A brief practical introduction to the use of climate forecast data

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Climate forecasting for energy– online workshop – 4th December 2020

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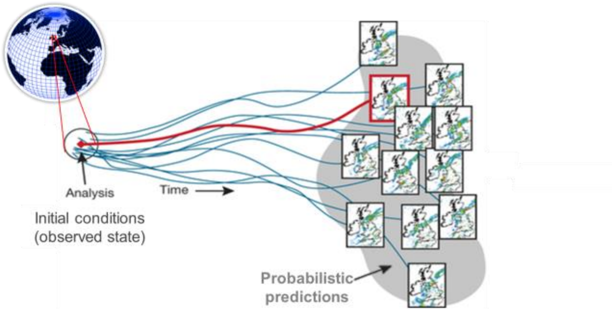
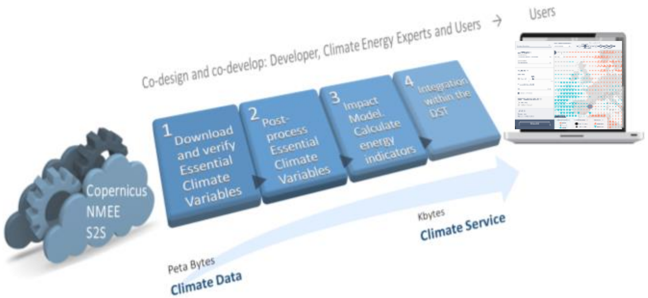
Outlook

- **Climate predictions: Some basic concepts**
  - Time scales
  - Sources of predictability
  - Probabilistic predictions



- **Climate services chain**
  1. Data acquisition
  2. Post-processing
     - Lagged ensembles
     - Bias adjustment
     - Forecast quality assessment
  3. Impact models
  4. Decision Support Tool



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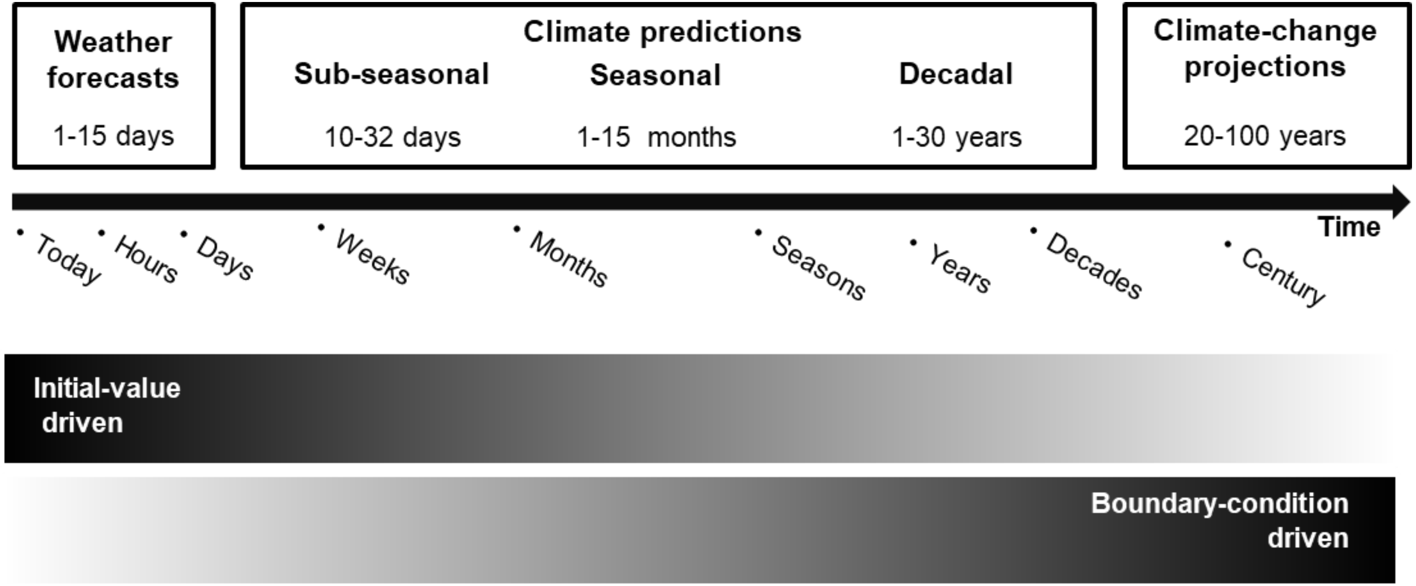
Climate time scales



Adapted from: Meehl et al. (2009)

