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

Varya Bazilova,

Tjalling de Haas, Walter Immerzeel

- **BSc.**: Lomonosov Moscow State University (hydrology/hydrometeorology)

  Sediment yield of the glacierized catchment

- **MSc.:** Universitet i Oslo (glaciology/remote sensing)

  Glacial lake changes from cloud processing of optical satellite images

- *Research Assistant in cryosphere remote sensing (UiO)*

Case study:
Djankuat glacier, Central Caucasus

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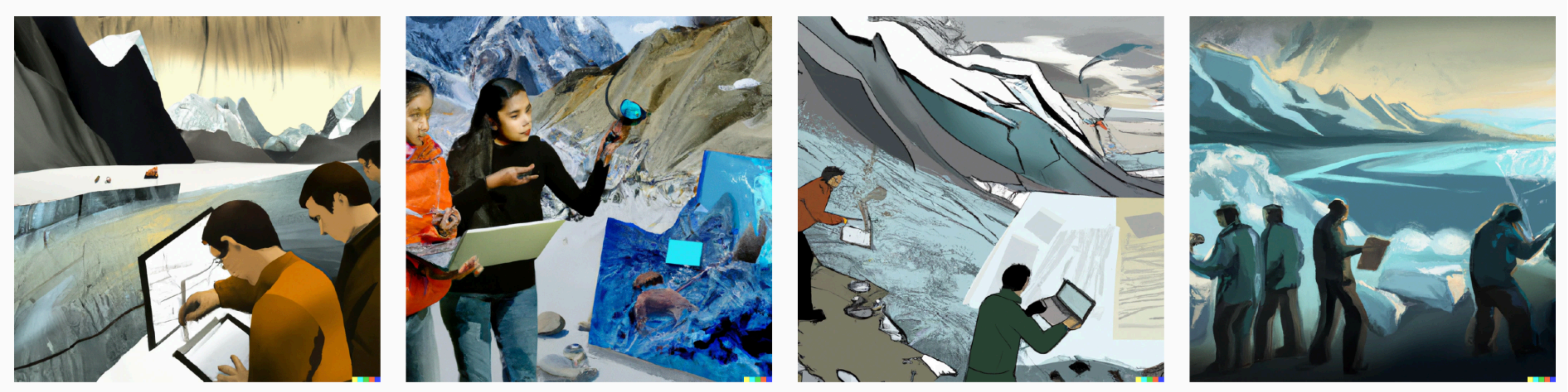
- **1st year PhD student**: Utrecht University (mountain hydrology/ debris flows/floods)



DALL-E: “scientists doing statistical modeling of debris flows next to glaciers”

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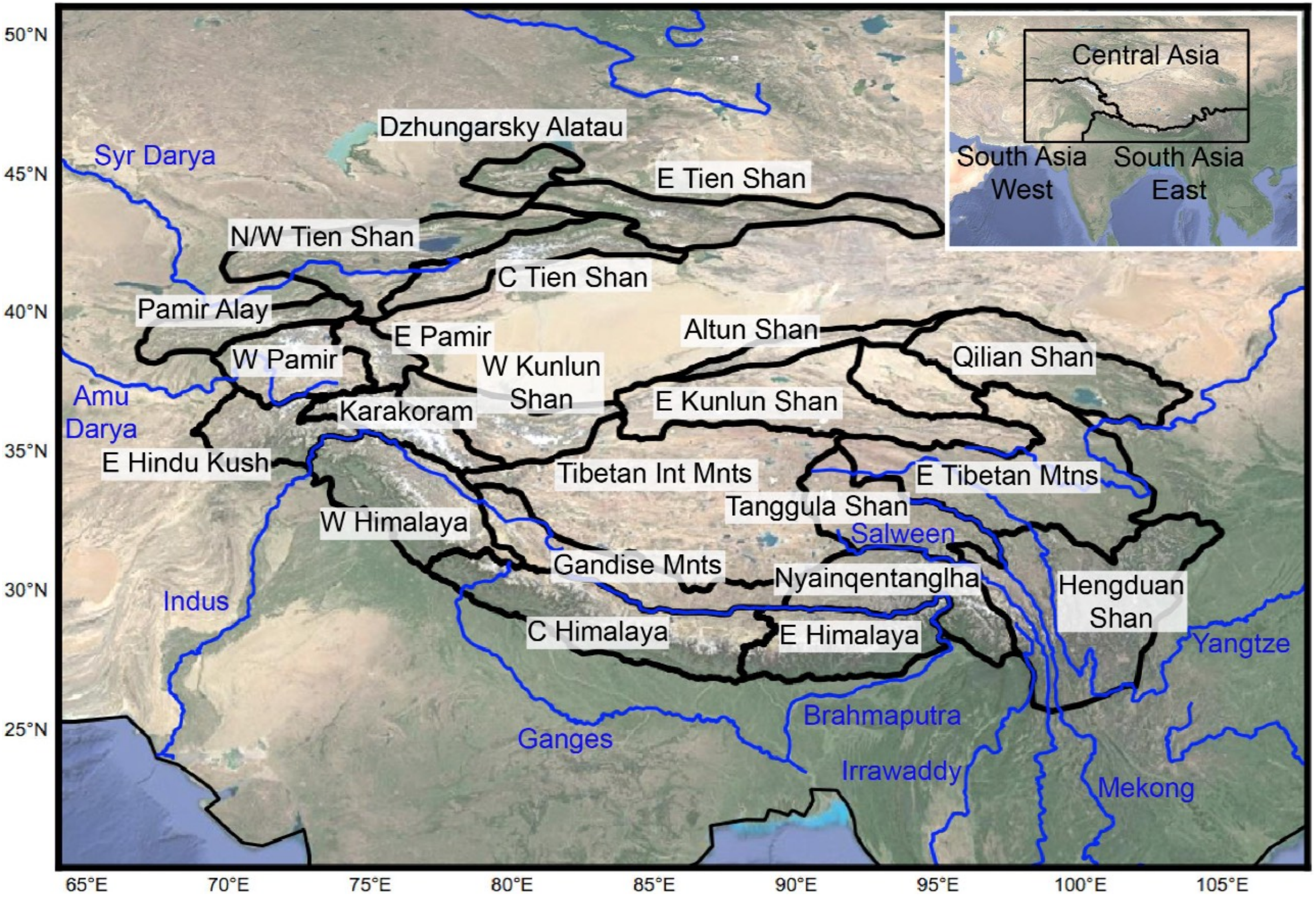
What is happening in HMA?



(D. Rounce et al., 2020)

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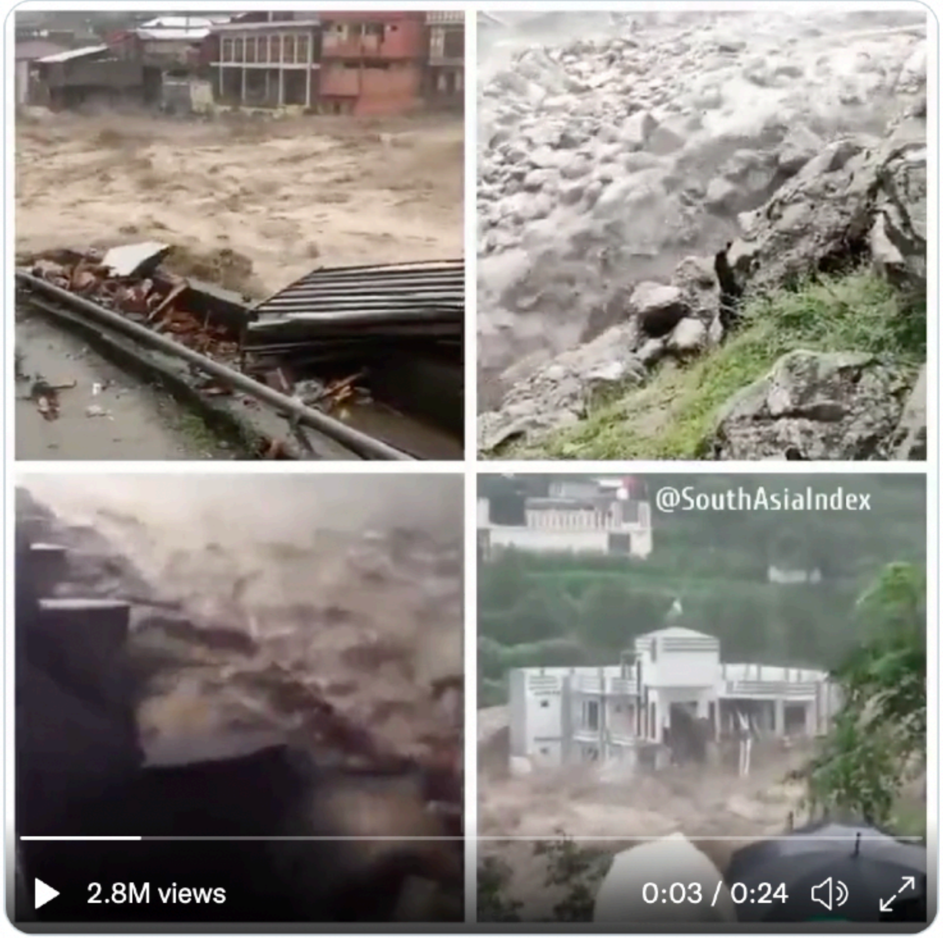
Landslide dam outburst seems to have Melamchi flooding in Sindhupalchowk, Nepal

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.

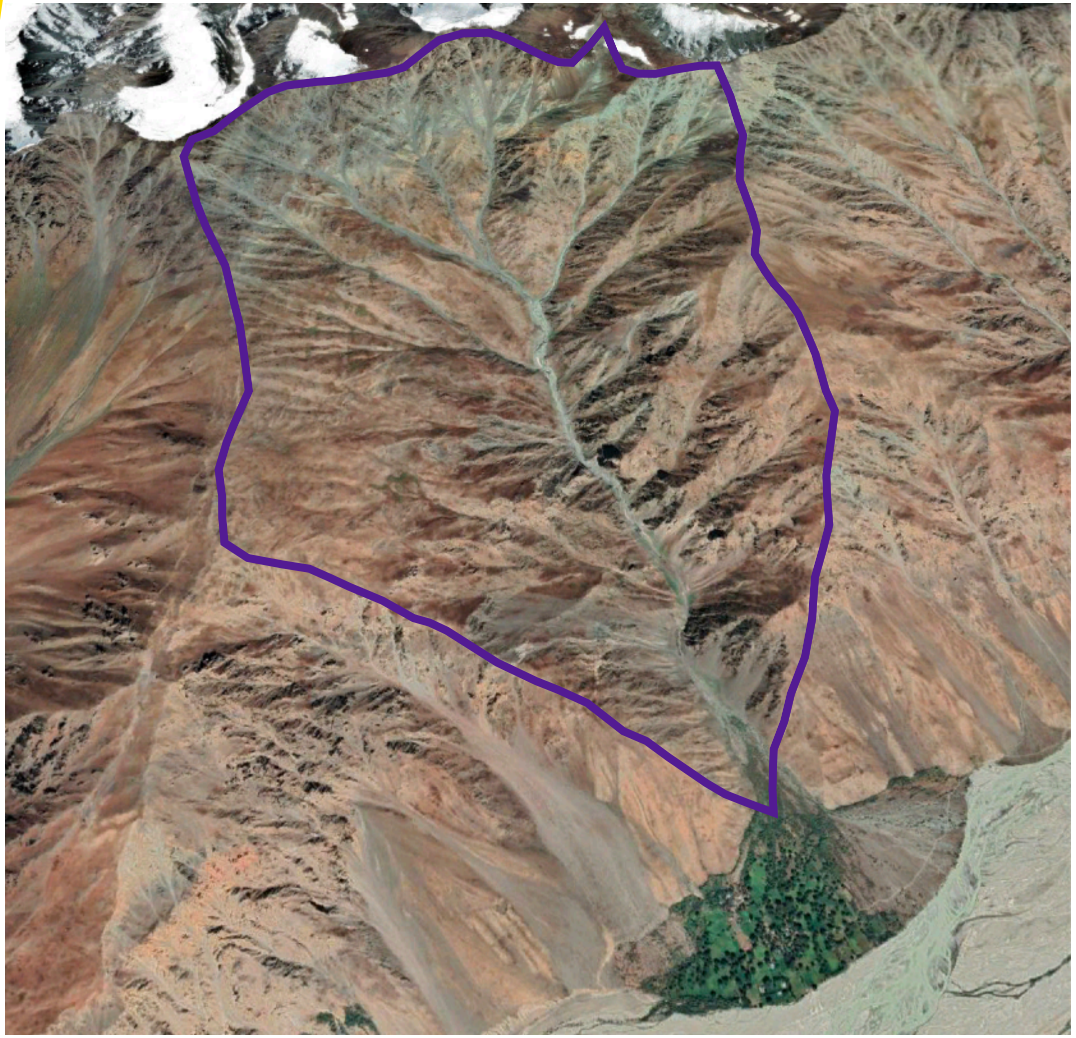
Nearly 1400 dead, 1 million houses damaged or destroyed, and 50,000,000 people displaced.

