Explaining the spatial pattern of debris flow and flood hazard in High Mountain Asia

Varya Bazilova,

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Dorje Dolma lama 🇳🇵
@DolmaLama444

Over 50 people are missing in the Melamchi and Indrawati rivers' flooding. The floods have also caused damages to the dam in Melamchi drinking water project, Timbu Bazaar, Chanaute Bazaar, Talamarang Bazaar and Melamchi Bazar.

8:37 PM · Jun 16, 2021 · Twitter for Android

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Kaushal Gnyawali
@KaushalGnyawali

Landslide dam outburst seems to have Melamchi flooding in Sindhupalchowk, Nepal

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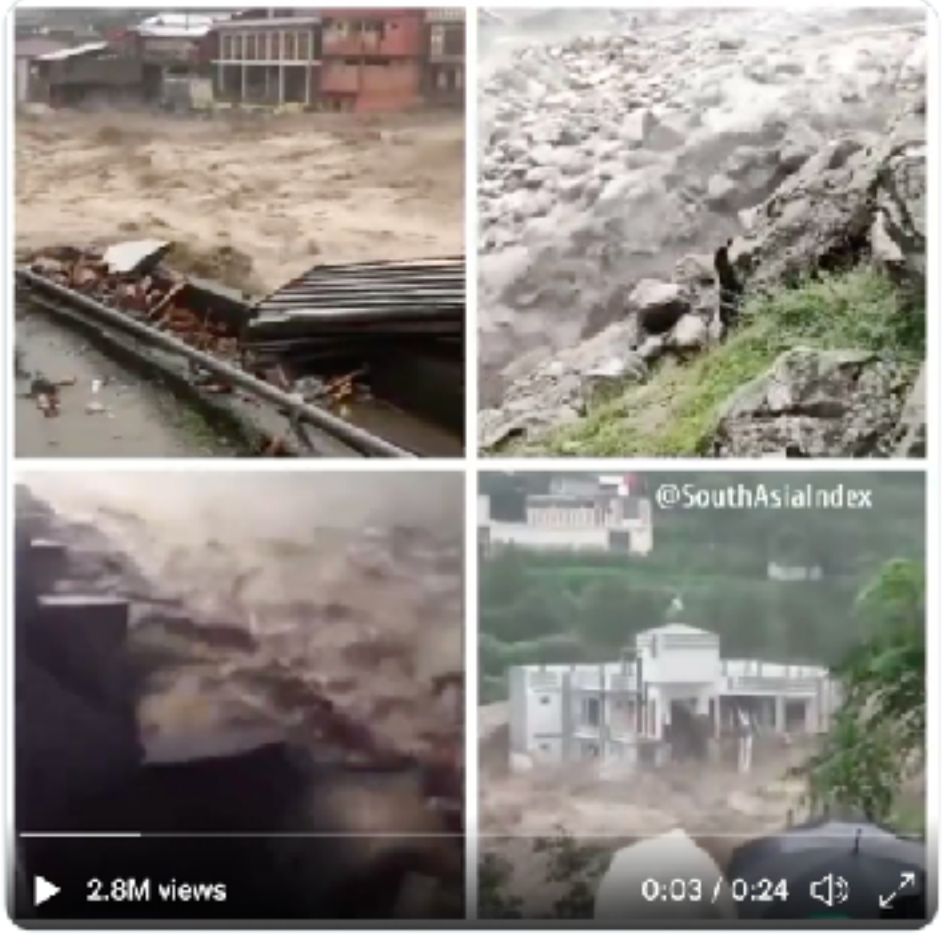
Landslide dam outburst seems to have Melamchi flooding in Sindhupalchowk, Nepal

Colin McCarthy @US_Stormwatch · Aug 30

Hard to comprehend the scale of the flood disaster in Pakistan, the 5th most populated nation in the world.

Nearly 1400 dead, 1 million houses damaged or destroyed, and 50,000,000 people displaced.

1/3 of the country is underwater.



Original Paper | Published: 19 October 2020

Morphometrical analysis of torrential flows-prone catchments in tropical and mountainous terrain of the Colombian Andes by machine learning techniques

María Isabel Arango, Edier Aristizábal & Federico Gómez

Natural Hazards 105, 983–1012 (2021) | Cite this article

Article | Open Access | Published: 29 August 2019

Assessing Susceptibility of Debris Flow in Southwest China Using Gradient Boosting Machine

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Scientific Reports 9, Article number: 12532 (2019) | Cite this article

Open Access | Article

Comparison of Different Machine Learning Methods for Debris Flow Susceptibility Mapping: A Case Study in the Sichuan Province, China

by Ke Xiong [1], Basanta Raj Adhikari [1,2], Constantine A. Stamatopoulos [3], Yu Zhan [4], Shaolin Wu [4], Zhongtao Dong [1] and Baofeng Di [1,4,*]

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Assessing Susceptibility of Debris Flow in Southwest China Using Gradient Boosting Machine

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Debris Flow Susceptibility Mapping Using Machine-Learning Techniques in Shigatse Area, China

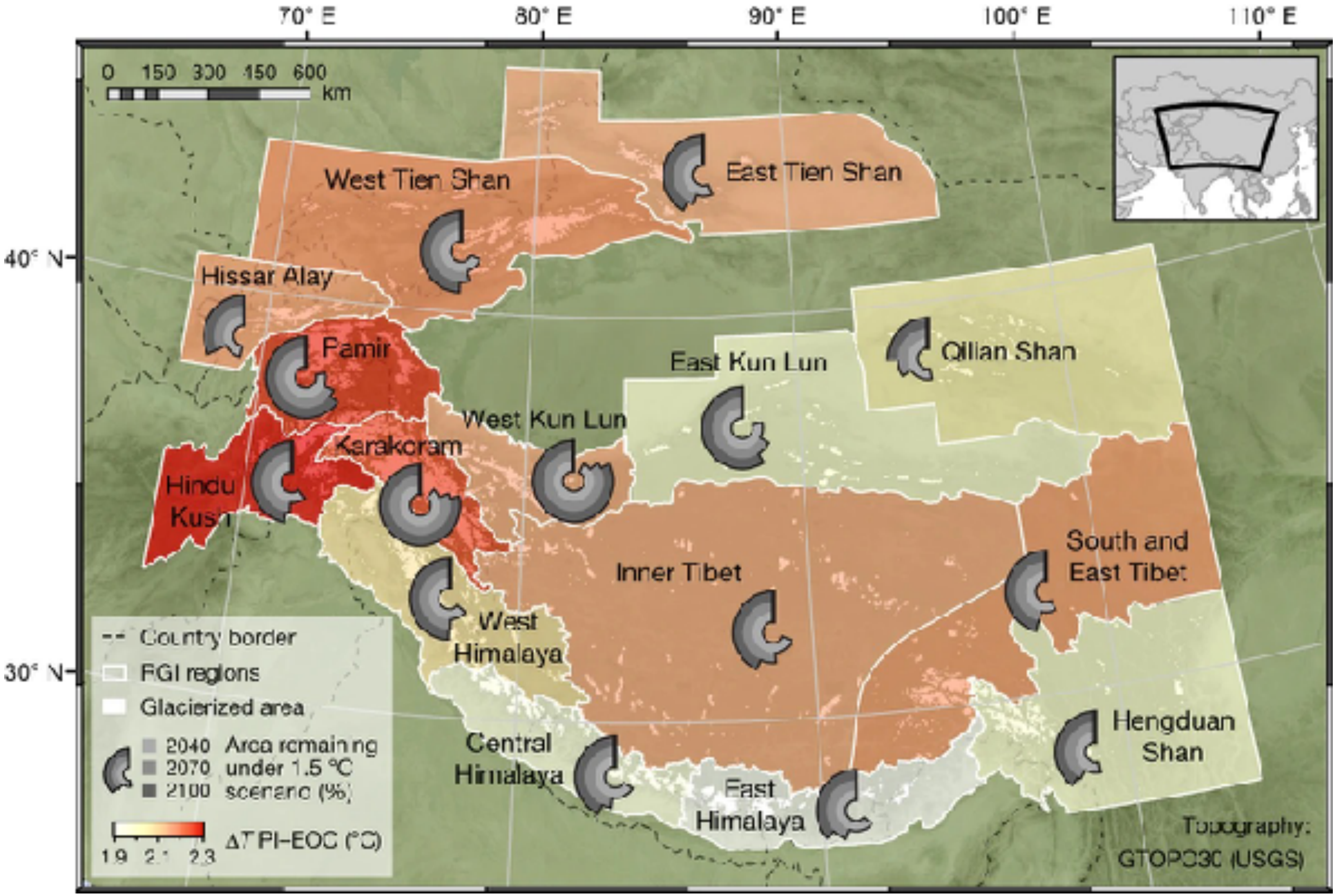
by Yonghong Zhang [1], Taotao Ge [1], Wei Tian [2,*] and Yuei-An Liou [3,*]

ELSEVIER

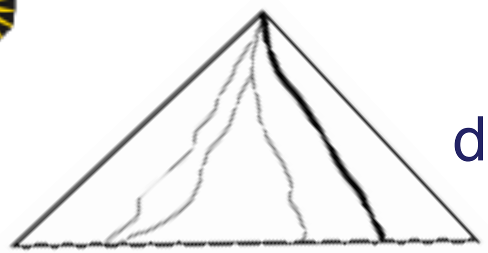
On predicting debris flows in arid mountain belts

Amelie Stolle, Maria Langer, Jan Henrik Blöthe [1], Oliver Korup

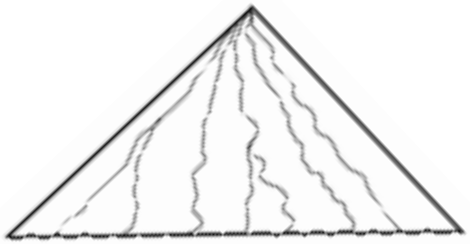
What is happening in HMA?



