This has led CCMEO's team to develop a new expertise in deep learning, more precisely Convolutional Neural Networks (CNNs), for automatic extraction of topographic features (Proulx-Bourque and Turgeon-Pelchat, 2018; Turgeon-Pelchat et al., 2019). The current work is more geoscience-related and explores the use of CNNs to automatically extract eskers from the HRDEM product. Eskers are glaciofluvial sediments that are important for northern road transportation network and remote predictive mapping. The intent of the experiment is to train, validate and test a fully convolutional network for semantic segmentation of eskers, using HRDEM.

Method and Workflow

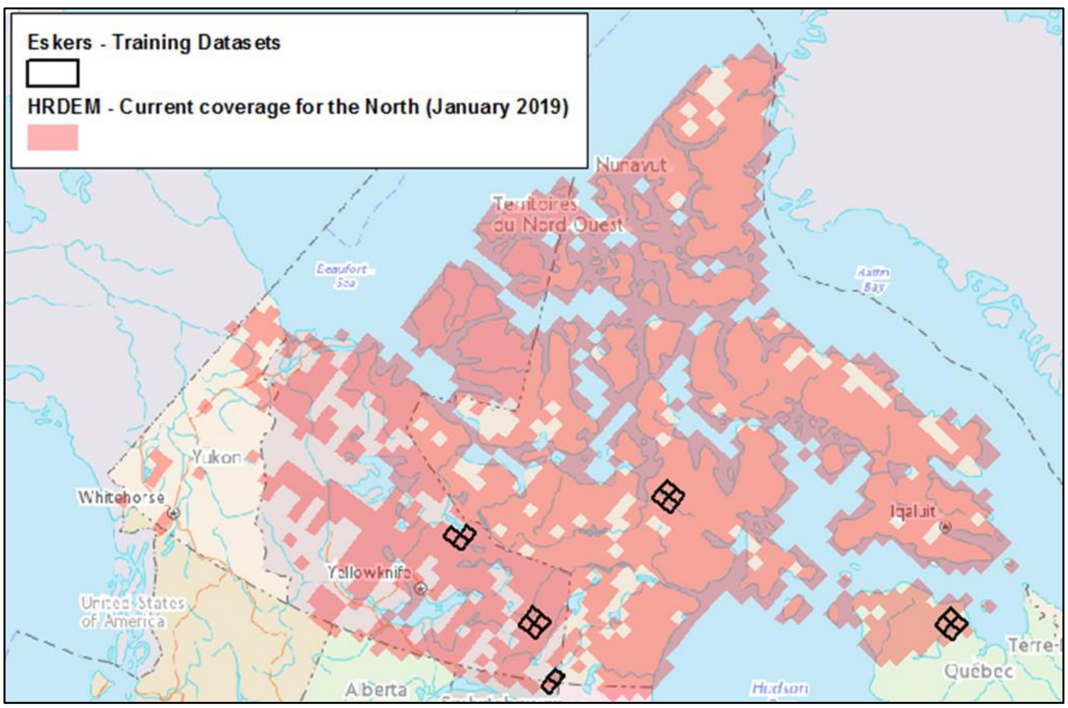

Figure 1. Study sites and HRDEM coverage

The study areas are spread across Northern Canada and are comprised of 17 50 km x 50 km HRDEM tiles, for a total coverage of 42 500 km^2. Figure 1 shows the study areas and HRDEM coverage. A group of GIS technicians manually digitized in vector format the reference esker polygons by visually interpreting the HRDEM tiles (Figure 2).

Figure 2.Representation of an esker on HRDEM (upper image) and the digitization of it (lower image)

The method includes DEM and reference data preparation, then training and validating multiple models and finally, evaluating the trained models. HRDEM tiles and reference data were split to obtain 70% (~30 000 km^2) of the data for training and validation and 30% (~12 500 km^2) for testing. Training and validation data were randomly selected and do not intersect with the test data.

Training and validation data were split into smaller patches of 256 x 256 pixels. Patches not containing any esker pixel were not used during the process. Furthermore, an overlap of 75% was kept between patches. This overlap requirement increases the number of patches created, therefore increasing model robustness. Training was performed using the geo-deep-learning system (Turgeon-Pelchat *et al.*, 2018). This open-source deep learning application uses Python programming language and is based on open source libraries including PyTorch, numpy, gdal, scikit-image, scikit-learn and h5py. For the purpose of this experiment, a UNET architecture (Ronneberger *et al.,* 2015) was used. This architecture was originally designed for semantic segmentation of medical imagery and has since been largely used with high-resolution EO imagery and DEMs. Multiple UNET models are trained, in order to find the best set of hyperparameters. Model performances are evaluated during training, validation and on the test data, using precision, recall and fscore. Qualitative assessment of the results on the test data is conducted by visual inspection.

Results, Observations, Conclusions

Results of this experiment will be known in the course of winter 2019 and will be presented at GeoConvention 2019. Using HRDEM as the only data source for esker extraction has not been done yet. We expect that the high quality of the manually digitized reference data and the spatial resolution of HRDEM will definitely help the model to characterize eskers. Given that HRDEM is available at multiple spatial resolutions, future work will compare the impact of spatial resolution on esker extraction accuracy and time required for training. Given good results on the test data, we will produce and assess the application of the trained model to larger areas of interest. Trained models and esker data could be shared with the community, on demand, for reproducibility purposes.

Novel/Additive Information

With the arrival of a vast number of new elevation datasets, machine learning technologies are essential in order to better identify the potential for deriving surficial geology information from elevation data. This current work is different from Latifovic et al. (2018) in the sense that it focuses specifically on eskers and only high-resolution DEMs (2-5 m) are used as inputs. Should the results be up to expectations, the methodology will be applied to other geological landforms. We believe that the use of deep learning along with HRDEM has the potential to improve remote predictive mapping techniques.

Acknowledgements

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