# Supplementary Material to Projected Loss of Rock Glacier Habitat in the Contiguous Western United States with Warming

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## Data

### Description of Rock Glacier Inventory

Rock glaciers were identified by Trcka (2020) based on surface topography using imagery from Google Earth (Google, Inc.), an approach common to other inventories over large spatial areas (e.g., Charbonneau and Smith, 2018; Rangecroft and others, 2014; Schmid and others, 2014). The inventory represents a re-evaluation of Johnson (2020) and all other regional inventories within the domain with the goal of identifying rock glaciers specifically, excluding related features of interest that are sometimes included in other periglacial inventories. Therefore, the Trcka (2020) inventory represents a conservative selection of rock glaciers that is smaller than the other inventories. We note that Trcka (2020) does not distinguish between rock glacier origins (glacial or periglacial); rock glaciers were classified into two categories, active and inactive. Active rock glaciers were defined as those that exhibit steep marginal slopes, apparently greater than the angle of repose, along the downslope terminal boundary. The slopes expose lighter-colored, less weathered debris compared to the darker, more weathered, rock glacier surface. The rock glacier body appears swollen or dilated (Barsch, 1996; Jones and others, 2019). Together these features suggest the presence of ice and movement. Inactive rock glaciers are characterized by a more gently sloping, less sharp-crested terminal boundaries exposing little or no un-weathered material. The body of the rock glacier appears deflated, suggesting no movement and little or no internal ice. An important additional characteristic, common to both categories, is significant extension into the valley, which demonstrates significant movement. Considering that the feature must move to be a rock glacier (or must show evidence of having moved in the past in the case of an inactive rock glacier), Trcka (2020) adopted this conservative approach to increase the accuracy of the classification. One drawback of this approach is that identification of rock glaciers from aerial imagery can be difficult, and the study did not include ground-based evaluation of rock glacier classification. However, Trcka compared their inventory with several smaller scale inventories, some of which did complete ground-based evaluation of rock glacier features (e.g., Millar and Westfall, 2019; Riffle, 2018; Johnson, 2006; Florentine, 2011; Kinworthy, 2016; Legg, 2016; Johnson, 2018)

### Description of Covariates

Climate is one key determinant of rock glacier distributions. Temperature is relevant to processes of snow accumulation and ablation, active layer thickness, and freeze-thaw debris production (Haeberli and others, 2006). Precipitation contributes to snow accumulation and ice flux to supply the rock glacier, however rain and meltwater also have the potential to infiltrate the surface debris layer, contributing to latent heating of the ice and to erosion of finer sediments from the rock glacier surface (Kenner and Magnusson, 2017). Solar radiation shapes the strong spatial variability of available energy in complex terrain and rock glaciers are often found in shaded areas such as northern aspects or cirques (Johnson and others, 2007). We consider the following metrics: mean, minimum, and maximum annual temperatures, annual number of temperature oscillations around 0°C, annual precipitation, annual rainfall, and mean annual downward solar radiation (Table S1).

Snow accumulation is necessary to provide the ice flux for rock glacier development and persistence. However, snow is not universally beneficial to rock glaciers. Too much snow can increase the ice to debris ratio, leading to the formation of a debris covered glacier or glacier instead of a rock glacier (Anderson and others, 2018). The insulating effects of snow are also a double-edged sword; snow cover limits the advection of air within the debris matrix which prevents warming when air temperatures are above freezing, but also can limit advective cooling when the air is cold (Wagner and others, 2019). The snow metrics we used included annual snowfall water equivalent (sfe), snow duration (duration), annual maximum snow water equivalent (maxswe), and the number of snow free days between the snow on and snow off dates (nosnowdays). Snow on (off) was defined as the first (last) day of the first (last) period of 5

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| **Environmental Covariate** | **Short Name** | **Data Source** | **Relevant Processes** |
| Minimum, maximum, and mean annual temperature, annual number of temperature oscillations around °0C | tmin, tmax, tmean, freeze-thaw | SnowClim1 | Snow accumulation, snow melt, freeze-thaw debris production |
| Annual precipitation | precip | SnowClim1 | Snow accumulation, water infiltration in rock matrix |
| Annual rainfall | rain | SnowClim1 | Precipitation heat flux, propensity to wash debris off of rock glacier surface |
| Mean annual downward shortwave radiation | solar | SnowClim1 | Available energy for melt, snow cover duration |
| Annual SFE, snow duration, annual maximum SWE, number of snow free days between snow on and snow off dates | sfe,  duration,  maxswe,  nosnowdays | SnowClim1 | Accumulation zone productivity, surface insulation |
| Aspect | aspect | Derived from NED2 | Solar radiation loading, snow ablation |
| Slope | slope | Derived from NED2 | Rock glacier driving stress, velocity |
| Headwall Area Metric (using 3x3 window and 5x5 window) | headwall3, headwall5 | Derived from NED2 | Debris supply source, avalanche supplementation of snowpack |
| Rock Type | rocktype | USGS3 | Fracture propensity, debris supply, clast size |

