Arctic Science

OPEN ACCESS | Research Article

Rock glacier inventory and predictive modeling in the Mackenzie Mountains: predicting rock glacier likelihood with a generalized additive model

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Abstract

Rock glaciers have been the subject of extensive research in recent years due to their potential to serve as indicators of past and present climate conditions and their potential impacts on water resources. Location and descriptive rock glacier data within the Mackenzie Mountains were used to build a rock glacier inventory that will serve as a valuable resource for future research and monitoring efforts. Additionally, this study maps the likelihood of rock glacier presence using extracted variables in a generalized additive model (GAM). The model incorporates attribute data, including potential incoming solar radiation (PISR), topographic position index (TPI), slope, elevation, and lithology as controls for rock glacier development. Topographic data were compiled for three study regions of the Mackenzie Mountains from a 30 m digital elevation model (DEM). The analysis of the GAM showed that the most significant explanatory variables were PISR, elevation, slope, and TPI. The GAM model had an accuracy of 0.87 with a sensitivity of 0.92. This study provides important insights into the controls, distribution, and dynamics of rock glaciers in the Mackenzie Mountains, as well as both the limitations and the potential of statistical models in predicting their occurrence.

Key words: rock glacier, permafrost, Mackenzie Mountains, generalized additive model

1. Introduction

As the effects of climate change continue to become more evident across landscapes, there is a need to understand the composition and distribution of landforms that are being impacted. Rock glaciers are under-researched in the region of the Mackenzie Mountains, with most research focused on oil and gas development (e.g., Hannigan et al. 2009; Shi and Guéguen 2017). Any research or exploration in the Mackenzie Mountains is difficult due to limited access. There are only two roads that lead into the Mackenzie Mountains, the North Canol Road from the Yukon and the Nahanni Range Road from the Northwest Territories (NT). The remote location and small population also account for the limited available data. Advancements in remote sensing techniques have increased the ability to better map and understand this region, though some periglacial landforms that cannot easily be detected using automated methods and do not show significant temporal changes may be overlooked (Kääb et al. 2003; Janke 2013). Rock glaciers are abundant geomorphological features in many mountain environments (Janke 2013), including regions of Canada (Jackson and Macdonald 1980; Ommanney 1980; Sloan and Dyke 1998; Carter et al. 1999; Koning and Smith 1999; Charbonneau and Smith 2018; Way et al. 2021). They are often used as a proxy for permafrost modeling, using lower and upper bounds of rock glaciers to map probable permafrost distribution (Marcer et al. 2017; Hassan et al. 2021). These features are also hydrologically significant, particularly in arid regions (Jones et al. 2019; Rangecroft et al. 2015).

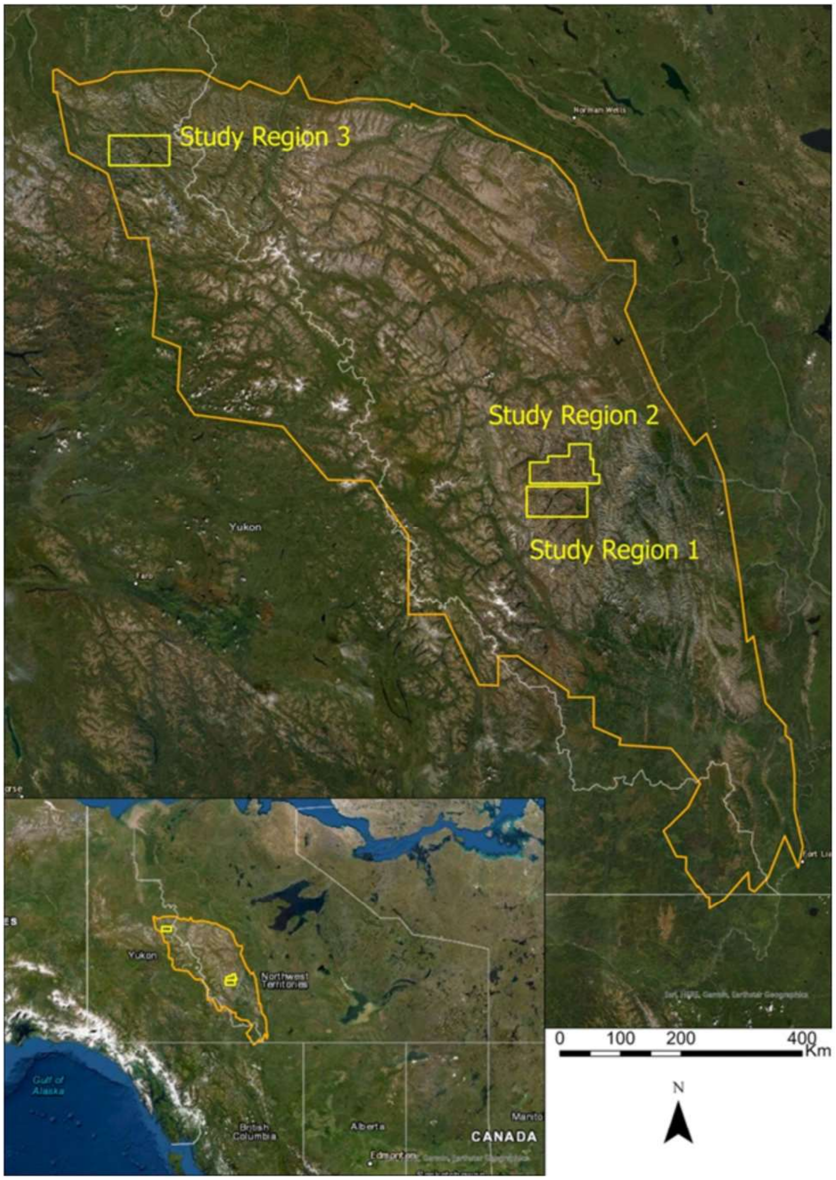
Rock glaciers are an accumulation of debris and ice that often develop in one of two ways: (1) debris covers the remnants of a glacier, with continued accumulation of debris and ice; or (2) precipitation infiltrates accumulations of debris and accretes interstitial ice in environments with low mean annual temperatures that are able to sustain permafrost. Rock glaciers also benefit from snow redistribution through avalanches, which increase local snow thickness, contributing to accumulated precipitation and infiltration (Anderson et al. 2018). The former development is commonly referred to as ice-cored rock glaciers and the latter rock glaciers of permafrost origin (Hamilton and 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 and Matsuoka 2002). Rock glaciers generally move anywhere from decimeters to meters annually (Giardino et al. 1987), with increased movement possibly occurring in the event of thaw (Bodin et al. 2009; Scapozza et al. 2014). Rock glaciers are often classified into different categories based on ice content and movement such as intact (containing ice) which includes both active and inactive rock glaciers and fossilized or relict rock glaciers. The nature of the remote environment as well as the difficulty associated with ground truthing rock glaciers themselves makes estimations of ice content challenging.

