

Identifying dominant drivers of northern European wildfires

Sigrid J. Bakke (s.j.bakke@geo.uio.no), Niko Wanders, Karin van der Wiel, Monica Ionita, and Lena M. Tallaksen



Photo: F. Persson 2014

Wildfires are natural hazards driven by a combination of meteorological, hydrological and biological conditions.

Aim: identify dominant predictors of wildfire to further improve predictions of wildfires in both current and future climate.

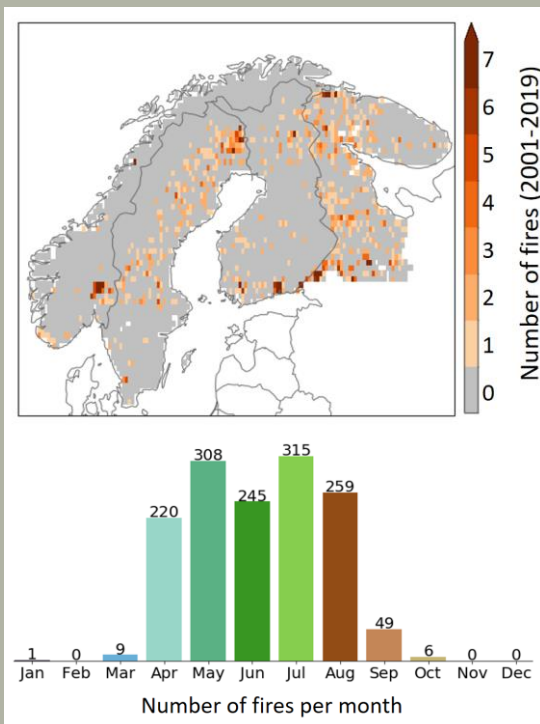
Preliminary results:

- ✓ Most fires occur within a certain range of the predictors' distributions
- ✓ A selection of important predictors identified by Random Forest

Challenges
and
ways forward

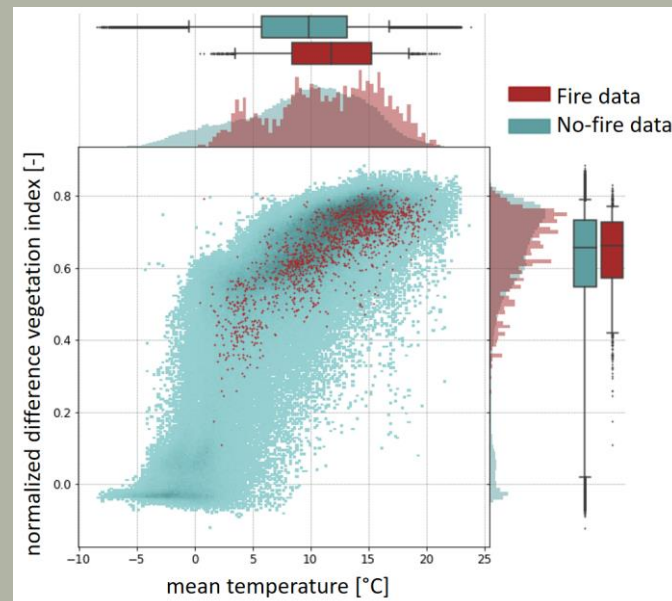
Fire data

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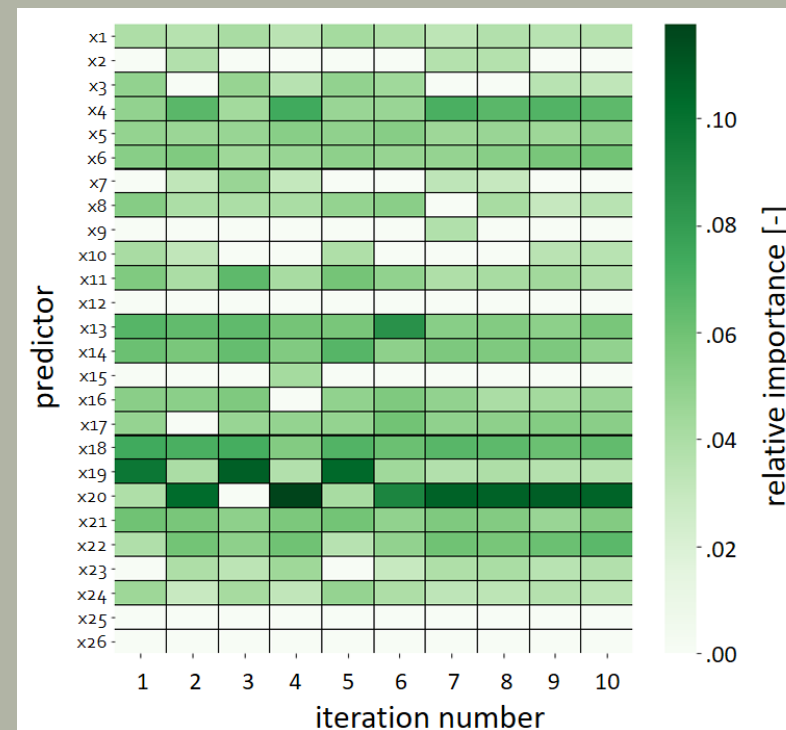
Example of Potential predictors

