ROCK GLACIER CATALOGUE AND PREDICTIVE MODELING IN THE MACKENZIE MOUNTAINS: PREDICTING ROCK GLACIER LIKELIHOOD WITH A GENERALIZED ADDITIVE MODEL

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ABSTRACT

Rock glaciers are important features of periglacial landscapes and have potentially significant hydrological, ecological, and geological impacts on alpine environments. The purpose of this study is to catalog rock glaciers in three regions of the Mackenzie Mountains, northwest Canada, and to develop a predictive model for rock glacier probability mapping. Identification of rock glaciers follows guidelines set by the International Permafrost Association (IPA) Rock Glacier Action Group, incorporating geomorphological approaches for identification. Of the 530 rock glaciers mapped within three regions of the Mackenzie Mountains,~90% were classified as active, with primarily northern orientations. The model utilizes variables such as potential incoming solar radiation (PISR), elevation, slope, aspect, lithology, and topographic position index (TPI) to understand rock glacier distribution. Modeling methods include a Generalized Additive Model (GAM), Random Forest (RF) and Forest-based Classification and Regression (FBCR). The comparison of models revealed that the GAM was the best model, with selected variables. The performance of the GAM was assessed using training (70%) and testing (30%) datasets. The confusion matrix for the training data indicated a total of 321 true negatives (0) and 322 true positives (1), with 50 false negatives and 49 false positives. The training accuracy was calculated to be 0.87, reflecting the proportion of correctly classified instances. An additional test site revealed that the GAM can be generalized to new regions within the Mackenzie Mountains, limiting the time needed for manual identification of rock glaciers in large regions. This research contributes to the existing knowledge on rock glacier formation and persistence and emphasizes the importance of comprehensive inventories for future research and monitoring.

PREFACE

Chapter one of this thesis includes an introduction to the topic and the objectives of the thesis. The literature and background information are also included in chapter one. This thesis describes the attributes of rock glaciers and provides a rock glacier inventory for three regions within the Mackenzie Mountains, northwest Canada, Yukon and Northwest Territories. The study regio is also presented in chapter one. Chapter one was written by Rabecca Thiessen and directed and edited by Philip Bonnaventure.

Chapter two provides the methods and materials used to conduct the research as well as detailed methodology used throughout the modelling process. The idea for the study was conceived by Philip Bonnaventure and me. Throughout the process, the research was guided by my supervisor, Philip Bonnaventure as well as discussions with my supervisory committee. I was the lead on the research and writing of this manuscript. It was edited by the supervisory committee; Hester Jiskoot and Peter Morse, Philip Bonnaventure with some edits to the extended publication by Caitlin Lapalme.

Chapter three presents the results of the thesis including the rock glacier inventory as well as the results form the modelling process. Caitlin Lapalme and I contributed to the inventorying of rock glaciers within the study regions.

Chapter four provides the discussion and conclusion sections. This chapter was written by me and edited by my supervisor, Philip Bonnaventure. Corrections and revisions were provided for all chapters by my supervisory committee to complete this manuscript.

ACKNOWLEDGMENTS

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Contents

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
ALOS	Advanced Land Observing Satellite
ANOVA	Analysis of Variance
AUC	Area Under the Curve
BIC	Bayesian Information Criterion
DCG	Debris-Covered Glacier
DE	Deviance Explained
DEM	Digital Elevation Model
DF	Degrees of Freedom
ESRI	Environmental Systems Research Institute
FBCR	Forest-based Classification and Regression
FOI	Feature of Interest
GAM	Generalized Additive Model
GCV	Generalized Cross-Validation
GIS	Geographical Information System
GLM	Generalized Linear Model
IDW	Inverse Distance Weighted
InSAR	Interferometric Synthetic Aperture Radar
IPA	International Permafrost Association
JAXA	Japan Aerospace Exploration Agency
LiDAR	Light Detecting and Ranging
MAAT	Mean Annual Air Temperature
MAGST	Mean Annual Ground Surface Temperature
MAP	Mean Annual Precipitation
MCC	Matthews Correlation Coefficient
MSE	Mean Squared Error
NWT	Northwest Territories
OOB	Out-of-Bag
PISR	Potential Incoming Solar Radiation
R^2adj	Adjusted R-squared
REML	Restricted Maximum Likelihood
RF	Random Forest
SR	Study Region
TPI	Topographic Position Index
VIF	Variance Inflation Factors
YT	Yukon Territory

Chapter 1: Introduction

1.1 Introduction

As the effects of climate change continue to become more evident in our landscapes there is a need to understand the composition and distribution of landforms that are being impacted. Features that cannot easily be detected using automated methods and do not show significant temporal changes are often among those overlooked (Janke, 2013; Kääb et al., 2003). Vast portions of the Canadian north are remote, located far from substantial populations. These areas contain many notable and important geomorphic features. Many geomorphic features in cold regions are hydrologically significant and are central to local and regional surface energy balance as well as impact local water and food security (Derksen et al., 2019; Harrington et al., 2018; Sorg et al., 2015). Rock glaciers are an example of such cold-region geomorphic features.

The purpose of this research is to identify rock glaciers in the Mackenzie Mountains, and document their general characteristics within the study region, as well as produce a probability model that is capable of mapping rock glacier likelihood in unmapped regions. I hypothesize that rock glacier distribution is controlled by several factors, including potential incoming solar radiation, elevation, slope, lithology, topographic position index and aspect regions (Brenning & Trombotto, 2006; Angillieri, 2010; Johnson et al., 2021; Trcka, 2020), and that these variables may be used to constrain a statistical model to determine probable rock glacier presence in different and larger regions. The development of such a model would allow for further characterization of large regions regarding rock glacier distribution without the need for intense manual identification. To achieve this, an inventory of rock glaciers is created using a consensus-based mapping method (Way et al., 2021). The characteristics of rock glaciers identified within select regions within the Mackenzie mountains were analyzed and compared to the surrounding terrain to interpret significant controls. Rock glacier attributes were also extracted from the dataset and used to inform and compare multiple statistical models; a generalized additive model (GAM), a random forest model (RF) and a forest-based classification and regression (FBCR). These models are utilized to generate rock glacier probabilities that can be interpolated into a continuous surface, reducing the area of investigation to high likelihood regions. Rock glacier identification through optical imagery can be very manually intensive and time consuming. Having a model based on variables that are expected to control rock glacier distribution and successfully predict probable rock glacier presence is a valuable tool in the creation of robust rock glacier inventories. Not only will the model reduce the area of investigation, which in turn reduces the time spent, generated probability maps can be used to explore novel areas in preliminary investigations. This may be useful when generating a research idea regarding rock glaciers. Extracting attribute data of a potential region and applying the successful model will help to identify areas of focus.

1.1.1 Objectives

I am testing the hypothesis rock glacier attribute variables may be used to constrain a statistical model to determine probable rock glacier presence in subsequent and larger regions. The development of such a model would be a first step in simplifying rock glacier identification and distribution in large regions, without the need for intense manual identification. To achieve this, I aimed to: (1) identify rock glaciers; (2) document their general characteristics within the study region; and (3) produce a probability model that is capable of mapping rock glacier likelihood in unmapped regions of the Mackenzie Mountains

1.2 Literature Research

Rock glaciers are an accumulation of debris and ice that often develop in one of two ways (1) debris covers the remnants of a glacier, with continued accumulation of debris and ice (2) precipitation infiltrates accumulations of debris and accretes interstitial ice. The former are commonly referred to as ice-cored rock glaciers and the latter rock glaciers of permafrost origin (Hamilton & Whalley, 1995). In both cases, with the continued accumulation of debris and ice, these features begin to flow downslope through the deformation of the internal ice and through the continuation of debris supply (Ikeda & Matsuoka, 2002). Rock glaciers range from a few hundred meters to several kilometers in length. Rock glaciers generally move with flow speeds from decimeters to meters annually (Giardino et al., 1987), with increased movement possibly occurring in the event of thaw, as meltwater lubricates the rock and sediment facilitating downslope movement (Bodin et al., 2009; Scapozza et al., 2014).

Rock glaciers are often classified into different categories using ice content and movement. The nature of the remote environment as well as the difficulty associated with ground truthing rock glaciers themselves makes estimations of ice content challenging. It is common practice to evaluate whether a rock glacier contains ice based on geomorphic characteristics (Ikeda & Matsuoka, 2002). Rock glaciers that appear convex are thought to contain ice and are classified as intact (Kellerer-Pirklbauer et al., 2012). Intact rock glaciers can be active or inactive. Active rock glaciers often have pronounced ridge and furrow topography on their surface that is indicative of flow (Angillieri, 2009) (Figure 1). They also have a steep frontal slope and little to no vegetation cover (Ikeda, 1999; Reato et al., 2021). While inactive rock glaciers may have the same features they are more muted, such as a gentler frontal slope and less apparent flow features (Ikeda & Matsuoka, 2002). Inactive rock glaciers may have some extent of vegetation cover as well because the lack of activity allows for succession of vegetation. Rock glaciers that appear concave (do not contain ice) and often have high vegetation cover are classified as fossilized or relict rock glaciers (Aoyama, 2005). Relict rock glaciers often have thermokarst features present on the surface (Jones et al., 2019). There are specifications often followed for classifying rock glaciers as active or inactive using optical satellite imagery, however, to acquire higher accuracy different approaches can be taken. Rock glacier activity may be monitored through the use of kinematic data that is acquired using remote sensing technologies. Interferometric Synthetic Aperture Radar (InSAR) uses microwave radar signals and image pairing technology to detect deformation over time that translates to active movement of rock glaciers (Brencher, et al., 2021). InSAR has been shown to be effective in the identification of active rock glaciers (Delaloye et al., 2013; Bertone et al., 2022; Lambiel et al., 2023). The downside to using InSAR for comprehensive rock glacier inventorying is that while it can reliably provide information on active rock glaciers, inactive rock glaciers are not accounted for. While seemingly dormant, inactive rock glaciers, despite their lack of current movement, remain pivotal components to their environment. Even in a state of inactivity, these rock glaciers can undergo internal ice-related alterations such as ice melt and increased water output that influences the surrounding hydrological systems (Harrington et al., 2018).

Figure 1: Active rock glacier. SR3, ESRI World Imagery Base Layer (ArcGIS Pro, version 2.9.3) with defined, steep terminus and lateral margins, ridge and furrow topography indicative of flow are also apparent. Some small thermokarst features also appear to be present indicating some melting of internal ice (Janke et al., 2015).

The outermost layer of rock glaciers, known as the active layer, is a substantial debris layer that experiences seasonal freezing and thawing, with thicknesses ranging from tens of centimeters to several meters (Humlum, 1997; Haeberli et al., 2006). This layer which is composed of large boulders and clasts, acts as a protective shield to the underlying ice by protecting it from external temperature fluctuations (Falaschi et al., 2014). The insulative properties are a product of multiple factors including the high thermal inertia of rocks, which allows them to absorb and dissipate heat more slowly than ice, as well as shielding the internal ice body from direct solar radiation (Brighenti et al., 2021; Kääb et al., 2021; Buckel et al. 2022). The active layer consists of coarse blocks characterized by open spaces that permit the circulation of air within it. Various researchers have explored this airflow mechanism, with some emphasizing vertical convection, akin to the upward movement of warm air, while others have described it as two-dimensional advection, which is referred to as the chimney effect (Barsch, 1971; Delaloye & Lambiel, 2005; Wilson, 2013). This convective airflow within the coarse blocky active layer exerts a substantial influence on the thermal dynamics, not only within the active layer itself but also extending its effects to the underlying permafrost, even at depths corresponding to the point where annual temperature variations cease. This thermal process plays a pivotal role in cooling the internal ice of the rock glacier, particularly during periods of temperature fluctuations, resembling the function of a temperature-regulating system, where the active layer serves as a dynamic conduit for temperature moderation (Wicky & Hauck, 2020). The insulating effects of the outer debris layer of a rock glacier helps to maintain relatively stable and cooler microclimates in the immediate area (Harris & Pedersen, 1998; Farbrot, et al., 2005). This stability offers refuge for species by providing ecological niches (Tampucci et al., 2017; Brighenti et al., 2021). Some arid communities, such as in the Andes, rely on glaciers as a source of fresh water (Rangecroft et al., 2013). However, as climate changes and glaciers face recession there is a need to find other sources of fresh water. The abundance of ice contained in rock glaciers and their ability to withstand warming temperature to a greater degree alludes to their potential hydrological significance (Janke & Bolch, 2021).

Rock glaciers are abundant geomorphological features in many mountain environments (Janke, 2013), including regions of Canada (Carter et al., 1999; Charbonneau & Smith, 2018; Jackson & Macdonald, 1980; Koning & Smith, 1999; Ommanney,1980; Sloan & Dyke, 1998).

However, their spatial distribution and characteristics are largely unknown in the Mackenzie Mountains. This mountain range represents a geographic location of pristine and rugged terrain that is poised to change considerably due to climate warming over the next few decades (IPCC, 2023). These changes will take place although this region is remote and largely outside of anthropogenic influence and infrastructure. Understanding and inventorying rock glaciers in this range will aid in predicting the evolution of these systems in a warming climate.

The identification of rock glaciers has evolved over time through technological advancements and a better understanding of their characteristics. Early inventories were based on aerial photographs and topographic maps (Luckman & Crockett, 1978; Kaufmann et al., 2007). Contemporary methods commonly uses satellite imagery, often freely available through platforms such as Google Earth Pro and Sentinel Hub, supplemented by field data (e.g., Charbonneau and Smith, 2018; Johnson et al., 2021; Trcka, 2020). A potential issue that arises with rock glacier identification through optical imagery is that there are many features that can be mistaken for rock glaciers. It is important that these features be well-defined within using established consensus within the literature. Remote sensing techniques, including Interferometric Synthetic Aperture Radar (InSAR), have confirmed rock glacier inventories, but suffer from problems such as poor image quality due to cloud and snow cover, and only detect active rock glaciers (Lambiel et al., 2008; Strozzi et al., 2020). Compiling a rock glacier inventory using remote sensing data and established methods for regions within the Mackenzie Mountains fills a regional gap. While this region has been primarily investigated for natural resources (e.g., Hannigan & Morrow, 2009; Shi & Guéguen, 2017), there has been very limited investigation into rock glacier presence. Having more information on rock glacier presence and likelihood allows for mitigation of potential hazards related to rock glaciers such as damage to infrastructure as well as providing initial data that can be further assessed to determine ecological impacts that rock glaciers may have.

Periglacial environments house several landforms and processes that resemble authentic rock glaciers (Figure 2). It is important that these features be well-defined using established consensus within the literature.

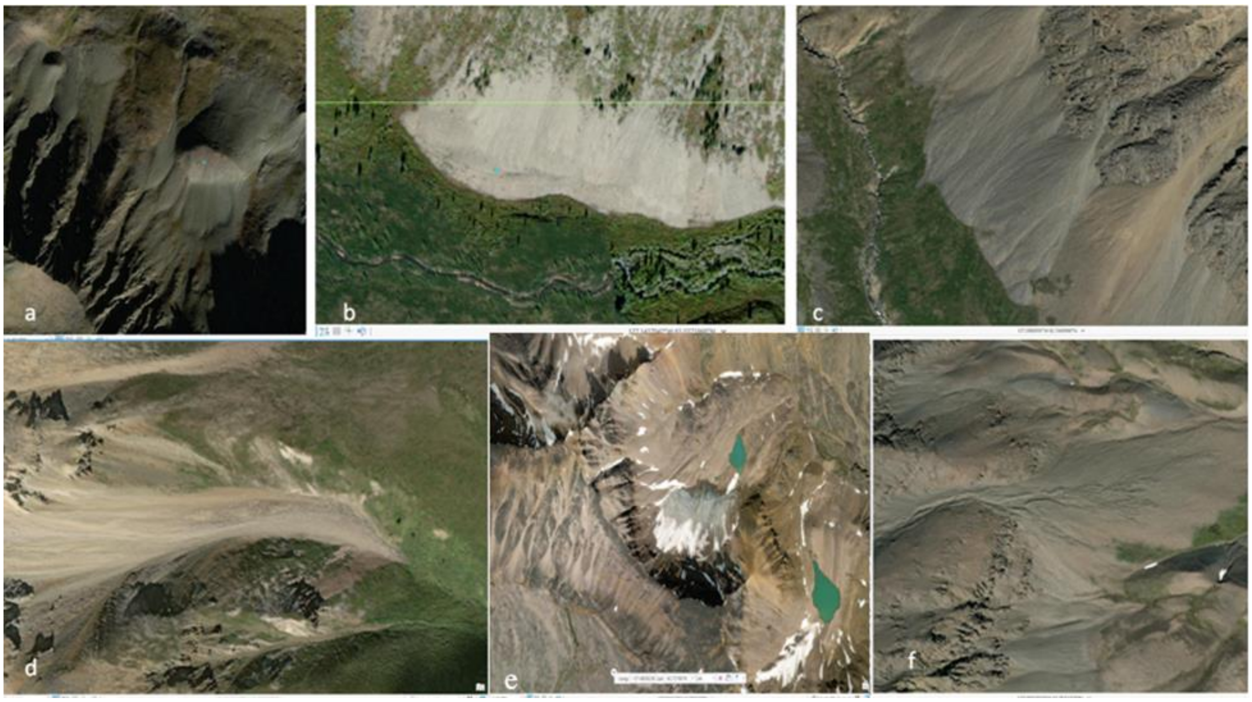


Figure 2: Periglacial landforms found within study regions. Some features are categorized as feature of interest (FOI). (a) Protalus lobe also referred to as embryonic rock glacier, from SR3, northern Mackenzie Mountains. (b) protalus rampart, SR2, 1:5,000; features that can be mistaken for rock glaciers include; (c) talus cones, SR1(d) rockslide, SA2 (e) debris-covered glacier, SA1 and (f) fluvial erosion over a talus slope,SR1. (ArcGIS Pro, version 2.9.3). Panels (a) and (b) are FOI. All imagery from the World Imagery Base Layer.