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 and Crockett 1978; Kaufmann et al. 2007). Contemporary methods commonly use 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). 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 (Lambeil et al. 2008; Strozzi et al. 2020). Another potential issue that arises with rock glacier identification through optical imagery is that there are many features that can be mistaken for rock glaciers (Burger et al. 1999). It is important that these features be well-defined within using established consensus within the literature. Compiling a rock glacier inventory using remote sensing data, utilizing established methods set out by the International Permafrost Association (IPA) Rock Glacier Inventories and Kinematics (RGIK) action group for regions within the Mackenzie Mountains fills a regional gap. While this region has been primarily investigated for resources (e.g., Hannigan et al. 2009; Shi and Guéguen 2017), there has been little to no 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 other ecological impacts that rock glaciers may have.

We are testing the hypothesis that these 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. The region of interest is the Mackenzie Mountains in Northern Canada. This geographic region merits investigation due to the probable presence of rock glaciers based on its topographic and climatic characteristics. However, there exists a notable gap in comprehensive research regarding permafrost distribution within this region, necessitating further investigation for a more comprehensive understanding. To achieve this, we 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, Canada. We assume that rock glacier distribution is controlled by several factors including, potential incoming solar radiation (PISR), elevation, slope, lithology, topographic position index (TPI) and aspect (Brenning and Trombotto 2006; Angillieri 2010; Johnson et al. 2021; Trcka 2020). To achieve this, an inventory of rock glaciers was created using a consensus-based mapping method adapting the methodology from Way et al. (2021). The characteristics of rock glaciers identified within select regions of the Mackenzie Mountains were analyzed and compared to the surrounding terrain to interpret which controls were in fact significant. Identifying rock glaciers and extracting relevant controls will contribute to cataloging rock glaciers within this region and support modeling. Rock glacier attributes were extracted from the dataset and used to inform a generalized additive model (GAM), which generates rock glacier probabilities that could be interpolated into a continuous surface reducing the area of investigation to high likelihood regions.

Modeling rock glacier distribution has been achieved by researchers such as Angilleri (2010) in the San Juan Andes of Argentina, using a statistical modeling approach and geomorphological mapping techniques. Angilleri's (2010) 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 modeling rock glacier distribution using either remote sensing data, terrain attributes derived from Shuttle Radar Topography Mission (SRTM) digital elevation models (DEMs), or a combination of both datasets. 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 Sentinal-2 imagery and Sentinal-1 interferometric coherence data, and DEMs. Choosing to employ a GAM for mapping rock glacier distribution offers a different approach in comparison to the already established methods utilized in previous studies. While logistic regression and other methods have proven effective in analyzing the factors influencing the distribution of rock glaciers, a GAM introduces a flexible and adaptable framework for capturing the complex relationships between environmental variables while remaining relatively easy to employ and interpret. GAMs can model complex nonlinear relationships between the predictor and dependent variables, which may not be fully addressed by logistic regression alone. This is especially valuable when dealing with topographic parameters, like those affecting rock glaciers, where the relationships can be nuanced and nonlinear. This approach is highly influenced by a successful study using a GAM to model active layer detachments, by Rudy et al. (2017).

Fig. 1. Mackenzie Mountain range in the orange border, inset are the three study regions within this range where rock glaciers have been mapped. Study Region 1 is 5000 km^2; Study Region 2 is 5275 km^2; Study Region 3 is 5000 km^2. Each region was chosen based on the assumption that there would be a presence of rock glaciers based on relief, debris availability, mean annual temperature and image resolution. Study region 3 is located further North to include heterogeneity of the landscape and to be utilized as a comparison area. 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 (Rivas et al. 2017).



2. Study area

The Mackenzie Mountain range is the northern extension of the Cordilleran orogeny that lies between Lat. 65°33′ and 60°0′31″N. The range spans over 700 000 km^2 (Fig. 1). The range is situated along the border of the NT and the Yukon Territory (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 dynamic 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 accumulation of post-glacial till (Matsuoka and Ikeda 2001). During the Pleistocene, the Mackenzie Mountains experienced several glaciations (Duk-Rodkin and Hughes 1992). The climate within the study region is relatively cold and dry with a mean annual air temperature (MAAT) of -6.8 ° C; and the mean annual precipitation (MAP), 527 mm (Wang et al. 2016).

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

	Max elevation (m)	Min elevation (m)	Mean elevation (m)	Hydrology (%)
Study Region 1	2639	890	1.753	1.08
Study Region 2	2.558	727	1639	0.69
Study Region 3	2.542	630	1576	1.56

This thus provides conditions suitable for rock glacier development (Schrott 1996). The relief of the mountain range (minimum elevation, 107 m; maximum elevation, 2947 m; mean elevation, 1296.44 m) is also suitable for rock glacier development (Scotti et al. 2013; Munroe 2018). 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 more human interaction with the environment, 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 previous rock glacier investigations in the Andes (i.e., Brenning 2005) and the Selwyn Mountains (i.e., Sloan and Dyke 1998). These elements include steep slopes, debris sources and arid conditions, characteristics that have all been correlated with the presence of rock glaciers (Brenning and 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°W 62°N; SR2, 126°W 63°N), and a third in the north, SR3, (133°W 65°N). General relief of each region and percentage of water bodies present, 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.

