

# Subseasonal Prediction of European Extreme Temperature Events in S2S hindcasts

Ole Wulff

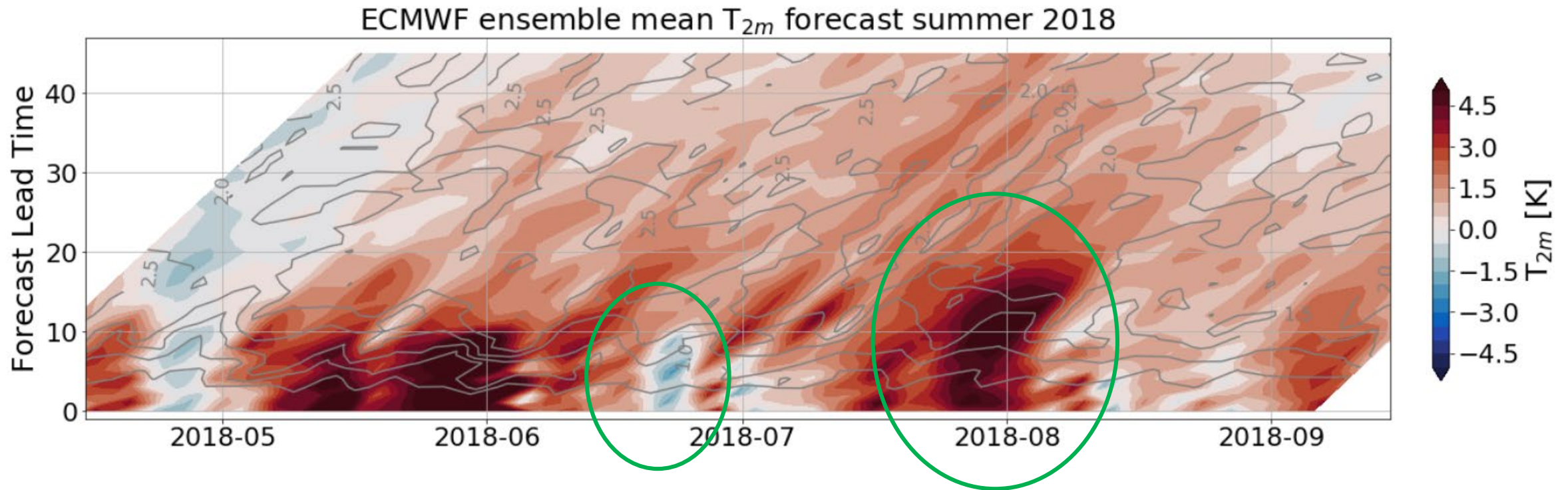
&

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# Summer of 2018



ECMWF Ensemble mean 2m temperature anomaly forecast (shading) and ensemble spread (contours) averaged over Scandinavia

# Objectives

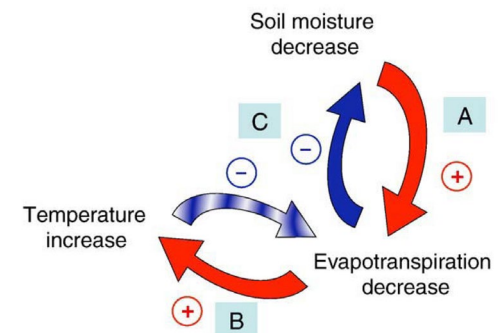
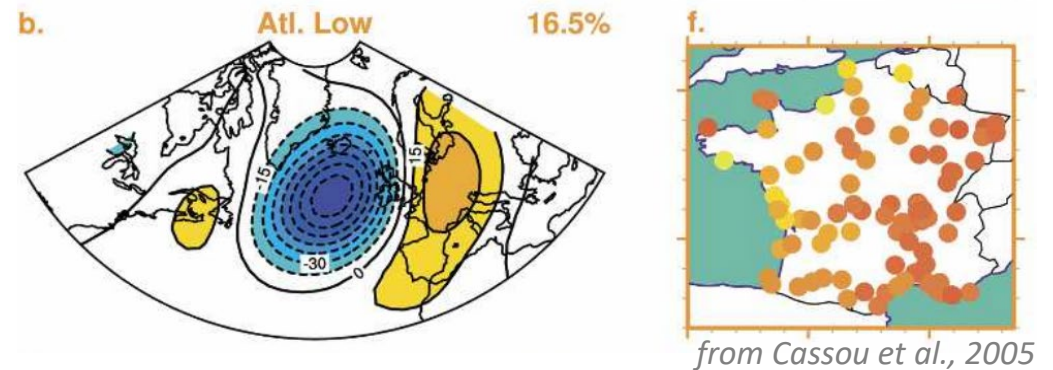
Is there extended prediction skill for extreme surface temperature events (compared to climatologically average ones)?

What is the role of persistence?

# Verification of S2S ensemble hindcasts

Surface temperature variability can be determined by components with predictability potential on S2S time scales:

- low-frequency atmospheric variability (possibly influenced by ocean variability, *Cassou et al., 2005*; *Wulff et al., 2017*)
- land-atmosphere interactions (soil moisture memory, *Seneviratne et al., 2010*)



from Seneviratne et al., 2010



# Data & Methods

## Data:

Hindcasts: S2S ensembles (*Vitart et al., 2016*)

- mostly ECMWF: 11 members, initialized twice weekly, only model versions 2016+

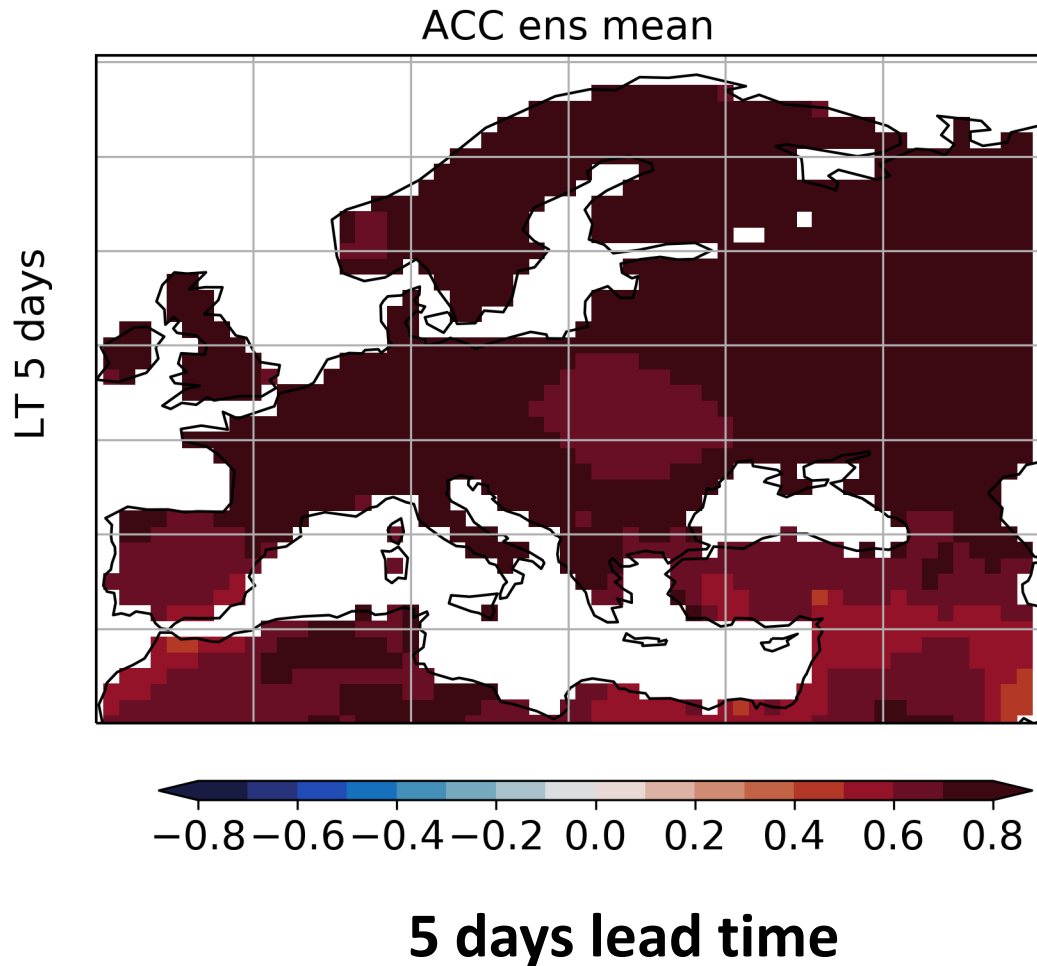
Verification: ERA-Interim reanalysis (*Dee et al., 2011*)

## Methods:

Consider pentad mean anomalies of  $T_{2m}$  in JJA with respect to the 1999-2010 lead time-dependent climatology

Extreme temperature event: exceedance of the 95<sup>th</sup> percentile of the  $T_{2m}^{5d}$  distribution (again lead time-dependent)