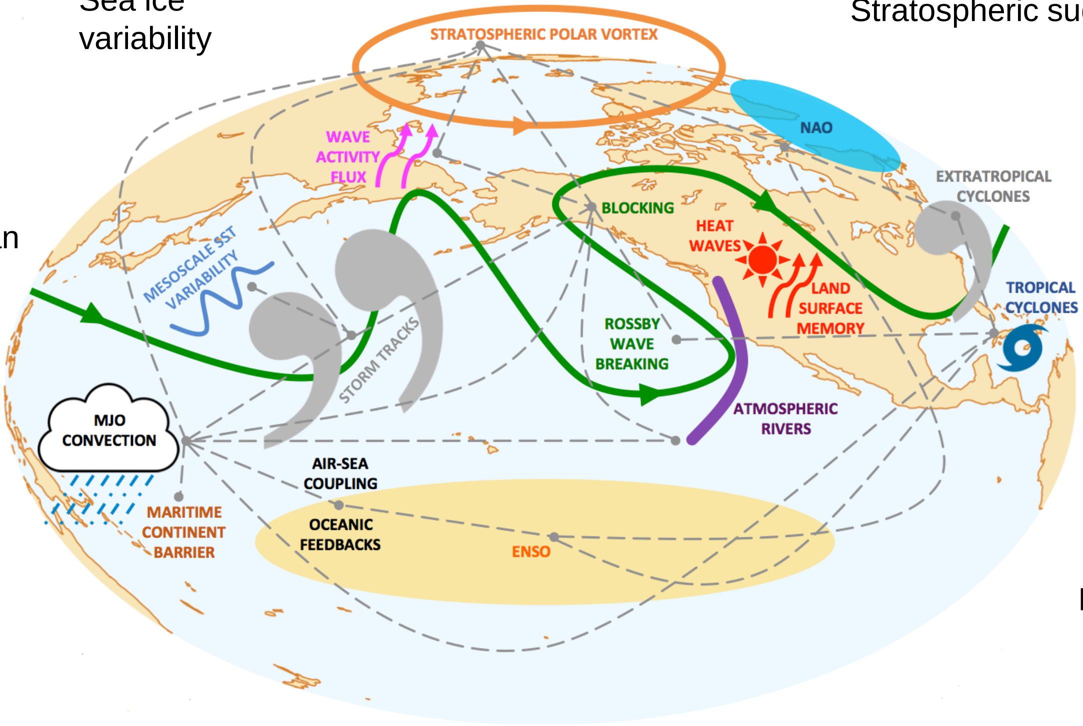
Sources of predictability

Sea ice variability

Stratospheric sudden warmings

Anomalies in surface temperature in the ocean

Land surface conditions (temperature/soil moisture)



Madden Julian Oscillation (MJO)

ENSO

Credit: Andrea Lang (U. of Albany)

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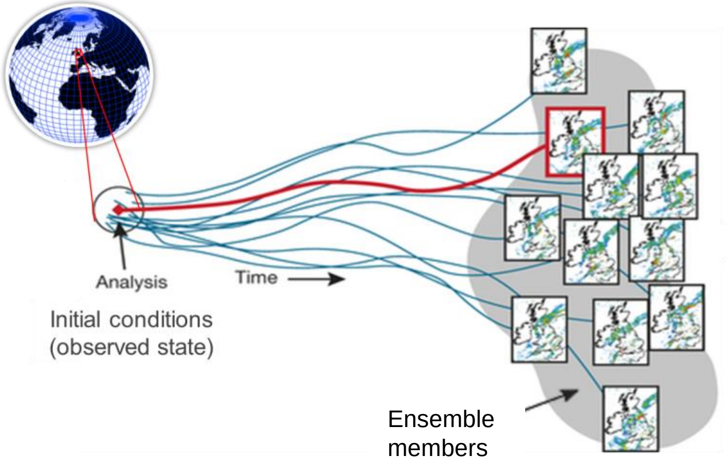
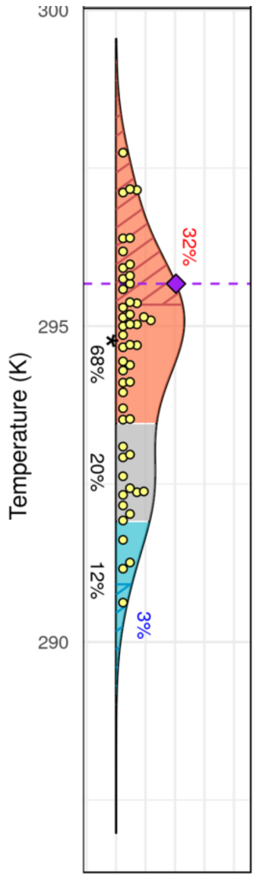
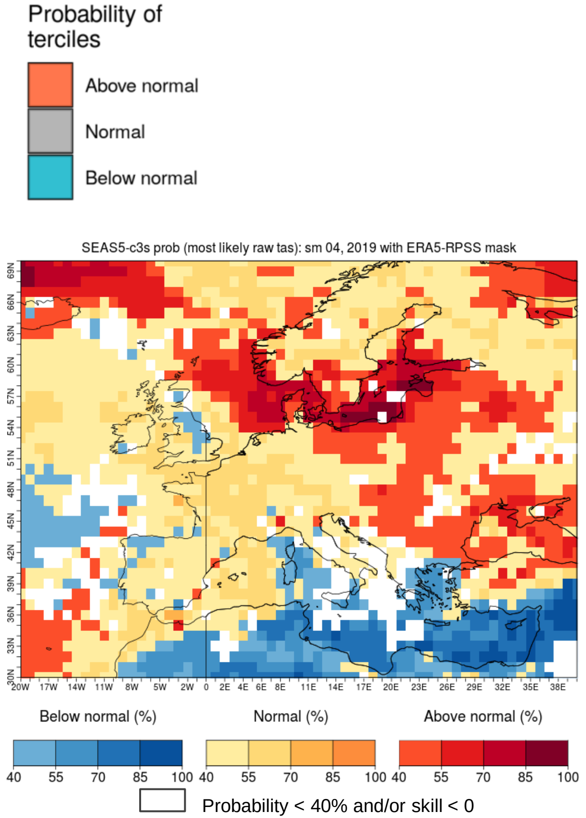
Probabilistic predictions



