

**Python Automation Tool of a Remote Sensing Analysis of Satellite Imagery of  
Identification and Classification techniques for Alpine Permafrost**

by

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## **Abstract**

Climate change has accelerated at an unprecedented rate resulting in wide ranging changes to environmental systems. One of the most important of these systems is that of the cryosphere which has begun to be significantly altered and diminished due to climate change, and one the key elements within the cryosphere is extremely vulnerable but undervalued, permafrost (Westermann et al., 2015). Permafrost is ground that has stayed at 0°C for a minimum of 2 consecutive years and covers over 22.29 million square-kilometers of the northern hemisphere or about 24% of land cover (SOTC: Permafrost and Frozen Ground, 2020). The thawing and freezing of permafrost and frozen soil plays a crucial role in the hydrological, lower atmosphere, and ecosystem functions, but is also crucial to many northern communities' infrastructure, health, and lively hood. This project seeks to provide a python coded permafrost classification tool for the ESRI ArcGIS Pro software. This process involves the use of proxy data including digital elevation model (DEM), normalized difference vegetation index (NDVI), and land surface temperature (LST) to classify permafrost from only satellite derived imagery. The hopes is that the work done in this project lays the groundwork for future development of satellite derived permafrost distribution tools.

## **1. Introduction**

### **1.1 Objective:**

The objective of this project is to develop a python coded automated GIS tool for identifying and classifying alpine permafrost from satellite imagery for the ESRI ArcPro software.

### **1.2 Background:**

Climate change has accelerated at an unprecedented rate resulting in wide ranging changes to environmental systems. One of the most important of these systems is that of the cryosphere which has begun to be significantly altered and diminished due to climate change, and one the key elements within the cryosphere is extremely vulnerable but undervalued, permafrost (Westermann et al., 2015). Permafrost is ground that has stayed at 0°C for a minimum of 2 consecutive years and covers over 22.29 million square-kilometers of the northern hemisphere or about 24% of land cover (SOTC: Permafrost and Frozen Ground, 2020). The thawing and freezing of permafrost and frozen soil plays a crucial role in the hydrological, lower atmosphere, and ecosystem functions, but is also crucial to many northern communities' infrastructure, health, and lively hood. (Zheng et al., 2020 and Hjort et al.2018) Also, due to the amount of organic material found within permafrost as it thaws large amount of CO<sub>2</sub>, N<sub>2</sub>O, and methane are released in the atmosphere further exacerbating the climate change process with estimates of a change in temperature of 1.5 to 5.8°C by 2100. (SOTC: Permafrost and Frozen Ground, 2020, Wu et al.,2019) However, in situ locating and observing permafrost and frozen soil is extremely difficult to achieve due to the environmental conditions and locations such as the Alpine permafrost of the Swiss alps.

The Alps, one of the most picturesque range of mountains in the world with an estimated 60 to 80 million people visiting them each year as tourist, however the natural beauty of the Alps is at risk.(Climate Change Post) It is estimated that over 15% of the Alpine area is covered in permafrost, and plays a crucial role to the areas maintaining soil integrity and local hydrology that surrounding ecosystems and communities rely (Climate Change Post

and Shi, Nin, Yang, Che, Lin, and Luo 2018). A temperature increase of 0.5 to 0.8°C can lead to permafrost thaws that may result in rock wall instability and can potentially trigger landslides or jeopardize local infrastructure. (Rode et al., 2020) Due to the continual increase temperatures during the winter months the Alps permafrost is not freezing as thoroughly before. (Schneider et al., 2011) Warmer winter compounded with the decreases in snow cover the Alpine permafrost lower limit is expected to increase by potentially hundreds of meters from 2400 meters at present (Schneider et al., 2011 and Wilfriend et al., 1998).

Therefore, the development of remote sensing techniques for the identification and monitoring of permafrost is crucial. Due to permafrost being a subsurface layer of soil/rock satellite derived remote sensed imageries cannot be directly used with tradition classification methods/tools and must resort to the use of proxy signs for permafrost identification. (Shi et al., 2018) “*Permafrost Presence/Absence Mapping of Qinghai-Tibet Plateau Based on Multi-Source Remote Sensing Data*” by Shi et al., outlines a way to use multiple proxy data sources for permafrost identification by using ranges of elevation, land surface temperature (LST) , normalized difference vegetation index (NDVI). Though permafrost is relatively resilient to atmospheric increase in temperature in regard to thawing, the usage of simple to acquire proxy data may be the key to keeping a relatively quick means to track an monitor permafrost distribution (Zou et al.,2016).

