**Remote Sensing of Permafrost Thaw and Associated Infrastructure Damage Using Very High-Resolution Imagery**

Anna Zirkes

1. *Introduction*

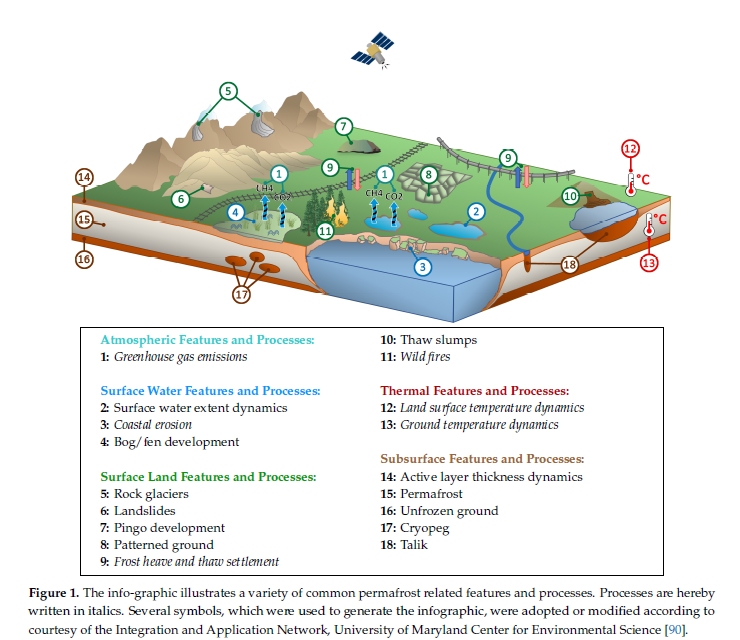
The Arctic is warming two to four times as fast as the global average[[1]](#endnote-1). Permafrost thaw is one of the most consequential changes occurring in the Arctic due to climate change. Permafrost thaw leads to a tremendous release of greenhouse gases[[2]](#endnote-2), and has also been shown to impact human health[[3]](#endnote-3), water quality[[4]](#endnote-4), and vegetation[[5]](#endnote-5). Additionally, thaw destabilizes permafrost and leads to catastrophic infrastructure failure[[6]](#endnote-6), which is the focus of this review.

* 1. *Basics of Permafrost*

Permafrost, which is defined as ground that remains frozen for at least two consecutive years[[7]](#endnote-7), underlays approximately one fifth of the Earth’s surface[[8]](#endnote-8). Importantly, permafrost is not confined to the Arctic, and it exists in other regions such as the Tibetan Plateau, Rocky Mountains, Himalayas, and Antarctica[[9]](#endnote-9). The percent cover of permafrost does vary by location and is described as continuous (90% – 100%), discontinuous (50% -90%), sporadic (10% - 50%), and isolated patches (10% or less)[[10]](#endnote-10). When permafrost warms, the ice within permafrost melts[[11]](#endnote-11) and the active layer, which is the portion that seasonally freezes and thaws[[12]](#endnote-12), becomes thicker[[13]](#endnote-13).

* 1. *Remote sensing of permafrost thaw*

Certain features of permafrost, such as active layer thickness[[14]](#endnote-14) and talik formation[[15]](#endnote-15) (areas of unfrozen ground within permafrost[[16]](#endnote-16)), can be directly measured using remote sensing tools. However, these measurements are often difficult as permafrost exists underground. Remote sensing of permafrost typically focuses on secondary, aboveground features of permafrost, such as those outlined in Figure 1. Dietz et al. (2021) divide these features and processes into five categories, and through bibliometric analysis found that nearly half of all articles fall within the “Surface Land Features and Processes” category. An additional 25% fall within the “Surface Water Features and Processes” category[[17]](#endnote-17). In this review I will focus specifically on the remote sensing of two Surface Land Features and Processes - retrogressive thaw slumps (RTS) and ice wedge polygons (IWP). Additionally, I will focus on the use of very high resolution (VHR) imagery as it is increasingly gaining traction in this field[[18]](#endnote-18).



**Figure 1.** Common permafrost related features and processes (in italics). From Phillip et al. (2021)[[19]](#endnote-19).