3. Methods

3.1. 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 2023) 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 regularly. 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 2023) or Sentinel Hub (2022). Point features were later digitized to polygon features (see section 3.3).

A DEM sourced from ALOS AW3D30 (JAXA 2020) was used to extract terrain information for subsequent geospatial analyses. The DEM was harnessed within ArcGIS Pro to derive a suite of raster datasets, encompassing aspect, slope, PISR, elevation, and the TPI. 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. PISR, a fundamental factor for understanding solar energy distribution, was computed. TPI was generated, characterizing landform positions within the landscape. TPI was calculated by analyzing the elevation of a central cell compared to the average elevation of its surrounding cells within a defined window, in this case 33 by 33 cells, to determine whether the central cell is located in a depression, ridge or flat area relative to its surroundings. 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 NT (Okulitch and Irwin 2014) and the YT (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. The data were analyzed to determine the composition of rock glacier material and whether there was indeed a relationship between the clustering of rock glaciers and lithology. 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 were also used to train the statistical model in the cases of slope, elevation, lithology, TPI, and PISR.

3.2. 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 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 have a confidence level of 3 from both mappers, the data are 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. Including all features that were identified was thought to make the model more robust when considering nuances of probable rock glacier features. 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.

3.3. Digitizing the spatial extent of rock glaciers

Each identified feature was digitized using the polygon tool in ArcGIS Pro. Rock glaciers were digitized at a scale of 1:5000 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. 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 observed. The rooting zone was often recognized by a slight depression between the debris accumulation and the body of the rock glacier.

3.4. 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; the median of the polygon) 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 rock glacier were redistributed. Random point distribution was achieved using the Create Random Points toll in ArcGIS Pro, resulting in a near-even allocation across the three study regions. Ensuring a balanced dataset of background points relative to observed points is essential for maintaining statistical robustness and reducing bias in spatial analysis, enhancing the reliability of the findings.

3.5. Predictive model and model optimization

The spatial distribution of rock glaciers was modeled using a GAM in R (R Studio, Version 4.2.2). GAMs have previously been used for investigating the spatial distribution of rock glaciers in remote regions (Brenning et al. 2007) and other geomorphology studies (Miska and Jan 2005; Rudy et al. 2017). In this study, a GAM in R with a 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, TPI, lithology, elevation, aspect, and PISR. 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 and 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. Although aspect was removed from the modeling, it was still considered for the rock glacier inventory. The remaining variables included in further model iterations had variance inflation factor (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 and Surles 2002).

Model optimization involved several steps that enhanced the model's performance and interpretability. First, feature selection was undergone by iteratively removing nonsignificant variables from the model based on statistical significance tests. 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. This resulted in a subset of significant independent variables contributing to explaining variation in the response variable.

Incorporating smoothing parameters is a crucial aspect of GAMs to capture nonlinear relationships with the response variable. Therefore, the next step employed a data-driven approach utilizing the generalized cross validation (GCV) criterion to select the optimal smoothing parameters. This criterion balance model fit and complexity, preventing overfitting and ensuring that the model captured underlying data patterns effectively. Cross-validation was subsequently employed 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. Finally, 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 nonlinear relationships and demonstrated its 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 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). Subsequently, each class was defined based on a combination of these characteristics, ensuring that rock types within each class exhibited similar properties. This process allowed for the systematic grouping of lithology types into cohesive classes, facilitating clearer interpretation and analysis within the model framework. 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 two 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 and Smith 2018). Second, it facilitates uncovering the potential influences of specific lithology classes on the response variable.

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 follows:

$$y = f1\,(x1) + f2\,(x2) + \cdots + fp\,(xp) + \varepsilon \tag{1}$$

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.

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 Akaike information criterion (AIC). The thin-plate regression spline is a type of spline that uses a radial basis function as the basis for constructing 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. 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), AIC, and Bayesian Information Criterion (BIC). The DE and R2adj 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. VIFs were used to determine the degree of multicollinearity between the variables and therefore the validity of the model results (Thompson et al. 2017).

Interaction terms among the variables were analyzed by running multiple model iterations with all possible interactions among the significant variables. The DE 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). Ultimately, no interaction terms were included in the final model.

3.6. Rock glacier probability mapping

The probability values generated from the successful GAM were used in conjunction with Inverse Distance Weighted (IDW) interpolation to visualize the probabilities from the validation data (30%) as well as new test data from a test region adjacent to SR1. Interpolating the probabilities of the positive class from the GAM to create a surface for rock glacier likelihood using the IDW tool in ArcGIS Pro (V. 2.9.3) offers a promising approach for assessing the spatial distribution and potential occurrence of rock glaciers. This method leverages the predictive capabilities of the GAM and combines them with spatial interpolation techniques to generate a continuous surface representing the likelihood of rock glaciers. IDW interpolation calculates the likelihood values

 Arctic Science **10:** 653–672 (2024) | dx.doi.org/10.1139/as-2023-0065

at unmeasured locations based on the weighted average of nearby data points, giving higher weights to close points. In the context of rock glacier likelihood, this means that the probabilities of the positive class obtained from the GAM model are assigned to unsampled locations based on the proximity and influence of known data points. Analysis of the resulting probability map generated in SR1 from the test data was compared to the observed rock glaciers. To validate the spatial transferability of the model, a novel region of 255 km^2, approximately 30 km south of SR1, 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: 62.56°N, 62.50°N, −127.10°W, −126.97°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 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 subsequently used to assess the distribution and prevalence of rock glacier probabilities in comparison to observed rock glaciers.

