Digital Waters
PhD Pilot

Feature importance for deep learning rainfall-runoff modeling in the boreal zone

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Iiro Seppä 04.05.2026

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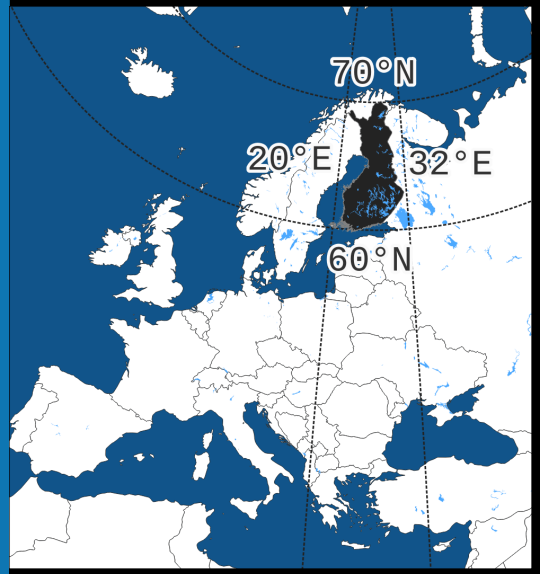
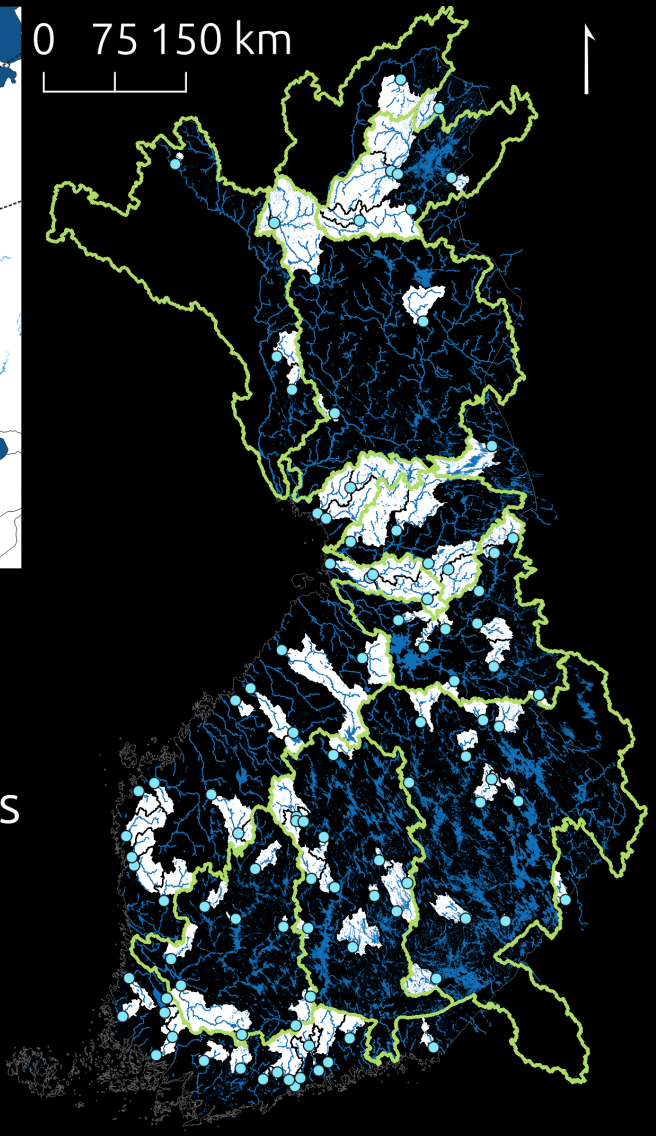
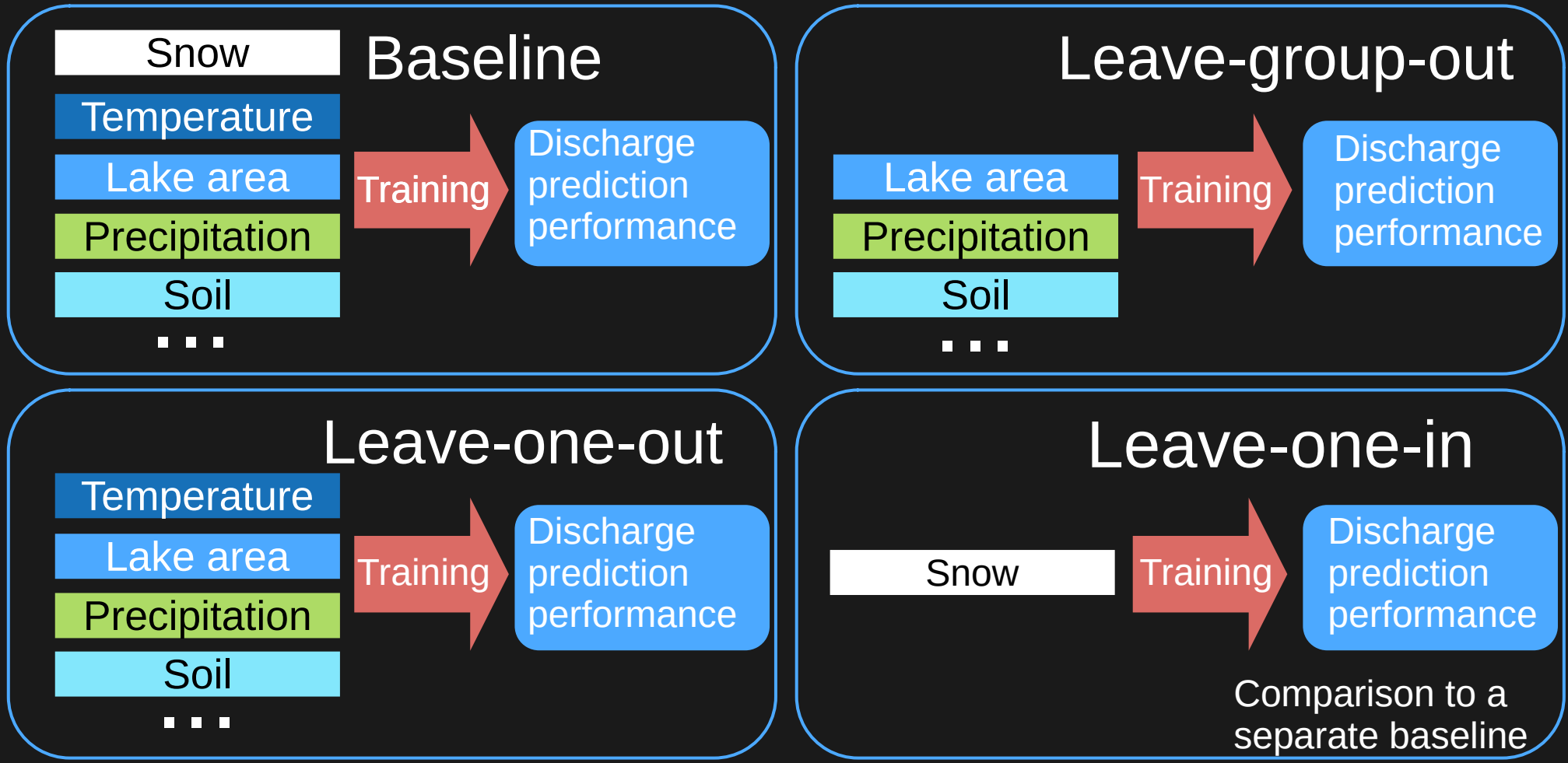
The data