Table S1 Environmental covariates used in the Maxent model. 1Lute and others (2022); 2Gesch and others (2018); 3Anning and Ator, (2017).

consecutive days of snow cover each year. Duration was calculated as the difference between the snow on and off dates.

Aspect is indicative of solar radiation loading which provides energy for snow and ice melt as well as for freeze-thaw debris production, and can be associated with preferential snow loading if aligned with prevailing winds. Slope is a key variable for calculating the driving stress and velocity of rock glaciers and provides a constraint on suitable rock glacier locations since rock glaciers are typically located on 5°-30° slopes which promote downslope movement but are not so steep that the rock glacier detaches from sources of debris and ice (Kenner and Magnusson, 2017; Sloan and Dyke, 1998).

Several studies have demonstrated the importance of rock headwalls as sources of debris and avalanched snow for rock glaciers (Morris, 1981; Müller and others, 2016). We assessed two different headwall metrics, described in the main text. One used a five by five window and the other used a three by three window of grid cells centered on the target pixel and both used a slope threshold of 30°. Similar headwall metrics showed up as key predictors of rock glacier presence in preliminary work.

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| Class number | Class abbreviation | Class description |
| 1 | CARB | sediments and sedimentary rocks. Carbonate rocks such as limestone and dolostone. Generally, any rock including any minor carbonate lithology is included in this group. Some special cases exist where carbonates are also identified based on LITH62MINO field. |
| 2 | CLAST\_C | sediments and sedimentary rocks. Clastic sediments/rocks primarily made of sands, gravels, cobbles, or larger clasts. |
| 3 | CLAST\_F | sediments and sedimentary rocks. Clastic sediments/rocks primarily made of fine-grained materials such as shale, siltstone, claystone, mudstone, etc. |
| 4 | CLAST\_U | sediments and sedimentary rocks. Clastic sediments/rocks of unknown or highly variable clast sizes. |
| 5 | EVAP | sediments and sedimentary rocks. Evaporites or playas. |
| 6 | META | Metamorphic rocks. |
| 7 | PLUT\_OTH | Igneous, generally mafic, other less quartz-rich plutonic rocks, such as monzonite or gabbro. |
| 8 | PLUT\_QTZ | Igneous, generally felsic, quartz-rich plutonic rocks such as granitoids, granite, granodacite. |
| 9 | VOLC\_OTH | Igneous, generally mafic, volcanic rocks, such as basalt that are mineralogically equivalent to the less quartz-rich plutonic rocks. |
| 10 | VOLC\_QTZ | Igneous, generally felsic, volcanic rocks such as rhyolite and dacite that are mineralogically equivalent to the quartz-rich plutonic rocks. |
| 11 | WATER | Water or ice |
| 12 | NONE |  |

Table S2 Descriptions of numeric lithology classes which were used as a categorical variable in the Maxent model. Data is from Anning and Ator (2017).

Geologic considerations are also relevant to rock glacier distributions. In particular, the fracturing propensity and characteristic clast size of the rock help determine the rate of debris supply and the size of the debris, which is relevant to rock glacier energy budgets (Ikeda and Matsuoka, 2006; Kenner and Magnusson, 2017). Explanations of the classes in the generalized lithology layer we used (Anning and Ator, 2017) are provided in Table S2.

### Covariate Preparation

Collinearity of predictor variables can hamper the interpretation of the importance and effect of different predictors and can degrade model transferability when the collinearity structure changes between calibration and projection datasets (Dormann and others, 2013; Feng and others, 2019). Collinearity was assessed by computing Pearson correlations coefficients (r) between each pair of predictors (Fig. S1). Combinations with |r|>0.7 were considered to be problematic (Dormann and others, 2013). In cases with |r|>0.7, we chose which collinear variable to include/remove by considering the results of the Maxent jackknife procedure (similar to Fig. 2a). The approach calculates the loss in regularized training gain when each variable is left out of a model and calculates the regularized training gain of a model built on that variable alone. For these models we used default parameter options. This resulted in the removal of headwall3, tmin, tmax, maxswe, duration, and precip, leaving 10 covariates.