4. Results

4.1. Rock glacier inventory

Over 500 potential rock glacier features were identified across the three study regions in the Mackenzie Mountains (Fig. 2). Characteristics for rock glaciers were extracted and analyzed (Table 2). 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. Between both mappers, 381 FOI were identified. There were 149 FOI identified in SR1, 91 and 141 for SR2 and SR3, respectively. We observed minimal disparity in rock glacier properties across the studied regions, underscoring the uniformity in morphological features and activity statuses within these periglacial environments. As depicted in Fig. 3, the subtle distinctions in shape, lithology, and activity status among the examined rock glaciers across diverse study regions highlight the consistency in their geomorphic attributes. The rock glaciers identified in the study region exhibit unremarkable characteristics, mirroring those found in other regions such as Jasper National Park (Luckman and Crockett 1978). Similar lithologies, aspect orientations, and mid-range elevations are common traits shared by these rock glaciers across various geographic locations (Krainer and Ribis 2012; Charbonneau & Smith 2028). This consistency suggests a degree of uniformity in rock glacier formation processes and environmental conditions, underscoring their broader geomorphological significance.

4.2. Rock glacier inventory attributes

Rock glacier characteristics were assessed across three study regions, with average size measurements recorded and analyzed (Table 3). One-way ANOVAs revealed significant differences in both width and area among the study regions ($P < 0.05$). Slope variations were also observed, with average values of 16° (SR1), 17° (SR2), and 15°(SR3); a one-way ANOVA indicated a significant difference in slope values between regions ($P = 0.002298$). The potential activity of rock glaciers in each region is summarized in Table 4. Additionally, analyses of slope, elevation, TPI, and PISR highlighted significant disparities between rock glacier presence and absence data (Table 5).

Aspect analysis demonstrated distinct orientation patterns across regions (Fig. 4), with notable occurrences on northeast and northwest-facing slopes in SR1, and predominantly east and northeast orientations in SR2. Active rock glaciers displayed varying aspect preferences, notably with northeast and northwest orientations prevalent in SR1, while SR2 and SR3 exhibited east and northeast orientations predominantly.

Lithological compositions within each region varied, with sedimentary rocks comprising the majority. SR1 was predominantly mudrock (38%) and sandstone (32.16%), SR2 showed a higher occurrence of carbonate lithologies, primarily dolostone (24.48%) and limestone (12.68%), while SR3 was characterized by siltstone (48.23%) and shale (38%). Sedimentary rocks dominated the entire mountain range, with shale (20%), dolostone (17.2%), and limestone (17.2%) being the most abundant lithologies.

4.3. 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 6. 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

Fig. 2. 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).

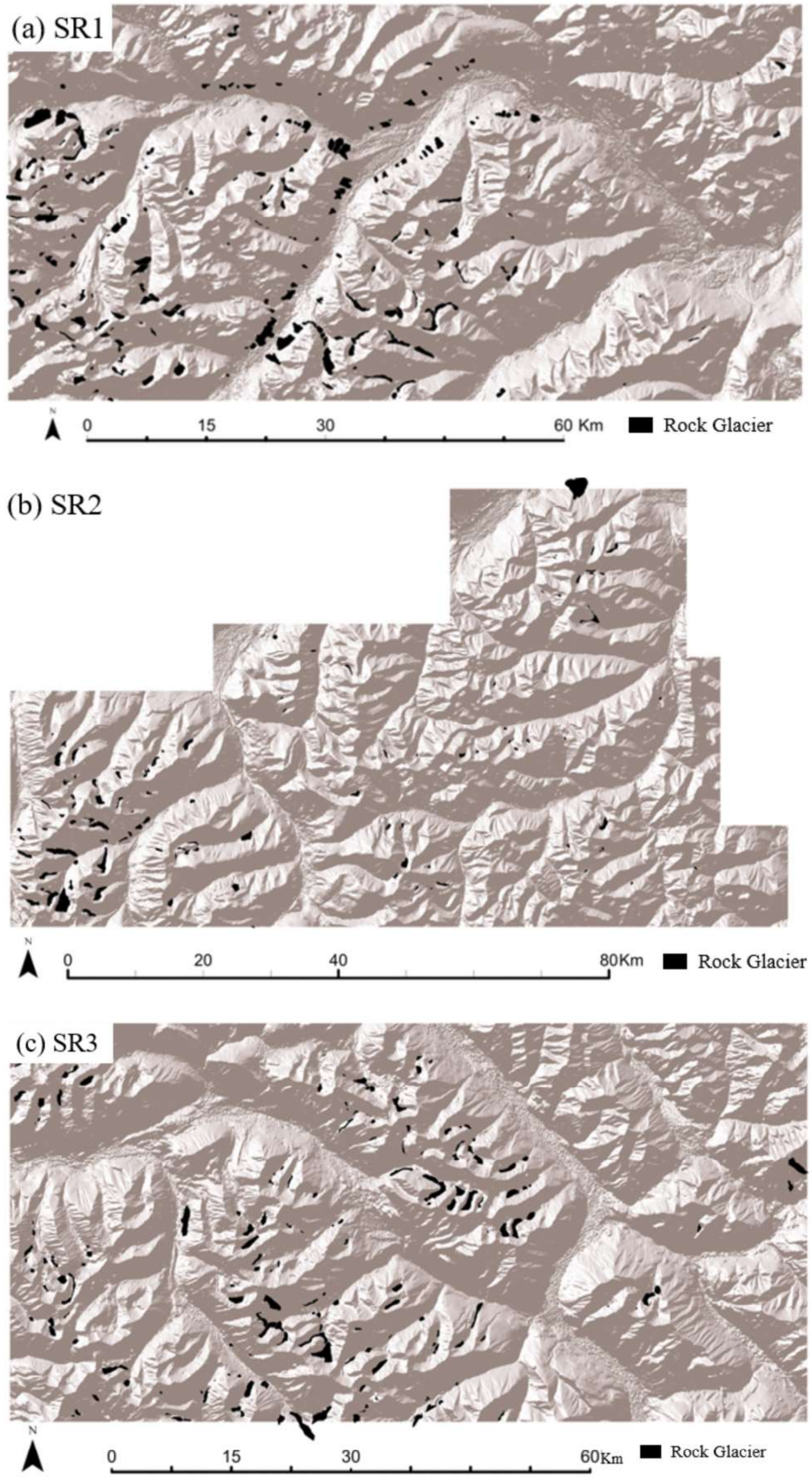


Table 2. Summary statistics for attributes of each rock glacier polygon within each study region with minimum, maximum, and median values for elevation, slope, TPI, and PISR ($N = 530$).