- CAMELS-FI
- Selection of 101 non- or weakly regulated catchments with complete time series for the study period 1989-2020
- 13 weather variables (6 different types), 24 static variables selected
- Many strong correlations

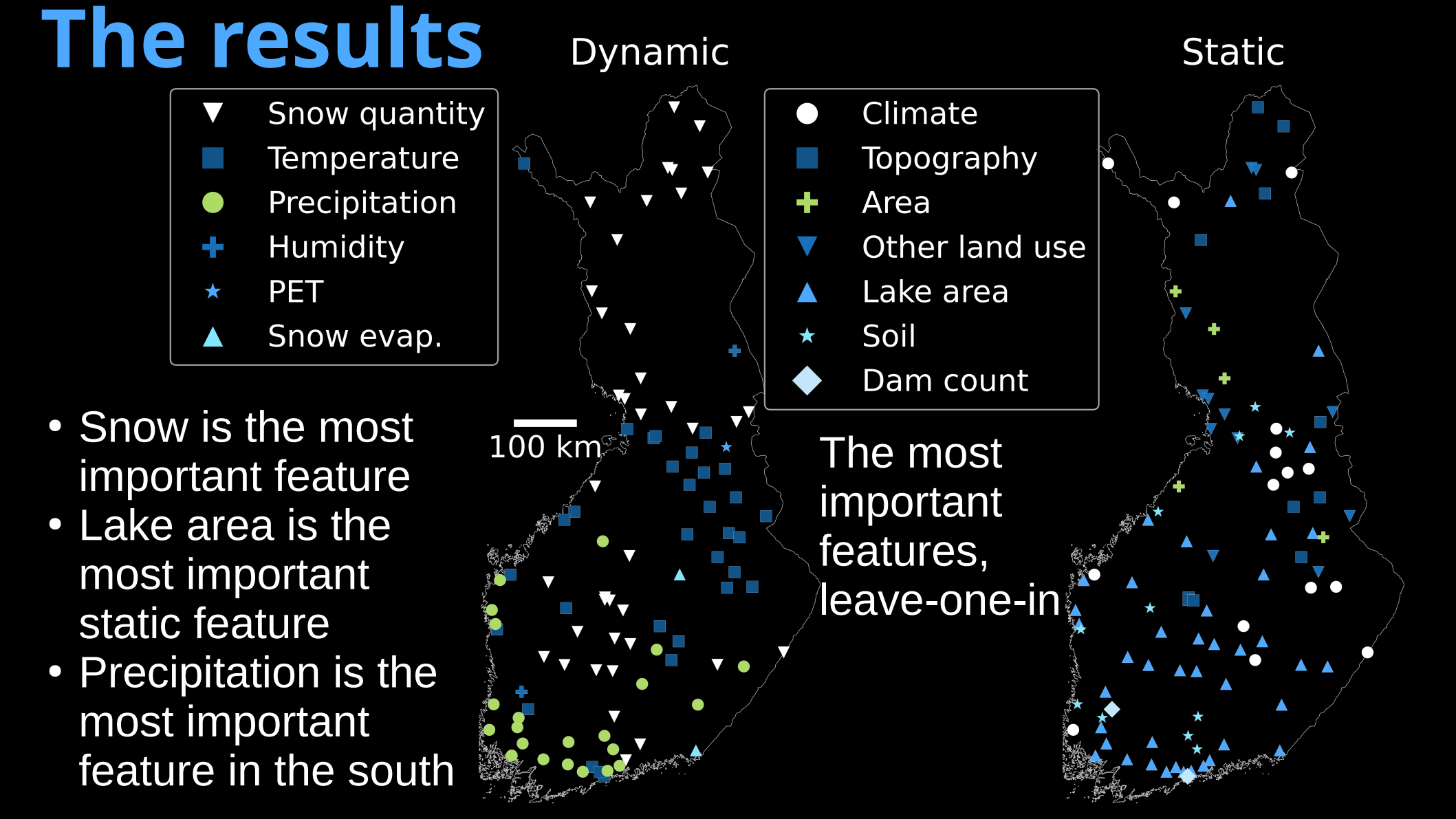




General methodology



The results



- Snow is the most important feature
- Lake area is the most important static feature
- Precipitation is the most important feature in the south

The most important features, leave-one-in

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Feature importance

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- Tries to measure the impact of different inputs for the quality of predictions of a machine learning model
- Many methods analyze the behavior of a trained model
  - However, these methods may be suboptimal if the focus is on the phenomena and not the model
- Permute and relearn can help with these issues