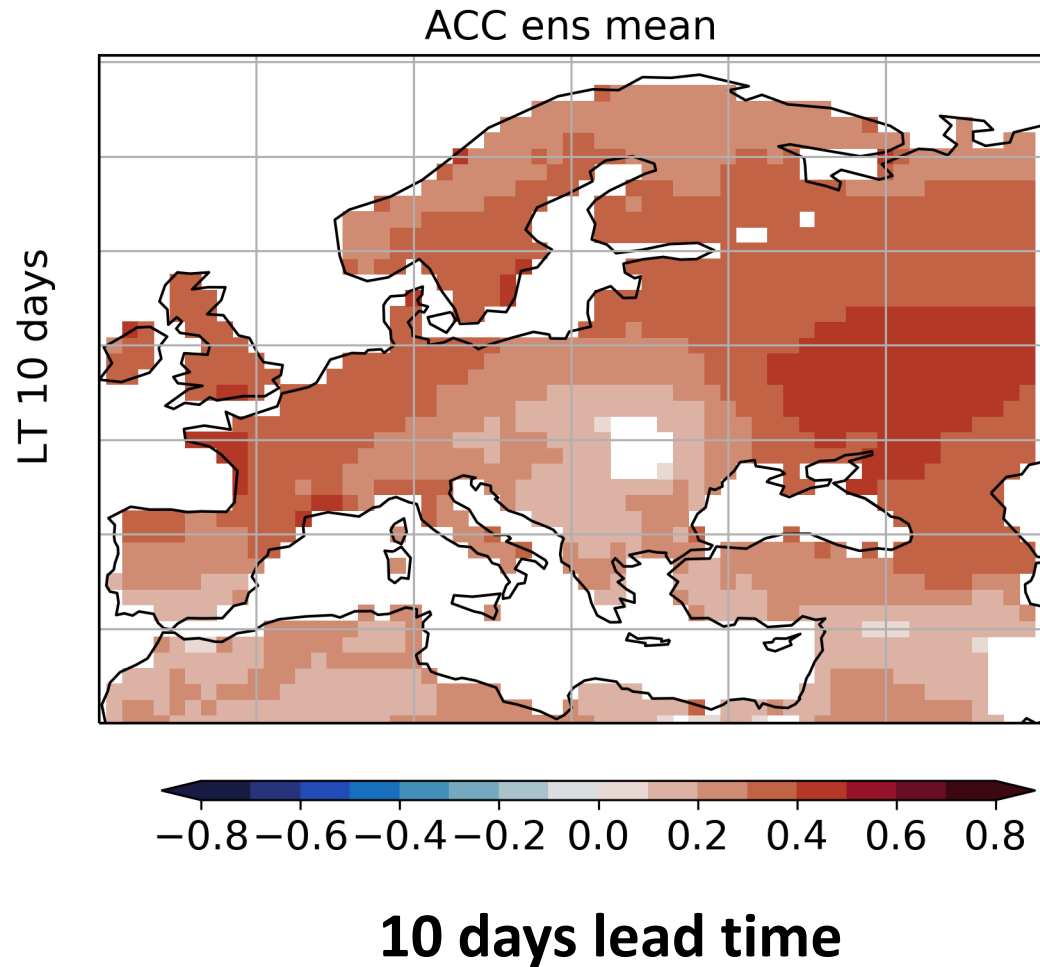
# Surface temperature prediction skill



## Anomaly correlation coefficient (ACC)

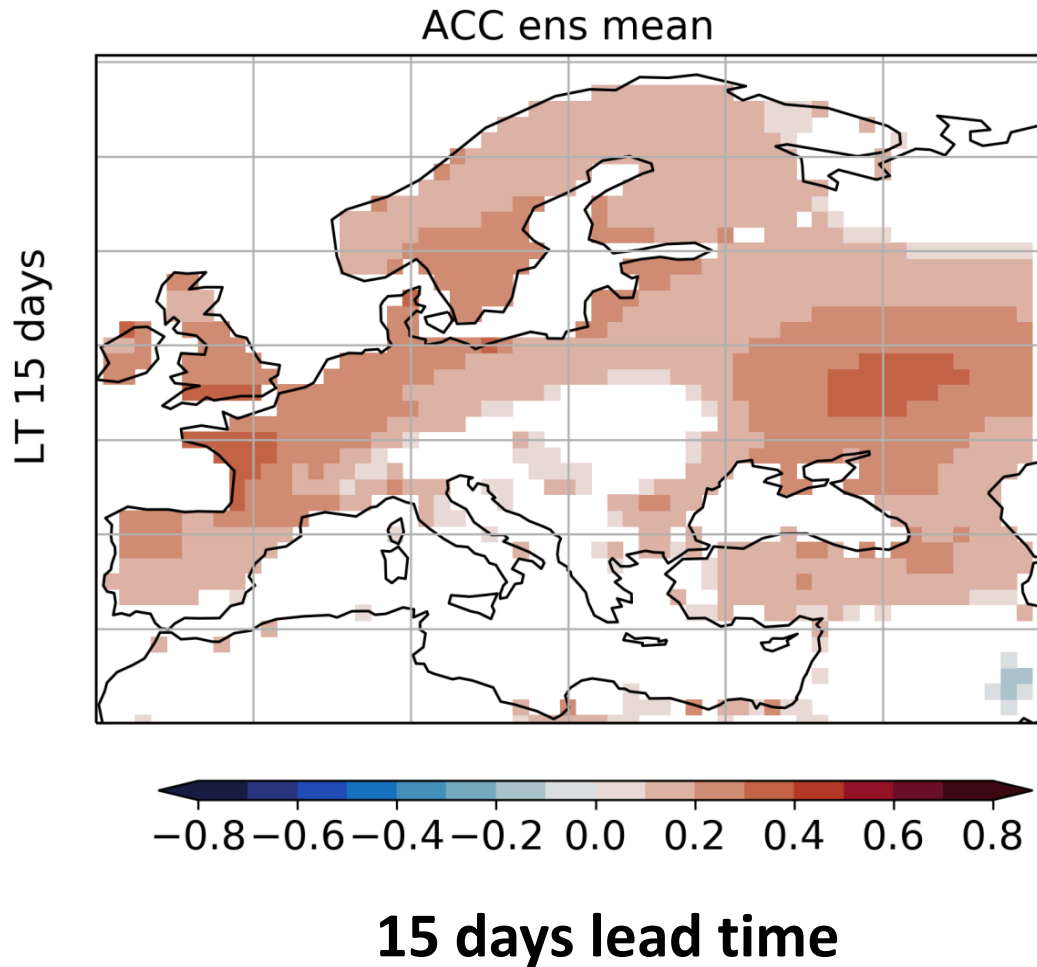
At each grid point & for each lead time:  
→ correlation over dimension of  
initialization time