This project will use a simplified application of proxy data to develop a python coded automated GIS tool for identifying and classifying alpine permafrost from remote sensed data for the ESRI ArcPro software. By doing so, will make performing monitoring analysis and classifying of permafrost from satellite imagery easier and faster and introduce a permafrost classification tool to the ESRI ArcPro software that currently has no built in means for classifying permafrost such as the NDVI tool. The hope is, as well, to lay the groundwork necessary to develop a more robust permafrost classification tool in the future that can be expanded beyond the European Alps

## **2. Methods and Materials**

### **2.1 Data:**

The initial data used for the development of this project’s python automated ArcGIS pro tool for the identifying and classifying alpine permafrost includes: an EU-DEM raster image and Landsat 8 imagery identified in Table 1 below. The Landsat 8 data used is level 1 data with a 30m spatial resolution containing all nine spectral bands and two thermal bands, and a 16-day temporal resolution sourced from the United State Geological Survey’s earth explorer website. The level 1 Landsat data was chosen because of the need for the two thermal bands used in the production of a land surface temperature (LST) dataset. The dates chosen for the Landsat 8 imagery were August 16<sup>th</sup> and August 25<sup>th</sup> and contained two image tiles for each of the dates to minimize the impact of snow and cloud coverage. The EU-DEM v1.1 is a raster dataset that was developed by the European Environmental Agency (EEA) under the framework of the Copernicus program. The dataset breaks Europe into 1000 x 1000 km tiles that have then been grouped together. The DEM has 25-meter resolution with +/- 7-meter vertical accuracy and was created in 2011 and published in 2016. This data was accessed through the Copernicus website at <https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1>, and the test area of interest was located in the E40 N20 group (Switzerland).

<b>Data Product</b>	<b>Imagery Date(s)</b>	<b>Study Area</b>	<b>Website Source</b>	<b>Spatial Resolution</b>	<b>Spectral Bands</b>
Landsat 8	8-16- 2019 and 8- 25-2019	Switzerland	<a href="https://earthexplorer.usgs.gov/">https://earthexplorer.usgs.gov/</a>	30M	9
EU-DEM	2011	Switzerland E40N20 group	<a href="https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1">https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1</a>	25M, +/- 7 vertical accuracy	N/A

Table 1. Sources of data.

### 2.3 Methods:

#### Python Toolbox Structure:

This project is developed in ESRI's ArcGIS Pro software as a python toolbox. The toolbox will contain two tools that will help in developing a permafrost classification tool these will include a Preprocessing tool and a Permafrost Classification tool. The Preprocessing tool is designed to take Landsat 8 tiles and a DEM file to create the prerequisite data needed for the Permafrost Classification tool. The data produced includes 11 raster files containing mosaiced images of corresponding to each Landsat 8 bands 1 through 11, a mosaiced composite band image of all the Landsat 8 tiles, A masked DEM , a NDVI file, and a Land Surface Temperature (LST) file. The Permafrost Classification tool will take the outputs of the Preprocessing tool or any DEM, NDVI, and LST data that corresponds with the Alps and create a raster image classifying the Alps' potential permafrost distribution.

#### Preprocessing Tool:

##### EU-DEM data processing:

Due to the large size of the eu-dem-v1.1 data this will be reduced to fit only the area covered by the Landsat 8 tiles that cover the Alps. The process of reducing the size of this data will be by coding the ESRI Extract by Mask tool and using the Composite Bands Landsat 8 image as the extent. By reducing the size of this data that will eventually be feed into the Permafrost Classification tool will help minimize the amount of processing time needed.

##### Landsat 8 image processing:

The processing of the Landsat 8 imagery involves coding three ESRI tools: Create Raster Dataset, Mosaic, and Composite Bands. The first tool required to process the Landsat 8 tiles is automate the Create Raster Dataset tool to create 11 empty raster dataset files to be used by the Mosaic to New Raster tool. Once these files were created the code proceeds to use these as the target raster for the Mosaic to New Raster tool to mosaic together each of the Landsat 8 tiles based on band number. This results in 11 files that contain mosaiced images of the Alps included one for each spectral band and thermal bands. Once these mosaiced images are created the next step is use the Composite Bands tool to composite all 11 files into a singular composite image that will be used for input in creating an NDVI raster.

