~~wavelets and~~ Identifying drivers for heat waves using machine learning approaches

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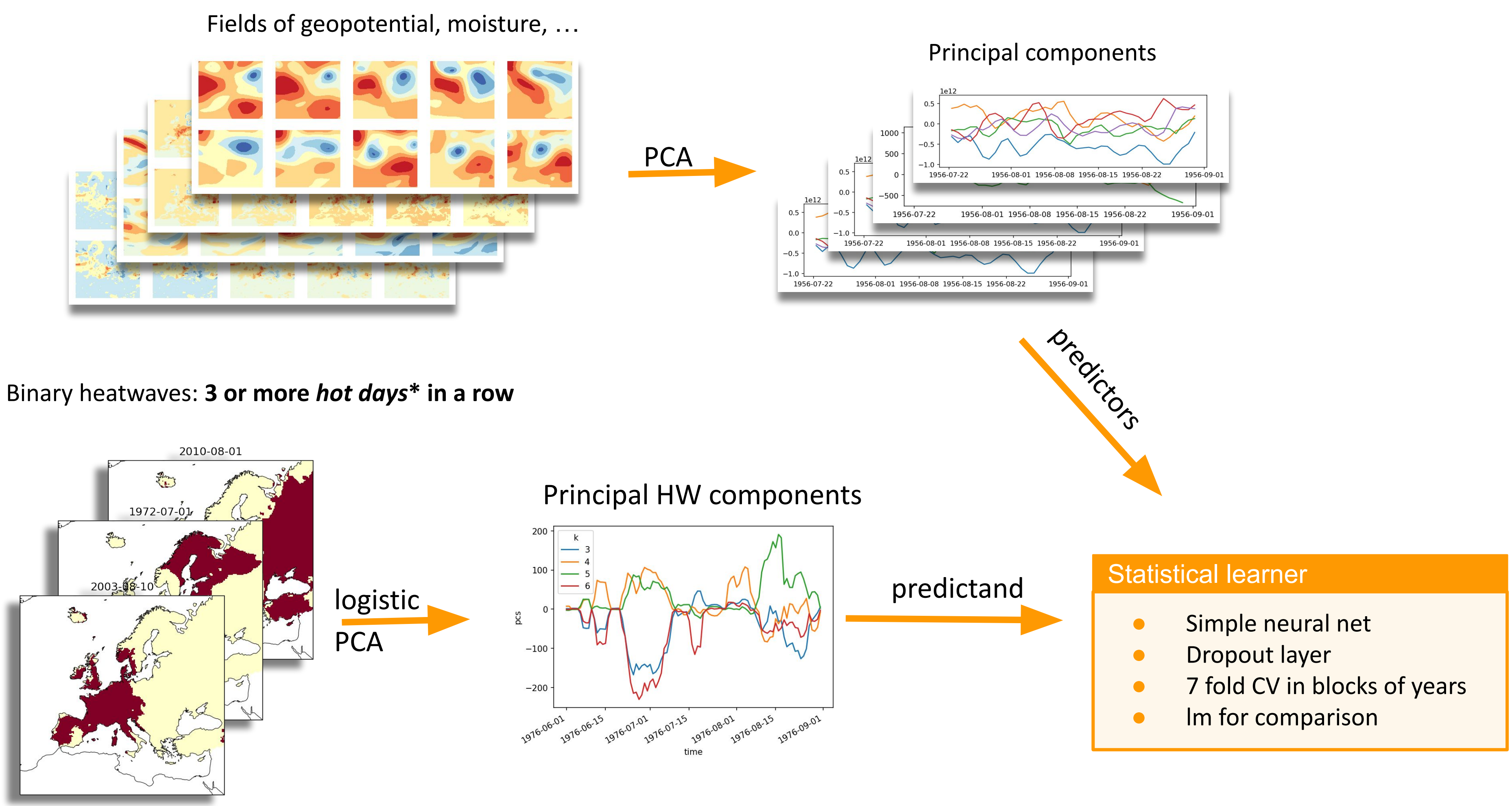
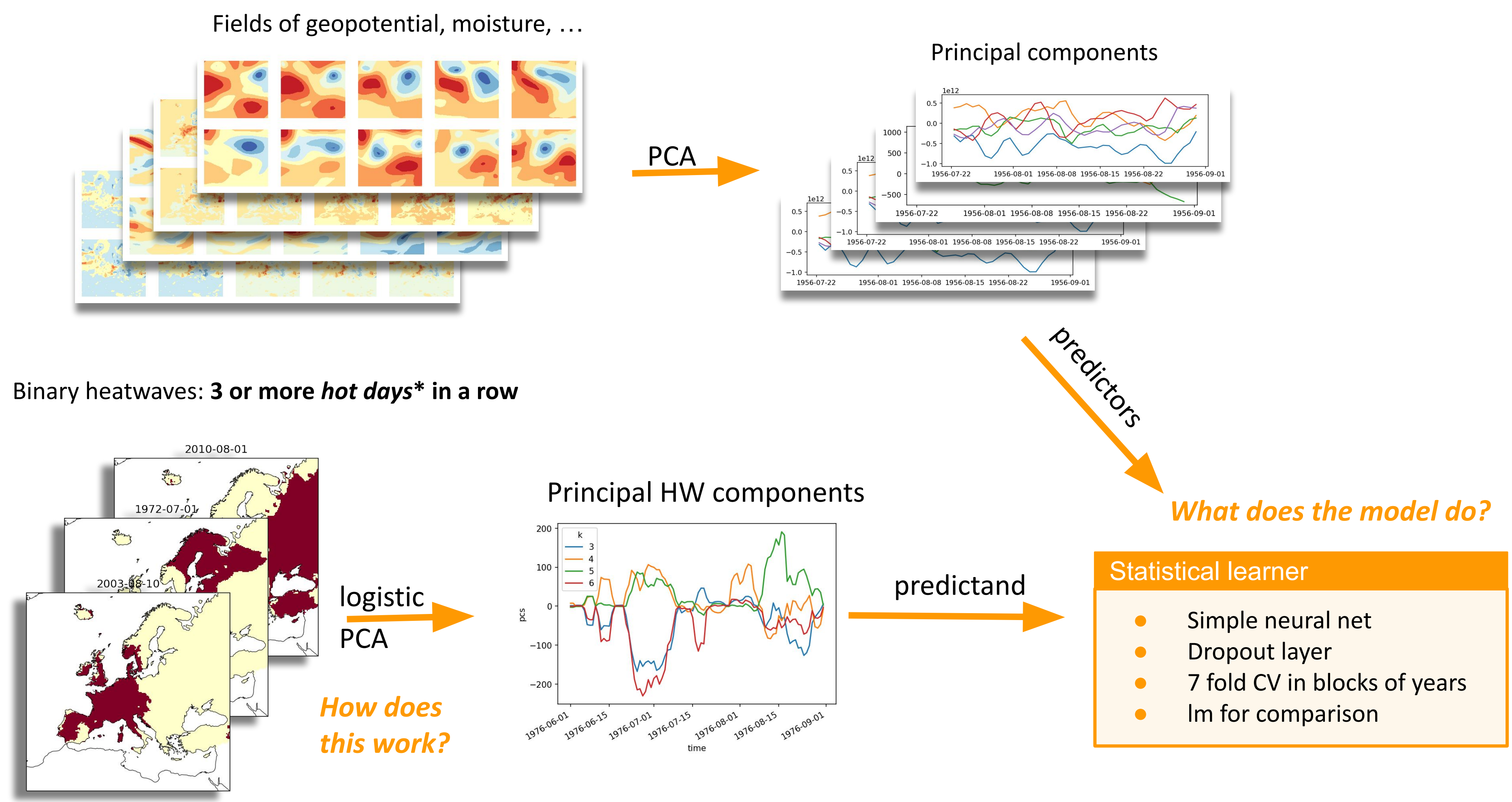
FONA Research for sustainability