# Surface temperature prediction skill



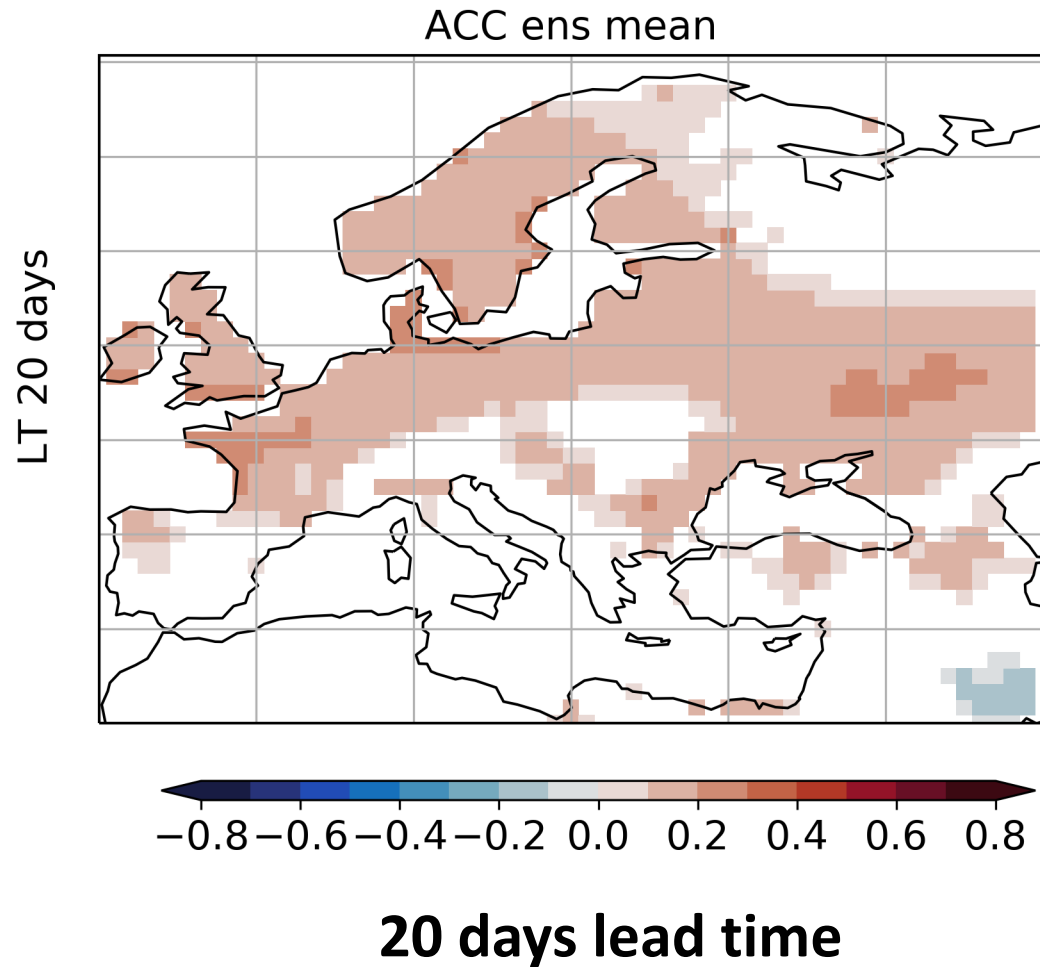
ACC < 0.5 over whole domain

# Surface temperature prediction skill



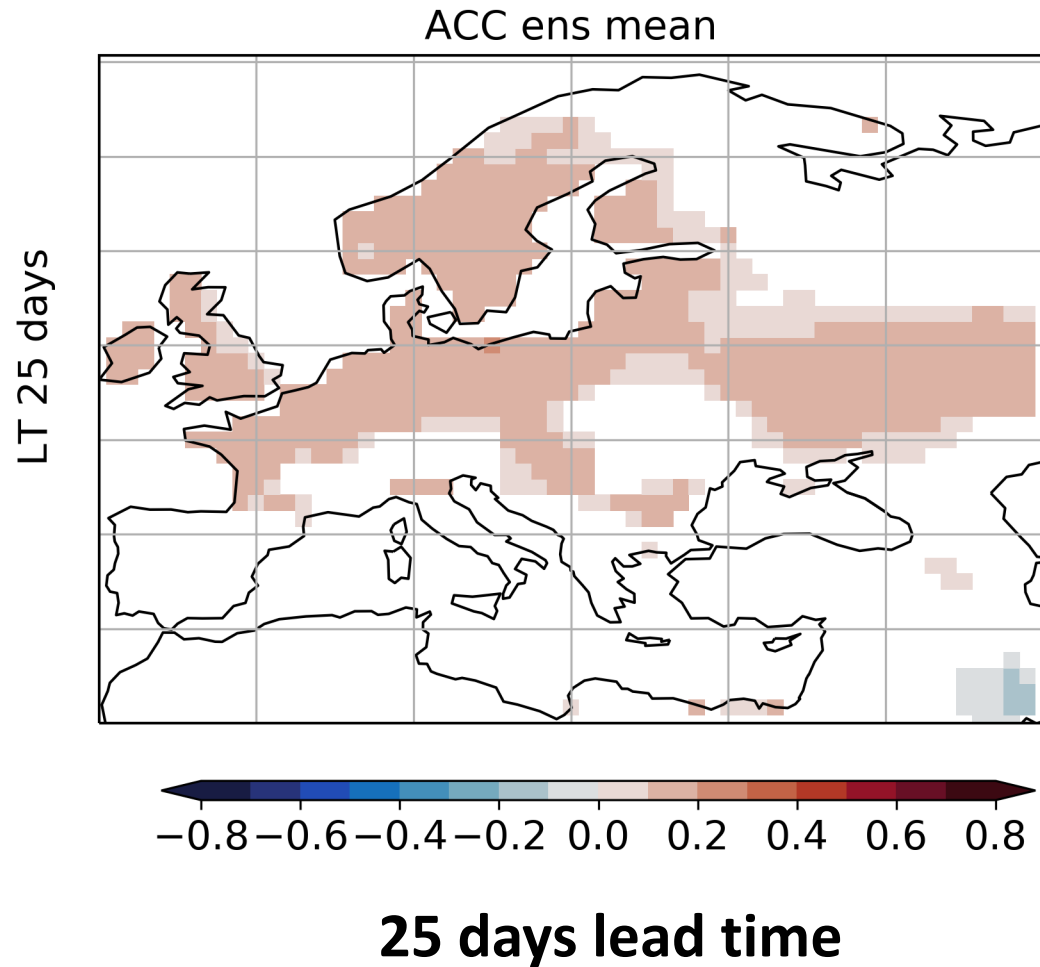
ACC < 0.4 over whole domain

# Surface temperature prediction skill



ACC < 0.3 over whole domain

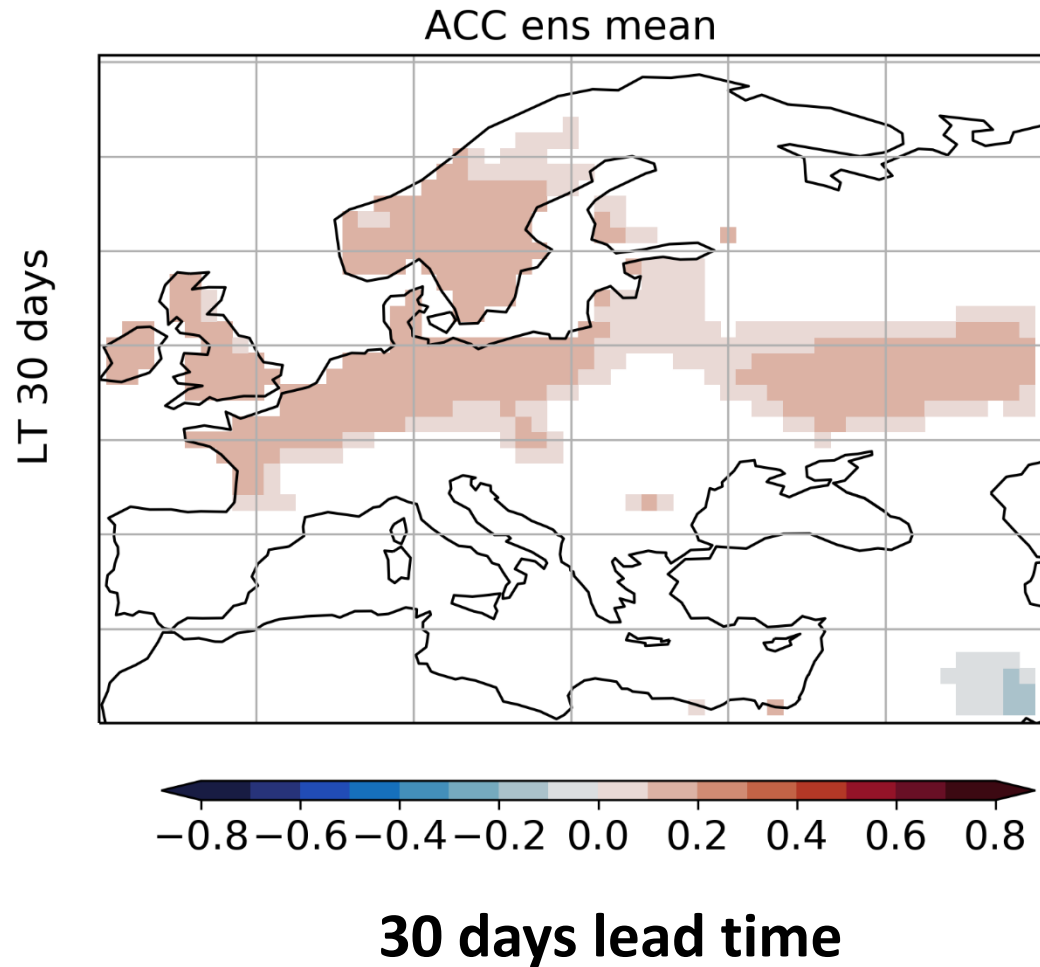
# Surface temperature prediction skill



ACC < 0.2 over whole domain

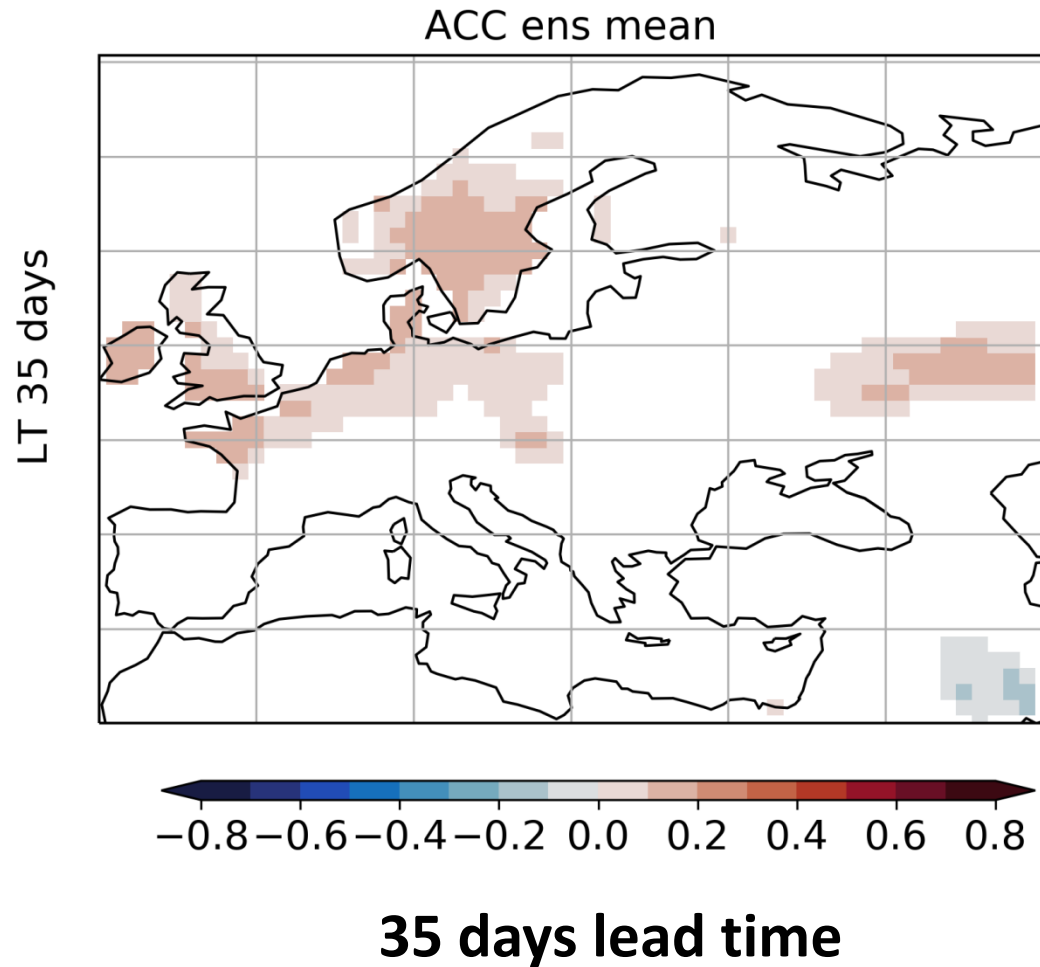


# Surface temperature prediction skill

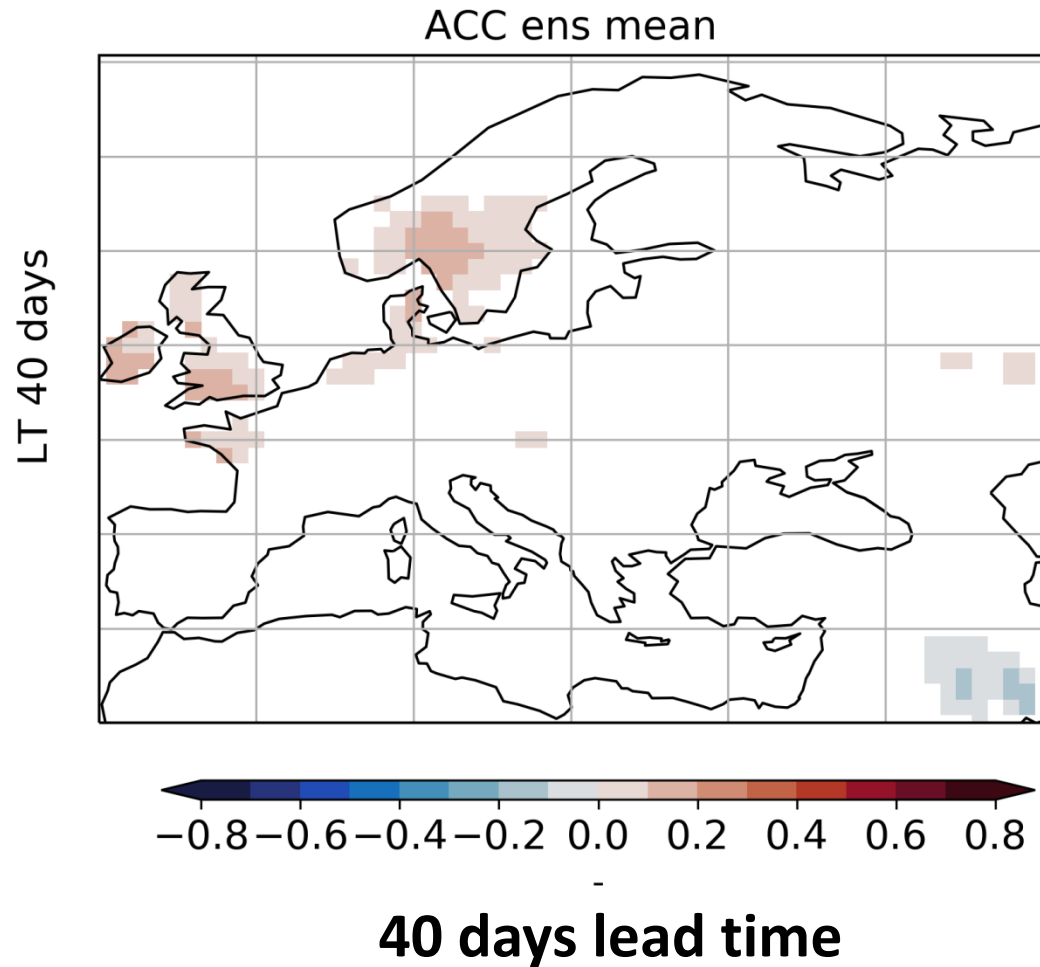


Small but significant predictable signal remains

# Surface temperature prediction skill



# Surface temperature prediction skill



# Are extremes more predictable than climatology?

- Need a **base rate independent** measure for the prediction skill  
→ the Odds Ratio (**OR**, *Stephenson, 2000*)
  - Ratio of odds of making a hit to the odds of making a false alarm
- Transform to Skill Score: OR Improvement over **random** forecast  
→ the **ORSS**
  - Compare forecasts of 50<sup>th</sup> vs. 95<sup>th</sup> percentile events
- Skill Score relative to **persistence**  
→ OR Benefit Skill Score (**ORBSS**, *Mittermaier, 2008*)