NDVI:

Creating the NDVI raster is done by using the ESRI's NDVI raster tool and inputting the Composite band image and selecting band 5 and 4 corresponding to the NIR and Red spectral band respectively.

Land Surface Temperature:

The creation of the land surface temperature involves coding multiple raster calculation tools to take the two thermal mosaicked bands of Landsat 8 data (bands 10 and 11), and apply two calculations (Figure 1 and Figure 2) after which the product of those calculations will go into the Cell Statistics tool to produce a raster that gives the mean temperature reading for each of the cells across the mosaic Landsat image. This image can then be used for the LST input. The first calculation involves converting the digital number values of the two thermal bands from the Landsat 8 data to the Top of Atmosphere spectral radiance. This is done by using the following formula:

$$L_{\lambda} = M_L Q_{cal} + A_L$$

Where:

$L_{\lambda}$  = TOA spectral radiance (Watts/( m<sup>2</sup> \* sr \*  $\mu$ m))

$M_L$  = Band-specific multiplicative rescaling factor from the metadata  
(RADIANCE\_MULT\_BAND x, where x is the band number)

$A_L$  = Band-specific additive rescaling factor from the metadata (RADIANCE\_ADD\_BAND x, where x is the band number)

$Q_{cal}$  = Quantized and calibrated standard product pixel values (DN)

*Figure 1 DN to TOA conversion formula outlined by Dr. Amber Ignatius of the University of North GA*

Once the TOA radiance of each band is determined the code will execute the conversion of TOA to the at-satellite brightness using the Landsat 8 metadata and the formula as specified by Figure 2.

$$T = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)}$$

where:

$T$  = At-satellite brightness temperature (K)  
 $L_\lambda$  = TOA spectral radiance (Watts/( m2 \* sr \*  $\mu$ m))  
 $K_1$  = Band-specific thermal conversion constant from the metadata  
 (K1\_CONSTANT\_BAND\_x, where x is the thermal band number)  
 $K_2$  = Band-specific thermal conversion constant from the metadata  
 (K2\_CONSTANT\_BAND\_x, where x is the thermal band number)

Figure 2 TOA to T conversion formula outlined by Dr. Amber Ignatius of the University of North GA

### Permafrost Classification Tool:

The Permafrost Classification Tool is designed to take the inputs of a DEM, NDVI, and Land surface temperature raster of the Alps and then produce an estimated permafrost distribution across the Alps. This is achieved by using ESRI's built in python spatial analyst Con tool which sets conditional statements that correspond with known traits of permafrost in the Alps. These traits include elevation greater than or equal to 2400 meters, NDVI values between -0.03 (bare earth) to 0.05 (small plants and grasses), and Land surface temperatures less than or equal 20 degrees Celsius (FOEN, 2019). This results in the permafrost distribution by excluding any data outside of these values ranges.

## **3. Results and Discussion**

### **3.1 Coded Toolbox performance:**

The coded ESRI python Permafrost Classification Toolbox performed exactly as intended. The Preprocessing tool created the NDVI, LST, masked DEM, the raster files for the Mosaic Tool, the composite land sat image, and ran the Mosaic to New Raster Tools as it was designed to do. The Preprocessing tool alone is a significant boon in expediting the processed needed to manipulate large amounts of Landsat 8 data tiles. As can be seen in Figure 3 the manual process for developing the empty raster files and the mosaic files for each band requires a significantly amount of manual inputs. The manual process takes a considerable time with multiple points potential human error as compared to the Preprocessing Tools interface as shown in Figure 4. The run time for the Preprocessing tool does run around 15+ minutes depending on the computer. This long run time is due to the amount of data that is being processed, but being coded in python allows for this tool to be easily run multiple times and using as many Landsat 8 tiles as desired/ capable of ArcGIS Pro software to handle. The manual process for creating 11 mosaic images for each band for 4 tiles of Landsat 8 can take upwards of 20 minutes not including the development time for NDVI or LST rasters that the Preprocessing tool does in 15 minutes.

