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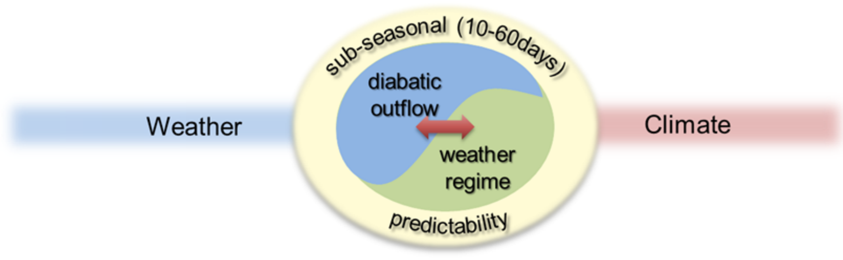
RESEARCH FOR GRAND CHALLENGES



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Flow-dependent sub-seasonal forecast skill for Atlantic-European weather regimes

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Introduction and motivation

Sub-seasonal weather forecasts

- Growing use of operational subseasonal-to-seasonal (S2S; 10 – 60 days) weather forecasts due to continuous increase in computational power and improvement of NWP models
- Sub-seasonal forecasts hardly have **skill** for local day-to-day weather but **rather for weather variability on regional and multi-daily scales**, which is represented by **weather regimes** (WR)

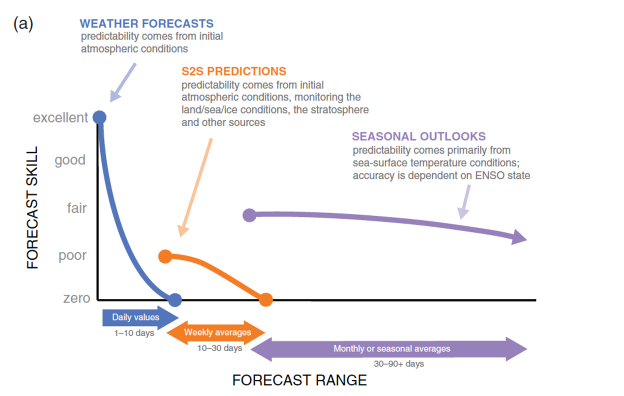


Fig. 1a from White et al. (2017): Qualitative estimate of forecast skill for different forecast ranges and corresponding predictability sources

Sub-seasonal forecast skill

- **Low-frequency climate modes** such as the stratospheric polar vortex, MJO, ENSO, or SST variations can **enhance** sub-seasonal forecast skill (Robertson & Vitart, 2019)
- **Synoptic-scale activity such as warm conveyor belts (WCBs)** can potentially **dilute** (sub-seasonal) forecast skill (e.g., Grams et al., 2018)

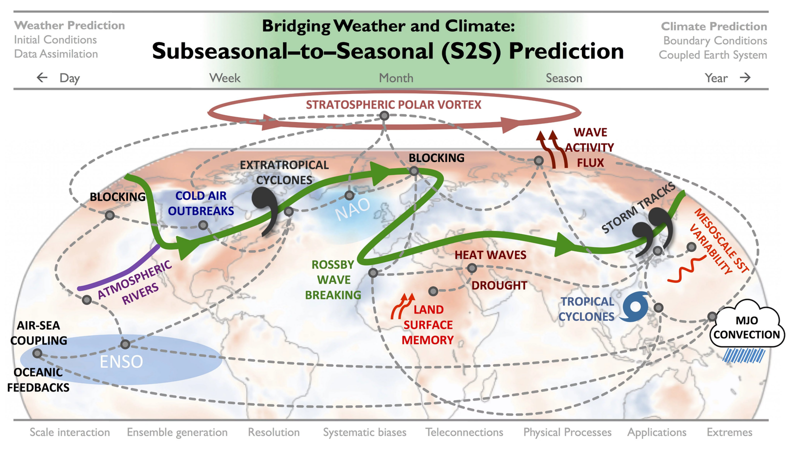


Fig. 1 from Lang et al. (2020): Schematic of various low-frequency and synoptic-scale processes influencing sub-seasonal predictability and thus forecast skill

- Previous studies investigated sub-seasonal forecast **skill for classical 4 Atlantic-European WR** (NAO+, NAO-, blocking, Atlantic ridge; e.g., Ferranti et al., 2018)

Research questions

- What is the **flow-dependent sub-seasonal (re)forecast skill** of ECMWF in **predicting 7 Atlantic-European WR**?
- How do **low-frequency climate modes** such as **synoptic-scale activity** affect this flow-dependent forecast skill?