1. Snow
2. Temperature
3. Lake area
4. Precipitation
5. Soil

Gap in previous research

- Only a few hydrological studies have applied feature importance methods for deep learning models
  - None of them focusing in the Boreal zone
- Most common feature importance metrics are suscpectible to strong relationships between features
- Almost all hydrological features correlate strongly with another feature
- No previous study has applied permute and relearn to most individual features of a CAMELS-dataset

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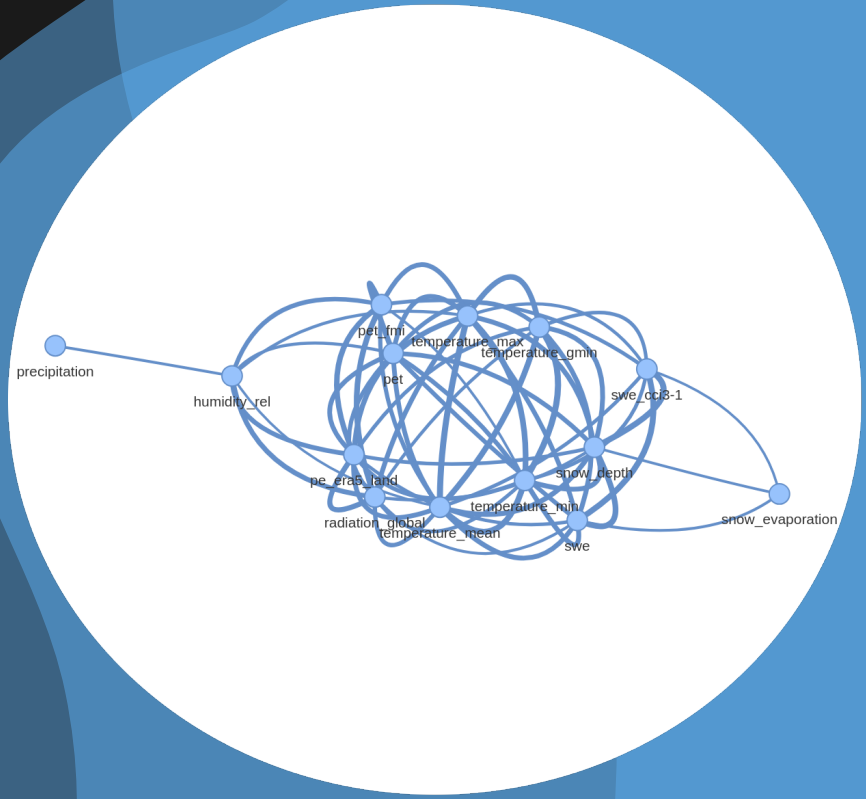

Absolute correlations > 0.4
in weather variables of CAMELS-FI

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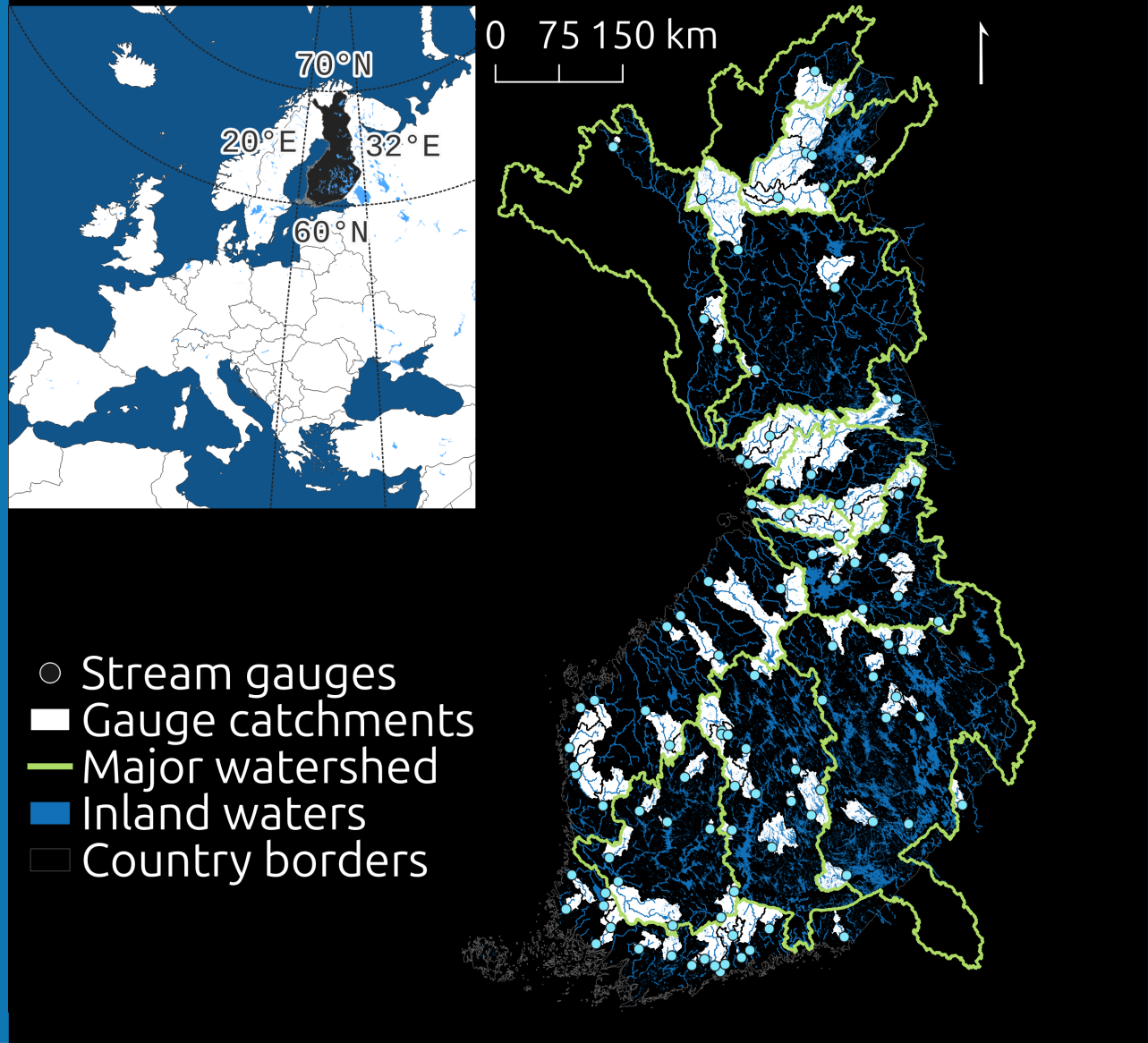

