Identifying the atmospheric drivers of drought and heat using a smoothed deep learning approach

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Motivation

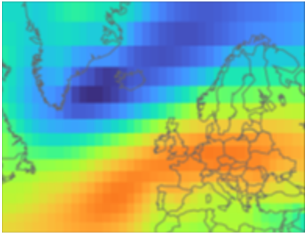

Figure 1: Circulation pattern with high pressure ridge over Europe

- Several extreme events of heat and drought in recent European summers (e.g., 2003, 2010, 2018)
- Atmospheric drivers of drought and heat: six specific circulation patterns with anticyclonic features

⇒ Research question: how does climate change alter the occurrence of these atmospheric drivers?

⇒ Classification of atmospheric drivers in large ensembles of climate models

Data

Training data:

- classifications for 1900-2010; daily (total: 40500 observations)
- two channels: sea level pressure and geopotential height at 500 hPa

Challenges:

- noisy labels (subjectiveness)
- undefined transition days
- fixed dwell time (>= 3 days)
- imbalanced class distribution

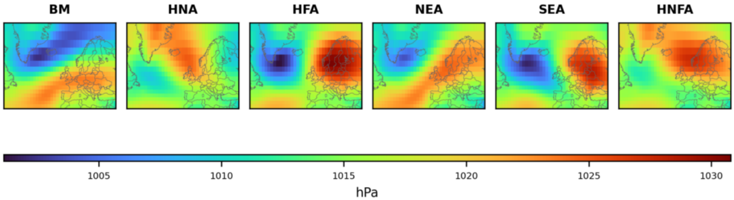

Figure 2: Six anticyclonic circulation patterns at sea level pressure

Smoothed deep learning approach

Adaptation for data-specific characteristics:

- Error weighting
- Label smoothing for first and last day of a circulation pattern
- Transition-smoothing step:

  The final predicted class $\tilde{y}_t$ at time point t is given by

$$\tilde{y}_t = \begin{cases} \hat{y}_{t-1} & \text{if } \hat{y}_{t-1} = \hat{y}_{t+1} \text{ (Neighborhood Consistency)}, \\ \hat{y}_{t-1} & \text{if } \hat{y}_t = \hat{y}_{t+1} \wedge \hat{y}_{t-1} = \hat{y}_{t+2} \text{ (2-days Consistency)}, \\ m(\hat{\pi}_{t-1}, \hat{\pi}_{t+1}) & \text{if } \hat{y}_t \neq \hat{y}_{t+1} \wedge \hat{y}_{t-1} \neq \hat{y}_{t+1} \text{ (Transition Membership)}, \\ m(\hat{\pi}_{t-1}, \hat{\pi}_{t+2}) & \text{else}, \end{cases}$$

  where $\hat{\pi}_t$ denotes the predicted probability vector at time t, $\hat{y}_t = \hat{\pi}_t$ the predicted class prior to the transition-smoothing step, and

$$m(\pi_s, \pi_t) = \{\pi_{u^*}\} \text{ with } u^* =_{u \in \{s,t\}} \{\max(\pi_u)\}.$$

Ablation Study

Final network:

- Accuracy: 0.60
- Macro F1-score: 0.38
- best performance for classes HNA and BM

Smoothed Approach:

- Transition-smoothing is key to performance gains (+ 4% for accuracy, + 2% for accuracy)
- low impact of label-smoothing

MODEL	BM	HNA	HFA	NEA	SEA	HNFA	Residual	**Accuracy**	**F1-score**
Proposed network	**0.41**	**0.36**	**0.28**	0.39	**0.26**	**0.26**	**0.74**	**0.60**	0.38
No LS	**0.41**	**0.36**	**0.28**	**0.40**	**0.26**	**0.26**	**0.74**	**0.60**	**0.39**
No TS	0.39	0.33	0.25	0.36	0.23	0.23	0.70	0.56	0.36
No LS and TS	0.39	0.33	0.25	0.37	0.23	0.23	0.70	0.56	0.36

Conclusion and Outlook

- Results:
  - high potential of deep-learning based approach for circulation type classification
  - adaptation for data-specific characteristics necessary
- Contribution:
  - possibility of identification of drivers of heat and drought extremes in large ensembles of climate models
- Outlook:
  - Conv-LSTM to take temporal dependence structure into account
  - Hidden Markov model