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

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) (Fig. 5). 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.

4.4. Generalizability of the GAM

Within a 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 these 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 (Fig. 6). Five probability intervals were defined (Table 7). 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 (Fig. 6), indicating an elevated level of agreement between the GAM model and the observed data. This test region is 255 km^2, approximately 30 km south of SR1 (62.56°N, 62.50°N).

5. Discussion

5.1. 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 IPA. The IPA has composed a rock glacier action group that presents 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. 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 FOI 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 PISR, elevation, slope, TPI, 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

Fig. 3. Morphological Variability and Activity Status of Rock Glaciers across Different Study Regions. (*a*) Spatulate rock glacier with two lobes in Study Region 1 (SR1), predominantly composed of shale, exhibiting an active state. Lobes are distinguished: Lobe 1 (left) measures 1488 m in length and 487 m in width, while Lobe 2 (right) spans 1007 m in length and 970 m in width. (*b*) Spatulate rock glacier in SR1, primarily comprising shale, and displaying an active state. Dimensions are measured at 939 m in length and 458 m in width. (*c*) Tongue-shaped rock glacier situated in Study Region 2 (SR2), characterized by shale lithology and an active state, with measurements of 1141 m in length and 750 m in width. (*d*) Spatulate rock glacier within SR2, comprised of shale and identified as inactive, spanning 1488 m in length and 487 m in width. (*e*) Tongue-shaped rock glacier in Study Region 3 (SR3), predominantly consisting of mudstone and exhibiting an active state, with dimensions of 952 m in length and 490 m in width. (*f*) Tongue-shaped rock glacier within SR3, composed of shale lithology and displaying an active state, with substantial dimensions measured at 3184 m in length and 1032 m in width. (World Imagery Base Layer, ArcGIS Pro, V. 2.9.3).

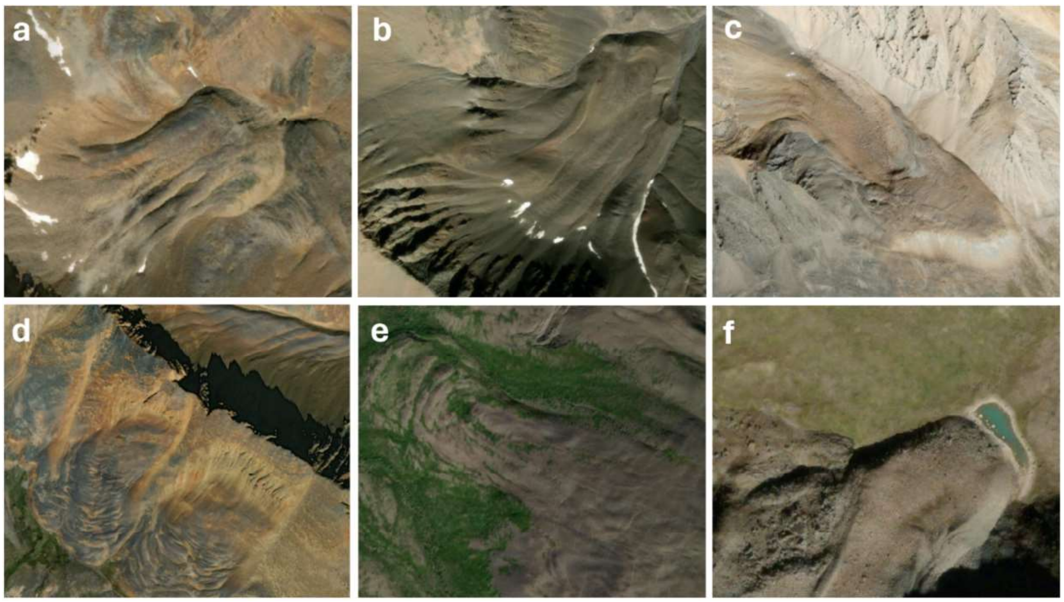


Table 3. Summary statistics for rock glacier size within each study region ($N = 530$).

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 (%)	2.44	1	2

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
1	35	199	234
2	18	102	120
3	18	176	176