CLIMXTREME Climate Change and Extreme Events



***hot day**: daily T_{max} > 90% quantile for the current calendar day

Data: ERA5 JJA, 1950-2020, EURO-CORDEX domain



****hot day**: daily T_{max} > 90% quantile for the current calendar day*

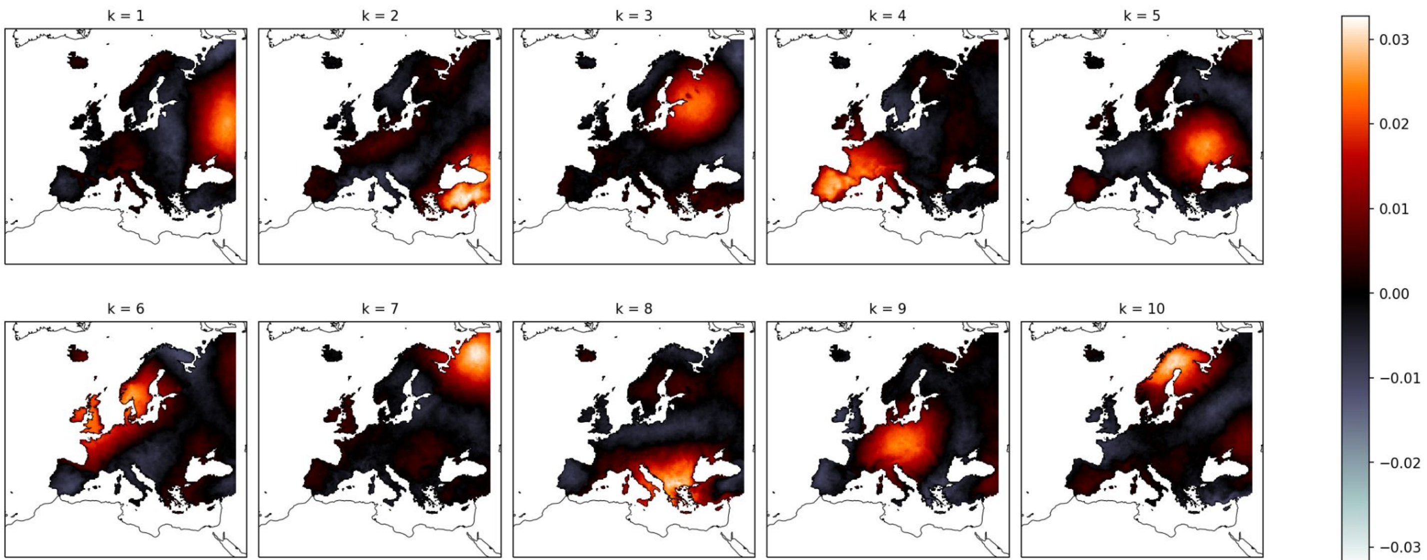
Data: ERA5 JJA, 1950-2020, EURO-CORDEX domain

PCA for binary fields (!)

Regular PCA ("EOFs"): given data $\mathbf{X}$, find vectors $\mathbf{U}$ such that $|\mathbf{X} - \mathbf{U}\mathbf{U}^T\mathbf{X}|^2$ is minimal
$\rightarrow$ minimize *Gauss deviance*, solution: eigenvectors of $\mathbf{X}^T\mathbf{X}$

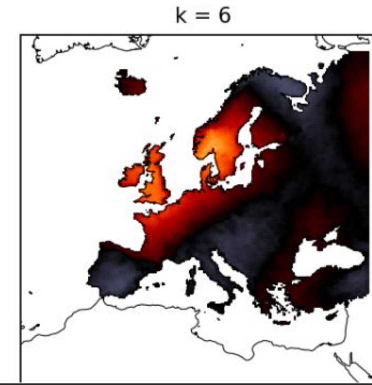
Landgraf and Lee (2020): assume exponential family, compute natural parameters $\boldsymbol{\theta}$
$\rightarrow$ **iteratively** search a projection $\boldsymbol{\theta}\mathbf{U}\mathbf{U}^T$ that minimizes the relevant deviance

Binary data: Bernoulli distribution, $\boldsymbol{\theta} = \log(\mathbf{p} / (1 - \mathbf{p}))$



10 rotated "logistic EOFs" for European heatwaves

Modelling heatwaves in the reduced space



Predictand: 10 rotated logistic PCs of heatwaves
Predictors: 20 PCs of soil moisture and geopotential at 1000, 800, 500, 300 and 100 hPa