RTSs are like landslides and occur abruptly when ice-rich permafrost thaws[[20]](#endnote-20). RTSs are usually less than 10 hectares, like the RTS depicted in Figure 2[[21]](#endnote-21). Notably, the largest known RTS is the Batagaika crater in Russia, which has an area of 87 hectares[[22]](#endnote-22). Typically, the headwall of an RTS continues to retreat over time as surrounding permafrost thaws; it eventually stabilizes as bedrock is exposed. Headwall retreat rates of 5-40 m/year are typical, but rates vary widely by region[[23]](#endnote-23). A close-up of a crater

Description automatically generated

**Figure 2**. Retrogressive thaw slump in Thetis Bay, Herschel Island, July 1986. From Lantuit et al. (2007)[[24]](#endnote-24).

IWPs refer to cracks in the ground that are caused by repeated freezing and thawing of water over hundreds of thousands of years. These cracks form a network of polygon shapes. Permafrost thaw leads to the degradation of IWPs, which in turn causes hydrological changes such as increased water runoff, which is shown in Figure 3[[25]](#endnote-25).

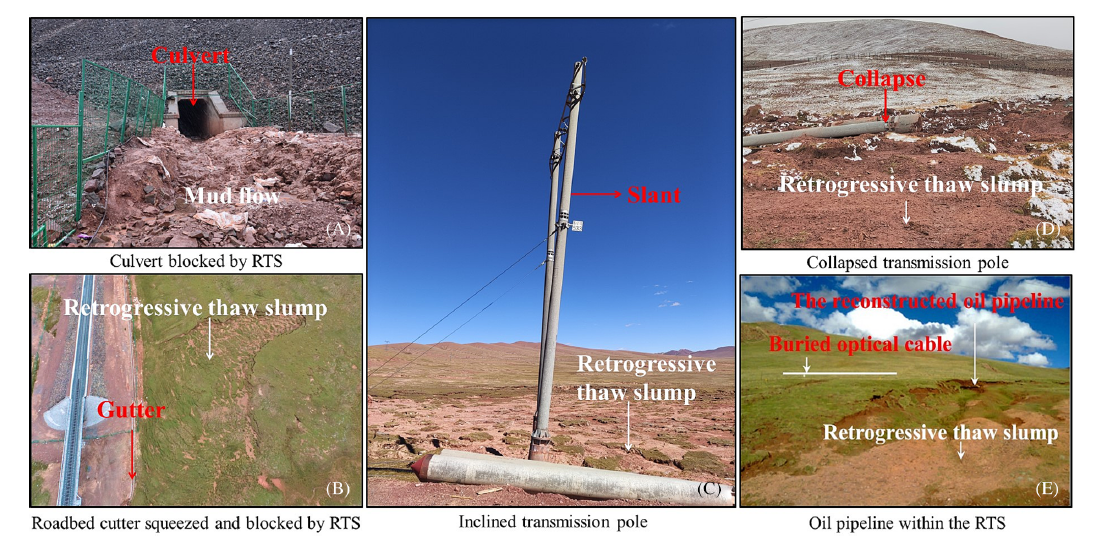
A cross section of a brown square with green and blue patches

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**Figure 3**. Diagram depicting ice wedge degradation from Bennett (2024)[[26]](#endnote-26).

* 1. *Effects of permafrost thaw on infrastructure*

Alongside the features of permafrost thaw, it is important to understand the effects that thaw has on infrastructure. Frozen soil has a much higher mechanical strength and is more stable than thawed ground, leading to the dramatic effects thaw has on infrastructure[[27]](#endnote-27). Climate change is expected to decrease the mean bearing capacity of permafrost by 40-70% [[28]](#endnote-28). The secondary processes detailed in Figure 1 also pose risks to infrastructure and specific examples of infrastructure damage due to RTSs can be seen in Figure 2. Furthermore, approximately 4 million people, 1200 settlements, and 70% of Arctic infrastructure reside on permafrost that is at risk of thawing by 2050[[29]](#endnote-29), [[30]](#endnote-30). On top of enormous cultural and social costs, there will be an extreme economic cost to these damages. Depending on the climate scenario that is used, these damages could cost $180 - $270 billion[[31]](#endnote-31),[[32]](#endnote-32).



