

Automated Recognition of Human-Built Infrastructure in the Arctic Permafrost Landscapes using Commercial Satellite Imagery

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Abstract

Very high spatial resolution (VHSR) commercial satellite imagery affords permafrost scientists the ability to monitor the pan-Arctic system at a fine-scale, enabling detailed monitoring of both the natural and human environments. Geo-AI mapping applications based on the deep learning (DL) convolutional neural network (CNN) have been successful in translating this big imagery resource into Arctic science-ready products. However, many models are computationally intensive due to the constraints of the large geographical extent and complexity of VHSR imagery. In addition, feature recognition is challenged by scarcity of manually-annotated training data and image complexity at fine scales. In this exploratory study, we investigated the ability of a lightweight U-Net DLCNN to efficiently perform semantic segmentation of VHSR commercial satellite imagery with limited training data in automated recognition of human-built infrastructure, including residential, industrial, public, commercial buildings, and roads, in the permafrost affected regions of the Arctic. We conducted a systematic experiment to understand how image augmentation improves the performance of DL-based semantic segmentation of VHSR imagery. Different standard augmentations, including flipping, rotation, and transposition, were applied to input imagery in order to test their impacts on infrastructure recognition and determine the optimal set of augmentations. With a relatively low number of model parameters, limited labelled training data, short training time, and high segmentation accuracy, our findings suggest that overall, the U-Net DLCNN, coupled with image augmentation, could serve as an accurate and efficient method for mapping infrastructure in the Arctic permafrost environment without compromising spatial details and geographical extent.

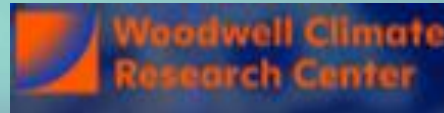
AUTOMATED RECOGNITION OF HUMAN-BUILT INFRASTRUCTURE IN THE ARCTIC PERMAFROST LANDSCAPES USING COMMERCIAL SATELLITE IMAGERY

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RESEARCH MOTIVATION

- Lack of consistent and complete Arctic infrastructure geospatial datasets.
- Satellite image-based recognition of Arctic infrastructure is difficult due to size of features; VHSR satellite imagery is needed.
 - Most publicly-available datasets are based on low to medium resolution imagery, missing many structures and lacking detailed classification.
- Methodological gaps exist in dealing with VHSR imagery and scalability of mapping. Deep learning-based regional scale approaches are hampered by the need for large amounts of training data.

