A data-driven model for Fennoscandian wildfire danger

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MOTIVATION

Wildfires are typically hard to predict, as their exact location and occurrence are driven by a variety of factors. Data-driven (machine-learning) models can identify dominant factors of complex and partly unknown processes, and can ultimately improve predictions and projections of wildfires in both the current and a future climate.

WHAT DID WE DO?

We developed a temporally and spatially explicit data-driven model for Fennoscandia to reach two main objectives:

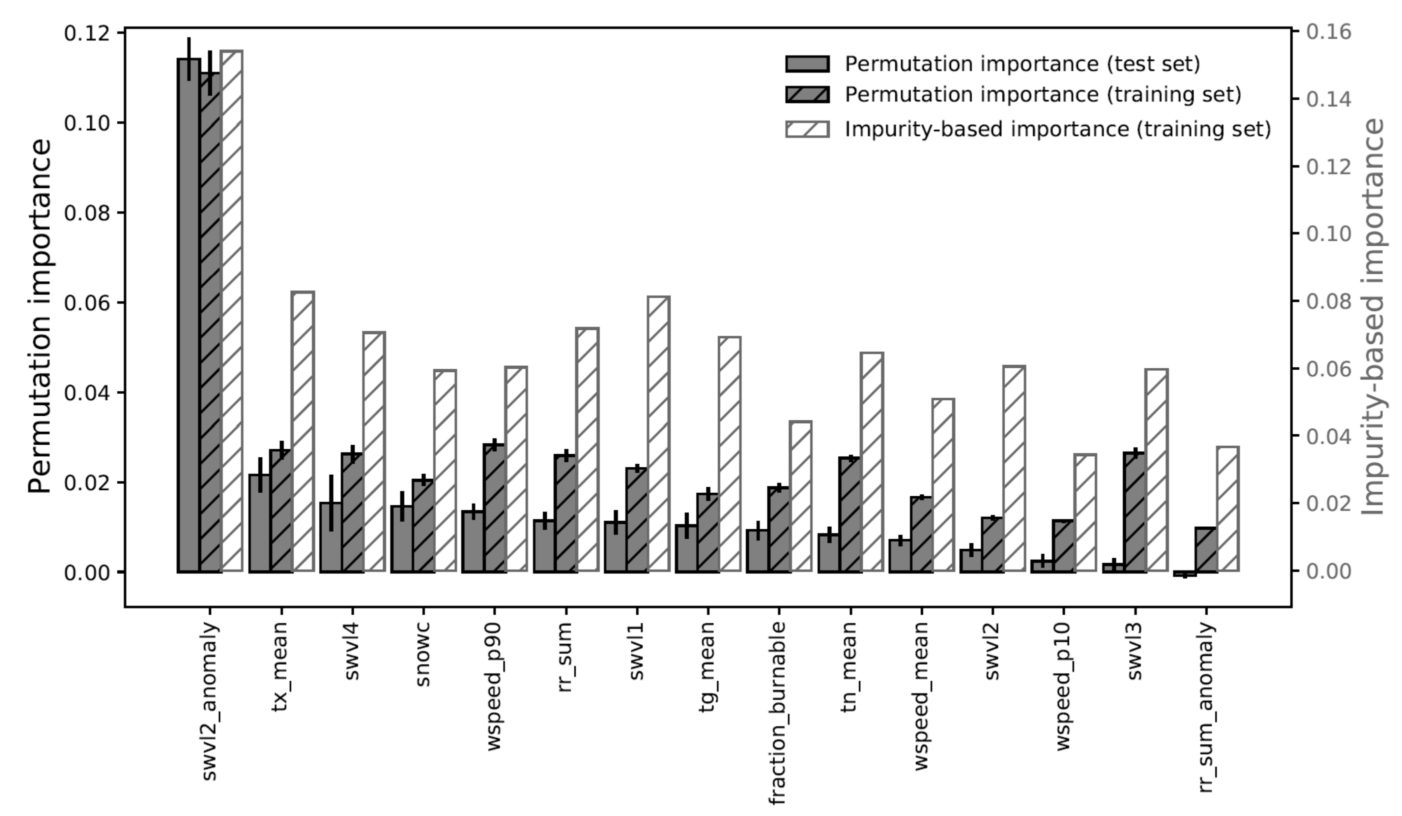
- **identify dominant predictors of wildfires**
- **construct monthly fire danger probability maps**

We evaluated our model by comparing its performance (test set ROC-AUC) with that of the established fire danger index FWI (Canadian forest fire weather index).