1/3 of the country is underwater.



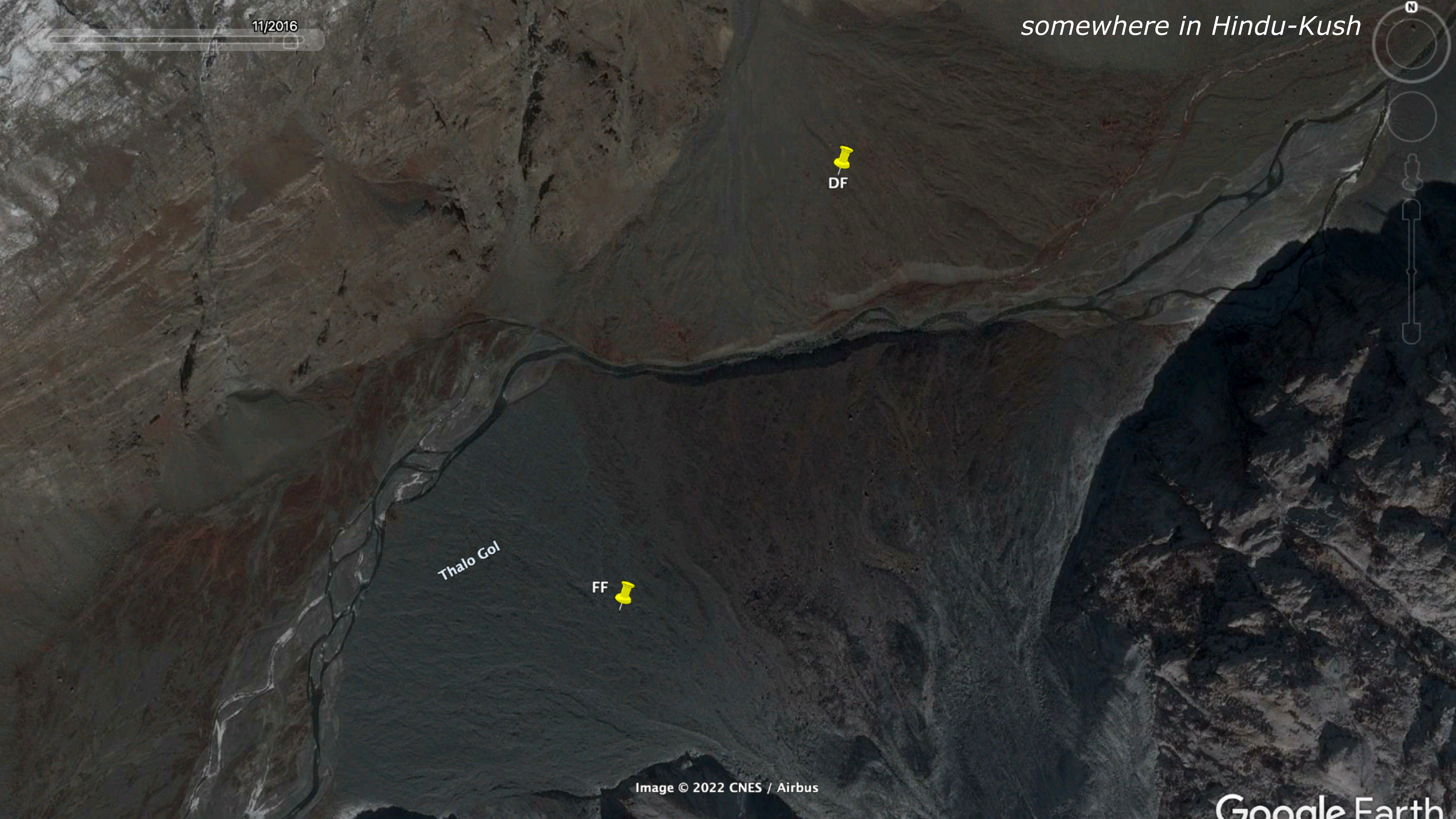
- Most types of natural hazards are projected **to change in frequency, magnitude and areas** affected as the cryosphere continues to decline *(high confidence)*.
- Glacier retreat and permafrost thaw are projected to **decrease the stability of mountain slopes** <…> *(high confidence)*. Resulting landslides and floods, and cascading events, will also **emerge where there is no record of previous events** *(high confidence)*.
- As documented for sites in the European Alps and Scandinavia < … >, rock glaciers replenished debris flow starting zones at their fronts, so that the intensified material supply associated with **accelerated movement contributed to increased debris flow activity** *(higher frequency, larger magnitudes)* or slope destabilisation.
- At lower elevations < … > climate driven changes such as a **reduction in number of freezing days** are projected to lead to a reduction in debris flows.

