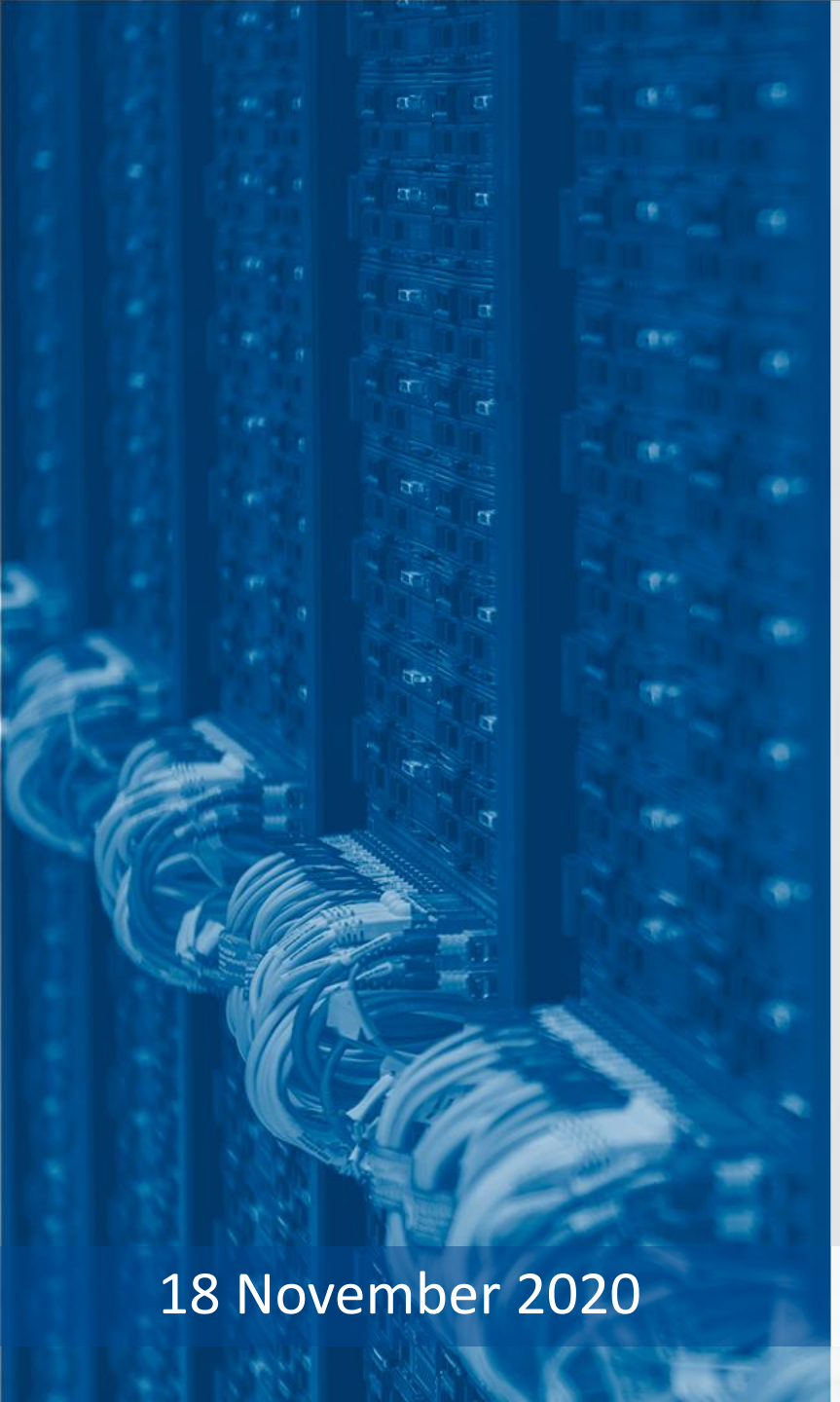

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Choices in the verification of S2S forecasts

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18 November 2020

2020 International Verification Method Workshop Online

Outlook

1. S2S Predictions and Climate Services
2. Challenges in verification of S2S predictions
3. Implications for skill scores

Manrique-Suñén, A., N. Gonzalez-Reviriego, V. Torralba, N. Cortesi, and F. J. Doblas-Reyes, 2020: Choices in the Verification of S2S Forecasts and Their Implications for Climate Services. *Mon. Wea. Rev.*, **148**, 3995–4008, https://doi.org/10.1175/MWR-D-20-0067.1.