$$OR = \left( \frac{H}{1-H} \right) \left( \frac{F}{1-F} \right)^{-1}$$

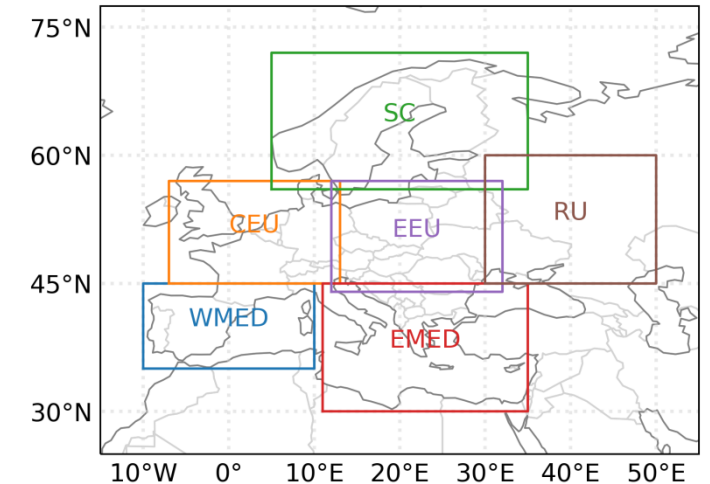
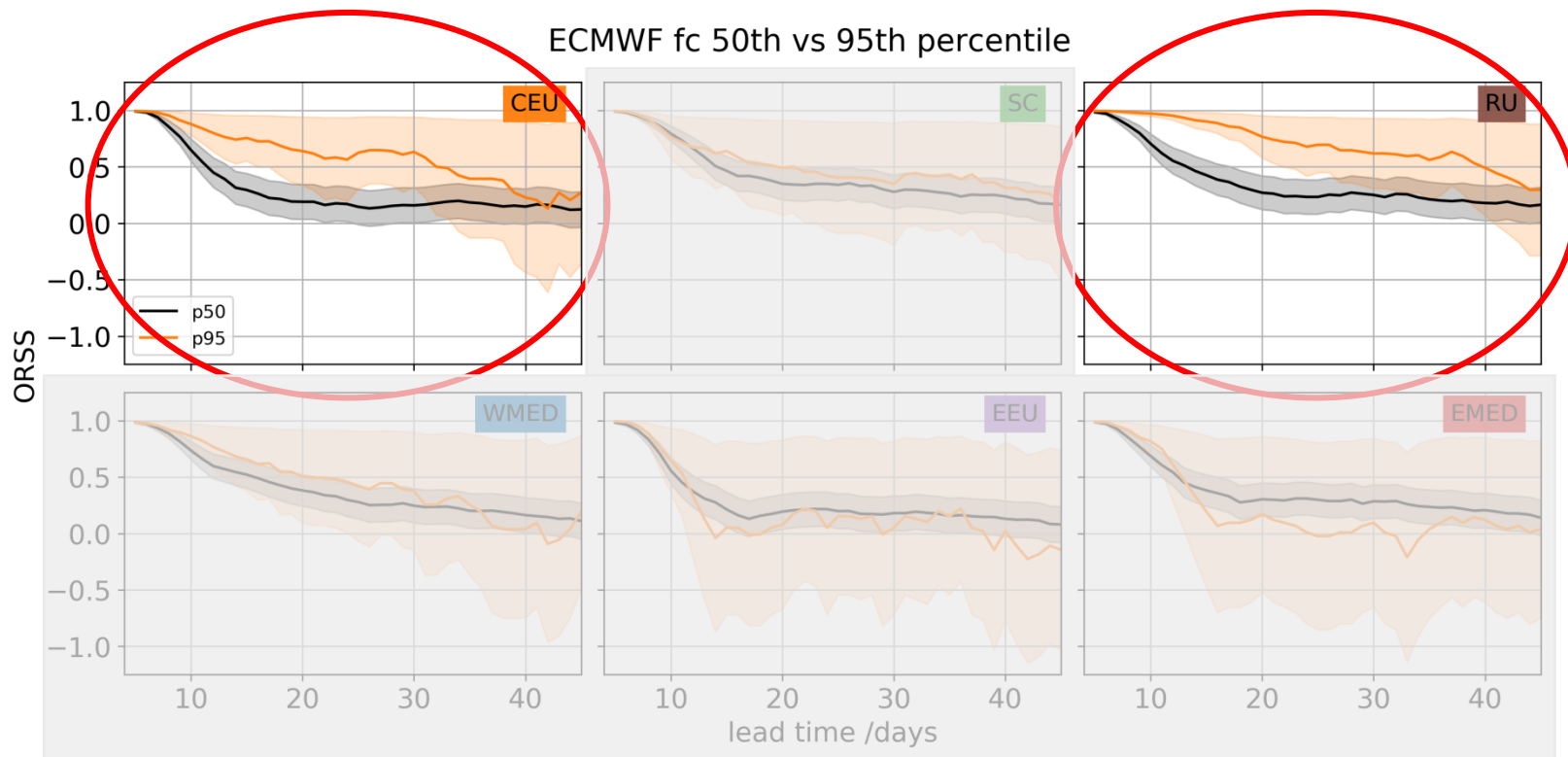
$$ORSS = \frac{OR - 1}{OR + 1}$$

$$ORBSS = \frac{OR - OR_p}{OR + OR_p}$$

H: hit rate;

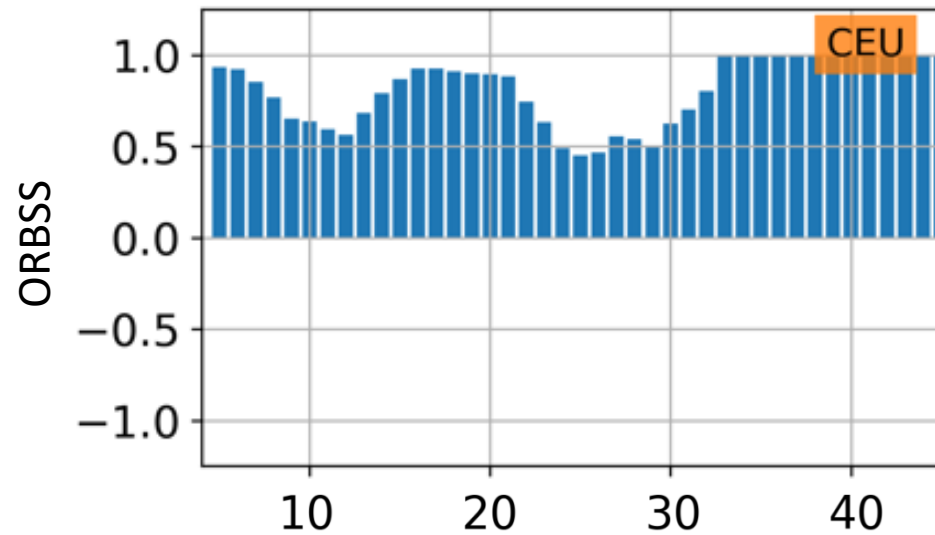
F: false alarm rate

# Extended predictability of extremes in CEU & RU regions

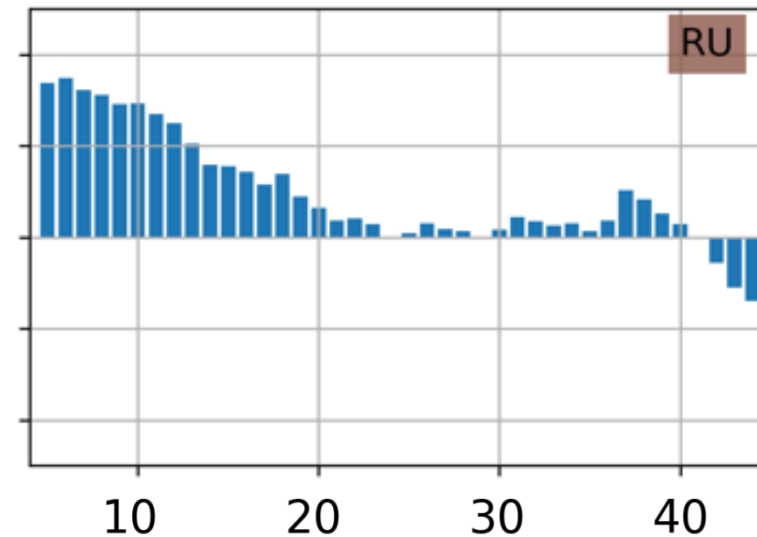


ORSS indicates extended predictability of extreme temperatures in western Europe (CEU) and western Russia and the Ukraine (RU)

# Extreme temperature skill through persistence?



Persistence cannot explain the skill in the CEU region

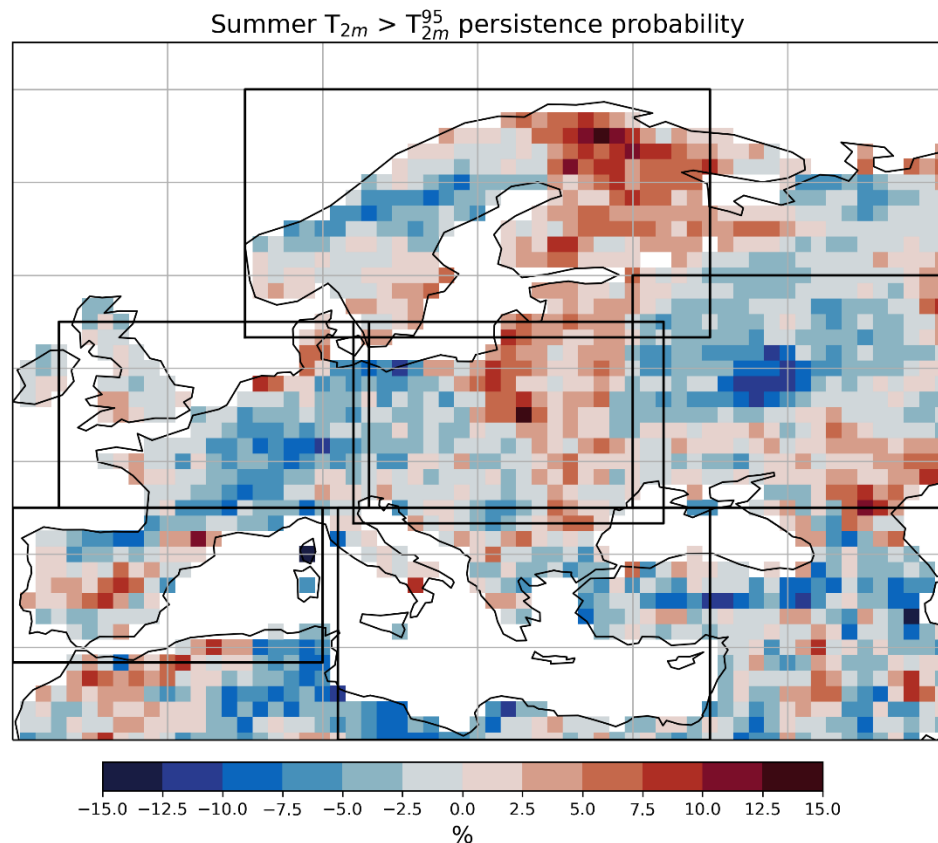


Large part of the skill at sub-seasonal lead time in RU region comes from persistence



# Extreme temperature persistence in ECMWF model

ERA-Interim - ECMWF hindcasts lead time 18-22 days



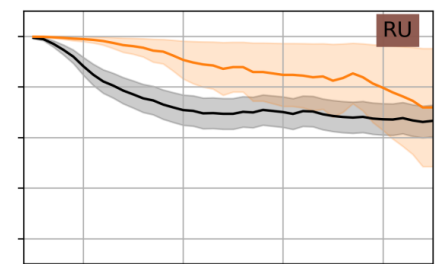
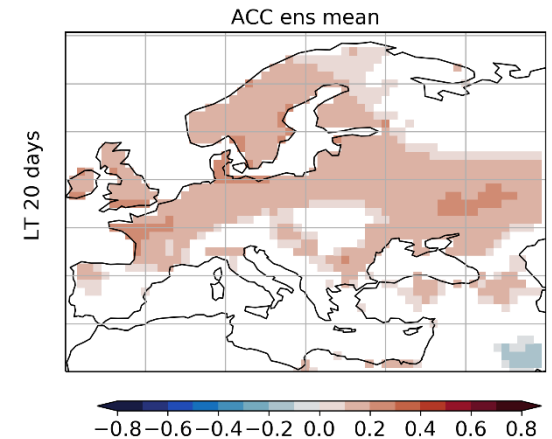
Difference in persistence probability for 95<sup>th</sup> percentile events between ERA-Interim and ECMWF model