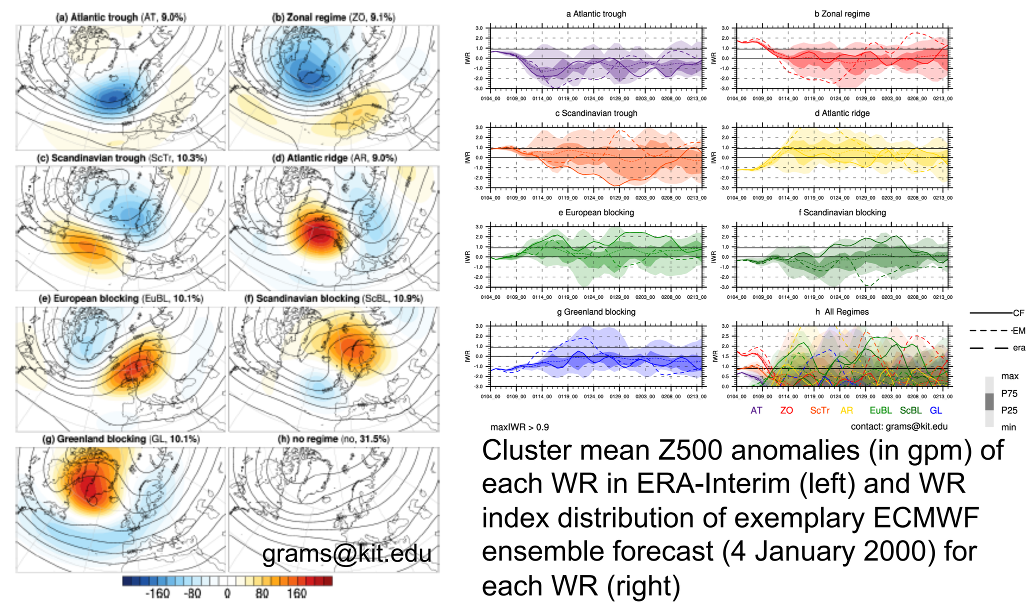
Data and methods

Model and observational data

- **ECMWF sub-seasonal model** from S2S database (Vitart et al., 2017): 4080 reforecasts, 1997 – 2017, 46d lead time, 11 ensemble members, initialized from ERA-Interim
- **ERA-Interim** as observational reference

Weather regime (WR) identification

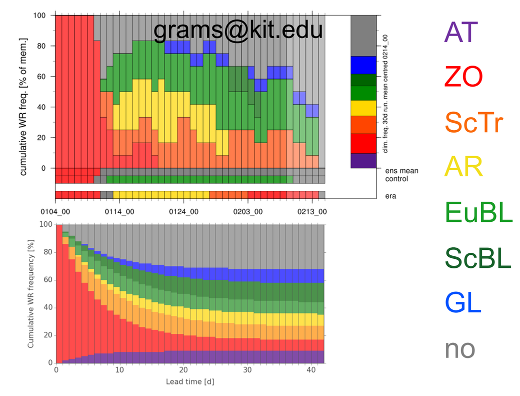
- New definition of **7 year-round Atlantic-European WR,** with certain benefits compared to classical 4 WR (e.g. Grams et al., 2017; Beerli & Grams, 2019)
- WR identification (see also Grams et al., 2017)
  - **EOF analysis** of 5-day low-pass filtered **Z500 anomalies** in ERA-Interim (1979 – 2018) → **k-means clustering** in EOF space → **7 WR**
  - Projection of Z500 anomalies (of model and ERA-Interim) on 7 cluster mean anomalies → **WR index I_{WR}** (following Michel & Rivière, 2011) → **calibrate WR index** (by removing WR index bias)
  - Define **active WR life cycle** if maximum WR index is above a threshold (I_{WR} > 0.9) for at least 5 consecutive days → "no regime" if no WR is active