**Figure 4**. Impacts of retrogressive thaw slumps (RTS) on infrastructure. A) Culvert blocked by RTS. B) Roadbed cutter squeezed and blocked by RTS. C) Inclined transmission pole. D) Collapsed transmission pole. E) Oil pipeline within an RTS. From Li et al. (2024)[[33]](#endnote-33).

These projections do provide important insights, yet it is necessary to note certain limitations, specifically the narrow modeling approach. For example, Suter et al. (2019) does not include damage due to frost heaving, coastal erosion and other non-economic costs such as the loss of culturally important resources. Furthermore, the climate projections that were used in this study have significant uncertainty[[34]](#endnote-34).

1. *Mapping features of permafrost thaw using VHR Imagery*

*2.1. Common Methods*

VHR data is used in most RTS and IWP studies as these features are relatively small (typically < 10ha), although some permafrost features such as surface water dynamics may allow for the use of medium resolution data[[35]](#endnote-35). Additionally, Philipp et al. (2021) found that over half of the articles in their review used optical platforms, while synthetic aperture radar was the second most common platform[[36]](#endnote-36). Notably, Rodenhizer et al. (2024) compared the performance of Worldview, Planetscope, and Sentinel-2 for identifying RTS using a Convoluted Neural Network (CNN) and found that Worldview performed the best as it had the highest Intersection over Union (IoU) and missed the fewest RTSs. This is likely because Worldview has a smaller radiometric footprint and full width at half maximum than Planetscope and Sentinel 2, leading to crisper images. Nevertheless, they note the higher cost of Worldview data and conclude that for areas with a higher median RTS area, Planetscope or Sentinel 2 data may be acceptable[[37]](#endnote-37).

Alongside VHR, deep learning is commonly used to automate RTS and IWP detection, especially when VHR imagery means large amounts of data[[38]](#endnote-38). Nitze et al. (2021) assessed the performance of three deep learning models, UNet, UNet++, and DeepLabv3, in the identification of RTSs and found that on average UNet++ performed the best and had a higher IoU[[39]](#endnote-39).

In addition to common data types and methods, most permafrost thaw studies occur on local scales; less than 10% of the articles reviewed by Philipp et al. (2021) occurred at a pan-Arctic scale. Philipp et al. (2021) noted commonly studied locations, which include the Mackenzie Delta in Canada, the North Slope Borough in Alaska, the Lena River Delta in Russia, and the Qinghai-Tibet Plateau in China. Although local studies provide useful insights, pan-Arctic studies, especially those that utilize high spatial and temporal resolution data, are required to more fully understand global climate change and permafrost thaw dynamics[[40]](#endnote-40). This is especially true as permafrost dynamics have high regional variability and locally trained classification models often have poor transferability[[41]](#endnote-41).

* 1. *Pan-Arctic Mapping*

A pan-Arctic map of permafrost features such as RTSs and IWPs has recently become a goal in the permafrost research community, especially with the development in deep learning and VHR satellites[[42]](#endnote-42). However, challenges include limited training data sets, variability of ecosystems and image properties, and computational complexity[[43]](#endnote-43), [[44]](#endnote-44). A pan-Arctic permafrost feature map, the Mapping Application for Arctic Permafrost Land Environments (MAPLE), is under development and has shown promising results, but the method requires a high-performance computing system[[45]](#endnote-45).

As the Arctic is extremely variable, a vast amount of training data is required to produce an accurate model. Work by Yang et al. (2023) indicates large within class variability in RTSs, which highlights the importance of pan-Arctic training data. They found that adding imagery from a foreign region only improved performance for a model trained on multiple regions and performance was not improved for a model trained on a singular region[[46]](#endnote-46).

One approach given the limited availability of training data is training a model using imagery with varying spatial resolutions. Zhang et al. (2020) found that the combination with the highest F1 scores (0.72) was a model trained on VHR aerial imagery and satellite imagery and then applied to another VHR satellite image[[47]](#endnote-47). This suggests that training a model on multiple spatial resolutions of imagery improves accuracy.