Impact of a global temperature rise of 1.5 degrees Celsius on Asia's glaciers (P. Kraaijenbrink et al., 2017)



debris flow dominated



fluvial flow dominated

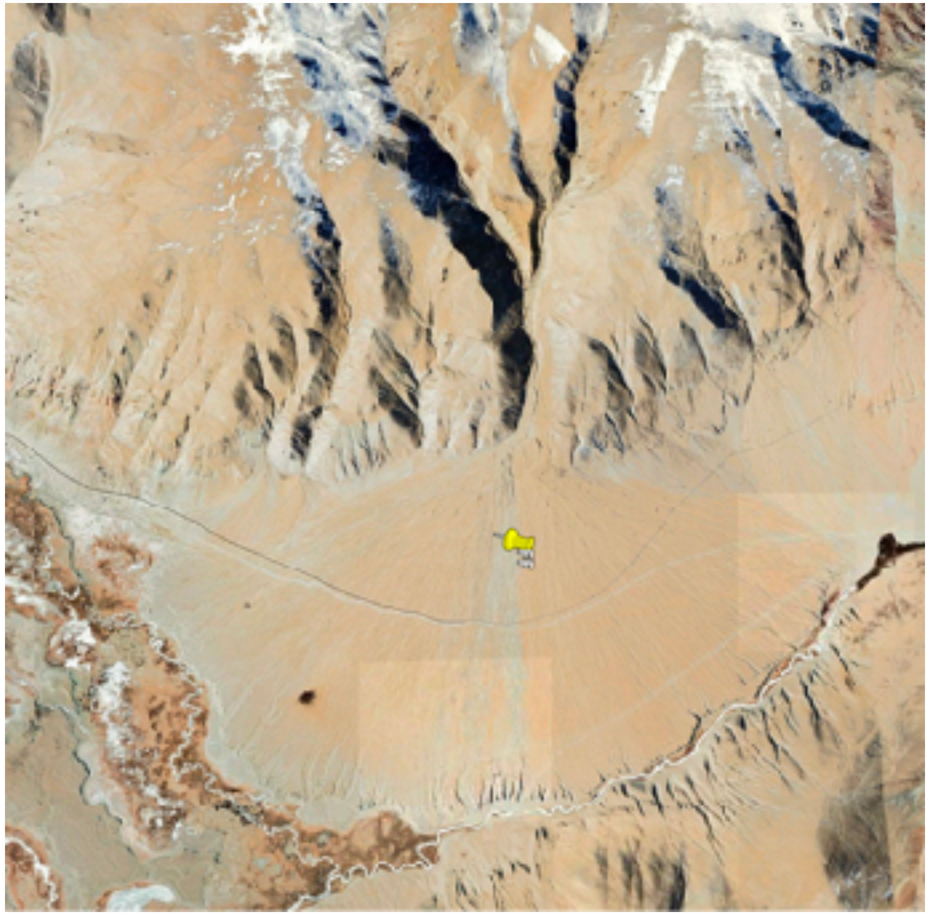


Image source: Google Earth

Research questions

- to use ML classifier to estimate probabilities of debris-flow vs flood dominated system
- to identify the parameters, that matter for the classification
- to see if adding climatic features affects the classification
- to find out if there are any regional differences

- to make projections based on climate scenarios

frame the question

get data clean up

split data: train & test

machine learning: build the model

tune the model

evaluate the model

make predictions

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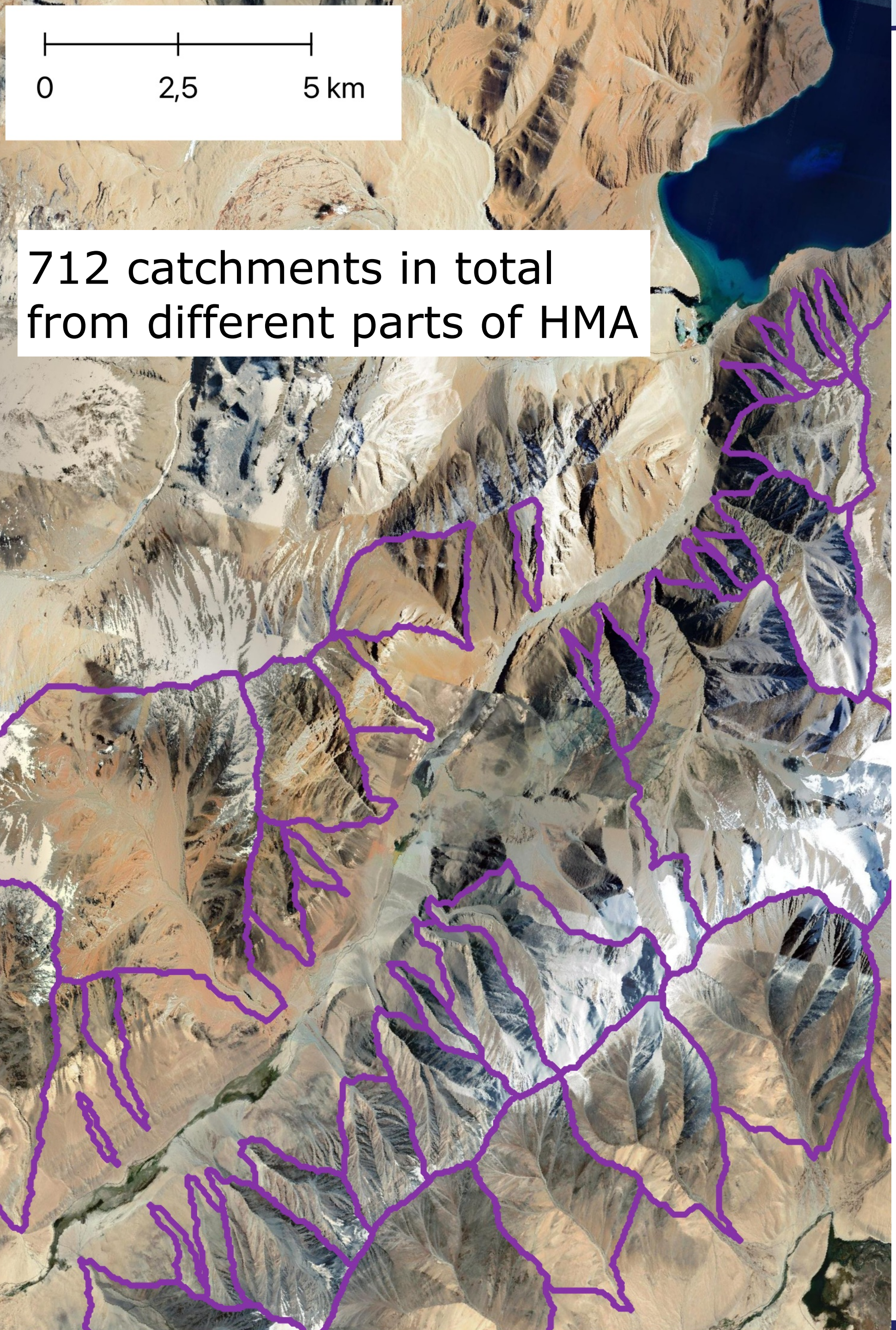


Morphometric + climate

Morphometric

- x_centroid
- y_centroid
- area_m
- perimeter
- mean_elevation
- median_elevation
- std_elevation
- min_elevation
- max_elevation
- range_elevation (relief)
- variance_elevation
- mean_slope
- median_slope
- std_slope
- min_slope
- max_slope
- range_slope
- variance_slope
- Melton_ratio (relief*area$^{0.5}$)
- circularity_ratio
- compactness_coefficient
- **region**

- mean_annual_temp
- mean_jan_temp
- mean_jury_temp
- mean_monsoon_temp
- mean_outside_monsoon_temp
- temp_crosses_zero (frost cracking)
- belowzero_fraction_of_year
- mean_daily_precipitation
- mean_annual_sum_precipitation
- mean_daylymonsoon_precipitation
- mean_monsoon_sum_precipitation
- monsoon_precipitation_fraction
- n_rainy_days (>10mm)
- rainy_days_fraction
- **avgtemp_belowzero**

- glacier_area_sum
- glacier_area_fraction
- **glacier**

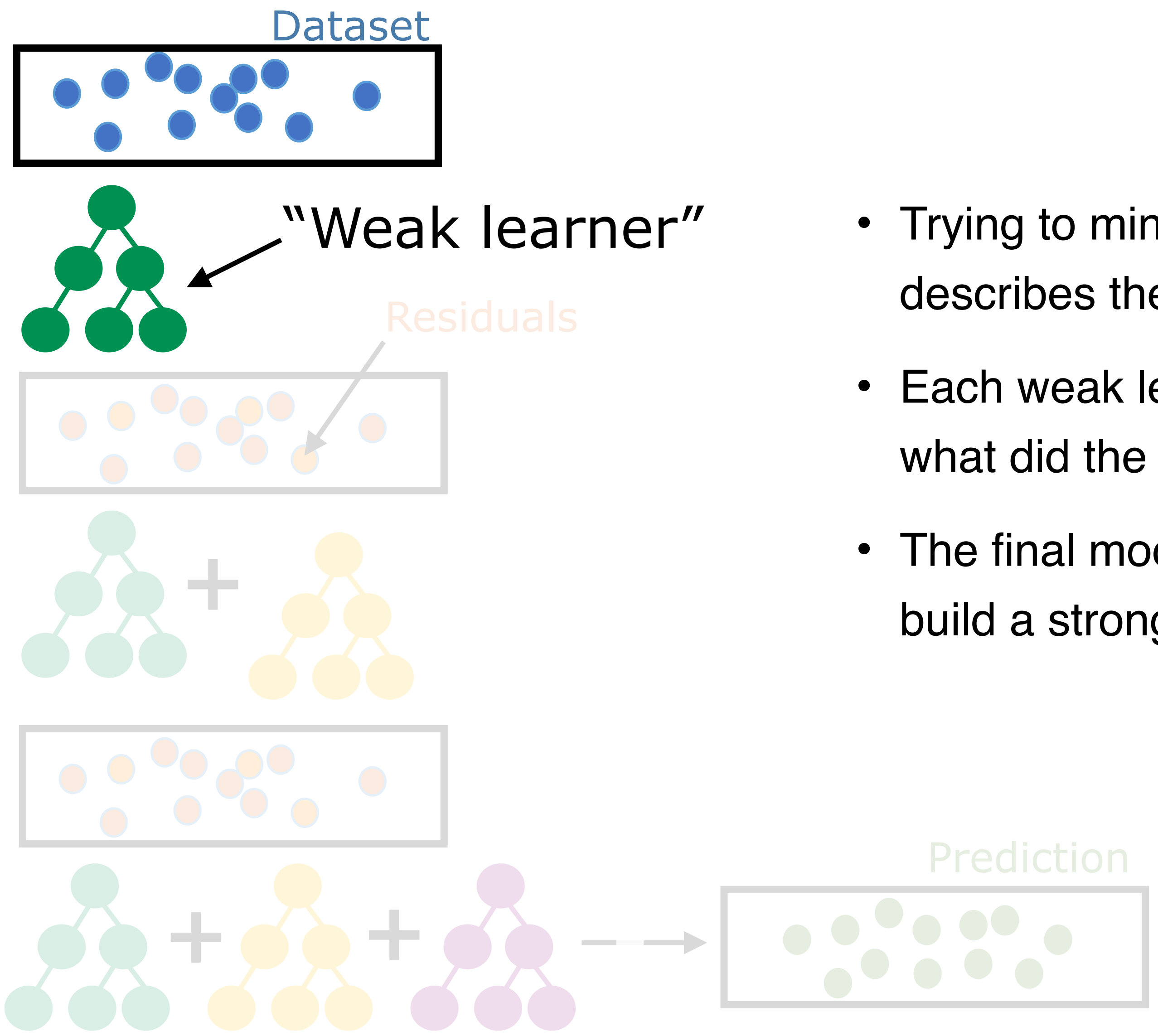
- isolated_permafrost_area
- sporadic_permafrost_area
- discontinious_permafrost_area
- continuous_permafrost_area
- sporadic_permafrost_frac
- discontinious_permafrost_frac
- isolated_permafrost_frac
- continious_permafrost_frac
- all_permafrost_frac
- **cont_permafrost_frac > 50%**
- **any_permafrost**