- IPCC SROCC, 2019

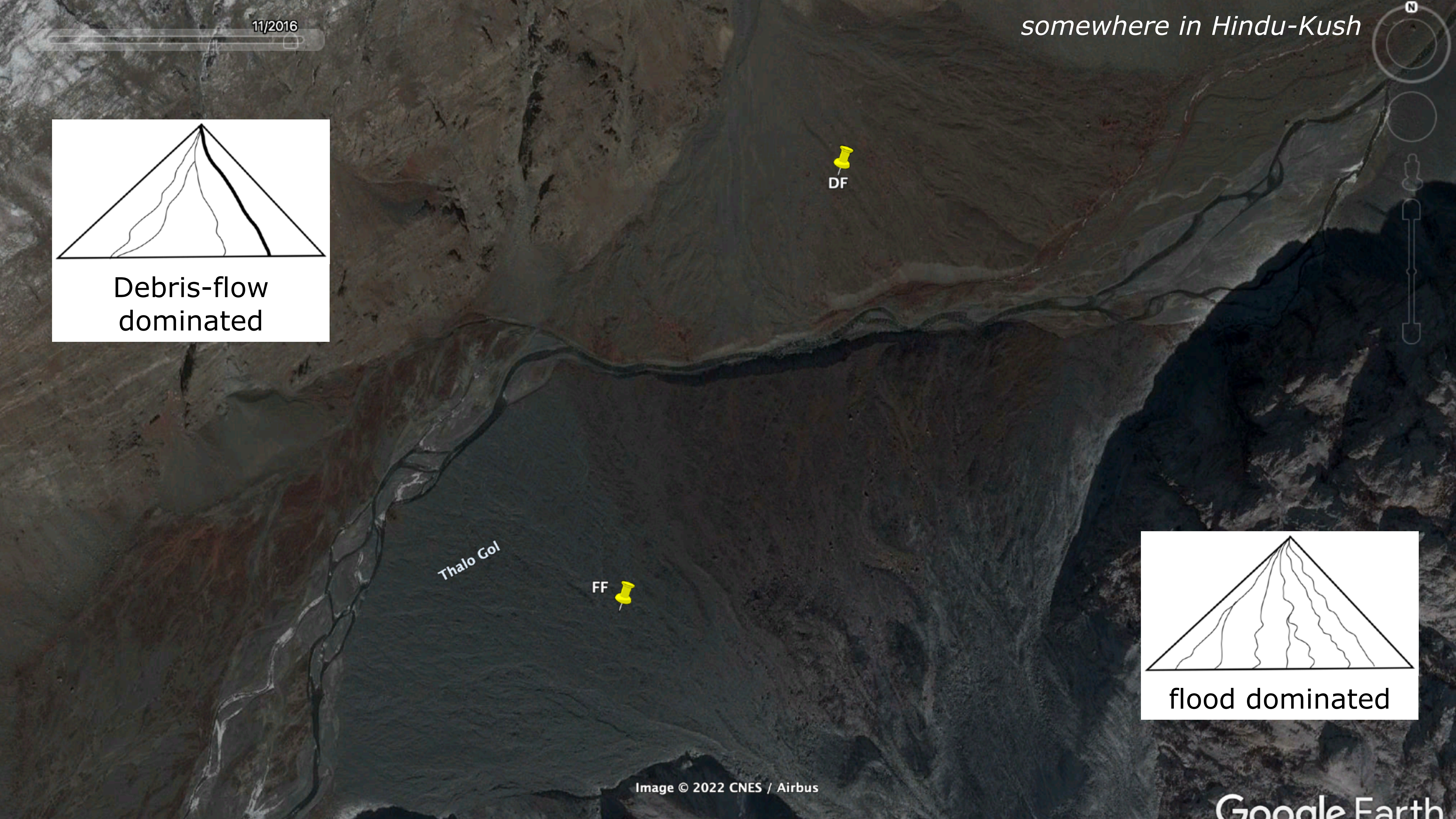


somewhere in Pamir

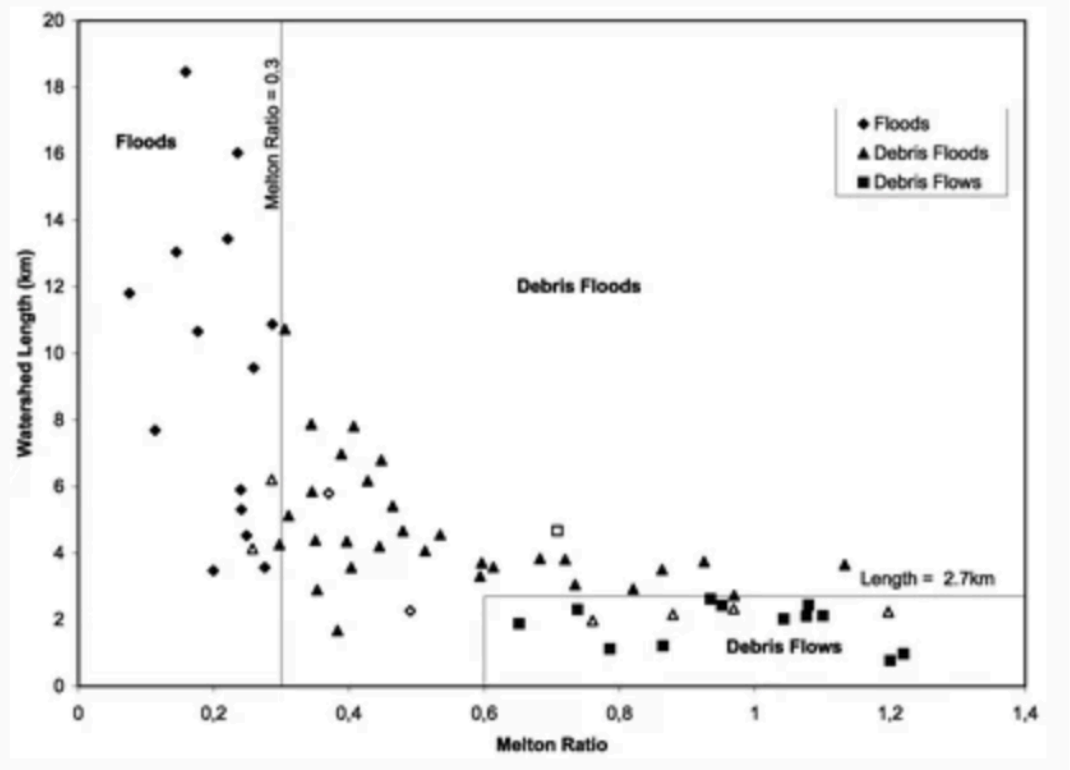
Image source: Google Earth

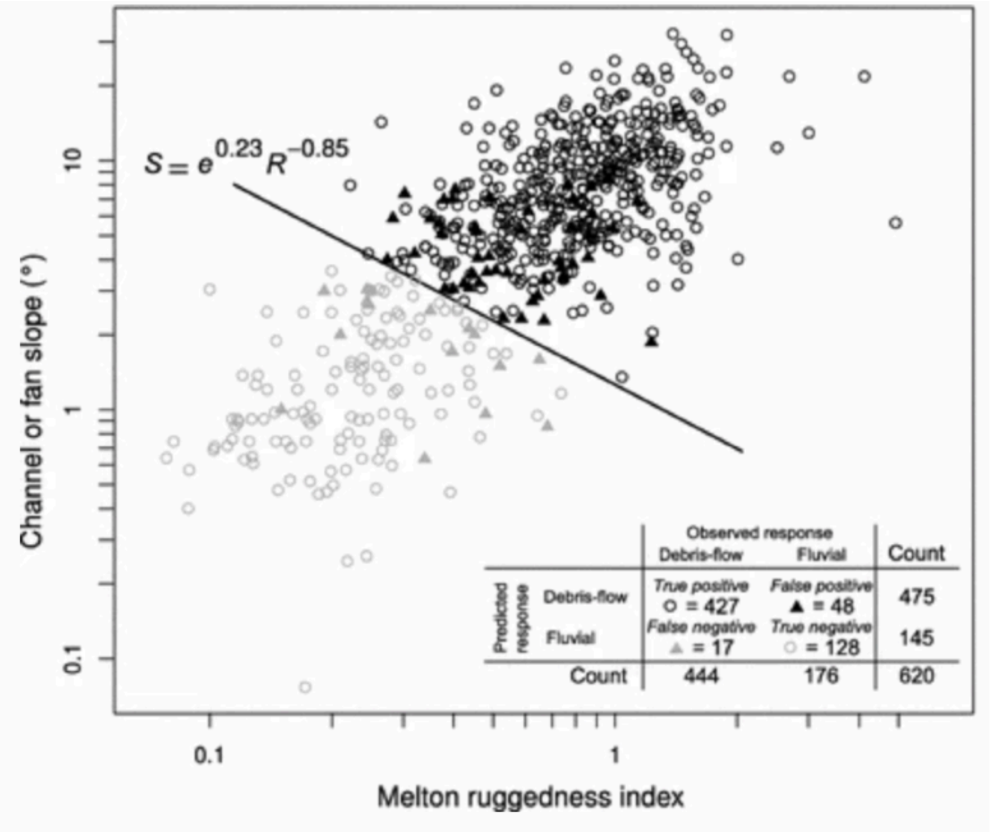


11/2016
somewhere in Hindu-Kush
DF
Thalo Gol
FF
Image © 2022 CNES / Airbus
Google Earth


11/2016
somewhere in Hindu-Kush
N
Debris-flow dominated
DF
Thalo Gol
FF
flood dominated
Image © 2022 CNES / Airbus
Google Earth

Morphometry threshold for classification





- Field based -> small scale
- Melton index and watershed length are good enough

(Wilford et al., 2004)

- Dataset from all over the world (review)
- Only Melton index and the fan slope as predictors

(Bertrand et al., 2013)

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

Baofeng Di, Hanyue Zhang, Yongyao Liu, Jierui Li, Ningsheng Chen, Constantine A. Stamatopoulos, Yuzhou Luo & Yu Zhan

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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Open Access | Article

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

Research questions and the goals:

- 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

machine learning: build the model

tune the model

evaluate the model

make predictions

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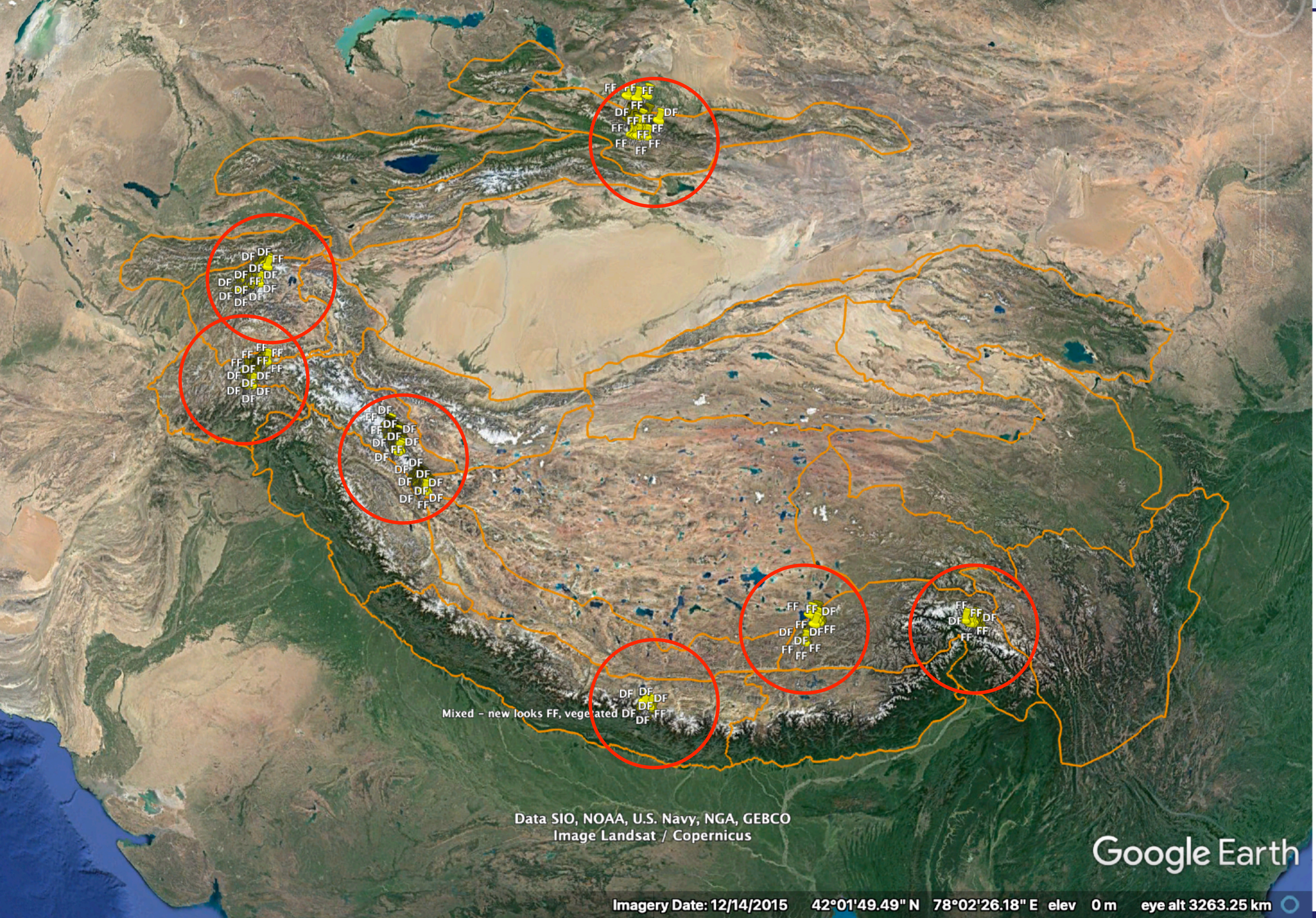
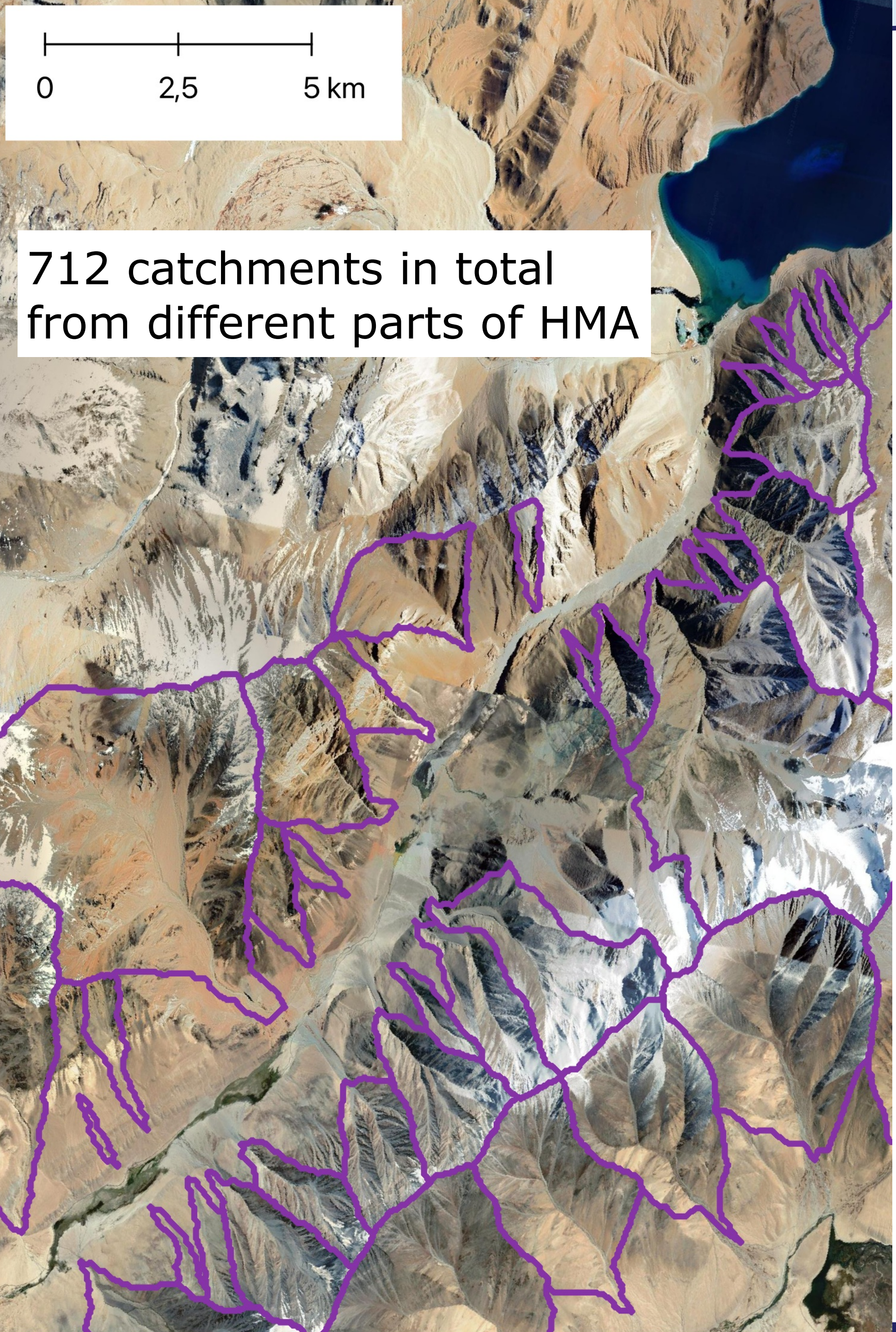

Mixed - new looks FF, vegetated DF
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Image Landsat / Copernicus
Google Earth
Imagery Date: 12/14/2015 42°01'49.49" N 78°02'26.18" E elev 0 m eye alt 3263.25 km



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

Implementation: Catboost

- Does a good job as an “out of the box” tool
- Supports **categorical features** (predictors) as an input
- Each iteration (i.e. tree/weak learner) is trying to learn what did the previous one did “wrong” and do better

Morphometric

- Accuracy : 91 %

(fraction of correct predictions)

- AUC = 0.91
- Confusion matrix: [145., 28.]
[17., 522.]