Rock glaciers have been used as a proxy for permafrost modeling, using lower and upper elevation limits of rock glaciers to map probable permafrost distribution (Marcer et al., 2017; Hassan et al., 2021). Permafrost modeling often incorporates ground truthing using instruments such as temperature probes to measure mean annual air temperature (MAAT) and mean annual ground surface temperature (MAGST), as well as borehole temperature data, thaw tubes, etc. Similarly, field investigations of rock glaciers often involve boreholes which provide access to the internal structure allowing for observation and measurement of properties such as ice content, temperature, and thermal regimes (Barsch et al., 1979; Arenson et al., 2002; Luethi et al., 2017). Electrical resistivity tomography (ERT) is another technique utilized for rock glacier investigation. ERT uses the measurements of low-intensity electric currents to create detailed representations of the internal structure of rock glaciers, providing information on ice distribution, permafrost, and type of substrate and its properties (Ribolini et al., 2010; Leopold et al., 2011). Ground penetrating radar (GPR) is another approach that uses radar pulses to image the subsurface (Monnier et al., 2011; Merz et al., 2015). While these standard field practices are effective for assessing rock glacier compositions and processes, the poor accessibility of the Mackenzie Mountains restricts the utilization of such valuable field data. It is also noted that many studies focusing on rock glaciers often concentrated their efforts on only a limited number of features. While that approach provides detailed insights for specific sites, it may not be suitable for mapping large regions and constructing comprehensive models. Satellite data and data extracted from DEMs can be used to identify rock glaciers in large regions and inform potential statistical models.

The research reviewed below has shown that rock glacier distribution is influenced by various factors, including elevation, slope inclination, potential incoming solar radiation (PISR), aspect, and lithology. Topographic position index (TPI) is a geospatial tool used to analyze terrain characteristics, determining elevation values. Positive TPI values indicate higher elevations of a point of interest compared to the average elevation of its surrounding, while negative values indicate a lower elevation point in comparison to its surrounding. Elevation contributes to rock glacier development by reducing temperatures, allowing for the preservation and accumulation of ice within rock glaciers. Higher elevations, such as the Mackenzie

Mountains, provide a high elevation terrain suitable for rock glacier development. Slope inclination also plays a role in rock glacier development. Some studies suggest that rock glaciers tend to occur on slopes between 10-30 degrees, with steeper slopes inhibiting their development due to increased erosion and instability, while gentler slopes lack the necessary conditions for rock glacier formation (Blagbrough & Farkas, 1968; Johnson, 1984; Brenning & Trombotto, 2006; Janke et al., 2017). Depending on the slope angle, debris may accumulate with ice and develop into a rock glacier which may continue to experience movement and growth down slope through the deformation of the internal ice. Potential incoming solar radiation (PISR) influences temperature regimes. Higher incoming solar radiation leads to warmer temperatures that can influence the melting of snow and ice, allowing deeper infiltration of precipitation and meltwater into the rock glacier which refreezes when it reaches the internal ice body, contributing to the growth of the internal body, as well as cooling it through latent heat exchange (Jansen & Hergarten, 2006). Regions with lower solar radiation have cooler surface temperatures, promoting the preservation of ice within the rock glacier. Aspect, the direction of a slope, affects the amount of solar radiation received, as well as the spatial distribution of snow accumulation (Angillieri, 2010). In the northern hemisphere, south facing slope receive more direct solar radiation than north facing slopes (Khandsuren et al., 2023). Consequently, north facing slopes are cooler which promotes the preservation of ice. It follows that rock glaciers in the northern hemisphere are commonly found on north facing slopes (Guglielmin & Smiraglia, 1998; Janke, 2007; Krainer & Ribis, 2012; Charbonneau & Smith, 2018). Rock glaciers found on south facing slopes may experience warmer temperatures leading to increased melt of the ice body. Prolonged exposure to high temperatures may lead to total loss of the internal ice and therefore inactivity of the rock glacier. Rock glaciers that experience complete loss of internal ice are classified as fossilized rock glaciers (Colucci et al., 2019; Reato et al., 2021). The lithology of a region is also expected to influence the development and distribution of rock glaciers. The porosity and permeability of lithological materials can affect the flow of ground water and storage which in turn can influence the presence and behaviour of rock glaciers (Johnson et al., 2007). The accumulation of debris from source walls with less resistant lithologies leads to the formation of pebbly rock glaciers, while source walls with more resistant lithologies result in the development of bouldery rock glaciers (Ikeda & Matsuoka, 2006). Different lithologies will also contribute to the size of rock glaciers (Onaca et al., 2017).

Modeling rock glacier distribution has been achieved by researchers such as Angillier (2010) in the San Juan Andes of Argentina, using a statistical modeling approach and geomorphological mapping techniques. Angilleri's study focuses on the assessment of environmental factors like altitude, aspect, slope, lithology, and solar radiation in relation to active rock glaciers. They utilize statistical techniques, such as Pearson correlations and logistic regression, to analyze these factors' influence and provide insight into the environmental conditions favoring rock glacier presence (Angillieri, 2010). Brenning and Trombotto (2006) used logistic regression and a stratified random sampling design based on elevation and aspect classes to conduct a comprehensive land cover survey. Their model offers insight into the suitability of different areas for the development of rock glaciers and glaciers based on climatic and topographic controls. Another study by Brenning (2009), compared different modeling techniques for modelling rock glacier distribution using a remote and terrain data or a combination of the two. Choosing to employ a Generalized Additive Model (GAM) for mapping rock glacier distribution offers distinct advantages in comparison to the already established methods utilized in studies like Angillieri's 2010 investigation, Brenning and Trombotto's 2006 work, and Brenning's 2009 study. Robson et al., (2020) present a sophisticated model based on deep learning and object-based image analysis. The authors incorporate both convolutional neural networks and object-based imagery using Sentinel – 2 imagery and Sentinel-1 interferometric coherence data, and DEMs.

1.3 Study Area

The Mackenzie Mountain range is the northern extension of the Cordilleran orogeny that lies between Lat. 65°33' - 60°0'31"N. The range spans over 700,000 km^2 (Figure 3). The range is situated along the border of the Northwest Territories (NT) and the Yukon (YT), in Sub Arctic Canada, in the Boreal Climatic Region (Szeicz et al., 1995). The Mackenzie River Basin houses multiple watersheds including the Athabasca, Great Slave and Mackenzie Main Stem watersheds (Aziz et al., 2006). Though sporadic tarn lakes, meltwater lakes and smaller river systems litter individual study regions, the percentage of water accumulation areas is low. The diverse sedimentary strata of the Mackenzie Mountains house a multitude of mineral deposits (Ootes et al., 2013). The susceptibility of sedimentary rock to weathering allows for ample debris supply for the development of rock glaciers, as does the reworking and reaccumulating of till (Matsuoka & Ikeda, 2001). During the Pleistocene, the Mackenzie Mountains experienced several glaciations (Duk-Rodkin & Hughes, 1992). The current climate within the study region is relatively cold and dry. The mean annual air temperature (MAAT) of -6.8 °C and the mean annual precipitation (MAP) of 527 mm (Wang et al., 2016) provide conditions suitable for rock glacier development (Schrott, 1996). The relief of the mountain range (minimum elevation, 107 m; maximum elevation, 2947 m; mean elevation, 1296 m) is also suitable for rock glacier development (Munroe 2018; Scotti et al., 2013). Nahanni National Park Reserve is situated in the southernmost portion of the Mackenzie Mountains, and Nááts'ihch'oh National Park Reserve lies North of Nahanni. These Park areas present opportunities for human interaction with the landscape, so it is important to have a comprehensive interpretation of the landscape to determine any risks that may be present.

The Mackenzie Mountains have similar morphological and topographic characteristics as those identified in previous rock glacier investigations in the Andes (i.e., Brenning, 2005) and the Selwyn Mountains (i.e., Sloan & Dyke, 1998). These elements include steep slopes, debris sources and arid conditions (Brenning & Trombotto, 2006; Janke, 2013; Scotti et al., 2013). This study focuses on three regions within the range, Study Region 1 (SR1), Study Region 2 (SR2) and Study Region 3 (SR3): two locations in the southwest (SR1, 127.1364066°W 62.8018849°N; SR2, 126.9482599°W 63.0254743°N), and a third in the north, SR3, (133.3434935°W 65.0825408°N). General relief of each region and surface hydrology percentage are presented in Table 1. All sites were chosen based on the initial investigation looking for debris, slopes and catchment areas and relatively clear resolution data available, ensuring that identification through imagery would be possible in the selected regions. The diverse and complex terrain of the Mackenzie Mountains provides an ideal setting for investigating rock glaciers, given its similarities to other regions where these features have been studied. A defined methodology is used to identify and map rock glaciers across three distinct study regions within the range. Leveraging a combination of satellite imagery, DEM data, and a consensus-based mapping approach.

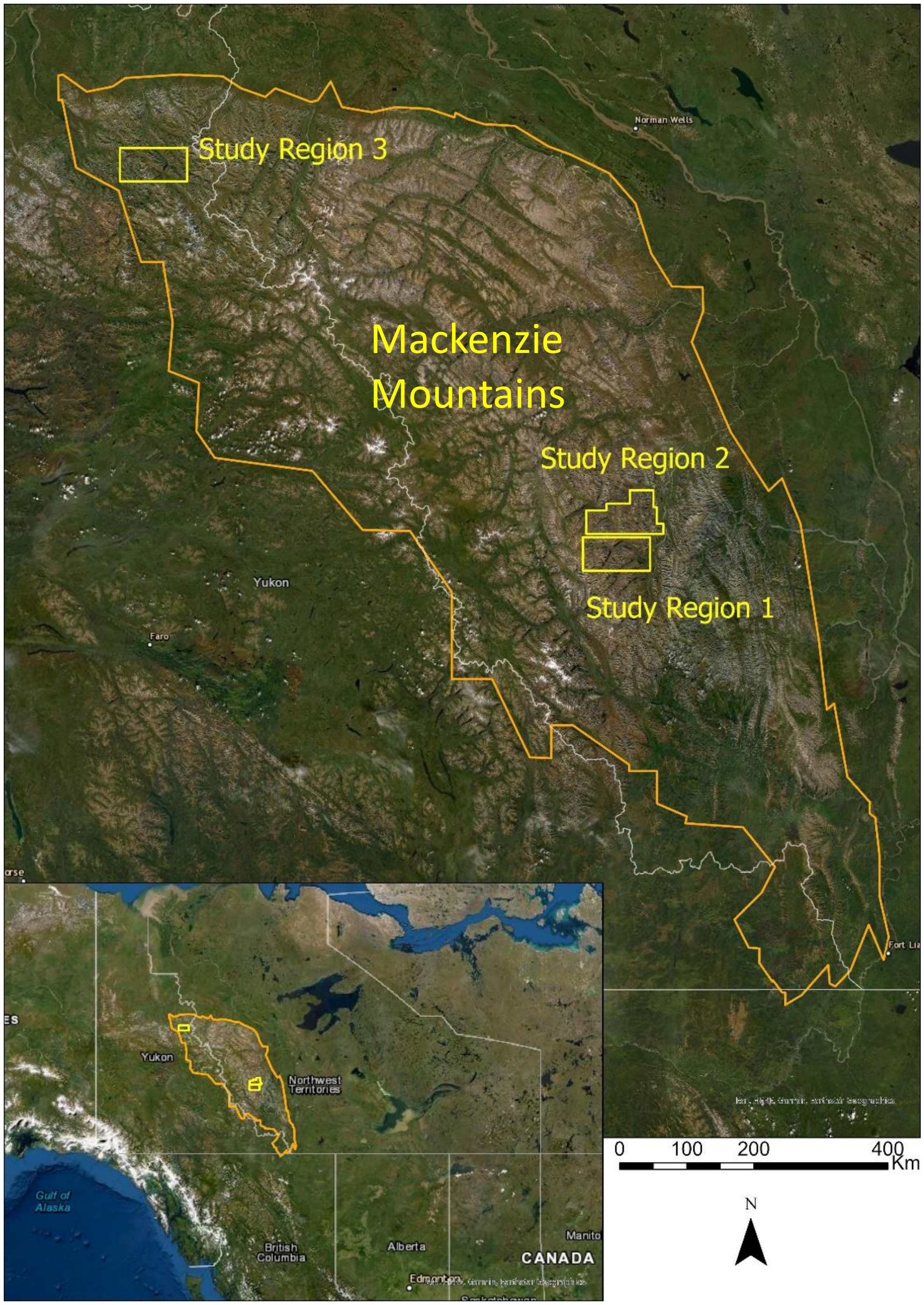


Figure 3: Location of the study area in the Mackenzie Mountains, northwest Canada, bordering Yukon and the Northwest Territories. ERSI World Light Grey Reference base layer; version 2.7.2. Study regions 1, 2, and 3 in black boxes, each approximately 5000 km2 within the Mackenzie Mountain range. World imagery base layer; sources: Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community. WGS 1984 Web Mercator (auxiliary sphere). Mountain range border from Rivas et al. (2017).

Table 1: Elevation summary statistics and surface hydrology estimates for individual study regions

	Max Elevation (m)	Min Elevation (m)	Mean Elevation (m)	Hydrology (%)
Study Region 1	2,639	890	1,753	1.08
Study Region 2	2,558	727	1,639	0.69
Study Region 3	2,542	630	1,576	1.56

Chapter 2: Methods

2.1 Data Sources and Preparation

This study aimed to manually identify rock glaciers from satellite imagery within an ArcGIS Pro 2.9.3 environment (ESRI Inc. 2021), Google Earth Pro 7.3.6 (Google Earth, 2022) and Sentinel Hub (Sentinel Hub, 2022). Identification of rock glaciers was achieved using The World Imagery base map in ArcGIS Pro (version 2.9.3); which is typically composed of multiple data sources, including aerial photography, satellite imagery, and image mosaics. These data sources are processed and combined to create a seamless, high-resolution image of the Earth's surface. The data sources are often optimized for display in ArcGIS Pro and are adjusted to ensure that they align correctly with other geographic data. The ArcGIS Pro World Imagery Base Layer is composed of image mosaics from various sources collected over multiple time frames and updated every three to five years. The collection of image mosaics for the World Imagery Base Layer in ArcGIS Pro involved a systematic approach utilizing various satellites, each with specific collection dates and resolutions tailored to the study regions. Primary identification involved labelling features that met the criteria of a rock glacier with a point. Features that were unclear due to image resolution, cloud cover or needed further clarification were also viewed in

Google Earth Pro (Google Earth, 2022) or Sentinel Hub (2022). Point features were later digitized to polygon features (see section 3.3).

A Digital Elevation Model (DEM) sourced from ALOS AW3D30 (JAXA, 2020) was used to extract terrain information for subsequent geospatial analyses. This DEM was chosen because it covered the area of all three study regions, while higher resolution DEM tiles were available for small regions, full coverage was only available for the 30m ALOS DEM. The DEM was harnessed within ArcGIS Pro to derive a suite of raster datasets, encompassing aspect, slope, potential incoming solar radiation, elevation and the topographic position index. The process involved leveraging ArcGIS Pro's geoprocessing capabilities to extract terrain attributes from the DEM. Aspect, representing the directional orientation of each terrain pixel, was calculated, providing essential insights into slope aspects across the study area. Slope, ascertaining the steepness of terrain, was derived to assess surface gradients. Potential incoming solar radiation (PISR), a fundamental factor for understanding solar energy distribution, was computed. Topographic position index (TPI) was generated, characterizing landform positions within the landscape.

