How-to guide

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Subseasonal prediction of extreme European temperatures in S2S hindcasts

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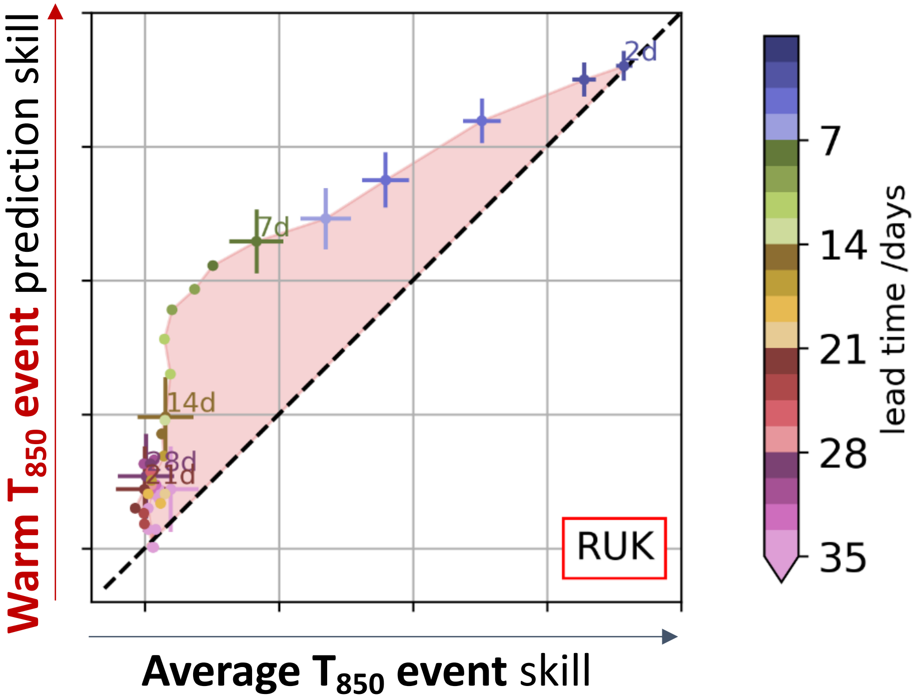
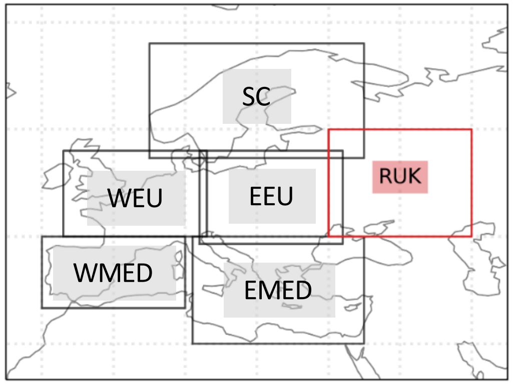
Subseasonal hindcasts exhibit more skill at predicting summer heat waves than average temperatures





See for other regions

→ Conclusions?

1. In the RUK region, prediction skill is significantly higher for warm than for average temperature events in subseasonal hindcasts.
2. We hypothesize the persistence of anticyclonic flow and resulting temperature persistence to be the main reason for the enhanced prediction skill at subseasonal lead times in summer.

Subseasonal hindcast database

We use hindcasts from the ECMWF Integrated Forecasting System (IFS) available through the S2S prediction project database (*Vitart et al., 2016*)

Resolution: 16 km up to day 15; 31 km after day 15

Components: Interactive ocean and sea ice

Initializations: 11-member ensemble hindcasts initialized every Monday and Thursday from ERA-Interim (atmosphere) and ORAS5 (ocean)

Period: **Hindcasts from 1998 – 2017** resulting in $20 \times 26 = 520$ hindcasts for the summer season (JJA)

Definition of events

Warm extreme: days on which the (centered) 5-day running mean T_{850} anomaly exceeds the 95th monthly percentile.

Average event: days on which the temperatures are inside the inner-quartile range of the temperature distribution

- *In reanalysis*: anomalies w.r.t. the seasonal cycle
- *In hindcasts*: anomalies w.r.t. the **lead time dependent seasonal cycle**

The seasonal cycle is estimated by fitting 4 harmonics to the daily temperature climatology.

By using percentiles of the distribution of anomalies with respect to a daily climatology, we **eliminate contributions** to the forecast skill resulting from a successful **reproduction of the seasonal cycle.**

Skill measure: The Extremal Dependence Index (EDI)

We use a deterministic measure for skill treating the forecasts as binary (they either show an event or they do not) and validate against the ERA-Interim reanalysis (*Dee et al., 2011*).