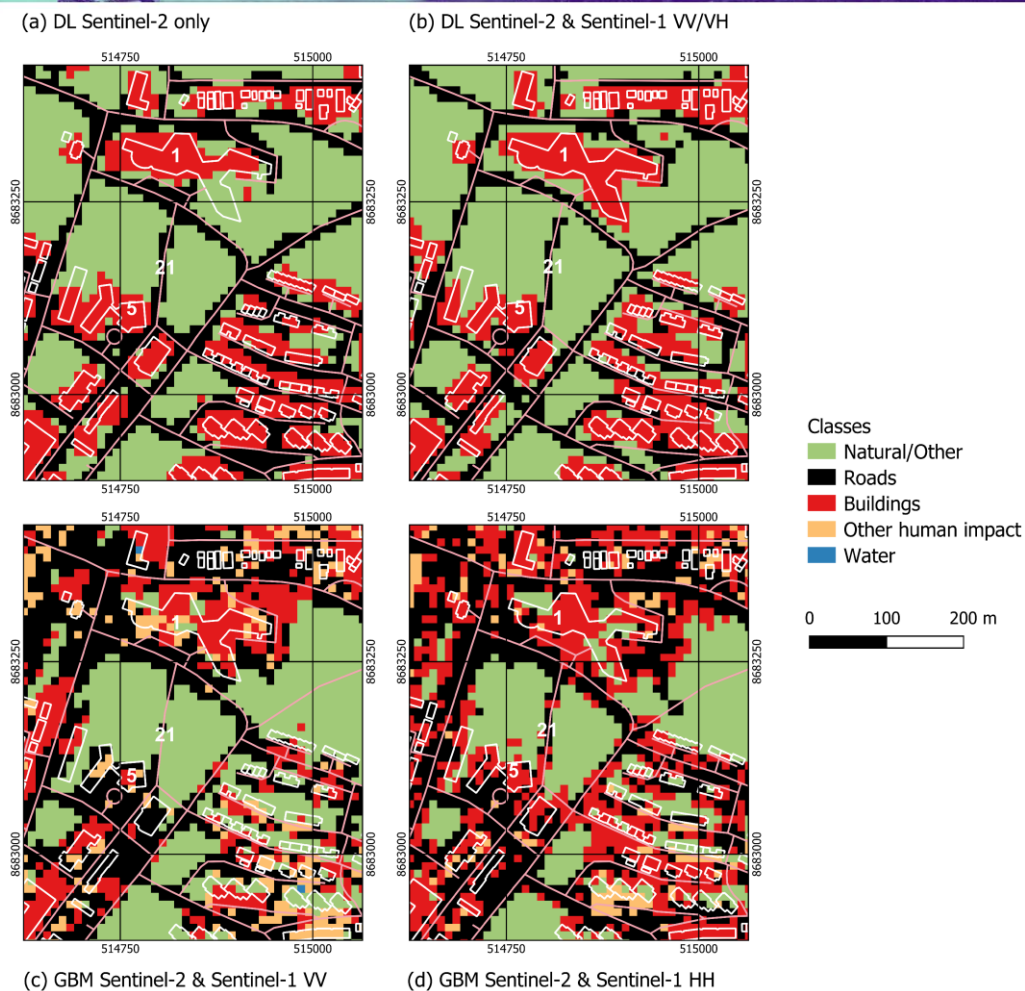


Figure 1: Infrastructure classification results from Bartsch et al., 2020.



STUDY OVERVIEW

- Train a U-Net deep learning convolutional neural network (DLCNN) to automatically recognize roads, residential/commercial, public, industrial buildings using multiple WorldView-2/QuickBird-2 images of Barrow and Prudhoe Bay, Alaska.
- Test the model on images of unseen sites from those settlements.

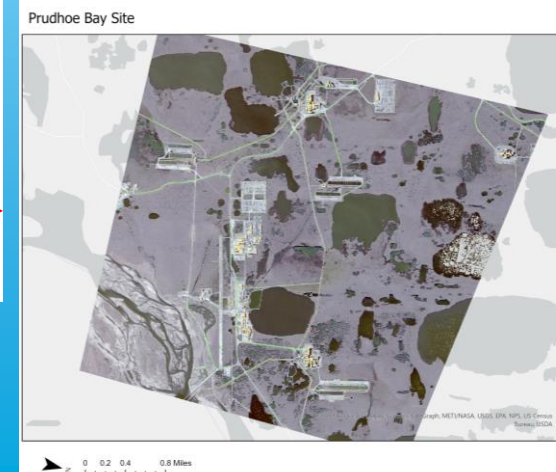
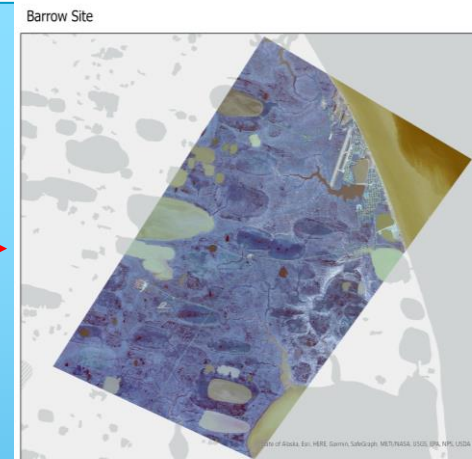
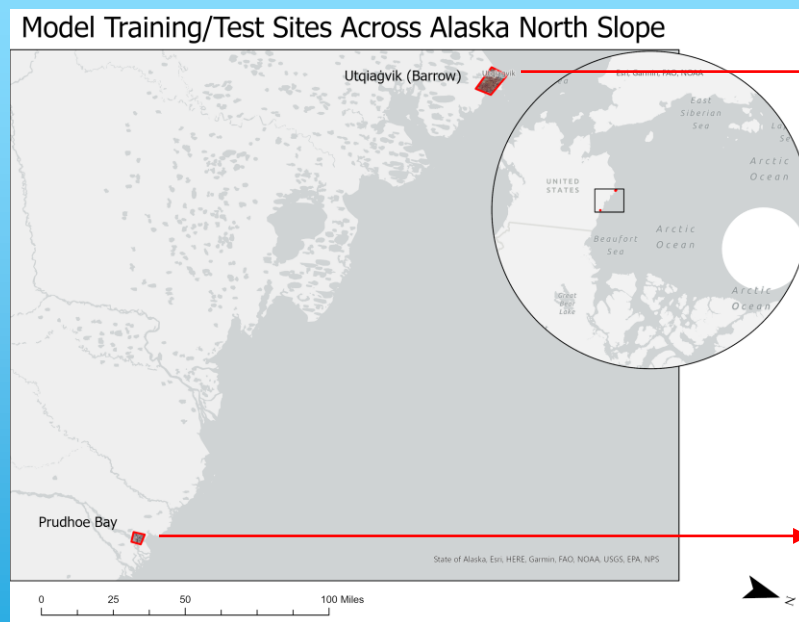