The integration of these derived raster datasets from the DEM facilitated comprehensive terrain analysis and data extraction. The lithology variable was extracted using geologic bedrock compilation maps for the Northwest Territories (Okulitch & Irwin, 2017) and the Yukon Territory (Government of Yukon, 2022) uploaded to ArcGIS Pro (Version 2.9.3). The geology layers were spatially joined to the rock glacier polygons using the Spatial Joins tool available in the Spatial Analyst toolbox in ArcGIS Pro. A one-to-one join was performed to merge attributes from the geology feature layer to the rock glacier points based on their spatial relationship. Lithology types that represented each rock glacier were recorded for the inventory and grouped into 6 classes for modeling purposes. The decision to classify different lithology types into larger groups for modeling purposes was driven by the need for a more parsimonious and interpretable model (Table 2). With more than 10 lithological classes, modeling becomes very complex and computationally demanding. Including a high number of specific lithology types may also reduce the generalizability of a statistical model. By grouping lithology types into larger categories, the number of variables that the model needs to consider is reduced. Combining lithology types into grouped categories also mitigates having specific lithology types that have limited representation in the dataset which may lead to bias within the model. I aim to capture the varied lithological characteristics that may impact the distribution of rock glaciers and contribute to a more comprehensive understanding of this complex geological phenomenon.

Table 2: Lithological classes based on properties of each lithology type and descriptions.

Lithology	Class	Description
Sandstone, quartz arenite, chert, breccia, megabreccia, quartzite	1	The inclusion of this category reflects the prevalence of sandstone and related lithologies in the study area. These lithological types have been recognized as potential source materials for rock glaciers in various studies, as sandstone can be an important factor in the development of these landforms (Ruppel & Lopez, 1988; Haeberli et al., 2006).
Diamictite	2	Diamictite represents a lithology characterized by a mixture of different rock fragments, which can include materials like conglomerate and breccia (Jago, 1974). This category was selected to account for the variability in lithological composition and its potential influence on rock glacier distribution.
Shale	3	Shale is known for its distinct characteristics, such as its fine-grained and easily erodible nature. It is noted that shale contributes to pebbly rock glaciers (Matsuoka & Ikeda, 2001). Its high presence in the study area makes it a significant lithological class that needs to be considered when examining the factors contributing to rock glacier distribution
Mudstone, Mudrock	4	Mudstone and mudrock are lithological categories characterized by fine-grained sediments. Their high count in our classification reflects their potential relevance in understanding rock glacier occurrence.
Dolostone, limestone, grainstone	5	These carbonate lithologies are chosen due to their potential as source materials for rock glaciers. Limestone, in particular, has been identified as a lithology that can contribute to the formation of rock glaciers, making it essential to include in our classification (Wahrhaftig & Cox, 1959).
Siltstone	6	Siltstone, with its fine-grained composition, can play a role in influencing the geological characteristics of the area. This category acknowledges the presence of siltstone and its potential significance in understanding the distribution of rock glaciers in the study region

The DEM derived variables and geology layers were used to extract data for individual rock glaciers, providing attribute data for the rock glacier inventory. The extracted data was also used to inform the statistical model in the cases of slope, elevation, lithology, TPI and PISR. TPI was calculated using a 33-cell window. The median TPI values form each rock glacier polygon were extracted to reflect TPI for individual rock glacier based on the average of their surrounding.

2.2 Consensus Method for Mapping Rock Glaciers

Identifying rock glaciers can be challenging, especially from satellite imagery, as they often appear similar to other landforms such as protalus lobes, protalus ramparts or rockslides. To overcome this challenge, an adapted consensus-based mapping method was utilized (Way et al., 2021), using two mappers and multiple stages of feature mapping to reduce subjectivity and expand the feature database. Additionally, features were identified using criteria following the International Permafrost Associations Working Group (RGIK, 2022) including vegetation patterns, color, ridge, and furrow features. Each mapper independently searched for rock glaciers in ArcGIS Pro within Study Regions 1 - 3. The mappers included the lead author (Rabecca Thiessen), as the primary mapper and (Caitlin Lapalme), an experience rock glacier mapper, as the secondary mapper. The two datasets were then aggregated, and each mapper assigned a confidence level to individual rock glaciers, ranging from 1 (low confidence) to 3 (high confidence) (Way et al., 2021). Once the mappers assigned their confidence levels, the data were analyzed to determine the final dataset to be used for further analysis. If 50% or more of the data points had a confidence level of 3 from both mappers, the data was considered sufficient and is used as the final dataset. If the frequency of datapoints at confidence level 3 are lower, another round of identification would have been done to refine the dataset and improve its accuracy. Although confidence levels were assigned through the mapping process (see section 3.1), it was decided to use the entire aggregated dataset of 530 rock glaciers for the inventory as well as modeling. Including all features that were identified was thought to make the model more robust when considering nuances of probable rock glacier features. In future studies it may be pertinent to use a finer sample size, only including features which both mappers identified at confidence level 3, in future model iterations.

Features of interest (FOI) were mapped by both mappers. FOI include protalus lobes (embryonic rock glaciers), protalus ramparts, debris-covered glaciers and highly obscured features. These features are not considered rock glaciers or cannot be fully identified due to resolution issues but may become relevant to the study region as they develop, or improved image quality is obtained. The FOI from both mappers were aggregated into one dataset that can be further investigated in future work. Rock glacier activity was determined using the guidelines presented in section 1.1.

2.3 Digitizing the Spatial Extent of Rock Glaciers

Digitizing rock glaciers is the process of converting analog data or images of rock glaciers into digital format using Geographic Information System (GIS) software. The resulting digital data can be used to analyze the distribution, characteristics, and dynamics of rock glaciers over time. Rock glaciers were initially identified by mappers using points. Each identified feature was then digitized using the polygon tool in ArcGIS Pro. Rock glaciers were digitized at a scale of 1:5000 (Munroe, 2018) using the extended geomorphological footprint (EGF). The EGF, as specified by the IPA, encompasses the entire rock glacier, from the rooting zone to the external frontal and lateral margins. Digitizing rock glaciers can be challenging, particularly when it comes to the rooting zone. The rooting zone is the area of sediment and rock that surrounds and supports the head of the rock glacier and is critical for understanding the stability and evolution of the feature. Accurately digitizing the rooting zone can be difficult for several reasons. One of the main challenges is the variability of the landscape. The rooting zone can be obscured by vegetation or snow, making it challenging to accurately map. The complex structure of the rooting zone, including the presence of ice, can also make it challenging to accurately digitize. In this study, the rooting zone was considered to be located near the head of the rock glacier, close to the debris source, and where the first indications of movement were seen. The rooting zone was often recognized by a slight depression between the debris accumulation and the body of the rock glacier.

2.4 Background Data Points Representing the Absence of Rock Glaciers

Having a balanced data set with equal numbers of presence (i.e., a point that represents an inventoried rock glacier) and absence (i.e., a point that represents the absence of a rock glacier) points is essential for achieving accurate and robust results (Barbet-Massin et al, 2012). Without sufficient absence points, the model may produce biased or misleading results (Barbet-Massin et al., 2012). Therefore, 530 random points (equal to the number of rock glaciers) were generated to ensure the data were balanced for statistical analyses. These absence (or background) points were randomly distributed between the three study regions and any points that fell within one meter of a mapped rock glacier were redistributed until they were outside of a mapped rock glacier.

2.5 Predictive Model and Model Optimization

2.5.1 Random Forest Model

Random forest is a machine learning technique that is often used for classification and regression tasks (Marmion et al., 2008; Belgiu & Drăguț, 2016; Janowski et al., 2021). Random forest methods have been used in a variety of applications, including remote sensing and environmental studies, due to the high accuracy and ability to manage complex datasets (Gislason et al., 2006; Belgiu & Drăguţ 2016). In the context of modeling rock glacier distribution, random forest has shown promise in accurately predicting the activity of rock glaciers based on high-resolution imagery, kinematic estimates, and rock glacier detection (Brenning, 2009; Groh & Blöthe 2019). The random forest model uses a decision tree algorithm that generates a 'forest' in which each tree is trained on a subset of randomly selected data

(Breiman, 2001). Once the random forest model was trained, it was used to make predictions on the validation subset of data as well as on original testing data. The model was evaluated using various metrics such as accuracy, precision, recall, F1 score, and a confusion matrix. The random forest model was used to predict the response variable of rock glacier presence or absence. The variable importance function was used to determine the importance of the predictors in the model. All statistical analysis and model evaluations for this model were performed using R Studio version 4.2.2. In a Random Forest model, the algorithm generates a decision tree for each tree in the forest. Various configurations were explored, including different values for the *ntree* (number of trees) parameter (25, 75, 100, 200 and 500). The percentage of the response variable explained by the model was assessed for each configuration, with the model utilizing 100 trees yielding the highest metrics. Furthermore, different values of the *mtry* (the number of variables included in each tree), parameter were examined, ultimately determining *mtry* = 2 as the optimal choice. In this case, there were two variables randomly selected for each tree. There are several advantages to using forest-based classification for rock glacier modeling. One advantage is that it can manage multiple predictor variables, making it possible to identify complex relationships between environmental factors and rock glacier presence or absence. Another advantage is that it is relatively easy to interpret, making it a useful tool for identifying the most important environmental factors. Previous studies demonstrate the power of forest-based classification for permafrost and thaw susceptibility modeling (Konig et al., 2019; Rudy et al., 2019; Zhao et al, 2022).

2.5.2 Forest-based Classification and Regression Model

In a geographical information system such as ArcGIS Pro, an adaptation of Breiman's (2001) random forest algorithm, the forest-based classification and regression (FBCR) model can be employed in the same way as an RF model to investigate spatial data. Forest-based classification is another tool that can be used for modeling rock glacier presence and absence. The process involves using machine learning algorithms to identify relationships between rock glacier presence and various environmental factors, such as topography and geology. The goal of the analysis is to create a predictive model that can be used to identify areas where rock glaciers are likely to be found. There are several parts to the forest-based classification process, each of which plays a key role in creating an accurate model. The measures used to evaluate the random forest model include Model out-of-bag (OOB) error, variable importance, classification diagnostics training, classification diagnostics testing, and confusion matrix prediction. The OOB error rates were calculated for different numbers of trees. The variable importance represents the percent contribution of each variable in building the model. The classification diagnostics provide information on the accuracy, sensitivity, specificity, F1 score, and Matthews Correlation Coefficient (MCC) for both training and testing data. Finally, the confusion matrix provides information on the number of true positives, true negatives, false positives, and false negatives. In evaluating the models, the following were considered; the OOB error, MCC, and confusion matrix collectively to determine the overall quality of each model run. A better model would exhibit a lower OOB error, a higher MCC value, and a more balanced and informative confusion matrix, indicating superior predictive capability. The application of FBCR to rock glacier modeling shows promise in producing probability surfaces derived from supervised machine learning when supplied with relevant explanatory variables. It is important to note that the Forest-based classification and regression tool creates a prediction surface based on rasters and produces binary presence (1) and absence (0) surfaces rather than providing probabilistic values, facilitating a clear delineation of rock glacier likelihood.

2.5.3 Generalized Additive Model

The spatial distribution of rock glaciers can be modeled using a generalized additive model (GAM) in R (R Studio, Version 4.2.2). In this study, a GAM in R with restricted maximum likelihood (REML) method was used to model the spatial distribution of rock glaciers with a binary dependent variable, '0' and '1' absence and presence, respectively, and six independent variables: slope, aspect, topographic position index, lithology, elevation, and potential incoming solar radiation.

In the pursuit of accurately modeling the relationships between independent and dependent variables in the context of rock glacier likelihood prediction, this study employed a rigorous process of model optimization. The optimization of the Generalized Additive Model (GAM) involved several key steps, each geared toward enhancing the model's performance and interpretability. Feature selection played a pivotal role in this optimization process. By iteratively removing non-significant variables from the model based on statistical significance tests, a subset of relevant independent variables contributing significantly to explaining variation in the response variable was identified. This step not only improved model interpretability but also streamlined its performance. Incorporating smoothing parameters is a crucial aspect of GAMs to capture non-linear relationships with the response variable. To select the optimal smoothing parameters, a data-driven approach utilizing the Generalized Cross Validation (GCV) criterion was adopted. This criterion helped strike a balance between model fit and complexity, preventing overfitting and ensuring that the model captured underlying data patterns effectively. The use of the Restricted Maximum Likelihood (REML) method further solidified the model optimization process. By accounting for the complexity of the model and estimating random effects, REML ensured robust estimates of fixed effects, ultimately enhancing model accuracy and generalizability. This approach considered both model fit and complexity, complementing the GCV criterion's focus on performance assessment. Cross-validation was employed as a key tool to evaluate the optimized GAM's performance.

By splitting the data into training and validation sets, the model's predictive ability was assessed using unseen data. Additionally, the model's assessment on data from a testing site with no presence or absence labels added an extra layer of validation to its generalizability. This comparative analysis affirmed the GAM's suitability for capturing non-linear relationships and demonstrated its superior predictive performance.

The optimization techniques, elucidated that elevation, slope, PISR and TPI were the significant variables in predicting rock glacier presence. The significant independent variables were included in the model as continuous variables apart from lithology. Lithology was included as the only categorical variable in the model. This variable was classified into six classes by considering lithological characteristics such as erodibility, grain size, and composition based on literature (Haeberli et al., 2006; Weckworth & Pisarska-Jamrozy, 2015; Moosdorf et al., 2018). Classifying lithology into six classes enhances the interpretability of the model results by grouping lithology types with similar characteristics together, allowing for clearer insights and patterns to be revealed. This method was chosen for several reasons: first, it simplifies the model without sacrificing essential information, as lithology has been shown to affect rock glacier spatial distribution (Johnson et al, 2007; Charbonneau & Smith, 2018). Secondly, it facilitates uncovering the potential influences of specific lithology classes on the response variable.

The ‘aspect’ variable is commonly converted from a cyclical variable to linear variables ‘eastness’ and ‘northness’ to reduce dimensionality and error caused by the cyclical nature (Ramskogler et al., 2023).

Spearman’s Rank Correlation coefficient was used to evaluate multicollinearity amongst the variables. This method measures the statistical dependence between two variables. Eastness and PISR had the strongest correlation (0.72). All other variables had weaker correlations, (< |0.5|). Due to the high correlation of PISR and Eastness, the latter was removed from the final model. Although the Spearman’s rank correlation did not indicate a strong correlation association between PISR and northness as it did with eastness, it is well-established that there exists a relationship between these variables (Piedallu & Gégout, 2008). Northness also returned as not significant in all model iterations and was therefore left out of the final model. Thus, the exclusion of aspect from the model is justified, given that the PISR variable is still included. The variables included in further model iterations had VIF values that were less than 3. This suggests that they are not highly correlated with each other and are suitable for use in the model (Craney & Surles, 2002).

Generalized Additive Models (GAMs) have previously been used for investigating the spatial distribution of rock glaciers in remote regions (Brenning et al., 2007). GAMs have been used successfully in other geomorphology studies (Miska & Jan 2005; Rudy et al., 2017). There are several reasons why a GAM is an appropriate model selection for this purpose, compared to other models. GAMs are highly flexible and can capture non-linear relationships between predictors and the response variable (Hastie and Tibshirani, 1990). Rock glacier spatial distribution is likely to be influenced by a range of factors such as slope, aspect, and topography, which are unlikely to have a linear relationship with the occurrence of rock glaciers. A GAM can incorporate non-linear terms in the model, allowing for a more realistic representation of the complex relationships between the predictors and response (Hastie and Tibshirani, 1990). GAMs can handle missing data and outliers effectively, which is important for analyzing data collected in remote regions where data quality may be compromised (Wong et al., 2014). By incorporating smoothing splines in the model, GAMs can estimate the response variable at each location even if some predictors are missing or if there are outliers in the data. This makes GAMs a more robust model selection for analyzing spatial data than other models that may be more sensitive to missing data and outliers. Finally, GAMs are computationally efficient and can handle large datasets, which is important when working with spatial data (Wood, 2017).

In R, the default smooth term in a GAM is a thin-plate spline, which is a type of basis function that is smooth and flexible. The general equation for a GAM can be written as:

$$y = f1(x1) + f2(x2) + \cdots + fp(xp) + \varepsilon \quad (1)$$

where y is the response variable, f1 to fp are the smooth functions representing the relationship between each predictor variable x1 to xp and the response variable, and ε is the error term. The goal of a GAM is to estimate the smooth functions f1 to fp that best fit the data while minimizing the error term ε. The GAM was implemented in RStudio version 4.2.2 using the 'mgcv' package version 1.8.41 (Wood, 2011). The response variable was binary and represented the presence or absence of rock glaciers. The explanatory variables were potential incoming solar radiation (PISR), aspect, topographic position index (TPI), slope, elevation, and lithology. These variables were selected based on their known association with rock glacier development (e.g., Barsch, 1996; Janke et al., 2013).