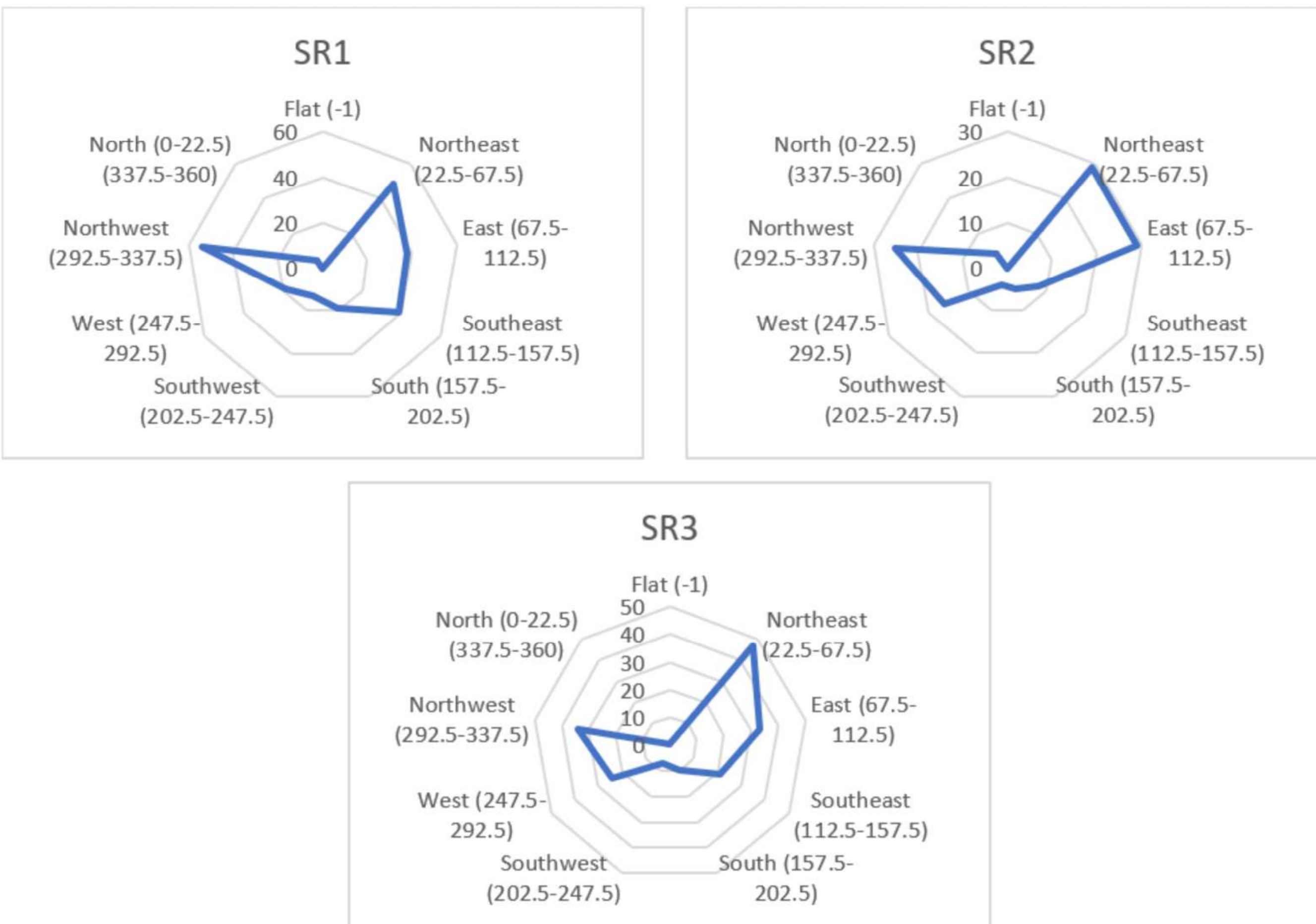
subjectivity. The reduction in subjectivity is driven by using a quantitative basis for determining the likelihood of rock glacier occurrence based on a statistical model that incorporates terrain attributes rather than the reliance on individual mappers.

This rock glacier inventory is a first step in exploring these features in the Mackenzie Mountains. While several rock glaciers and FOI 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. Hydrological analysis of rock glaciers may involve studying their influence on water storage, release dynamics, and downstream hydrological regimes. This analysis could include assessing the contribution of rock glaciers to streamflow, groundwater recharge, and the modulation of meltwater fluxes. This would provide insights into their role in alpine hydrology and potential implications for water resource management and ecosystem dynamics. The consensus method used in this case provided a useful strategy

Table 5. 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/m^2
Most common range	1100–1970	10–36	(–)40–4	144–234, 369–459
Maximum	2431	70.58	175.65	547.06
Minimum	666	0	–130.15	54.26
Average	1517	24.24	–0.42	327.95
		Rock glaciers		
Variable	Elevation m a.s.l	Slope (°)	TPI	PISR W/m^2
Most common range	1200–2000	10–25	(–)70 –(–) 25	182–212, 402–422
Maximum	2181	33.49	31.1	435.65
Minimum	939	5.05	–146	182.22
Average	1610.11	16.58	–39.96	290.82

Fig. 4. Rose charts depicting the occurrence of aspect for rock glaciers within each study region. Northernly aspects are most common among the rock glaciers in each region.



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.

5.2. Rock glacier characteristics

The lack of significance found regarding rock glacier length, width, and area using ANOVA tests suggests that the observed variations in average length, width, and area could be attributed to random fluctuations rather than actual disparities between the regions. These findings imply that

Table 6. Confusion matrices produced by the GAM for both the training data (70%) and the validation data (30%).

Actual		GAM training (70%)			GAM validation (30%)	
		Predicted				
		0	1		0	1
	0	321	49	0	134	26
	1	50	322	1	25	133

Note: 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).

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. Different lithological compositions can affect factors such as permeability, water-holding capacity, and mechanical properties of the rock (Traczyk and Migoń 2003; Haeberli 2006). In some studies 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 and Matsuoka 2006). However, others have found that fine-grained rock glaciers can also reach considerable sizes (Brenning and Azócar 2010; Zalazar et al. 2020). Consequently, the influence of lithology on rock glacier dimensions may manifest differently depending on regional geological characteristics and environmental conditions. 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 and Ribis 2012).