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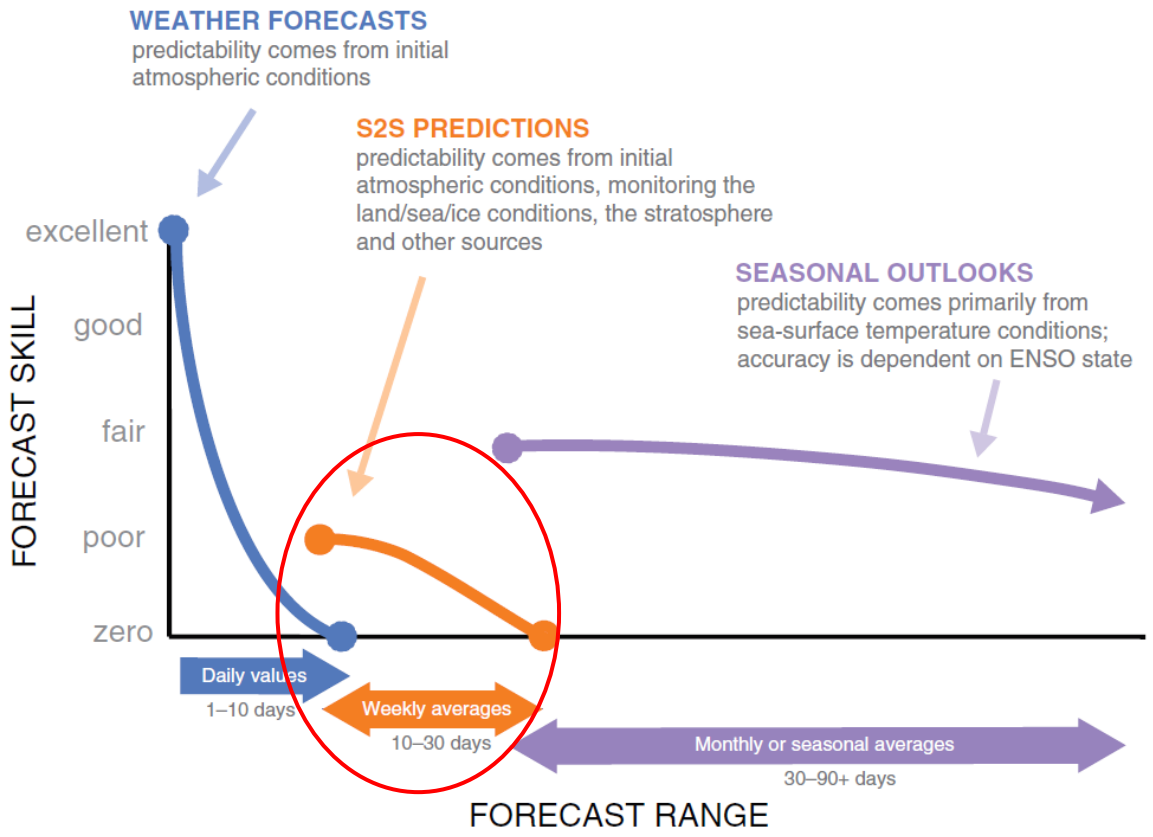
S2S Predictions and Climate Services



Qualitative estimate of forecast skill based on forecast range from short-range weather forecasts to long-range seasonal predictions, including potential sources of predictability. Relative skill is based on differing forecast averaging periods. (Source: White et al., 2017)

- S2S forecast range corresponds to timing useful for many societal sectors


Renewable energy


Agriculture

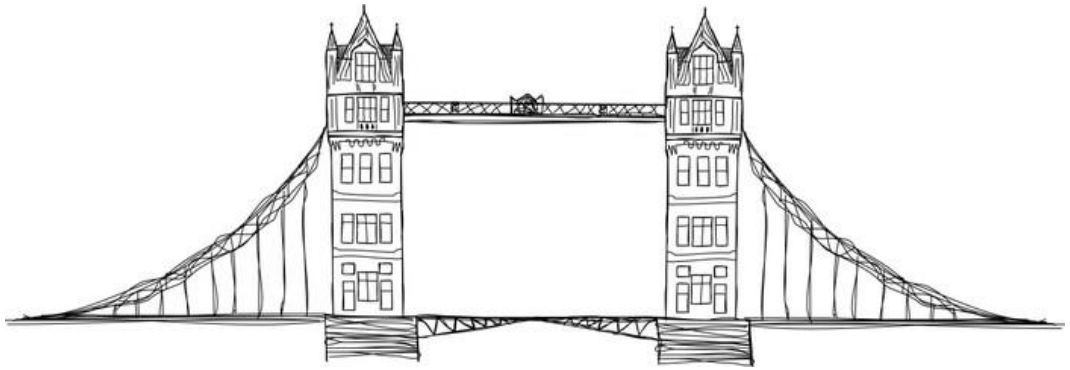

Disaster risk preparedness


Retail

- The uptake of S2S predictions into actionable decisions comes with many challenges

Challenges of climate services

- **User**: How much energy will I produce next month?