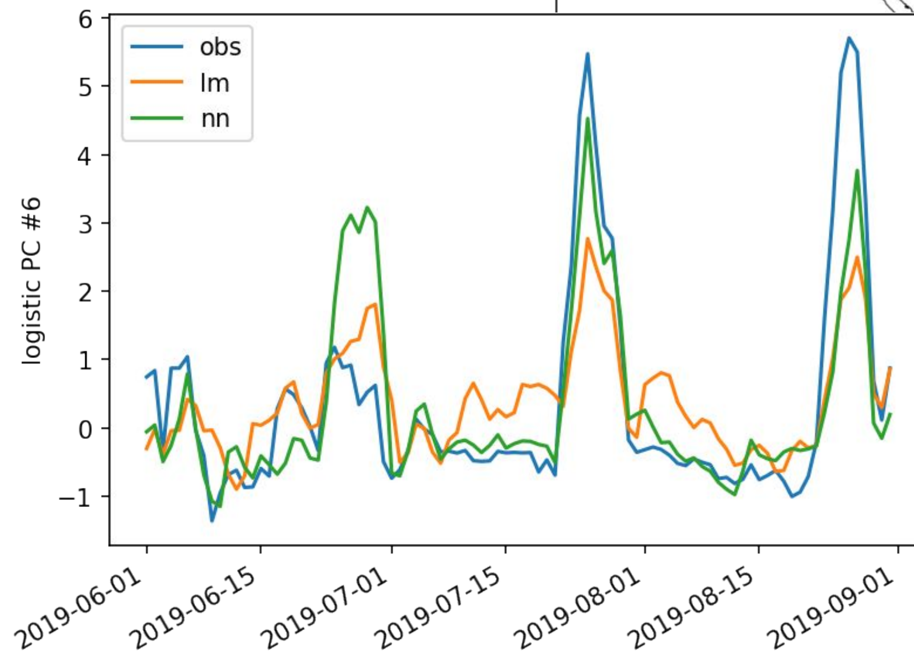
Multivariate linear regression

- 10 + 20 × 10 = 210 parameters
- Least squares fit
- **R^2=0.46**

vs.

Simple feed forward neural net

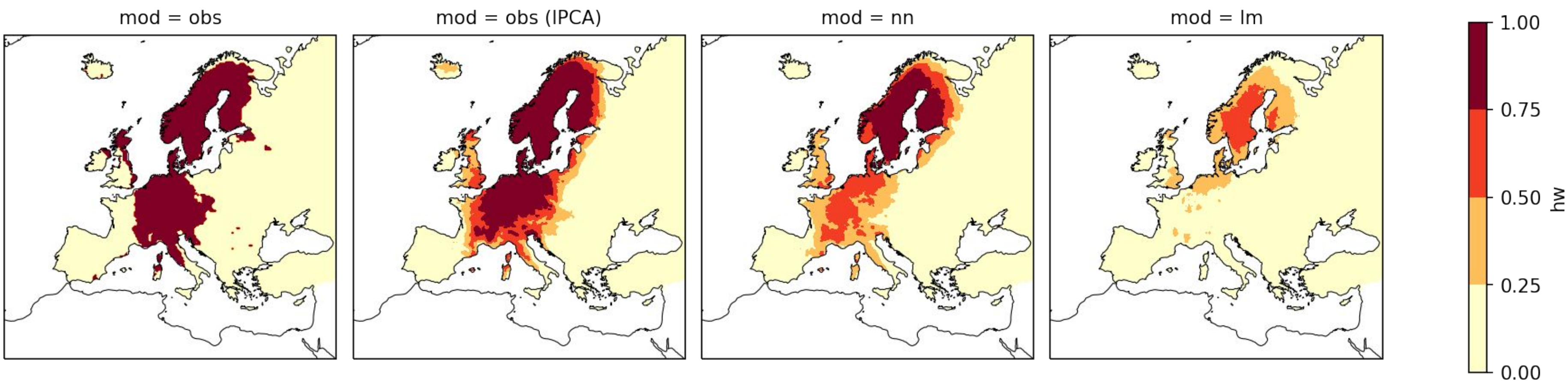
- One hidden layer with 40 nodes
  → (20+1) × 40 + (40+1) × 10
  = 1250 parameters
- ReLu activation, 20% dropout
- Optimized with *Adam*
- **R^2=0.75**