List of used variables

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Dynamic (daily)

- Snow depth
- SWE (ERA5)
- SWE (ESA CCI3-1)
- Precipitation
- Snow evaporation
- Global radiation
- PET (FMI)
- PE (ERA5-Land)
- Relative humidity
- Temperature max
- Temperature mean
- Temperature min
- Temperature gmin

Static

Climate	P mean, PET mean, mean annual temperature, aridity index, P seasonality, Snow fraction of P, High P frequency and duration, low P frequency and duration
Human influence	Dam, reservoir and other regulation count, reservoir capacity
Area	Area
Soil	Soil depth, areal percentages of bedrock, silt, till, clay and peat
Land cover	Areal perentages of lakes, evergreen & deciduous forests, wetlands, urban areas, grasslands, shrubs and croplands
Topography	Slope, elevation range, elevation 10th, 50th and 90th percentile

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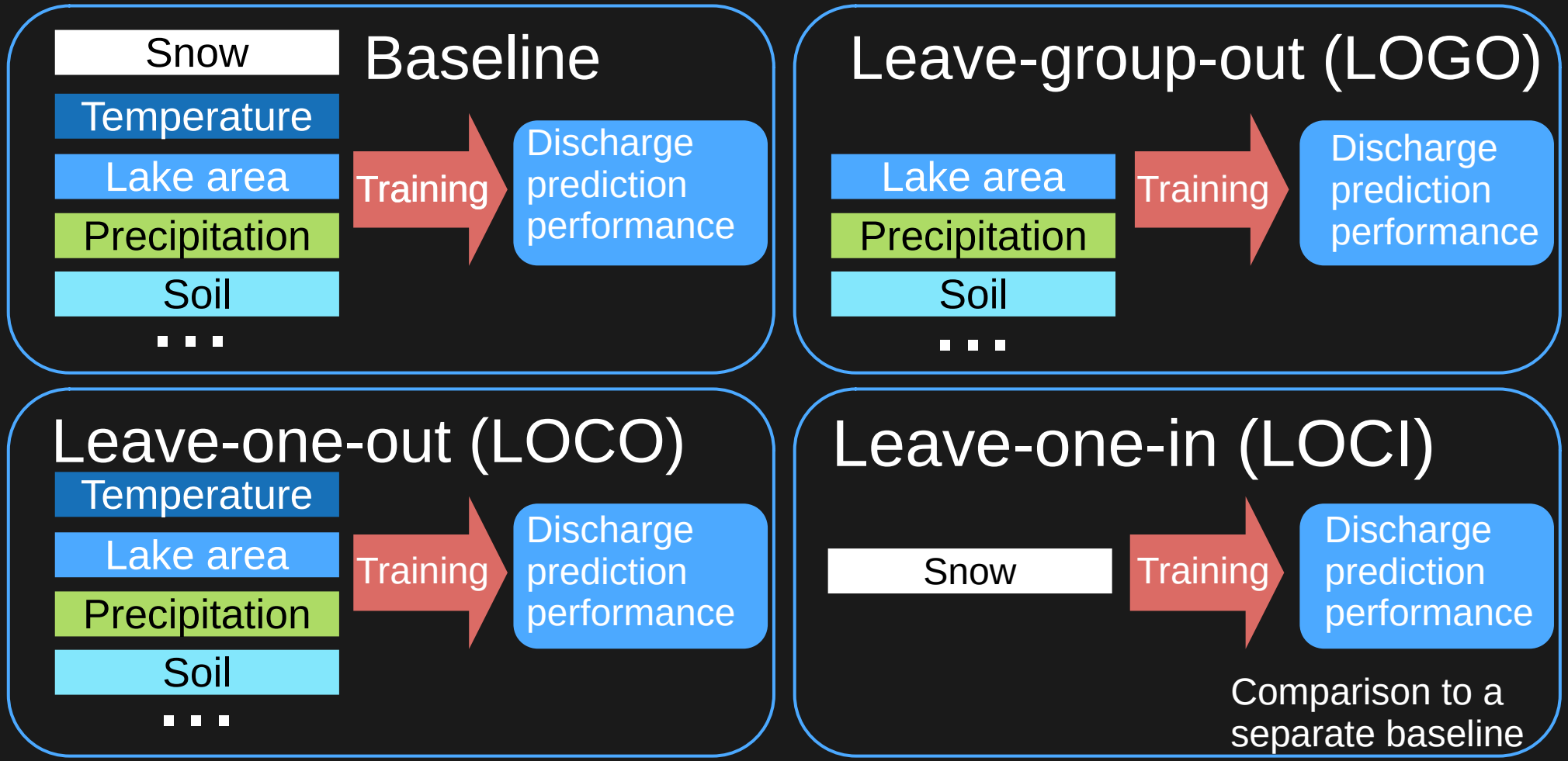
General methodology



Notes on the experiments

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- Leave-one-out is affected by relationships (such as correlations)
  - ➔ However, it gives very useful information on the unique importance of the feature
- The groups for leave-group-out are formed separately for all features by removing all features with absolute spearman correlation above 0.24 with the feature.
- Leave-one-in uses different baselines than the other two experiments
  - Static features use a model trained with only dynamic features as a baseline
  - Dynamic features use a model with only statics as a baseline (predicts mean discharge of each catchment)