In RU region rather underpersistence for subseasonal lead times

→ The model does not just predict persistence all the time

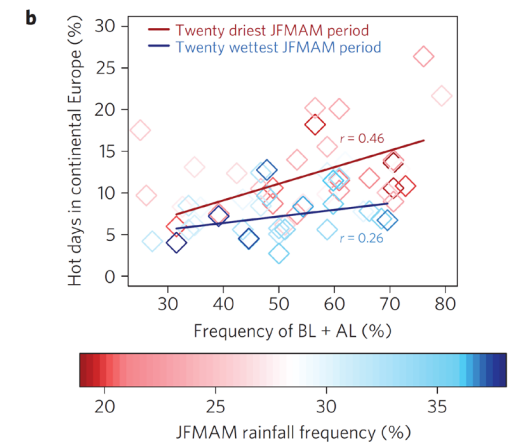
# Conclusions

- There are predictable signals in weekly surface temperature at subseasonal lead times in some European regions
- In north-western Europe (CEU) and western Russia and the Ukraine (RU), **prediction skill for surface temperature extremes is larger than for average temperatures**
- In RU, large part of the skill can be attributed to persistence of extreme temperatures (especially during the 2010 event)



# Outlook

- How strongly is persistence determined by land-atmosphere interactions?
- What is the role of atmospheric circulation regimes in extreme temperature forecast skill at S2S lead times?
- What is the influence of a drift of the main modes of circulation?
- How do different S2S hindcast products compare?



from Quesada et al. (2012)

Thank you for your attention!

# References

**Cassou et al.**, *Tropical Atlantic influence on European heat waves*, 2005, *Weather* 59 (8)

**Duchez et al.**, *Drivers of exceptionally cold North Atlantic Ocean temperatures and their link to the 2015 European heat wave*, 2016, *Environ. Res. Lett.* 11 (20)

**Mittermaier**, *The Potential Impact of Using Persistence as a Reference Forecast on Perceived Forecast Skill*, 2008, *Weather and Forecasting* 23 (5)

**Stephenson**, *Use of the “Odds Ratio” for Diagnosing Forecast Skill*, 2000, *Weather and Forecasting* 15 (2)

**Vitart et al.**, *The subseasonal-to-seasonal (S2S) prediction project database*, 2016, *Bull. Amer. Meteorol. Soc.* 98 (1)

**Wulff et al.**, *Tropical Forcing of the Summer East Atlantic Pattern*, 2017, *GRL* 44 (21)

# Odds Ratio

$$OR = \frac{\left(\frac{H}{1-H}\right)}{\left(\frac{F}{1-F}\right)}$$

$$H = \frac{\text{hits}}{\text{hits} + \text{misses}}$$

$$F = \frac{\text{false alarms}}{\text{false alarms} + \text{correct negatives}}$$

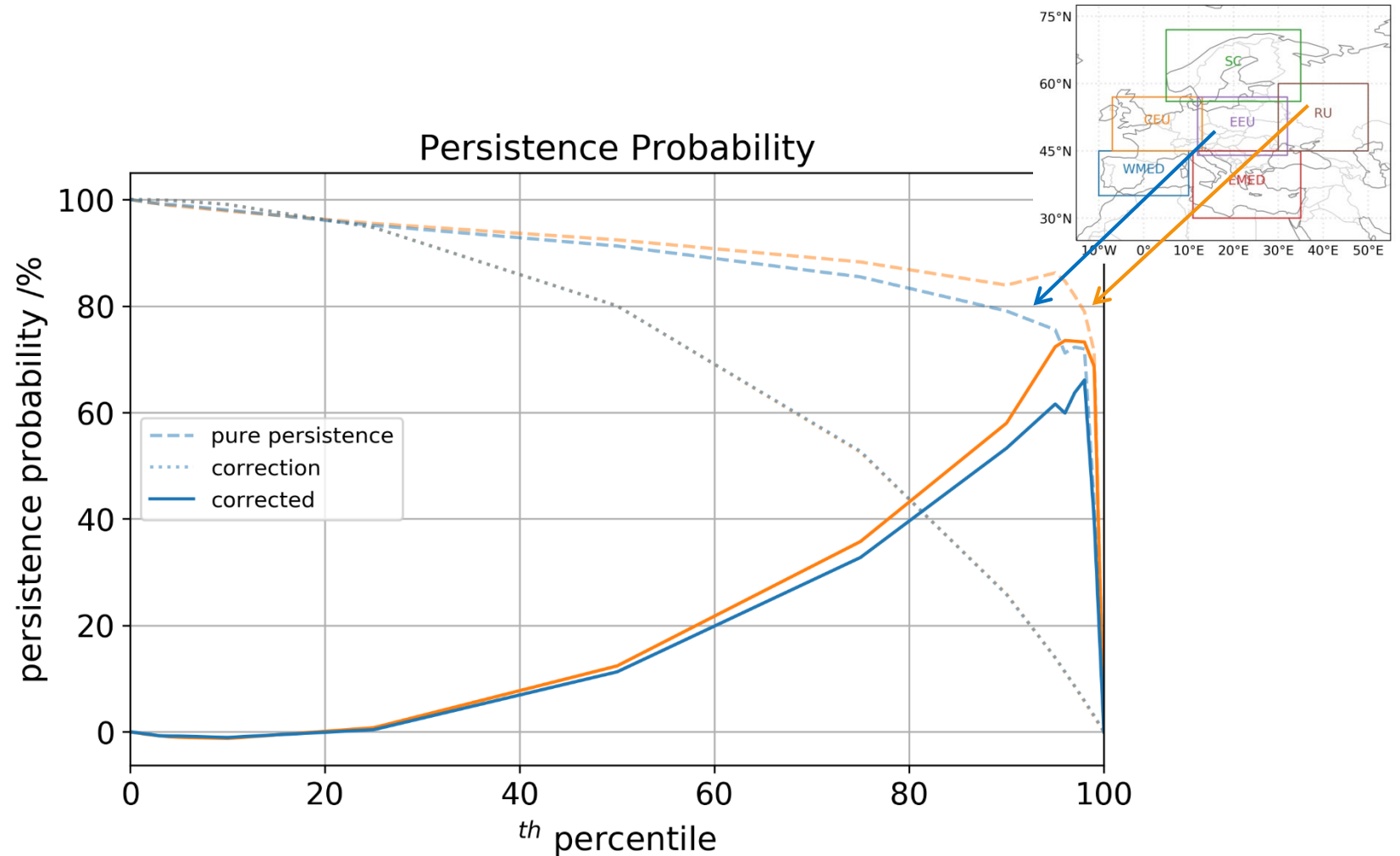
OR is the ratio of the odds of a “yes” forecast being correct to the odds of a “yes” forecast being wrong

(see <http://www.cawcr.gov.au/projects/verification/>)

# Persistence probability dependence on threshold

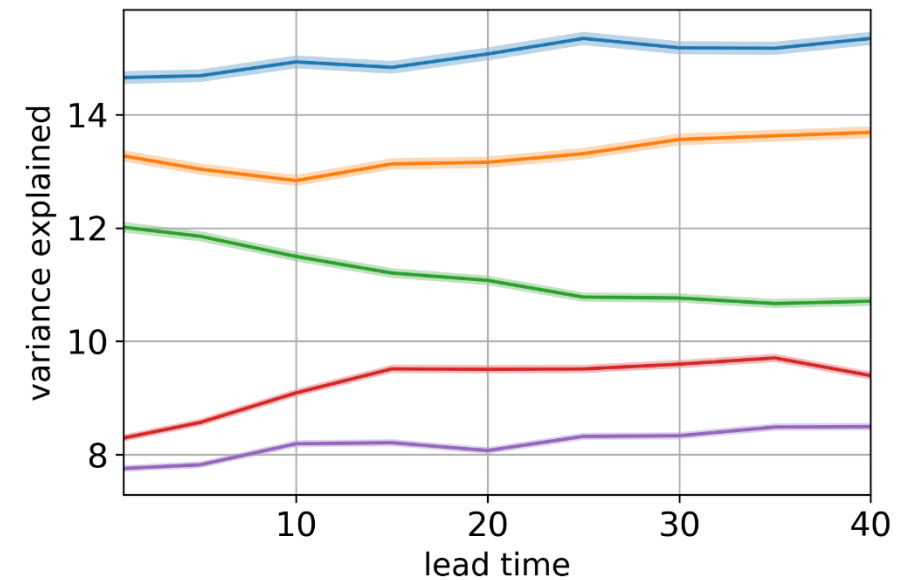
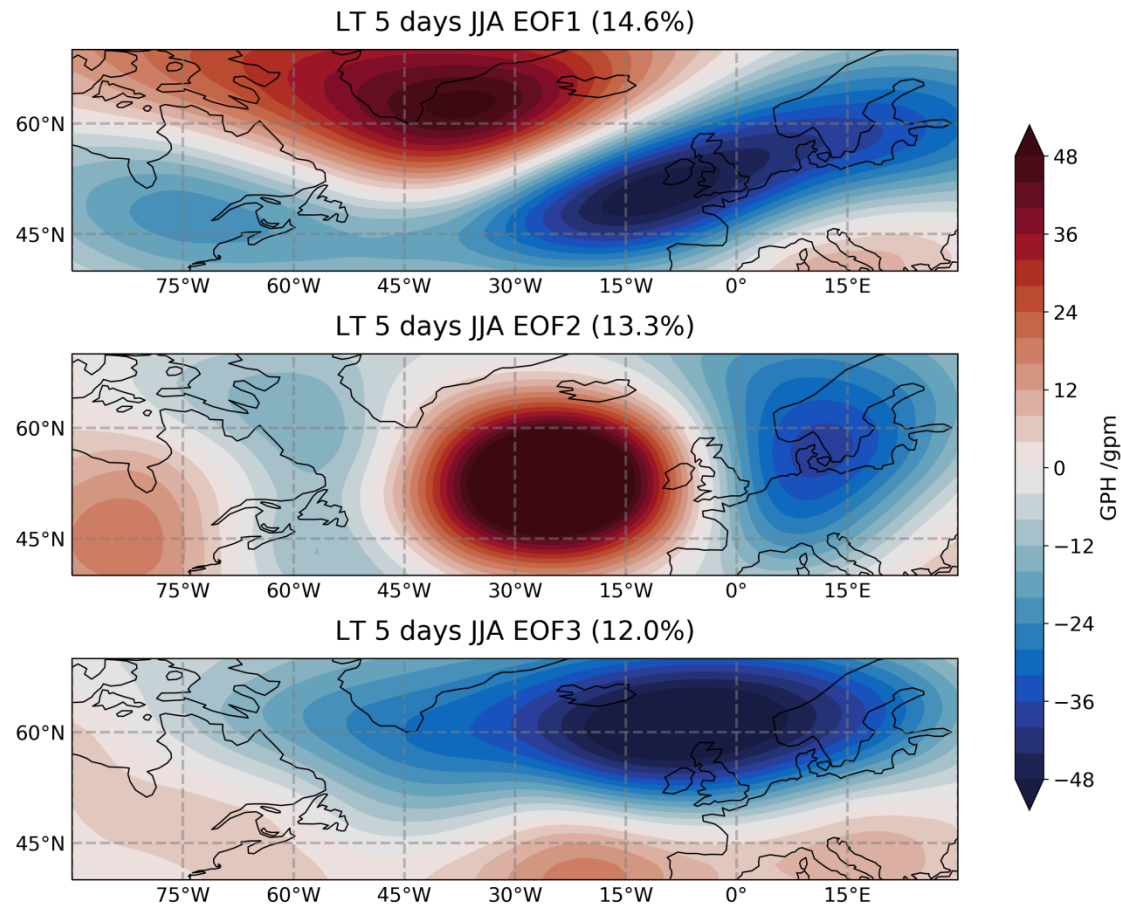
Strong dependence on chosen percentile threshold remains after correcting