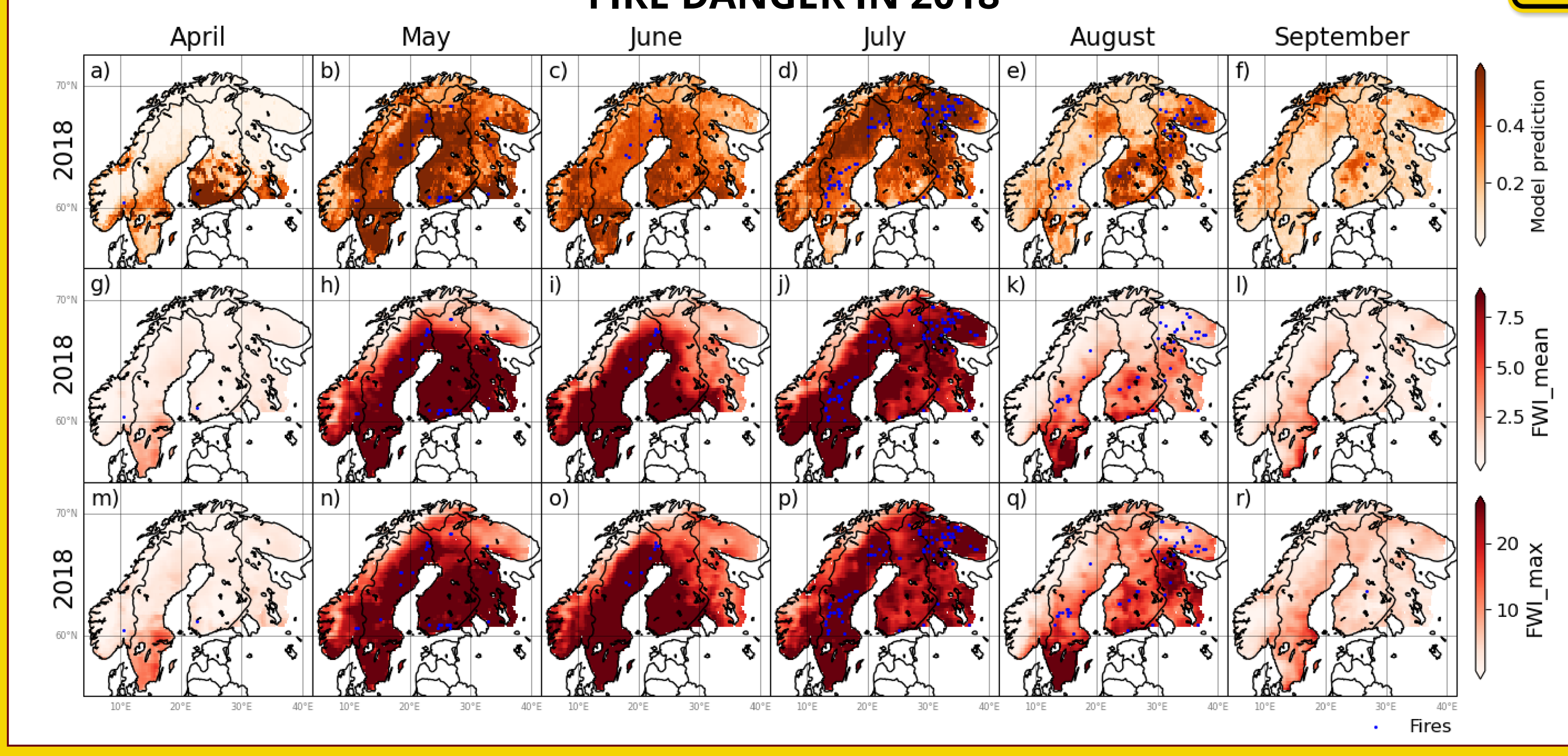
KEY FINDINGS

- The dominant predictor of wildfire is shallow soil moisture anomaly
- The predictors emphasise the importance of other predictors than weather alone, as has traditionally been used for fire danger indices
- The model produced somewhat different monthly fire danger maps as compared to FWI
- The model slightly outperformed FWI with an ROC-AUC of 0.79 vs 0.78 for FWI.