After several model iterations, the decision was made to use the default values for the GAM, including the thin-plate regression spline smooth function for continuous predictors and a binomial distribution for the response variable, due to the higher performance of the default model. This was determined by evaluating model metric AIC. The thin-plate regression spline is a type of spline that uses a radial basis function to construct the spline function (Wood, 2003). It estimates the response variable as a weighted sum of radial basis functions evaluated at each data point, where the weights are determined through a fitting process. The degrees of freedom (DF) were selected based on generalized cross-validation (GCV) techniques, with the lowest GCV being produced with 4 DF. The model was fit using restricted maximum likelihood (REML) estimation to restrict the smoothing parameter (Wood, 2011). The significance of each variable was determined using a likelihood ratio test (LRT) with a p-value of 0.05 as the threshold for statistical significance. Backward-step regression was used to determine which variables had the most effect on determining rock glacier presence. This method was also used when introducing interaction terms. To account for variability when running multiple model iterations, a random subset of the data was selected for each model iteration. No missing or zero values were found across the dataset, and presence and absence points were evaluated for potential imbalances with each iteration.

The performance of the default GAM was evaluated using model diagnostics, including the deviance explained (DE), adjusted R-squared (R2adj), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The DE and R^2adj values were used to quantify the amount of variance in the data that was explained by the model. Higher values indicate better performance. Model accuracy was evaluated using a confusion matrix. A confusion matrix calculates and displays the number of true positives, true negatives, false positives, and false negatives. Variance inflation factors (VIFs) were used to determine the degree of multicollinearity between the variables and therefore the validity of the model results (Thompson et al., 2017).

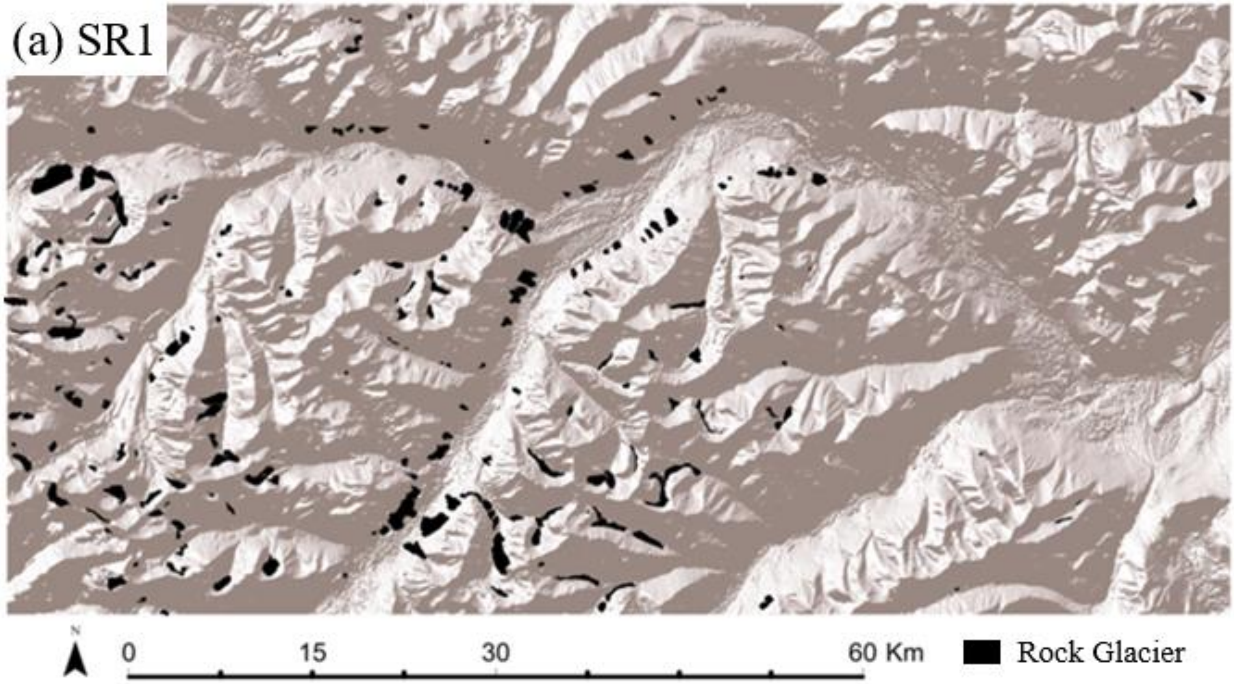
2.6 Rock Glacier Probability Mapping

The probability values generated from the successful model were used in conjunction with Inverse Distance Weighted (IDW) interpolation to visualize the probabilities from the test data (30%) as well as new test data from a test region adjacent to SR1. Analysis of the resulting probability map generated in SR1 form the test data was compared to the observed rock glaciers. To validate the generalizability of the model, a novel region 255 km^2 was delineated. Independent variables slope, elevation, TPI, PISR, and lithology were extracted from 10,000 regularly spaced points within this test region adjacent to SR1 (Extent: 62.564337°N, 62.502392°N, -127.108927°W, -126.975316°W). This test region was chosen based on the clarity of the imagery, an initial investigation confirming that rock glaciers were present, and little to no cloud cover that would obscure features. The 10,000 points with extracted variables were then run through the GAM model, which generated probabilities of rock glacier presence at each point. A surface representing the probabilities of rock glacier presence was generated using the Inverse Distance Weighting (IDW) tool in ArcGIS Pro (V. 2.9.3), interpolating the values of each point. The resulting surface represents the spatial distribution of rock glacier probabilities across the test region. The IDW surface was classified into five probability intervals based on manual breaks. Rock glaciers were then delineated within the test region and rasterized based on the IDW surface and probability data points. The counts of pixels falling into each probability category were determined by analyzing the reclassified rock glacier rasters. The counts were used to assess the distribution and prevalence of rock glacier probabilities that occurred in positive cases of rock glaciers.

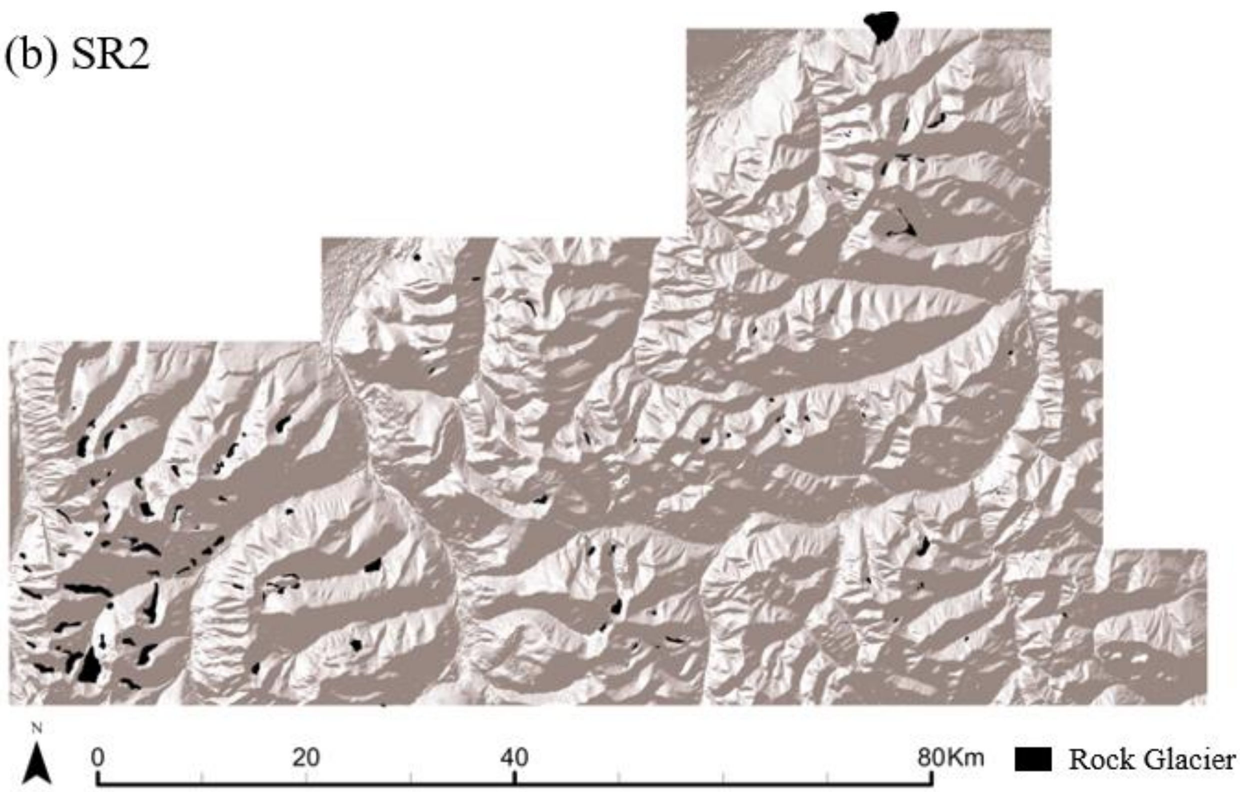
Chapter 3: Results

3.1 Rock Glacier Inventory

Over 500 potential rock glacier features were identified across the three study regions in the Mackenzie Mountains (Figure 4). Each rock glacier was digitized by the primary mapper at a scale of 1:5,000 using the extended geomorphological footprint, which includes the rooting zone, frontal and lateral margins (RGIK, 2022). Examples of active digitized rock glaciers are presented in Figure 5. Topographic and potential radiation characteristics for rock glaciers were extracted and computed (Table 3). The final count of rock glaciers identified and assigned a confidence level of three by both mappers was 158/234 rock glaciers in SR1, 83/120 in SR2, and 96/176 in SR3. Each region has >50% of rock glaciers identified at confidence level 3. Of the total number of mapped features (530), 337 were matched at confidence level 3, resulting in 64% agreement at level 3 confidence. The potential activity of rock glaciers in each region is summarized in Table 4. Between both mappers, 381 FOI were identified. There were 149 FOI identified in SR1, 91 and 141 for SR2 and SR3, respectively.



(a) SR1
0
15
30
60 Km
Rock Glacier



(b) SR2
0
20
40
80Km
Rock Glacier

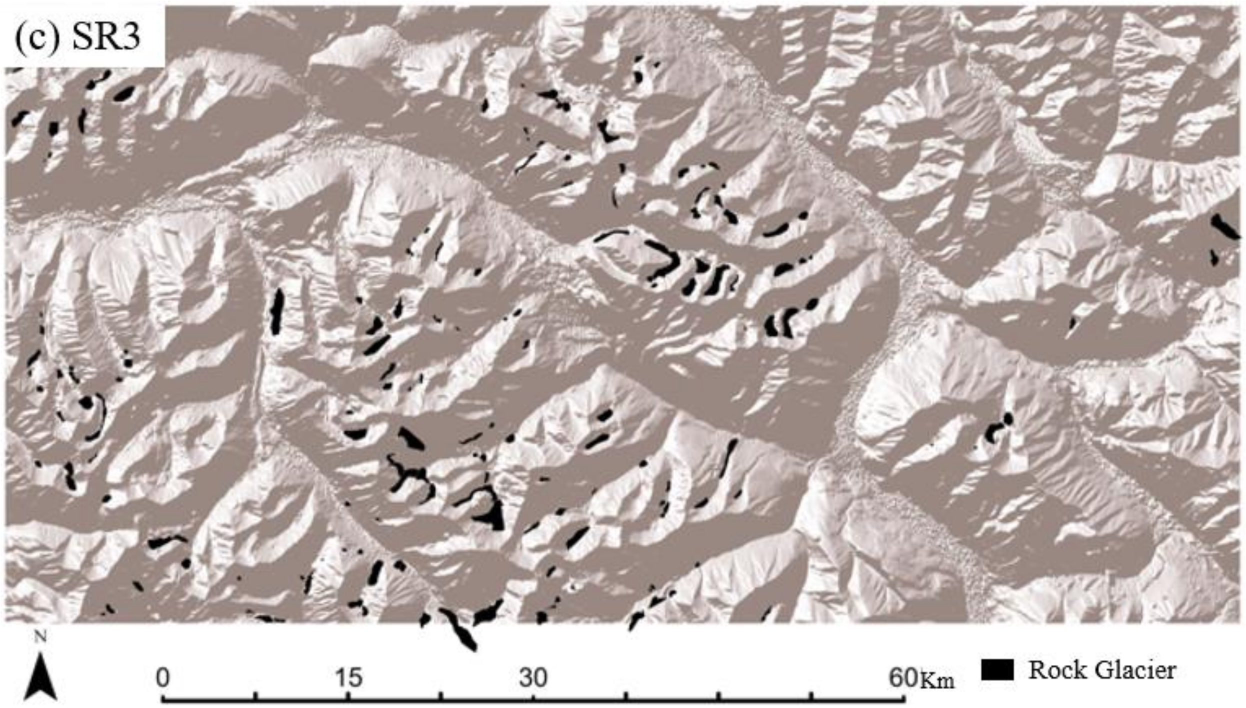


Figure 4: Rock glacier polygons in each individual study region. (a) 234 rock glaciers digitized in study region 1 (127.1014994°W, 62.7930522°N). (b) 120 rock glaciers digitized in study region 2 (127.0056380°W, 63.0115499°N) (c) 176 rock glaciers digitized in study region 3 (133.3585886°W, 65.0840868°N).). World imagery base layer; sources: Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community. WGS 1984 Web Mercator (auxiliary sphere).

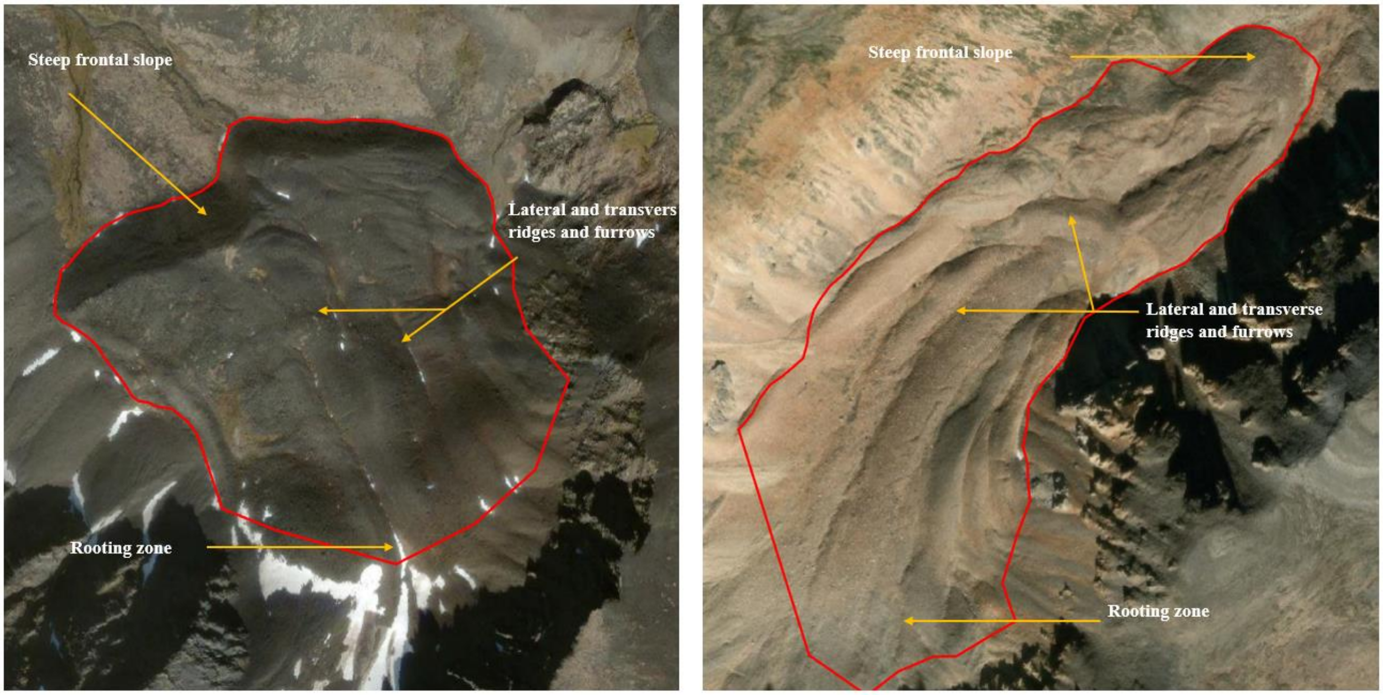


Figure 5: Examples of digitized rock glaciers. (a) active rock glacier located in SR3 (133.6974351°W 65.0523500°N) (b) active rock glacier located in SR2 (127.2784354°W 63.0250928°N). The red line is the extent of each rock glacier from the rooting zone to the steep frontal slope. Both rock glaciers exhibit ridge and furrow topography, indicating an active status. World imagery base layer; sources: Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community. WGS 1984 Web Mercator (auxiliary sphere).