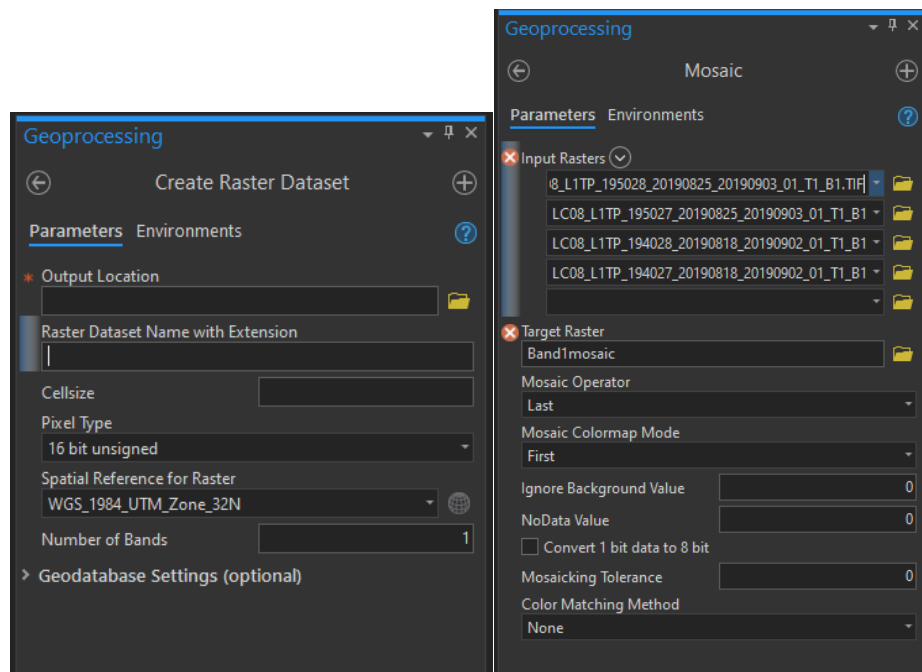


Figure 3: Image of the ESRI ArcGIS Pro's Create Raster Dataset(Left) and Mosaic Tools(Right) Graphical User interface.