Setup

- Neuralhydrology python-library
- Ensemble of Long short-term memory (LSTM) networks (10), trained with all training catchments
- NSE loss
- Aggressive early stopping

Periods (water years Sep-Aug):

- Training 1989-2007
- Validation 2009-2012
- Test 2014-2020

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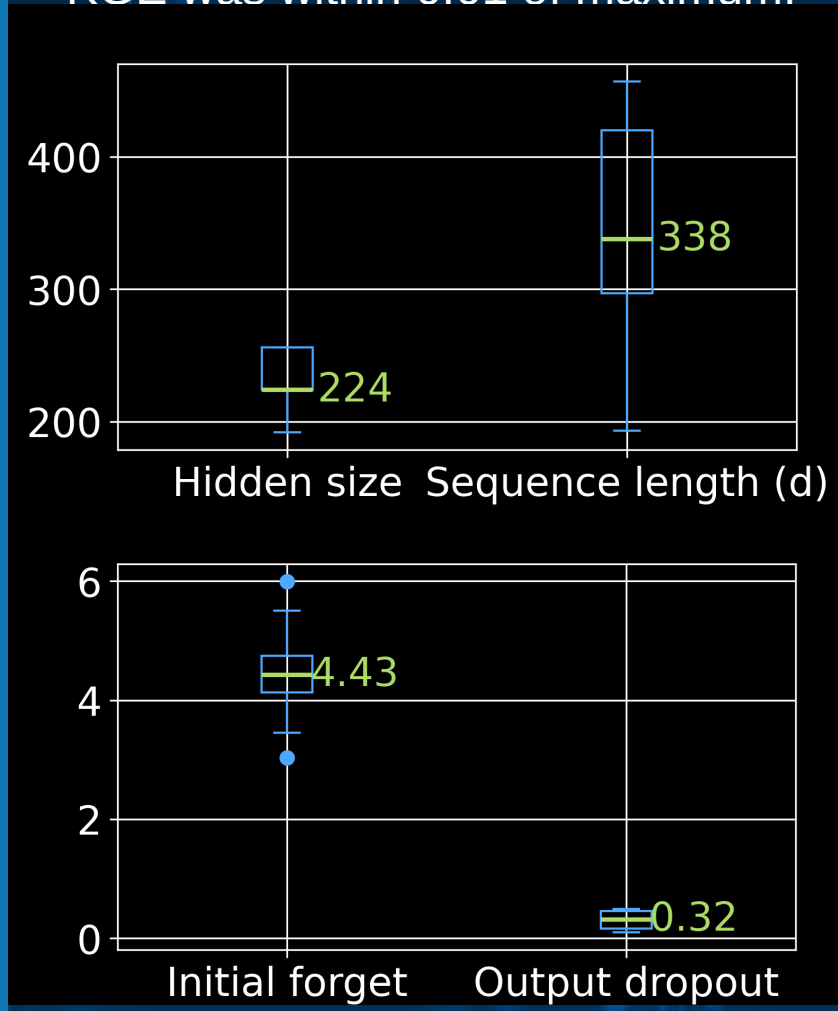
NEURAL HYDROLOGY

Hyperparameter tuning

- Used Optuna
- Batch size, learning rate, Hidden size, Sequence length, initial forget bias & output dropout were optimized
- After 66 runs stable batch size (>32) and learning rate (< 0.005) were determined, and the values were set to **128** and **0.0001**, respectively
- Additional 285 runs were done for the remaining four variables
  - Medians of runs with KGE within 0.01 of the maximum are used

Parameter ranges of runs where KGE was within 0.01 of maximum.



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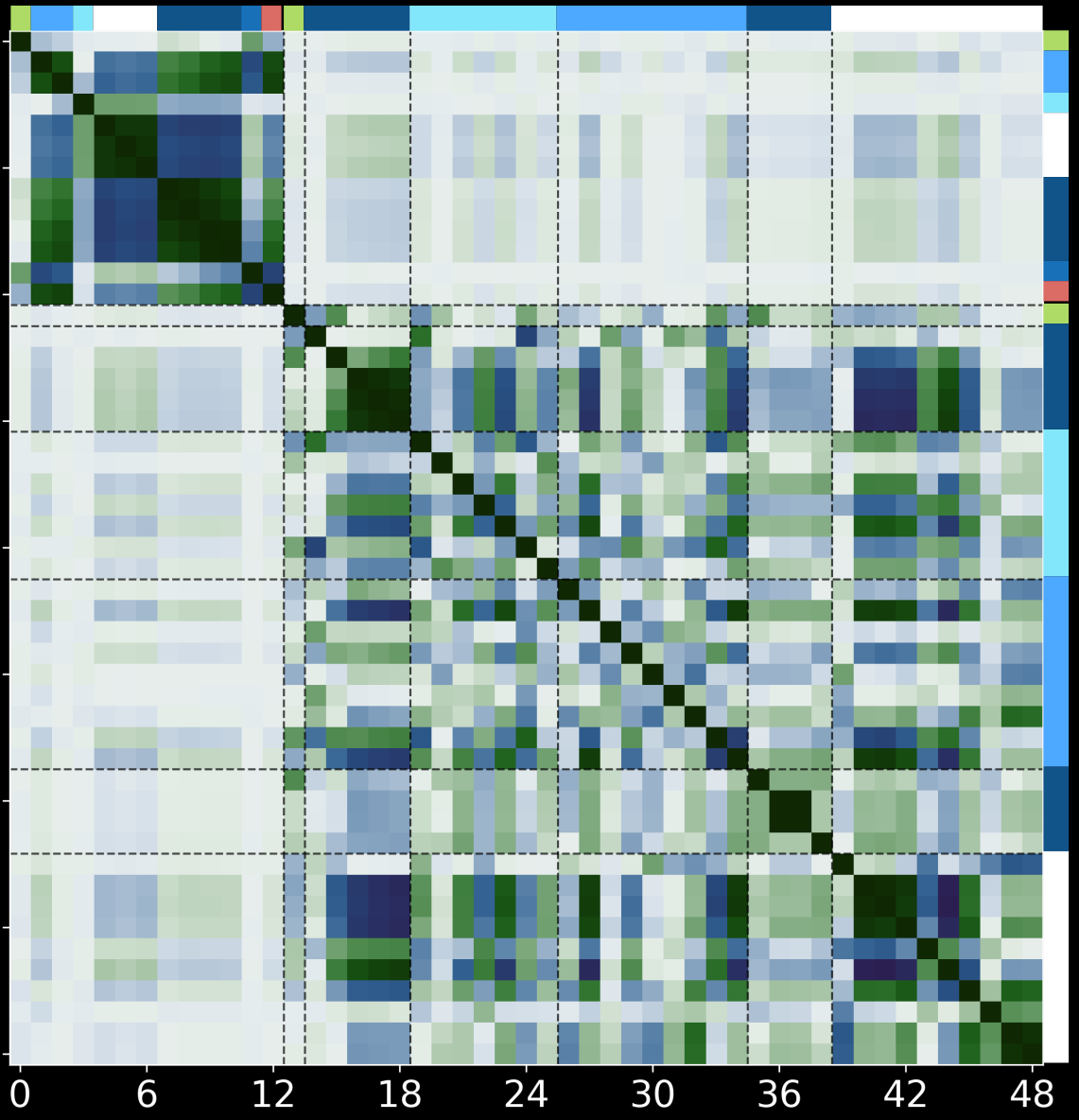
Correlations