BIAS ADJUSTMENT

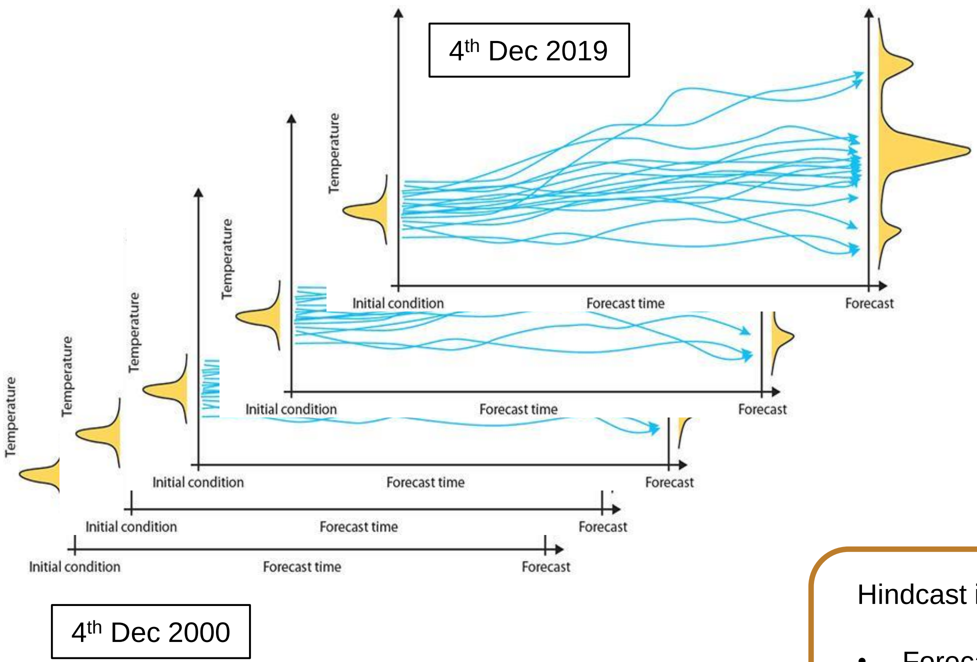
FORECAST QUALITY ASSESSMENT



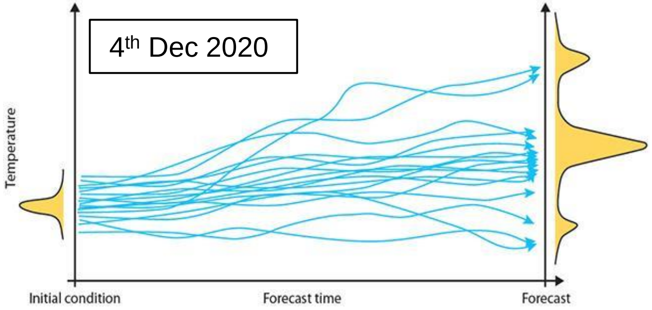


Forecast and hindcasts

Hindcasts



Forecast



Hindcast is used for:

- Forecast quality assessment
- Bias adjustment

Adapted from: https://www.ecmwf.int/

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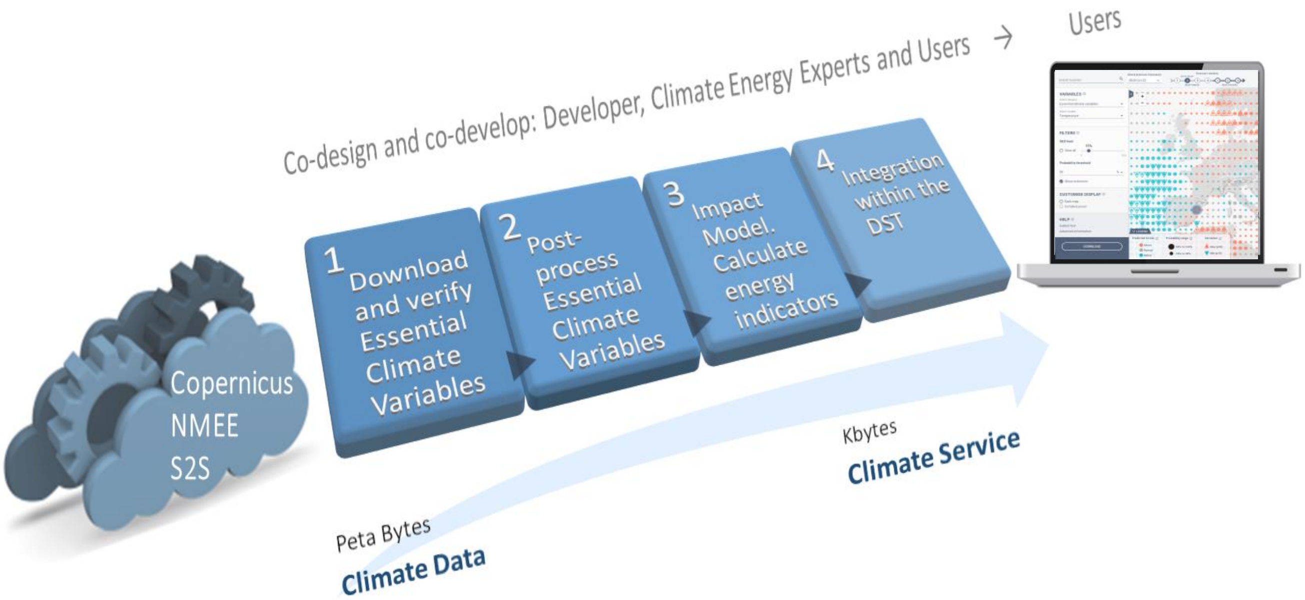
Climate services chain