Gael Varoquaux
@GaelVaroquaux

For thousands of data points and moderate dimensionality (99% of cases), gradient-boosted trees provide the necessary regression model
scikit-learn.org/stable/modules...
They are robust to data distribution and support missing values (even outside MAR[*] settings
arxiv.org/abs/1902.06931)

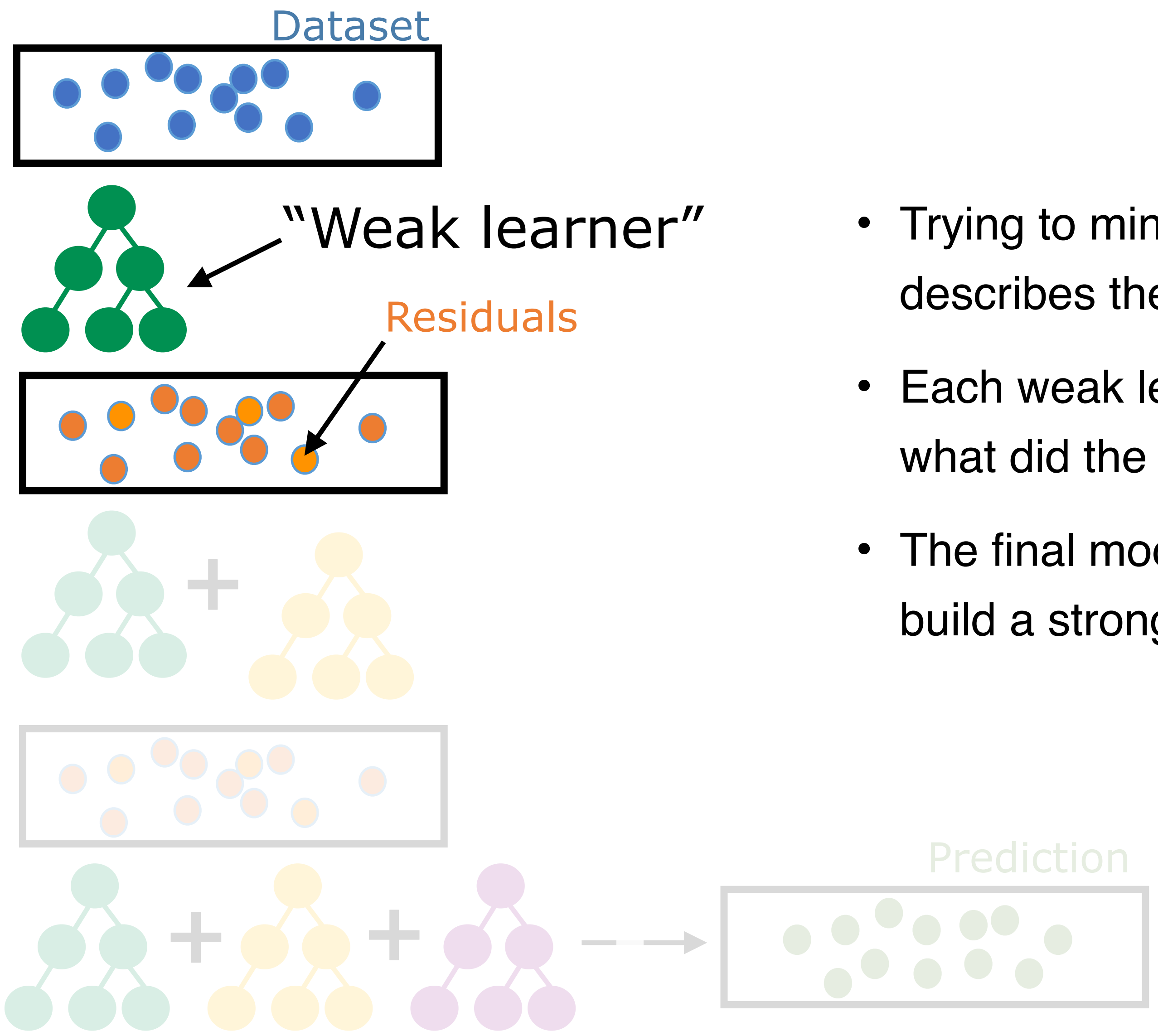
* MAR = Missing At Random

Gradient boosted decision trees



- Trying to minimize the "loss function" (function, that describes the error) on every iteration
- Each weak learner (i.e. tree/iteration) is trying to learn what did the previous one did "wrong" and do better
- The final model is the "combination" of all weak trees to build a strong classifier

Gradient boosted decision trees



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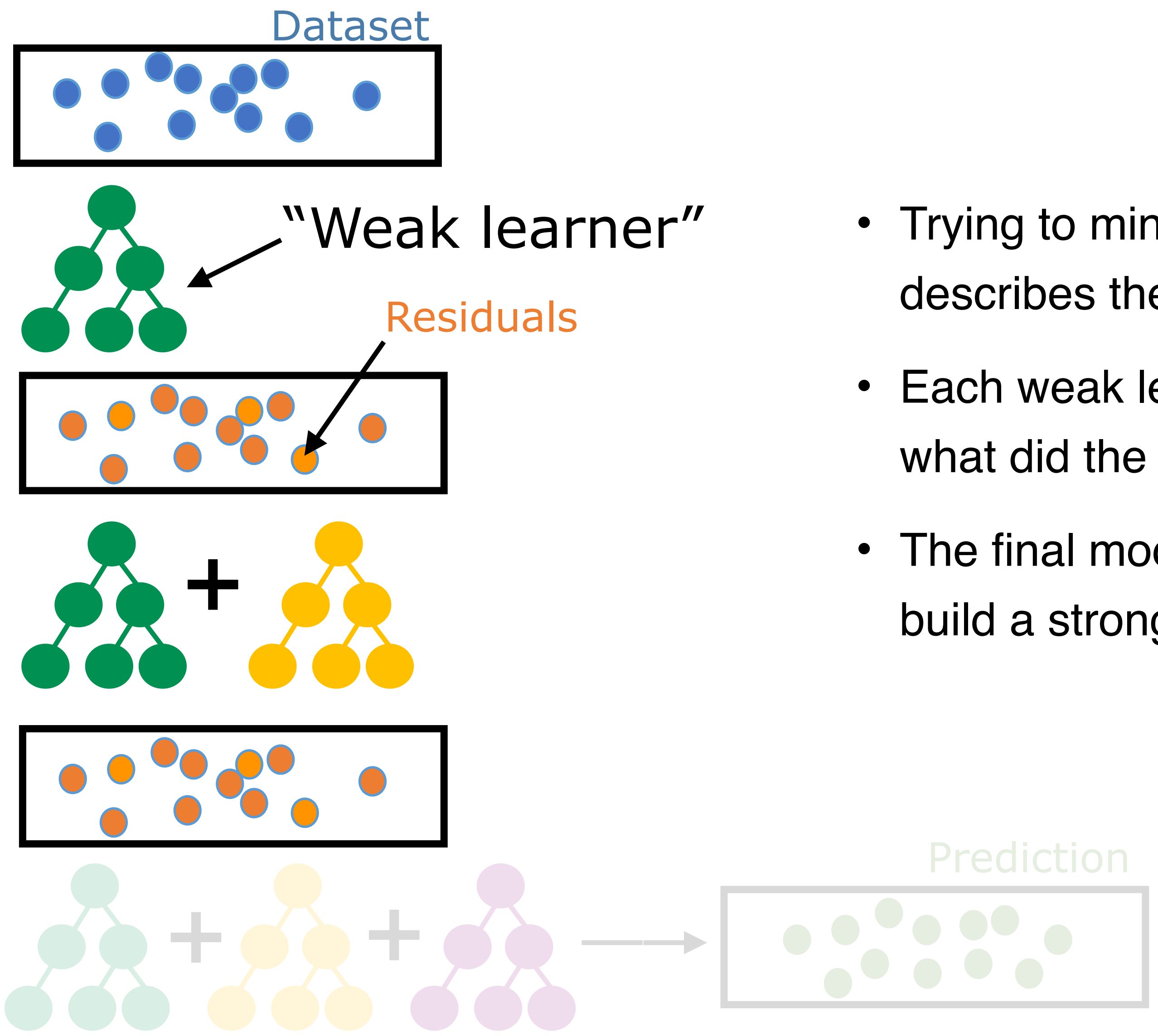

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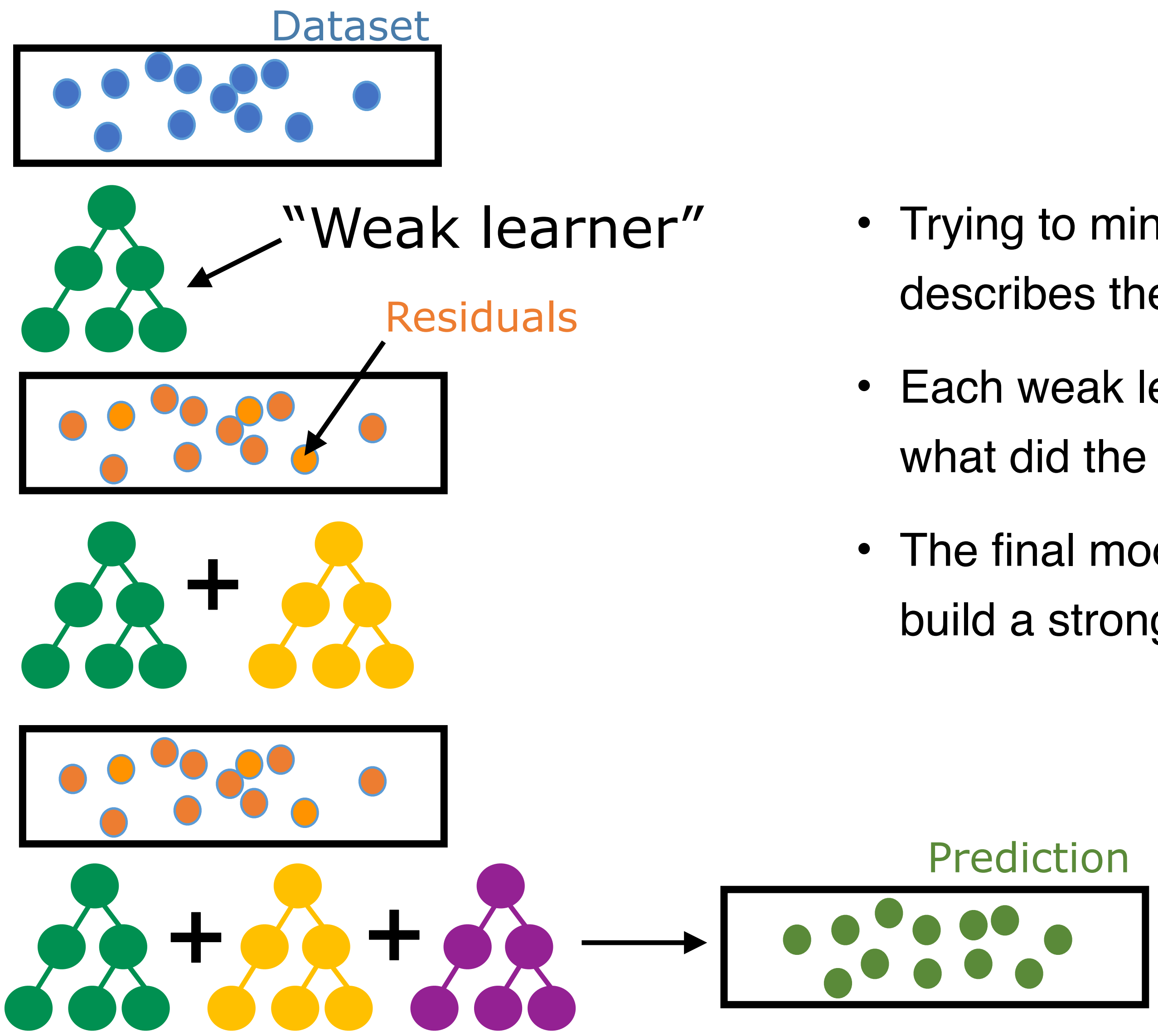
Gradient boosted decision trees