Persistence probability for high temperatures exceeds what is expected for a random time series more strongly than for average temperatures

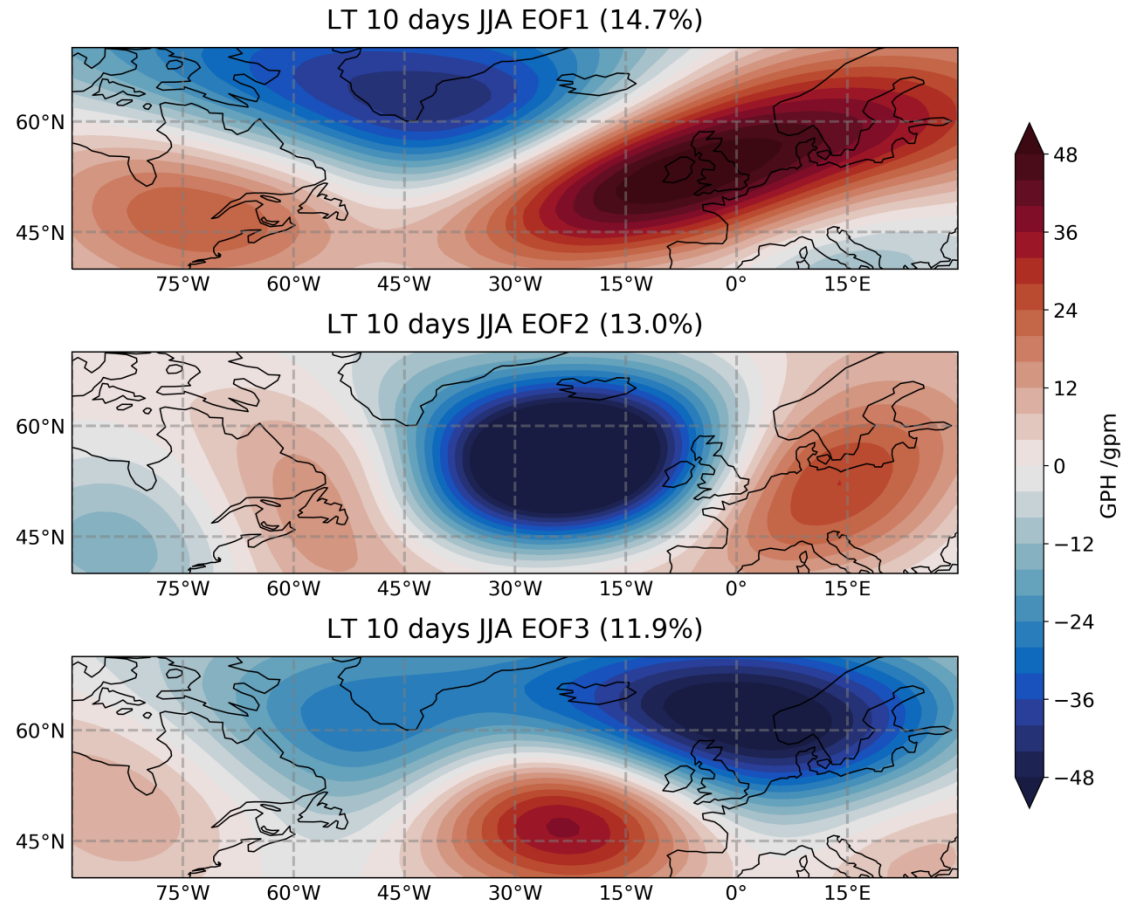




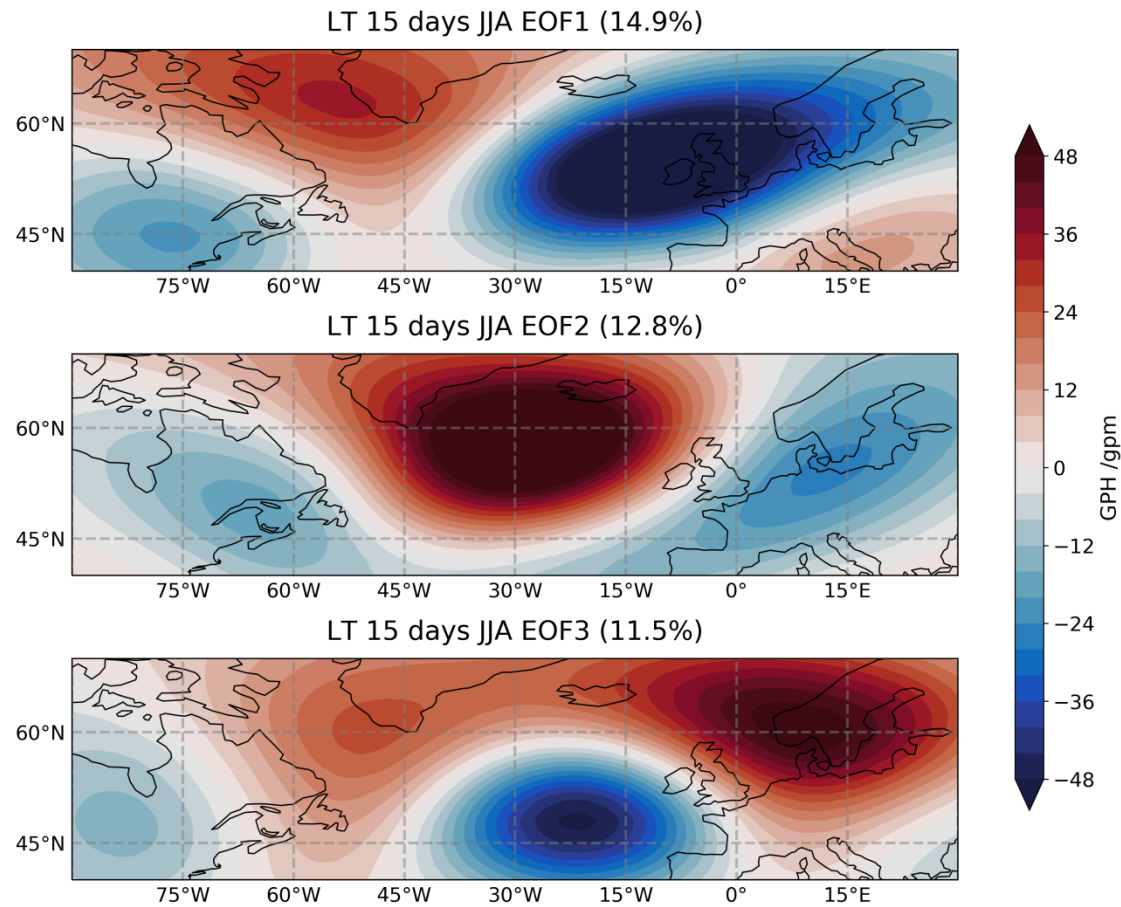
# How are SNAO and SEA predicted?