Cluster mean Z500 anomalies (in gpm) of each WR in ERA-Interim (left) and WR index distribution of exemplary ECMWF ensemble forecast (4 January 2000) for each WR (right)

Brier skill score (BSS)

- How well does the model ensemble predict the active WR compared to a climatological reference forecast?
- Reference forecast is based on day-to-day transition climatology in ERA-Interim and WR at initial time
- **BSS = 1** => perfect, **BSS = 0** => equally good as reference, **BSS < 0** => worse than reference



Relative number of ensemble members attributed to one of the 7 WR (or to no regime) in the exemplary forecast (top) and corresponding climatological reference forecast determined by WR at initial time (bottom)

Results

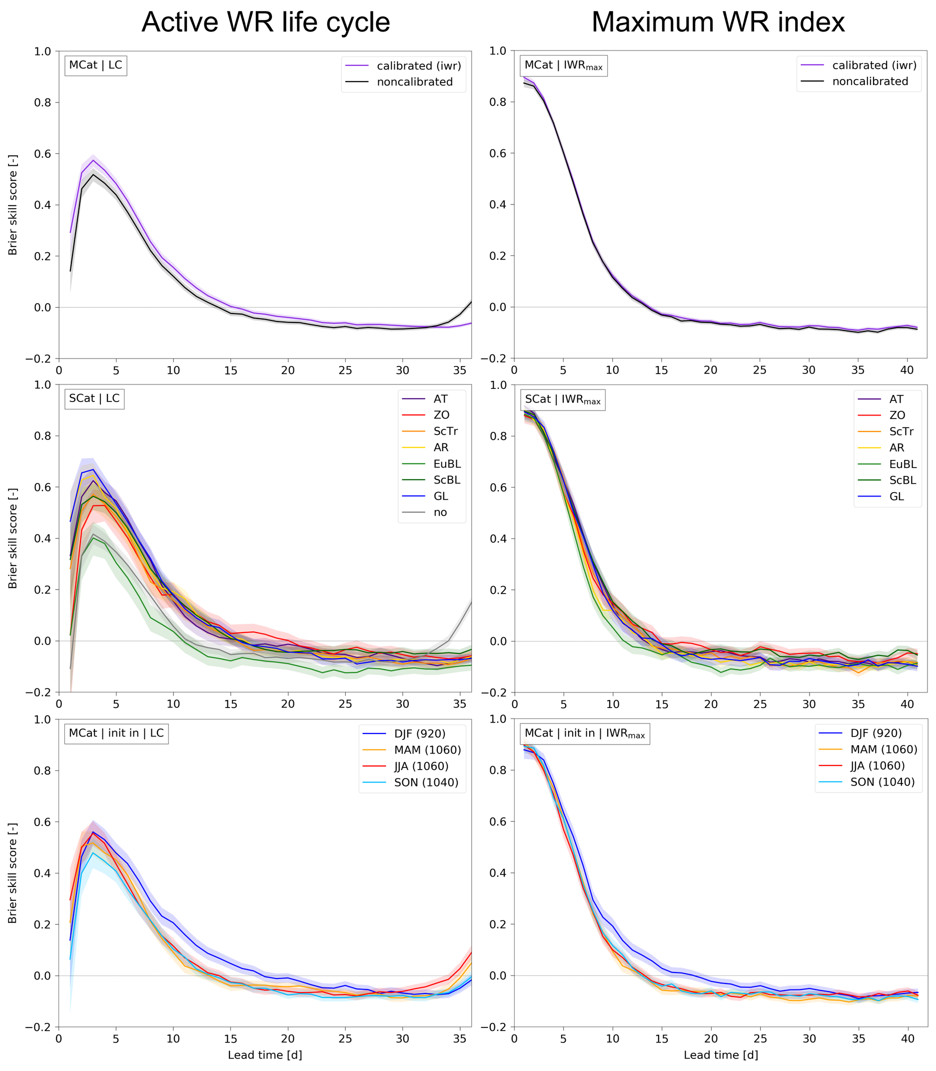
Year-round and seasonal skill for all WR and for individual WR