Figure 2: Map of Alaskan North Slope settlements of which VHSR satellite imagery were used to train and test a U-Net DLCNN.
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OBJECTIVES

- Overall goal: Development of a U-Net DLCNN to automate recognition of infrastructure (roads, residential/commercial, public, industrial) with limited training data.
- Experiment: Understand how image augmentation improves the performances of DL-based semantic segmentation of VHSR imagery.
 - Determine the optimal image augmentation method(s) for infrastructure recognition.



METHODOLOGY OVERVIEW

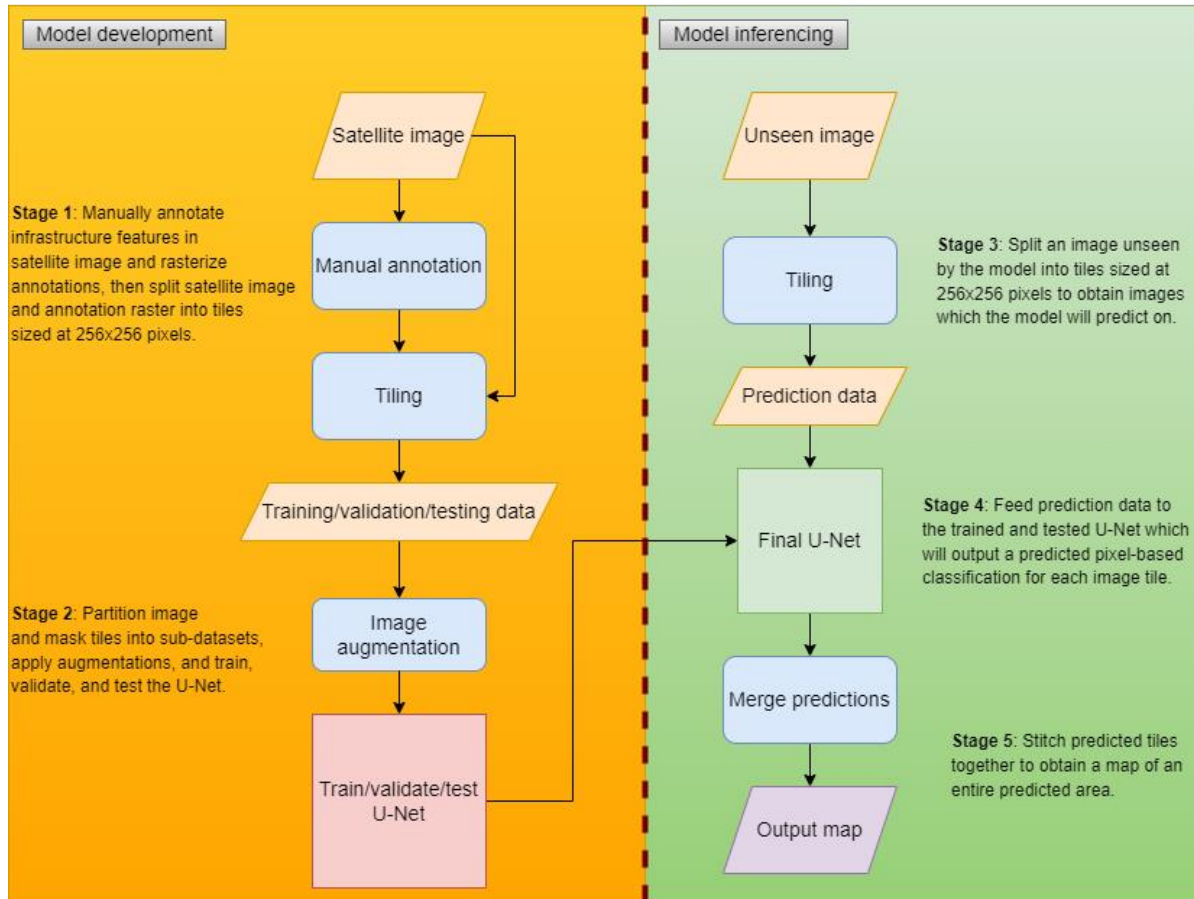


Figure 3: Diagram of U-Net DLCNN-based recognition workflow, including both model development and application of model in inference mode.