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1. Data acquisition: Sources

SUBSEASONAL PREDICTIONS

- **S2S Prediction Project** (http://www.s2sprediction.net/)
  - Data base: Collection of 11 systems for research
    https://apps.ecmwf.int/datasets/data/s2s/levtype=sfc/type=cf/
    http://s2s.cma.cn/index
  - S2S Real-time Pilot Initiative (16 projects involved)

Subseasonal-to-Seasonal S2S Prediction Project

- **The Subseasonal Experiment (SubX):**

  Collection of 7 North American and Canadian systems in real time

  http://iridl.ldeo.columbia.edu/SOURCES/.Models/.SubX/

- **NOAA NCEP CFSv2**

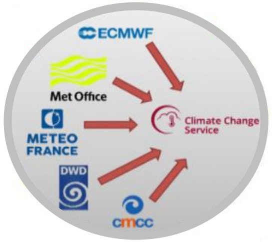
  https://www.ftp.ncep.noaa.gov/

SEASONAL PREDICTIONS

- **Copernicus Climate Change Services (C3S)**

  7 systems (ex. ECMWF SEAS5)

  https://cds.climate.copernicus.eu/api-how-to/



Climate Change Service

OBSERVATIONS / REANALYSIS PRODUCT

- **Copernicus Climate Change Services (C3S)**

  ERA-5

  https://cds.climate.copernicus.eu/api-how-to/

S2S predictions systems

Forecast

Hindcasts

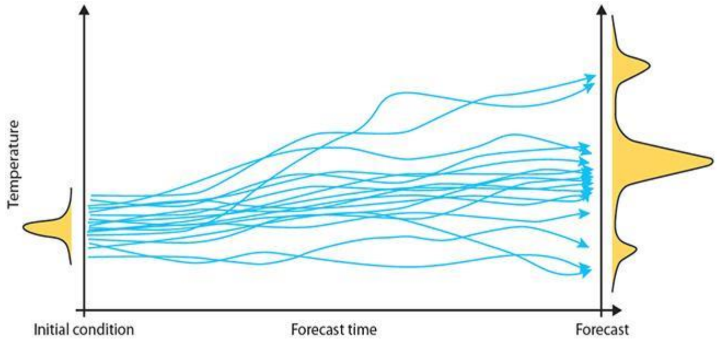
Status on 2020-10-27	Time range	Resolution	Ens. Size	Frequency	Re-forecasts	Rfc length	Rfc frequency	Rfc size
BoM (ammc)	d 0-62	T47L17	3*11	2/week	fixed	1981-2013	6/month	3*11
CMA (babj)	d 0-60	T266L56	4	2/week	on the fly	past 15 years	2/week	4
CNR-ISAC (isac)	d 0-32	0.75x0.56 L54	41	weekly	fixed	1981-2010	every 5 days	5
CNRM (lfpw)	d 0-47	T255L91	25	weekly	fixed	1993-2017	every 7 days	10
ECCC (cwao)	d 0-32	39 km L45	21	weekly	on the fly	1998-2017	weekly	4
ECMWF (ecmf)	d 0-46	Tco639/319 L91	51	2/week	on the fly	past 20 years	2/week	11
HMCR (rums)	d 0-61	1.1x1.4 L28	20	weekly	on the fly	1985-2010	weekly	10
JMA (rjtd)	d 0-33	Tl479/Tl319L100	50	weekly	fixed*	1981-2010	2/month	13
KMA (rksl)	d 0-60	N216L85	4	daily	on the fly	1991-2016	4/month	3
NCEP (kwbc)	d 0-44	T126L64	16	daily	fixed	1999-2010	daily	4
UKMO (egrr)	d 0-60	N216L85	4	daily	on the fly	1993-2016	4/month	7