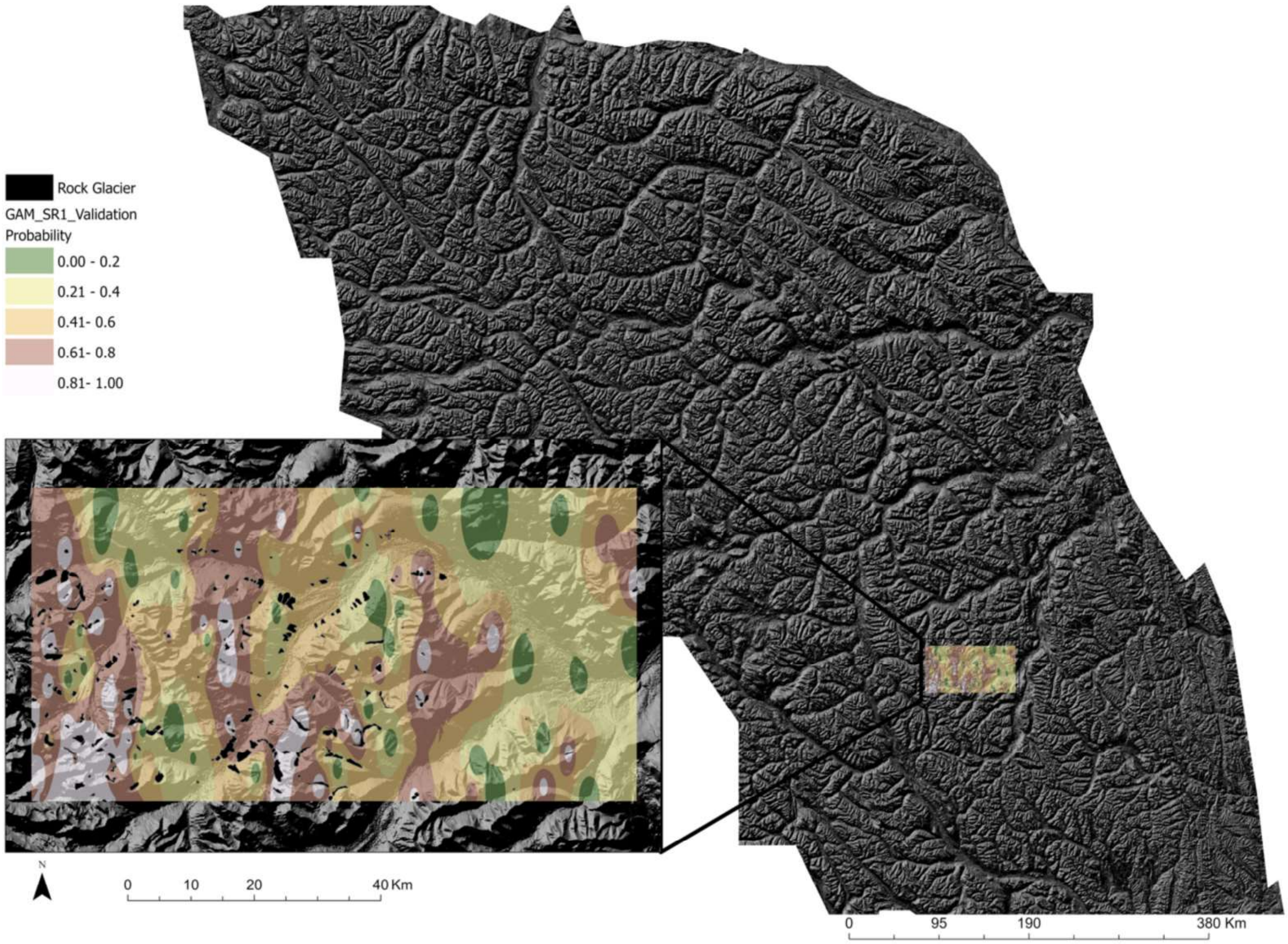
The slope of the terrain has a significant impact on the development and morphology of rock glaciers (Johnson 1984). Slopes generally favor greater downslope movement, which affects the length of rock glaciers and the gravitational force that affects their movement (Monnier and Kinnard 2017). The average 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 contributed to 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, 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).

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. The cirque basins within the study regions further contribute to the aspect patterns observed in rock glaciers. These basins, formed by glacial erosion (Nelson and 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. 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 high 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

Arctic Science **10:** 653–672 (2024) | dx.doi.org/10.1139/as-2023-0065

Fig. 5. 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). The probabilities used for interpolation were generated from the 30% validation data. The training data consisted of 70% of the rock glacier presence and absence dataset. 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).



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 aids in identifying ridge and valley areas impacting rock glacier distribution by highlighting elevation disparities (Weiss 2001). Positive TPI values indicate ridge locations while negative values indicate valleys, potentially suitable for rock glacier formation due to protection from solar radiation by higher elevations (Johnson 1980). Rock glaciers tend to occur downslope from headwalls, which supply the necessary debris for their development.

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 and 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, 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 ac-

Fig. 6. Distribution of rock glaciers in a test site 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 color scale ranging from green (0.00) to near white (1.00).10 000 regularly spaced data points were used to extract covariates. Probability ranges from 0.00 to 1.00. 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).