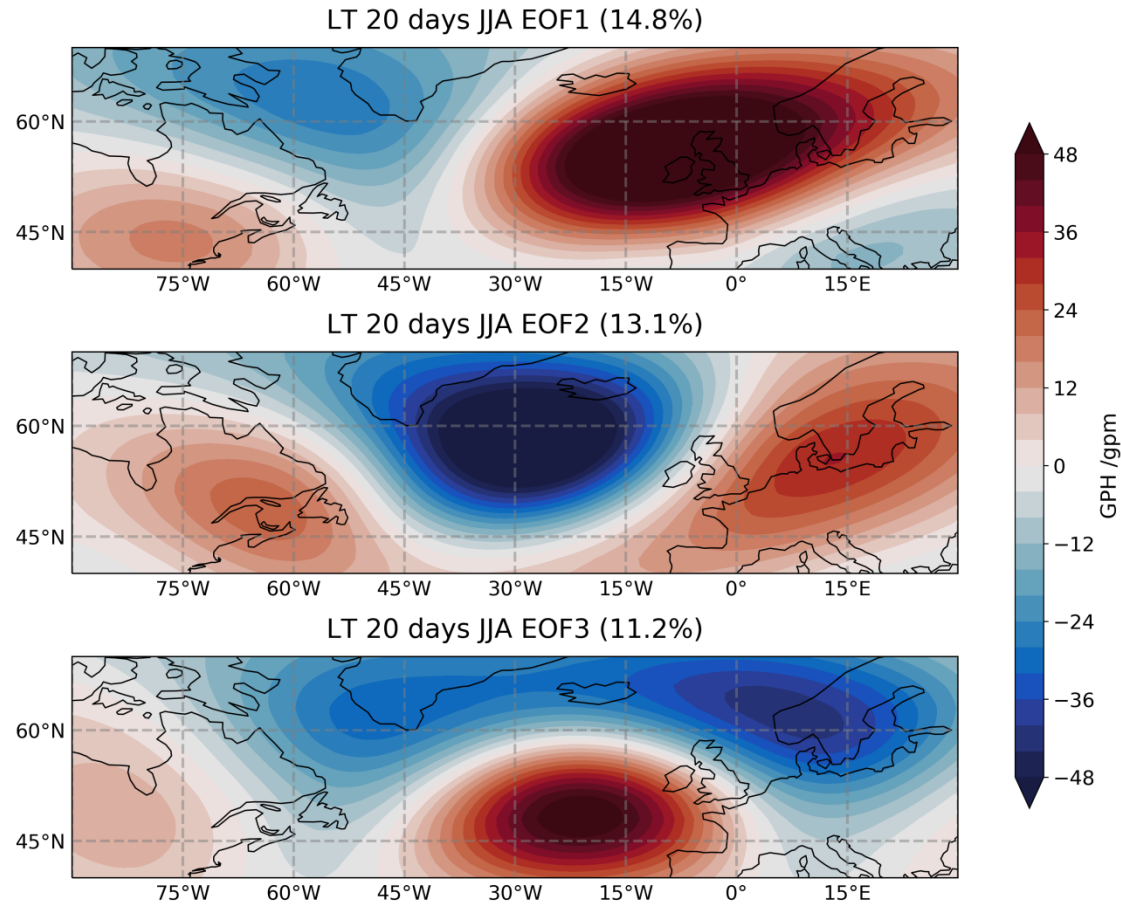
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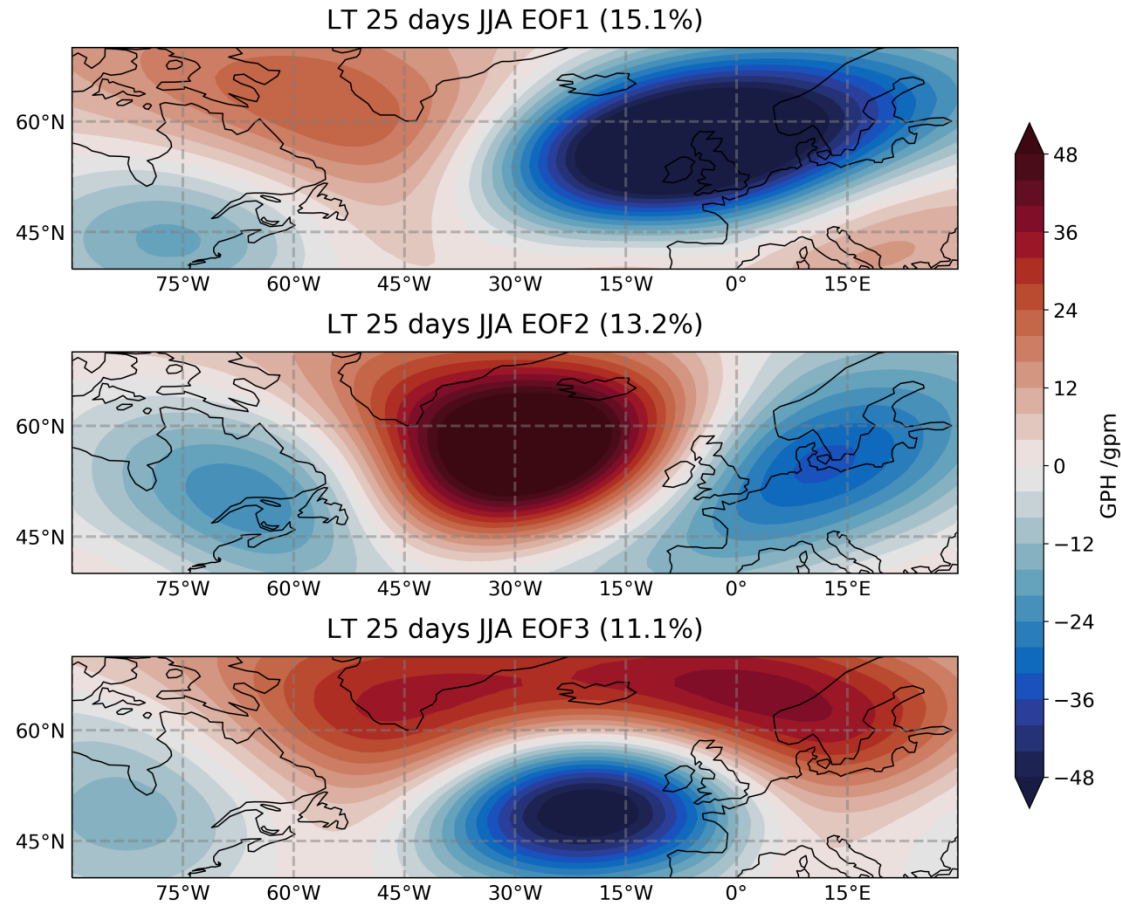
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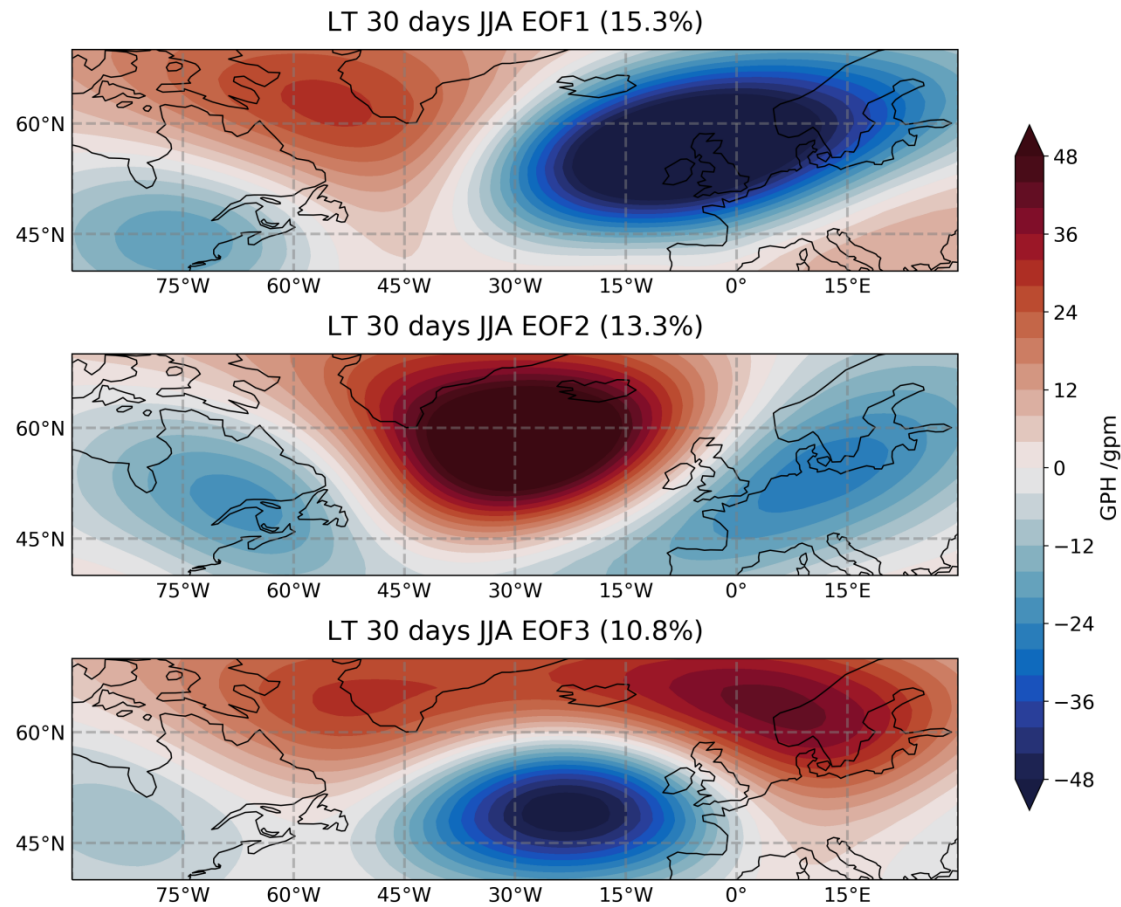
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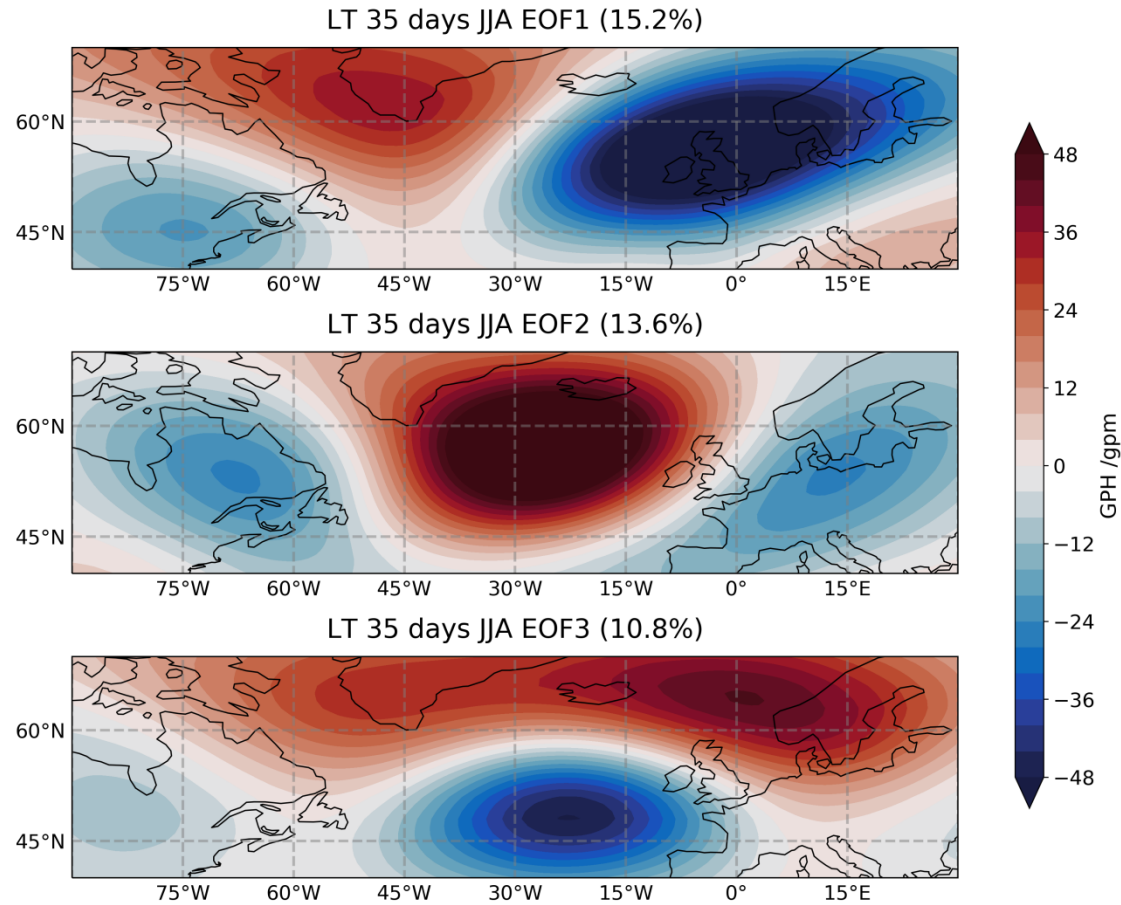