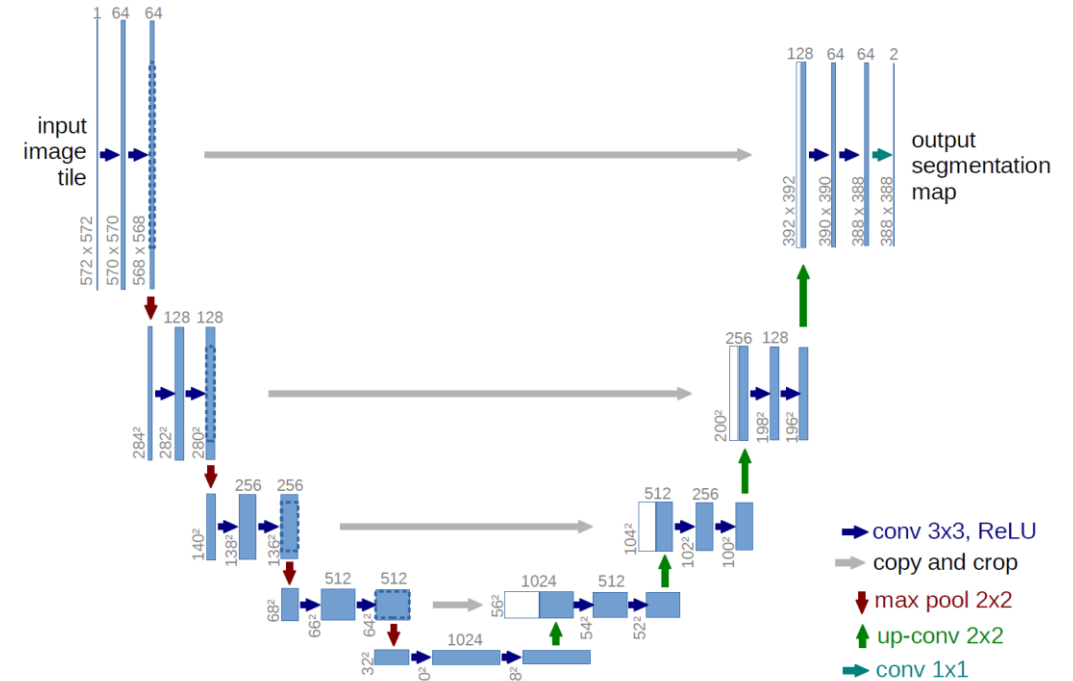


Figure 4: Diagram of U-Net architecture (Ronneberger et al., 2015).

- U-Net is a convolutional neural network that can learn to automatically classify each pixel in an image and output a classified mask.