[Click for more](#)



Relative importance of predictors using 10-fold cross validation and Random Forest

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Data sources: CDR Fire Burned Area, MOD13 NDVI, E-OBS v21.0e and ERA5

[Data credit](#)

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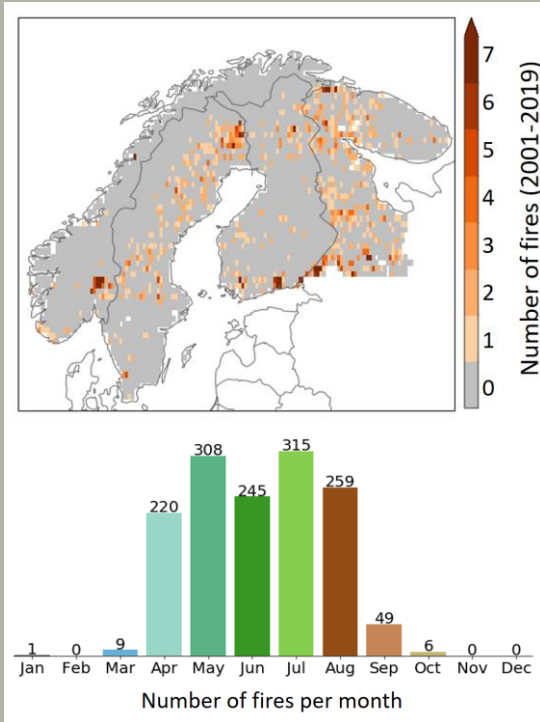
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Fire data

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To construct a supervised learner to predict fire, we use the CDR Fire Burned Area data to **classify target data points as either *fire* or *no-fire*** for a monthly time step.

Only 0.3% of data points are classified as *fire*

Spatial domain: Fennoscandia

Temporal domain: 2001-2019

April–September was selected due to the low number of fires in October–March

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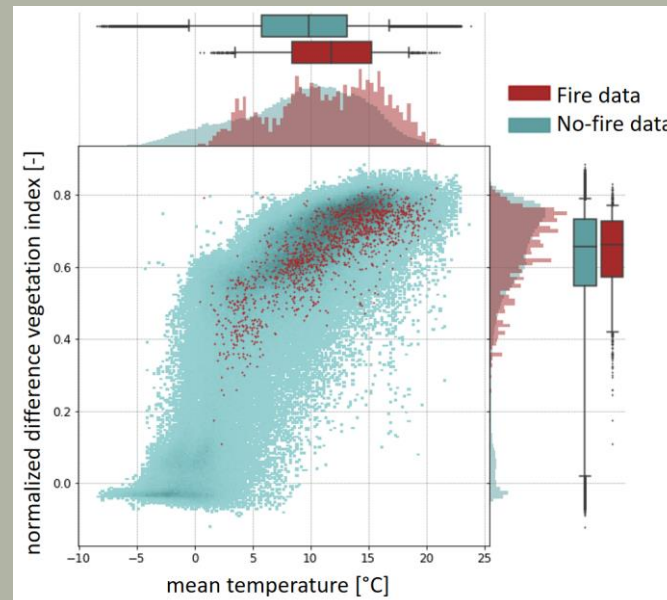
This figure shows an example of two potential predictors' joint and marginal distributions for the fire and no-fire data points separately.

This (and similar) figures illustrate the following:

- ✓ most fires occur within a certain range of a predictor's distribution
- ✓ a predictor is not necessarily in an extreme state for a fire to occur
- ✓ none of the predictors make up a good prediction alone
→ a combination of predictors are needed

Example of
Potential predictors

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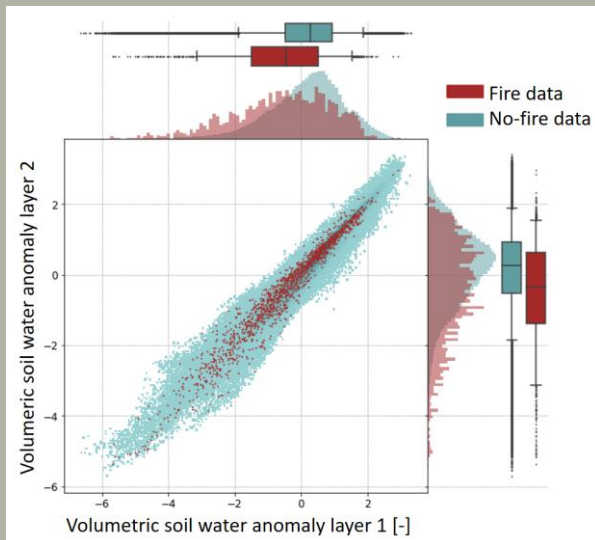
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This heat map shows preliminary results of the relative importance of the different potential predictors using Random Forest. These constructed Random Forest models predict ~70% of unseen true fires and ~80% of unseen true no-fires correctly.