Active WR life cycle — Maximum WR index

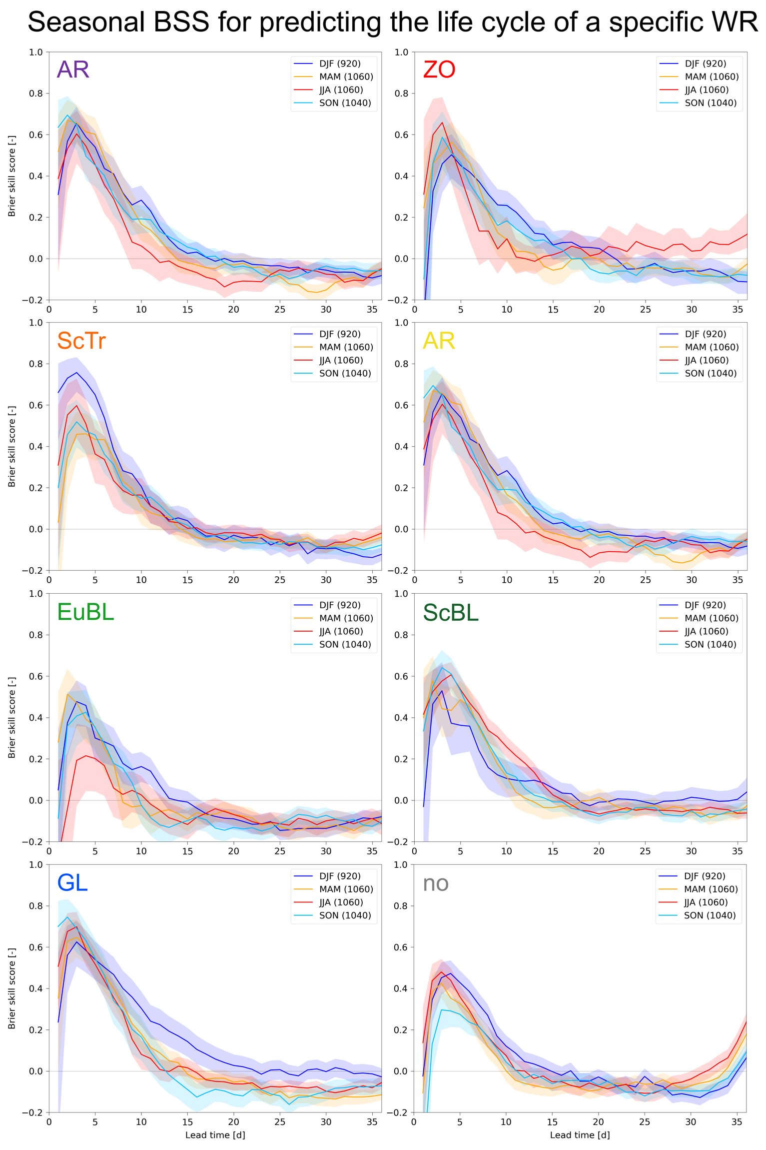
Year-round BSS for all WR for noncalibrated and calibrated model