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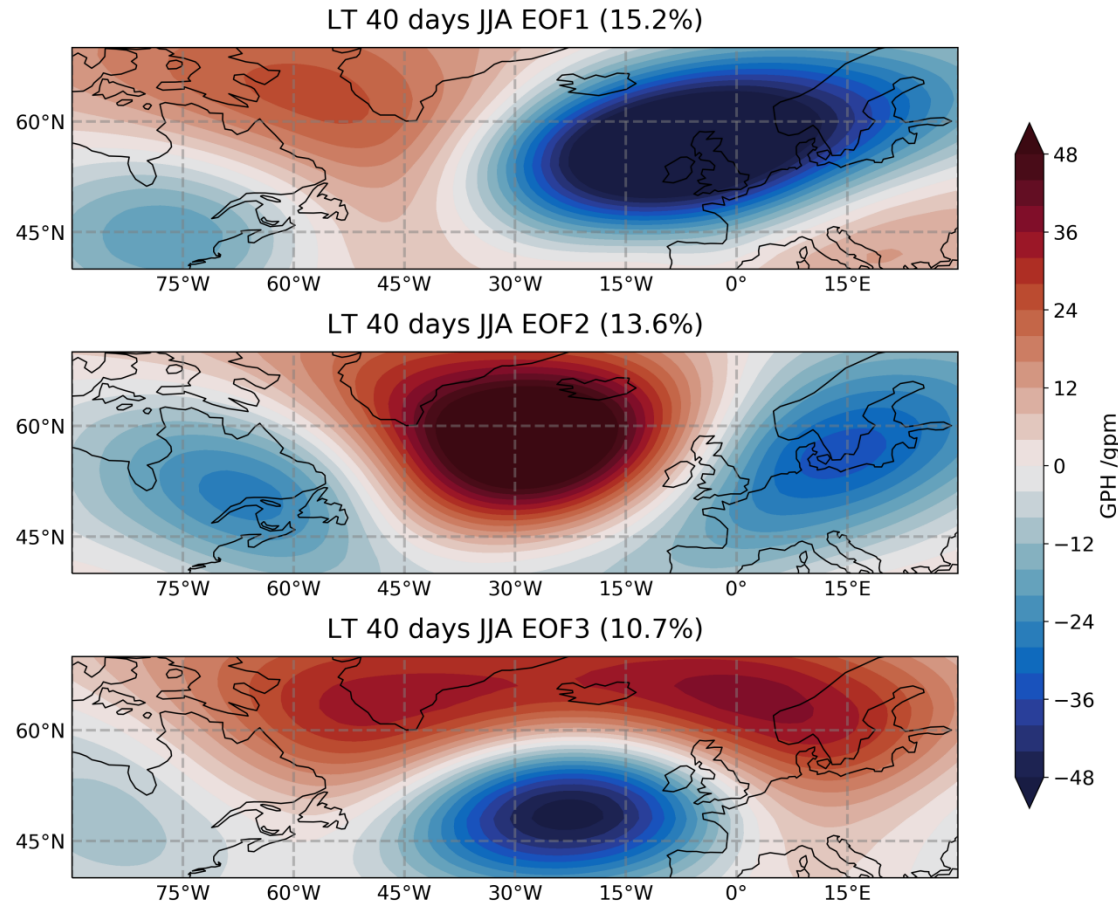




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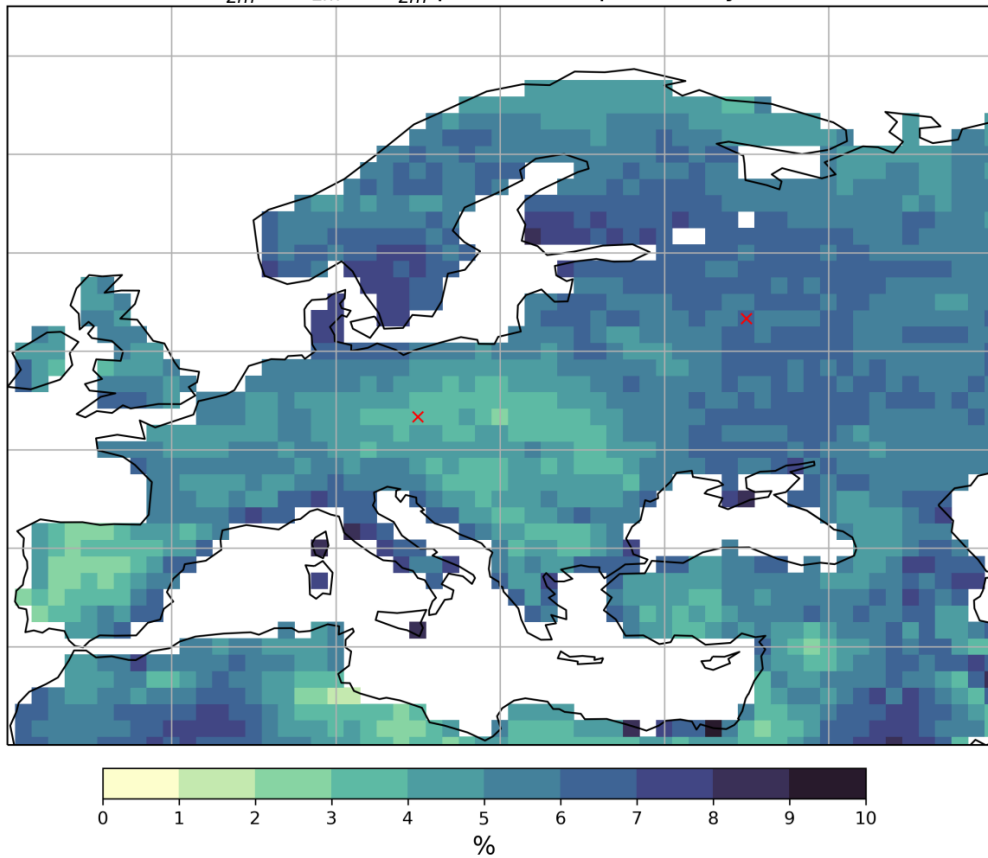


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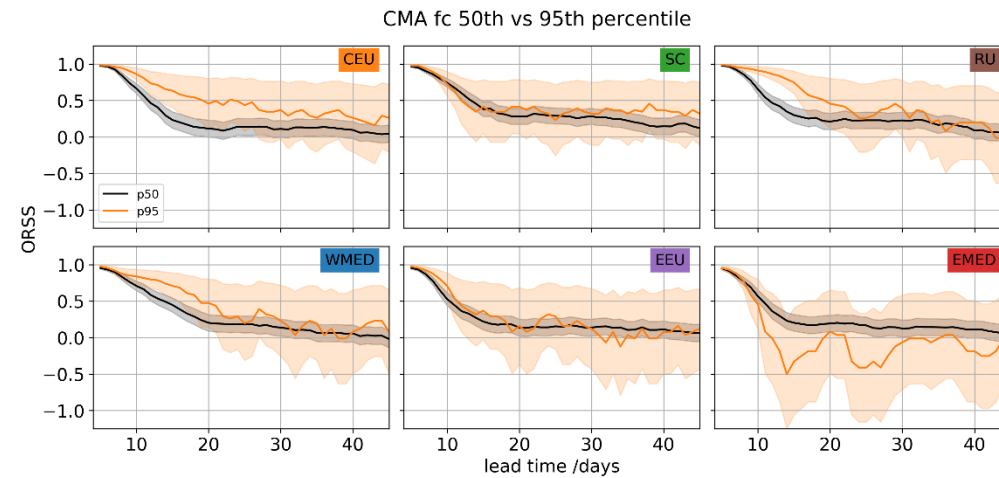
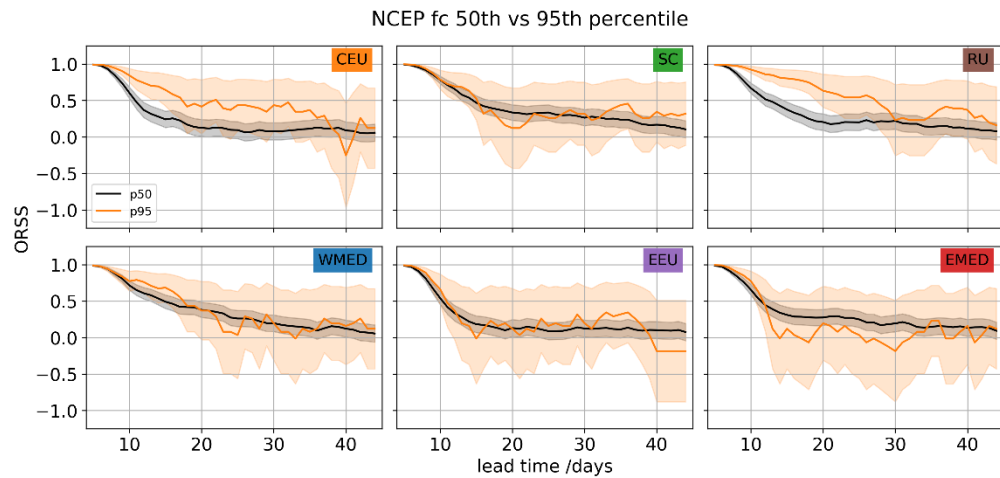
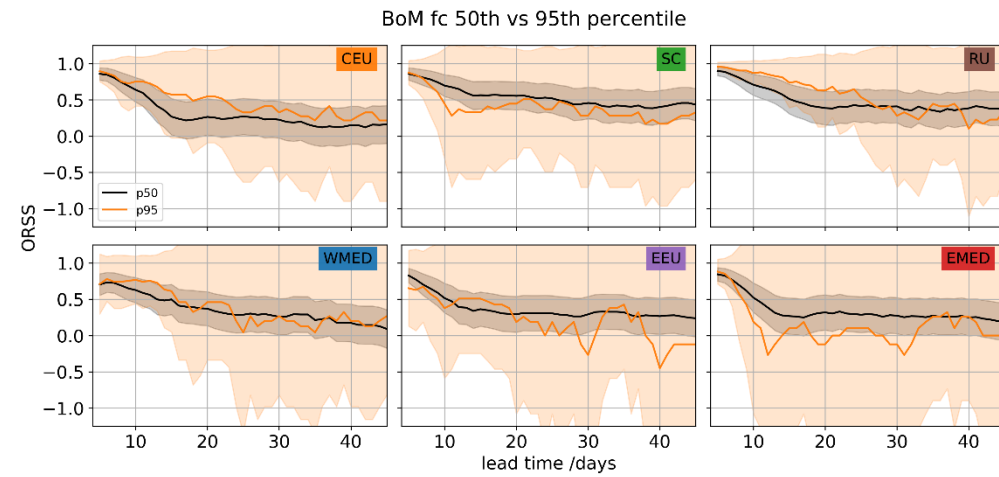
Similar for all models but some (CMA, NCEP) do not separate EOF2 and 3 anymore at longer leads

Summer  $T_{2m}^{25} > T_{2m} > T_{2m}^{75}$  persistence probability (1985-2014)



ERA-Interim persistence of inner quartile temperatures

# 50<sup>th</sup> vs 95<sup>th</sup> percentile forecast skill other models



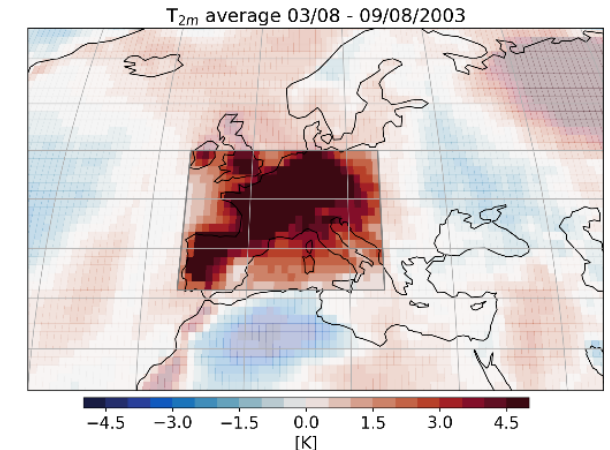
# Extreme temperature events

## Extreme temperature event

Defined as a period of at least 3 days in which **2m temperature exceeds the 95<sup>th</sup> percentile of the monthly climatology**. Each event must be separated from the previous by at least 3 days.

Here limited to **JJA** and **land areas** in the region indicated to the right

→ **11 events** in the period of 1999-2010 obtained from daily **ERA-Interim** reanalysis



## Ensemble hindcasts

From 4 forecasting systems (ECMWF, BoM, CMA, NCEP) in the S2S data base (Vitart et al., 2016) with:

- Different ensemble sizes
- Different initialization strategies (frequency, ensemble generation)
- Common period covered: 1999-2010
- Ocean and sea ice coupled
- ...