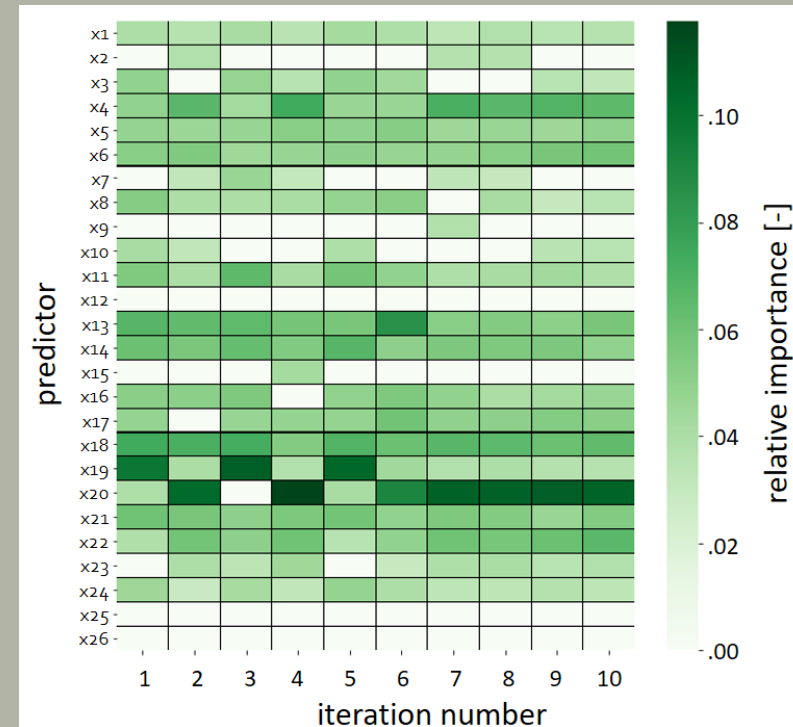
The Figure's x- and y-axes list 10-fold stratified cross-validation (CV) iterations and the 26 potential predictors, respectively. The darker the colour, the higher relative importance a predictor has for the given CV iteration, and vice versa.



X19 or X20 has the highest relative importance for all CV iterations. These predictors are the highly correlated volumetric soil water anomaly in layer 1 (0-7 cm) and 2 (7 -28 cm).

Relative importance of predictors
using 10-fold cross validation and Random Forest

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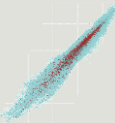
Challenges and ways forward



There are **many options of supervised learning**. We want to test whether the Generalized Additive Model (GAM) with a logistic lik function is a good alternative or supplement to the Random Forest.



We need to **deal with a strong imbalance** in the fire data, and will test out alternatives to the current undersampling method applied.



The dataset include many statistically dependent predictors, and we need a way to **deal with multicollinearity** in the selection and evaluation of dominant predictors.



The derived relationships between wildfires and its compound drivers will further be used to **assess the potential changes** in such a combination of factors under different climate scenarios using large-ensemble global climate simulations.

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Data credit

We greatly acknowledge the providers of the data used in this analysis:

- CDR gridded fire burned area from 2001 to present derived from satellite observations. Developed as part of the Fire ECV Climate Change Initiative Project (Fire CCI). Accessed 19.11.2020. DOI: 10.24381/cds.f333cf85
- Didan, K. (2015). MOD13A3 MODIS/Terra vegetation Indices Monthly L3 Global 0.05 Deg V006. NASA EOSDIS Land Processes DAAC. Accessed 15.02.2021. DOI: 10.5067/MODIS/MOD13A3.006
- E-OBS v21.0e: Cornes, R., G. van der Schrier, E.J.M. van den Besselaar, and P.D. Jones. 2018: An Ensemble Version of the E-OBS Temperature and Precipitation Datasets, J. Geophys. Res. Atmos., 123. DOI:10.1029/2017JD028200
- ERA5: Muñoz Sabater, J., (2019): ERA5-Land monthly averaged data from 1981 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). (Accessed on 15.02.2021), DOI: 10.24381/cds.68d2bb30
- The picture in the presentation header is modified from F. Persson/ TT / NTB scanpix, 2014. Sweden. Available at <https://www.nationen.no/nyhet/sverige-en-av-ti-skogbranner-kan-skyldes-skogsarbeid/> (Accessed on 22.04.2021).