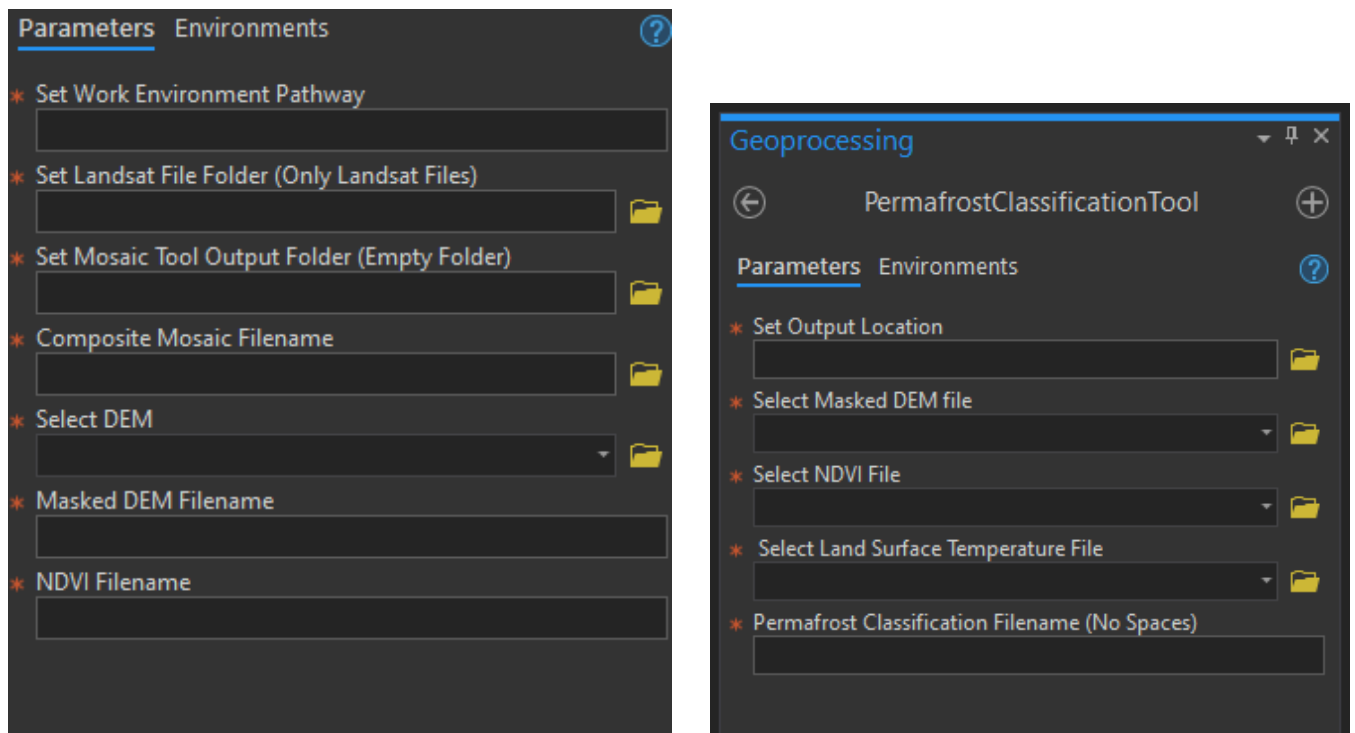


Figure 4: Preprocessing (Left) and Permafrost Classification (Right) Tool's graphical user interface inside ArcGIS Pro

The Permafrost Classification Tool as runs as intended and produces a raster image that clearly shows the potential distribution of permafrost based on the input proxy data derived from the Preprocessing Tool as can be seen in Figure 5. Usage of the Perm frost Classification tool is also exceptionally more simple than using ESRI's Raster



Calculator tool as the Permafrost Classification tool does not require understanding the constraints needed for to have the proxy data give a relatively visual accurate permafrost classification. The tool takes approximately one minute to run and is therefore would be exceptional for running repeatably across multiple areas, but this tool does have hard coded values corresponding to conditional statements as outlined in the method sections. Meaning that the Permafrost Classification Tool can only be used , in its current iteration, as a way to classify the permafrost distribution in the European Alps.

The issues with the Permafrost Classification toolbox are numerous. The relative lack of flexibility of inputs. The tool can only use Landsat 8 data to produce the NDVI and LST needed for the Permafrost classification Tool, and the Permafrost Classification Tool has hard coded value ranges for the conditional statements for the proxy data meaning that it can only be used for the European Alps. Also, designing the code as a python toolbox working within the ESRI ArcGIS Pro software limits the usage of the code to exclusively to ESRI's arcpy for running the tools necessary to perform the overall analysis. Being in the ArcGIS Pro software also potentially increases the amount of run time for the toolbox and limits the potential users who may have access to the code without significant modifications due to the license requirement of ESRI products.