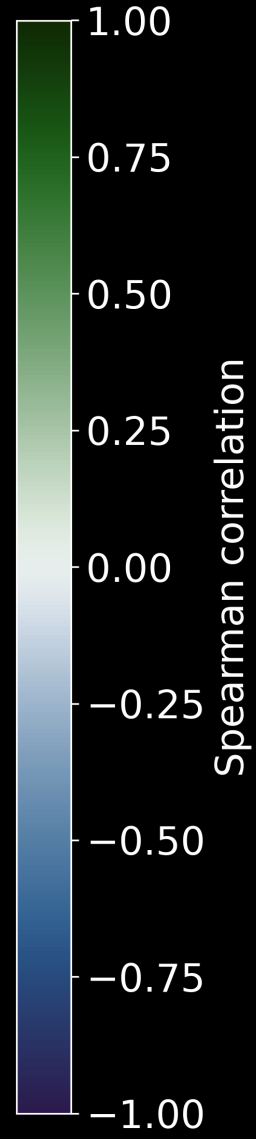
Dynamic

0 Precipitation
1-2 PET
3 Snow evaporation
4-6 Snow quantity
7-10 Temperature
11 Relative humidity
12 Global radiation

Static

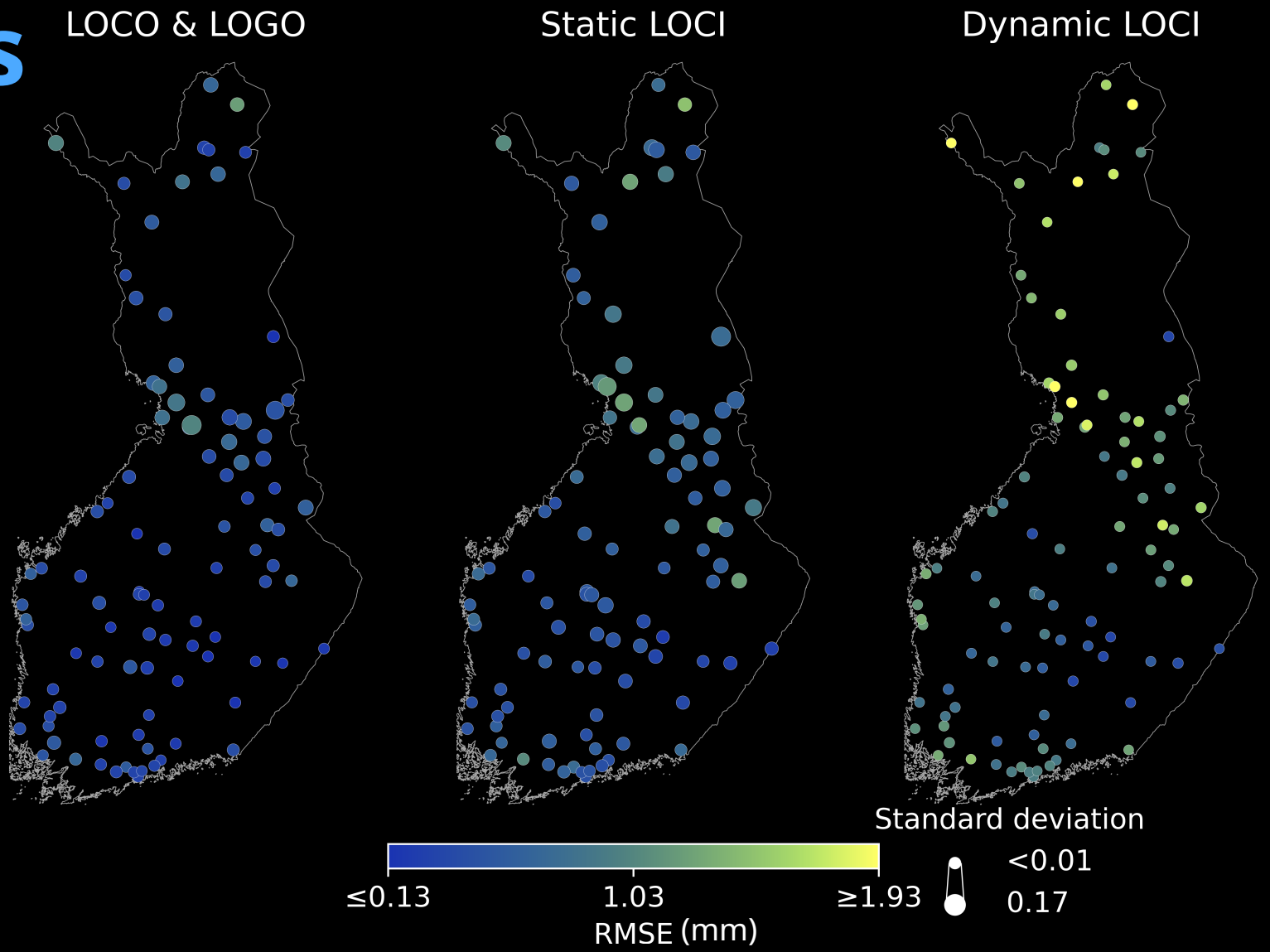
13 Area
14-18 Topography
19-25 Soil
26-34 Land cover
35-38 Human influence
39-48 Climate