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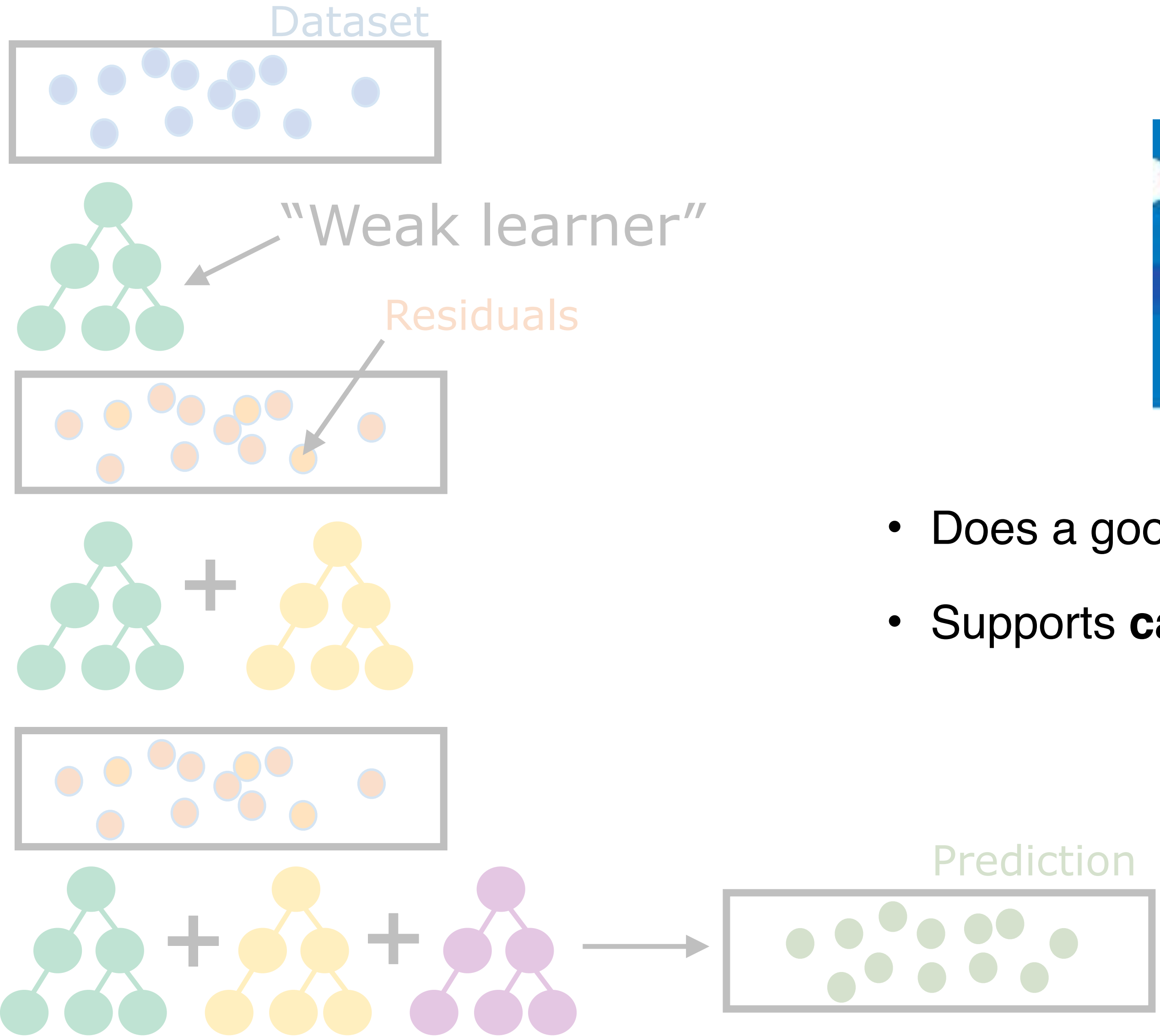
Implementation: Catboost



- Does a good job as an “out of the box” tool
- Supports **categorical** features (predictors) as an input

Building the model: how good is it?

Morphometric

- Accuracy : 91 %

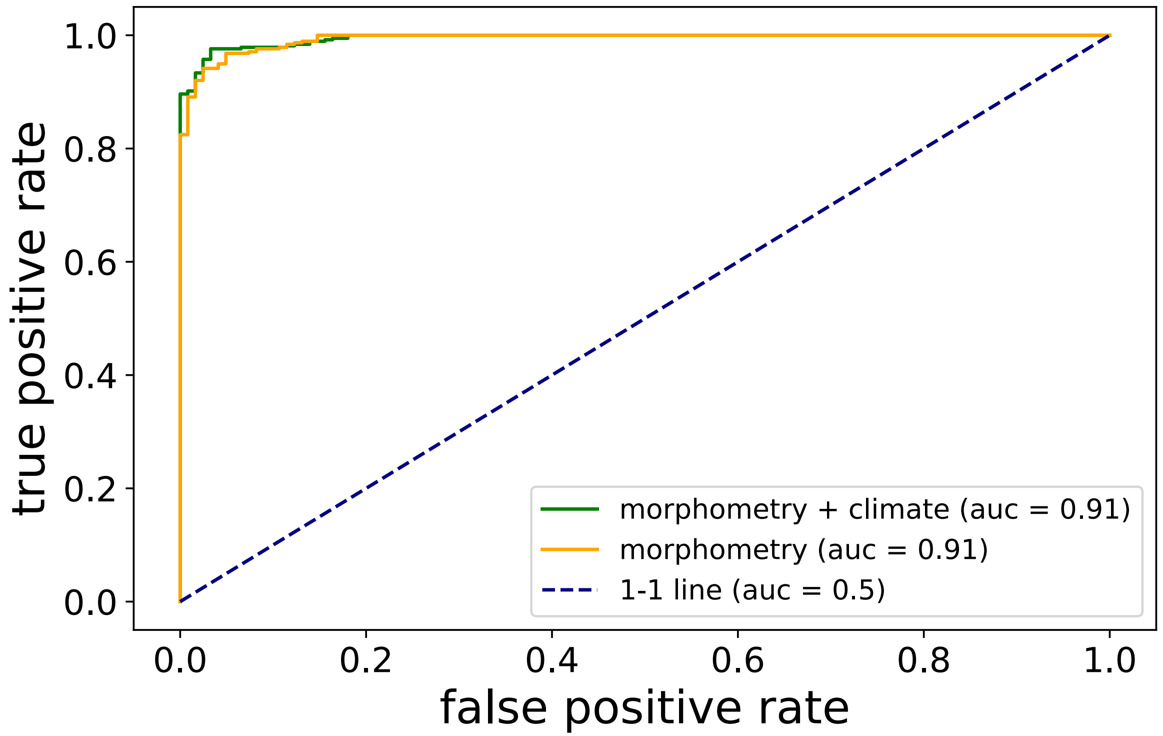
(fraction of correct predictions)

- Confusion matrix: [145., 28.]
  [17., 522.]

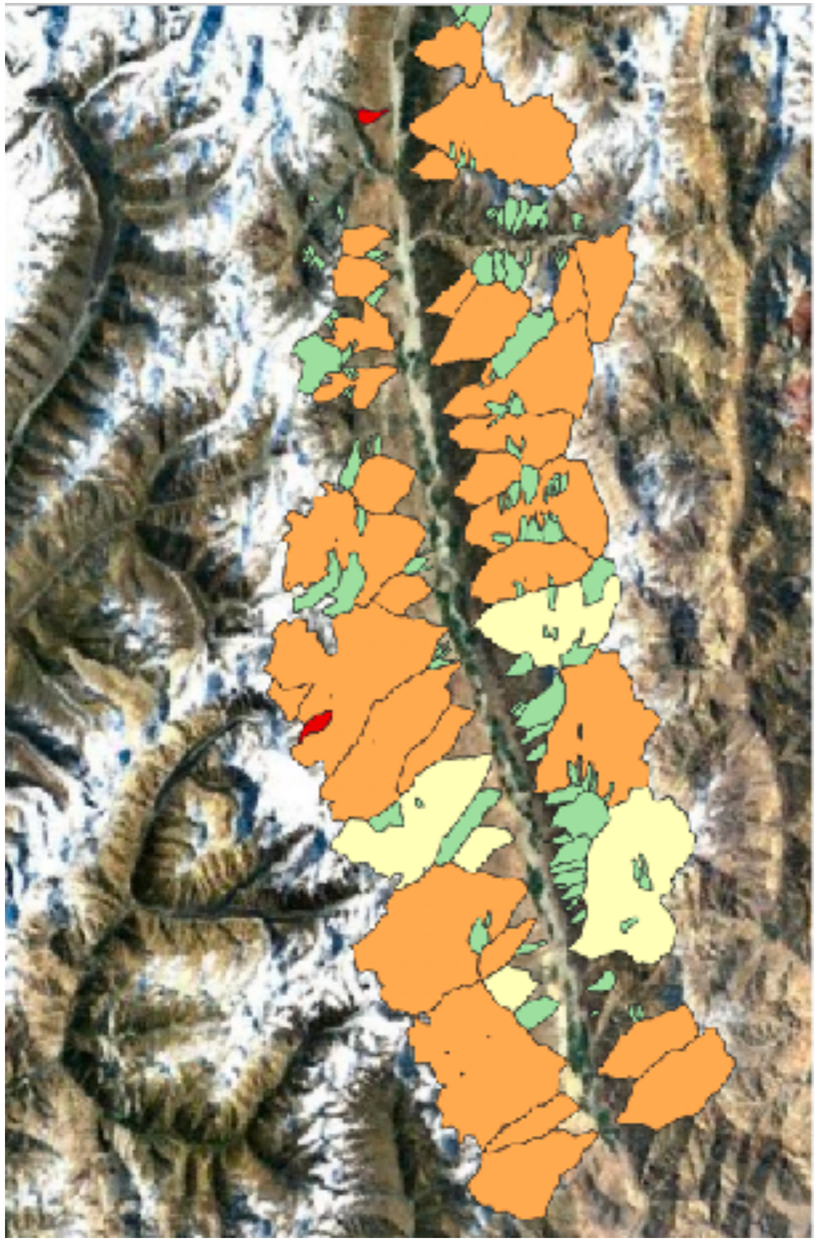
Morphometric + climate

- Accuracy: 92 %
- Confusion matrix: [148., 25.]
  [14., 525.]