Table 3: Characteristics of each rock glacier polygon within each study region with minimum, maximum, mean and range values for elevation, slope, TPI, PISR, length, width, and area. N=530.

Study Region	**SR1**	**SR2**	**SR3**
Elevation (m a.s.l.)			
Average	1667	1707	1467
Min	1120	939	1009
Max	2181	2070	1977
Range	1061	1131	968
Slope (˚)			
Average	17	17	16
Min	5	8	6
Max	29	31	33
Range	24	22	27
Topographic position index (TPI)			
Average	-36	-40	-45
Min	-128	-88	-146
Max	17	31	15
Range	144	119	161
Potential incoming solar radiation (PISR) (W/m^2)			
Average	300	283	284
Min	182	182	186
Max	436	431	431
Range	254	249	245

Table 4: Rock glacier activity status within each region using characteristics of activity and inactivity, classified using optical satellite imagery. N=530.

Study Region	**Inactive**	**Active**	**Total**
SR1	35	199	234
SR2	18	102	120
SR3	18	176	176

3.2 Rock Glacier Inventory Attributes

The length, width, and area of each rock glacier were recorded for each study region (Table 5). Three separate one-way ANOVAs were performed on the rock glacier size data to elucidate potential differences within the three study regions. The average slopes for rock glaciers were 16˚ (SR1), 17˚ (SR2) and 15˚(SR3). A one-way ANOVA revealed that there is a significant difference in slope values between the three study regions (P-value = 0.002298).

Table 5: Summary statistics for rock glacier size within each study region. N=530.

Study Region	**SR1**	**SR2**	**SR3**
Length (m)			
Average	897	909	1012
Min	122	101	125
Max	3826	4124	4186
Range	3703	4023	4061
Width (m)			
Average	988	941	948
Min	130	218	176
Max	3503	4723	3716
Range	3373	4505	3540
Area (km^2)			
Average	0.52	0.52	0.52
Min	0.01	0.01	0.03
Max	4.88	6.91	3.19
Range	4.86	6.89	3.17
Total Area of mapped rock glaciers (%)	2.44	1	2

The analysis of the rock glacier data revealed unique characteristics across the study regions. Slope, elevation, TPI, and PISR for the rock glaciers compared to the background points are summarized in Table 6. There is a significant difference in the minimum elevation, maximum slope, maximum TPI, and minimum PISR when comparing the presence and absence data of rock glaciers. All rock glaciers showed an average elevation of 1610 m (all elevations are a.s.l.), with the majority falling between 1200 m and 2000 m, with a range of 1242 m. The slope was calculated by taking the median from each rock glacier polygon. Many rock glaciers had slopes that ranged from 10˚ to 25˚, with an average slope of 16˚. The maximum slope observed was 33˚ and the minimum slope was 5˚. Most rock glaciers had negative TPI values, indicating that they were situated lower than their surroundings. The average TPI for rock glaciers was -39.96, with the majority ranging from -70 to -25. The maximum TPI was 30.10, while the minimum was -146. PISR values were extracted for the snow-free period, July 15 – September 15. The rock glaciers exhibited a wide range of PISR values. The average was 290 W/m^2, with the majority falling between 182-212 W/m^2 and 402-422 W/m^2. The maximum observed value of PISR was 436 W/m^2, while the minimum was 182 W/m^2. Rock glaciers are shown to cluster at lower levels of PISR and higher levels of PISR. The area covered by identified rock glaciers in each region was from 1% to 2.44% with SR1 having the greatest coverage of rock glaciers.

Aspect was analyzed for rock glaciers within the three study regions using the Aspect tool in ArcGIS Pro version 2.9.3 with a 30 m DEM. The median aspect values were extracted for each rock glacier polygon using the Zonal Statistics as Table tool (ArcGIS Pro, v. 2.9.3). The aspect values were divided into nine directional categories, representing different slope orientations. The frequencies of the rock glacier aspect were determined and are presented in Figure 6. In SR1, of the 234 identified features, many were found on northwest and northeast-facing slopes, with a total of 54 and 48 occurrences, respectively. In SR2, the most frequent orientations of the 120 identified features were northeast and east, with 29 occurrences each. The northwest aspect has only slightly less frequency (25). In SR3, the 176 features were noted to have the highest occurrence in the northeast, northwest, and East orientations, (47, 34, and 33, respectively). SR1 includes 199 active rock glaciers and 35 inactive ones. The predominant aspects of the active rock glaciers in SR1 are northeast and northwest. The 35 inactive rock glaciers have a predominant northwest aspect. In SR2, there are 102 active rock glaciers and 18 inactive ones. Active rock glaciers in this region are largely oriented east and northeast, with frequencies in the northwest and west also common. The 18 inactive rock glaciers in SR2 have a higher occurrence of northwest than other aspects. The third study region, the northern study region, has 158 active rock glaciers and 18 inactive rock glaciers. The 158 active rock glaciers in SR3 have predominantly northeast, northwest, and east aspects, while the inactive rock glaciers occur more commonly on southeast slopes.

The lithology data extracted form 530 rock glaciers from each study region revealed a variety of rock types, predominantly sedimentary (Table 7). SR1 exhibited mudrock (38%), shale (26%, and diamictite (16%) as the dominant rock compositions. While the overall bedrock lithology in SR1 was mainly sandstone (32%), mudrock (20%), and dolostone (17%). In SR2, the primary rock glacier lithology types consisted of sandstone (33%) and shale (25%). The overall bedrock lithology of SR2 was mainly dolostone (24%) and sandstone (24%). SR3 had a high occurrence of siltstone, accounting for 48% of its rock glacier lithology, followed by shale (38%). The overall lithology of SR3 was primarily siltstone (48%). Analyzing the entire mountain range, the primary lithologies were found to be shale (20%), dolostone (17%), and limestone (17%). Sedimentary rocks make up 64% of the total lithologies found in the bedrock geology of the Mackenzie Mountains.

Table 6: A summary of rock glacier attributes such as slope, elevation, PISR, and TPI compared to the background data points used for absence data. N=530 for rock glacier and N=530 for background points.

Background Points				
Variable	**Elevation m a.s.l**	**Slope (˚)**	**TPI**	**PISR W/m²**
Most Common Range	1100 - 1970	10 - 36	(-)40 - 4	144-234, 369-459
Maximum	2431	70.58	175.65	547
Minimum	666	0	-130.15	54
Average	1517	24.24	-0.42	328
Rock Glaciers				
Variable	**Elevation m a.s.l**	**Slope (˚)**	**TPI**	**PISR W/m²**
Most Common Range	1200 - 2000	10-25	(-)70 -(-) 25	182-212 , 402-422
Maximum	2181	33.49	31.1	434
Minimum	939	5.05	-146	182
Average	1610.11	16.58	-39.96	291

Table 7: Frequency of lithology types that occur within the entire study regions compared to lithology types that are predominately found within rock glacier polygons extracted for each rock glacier within the three study regions. Lithology data extracted from the bedrock geology layer (Okulitch and Irwin, 2017; Government of Yukon 2022).

Lithology Type	**Frequency in SR1 RGs (%)**	**Frequency in SR2 RGs (%)**	**Frequency in SR3 RGs (%)**	**Frequency SR1 (%)**	**Frequency SR2 (%)**	**Frequency SR3 (%)**
diamictite	16.2	1.7	0.0	6.0	6.0	0.00
dolostone	5.1	6.7	0.6	22.0	24.0	16.00
megabreccia	0.4	0.0	0.00	2.0	0.0	0.00
mudrock	38.0	13.3	0.00	7.0	12.0	0.00
sandstone	14.1	32.5	0.00	33.0	14.0	0.00
shale	26.1	25	37.5	7.0	13.0	17.00
grainstone	0.0	6.7	0.00	0.0	5.0	0.00
limestone	0.0	1.7	0.00	18.0	13.0	0.00
mudstone	0.0	3.3	11.9	2.0	7.0	6.00
quartz arenite	0.0	9.2	0.00	0.0	3.0	2.00
breccia	0.0	0.00	1.1	0.0	0.0	7.00
quartzite	0.0	0.00	1.1	0.0	0.0	9.00
siltstone	0.0	0.00	47.7	1.0	0.0	33.00
gypsum-anhydrite	0.0	0.0	0.0	1.0	1.0	0.0
conglomerate	0.0	0.0	0.0	1.0	0.0	0.0
mixtite	0.0	0.0	0.0	0.0	3.0	0.0
Chert	0.0	0.0	0.0	0.0	0.0	6.0
diorite	0.0	0.0	0.0	0.0	0.0	4.0

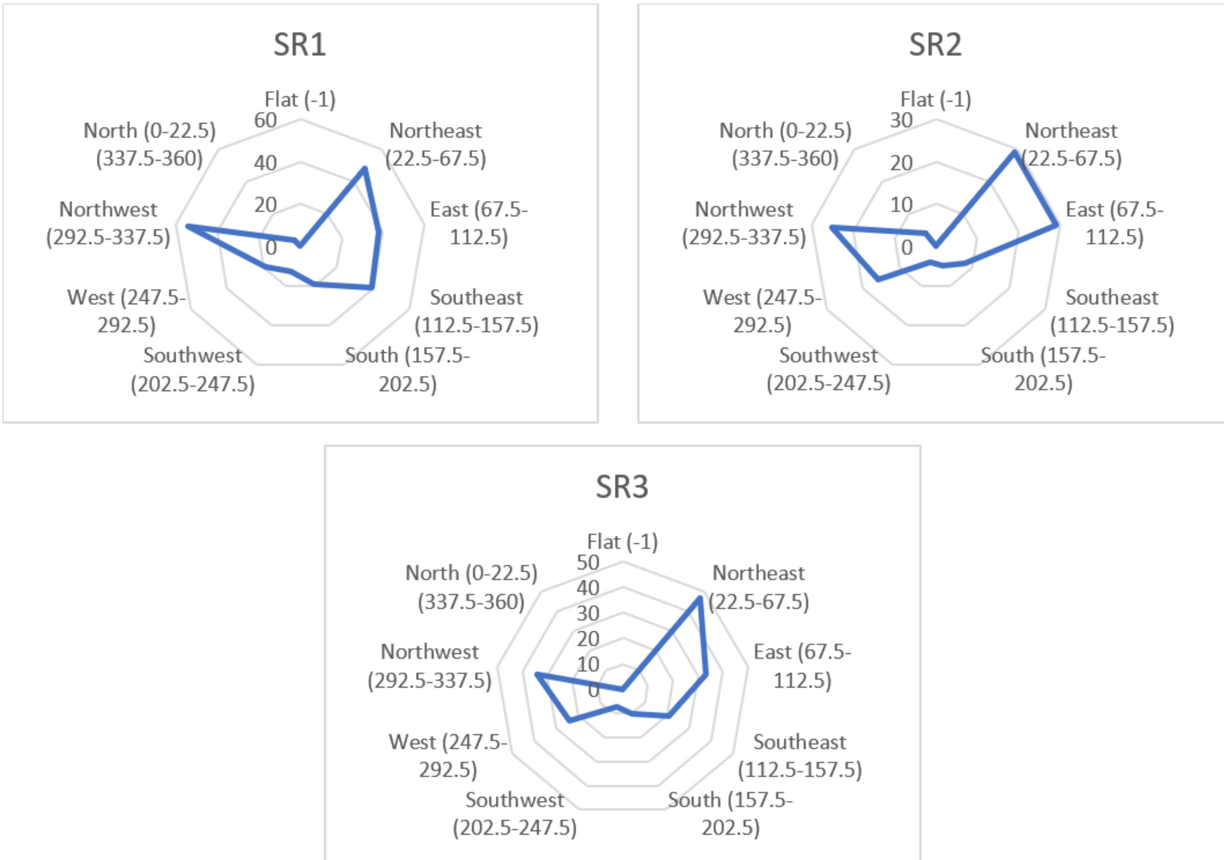


Figure 6: Rose charts depicting the occurrence of aspect for rock glaciers within each study region. Northwesterly and Northeasterly aspects are most common among the rock glaciers in each region. SR1, N=234, SR2, N=120, SR3, N=176.

3.3 Lithology Classification for Modeling

The selection of lithology categories was grounded in the geological diversity of the study area and supported by established literature that identifies these lithological types as potentially influential in rock glacier formation (Ikeda & Matsuoka, 2006; Johnson et al., 2007; Carbonneau & Smith 2018). The grouping of lithologies was based on the properties of each type from the literature and grouped into 6 classes (Table 2). In this study, I analyzed different models to investigate the influence of the categorical variable lithology on the distribution of rock glaciers. A Generalized Linear Model (GLM) was run in order to determine the effect of the specified lithology type on rock glacier presence. For each model, the significance of the class was considered. Class 3 and class 5 had some significance ($p<0.001$ and $p<0.01$, respectively), while all other classes were nonsignificant. With more than one class having some significance within the model, lithology was not removed from the optimal GAM model. However, when including lithology in a GAM model or a random forest model the significance of each class is not returned; instead only one significance is returned for the categorical variable, which was in both cases nonsignificant.

3.4 Random Forest Model

A random forest model was trained on 70% of the data and assessed on the remaining 30%. Each subset was randomly generated and had a balanced number of presence and absence points. The evaluation metrics for the random forest model were accuracy, precision, recall, F1 score, sensitivity, and specificity. The results are presented for both the training and validation datasets in Table 8. The random forest model achieved a perfect accuracy of 1 on the training dataset, indicating that all instances were correctly classified whereas for the testing data the accuracy was 0.87. The precision of the model, representing the proportion of correctly identified positive instances out of predicted positives, was determined to be 1 on the training data and 0.87 on the validation data.

Table 8: Random Forest model metrics for both training and testing data.

Metric	Training	Validation
Accuracy	1	0.874214
Precision	1	0.865031
Recall	1	0.886792
F1 Score	1	0.875776
Sensitivity	1	0.886792
Specificity	1	0.861635

3.5 Forest-based Classification and Regression Model

Several FBCR models were trained using different sets of explanatory variables to classify two categories of response data (1 and 0) indicating rock glacier presence and absence, respectively. After several iterations, the results of the two best models are presented in this section, models RF14 and RF16. The RF14 model does not include the lithology variable while the RF16 does. Both models used 100 trees and randomly sampled two variables per tree and 30% of the data was excluded for validation. The out-of-bag errors (OOB) for RF14 were 33.90 and 33.53 for 50 and 100 trees, with mean squared error (MSE) of 34.76 and 33.63 for category 0 (absence), and 32.93 and 33.39 for category 1 (presence). The variable importance rankings for RF14 were as follows: Slope (17.94%), PISR (16.63%), TPI (16.54%) and elevation (16.24%). The OOB errors for RF16 were 32.15 and 31.34. The MSEs were 30.88 and 29.83 for category 0, and 33.44 and 32.86 for category 1. The variable importance rankings for RF16 were as follows: Lithology (15.67%), TPI (14.14%), slope (13.95%), PISR (13.55%) and elevation (13.67%).

The classification diagnostics for the training data in both models were 1.00 (100%), indicating the model may be overfitting the training data. In model RF14, the classification diagnostics on the validation data showed an F1 score of 0.72, Matthews Correlation Coefficient (MCC) of 0.44, sensitivity of 0.71 and an accuracy of 0.72 for category 0. For category 1, the F1 score was 0.72, MCC was 0.44, sensitivity was 0.73 and the accuracy was 0.72. The confusion matrix showed 102 true negatives and 108 true positives. For model RF16, the classification diagnostics on the validation data showed an F1 score of 0.68, MCC of 0.34, sensitivity of 0.69 and an accuracy of 0.67 for category 0. All diagnostics were the same for category 1 as they were for category 0, except sensitivity, which was 0.66. The confusion matrix showed 107 true positives and 111 true negatives. Classification base prediction points were generated for both models. The RF14 model had 103 misclassifications and 941 correctly classified features, whereas the RF16 model had 131 misclassified features and 913 correctly classified features. Prediction classification surfaces were created for both (FBCR) models (Figures 7 and 8). The area predicted to be covered by rock glaciers for RF16 was 29.1% of the total area covered by the Mackenzie Mountain range, which spans over 700 000 km^2. This equates to still having to manually investigate over 200 000 km^2. The area needed to be manually investigated using the RF14 model prediction surface is 28.1% or over 200 000 km^2. While the binary classification has reduced the total area, the result is not significant enough to reduce the time it would take to investigate the total region for rock glacier occurrence.