KEY RESULTS

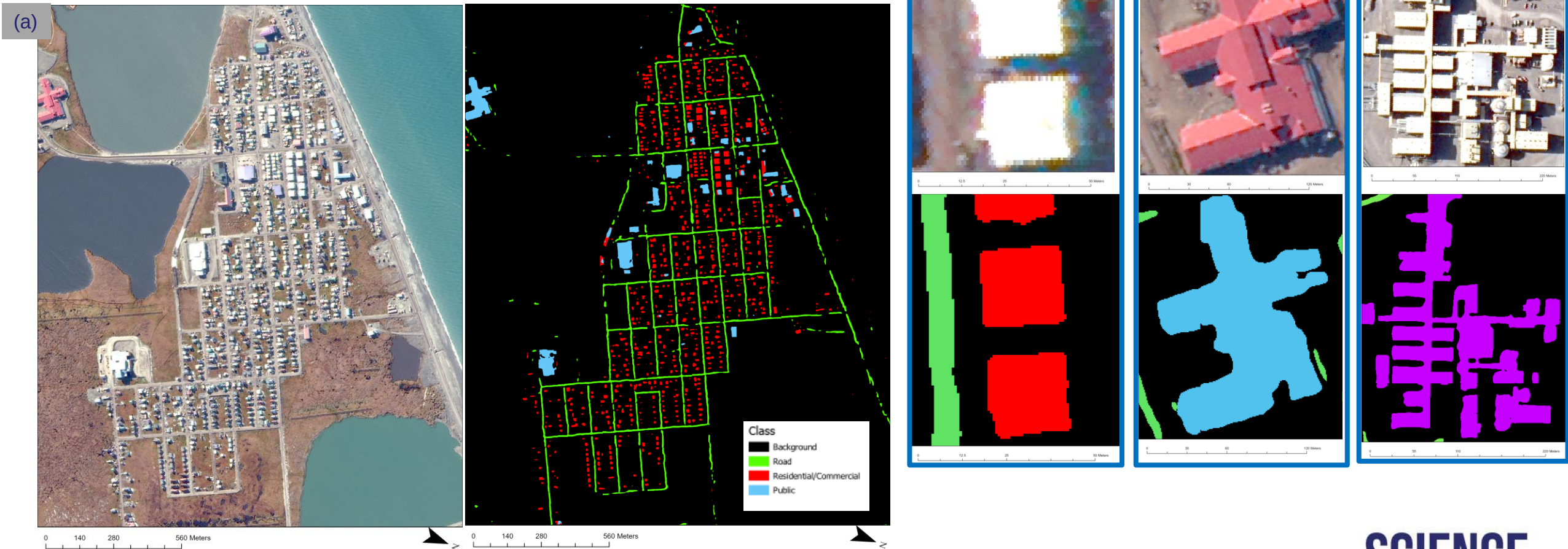


Figure 5: Automated infrastructure recognition results **(a)** predicted infrastructure for area of Barrow, Alaska **(b-d)** zoomed-in views of automated infrastructure recognition **(b)** residential buildings (red) and a road (green) in Barrow. **(c)** a large public building (blue) in Barrow. **(d)** a large industrial building (purple) in Prudhoe Bay. Imagery © 2009, 2014 DigitalGlobe, Inc.



INVESTIGATING IMAGE AUGMENTATION

- DLCNNs require a lot of training data to perform well. Arctic settlements are usually small, therefore manually annotated training data is scarce.
- Image augmentation allows us to synthetically expand the size of DLCNN training datasets by creating new copies of existing images through some transformation.

Augmentation method	F1-score					Average F1-score	Accuracy
	Background	Road	Residential/Commercial	Public	Industrial		
All	0.94	0.69	0.72	0.90	0.87	0.82	0.91
Transposition	0.94	0.69	0.72	0.93	0.85	0.83	0.90
Random 90-degree rotation	0.93	0.00	0.76	0.91	0.87	0.69	0.89
None	0.94	0.71	0.71	0.00	0.82	0.64	0.88
Horizontal flip	0.93	0.72	0.67	0.00	0.80	0.63	0.87
Vertical flip	0.93	0.70	0.60	0.00	0.85	0.62	0.88

Figure 6: Table of per-class segmentation metrics measuring U-Net performance when different augmentation methods were used in infrastructure recognition.

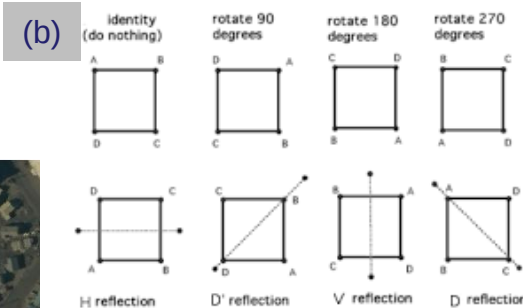
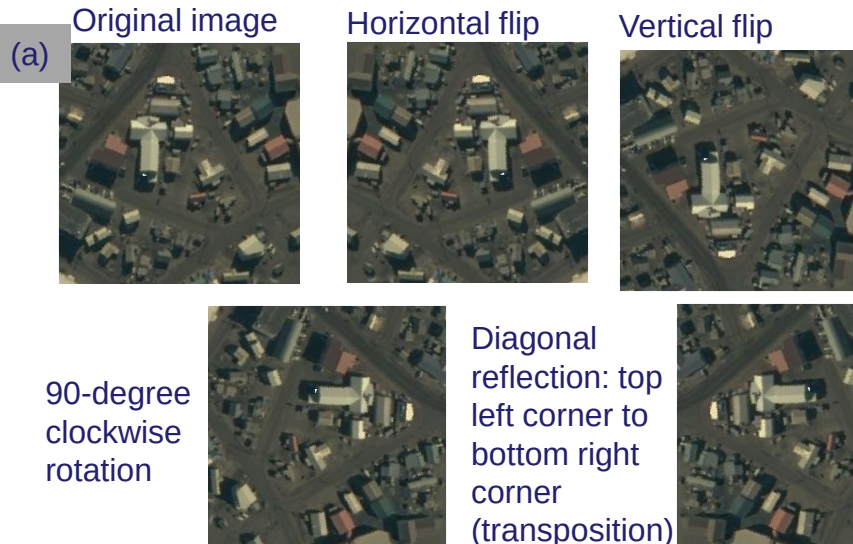