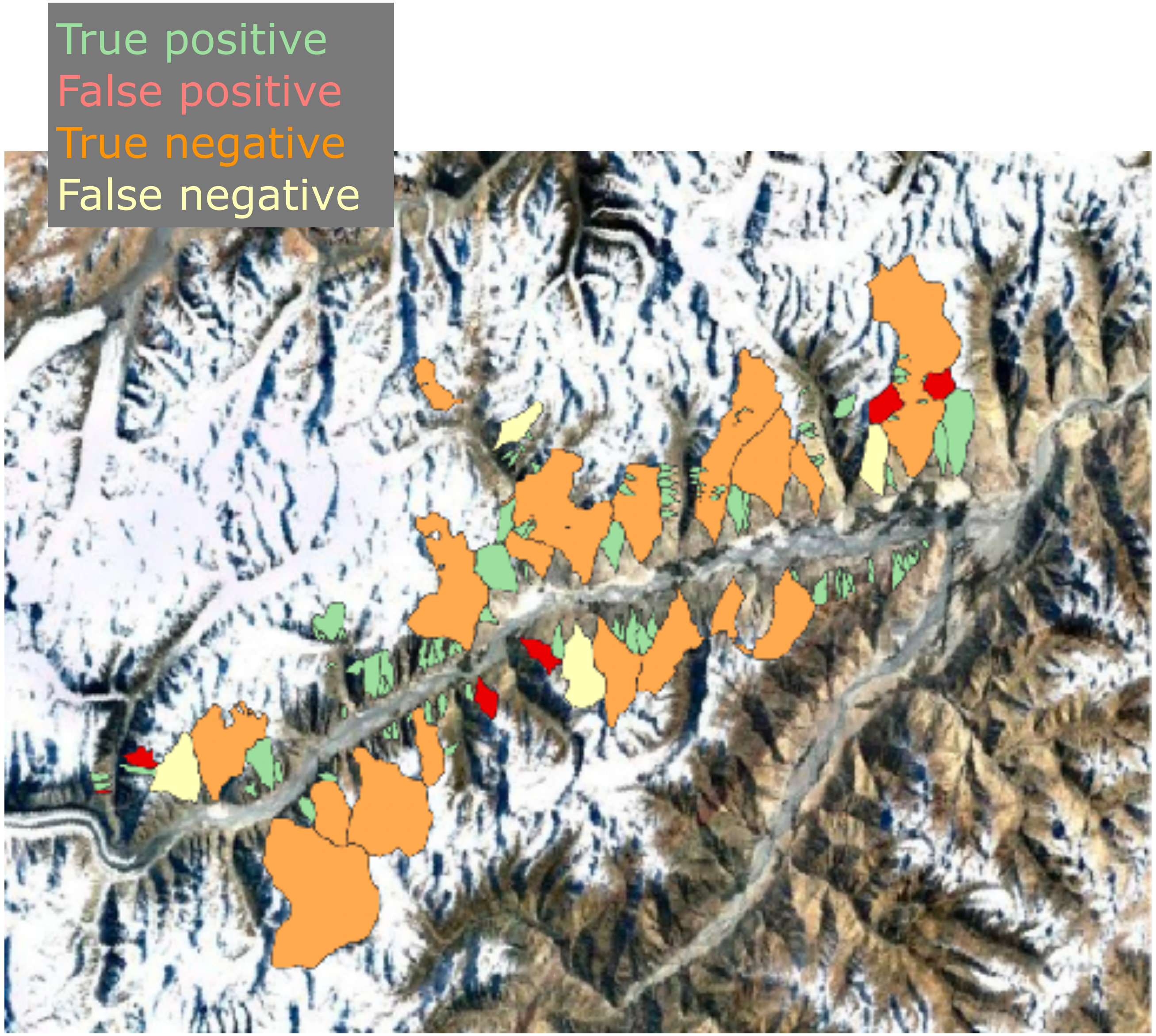
TP	FN
FP	TN



- auc = area under curve
- only “tuned” parameter: number of trees (iterations)
- debris flow (1): 539, flood (0): 173
- accuracy, when guessing randomly: 75.7 %

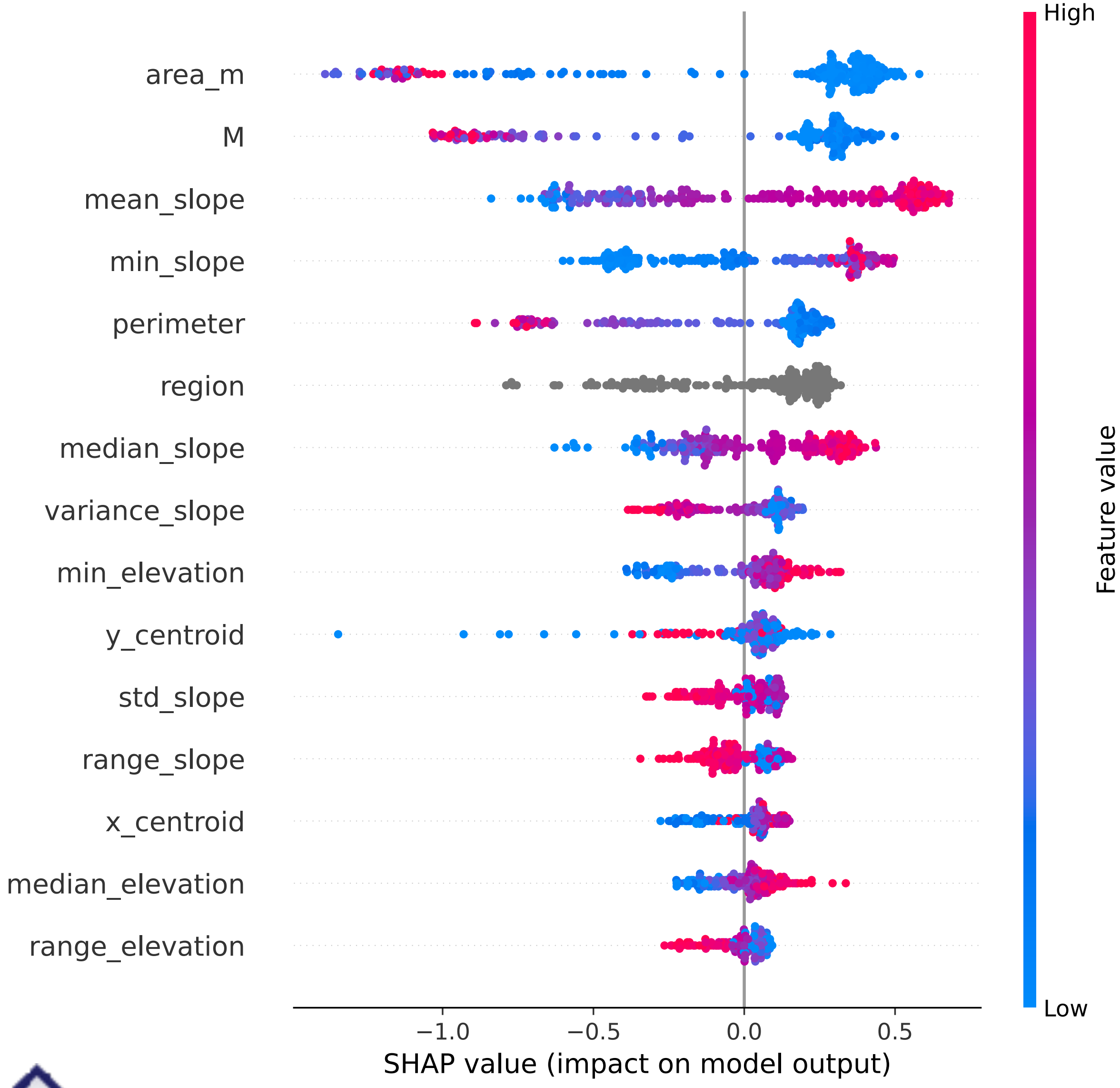


somewhere in Tajikistan

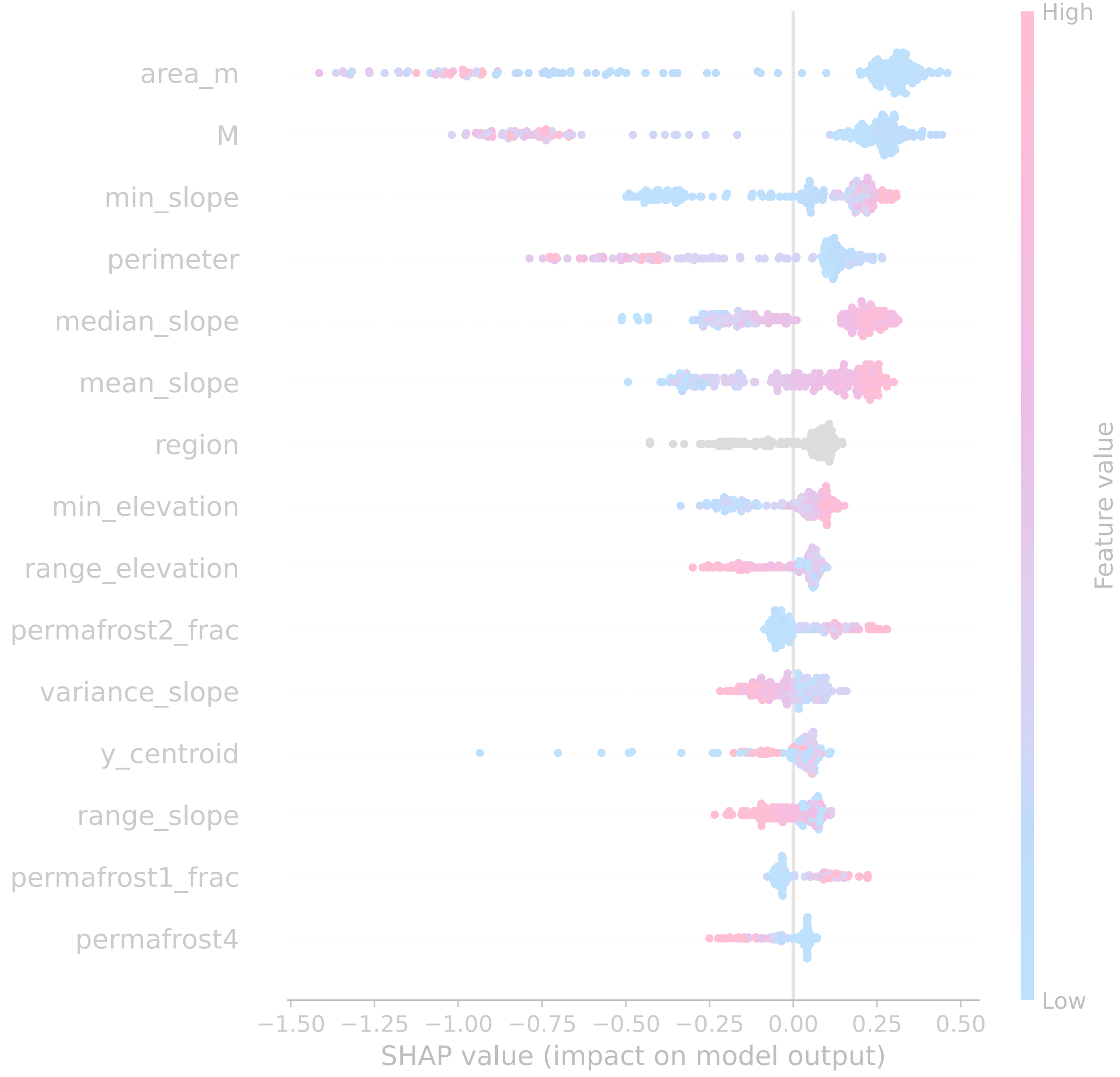


somewhere in Karakoram

Why does Catboost model make this predictions?