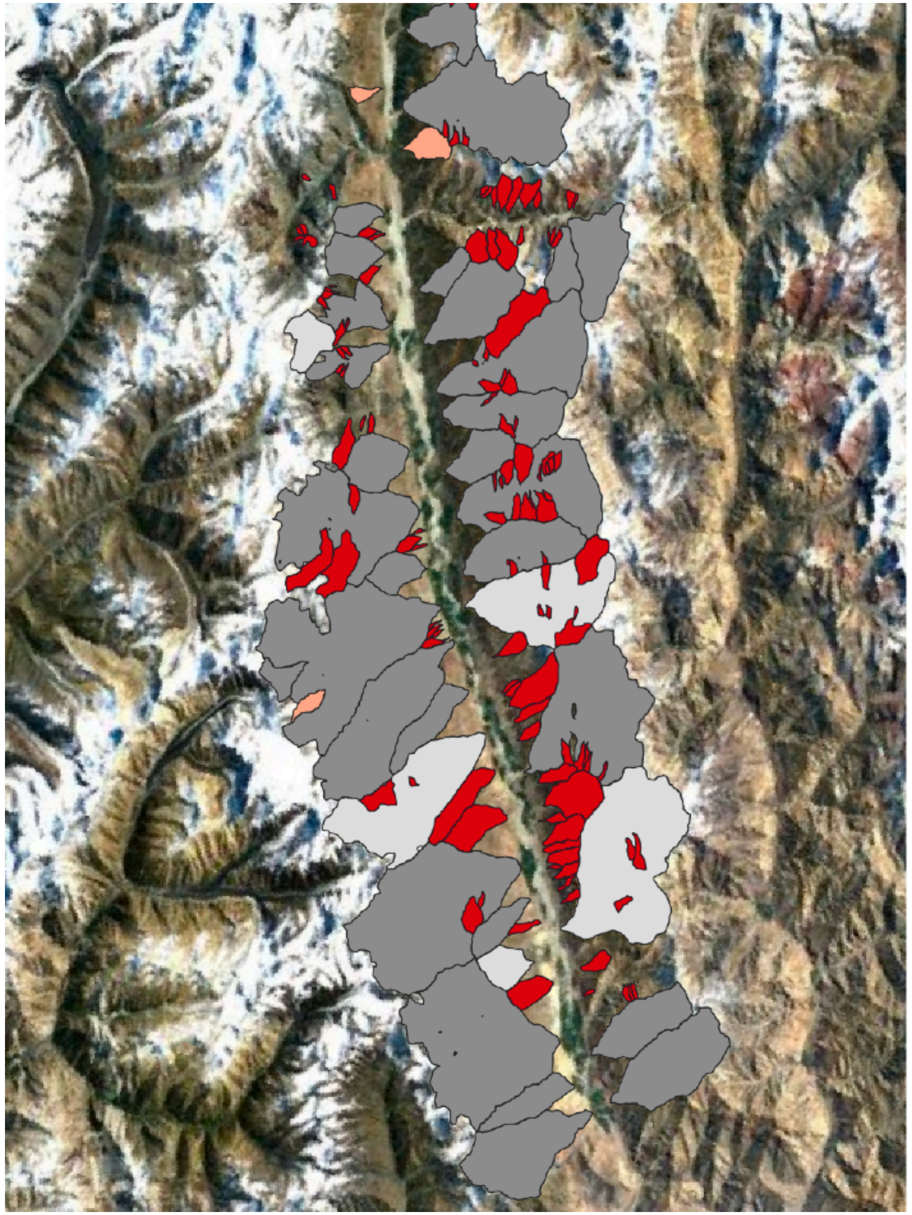
TP	FN
FP	TN

Morphometric + climate

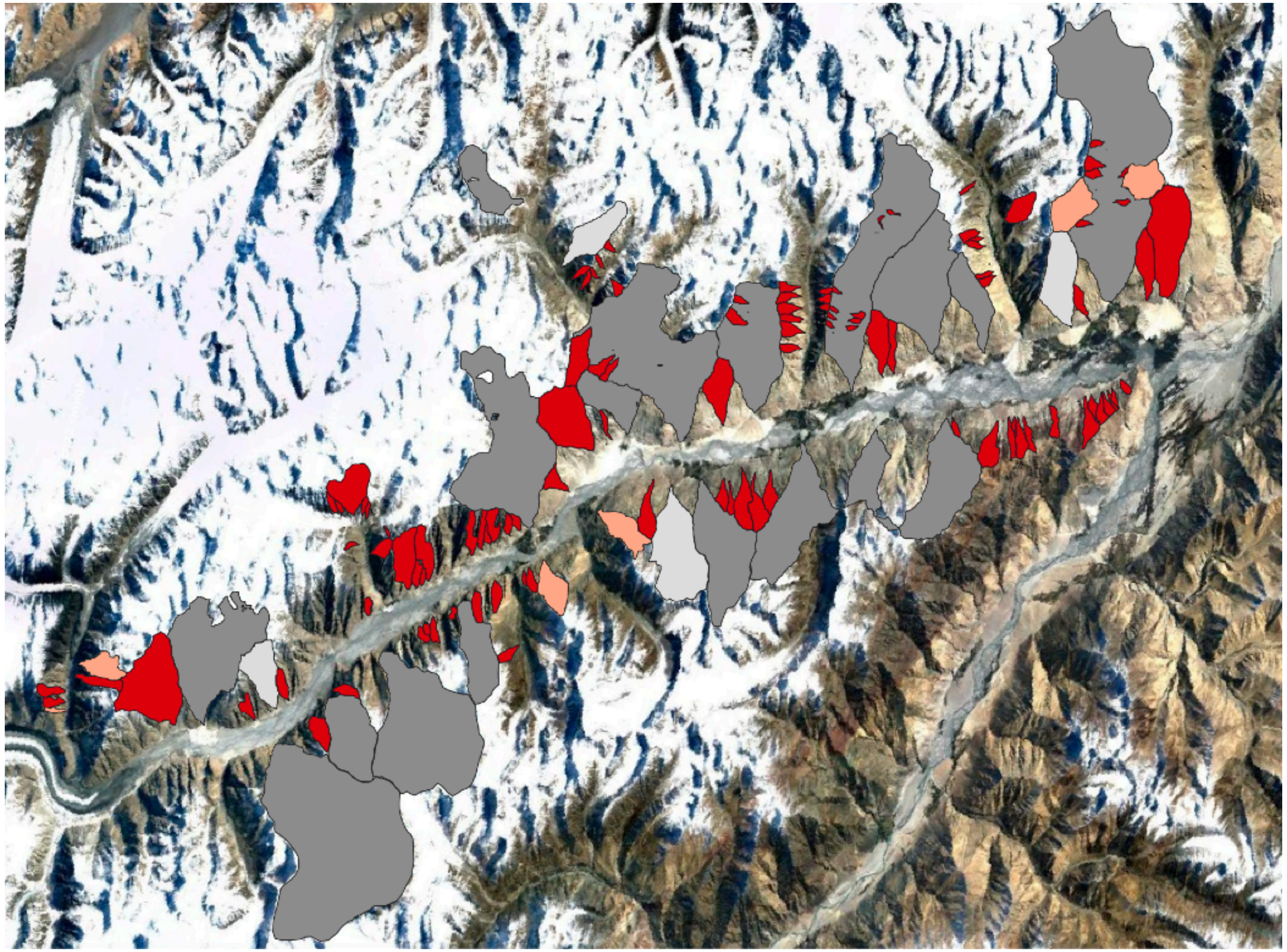
- Accuracy: 92 %
- AUC = 0.91
- Confusion matrix: [148., 25.]
[14., 525.]

When guessing randomly:

- Accuracy = 75.7 %
- AUC = 0.5



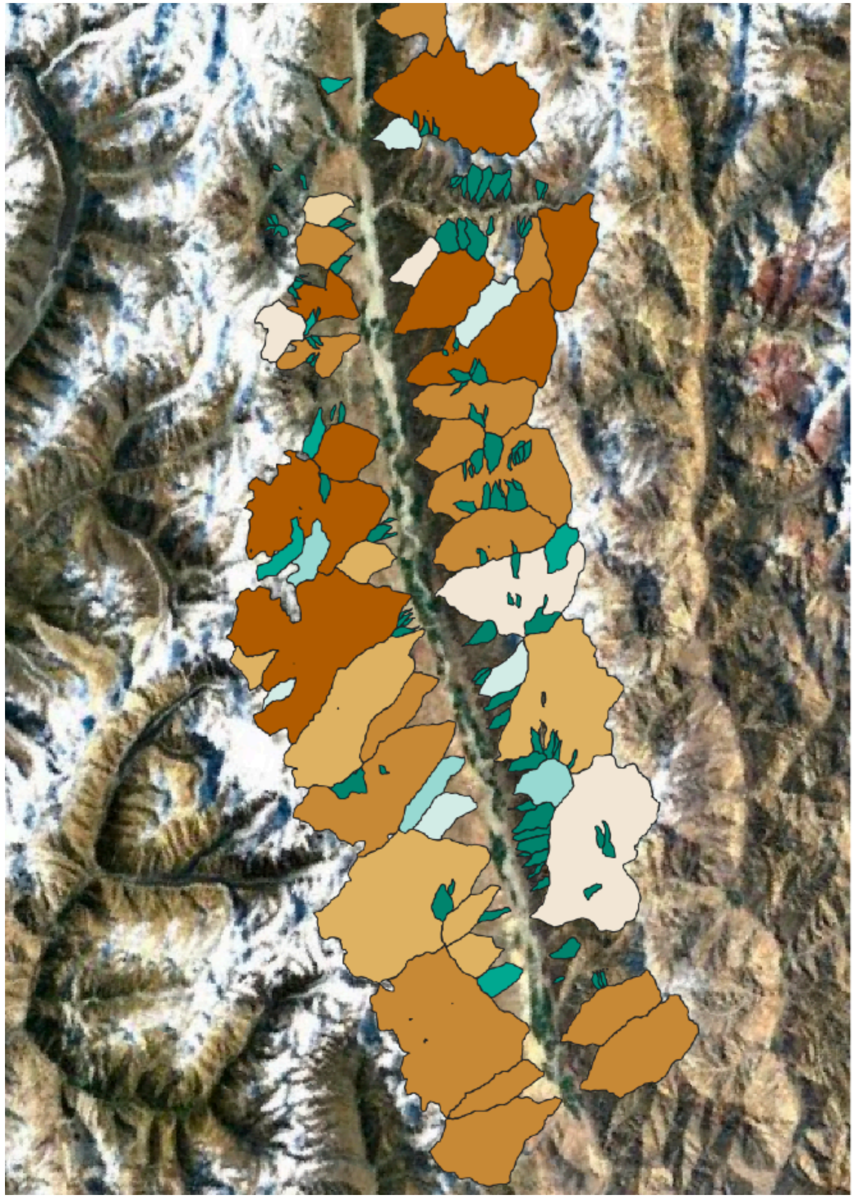
somewhere in Tajikistan



somewhere in Karakoram

flood debris flow

0% 50% 100%



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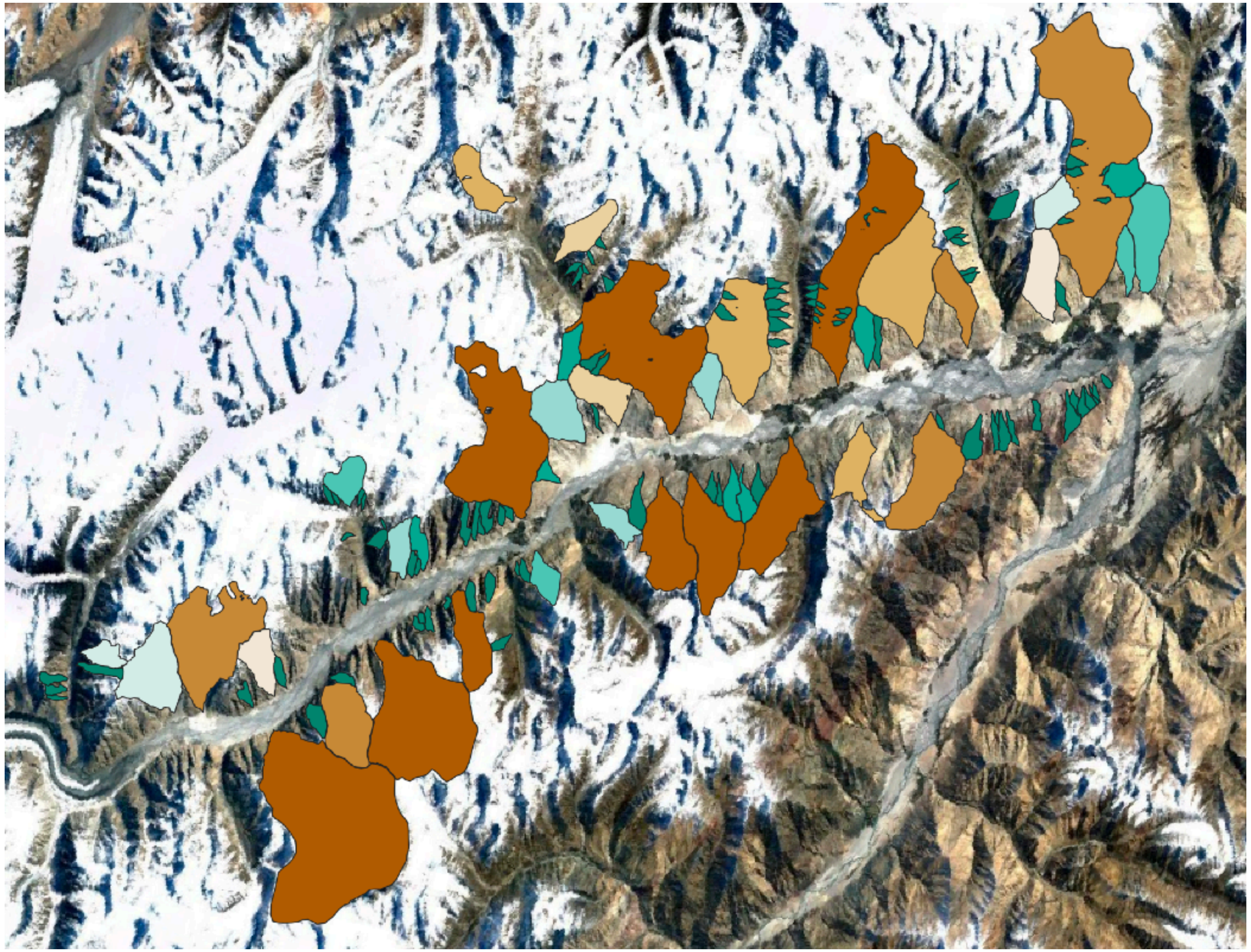
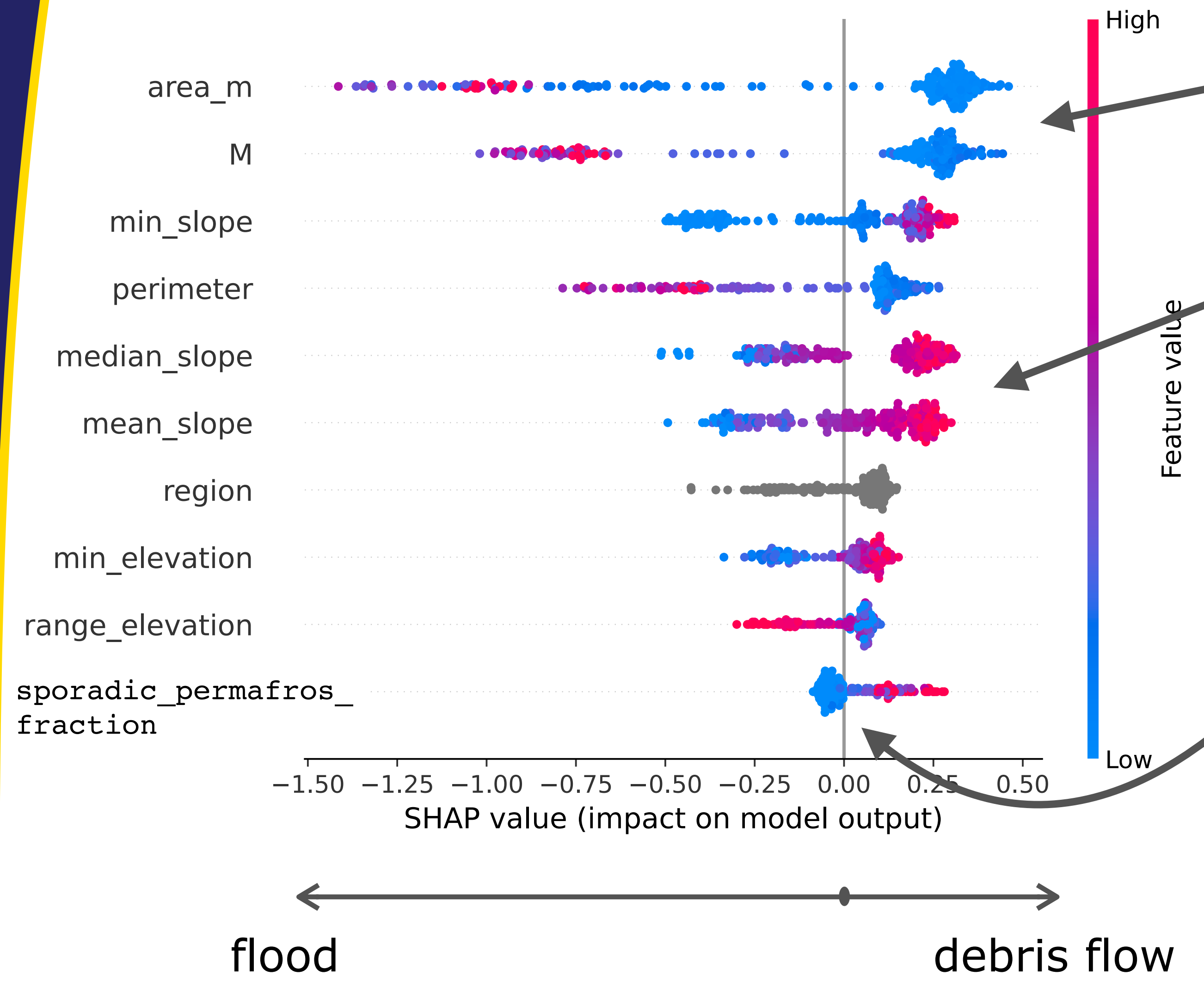


somewhere in Karakoram

Why does Catboost model make this predictions?



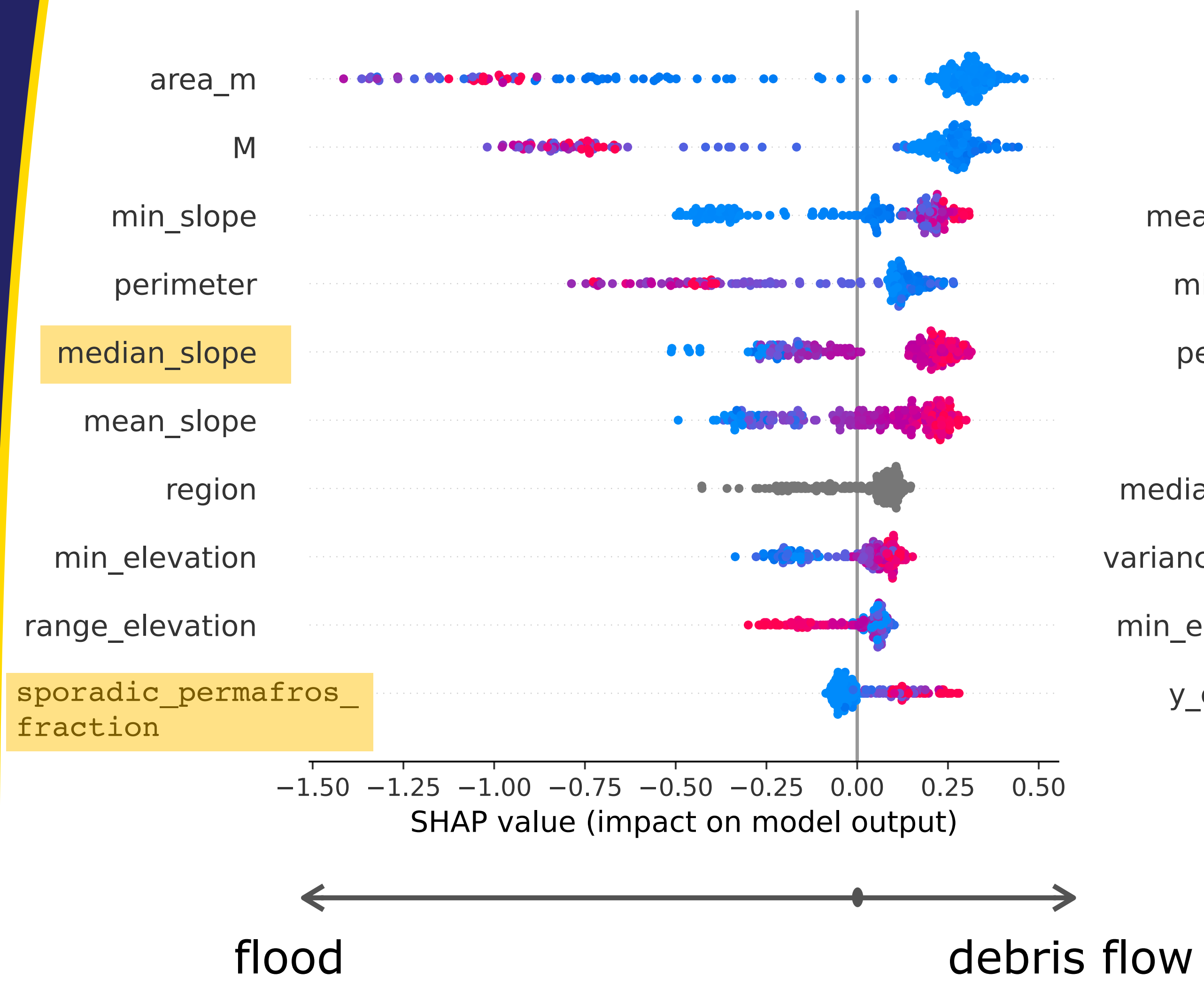
small areas, small Melton ratio make it more likely to be classified as “debris flow”(1)

high mean and median slope bring the model result closer to the “debris flow” class (1)