Observed and modelled heatwave PC # 6 in summer 2019

Modelling heatwaves in the reduced space

Predictand: 10 rotated logistic PCs of heatwaves
Predictors: 20 PCs of soil moisture and geopotential at 1000, 800, 500, 300 and 100 hPa

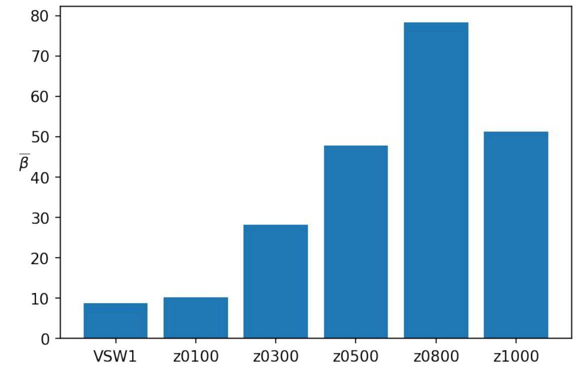


Observed, PCA reduced, and simulated heatwaves on 2019-07-26

Variable importance

Models are not bad, but how do they identify heatwaves?
Linear model: just look at coefficients (?)

What to do for the neural net? The coefficients tell us nothing !



Mean absolute regression coefficients
→ is Φ_{800} the most important predictor?

Idea (Shapley 1952, Lipovetsky and Conklin 2001): Split up the overall R^2 as follows:

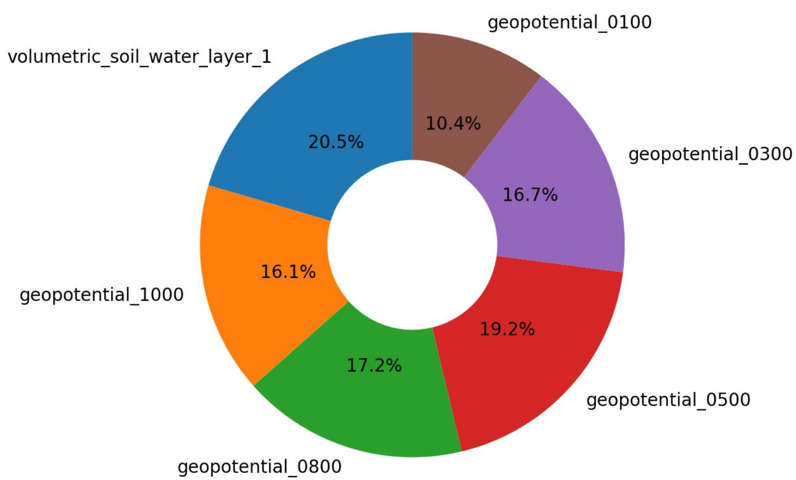
$$R^2 = f(X_1, \ldots, X_n) = \varphi_1 + \varphi_2 + \ldots + \varphi_n$$

$$\varphi_i = \underbrace{n^{-1}\sum_{j=0}^{n-1}}_{\text{mean over set sizes}} \underbrace{\binom{n-1}{j}^{-1}\sum_{\text{all } S \text{ with } |S|=j,\ X_i\notin S}}_{\text{mean over sets of size } j \text{ missing } X_i} \underbrace{f(S\cup X_i)-f(S)}_{\text{change if } i \text{ were added}}$$