Here, this is the EDI defined as in *Ferro & Stephenson (2011*):

$$EDI = \frac{\log F - \log H}{\log F + \log H}$$

where F and H are the false alarm rate (number of false alarms vs number of observed non-events) and the hit rate (number of hits vs number of observed events), respectively.

The EDI is a base-rate independent measure, allowing the comparison between event types with different climatological frequencies of occurrence.

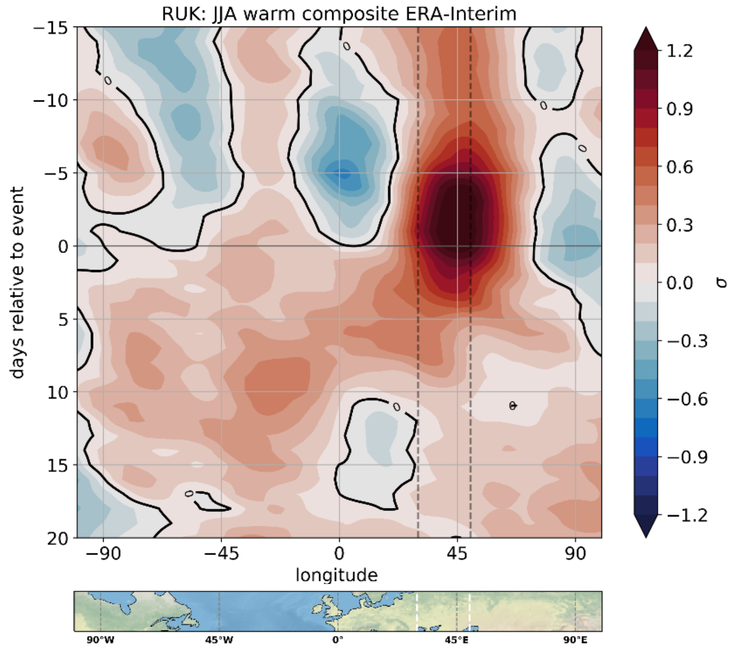
Perfect forecast: EDI = 1

No discrimination: EDI = 0

Persistent circulation in the RUK region during heat extremes successfully predicted

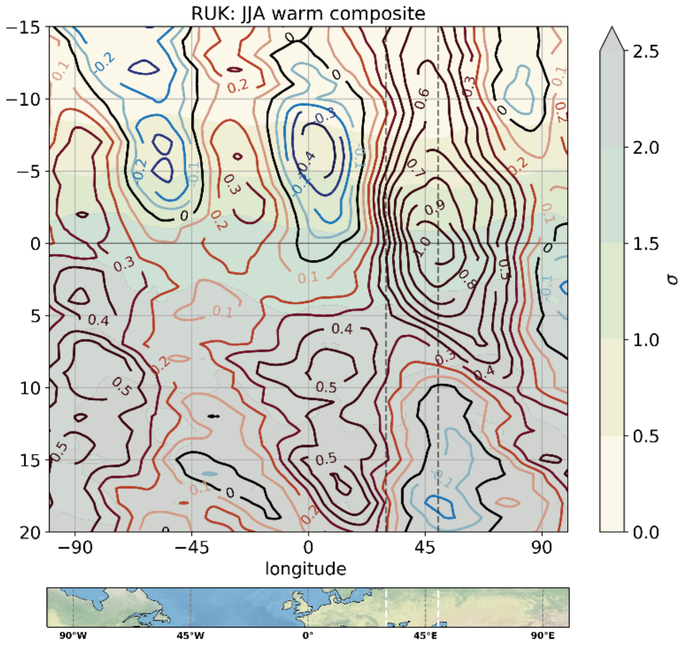
Normalized meridional mean Z_{500} anomalies