Subseasonal-to-Seasonal S2S Prediction Project

https://confluence.ecmwf.int/display/S2S/Models

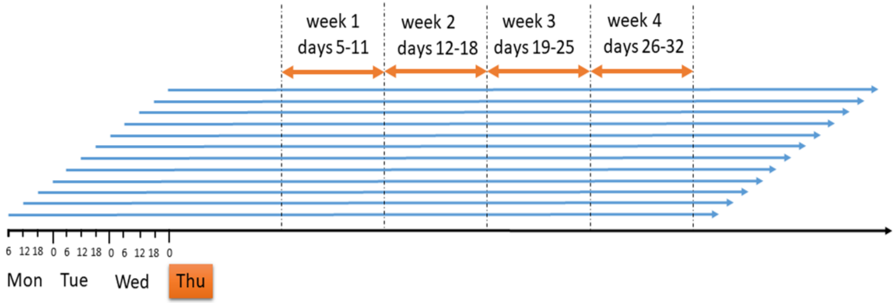
2. Post-processing: lagged ensembles

- **Burst ensemble**: Ensemble members are initialised at the same time with slightly different initial conditions



Source: https://www.ecmwf.int

- **Lagged ensembles**: Ensemble of forecasts from the same model initialised at different times but verifying at the same time.



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2. Post-processing: Bias adjustment and calibration

Raw model output at these timescales has systematic biases that need to be corrected

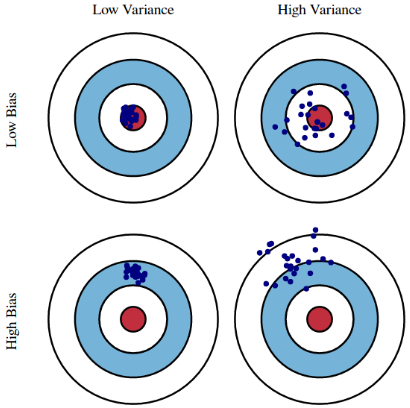

Fig. 1 Graphical illustration of bias and variance.

Source: Eric Stokes

- **Bias adjustment techniques to remove model errors and produce reliable and well calibrated forecasts (forecast distribution to have similar statistical properties to the reference)**
    - **Simple bias adjustment**
    - **Variance Inflation (Calibration)**
    - **Empirical quantile mapping**
    - **Machine learning**

R package:

https://CRAN.R-project.org/package=CSTools

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Bias adjustment and calibration

- Bias are lead-dependent -> Corrections need to be lead dependent
- Reference climatology -> The short hindcast length and fewer ensemble members can limit the representativeness of the climate distribution

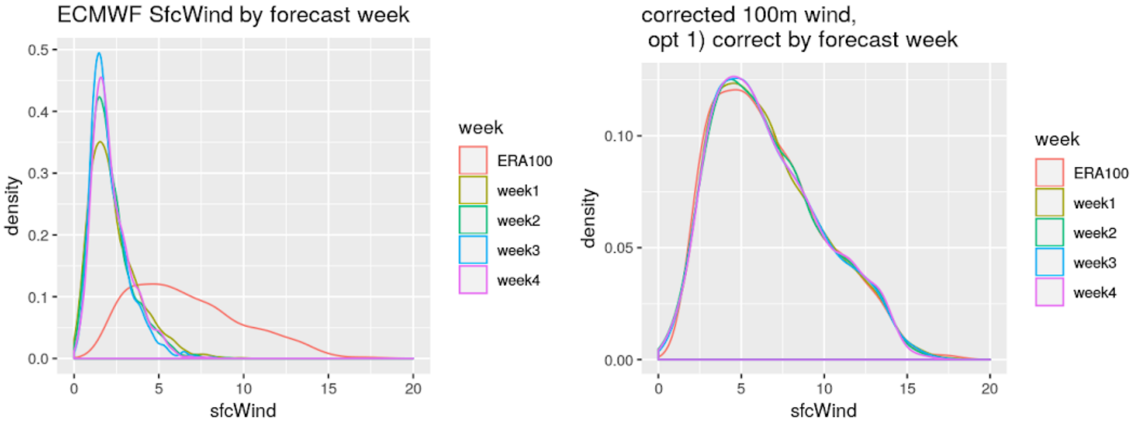

Figure: ECMWF sfcWind for for start date 20161222 and location (46.5 N ,6 E)

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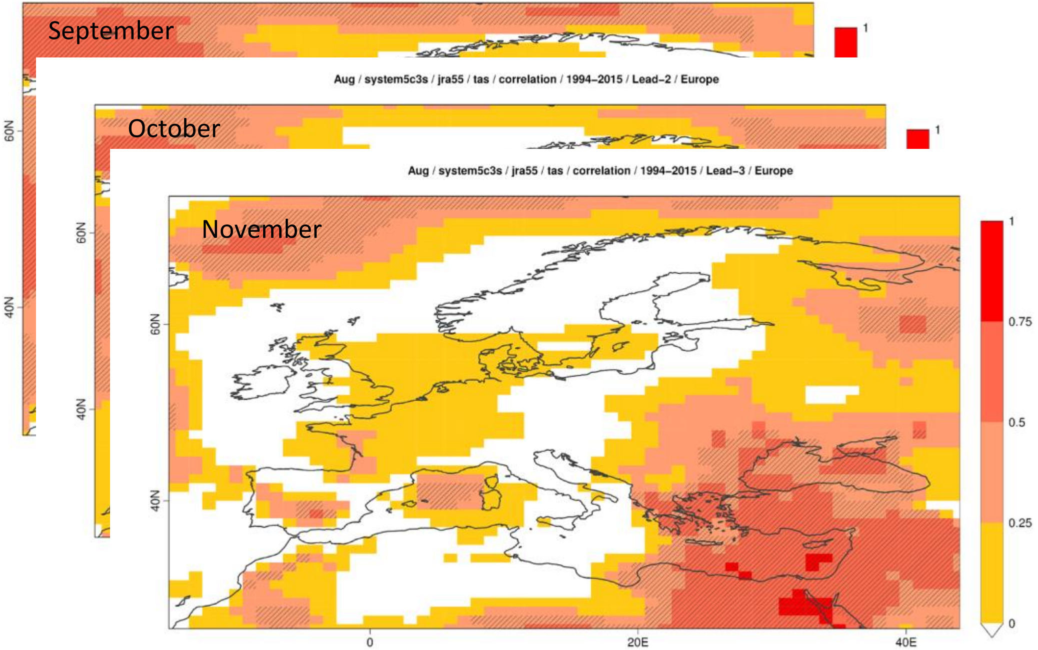
2. Post processing: Forecast quality assessment