The FBCR model was run on an individual study region (SR1) to determine if increasing the resolution would lead to greater accuracy of the model, reducing the area that needed to be investigated (Figure 9). The model metrics used to determine the model fit returned 100% accuracy for the training data and 71% accuracy for predicted presence and absence of rock glaciers (Table 9).

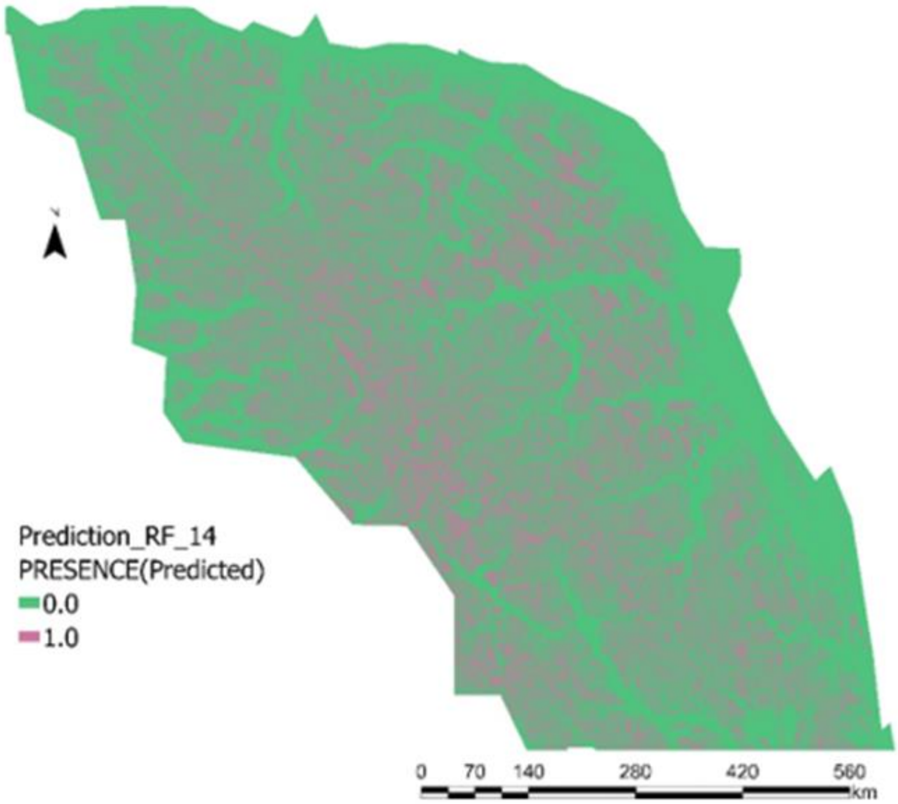


Figure 7: Prediction surface created from model RF14, forest-based classification, and regression (ArcGIS Pro, version 2.9.3). Represents the probability of the presence (1) and absence (0) of rock glaciers in the Mackenzie Mountains. The RF14 model includes variables slope, TPI, PISR, and elevation. Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community. WGS 1984 Web Mercator (auxiliary sphere).

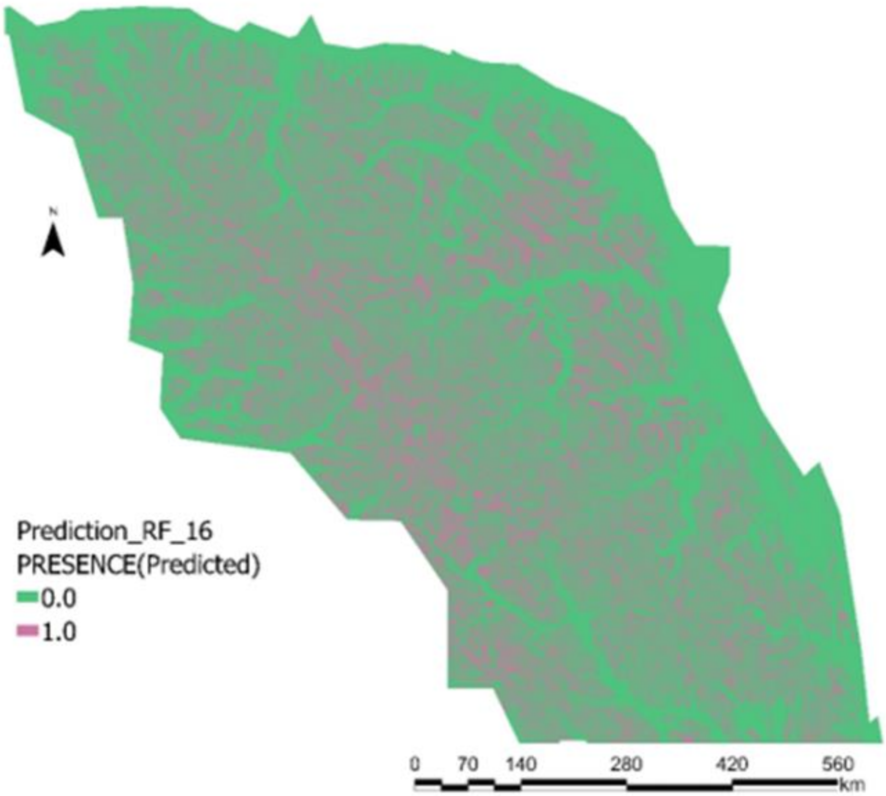


Figure 8: Prediction surface created from model RF16, forest-based classification, and regression (ArcGIS Pro, version 2.9.3). Represents the probability of the presence (1) and absence (0) of rock glaciers in the Mackenzie Mountains. The RF16 model includes variables slope, TPI, PISR, elevation, and lithology. Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community. WGS 1984 Web Mercator (auxiliary sphere).

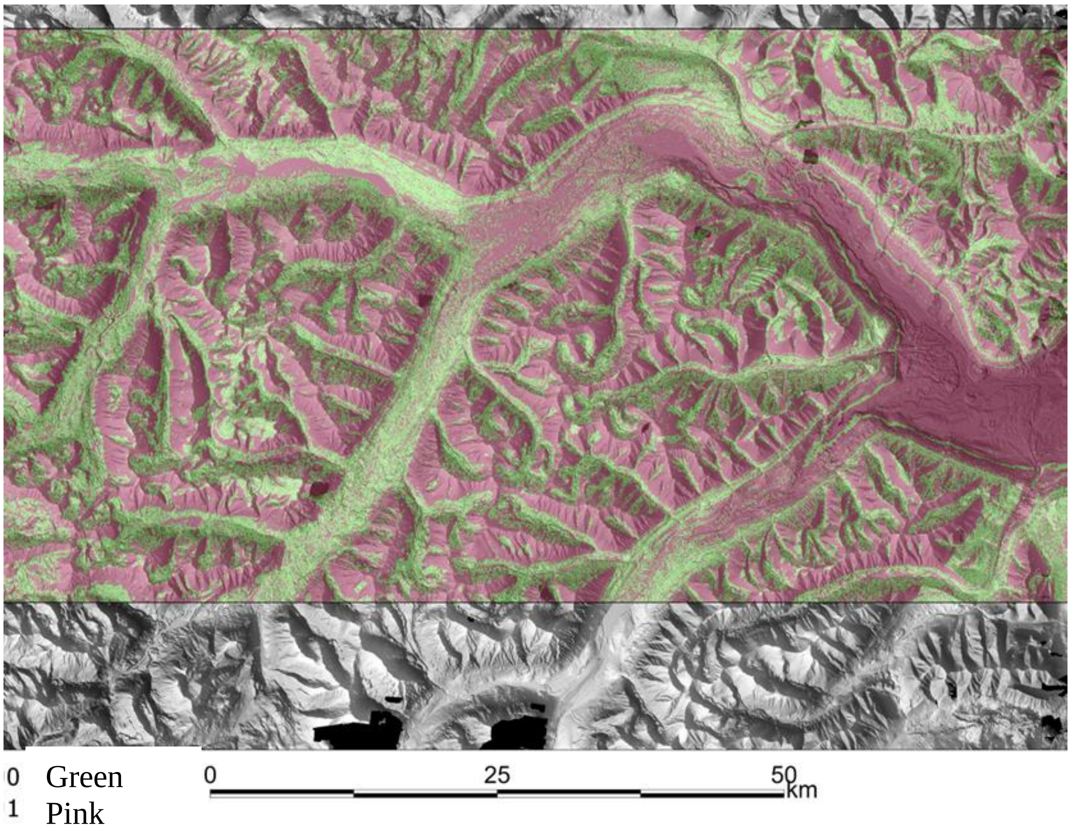


Figure 9: FBCR prediction surface for individual study region (SR1). The FBCR prediction surface generated for SR1 using variables slope, elevation, TPI and PISR. Green regions representing the predicted absence of rock glaciers (0), pink shading representing predicted presence of rock glaciers (1).

Table 9: FBCR model metrics for individual study region (SR1) for both predicted presence of rock glaciers (1) and predicted absence of rock glaciers (0). Training and validation data split 70/30. N=234.

Metric	Training (70%)	Validation (30%) Absence (0)	Validation (30%) Presence (1)
Sensitivity	1.00	0.74	0.68
Accuracy	1.00	0.71	0.71
F1 Score	1.00	0.74	0.68

3.6 Generalized Additive Model

The performance of the GAM was assessed using training and validation datasets. The confusion matrix for both the training data and the validation data are presented in Table 10. The training accuracy was calculated to be 0.87, reflecting the proportion of correctly classified instances. The precision of the model, representing the proportion of correctly identified positive instances out of the predicted positives, was 0.84. Additionally, the model had a sensitivity of 0.92 and a specificity (true negative rate) of 0.83. The Area Under the Curve (AUC) was 0.93, indicating the model's overall discriminative power. The validation accuracy was calculated to be 0.84. The precision for the testing data was 0.83. The model exhibited a sensitivity of 0.84 and a specificity of 0.84. The AUC was calculated to be 0.92. The evaluation metrics indicate that the GAM performed well on both the training and validation datasets, demonstrating high accuracy and precision. This suggests that the model can effectively classify instances and distinguish between positive and negative classes. Probabilities generated from the validation data (30%) were interpolated using the IDW tool in ArcGIS Pro (v 2.9.3) (Figure 10). Most of the rock glaciers were in the high-probability regions, with some falling outside, while two were found to be completely within the lowest-probability areas.

Interaction terms among the variables were analyzed by running multiple model iterations with all possible interactions among the significant variables. The deviance explained and AIC values were used to select the best variables and interactions to include in a final GAM model. With these results considered, the interaction terms for PISR and TPI were added to full GAMs. Two models were then compared, one that included the significant interaction term and all other variables and one without the interaction term. The first model included significant smoothed terms for each variable and explained 60.3% of the variation with good performance (AUC = 0.94), while the second model, incorporating an interaction term, did not significantly improve performance or show significance for the interaction term, and led to non-convergence when combined with a categorical variable (lithology).

Table 10: Confusion matrices produced by the GAM for both the training data (70%) and the validation data (30%). The actual classes represent the observed classes. The predicted represent the classes predicted by the GAM run in R Studio (Version 4.2.2). 0,0 represents the count of instances where the model correctly predicted class 0 when the actual class was 0 (true negative); 0,1 represents the count of instances where the model incorrectly predicted class 1 when the actual class was 0 (False positives); 1,0 represents the count of instances where the model correctly predicted class 0 when the actual was class 0; 1,1 represents the count of instances where the model correctly predicted class 1 when the actual was also class 1 (True positives).

Actual	**GAM Training (70%)**			**GAM Validation (30%)**		
	Predicted					
		0	1		0	1
	0	321	49	0	134	26
	1	50	322	1	25	133

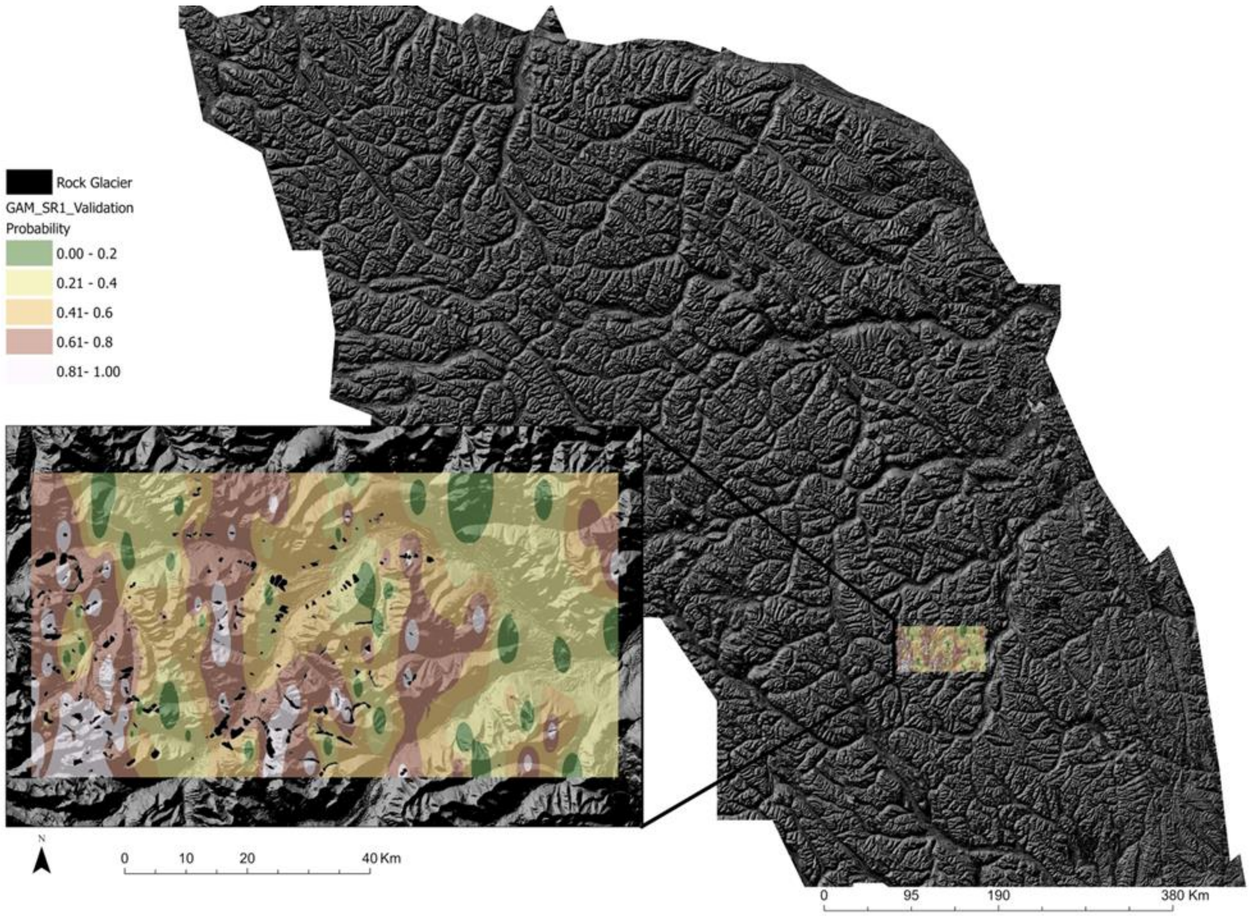


Figure 10: Spatial distribution of rock glaciers (black polygons) in SR1 overlain onto the prediction surface generated by the Inverse Distance Weighted (IDW) algorithm using ArcGIS Pro (Version 2.9.3). Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community. WGS 1984 Web Mercator (auxiliary sphere).

3.7 Generalizability of the Successful Model

To assess the generalizability of the GAM, a new test region of 255 km^2 was assigned. Within this test region, a dataset comprising 10,000 regularly spaced points with all relevant variables were extracted. The variables included slope, elevation, PISR, TPI, and lithology. The GAM model was applied to this data, and probabilities were generated for each point. To visualize the probability distribution across the test region, IDW was again employed. This method allowed for the creation of a continuous surface, illustrating the spatial variation of probabilities across the region (Figure 11). The figure reveals a strong correlation between high probabilities and the actual occurrence of rock glaciers, indicating an elevated level of agreement between the GAM model and the observed data. Five probability intervals were defined (Table 11). The analysis revealed a varying distribution of rock glacier probabilities within the identified rock glacier polygons. The interval with the highest count was interval 5 (0.77-0.97), indicating a high probability range. Interval 1 (0.00-0.26) had the lowest pixel count, indicating a low probability range. Rock glaciers are observed within the test site high probability regions, indicating an elevated level of agreement between the GAM model and the observed data. This test region is 225 km^2, approximately 30 km south of SR1 (62.56°N, 62.50°N).