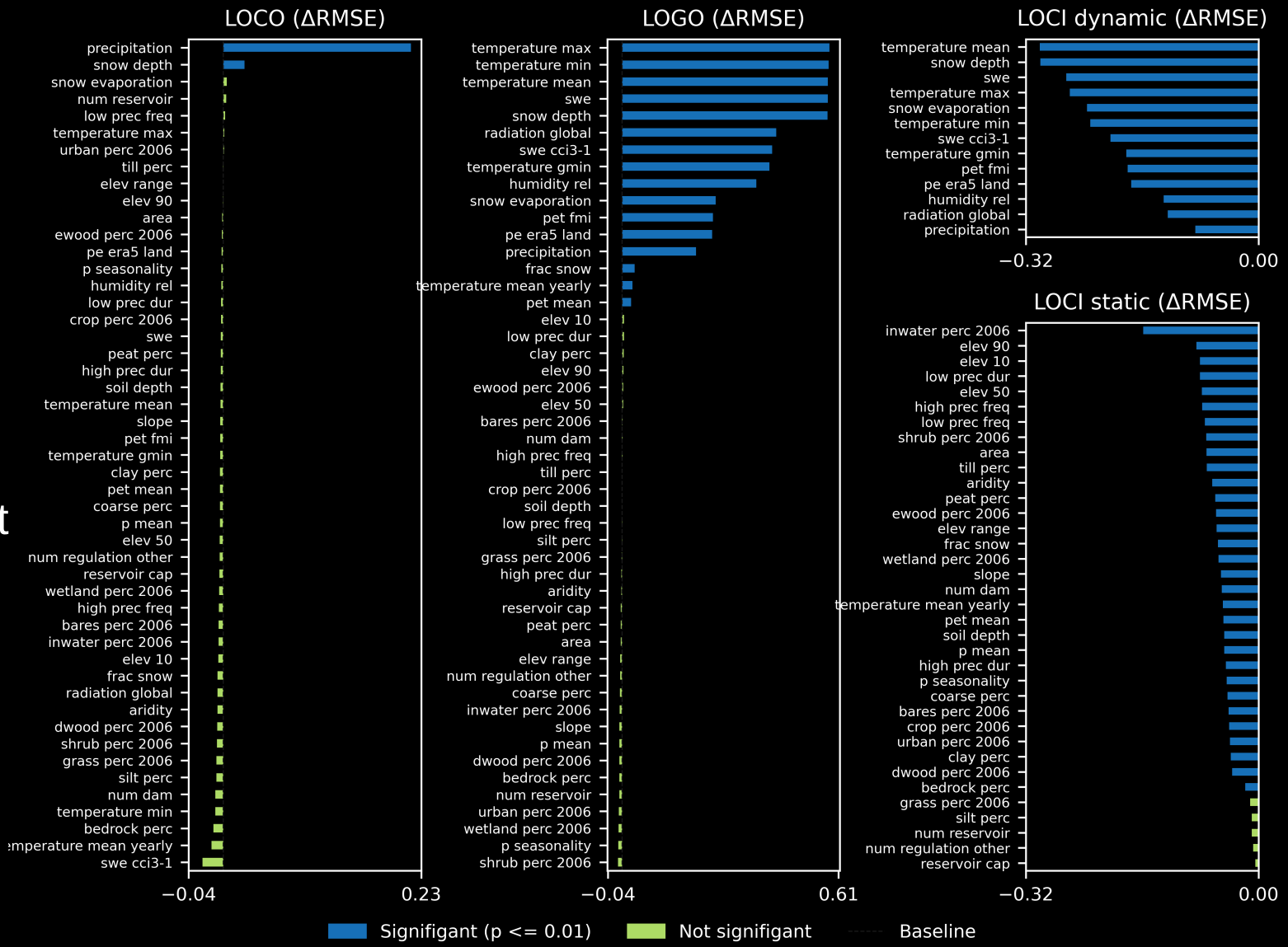
Baselines

- LOCO & LOGO baseline includes all the features in the study
  - ➔ Performance is overall excellent
- Static LOCI has all the dynamic features, none of the static features
  - ➔ ”Typical” catchments are effected only slightly, large
- Dynamic loci includes only static features
  - ➔ The worst performance