The quality (or skill) of climate predictions varies with:

REGION

MONTH/SEASON

TEMPORAL HORIZON



SKILL SCORES

- Relative measure of the **quality a system's forecasts** for the time period and location
- Typically measured on the system's **hindcast**
- For **tercile probabilities**: Fair Ranked probability skill score (fair RPSS)
- For **extremes** (p10, p90): Fair Brier Skill Score (fair BSS)

Skill > 0 → **In the long term, there is an added value of using climate prediction over the use of mean past observations.**

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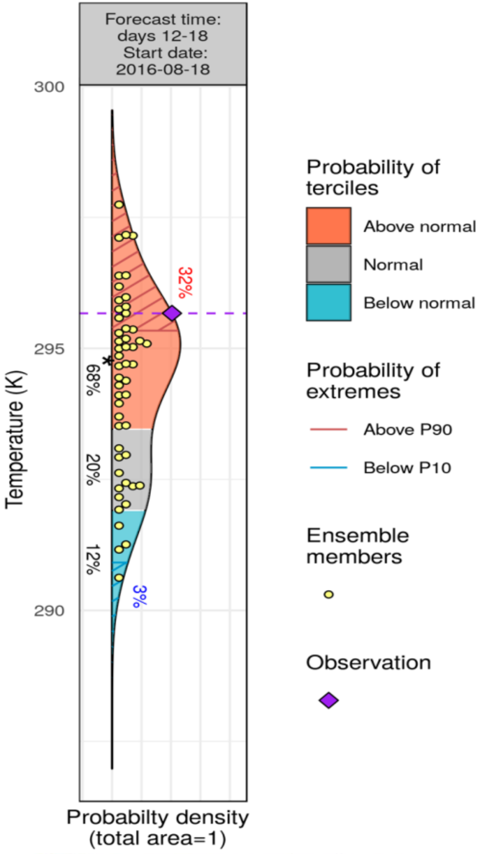
2. Post processing: Skill scores



- Ranked Probability Score (RPS)

$$RPS = \sum_{m=1}^{J}\left[\left(\sum_{j=1}^{m} y_j\right) - \left(\sum_{j=1}^{m} o_j\right)\right]^2$$

Forecasts: $y_1 = 0.12$ $y_2 = 0.20$ $y_1 = 0.68$
Observations: $o_1 = 0$ $o_2 = 0$ $o_3 = 1$

- Ranked probability Skill Sore (RPSS)

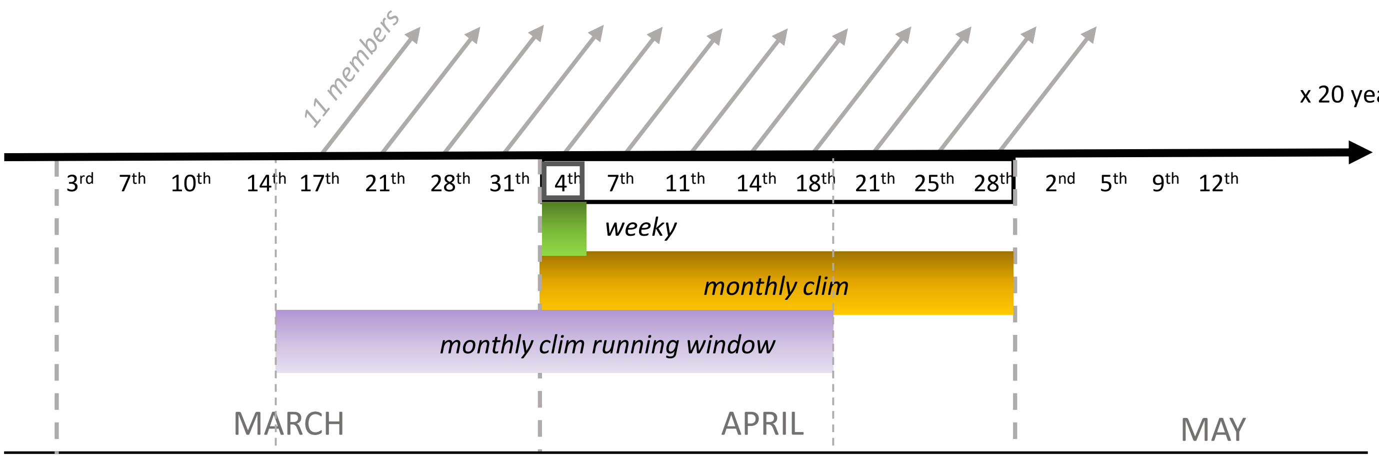
Relative measure of the quality a system's forecasts compared to a **reference** (e.g. climatological forecast or persistence)

$$Skill\ score = \frac{S_{fcst} - S_{ref}}{S_{perf} - S_{ref}} = 1 - \frac{S_{fcst}}{S_{ref}} \begin{cases} SS > 0 & \text{Forecast is better than reference} \\ SS < 0 & \text{Forecast is worse than reference} \end{cases}$$