Another approach relies on data augmentation, which creates new images from existing images. For example, Huang et al. (2022) used simple methods like flipping, cropping, and brightening images to generate new data. They concluded that although data augmentation can increase the diversity of training data, it doesn’t always improve transferability. A more complex augmentation method involves a generative adversarial network (GAN), which is a deep learning model that combines a generator, which creates the data, and a discriminator, which predicts whether the data is a part of the original source. Similarly, Huang et al. (2022) found that a GAN can improve temporal transferability, but not spatial transferability[[48]](#endnote-48). Notably, when Huang et al. (2019) tested the transferability of a model that had been trained with data augmentation, they found significantly lower precision, recall, and F1 scores - 0.532, 0.660, and 0.589, respectively, compared to original values of 0.863, 0.833, and 0.848[[49]](#endnote-49). Although these scores seem low, further testing of the transferability of this model trained without data augmentation would be needed to fully assess the effectiveness of data augmentation.

1. *Remote Sensing of Infrastructure using Unmanned Aerial Vehicles (UAV)*

*3.1 Overview*

As outlined in section 1.3, permafrost thaw poses a real threat to infrastructure. In other regions, researchers have turned to unmanned aerial vehicles (UAVs) to assess a wide range of infrastructure damage. For example, Jia et al. (2024) used UAV surveys and object-oriented classification to assess building damage after an earthquake in China, and Baker et al. (2020) used UAVs to assess damage to bridges under low-light conditions[[50]](#endnote-50),[[51]](#endnote-51). However, few researchers have applied these methods to infrastructure damage caused by permafrost thaw. Existing research is limited to pavement damage in the Tibetan Plateau[[52]](#endnote-52), [[53]](#endnote-53). Although there is a lack of journal articles on the subject, UAVs may be utilized for these purposes outside the academic sphere. It is also important to note that a few researchers have had success using VHR satellite imagery to assess Arctic infrastructure, such as Manos et al. (2024), Chai et al. (2023), Manos et al. (2022)[[54]](#endnote-54), [[55]](#endnote-55), [[56]](#endnote-56).

Globally, the most common application of UAVs in this field is bridge inspections[[57]](#endnote-57). Other applications abound, including routine and post-disaster assessment of pavement, railway, buildings, and dams[[58]](#endnote-58), [[59]](#endnote-59). UAVs are advantageous in this field as they keep inspectors safe from dangerous structures, improve efficiency, and provide VHR data[[60]](#endnote-60). Despite many different applications and advantages, there are numerous challenges that limit the use of UAV in this field. These include UAV parameters such as short battery life and range, environmental factors such as low illumination, weather conditions, and GPS-denied locations, as well as strict regulations[[61]](#endnote-61), [[62]](#endnote-62). Current research is focused on developing fully automated flight methods and further improving machine learning analyses and UAV parameters such as battery life[[63]](#endnote-63), [[64]](#endnote-64).

UAVs have been successfully used in permafrost regions to assess permafrost dynamics, although this information is rarely used to assess risk to infrastructure. This research has focused on developing methods using simple consumer grade UAV setups and general detection of permafrost landforms such as IWPs and RTSs[[65]](#endnote-65), [[66]](#endnote-66), [[67]](#endnote-67). Notably, Oldenborger et al. (2022) compared consumer-grade UAV data and VHR satellite imagery for assessing ground subsidence, surface geology, and periglacial landforms, and found local agreement. However, larger UAV surveys were limited by errors in camera calibration, which suggests that higher quality UAVs may be required for this type of mapping[[68]](#endnote-68).

1. *Conclusion*

Permafrost thaw is a growing problem that greatly affects ecosystems, infrastructure, human health and culture, and hydrology. Current permafrost research revolves around the use of VHR satellite imagery and deep learning to identify RTSs and IWPs[[69]](#endnote-69). Researchers are working to increase the spatial scale of research and produce a pan-Arctic map of permafrost thaw features. To address the dearth of training data, researchers have used images with varying spatial resolution and several data augmentation methods with varying degrees of success[[70]](#endnote-70),[[71]](#endnote-71). Future research needs to address the computational intensity of models, limited availability of training data, and high within class variability of permafrost features. Another good avenue for research lies in the use of UAVs to assess infrastructure damage due to permafrost. UAVs are commonly used to assess infrastructure damage across many regions and disciplines, yet few papers have been published that apply these methods in permafrost regions.

1. *Glossary of Acronyms*

CNN – Convoluted Neural Network

GAN – Generative Adversarial Network

IOU – Intersection over Union

IWP – Ice Wedge Polygon

RTS – Retrogressive Thaw Slump

UAV – Unmanned Aerial Vehicle

VHR – Very High Resolution

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