Results

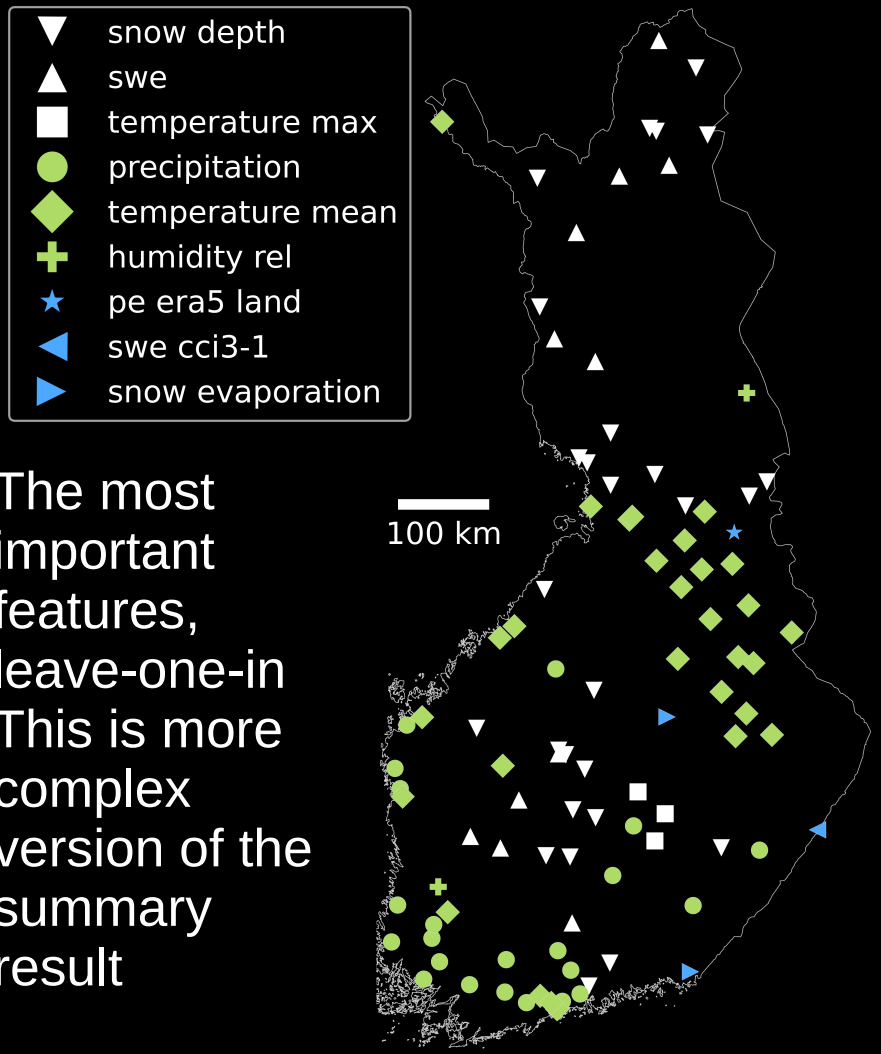
- Snow and it's correlates are overall the most important
- Lake area is the most important static feature
- Precipitation contains important and irreplacable information
- Leave-group-out mostly reflects Leave-one-in and correlation structure

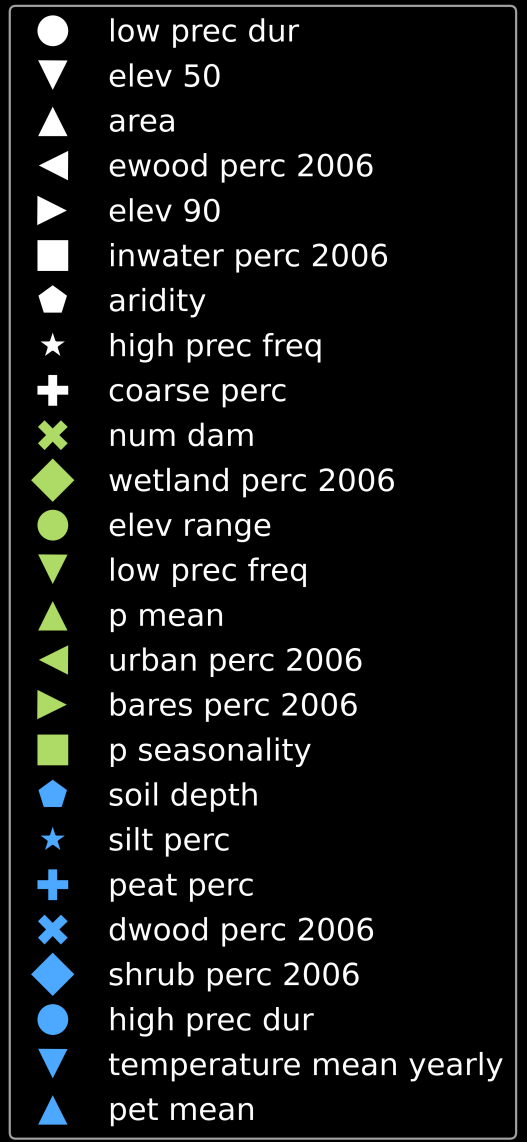


Results

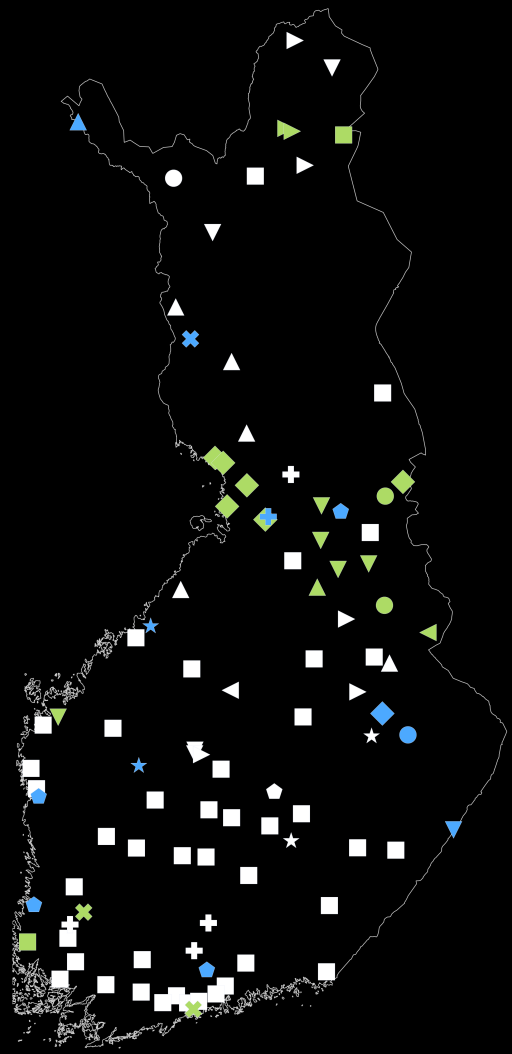
- The most important features, leave-one-in
- This is more complex version of the summary result

Dynamic





Static



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