Morphometric



Morphometric + climate

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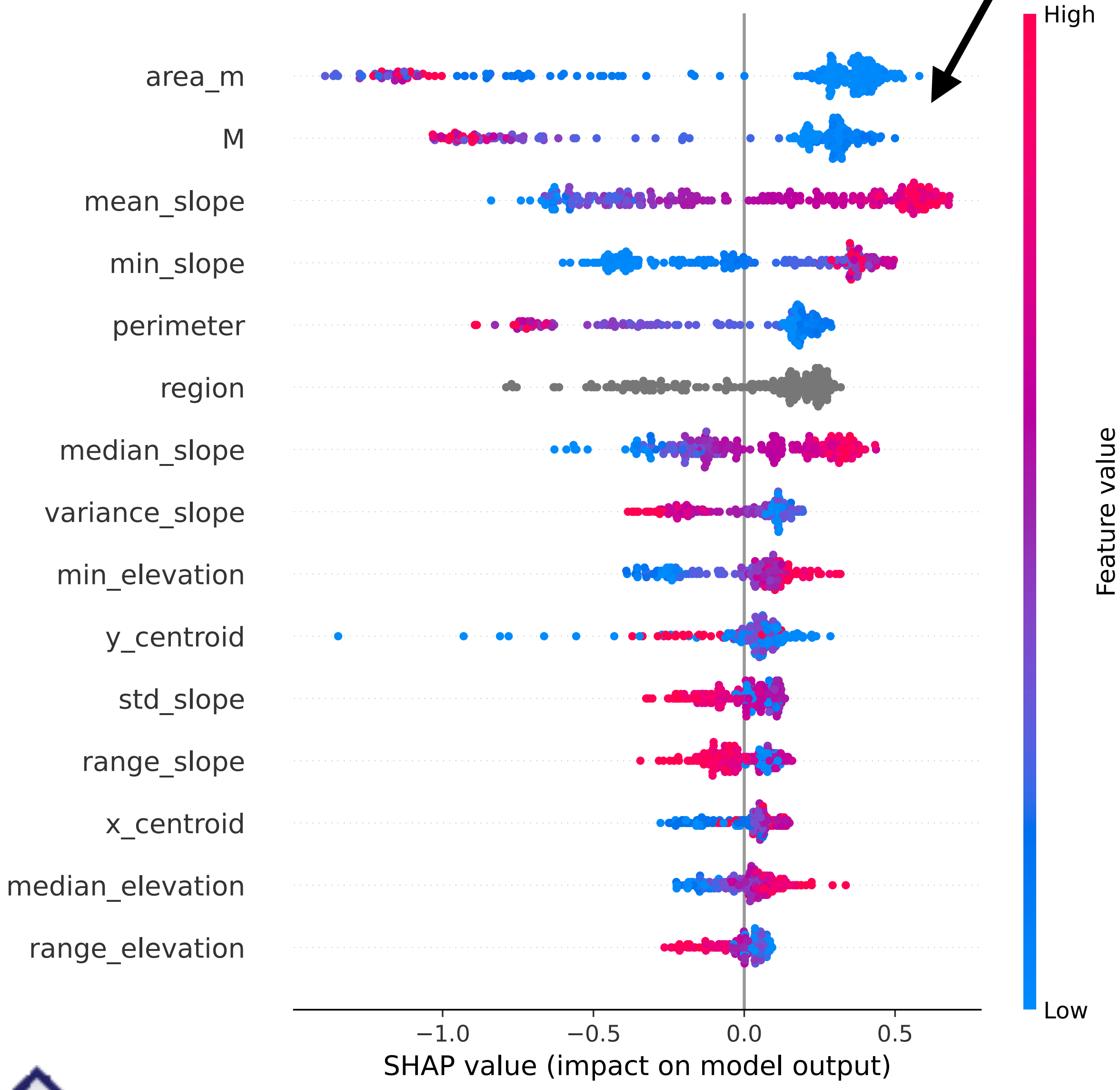
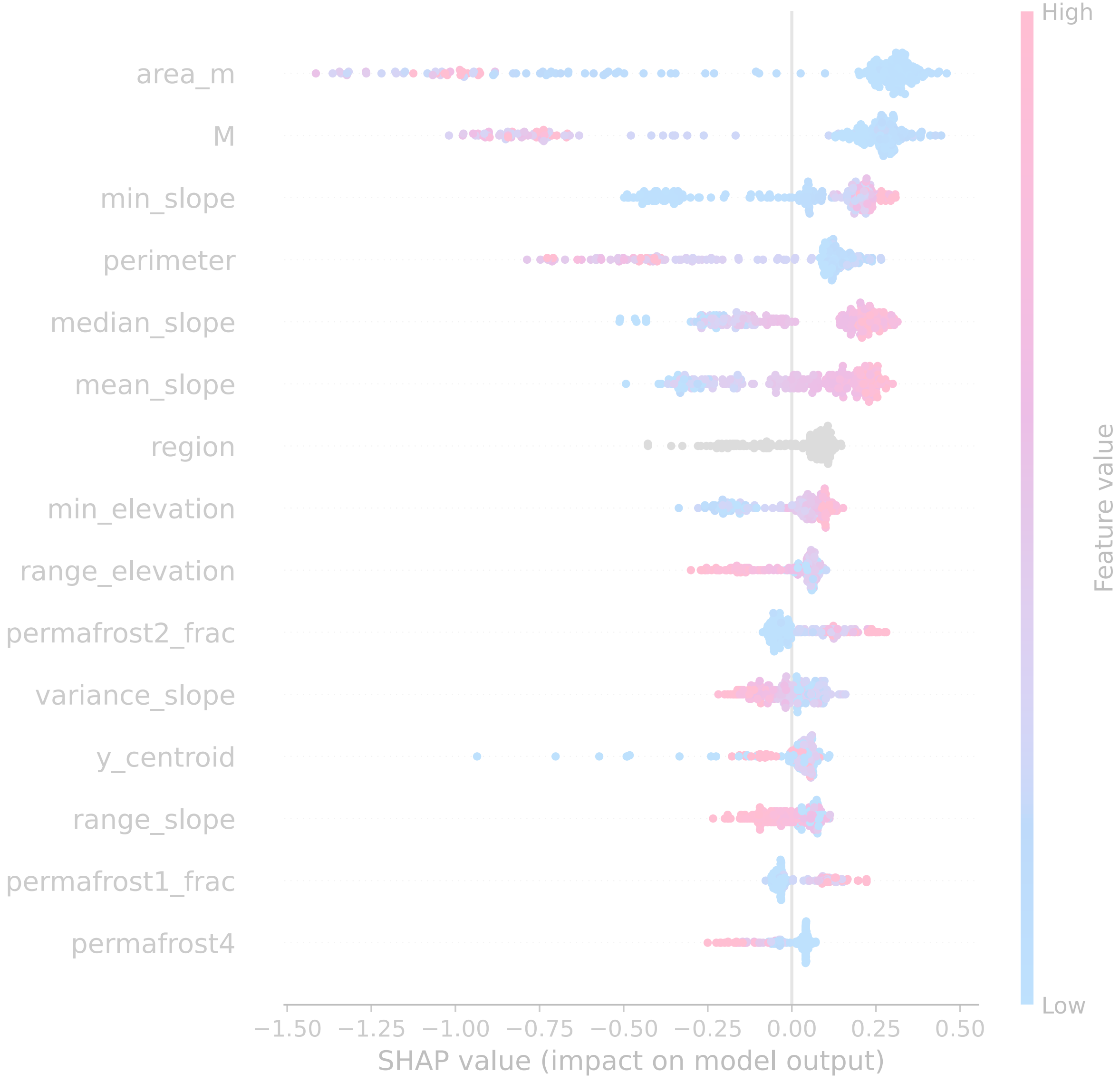