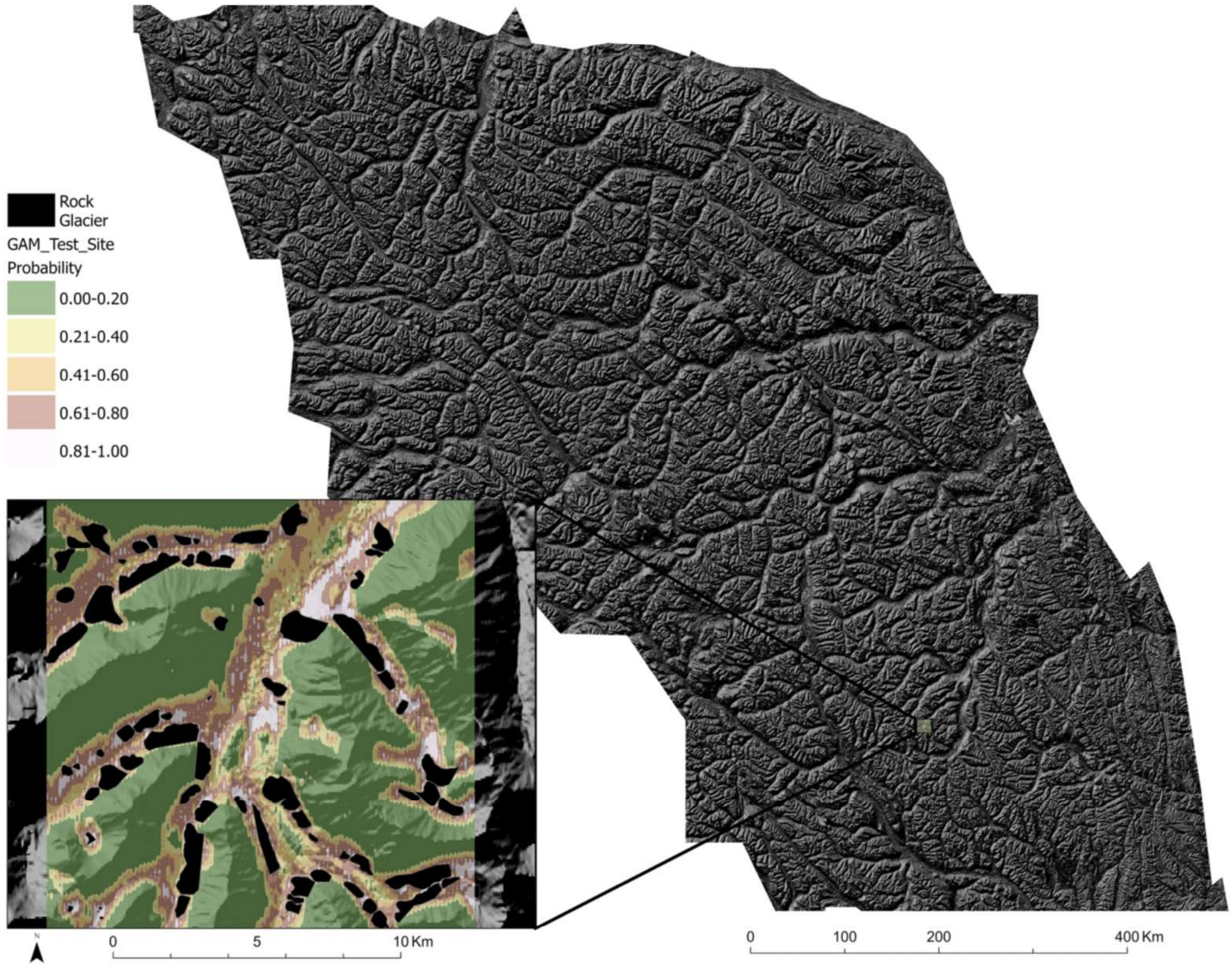


Table 7. Counts of pixels falling into each probability interval for rock glaciers identified in the test region.

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%)

tivity 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. 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 and Smiraglia 1998; Janke 2007; Krainer and Ribis 2012; Charbonneau and Smith 2018).

5.3. 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. 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), these rock glaciers were primarily assigned low confidence or were inactive. 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 and 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 and 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).

5.4. 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 and 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 pixels cover 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.

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).

5.5. Limitations and future studies

While this research provides valuable insights into rock glacier distribution, limitations exist that could be addressed in future studies. The inclusion of additional variables such as NDVI and curvature could enhance model precision, as evidenced by false positive points. Furthermore, restricting the model to only high-confidence features may improve accuracy. Considering climate variables like temperature and precipitation, known to influence rock glacier development, could also enhance model capabilities, although data availability in remote regions remains a challenge (Brazier et al. 1998; Brenning and 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 (Roberts et al. 2019; Noad and Bonnaventure 2022) Future research should focus on utilizing advancements in satellite technology and machine learning methods to refine rock glacier mapping and dynamics assessment. This preliminary inventory sets the stage for more extensive research on rock glacier hydrology, temperature regimes, and kinematics, enabling a better understanding of their significance and response to climate change. Continuous monitoring and improvement of rock glacier inventories are essential for informed decision-making regarding climate change impacts and resource management in vulnerable regions.

6. Summary and conclusions

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. The relevance of the GAM in modeling the likelihood of rock glaciers in the Mackenzie Mountains extends beyond this specific geographic region and holds promise for application in diverse settings. While our study focuses on the Mackenzie Mountains, the fundamental principles underlying the GAM framework—which allow for the flexible modeling of nonlinear relationships between predictor variables and the occurrence of rock glaciers—can be readily adapted to other mountain ranges. This adaptability stems from the recognition that key environmental factors influencing rock glacier distribution, such as topography and lithology, exhibit spatial variability but often operate according to consistent underlying principles. Therefore, the GAM methodology offers a transferable approach for assessing the likelihood of rock glacier presence in other mountainous regions with similar environmental characteristics. Mountain ranges characterized by complex topography, permafrost conditions, and a history of glacial activity, such as the Alps, the Andes, and the Himalayas, represent potential candidates for applying the GAM model to predict rock glacier occurrence. By leveraging the robustness and flexibility of the GAM framework across varied geographical contexts, our research aims to contribute to a deeper understanding of rock glacier dynamics globally. This will ultimately facilitate more informed assessments of cryospheric changes and their implications for mountain ecosystems and communities.

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 following:

- 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 modeling 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.

Acknowledgements

We wish to acknowledge the contributions of Marcus Dostie in assisting with resolving GIS-related issues encountered in this research. His expertise was instrumental in overcoming technological challenges. We also acknowledge the Dene people and their ancestors, elders, and communities that have lived and cared for the land within the Mackenzie Mountains for countless generations.

Article information

History dates

Received: 1 November 2023
Accepted: 11 June 2024
Version of record online: 13 November 2024

Copyright

Data availability

Data generated or analyzed during this study are available from the corresponding author upon request. Available data comprise two GIS shape files: one for the rock glacier inventory used in this study and the other for the FOI 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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Competing interests

The authors declare there are no competing interests.

Funding information

The authors declare no specific funding for this work.

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