IMPORTANCE OF MODEL PREDICTORS



FIRE DANGER IN 2018



DATA AND METHODS

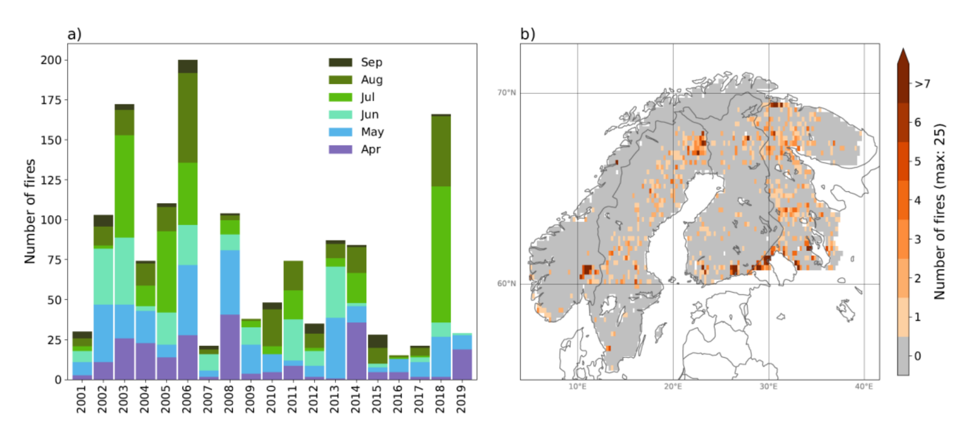
Target data:
Monthly fire occurrence from v5.1.1cds burned area product. The data is extremely imbalanced, with only 1439 of the 444 030 data points (0.3 %) classified as fire.

Potential predictors:
Hydrometeorological indices based on data from E-OBS, ERA5-Land and v5.1.1cds. We chose only predictors that are available in most climate models and transferable to different climate scenarios.

Machine learning algorithm:
The data-driven model was trained by using the Random Forest probability classifications, in which target data were weighted inversely proportional to the class frequencies.

Splitting of the data:
Whole years were assigned to the training set (14 years) and test set (5 years), as well as to each cross-validation fold (2 years), to reduce the dependencies between data points that could lead to too optimistic results.

TARGET DATA: FIRE OCCURRENCES



Model training:
We applied 7-fold cross-validation to tune the complexity parameter maximum tree depth and the number of predictors using backward elimination with updated permutation importances.

Model evaluation:
ROC-AUC (the area under the curve of the receiver operating characteristic). It tackles extreme imbalanced data and enable comparison of FWI and our model without a preset classification threshold. ROC-AUC calculates the area under the curve of true-positive rate vs. false-positive rate for different classification thresholds.

POTENTIAL PREDICTORS

Precipitation	rr_sum	Monthly precipitation sum
	rr_sum_anomaly	Anomalies of rr_sum
Temperature	tg_mean, tn_mean and tx_mean	Monthly mean of daily mean, daily minimum and daily maximum temperature
	tx_max	Monthly maximum of daily maximum temperature
	tg_mean_anomaly, tn_mean_anomaly and tx_mean_anomaly	Anomalies of tg_mean, tn_mean and tx_mean
Meteorological drought	SPI2, SPI3, SPI6 and SPI9	SPI [−3,3] over 2, 3, 6 and 9 months, calculated from rr_sum
	SPEI2, SPEI3, SPEI6 and SPEI9	SPEI [−3,3] over 2, 3, 6 and 9 months, calculated from rr_sum minus monthly potential evapotranspiration, calculated based on tg, tn and tx
Wind speed	wspeed_mean	Monthly mean 10 m wind speed
	wspeed_p10 and wspeed_p90	Monthly 10th and 90th percentile of daily 10 m wind speed
Snow	snowc	Monthly average fraction of grid cell occupied by snow
Soil moisture	swvl1, swvl2, swvl3 and swvl4	Monthly mean volumetric soil water in soil layer 1 (0–7 cm), layer 2 (7–28 cm), layer 3 (28–100 cm) and layer 4 (100–289 cm)
	swvl1_anomaly, swvl2_anomaly, swvl3_anomaly and swvl4_anomaly	Anomalies of swvl1, swvl2, swvl3 and swvl4
Land cover	fraction_burnable	Fraction of the cell corresponding to vegetated land covers that could burn

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