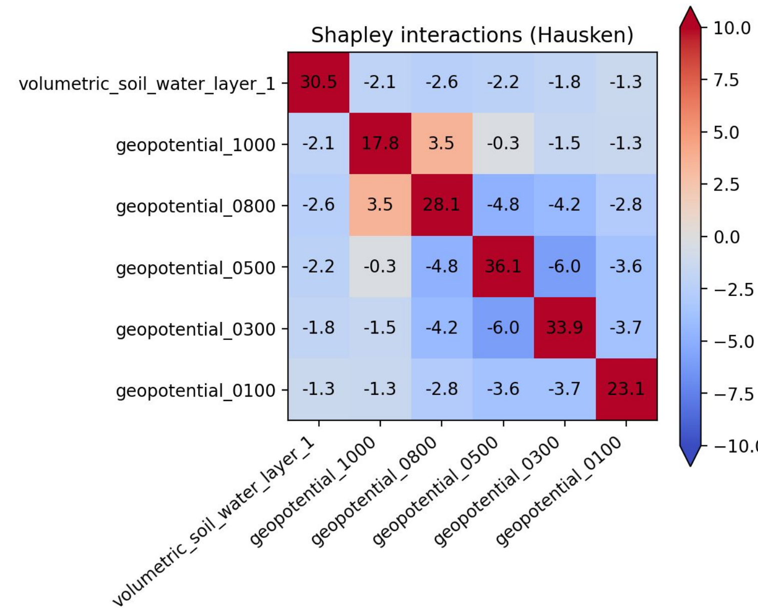
→ train all possible 2^6 models, compare their R^2 to get the Shapley values!

Variable importance: Shapley values

$$\varphi_i = \underbrace{n^{-1}\sum_{j=0}^{n-1}}_{\text{mean over set sizes}} \underbrace{\binom{n-1}{j}^{-1} \sum_{\text{all } S \text{ with } |S|=j,\ X_i \notin S}}_{\text{mean over sets of size } j \text{ missing } X_i} \underbrace{f(S \cup X_i) - f(S)}_{\text{change if } i \text{ were added}}$$



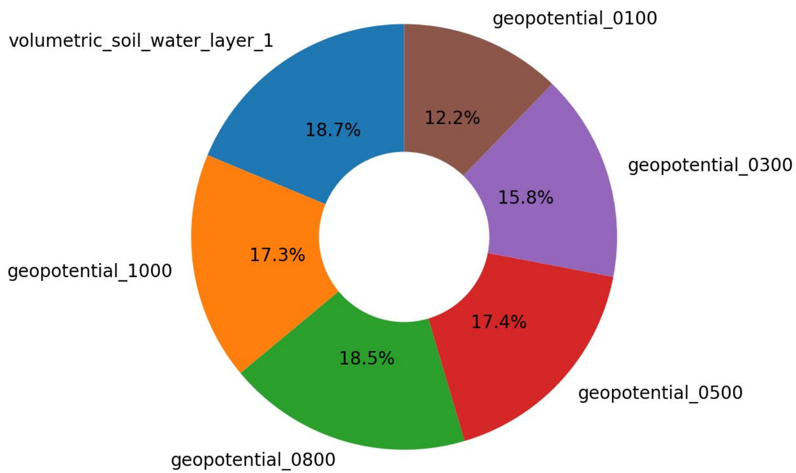
Percentage contributions to the overall model performance R^2 for the neural net



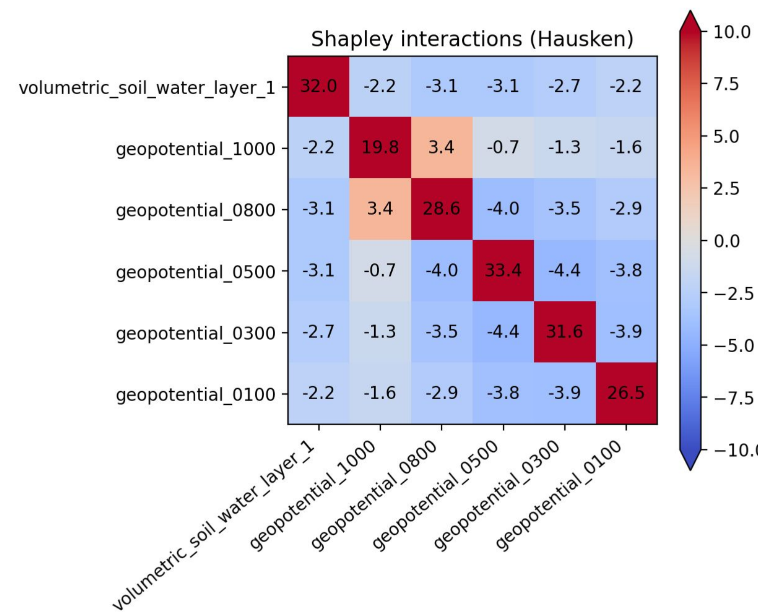
Recursive Shapley "interactions" (Hausken 2001) for the neural net