ERA-Interim



Composite time evolution of Z_{500} around the heat events in the RUK region

hindcasts

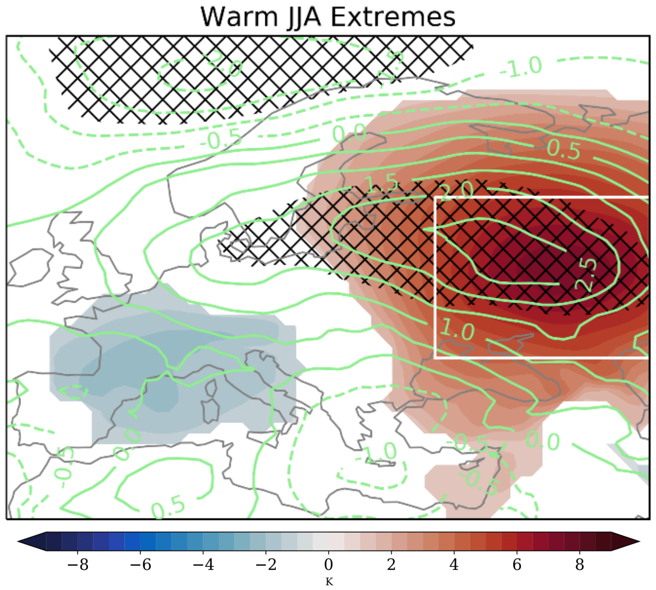


Ensemble mean (contours) and standard deviation (shading) of a composite of all forecasts initialized 15 days before the events

Z_{500} composites for heat events

- Heat events in the RUK region associated with **persistent anticyclonic conditions** in the region
- Hindcasts initialized 15 days before the events predict this persistence successfully
- This also manifests in the temperature
- However, the hindcasts do not show higher confidence (spread not reduced where blocking occurs)
- Note that **23% of heat events** in the RUK region are **in 2010**

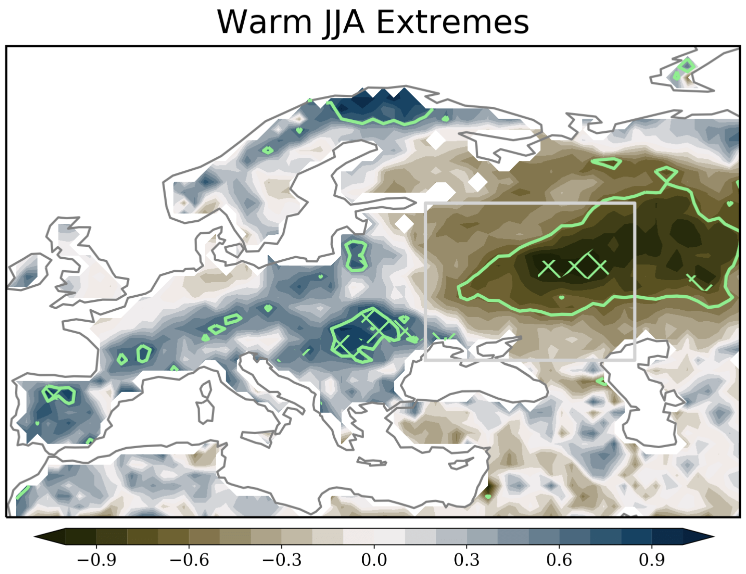
Warm anomalies visible weeks before the events



Shading: ERA-Interim T_{850} anomaly composite for days of heat events where they are significantly different from 0 at the 95% level;
Green contours: T_{850} composite 15 days before the events (contour every 0.5 K), black hatching where significant

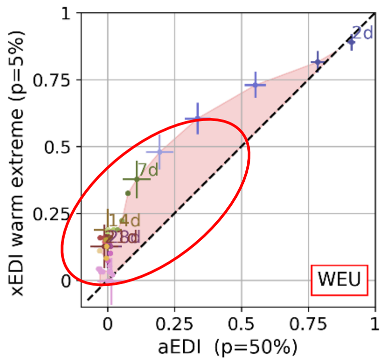
The persistence of the blocked flow situation results in significant temperature anomalies of the same sign already two weeks prior to the events.

The presence of dry anomalies before the occurrence of the heat events could further enhance surface temperatures.