Morphometric



Morphometric + climate

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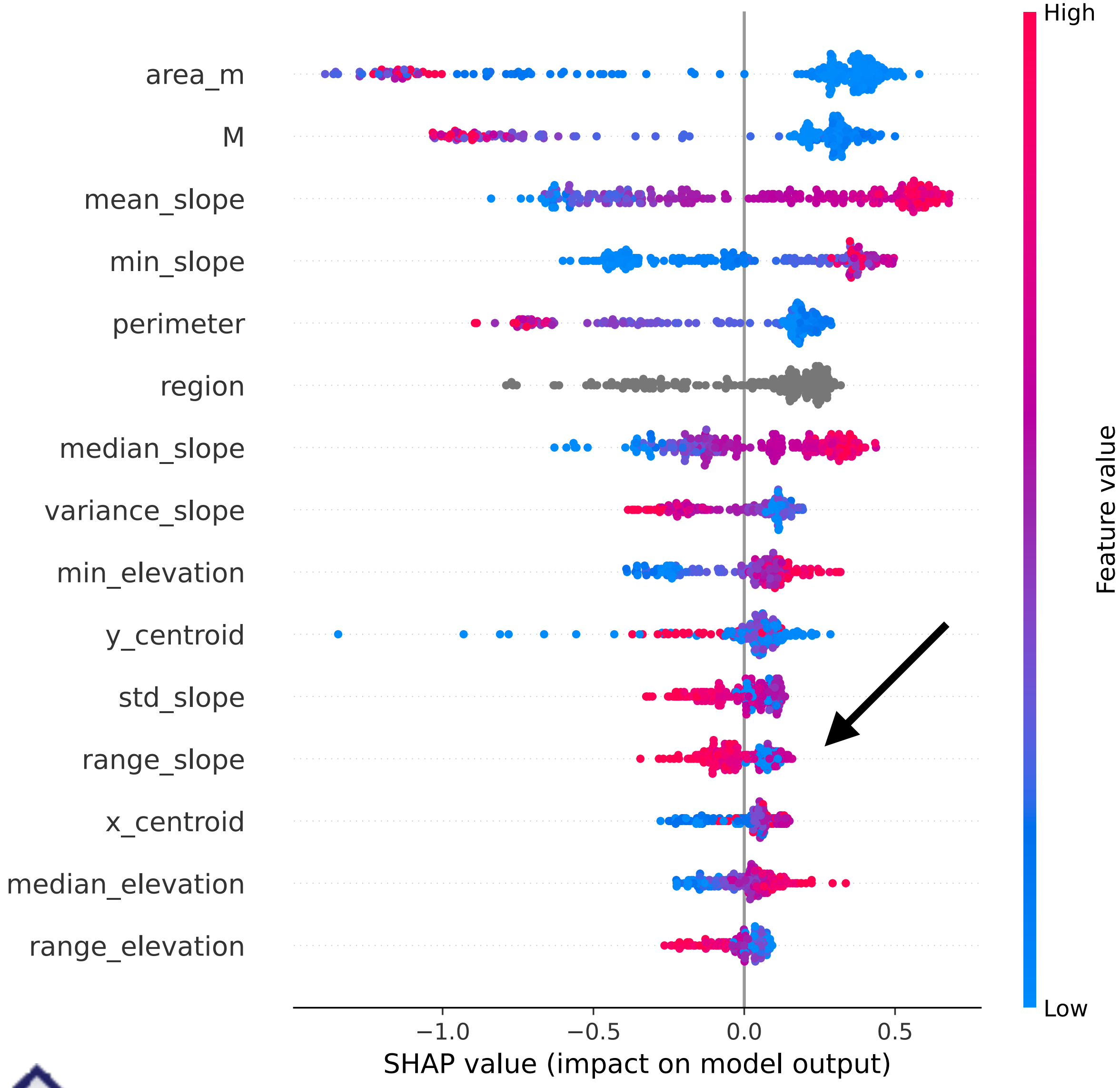
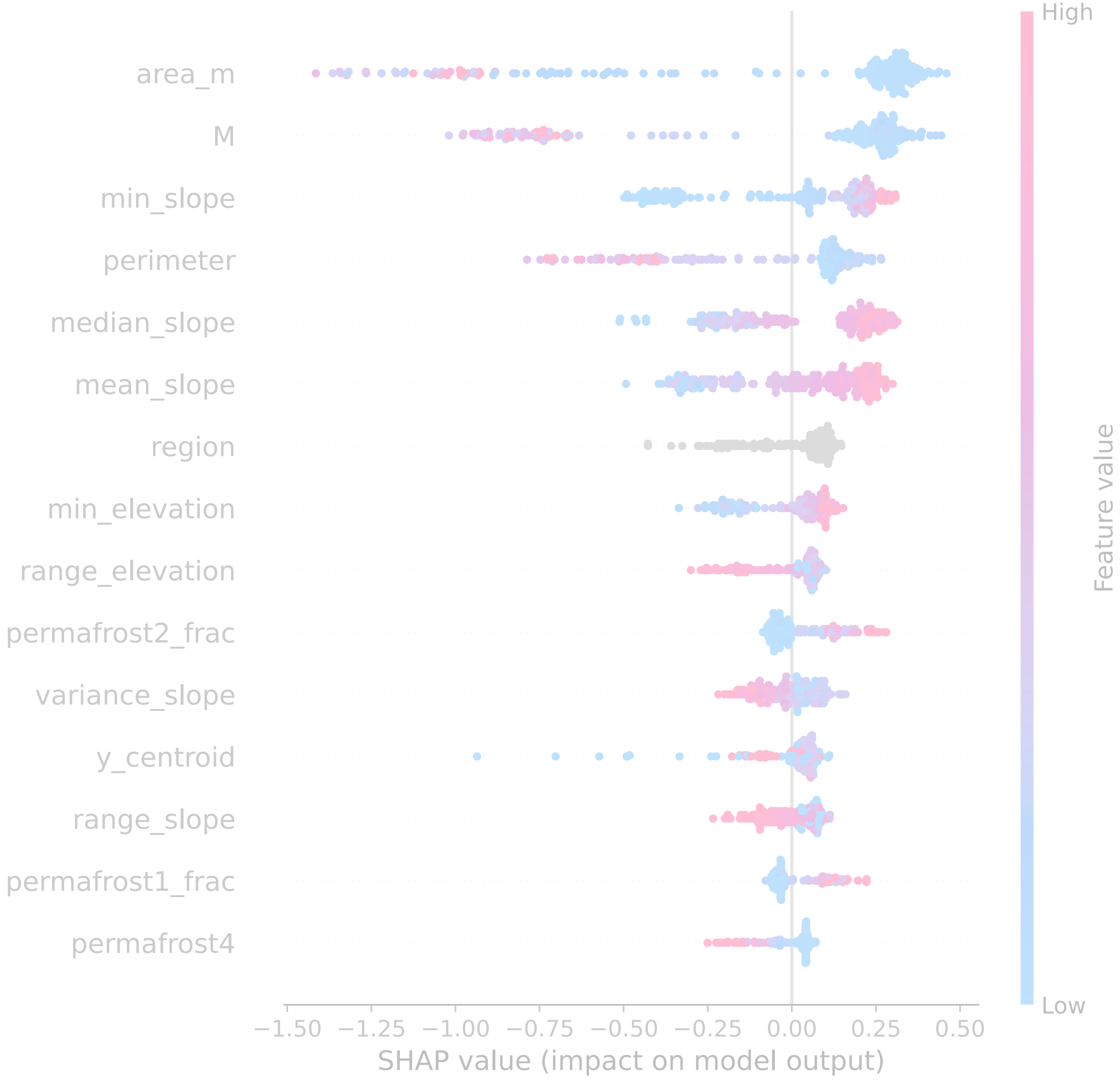


Morphometric



Morphometric + climate

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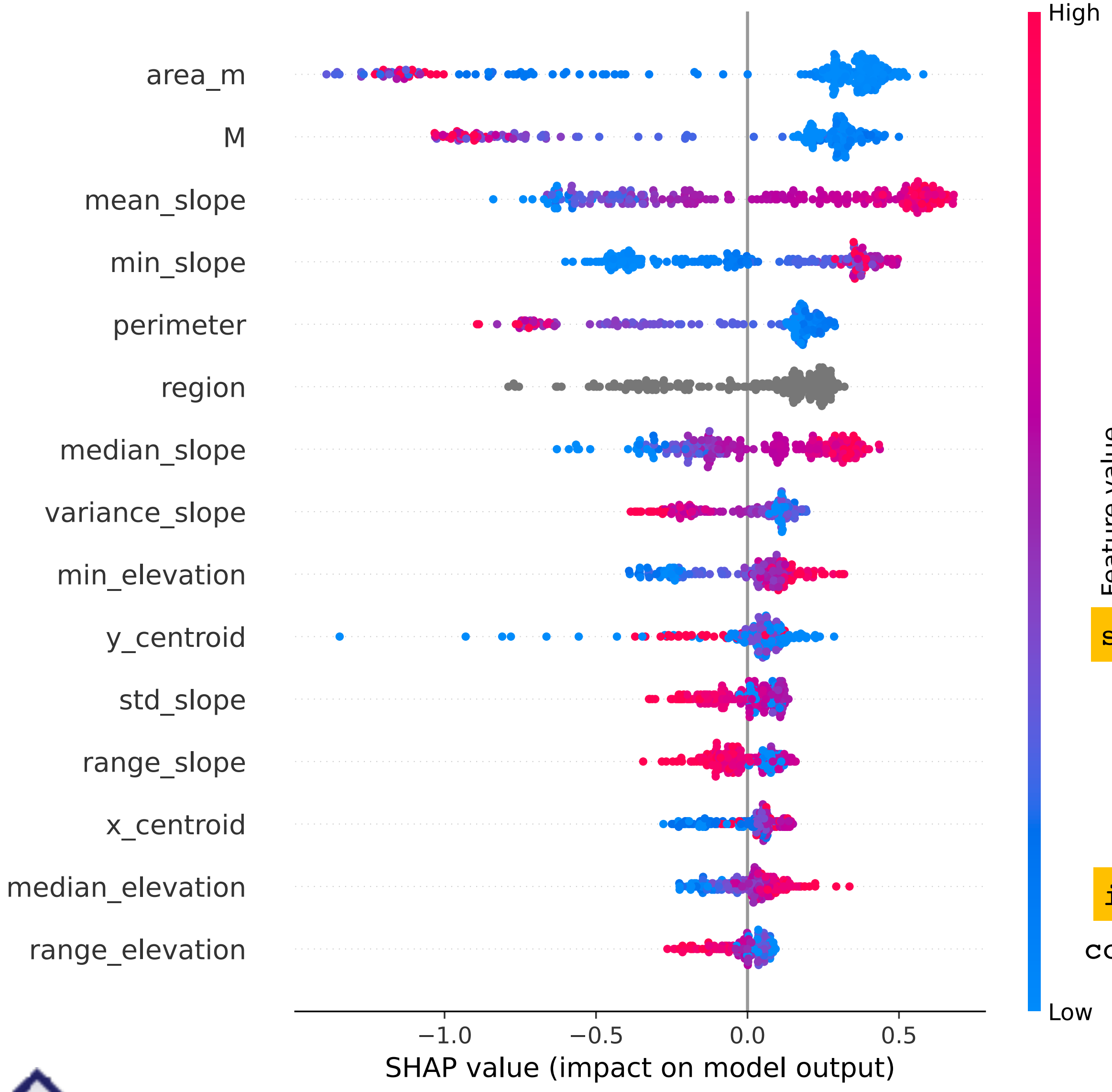
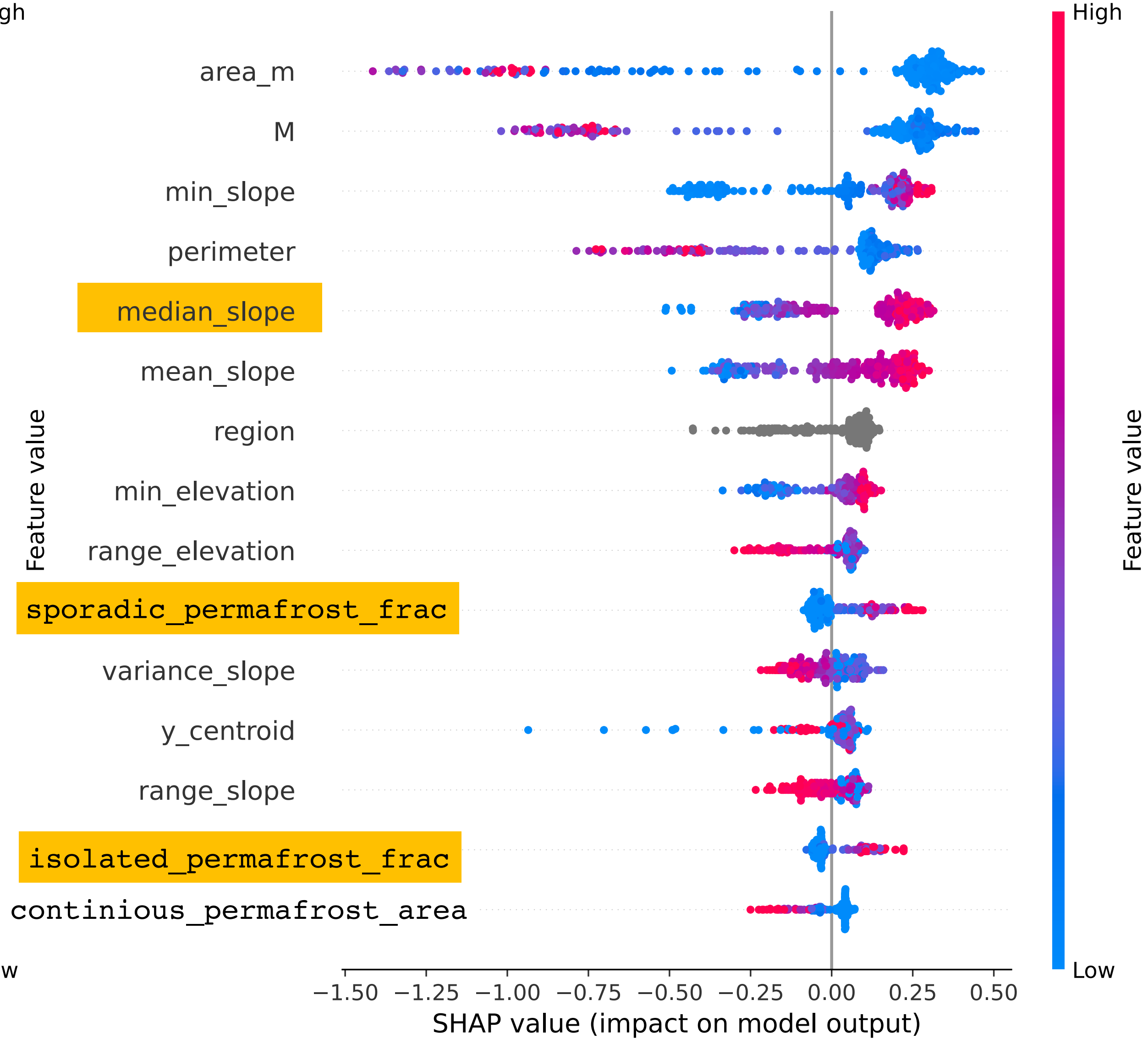