Variable importance: Shapley values

$$\varphi_i = \underbrace{n^{-1}\sum_{j=0}^{n-1}}_{\text{mean over set sizes}} \underbrace{\binom{n-1}{j}^{-1} \sum_{\text{all } S \text{ with } |S|=j,\ X_i \notin S}}_{\text{mean over sets of size } j \text{ missing } X_i} \underbrace{f(S \cup X_i) - f(S)}_{\text{change if } i \text{ were added}}$$



Percentage contributions to the overall model performance R^2 for the ***linear model***



Recursive Shapley "interactions" (Hausken 2001) for the ***linear model***

Summary

- There is a **PCA for binary variables** → reduced version of any binary event you want !
- A simple neural net can explain 75% of the reduced heatwave variability
- **Shapley values** and interactions reveal how much *can* be learned from each predictor, lm and neural net are not so different after all
- It seems that the model has learned $\Phi_{800} - \Phi_{1000} \sim T_{900}$ (hydrostatic relation)

References

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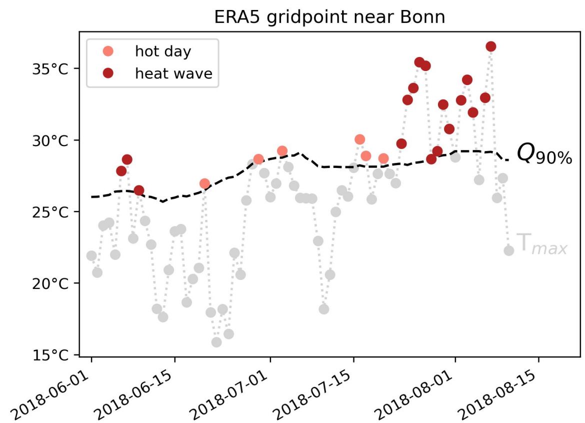
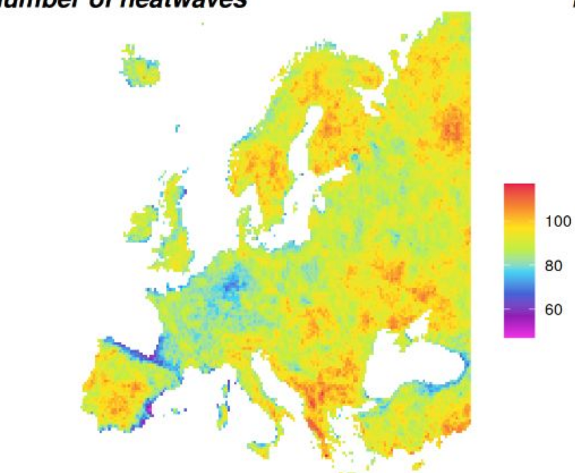
Heatwave definition and basic statistics

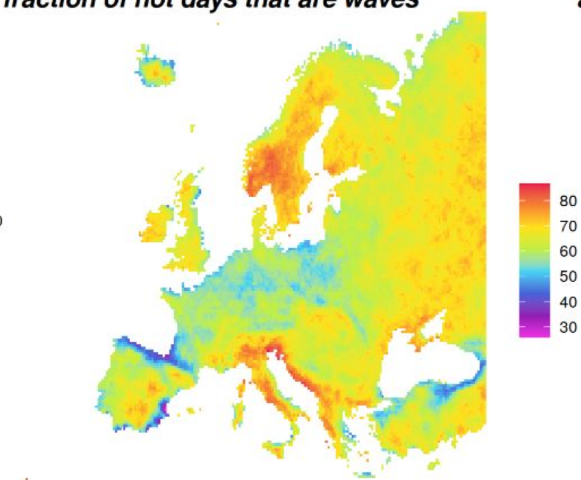


year of most intense HW

number of heatwaves



fraction of hot days that are waves



average duration