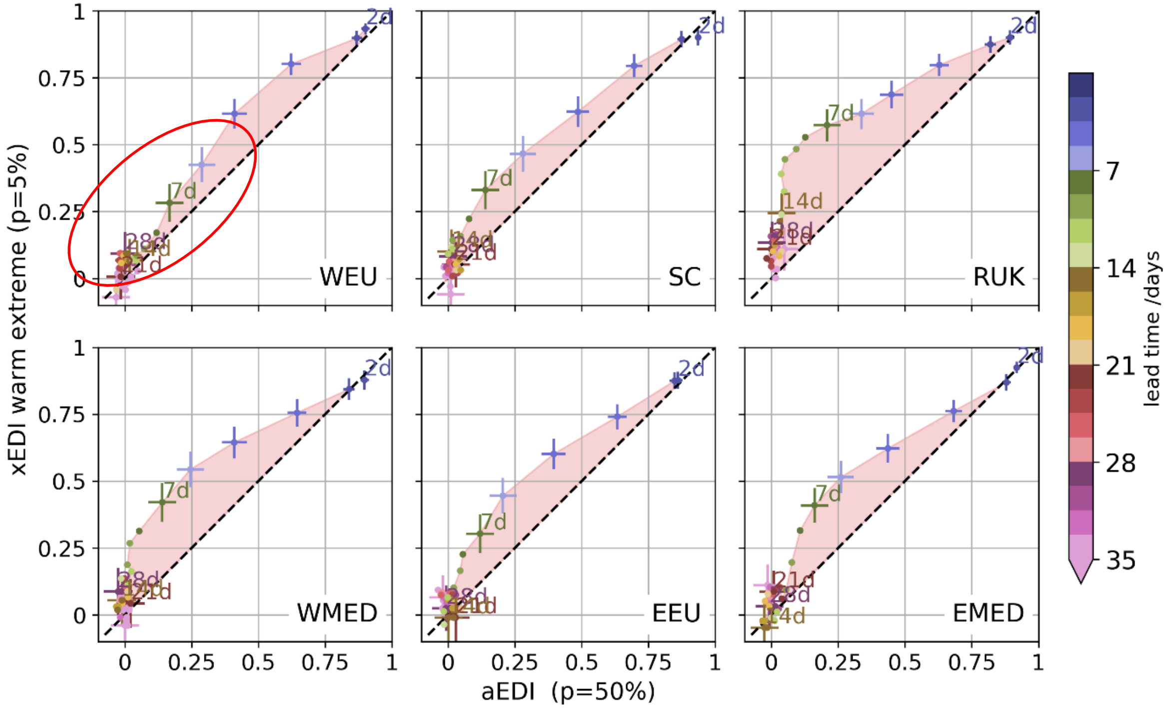
Shading: standardized ERA5/Land soil moisture of the top 100cm (SM100) composite for days of heat events, significantly different at the 95% level inside of green contours;
Green hatching: where SM100 was significant and of the same sign 15 days before the events.

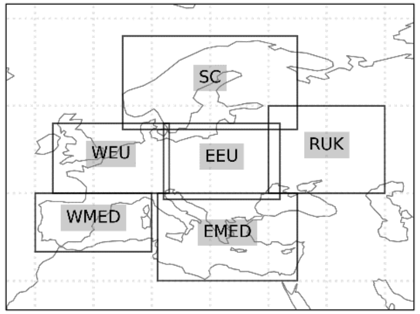
Extreme Temperature Skill for all European Regions



for T_{2m}

Extreme warm T_{850} vs. average T_{850} skill





- There is enhanced summer heat wave prediction skill over average temperature skill in all European regions.
- In addition to the RUK region, the difference at subseasonal lead times is only pronounced in the WMED and EMED regions.
- In the WEU region, enhanced subseasonal skill is only visible in 2m-temperature.

Conclusions

- Subseasonal prediction skill for extreme warm summer temperatures is higher than for average events in some European regions in the ECMWF system
  - for a comparison with other forecasting systems, see also our paper in GRL (*Wulff and Domeisen, 2019*)
- Persistent flow conditions present in the initial conditions are the major reason for enhanced prediction skill of warm extremes
- In the RUK region, dry soil moisture anomalies prior to the event could further enhance the temperatures. Their contribution to the skill has yet to be quantified (also for other regions)
- The higher skill at predicting warm extremes has implications for subseasonal forecasts in a future climate with presumably more warm extremes

References

- Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., et al. (2011). The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, *137*, 553–597. https://doi.org/10.1002/qj.828
- Ferro, C. A. T., & Stephenson, D. B. (2011). Extremal dependence indices: Improved verification measures for deterministic forecasts of rare binary events. *Weather and Forecasting*, *26*(5), 699–713. https://doi.org/10.1175/waf-d-10-05030.1
- Vitart, F., Ardilouze, C., Bonet, A., Brookshaw, A., Chen, M., Codorean, C., et al. (2017). The subseasonal to seasonal (S2S) prediction project database. *Bulletin of the American Meteorological Society*, *98*, 163–173. https://doi.org/10.1175/BAMS-D-16-0017.1
- Wulff, C. O., & Domeisen, D. I. V. (2019). Higher subseasonal predictability of extreme hot European summer temperatures as compared to average summers. *Geophysical Research Letters*, *46*, https://doi.org/10.1029/2019GL084314