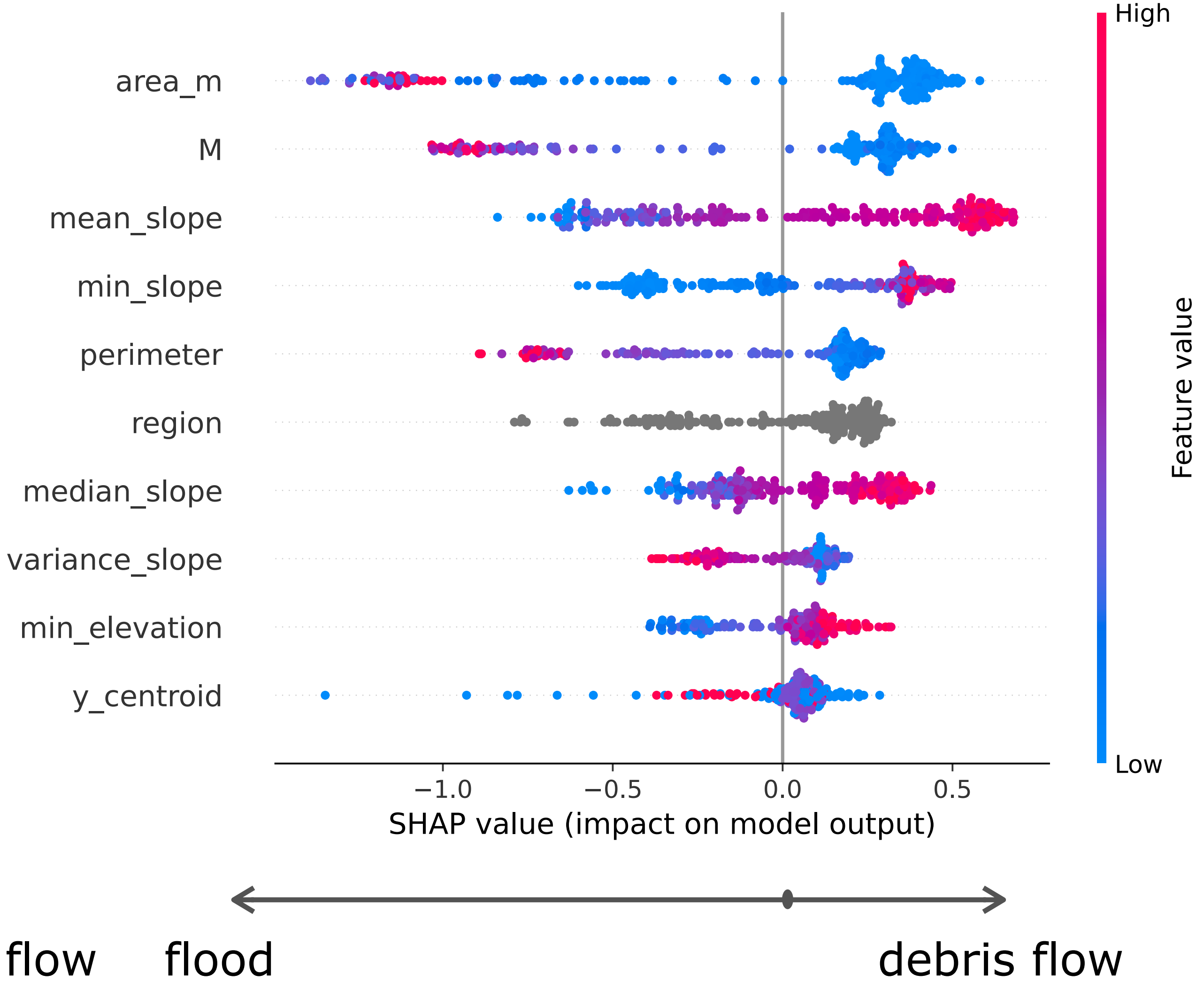
low fraction of sporadic permafrost drags the model towards “flood” (0) class

Morphometric + climate

Why does Catboost model make this predictions?



Morphometric + climate



Morphometric

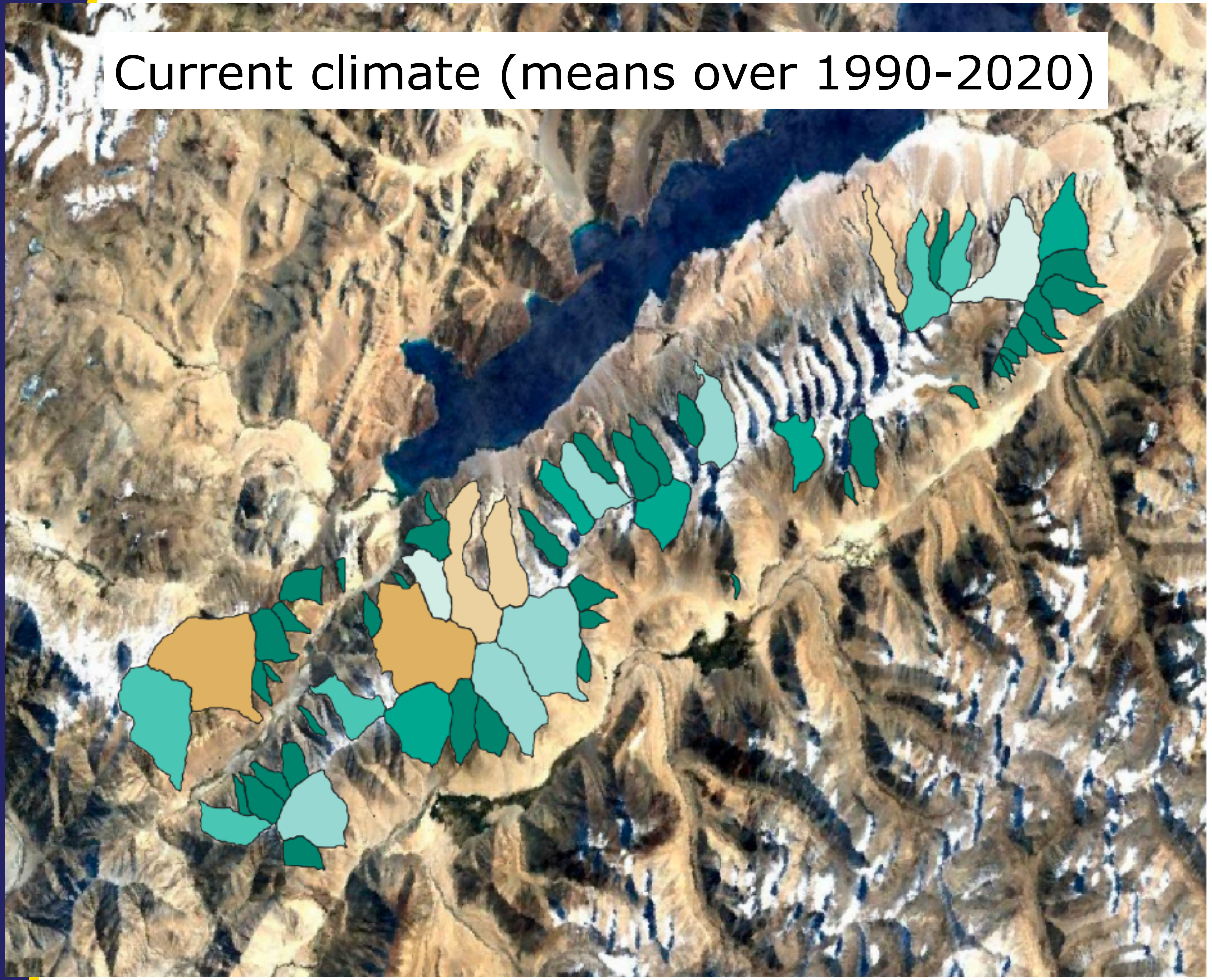
Climate change and projections:

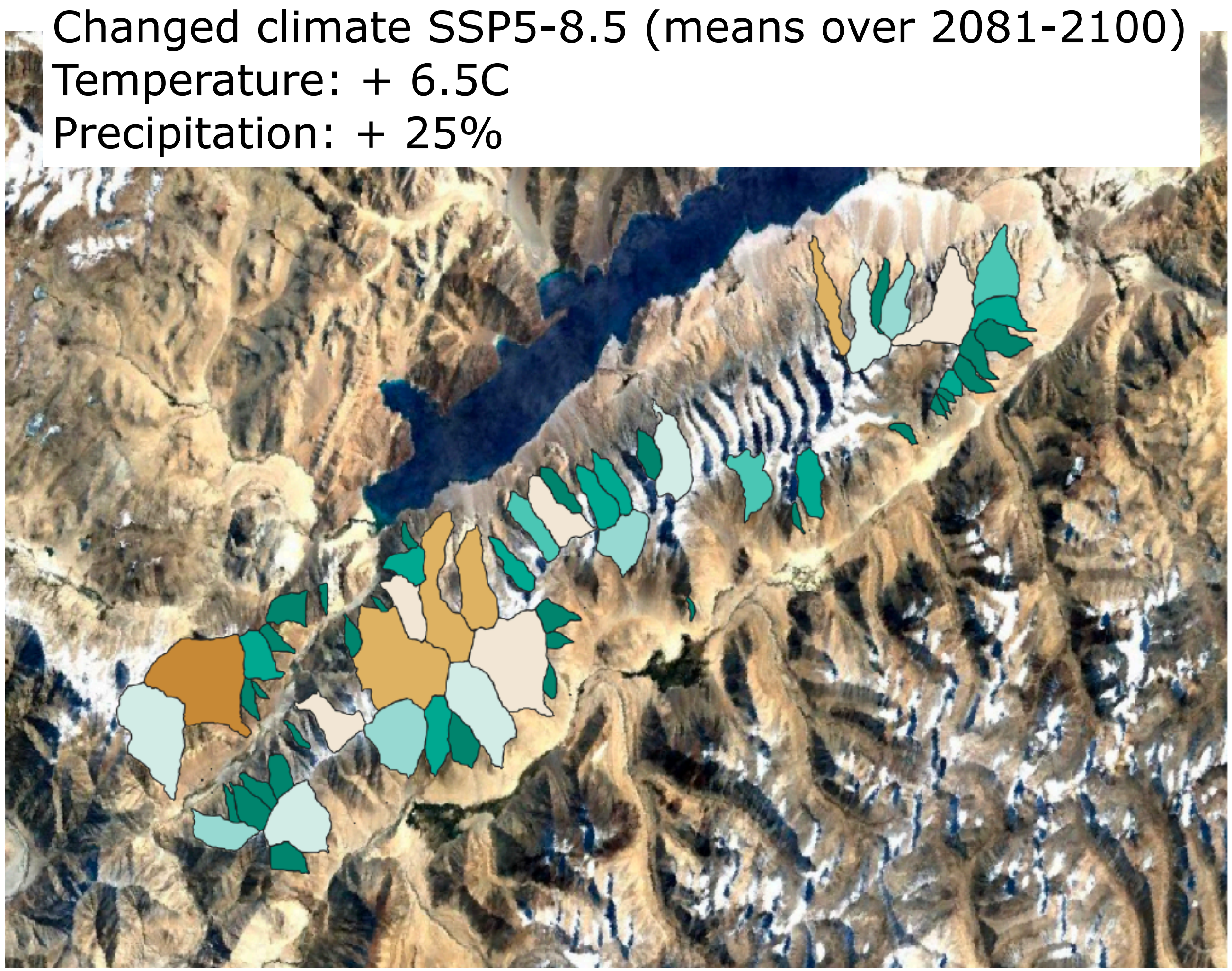
How will the probabilities will evolve over time?