Year-round BSS for a specific WR

Seasonal BSS for all WR



Seasonal BSS for predicting the life cycle of a specific WR



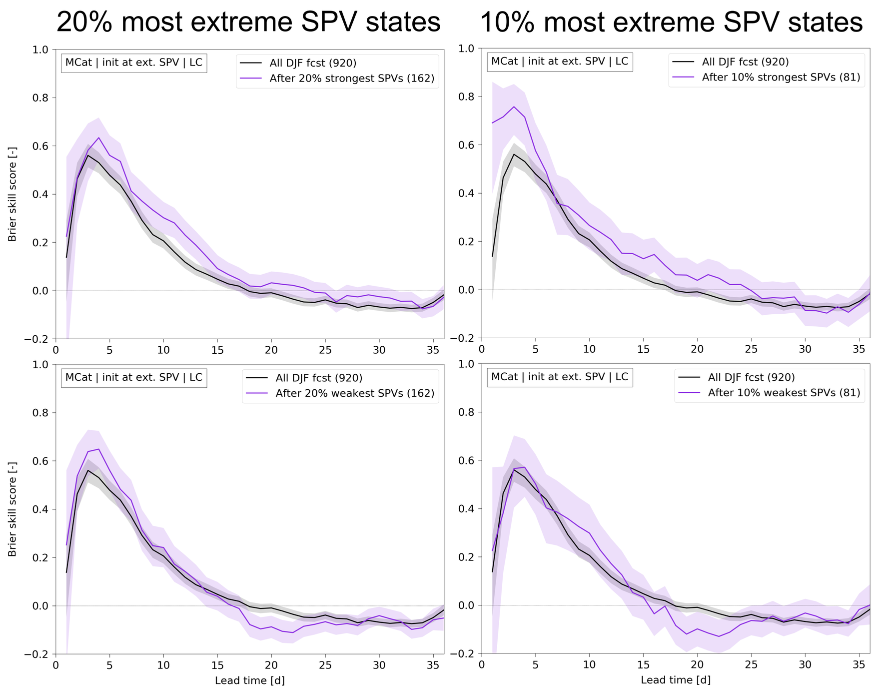
Shading in all BSS plots: bootstrapped distribution of BSS's obtained from 10^4 random resamples of *n* forecasts (with replacement) from the considered original forecast sample with size *n*

Role of climate modes for skill → stratospheric polar vortex

20% most extreme SPV states — 10% most extreme SPV states

BSS for predicting active life cycle (of all WR) after **strongest SPV states** in DJF (purple) and overall DJF BSS (black)

BSS for predicting active life cycle (of all WR) after **weakest SPV states** in DJF (purple) and overall DJF BSS (black)



Connection between WCB skill and WR skill?

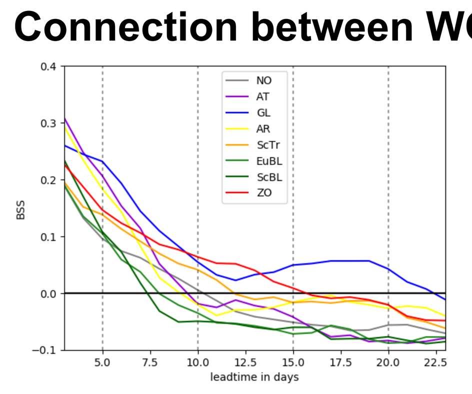


Figure by Jan Wandel: BSS (spatially averaged over Atlantic-European domain) for predicting weekly mean WCB outflow when there is an onset of a specific WR between 5 – 10 days lead time (DJF) → example: BSS for mean WCB outflow between 5 and 12 days (= value at day 5) is substantially lower when the onset of a EuBL or ScBL occurs between day 5 and 10 compared to when the onset of a GL occurs (WCB outflow is detected with a Eulerian logistic regression model developed by **Julian Quinting**)

First conclusions

- **Overall year-round skill (BSS)** for predicting life cycles of 7 Atlantic-European WR **vanishes beyond ~15 days** and **a few days later if model is calibrated flow-dependently**
- However, **skill substantially varies for different flow situations and seasons**, such as for example:
  - Year-round skill for EuBL life cycles vanishes ~5 days earlier than skill for all other WR (including ScBL) → problem of model in forecasting blocking life cycles (see also, e.g., Quinting & Vitart, 2019)
  - Skill in winter vanishes ~5 days later than in other seasons, but this differs strongly between different WR (for example, it is not the case for ScTr and ScBL)
- **Substantial effects from anomalous states of climate modes:** for example, skill vanishes several days later after strong compared to weak winter stratospheric polar vortex states (see also Büeler et al., 2020; Domeisen et al., 2020)
- **Synoptic activity:** skill for weekly mean WCB outflow varies strongly before / during different WR onsets

Outlook

- Analyze **additional skill scores** for (scalar) WR index
- Investigate **effects of further climate modes** on skill
- **Systematically link WR skill to WCB skill** (led by Jan Wandel): Can differences in WCB skill explain differences in skill for different WR, or more precisely, for their onset, maintenance, and decay? → For example: Is the lower skill for EuBL due to a bias in WCB outflow before its onset? In contrast, what is the role of WCB outflow for ScBL, whose skill is significantly higher?

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