Table 11: Counts of pixels falling into each probability interval for rock glaciers identified in the test region.

Class	**Probability Interval**	**Count of Pixels**
Low	0.00-0.20	450 (5%)
Low-medium	0.21-0.40	933 (10%)
Medium	0.41-0.60	1861 (19%)
Medium-high	0.61-0.80	4559 (46%)
High	0.81-1.00	2012 (20%)

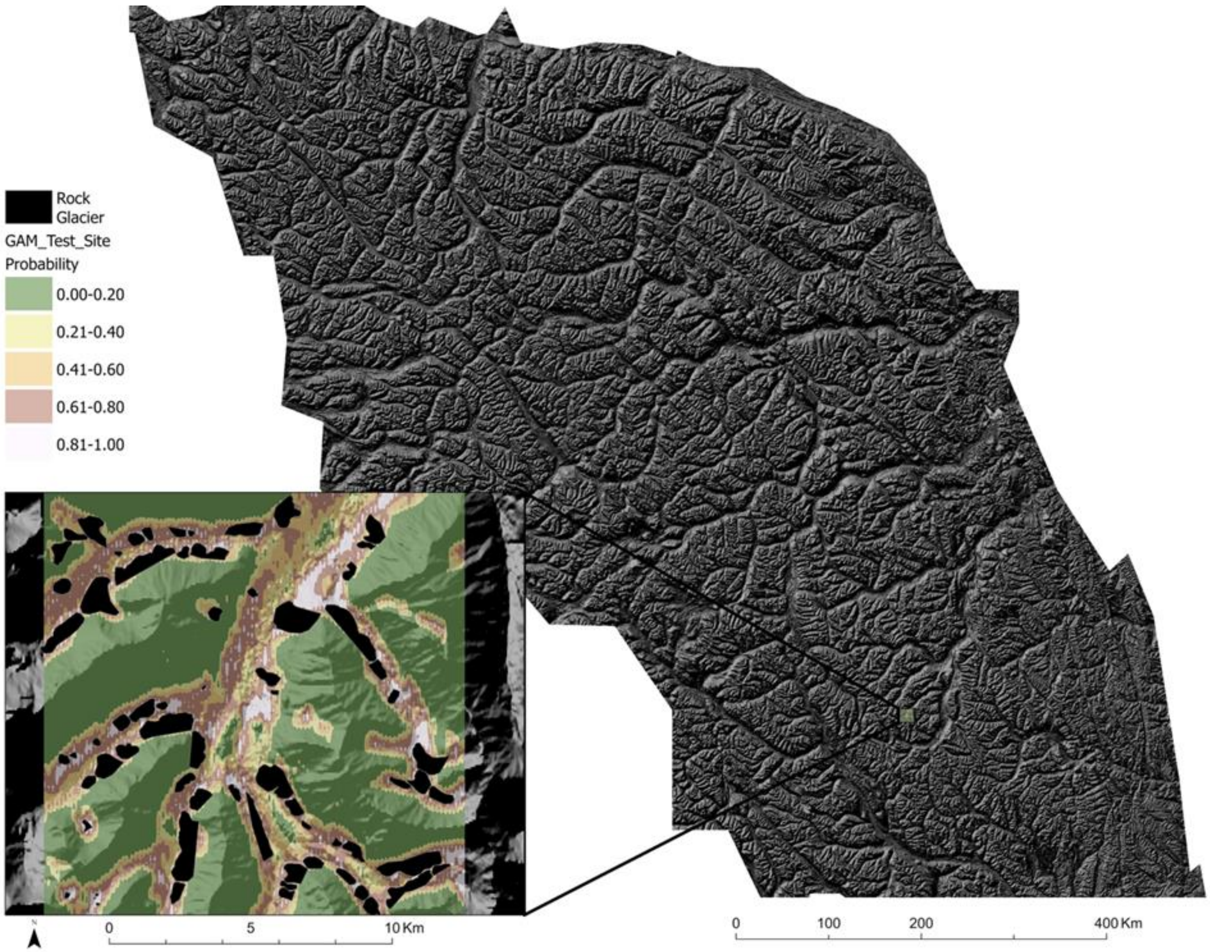


Figure 11:Distribution of rock glaciers in a test area depicted over an inverse distance weighted (IDW) surface created in ArcGIS Pro (Version 2.9.3). The probabilities for rock glacier presence were extracted from a Generalized Additive Model (GAM) and are represented by a colour scale ranging from green (0.00) to white (1.00).10,000 regularly spaced data points were used to extract covariates. This test region is 225 km², approximately 30 km south of SR1 (62.564337°N 62.502392°N). Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community. WGS 1984 Web Mercator (auxiliary sphere).

Chapter 4: Discussion and Conclusions

4.1 Consensus-based Mapping

Identifying rock glaciers via satellite imagery through consensus mapping was intended to reduce subjectivity and increase the extent of the inventory. However, because the decision was made to include all features from the aggregated datasets, those that were identified at all three confidence levels, the subjectivity was not reduced. Having two mappers independently search for rock glaciers reduces the omission of features that are considered rock glaciers. While variability between mappers still exists, it is thought that collaborative efforts may enhance objectivity in the mapping process. Others have reported that even with a consensus-based approach there is still variability in the number of features that are identified, and the extent of these features is also highly subjective (Brardinoni et al., 2019). The accurate identification of rock glaciers is also dependent on the resolution of the imagery. Brardinoni et al., (2019) point out that there is a need for standardized guidelines for the identification of rock glaciers and their extent. This limitation has been addressed by the International Permafrost Association (IPA). The IPA has established a rock glacier action group that compiled the needed guidelines for inventorying and digitizing rock glaciers.

Arguably, inventory accuracy would increase, and subjectivity would decrease with a greater number of skilled mappers. However, this inventory only used two mappers due to financial and availability constraints, and most of the work was done during the COVID-19 pandemic. Ideally, additional mappers would be used to create the final dataset to allow for its compilation to be independent from the initial mapping stages. High variability existed in the number of features identified by each mapper in the first mapping stage; just over 1000 features identified by one mapper and nearly half of that for the lead mapper. This variability was likely the result of different levels of experience and familiarity with the study region. An additional limitation was elucidated during the aggregation of the initial rock glacier mapping stage, where one mapper created a more conservative inventory than the other. This resulted from unclear expectations of the primary goal of the inventorying process, and the need to maintain a conservative approach to ensure a high degree of feature representation and accuracy for the subsequent statistical analyses. The explicit requirement that each feature be clearly visible to its full extent at a scale of 1:5000, was not clearly communicated and therefore one mapper's inventory was much larger than the other. A supplemental dataset was therefore created that included all features of interest for the region. The inclusion of identified rock glaciers at all confidence levels may have contributed to some of the inaccuracies of the model for example, two observed rock glaciers being found completely within the lowest probability interval. Still, modeling the relationship between potential incoming solar radiation, elevation, slope, topographic position index, and lithology using a GAM showed that rock glacier presence can be predicted with some level of accuracy using limited variables and an easily interpretable model. As such, probability maps can be a useful tool in future rock glacier inventories that provide mappers with a baseline region to be investigated, a reduction in the area that needs to be investigated, as well as possibly reducing subjectivity. The reduction in subjectivity is driven by using a quantitative basis for determining the likelihood of rock glacier occurrence based on a statistical model that incorporates terrain attributes rather than the reliance on individual mappers.

This rock glacier inventory is a first step in exploring these features in the Mackenzie Mountains. While several rock glaciers and features of interest have been identified, there is considerable work that needs to be done regarding monitoring and in-depth analysis of these features, such as hydrological analysis. The consensus method used in this case provided a useful strategy that can be further refined by including more mappers, including only the features with a high confidence level in final inventories, expanding the type of satellite data used to identify rock glaciers and having a comprehensive set of guidelines that aim to meet specific goals of individual research.

4.2 Rock Glacier Characteristics

The similarities in rock glacier length, width, and area using ANOVA tests, suggests that the geological and environmental factors influencing rock glacier size are relatively consistent across the study regions. Possible explanations for the non-significance of the size of rock glaciers between study regions are the similarity in lithological compositions rather than a similarity in climatic conditions, since one of the regions is 800 km north of the other two. Different lithological compositions can affect factors such as permeability, water-holding capacity, and mechanical properties of the rock (Traczyk & Migoń, 2003; Haeberli 2006). Bouldery rock glaciers have been shown to be primarily composed of granite, gneiss, sandstone, and limestone, forming larger rock glaciers, while lithologies that produce debris that is finer, such as shale, contribute to smaller rock glaciers (Haeberli 2006; Ikeda, 2006; Ikeda & Matsuoka, 2006). The influence of lithology on length, width, and area may be similar across the regions due to the comparable rock types between regions. Similarly, solar radiation can significantly affect the energy balance and temperature regime of rock glaciers (Pandey, 2019). It influences the rates of thawing and freezing, which are critical processes for the formation and movement of rock glaciers (Kääb et al., 1997). The three study regions also exhibit similar solar radiation patterns. Considering the lack of significant statistical differences among variables across the study regions that contribute to rock glacier development, the observation of similar-sized rock glaciers is plausible (e.g., Krainer & Ribis, 2012).

The slope of the terrain has a significant impact on the development and morphology of rock glaciers (Johnson, 1984). Slopes generally favor greater downslope movement, which affects the length of rock glaciers (Monnier & Kinnard, 2017). The average slope values indicate some differences in slope angles among the study regions. Although the slope appears to be significantly different based on the p-value (0.002298), it does not appear to have a significant effect on the size of rock glaciers in this case; however, it may have resulted from the difference in rock glacier counts between the regions. The slope angle influences rock glacier formation and distribution because it affects the stability of the debris accumulation. Slopes may have catastrophic failures, resulting in mass movements of debris. In periglacial environments, these mass wasting events can be triggered by freeze-thaw processes, which may weaken the shear strength of slopes (Millar, 2013; French, 2017). This process can contribute to the accumulation of debris necessary for rock glacier development further downslope (Anderson et al., 2018). A moderate slope that supports the materials without reaching the tipping point is more conducive to rock glacier formation because snow and ice have time to accumulate and infiltrate debris and accumulate ice internally, forming a cohesive body that in turn creeps downslope at slower rates (Millar, 2013). Steep-gradient slopes are more likely to experience rapid runoff. Differences in the presence, extent and temperature of permafrost between regions could be affecting rock glacier presence and absence and associated characteristics (Harris et al., 2001; Harris et al., 2009; Cicoira et al., 2021).

Rock glaciers in the Northern Hemisphere are commonly found on north to northeast-facing slopes due to limited solar radiation at these aspects in comparison to more southern aspects. The susceptibility of northern slopes to accumulate winter precipitation due to prevailing southwest winds also contributes to rock glaciers more commonly developing on northern slopes (Liu et al., 2013). This is a common finding among other rock glacier inventories compiled in the Northern Hemisphere (Guglielmin & Smiraglia, 1998; Janke, 2007; Krainer & Ribis, 2012; Charbonneau & Smith, 2018). The analysis of rock glacier aspects within the Mackenzie Mountains reveals insights into the potential influence of the NW-SE trend of the mountain range and the presence of a high number of cirque basins on the distribution of aspect orientations. These topographic features play a role in shaping the aspect preference of rock glacier development (Johnson, 1980). This also suggests that topographic shading may contribute to rock glacier distribution, as is known from literature. The cirque basins within the study regions further contribute to the aspect patterns observed in rock glaciers. These basins, formed by glacial erosion (Nelson & Jackson, 2002), often create concave depressions surrounded by steep slopes. They can act as natural amphitheaters, influencing the exposure of slopes to solar radiation and impacting the microclimate within the cirque (Wagner et al., 2019). Cirque basins can create shadowing effects, casting shade on certain aspects for a significant portion of the day. This shading may impact the thermal regime of slopes, influencing the presence or absence of ice or permafrost conditions, thus affecting the development of rock glaciers (Morris, 1981). Additionally, cirque basins can act as debris traps, collecting and accumulating material from eroding headwalls, which can subsequently contribute to the development and growth of rock glaciers (Ackert, 1998). Rock glaciers found in cirque basins may be the result of former cirque glaciers transforming into rock glaciers. The combination of the Mackenzie Mountains trend and the presence of numerous cirque basins creates a complex interplay between aspect orientation, solar radiation exposure, snow accumulation, and temperature variations. Overall, the results from the three study regions show that rock glaciers within the Mackenzie Mountains have predominant orientations of northeast to northwest, which aligns with the current literature on rock glacier distributions in the northern hemisphere regarding aspect (Baroni et al., 2004).

Solar radiation affects rock glacier distribution by influencing the rate of melting and stability of the ice within the rock glacier (Bodin et al., 2009). Surfaces that are shaded or sheltered from solar radiation are less likely to experience significant melting, and areas that receive considerable amounts of solar radiation are more likely to experience significant melting (Duguay et al., 2015). Hence, rock glaciers are typically more common on the northern slopes. However, this process can have confounding effects as well, where increased melting of snowpack allows precipitation to percolate down into the rock glacier where lower temperatures are found, contributing to refreezing and interstitial ice (Tenthorey, 1992). The freeze-thaw process also contributes to mechanical weathering, leading to an increased debris supply (Amschwand et al., 2021). The rock glacier attributes here show clustering at low and high solar radiation and dispersed through mid-solar radiation exposure. Therefore, solar radiation can play a significant role in the distribution of rock glaciers and can provide valuable information for understanding the conditions necessary for rock glacier formation and persistence.

TPI is useful in identifying areas of ridges and valleys that can impact the distribution of rock glaciers. TPI identifies areas of the landscape that have lower or higher elevations compared to their neighboring terrain (Weiss, 2001). For example, areas with a positive TPI value are typically located on ridges or high points in the landscape, while areas with negative TPI values are in valleys or low points. Areas with low TPI value can provide suitable conditions for rock glaciers to form because they are protected from solar radiation by surrounding higher-elevation areas (Johnson, 1980). Rock glaciers are typically found down slope from headwalls or lower than ridge lines. These headwalls often contribute to the debris supply necessary for rock glacier development (Degenhardt, 2009). Average TPI values for rock glaciers within each study region were negative which shows that they have elevations lower than their surrounding.

Elevation also plays a role in the distribution of rock glaciers. The relationship between elevation and rock glaciers is influenced by numerous factors, such as temperature, moisture, and topographic characteristics. Generally, rock glaciers tend to be more prevalent at higher elevations. This is primarily because higher elevations experience colder temperatures (Oke, 1987), contributing to conditions favorable to rock glacier formation and preservation (Wahrhaftig & Cox, 1959). Higher elevations, as in alpine regions, also have slopes, which are necessary for the movement of rock glaciers. The minimum elevation for a rock glacier was 939 m, found in SR2. While elevations for the entire range reach a minimum of just under 400 m. The minimum elevation for rock glaciers within each study area, suggests a minimum elevation at which rock glaciers occur regionally.

Rock glacier activity status was based on defining characteristics of activity seen through satellite imagery (e.g., Falaschi et al., 2015). While this method provides some rudimentary results, it is necessary to further analyze the activity of rock glaciers using kinematic methods such as InSAR technologies (e.g., Lambiel et al., 2008; Reinosch et al., 2021; Bertone et al., 2022). However, this primary investigation of activity revealed that most rock glaciers within the study regions are viewed as active (Table 4). The analysis of rock glacier activity and aspect revealed some variations in their distribution. The activity of rock glaciers, whether active or inactive, shows distinct preferences for certain directions across the regions. Among active rock glaciers, the primary aspect directions were northeast (25%), east (21%), and northwest (20%). Inactive rock glaciers are found primarily on northwest (29%), and southeast (21%) facing slopes. The prominent aspect of rock glaciers among the three study regions are northeast and northwest. The distribution of aspect directions within the study regions suggests that the orientation of slopes may play a role in rock glacier activity and distribution within the Mackenzie Mountains.