R packages:

SpecsVerification (https://cran.r-project.org/web/packages/SpecsVerification/index.html)
Easyverification (https://cran.r-project.org/web/packages/easyVerification/index.html)
s2dv (https://cran.r-project.org/web/packages/s2dv/index.html)

Choices in sample size for the skill score and definition of climatology



SAMPLE SIZE FOR SKILL SCORE:

- Single start date: 1 start date, 20 years
- Monthly start dates: 8/9 start dates, 20 years

DEFINITION OF CLIMATOLOGY:

Weekly: 1 start date, 20 years
Monthly: All start dates in a calendar month, 8/9 start dates, 20 years
Monthly running window: Running window with 4 start dates before and after the target week, 9 start dates, 20 years

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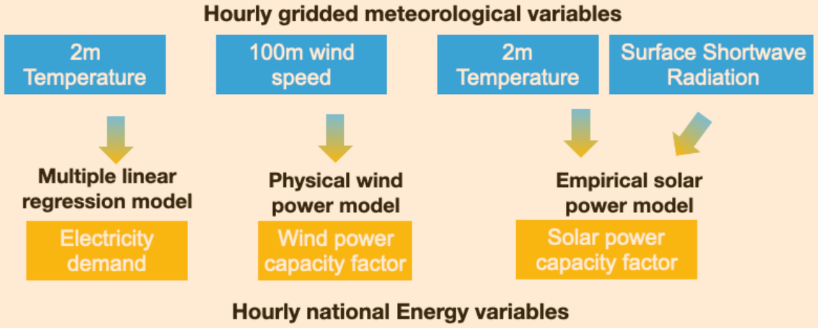
Manrique-Suñén et al. (2020)