We assessed changes in the collinearity structure between the pre-industrial, present, and future time periods by comparing correlation matrices for the three time periods. For the variables we retained from the previous step, the only variable that had substantial changes in collinearity was freeze-thaw; the sign of the correlation between freeze-thaw and several

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Figure S1 Correlation matrices for pre-industrial, present, and future time periods. White x’s denote correlations with absolute values greater than 0.7.

other variables changed between the pre-industrial and future time periods. To avoid complications in prediction, we excluded freeze-thaw from the model, leaving nine covariates.

## Model Complexity

To identify the appropriate level of model complexity, we constructed a series of models with varying values of the regularization parameter (beta) and feature classes (including linear (L), quadratic (Q), threshold (T), and hinge (H)). We excluded product features in the interest of interpretability of the results. We used the ENMeval package (Kass and others, 2021) in R to evaluate the performance of these models using the AICc statistic (Akaike, 1974), which penalizes model complexity and has been shown to outperform AUC based methods of selecting optimal Maxent model complexity (Warren and Seifert, 2011). We built a model for each combination of beta parameter (1 (the default), 3, 5, 7, 9, 11) and feature class (L, LQ, LH, LT, LQH, LQT, LQTH). The model with the lowest AICc was considered the best model. Our analysis showed that the model with a regularization beta of nine and linear, quadratic, and threshold features provided the optimal performance (Fig. S2). The selected model was used to map rock glacier probability of presence across the domain based on Maxent’s cloglog output.

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Figure S2 AICc values for different levels of regularization beta parameter and different feature class combinations.

A map of the land

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Figure S3 Map of spatial blocks used in the spatial cross validation analysis overlaid on western U.S. modeling domain. Blocks were grouped into folds as indicated by the number in each block.

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Figure S4. Marginal response functions illustrating the relationship between the covariate values (x-axis) and the rock glacier habitat suitability (y-axis) when all other variables are held constant at their average value.

A map of the state of washington

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Figure S5. Predicted pre-industrial suitability at known rock glacier locations. Color scale is divided at the threshold that excludes 10% of known rock glaciers (0.23).

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Figure S6. Pre-industrial covariate distributions at known rock glacier locations. Quartiles on the x-axis are quartiles of predicted suitability with one being the least suitable and four being the most suitable.

A map of the united states

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Figure S7. a) Rock glacier suitability under pre-industrial hydroclimatic conditions (same as Fig. 3a) and b) permafrost probability from Obu and others (2018).

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Figure S8. Distribution of covariates between pre-industrial (blue) and present (purple) time periods, grouped by suitability change category. For covariates that are not time-varying (bottom row), a single violin is shown for each suitability category. In the first subplot, percent values indicate the percent of the full modeling domain that falls into each category.

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Figure S9. Distribution of covariates between present (purple) and future (red) time periods, grouped by suitability change category. For covariates that are not time-varying (bottom row), a single violin is shown for each suitability category. In the first subplot, percent values indicate the percent of the full modeling domain that falls into each category.

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Figure S10. Changes in environmental covariates over time at locations corresponding to present-day glaciers and present-day rock glaciers. Topographic and geologic variables, which do not change over time, are represented by one violin for glaciers and one for rock glaciers.

Table S3. Summary of pre-industrial, present, and future rock glacier habitat, grouped by level III ecoregion. Suitable and unsuitable areas are defined by the 0.23 threshold as discussed in the text. Values are in km2, except for the percent changes which are in %. Total column shows the area of the whole ecoregion, whereas the Modeled column shows the area within the ecoregion that was included in the distribution model.



Table S4. Average modeled suitability at known active and inactive rock glacier locations under each climate scenario

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|  | Active Rock Glaciers | Inactive Rock Glaciers |
| Pre-industrial | 0.72 | 0.52 |
| Present | 0.57 | 0.38 |
| Future | 0.06 | 0.03 |

Table S5. AUC values from cross-validation experiments. Calibration AUC is the AUC from the model calibrated on the indicated spatial fold. Validation AUC is the AUC of the model calibrated on the other fold and validated on the indicated spatial fold. Delta AUC is the difference between the calibration and validation AUC values.

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|  | Calibration AUC | Validation AUC | Delta AUC |
| Spatial block fold 1 | 0.98 | 0.95 | 0.02 |
| Spatial block fold 2 | 0.97 | 0.87 | 0.10 |
| Cold to warm | 0.91 | 0.91 | 0.00 |

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