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” and the other way around?

Climate change:

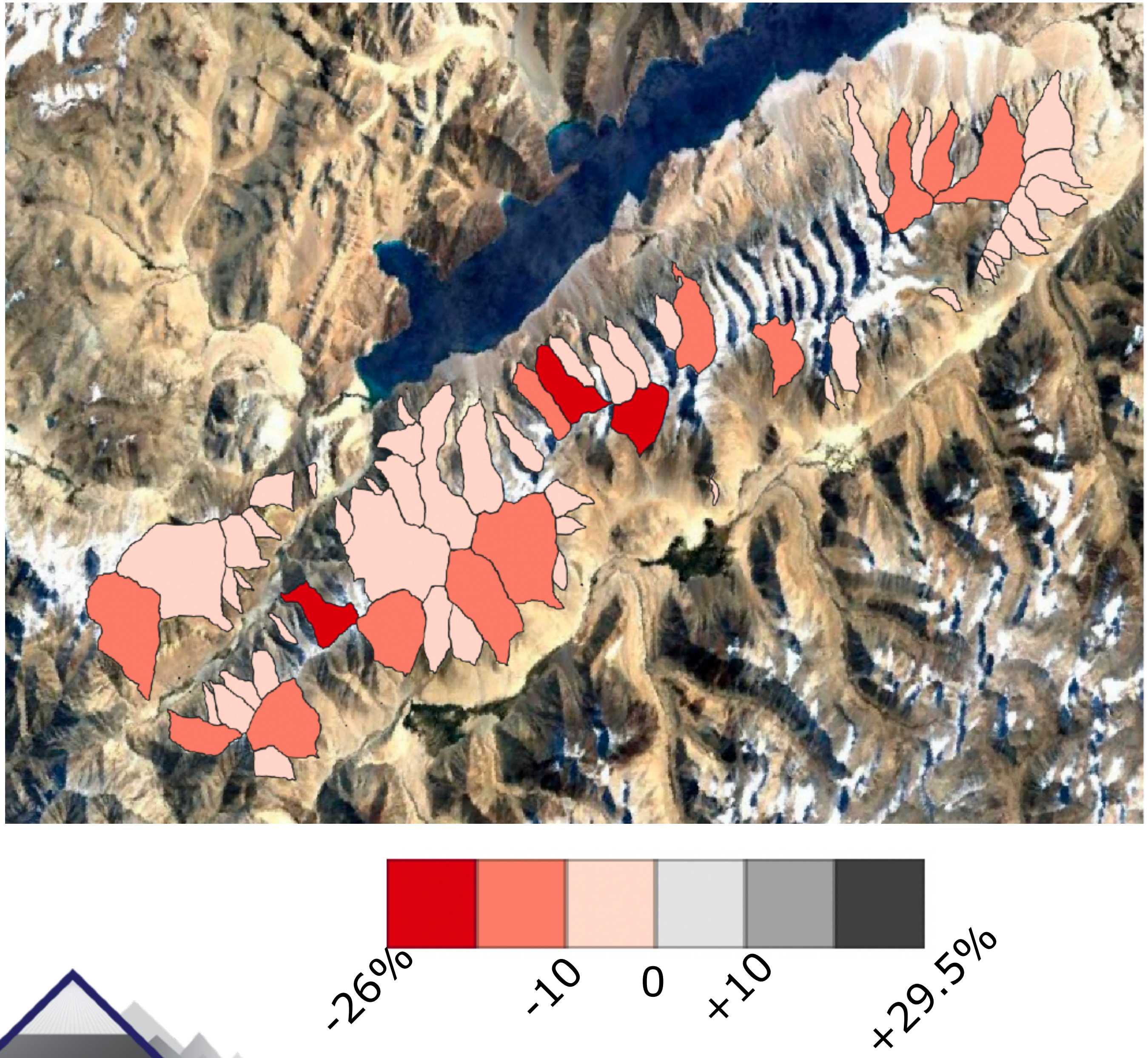




flood ⟷ debris flow

0% 50% 100%

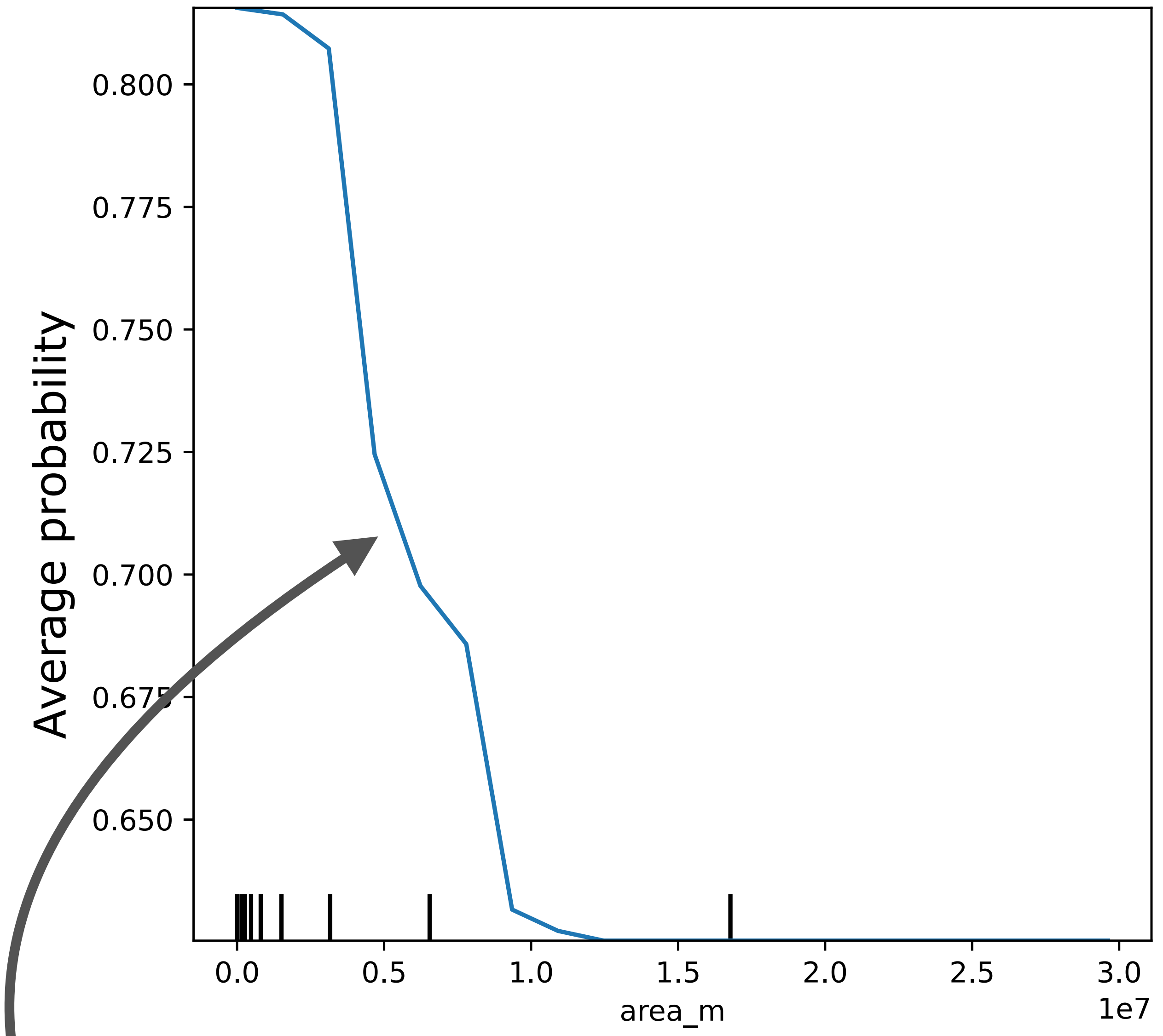
somewhere in Tajikistan



- Mean change in probability: -0.81%
- Increased (more likely to be debris flow): 210/712 catchments
- Decreased (more likely to be flood): 502/712 catchments
- Max changes: + 29.5%, - 26.2%

Model response:

Average model response to the changes in the input data: can it help us to identify the "threshold", responsible for the changes in the system?



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

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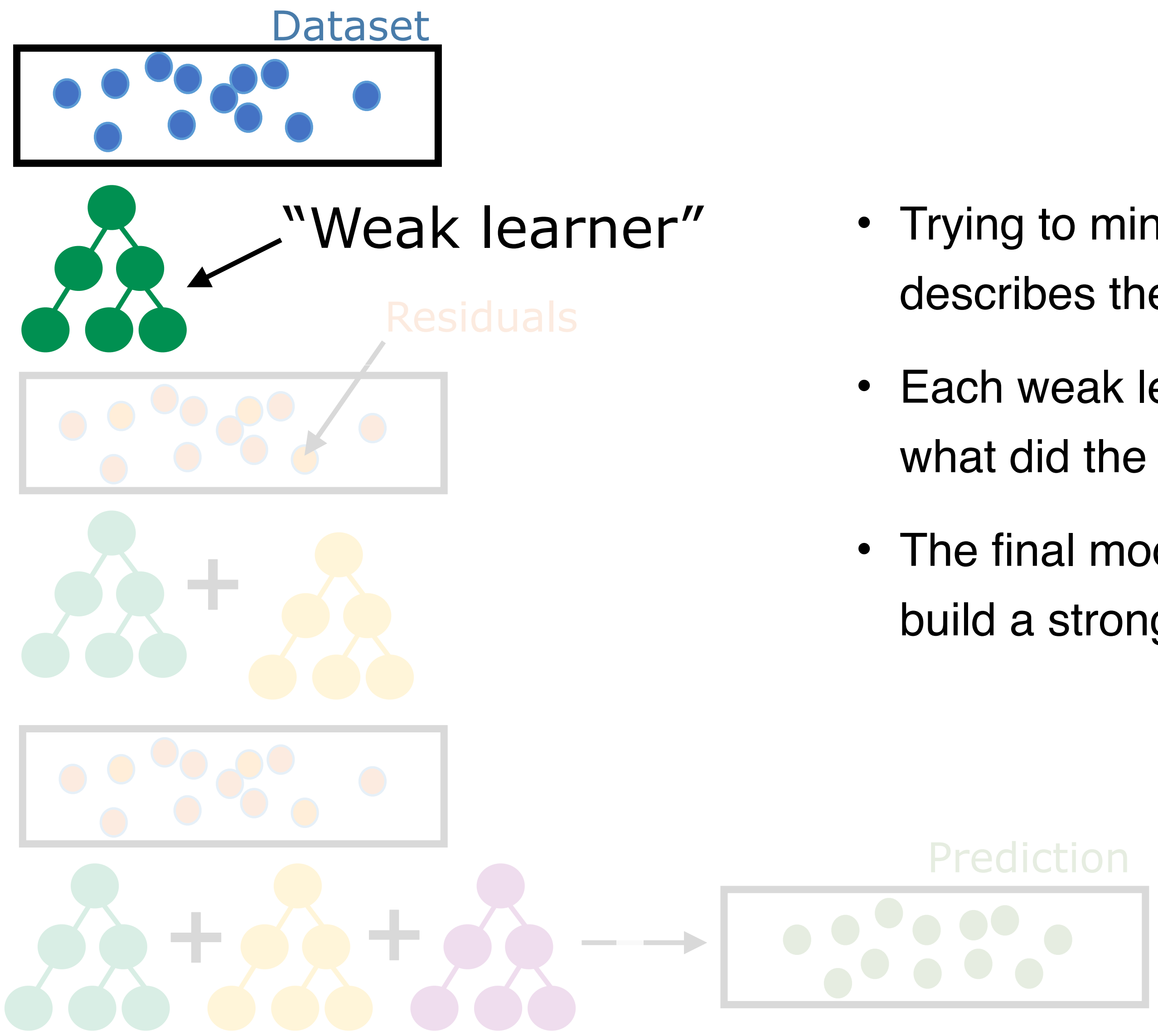
Outlook