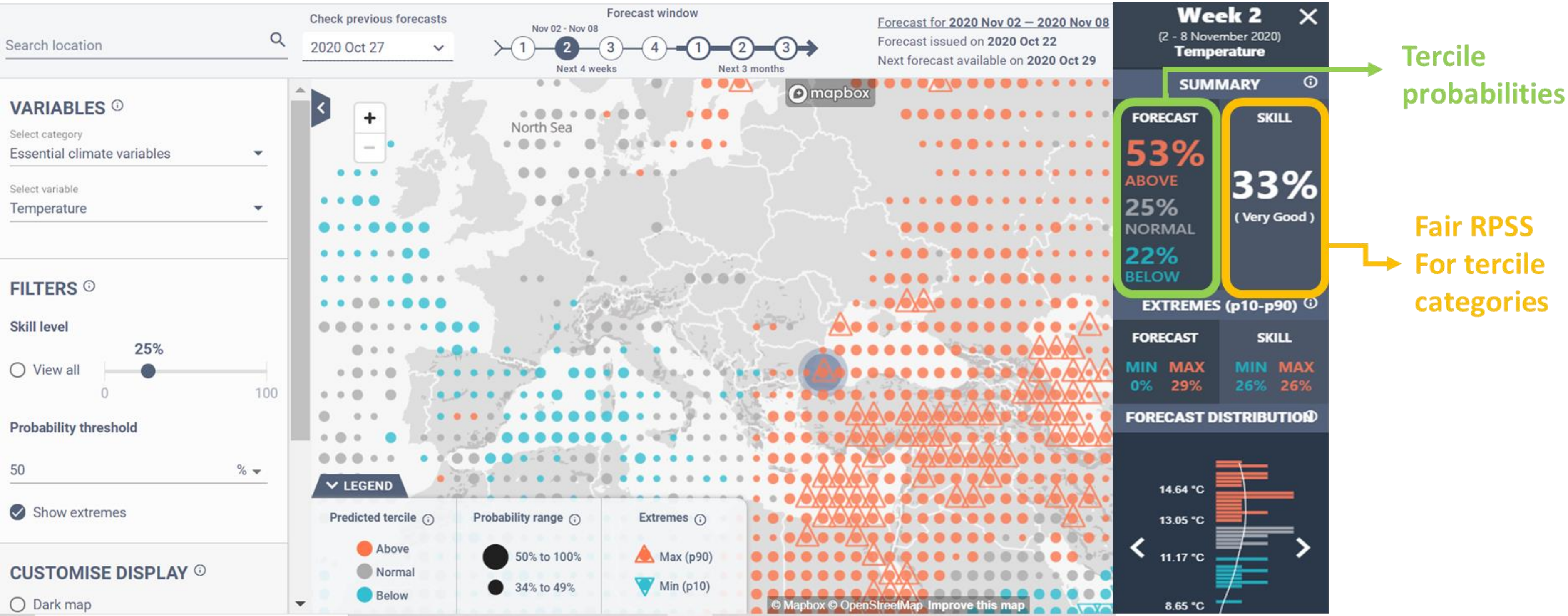
3. Impact models

- Conversion from essential climate variables to tailored variables

Addressed in next talk by Hannah Bloomfield



4. Integration within the DST



www.s2s4e.eu

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Take home messages

- Climate models can provide **climate predictions** for the next weeks and months
- Climate predictions are not like weather forecasts, they provide information on **probabilistic averaged statistical properties** (e. g. how likely it is that the average temperature next week/month will be above/normal/below average)
- Uncertainty in climate predictions due to random errors -> **Ensemble forecasts**
- Climate predictions have systematic errors that can be corrected -> **Bias adjustment**
- Forecast quality assessment has to be conducted to associate a level of **skill** to a certain forecast. Skill varies with location, time of the year and temporal horizon.

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Thank you

Public reports of the project are available for download on the S2S4E website: www.s2s4e.eu

Project coordinator: Albert Soret, Barcelona Supercomputing Center
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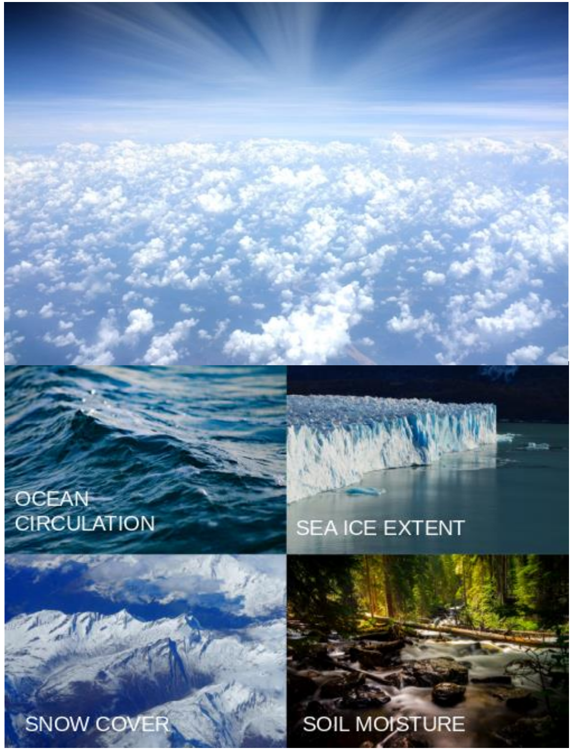
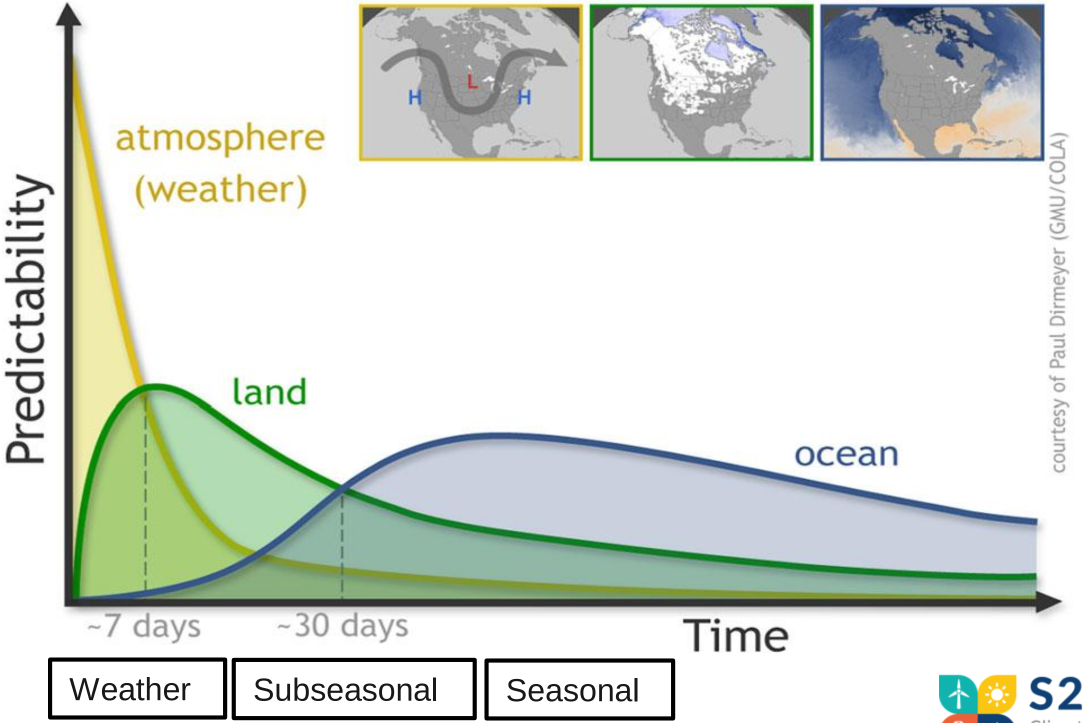
Earth components and sources of predictability





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