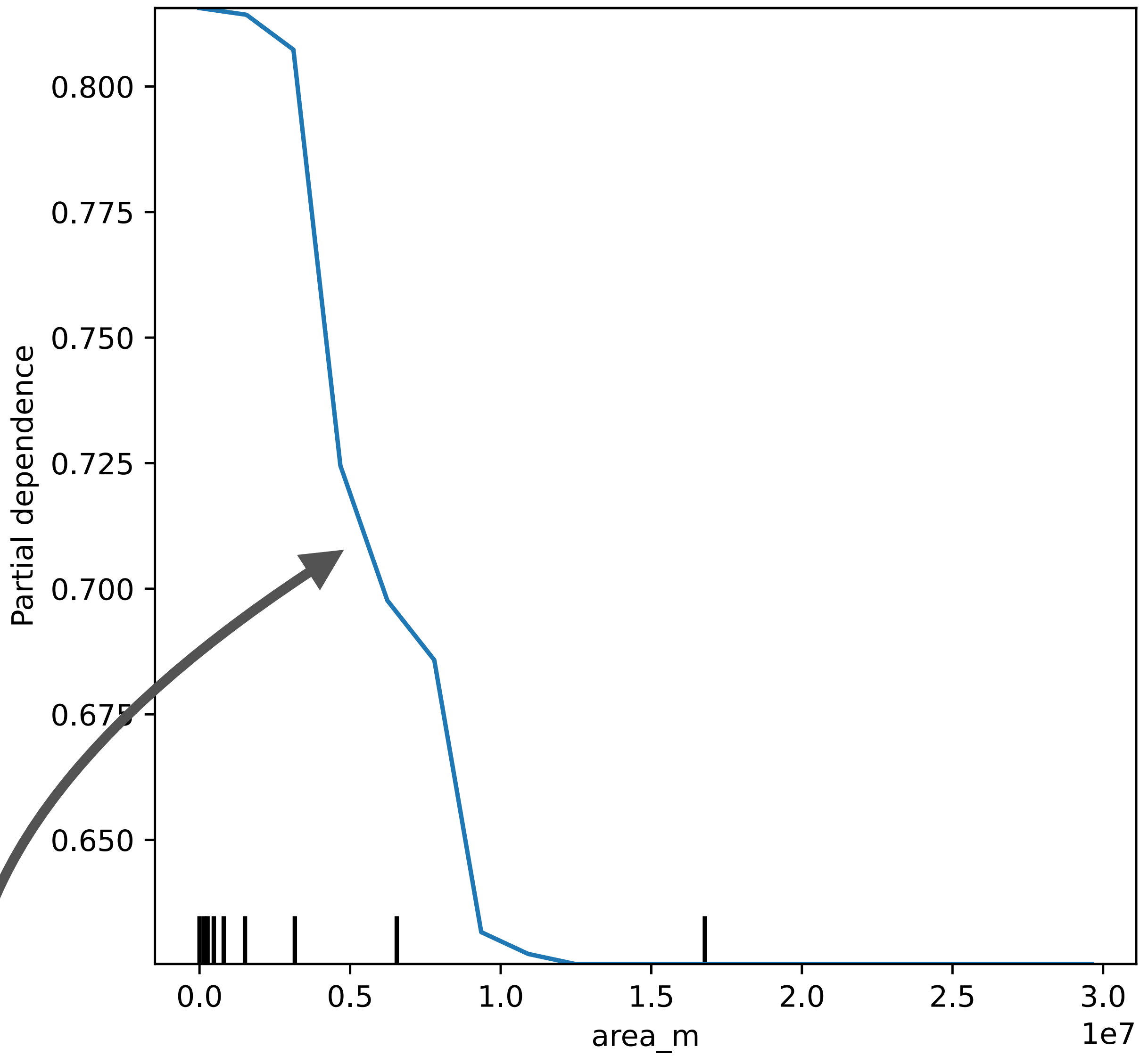
Morphometric



Morphometric + climate

What should we do to the catchment for it to "switch":

all things being equal, how can we make a "flood" catchment produce "debris flow"



average probability of a DF (1) for scenario, where all catchment have the same area (x-axis)

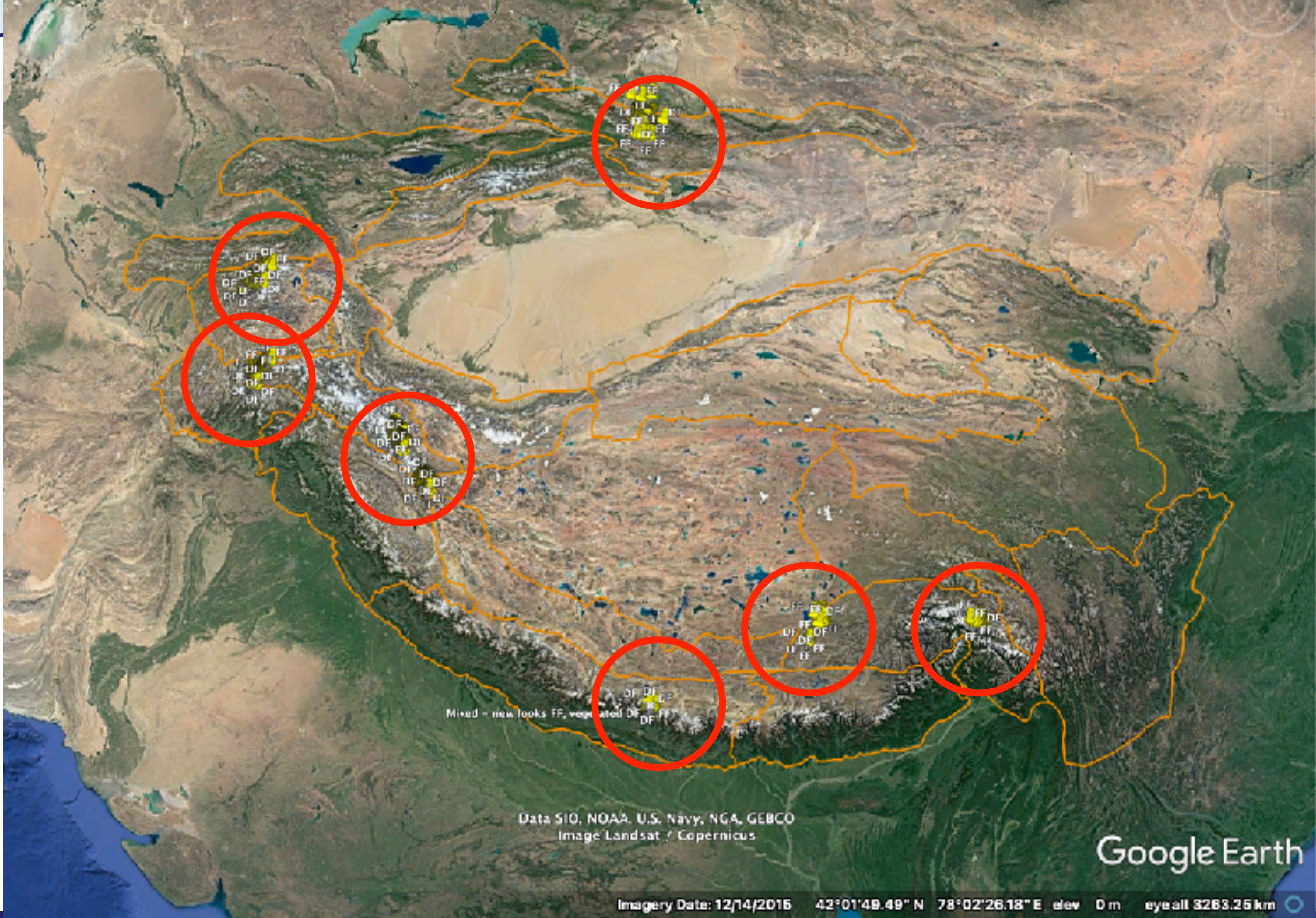
Conclusions

- We can build a machine learning classifier for distinguishing debris-flow dominated systems from flood dominated ones
- Climate data adds a lot of information to the model, but (all other things being equal) does not improve model performance

Outlook

- Extend the dataset for “creating” the model by covering more diverse regions
- Add vegetation cover to the feature list
- Apply the model to the “new” areas (i.e. catchments without alluvial fan)
- To see the effect of the climate change - use RCP scenarios as a climate information


Mixed - new looks FF, vegetated DF
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Image Landsat / Copernicus
Google Earth
Imagery Date: 12/14/2016 42°01'49.49" N 78°02'26.18" E elev 0 m eye alt 3263.25 km


Data SIO, NOAA, U.S. Navy, NGA, GEBCO
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Google Earth