Figure 7: (a) Visual examples of augmentation methods applied in experiment using an image from the training dataset. (b) A diagram displaying the transformations and possible combinations.

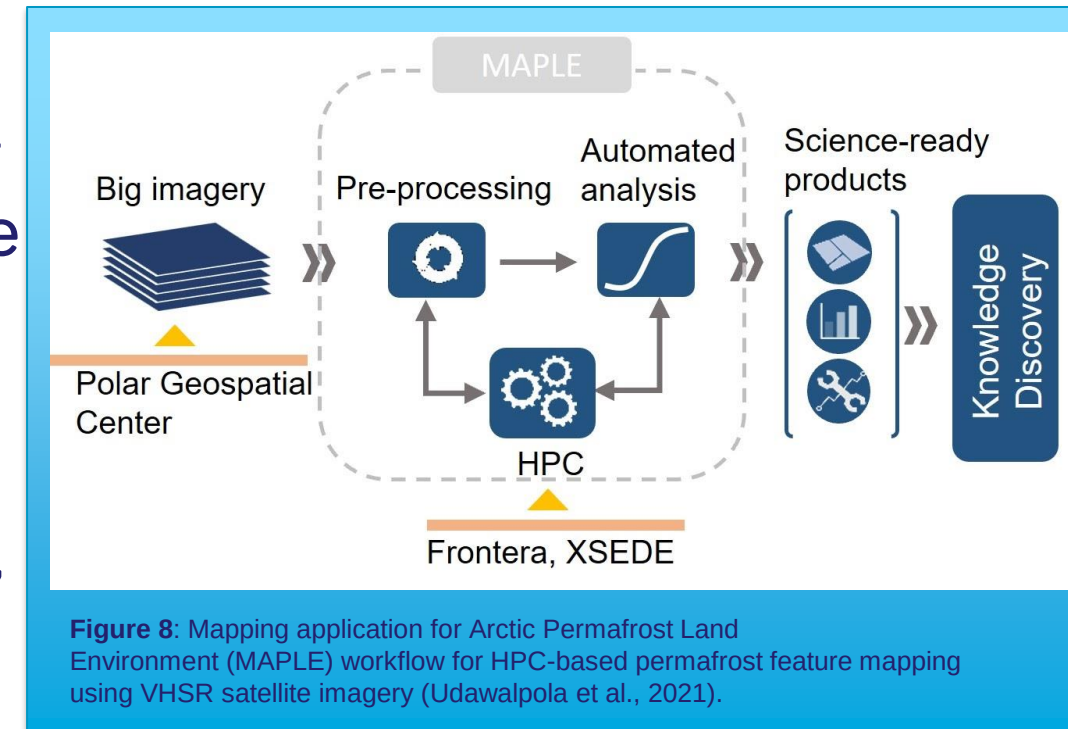
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- Applied basic geometric augmentations on training images/masks: horizontal flip, vertical flip, random 90-degree rotation, and transposition.
- All four augmentations applied together yield best performance for infrastructure recognition



SIGNIFICANCE

- This exploratory study provides the first insights into deep learning-based mapping of Arctic infrastructure from VHSR satellite imagery.
 - Individual structures can be classified and mapped accurately at a fine-scale, even with limited labelled training data, through image augmentation.
- Sets the stage for next step: training deep learning models on HPC frameworks for regional-scale continuous infrastructure mapping.





SCOPES OF IMPROVEMENT

- More manually-annotated training data should be created for infrastructure recognition, including data from other settlements, in order to improve U-Net performance overall and increase site transferability/scalability of approach.
- Utility pipelines and gravel pads should be included as infrastructure classes, especially in industrial areas like Prudhoe Bay.



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THANK YOU

Feel free to contact me at elias.manos@uconn.edu or check out the code for this project at <https://github.com/eliasm56>.

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