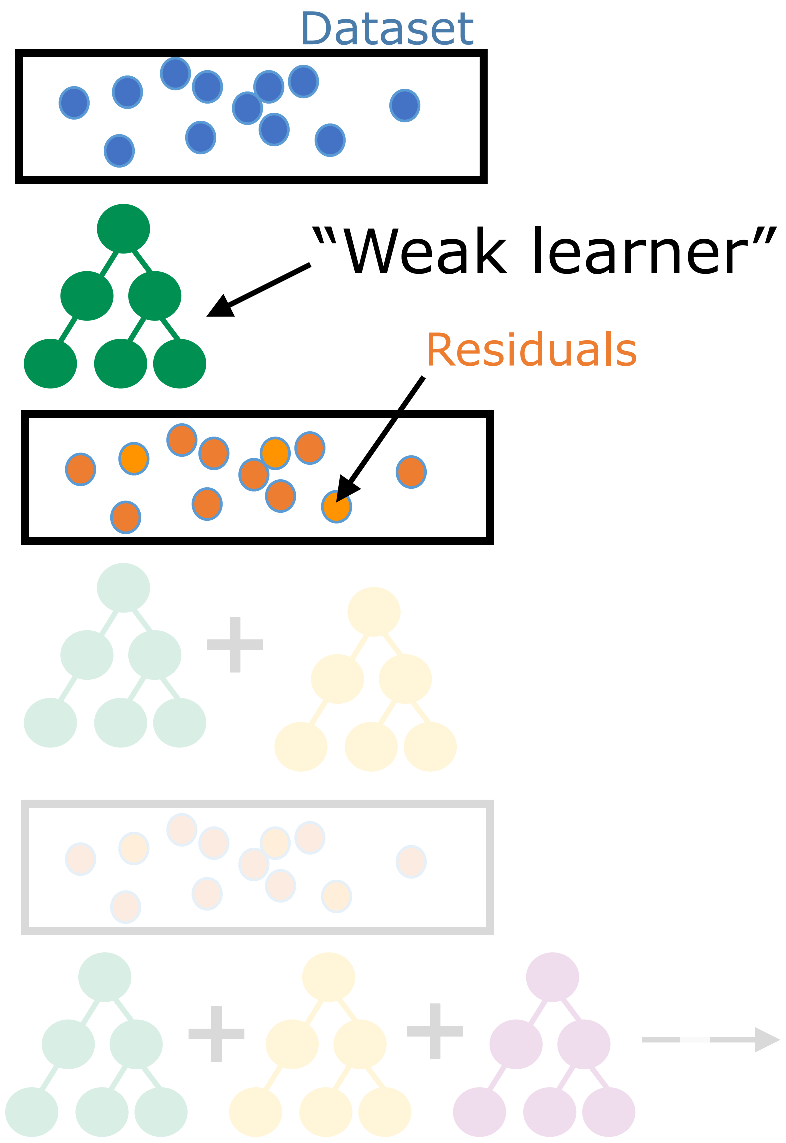
- Extend the dataset for "creating" the model by covering more diverse regions
- Add vegetation cover and geology to the feature list
- Apply the model to the "new" areas (i.e. catchments without alluvial fan)
- To see the effect of the climate change - use RCP scenarios as a climate information

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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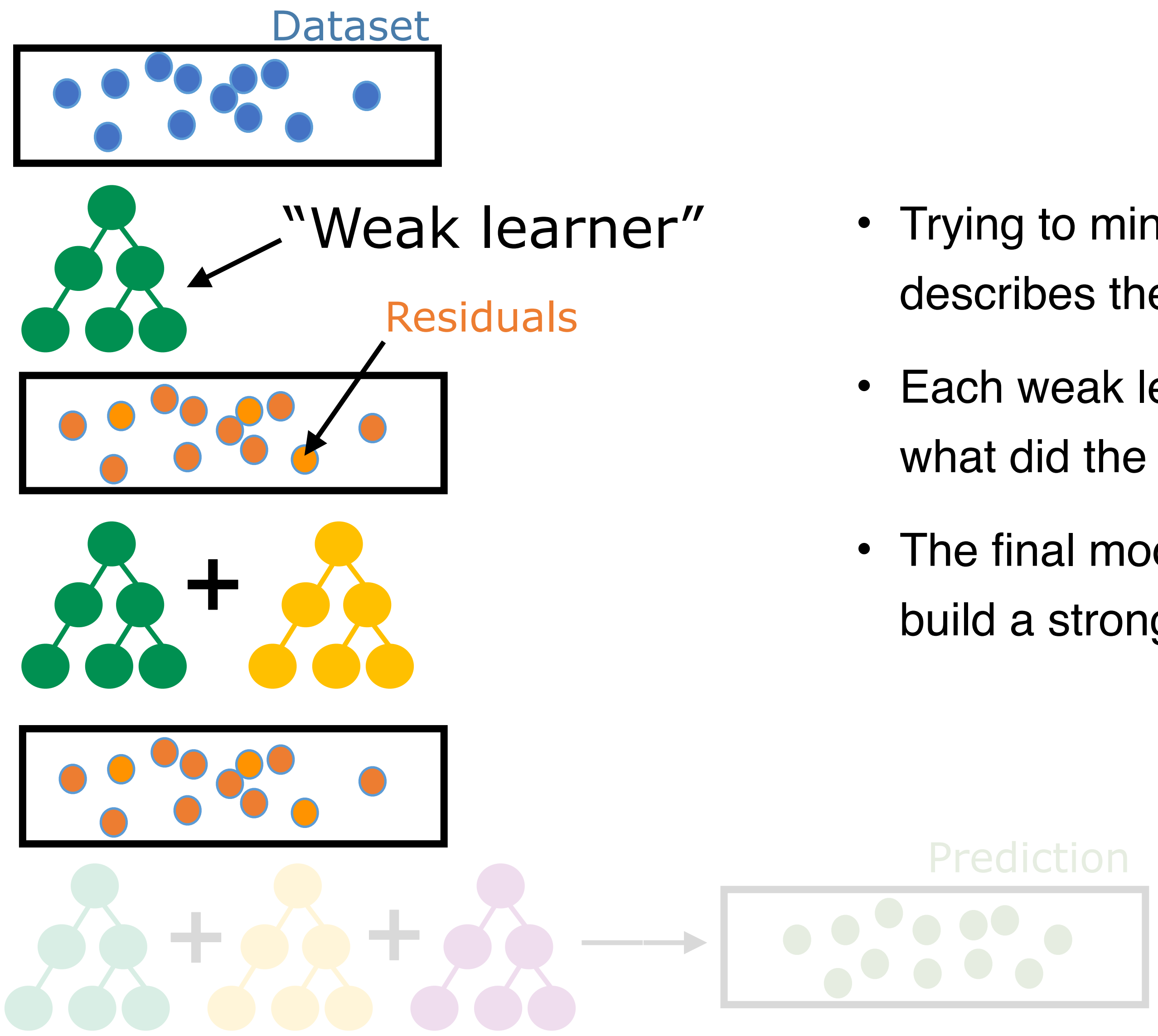

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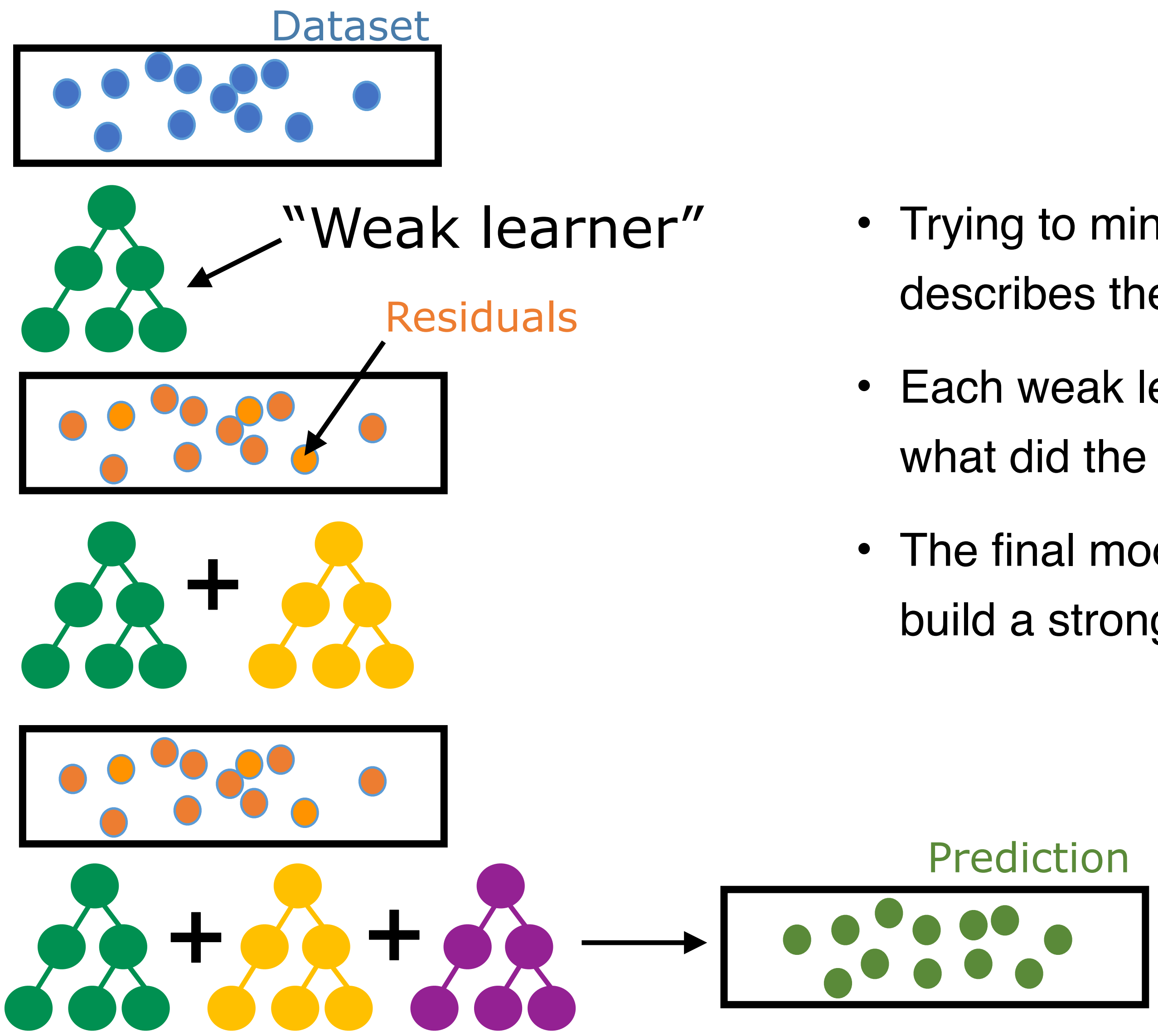

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