4.3 Comparison with Other Mountain Ranges

Rock glaciers are an important feature in periglacial environments. Unravelling the distribution and properties of these landforms is crucial for obtaining a deeper understanding of climate conditions, evaluating permafrost stability, conducting comprehensive geomorphological studies, mitigating natural hazards and advancing scientific knowledge. This section offers a comparison of three rock glacier inventories from similar regions. In the Greater Caucasus, Tielidze et al., (2023) conducted a rock glacier inventory which identified 1461 rock glaciers with a total area of 297.8 ± 23.0 km^2. Using the same techniques as this thesis to classify active and relict rock glaciers, 67% of the rock glaciers identified were classified as active. The remainder were classified as relict (Tielidze et al., 2023), while approximately 90% of the 530 rock glaciers identified here were classified as active. The remaining 10% of rock glaciers were classified as inactive rather than relict. Relict rock glaciers are defined as having a close to total loss of ice and movement (IPA, 2022). The choice to classify rock glaciers as active and inactive in this case, rather than relict reflects the uncertainty associated with evaluating ice content and movement via satellite imagery. Tielidze et al. (2023) found no distinct difference between the slopes of inactive and relict rock glaciers nor did the present study (mean slope inactive 18 ˚, mean active slope 17˚). This is concurrent with existing literature on the correlation between slope and rock glacier velocity (Janke & Frauenfelder, 2008), which shows greater influence of rock glacier length and thickness on velocity. The average elevation of rock glaciers within the study regions (1610 m) and the range of elevations in which most rock glaciers were found (1200 m – 1900 m) within the study regions, is comparable to rock glaciers inventories in the British Columbia Coast Mountains where Charbonneau & Smith (2018) reported that the majority of rock glaciers were distributed between 1900 m – 2300 m. Though the majority of rock glacier appear to be at higher elevations in comparison to the Mackenzie Mountains it may be reflecting the difference in overall relief and climate between the two regions. The British Columbia Coast Mountains reach a maximum elevation exceeding 4000 m, while the Mackenzie Mountains reach a maximum elevation of just over 3000 m. The predominant aspects of rock glaciers in both ranges were found to be northwest and northeast facing. Another similarity among the Mackenzie Mountains and the British Columbia Coast Mountains is the heterogeneous lithology across the regions (Charbonneau & Smith, 2018) which may have led to the insignificance of lithology on rock glacier development in this case. The resolution of the lithology data used in this study varies from 1:5 000 to a more generalized scale of 1:150 000 000 (Okulitch & Irwin, 2017, Government of Yukon, 2022). Higher resolution data may elucidate more influence of lithology on rock glacier development and distribution. It is evident that while there are some shared patterns in terms of elevation, aspect, slope and lithology influencing rock glacier distribution. These similarities may lend to the generalizability of the developed model.

4.4 GAM

The use of a GAM when modeling rock glacier distribution offers several advantages, including interpretability, relative ease of use, and optimization capabilities. In terms of performance, the GAM demonstrated satisfactory results on both the validation data and the new test dataset. The AIC (492) and BIC (596) values indicated a good fit of the model to the data when comparing the model iterations, while the AUC values suggested strong discriminatory power. The model accurately identified rock glaciers based on the available variables and exhibited a proficient level of predictive capability. While the lithology variable in the GAM with six classes did not yield statistically significant results, this does not negate the potential impact of lithology on the distribution of rock glaciers. Rather, it underscores the complex and multifaceted nature of this relationship, which may not conform to a linear representation.

There are certain aspects that could have enhanced the model's performance. After quantifying the probability map, it was found that the inclusion of additional variables such as curvature, and vegetation could have provided a more comprehensive understanding of the factors influencing rock glacier distribution. Analyzing the areas where the model identified high probabilities, but no rock glaciers were found, provides insights into potential limitations. Within the test data, 143 out of 173 rock glaciers with probabilities above 0.5 intersected with the rock glacier polygons. The remaining thirty points, identified as having a medium-high probability but not intersecting with rock glacier polygons, could be attributed to factors such as cloud cover, rockslides, protalus lobes, poor image quality, or the presence of what appear to be fossilized rock glaciers. The premise of using a conservative approach with rock glaciers included in the model was to ensure the model was trained on accurate data. However, the use of rock glaciers at every confidence level may have led to some inaccuracies in the model. To address these limitations, higher-resolution data and the incorporation of vegetation information within the model could improve accuracy and reduce false positives. Using multiple mappers and restricting the rock glaciers used for modeling to only level 3 confidence may also improve model results. Further examination revealed that fifteen out of 145 points with probabilities below 0.5 did intersect with rock glacier polygons (false negatives). When adjusting the threshold to 0.3, five of the 125 rock glaciers that were in this category intersected with rock glacier polygons. Conversely, when looking at the rock glaciers that fell above 0.7 probability, 124/147 did, in fact, intersect with rock glacier polygons. When investigating these points, it was found that human error was the main cause of error. Points that had a probability of 0.7 that were not on a rock glacier were often in areas with high cloud cover, poor resolution imagery, high snow cover, or, in some cases, on rock glaciers that were not identified by mappers. Another common occurrence was that some of these high-probability points were on talus cones. Talus cones are debris accumulations that form at the base of rock walls and have the shape of a cone. These debris accumulations grow upwards and grow wider with continued accumulation (Lempa et al., 2015), in contrast to a rock glacier that creeps forward under the weight of gravity and ice deformation (Cicoira et al., 2021). This flow induces the geometry of a rock glacier. Including geometry of rock glaciers in future modeling may reduce the occurrence of false positives on talus cones. Additionally, identifying rock glaciers based on the flow features and convexity allude to their having ice content (Colaprete & Jakosky, 1998). Rock glaciers that are considered fossilized often have apparent concavity due to ice thaw and higher amounts of vegetation cover reflecting their inactivity (Krainer & Ribis, 2012). In this case, vegetation density was not included in the model, but after assessing some of the rock glacier false positives, it may be pertinent to consider adding the Normalized Difference Vegetation Index (NDVI) component to the model for future use (Brenning, 2009; Kofler et al., 2020). It is important to note that a preliminary classification of rock glaciers that have vegetation cover is needed before considering including NDVI. Some studies have shown that the vegetation extent on intact vs. fossilized rock glaciers is dependent on the climatic region and may not be as informative (Colucci et al., 2016).

4.5 Random Forest and Forest-based Classification and Regression Model Comparison

While the random forest model showed better performance on the testing data compared to the GAM model, the possibility of overfitting needed to be considered. Overfitting occurs when a model becomes too complex and starts to memorize the noise or idiosyncrasies of the training data, leading to poor generalization to new or unseen data (Montesinos López et al., 2022). Overfitting can be problematic because the model may have learned specific patterns in the training data that are not representative of the underlying relationships in the broader population or new observations (Greener et al., 2022). On the other hand, despite the lower performance of the GAM on the testing data, it is less prone to overfitting due to control over smoothing parameters (Larsen, 2015). The GAM captures relationships between the predictors and the response variable using splines, which help to avoid overfitting by imposing smoothness constraints such as manipulating the k value (number of basis terms). The GAM, with its simpler structure and smooth relationships, provides a more interpretable and robust approach, especially in the case of a smaller dataset. The GAM performed comparably well on both the training and testing data sets. Reaching a plateau for both training and testing dataset is indicative of good model fit. Identified rock glaciers were found in the high-probability regions, with some falling outside, while only two rock glaciers were found to be fully in the lowest-probability areas. This accuracy is reflected in the confusion matrix evaluation metric. The RF model often performs better with larger datasets and more covariates (Ali et al., 2012). When the validation data (30%) is interpolated, there are six rock glaciers that are completely within very low probability areas as identified by the RF model. There are no significant differences in the attributes or location of these rock glaciers in comparison to rock glaciers found in high-probability areas, inferring that there may be some complexities that are not being captured by the model.

The FBCR model also had insufficient results for this research. While multiple models were tested, the RF14 model was selected as the preferred model due to the higher percentage of correct classification (F1 score). However, neither FBCR extrapolated prediction surface significantly reduced the area that would need to be investigated when searching for rock glaciers via satellite imagery. The FBCR only offers positive and negative classification, it does not offer probability. This results in a substantial portion of the region being classified as positive, which does not significantly reduce the investigation area. Therefore, this model was not identified as a good model fit in this case. Further capabilities of the FBCR model to display probability values would likely increase the functionality of this tool and provide a way to classify large regions. This model proved inadequate for this research due to its inability to reduce the areas of investigation. When applied to an individual study region, predicted presence of rock glaciers encompassed entire valley bottoms and some ridge lines while absence predictions were located on slopes below ridge lines, contradicting the typical distribution of rock glaciers. Rock glaciers are typically found in topographic conditions where there are moderate slope angles and sufficient debris accumulation (Scotti et al., 2013). Ridge lines and high slopes are often the debris source which accumulates downslope and contributes to the development of rock glaciers (Burger et al., 1999). The model's indiscriminate predictions failed to account for these factors. The model's performance may be reflective of the lower number of points used to inform the model (234-presnce, 234-absence, N=468). The FBCR model was eliminated from consideration based on the limited capabilities currently available within the ArcGIS Pro toolset that would allow for the delineation of probability categorization and the possibility that the data set was not sufficient to inform this model. The model metrics for this model also indicate that there may be overfitting occurring. This is an assumption made when training data results in 100% accuracy, as with the random forest model.

The GAM was chosen as the best model, verified by the results of the validation data and the test site. The test site data and probability map provide evidence that the GAM can be generalized, at least within the context of the Mackenzie Mountains. It may be pertinent to test the model in regions outside of the Mackenzie Mountains, such as in the Torngat Mountains (Northern Labrador), where a rock glacier inventory exists (Way et al., 2021); however, this was not performed due to time constraints.

4.6 Probability Surface Generated by the GAM

A benefit of IDW interpolation is its simplicity and ease of implementation. It provides a straightforward way to create a continuous surface that captures the spatial variation in rock glacier likelihood across an assigned region based on probabilities. It is essential to acknowledge some considerations and potential limitations when using IDW interpolation. The accuracy and reliability of the interpolated surface heavily depends on the distribution and density of the input data points (Setianto & Triandini, 2013). In this case, when using IDW on the 30% validation data, the generated surface showed high accuracy when comparing the observed rock glaciers to the expected, but due to the small data set, there was some error. This error can be minimized by extracting data from a larger number of points, for example, in the test site, ten thousand data points were extracted in an area of 255 km^2. The higher number of data points led to a more efficiently interpolated continuous surface where rock glaciers were observed in high-probability areas. Another implication of using IDW interpolation for rock glacier likelihood is the potential smoothing effect introduced by the interpolation process. The resulting surface may oversimplify local variations and fail to capture fine-scale features and heterogeneity in rock glacier distribution. Again, this drawback could be mitigated by including a larger number of data points. This issue may also be alleviated to some degree by increasing the number of relevant variables used in the modeling process. The results show that the IDW surface created from probabilities generated from the GAM model can help with the positive identification of rock glaciers in each area of interest based on the independent variables of slope, elevation, TPI, PISR, and lithology. While there are some pixels of rock glaciers that fall into low-probability intervals, most rock glacier pixels cover medium to high-probability pixels (Table 7). It is noted that the highest percentage of rock glacier pixels fall into the medium-high probability interval. This may be attributed to the fact that even though the utilization of a GAM model was successful in determining rock glacier likelihood with an accuracy of 87%, there are inherent uncertainties associated with any probabilistic model. These uncertainties may be due to variations in the terrain and or climate for example, that were not considered in the model. It is also important to consider the potential limitations of using the IDW interpolation method. IDW assigns values to points based on their proximity to known data points resulting in a smoothed surface. This smoothing effect may have led to broader distribution of probabilities, potentially causing fewer observed rock glaciers to be within the highest interval. While the GAM model provides valuable insights into rock glacier distribution, the observed distribution across probability intervals highlights the complexity of rock glacier formation and the influence of multiple environmental factors. Further techniques to refine the GAM model may be helpful to gain a deeper understanding of the specific factors that are contributing to the rock glaciers in this study region.

4.7 Limitations and Future Studies

It is critical to recognize some of this limitations of this research. The relevance of the chosen variables employed in the modeling process determines whether rock glaciers can be found in the expected locations of the interpolated probability map. To increase precision, additional pertinent variables should be considered, such as NDVI and curvature, as shown by the occurrence of false positive points. The inclusion of only high confidence features may also improve model capabilities. Climate variables such as temperature and precipitation have also been shown to be significant controlling factors in rock glacier development (Brazier et al., 1998; Brenning & Azócar, 2010). However, again due to the remoteness of the study area, there is a significant lack of available climate data with high resolution, so climate variables were not included here. While climate reanalysis products are available, it has been shown that there can be large discrepancies between observed climate data and reanalysis products (Noad and Bonnaventure, 2022; Roberts et al., 2019). The aim is to increase the accuracy of the model with reliable data rather than introduce climatic generalizations. The ability to remotely detect and map the spatial distribution of rock glaciers has become more common because of developments in satellite technology and machine learning methods.

Future research on the dynamics of rock glaciers in the Mackenzie Mountains region is made possible by this preliminary inventory by creating the possibility to map the entire mountain range using the statistical models created here. The availability of rock glacier data in this area will also enable more thorough research, which will then make it easier to grasp the substantial implications of rock glaciers through hydrological analysis, temperature regime assessment, and the gathering of kinematic data. The reliance on glaciers as a source of fresh water, particularly in arid regions may need to be reevaluated as climate warming further impacts these features (Brighenti et al., 2019). While Canada has an abundance of fresh water the possibility of negative impacts in the future of a warming climate needs to be considered. Providing rock glacier inventories that can be used for more in-depth analysis is a proactive approach to possible future consequences. Kinematic data will enable ongoing monitoring activities as well as refine and expand the rock glacier collection. Rock glacier activity monitoring also contributes to the understanding of how these features react to climatic changes (Bertone et al., 2022), as well as their hydrological significance, for example, a decrease in activity may be linked to substantial thaw of internal ice leading to an increase in water output (Brencher et al., 2021). Acquisition of kinematic data adds to our understanding of rock glaciers and their contribution to the landscape. By continuously improving rock glacier inventories and enhanced monitoring techniques we gain critical insights into the impacts of climate change and are better able to make informed decisions to mitigate potential hazards and future resource depletion in vulnerable regions.

4.8 Summary and Conclusions

This research makes a substantial contribution to our understanding of the presence and distribution of rock glaciers in the Mackenzie Mountains. The characteristics of more than 500 rock glaciers, including slope, PISR, TPI, lithology, aspect and elevation, were examined to acquire important insights into the variables affecting their distribution. With mid-range elevations and slopes averaging roughly 20 degrees, rock glaciers were mostly seen on slopes facing northeast and northwest. Despite having slightly less significance in the modeling process, the PISR variable was nonetheless essential to the formation of rock glaciers because its inclusion enhanced the model's overall performance. This research effectively handled its objectives within the defined study area by providing a rock glacier inventory for three regions within the Mackenzie Mountains. A custom automated method for identifying regions with high likelihood of rock glacier presence, informed by observed influential rock glacier attributes, was developed based on methods from previous literature for similar yet different geomorphic features (Rudy et al, 2017). By cataloging rock glaciers in the Mackenzie Mountains, this study bridges a regional knowledge gap since there is little information on rock glaciers in this location. The inventory serves as a starting point for future studies on rock glaciers in this remote location. For preliminary inventorying in remote areas where on-site verification is difficult, the statistical approaches used to predict rock glacier likelihood provide a realistic strategy that minimizes the need for knowledge and lessens the reliance on large, predetermined datasets. Given the high costs connected with travel and the use of helicopters to explore these terrains, locating rock glaciers in advance helps maximize resources. Researchers can carefully arrange field expeditions and concentrate their efforts on places where there is a higher likelihood of finding rock glaciers by using sustainable and easily accessible technology as preliminary study tools.

This study presents research in an understudied region, filling a regional knowledge gap as well as serving as a building block for future research. Major contributions include:

- The creation of a rock glacier inventory covering over 15,000 km^2 within the Mackenzie Mountains using multiple mappers.
- The testing of the consensus method for the identification of rock glaciers and evidence that consensus even with skilled and experienced mappers remains highly subjective. Although having multiple mappers may substantiate the number of rock glaciers in a region, human subjectivity remains a challenge.

- The identification of controls on rock glacier presence within the study regions (i.e., elevation, slope, TPI and PISR). These controls appear to be consistent with other rock glacier features in similar mountain ranges in the northern hemisphere however, more examination is still required.
- A presentation of a statistical modelling approach to mapping the likelihood of rock glaciers in larger regions. Application of this model will prove useful in mapping large regions and unknown regions, reducing the intense manual identification that is commonly used. Although there is enormous potential upside for a tool with these capabilities, testing within and outside the Mackenzie Mountains is required.
- The compiled inventory can be used for further, more in depth analysis of rock glaciers such as hydrological, lithological, and kinematic analysis.

This research achieved its objectives and tested its hypothesis, shedding light on the presence and characteristics of rock glaciers in the Mackenzie Mountains. An important regional knowledge gap was filled, and this research also lays the foundation for future research in this remote area. This research advances our understanding of rock glaciers and presents a strategic and practical approach for mapping additional regions.

4.9 Supplementary Data

Data generated or analyzed during this study are available from the corresponding author upon request. Available data comprises two GIS shapefiles: one for the rock glacier inventory used in this study and the other for the features of interest data set. Both shapefiles were created using ArcGIS Pro version 2.9.3. We are committed to facilitating the sharing of our research data to promote transparency and further scientific inquiry.

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