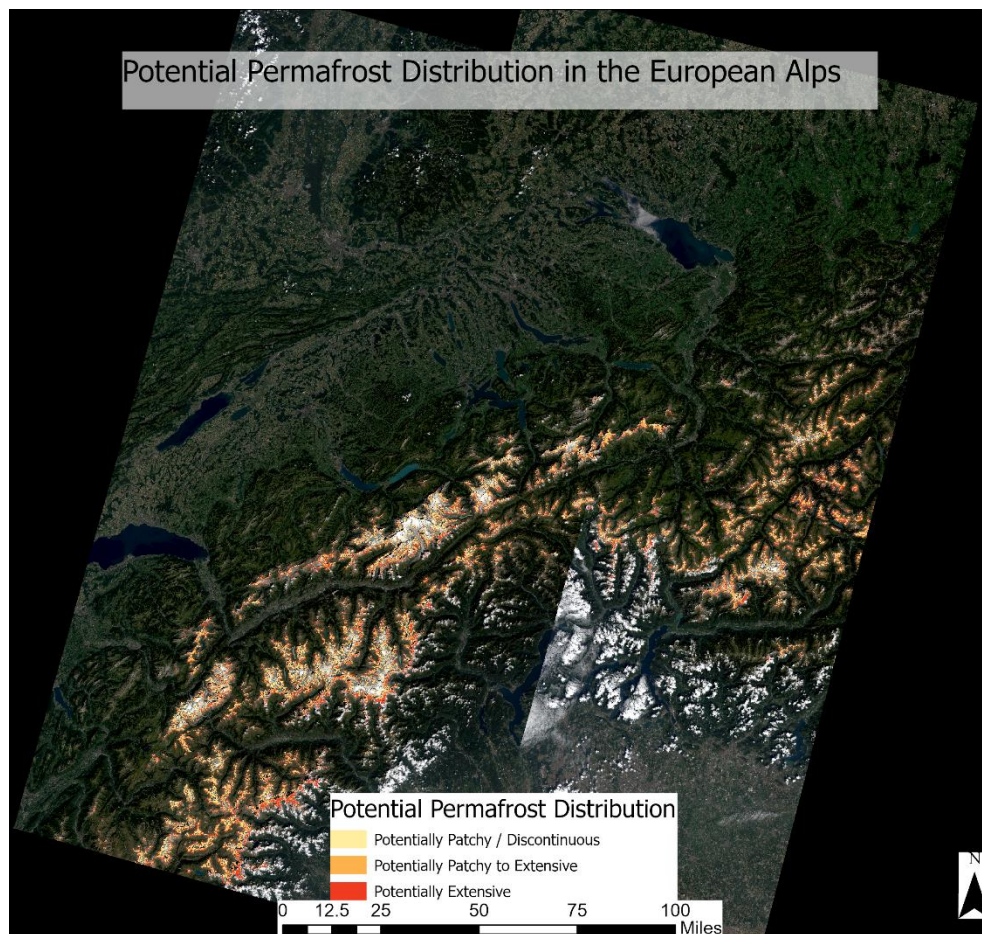


Figure 5: Map showing the Potential Permafrost distribution of the European Alps as produced by the Permafrost Classification Tool



### 3.2 Permafrost Distribution:

Due to lack of availability, there is not numerical means of validating the results of this project against. However, visually comparing the results of this project against the Federal Office for the Environment (FOEN) of the Swiss government's map of potential permafrost at

[https://map.geo.admin.ch/?zoom=2&bgLayer=ch.swisstopo.swissimage&layers=ch.bafu.permafrost&layers\\_opacity=0.7&lang=en&topic=bafu&E=2681689.04&N=1159776.64](https://map.geo.admin.ch/?zoom=2&bgLayer=ch.swisstopo.swissimage&layers=ch.bafu.permafrost&layers_opacity=0.7&lang=en&topic=bafu&E=2681689.04&N=1159776.64)

does show that there the end product of this project analysis does yield similar results. The map created by FOEN shows a range of permafrost divides the permafrost into six different categories ranging from patchy/discontinues to extensive and thick. The end result of Permafrost Classification Tool (Figure 5) also shows similar spatial patterns in permafrost distributions across the Alps although classified into three classes. Therefore, this python coded permafrost classification tool designed in the project does clearly show a that there is, at least on a basic level, a visual correlation between proxy data and permafrost distribution in Alpine permafrost.

The analysis used in this project is nowhere near as robust as many other permafrost classification models. Multiple models have been developed to attempt to model the distribution of permafrost for specific location using remote sensed data including Top of Permafrost (TTOP) model.(Shi et al.2018) Developed for identifying permafrost in the Qinghai-Tibet Plateau developed, the TTOP like many of these models rely on 'potential' permafrost spread, and this projects analysis falls into the same issues (Zou et al.,2017). Due to difficulty of gather in situ data the use of proxy data can, at best, only achieve an approximate idea of permafrost distributions (Zou et al.,2017). Without a numeric validation of the resulting permafrost distribution compounded with the 'proximate' side effect of this form of analysis, this projects analysis holds little merit in terms of determining if the methodology used gives an accurate representation of the permafrost distribution in the European Alps other than a subjective one.

## 4. Conclusion

As climate change and Earth's temperature is expected to continue to increase the need for a means to monitor permafrost become ever greater. The difficulty of in situ data collection for permafrost is not going to become any easier, so the use of remote sensed data is essential. (Shi et al.2018) Almost 70% the infrastructure from pipes, roads, railways, and buildings are developed upon permafrost facing issues of degradation due to thawing permafrost by mid-century. (Hjort. et al., 2018) Arctic feedbacks resulting in the temperature and humidity increasing due to permafrost thawing may even result in an increase in the rates of respiratory, skin, and intestinal infections alongside many other conditions due to bacterial, viral, parasitic agents. (Parkinson et al.,2014) It is critical for both cryosphere and those who depend upon it to monitor permafrost distributions.

The results of this project are extremely promising in term of using proxy data as a means to classify permafrost and especially shows that coding GIS analysis is the correct means for working with large dataset that require repeatable element. The code for this project would make a great foundation for multiple research projects into the

identification of not only permafrost, but potentially other subsurface soils or rocks. The next steps for taking this project to the next level would include looking into introducing more forms of remote sensing data, and other identification indices into permafrost distribution calculations such as: LiDAR, RADAR, or even UAV acquired data.

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