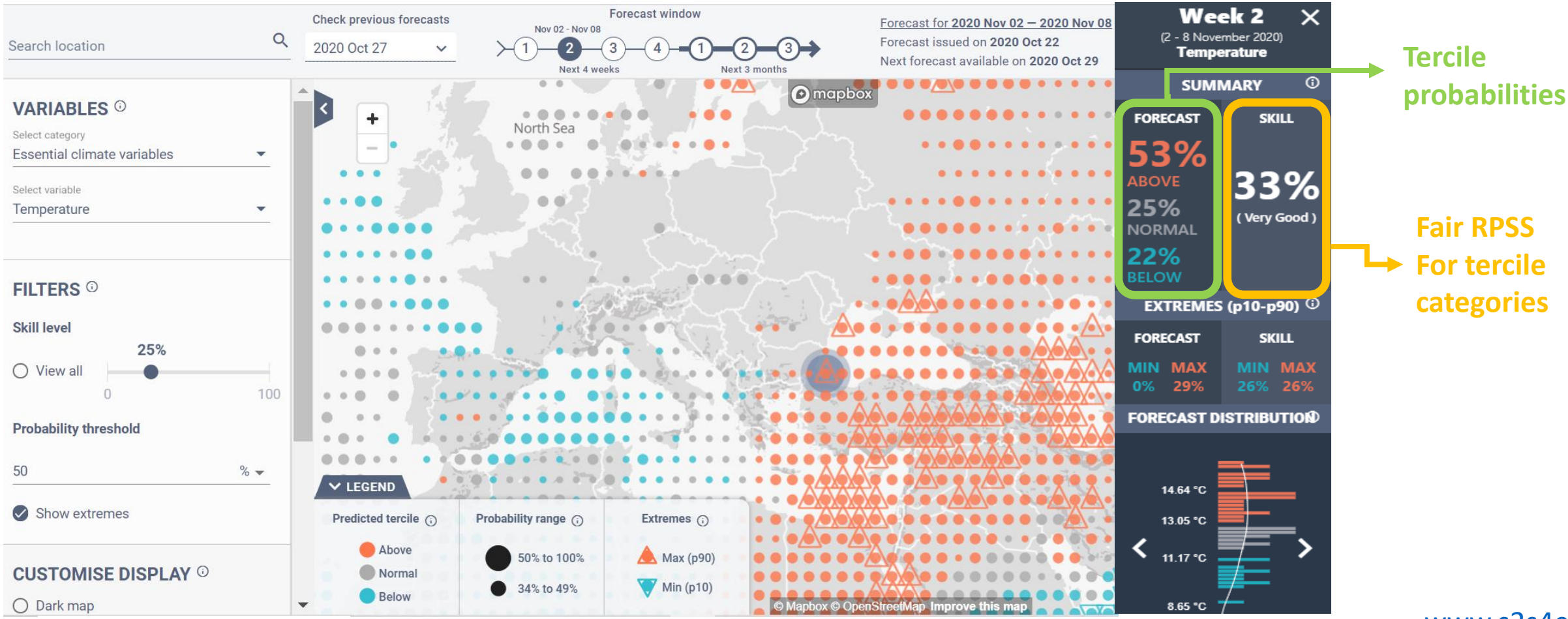
- **Scientist**: Probabilistic information, skill assessment, bias adjustment, etc.

1. The **probabilistic** nature of climate predictions
   - Convey probabilistic information in a clear way (i.e. most likely tercile map)
   - Convert a probability in to an actionable decision

2. Expectations on **quality** of predictions to increase usability:
   - Provide predictions with associated information on skill
     - Skill scores, not only how good, but home much better than a reference (i.e. RPSS)
     - Seasonal and regional dependence of skill

Need for a **probabilistic verification**

Example of a climate service: S2S4E Project Decision Support Tool



www.s2s4e.eu

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Challenges in the verification of S2S predictions

- **Heterogeneity** in the subseasonal systems
  - Initializations
  - Hindcast periods
  - Ensemble members

Forecast	Hindcast
✗ Fewer years of data	✓ More years of data
✗ Different system version	✓ Fixed system version
✓ More ensemble members	✗ Fewer ensemble members

- **Limited data** (even in hindcast)
  - Sample size for probabilistic skill scores
  - Definition of the climatology
  - Application of bias adjustment

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	TI479/TI319L100	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

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

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Verification setup in our study

- ECMWF-Ext-ENS 2016 System
- Hindcast period: 1996-2015, 11 members
- Reference: ERA- Interim reanalysis
- Target forecast weeks:

Startdate
e.g. Monday

- Bias adjustment: Simple bias correction

$$y_{ij} = \left(x_{ij} - \bar{x}\right)\frac{\sigma_{ref}}{\sigma_e} + \bar{o}$$

y_{ij} adjusted forecast, x_{ij} j: member, i: year

- Fair RPSS for tercile categories / Fair CRPSS

$$SS = \frac{S_{fcst} - S_{clim}}{S_{perf} - S_{clim}} = 1 - \frac{S_{fcst}}{S_{clim}}$$

SS > 0 Forecast is better than climatology

SS < 0 Forecast is worse than climatology

CHOICES:

- Sample size for skills cores: 2 options
- Definition of climatology: 3 options

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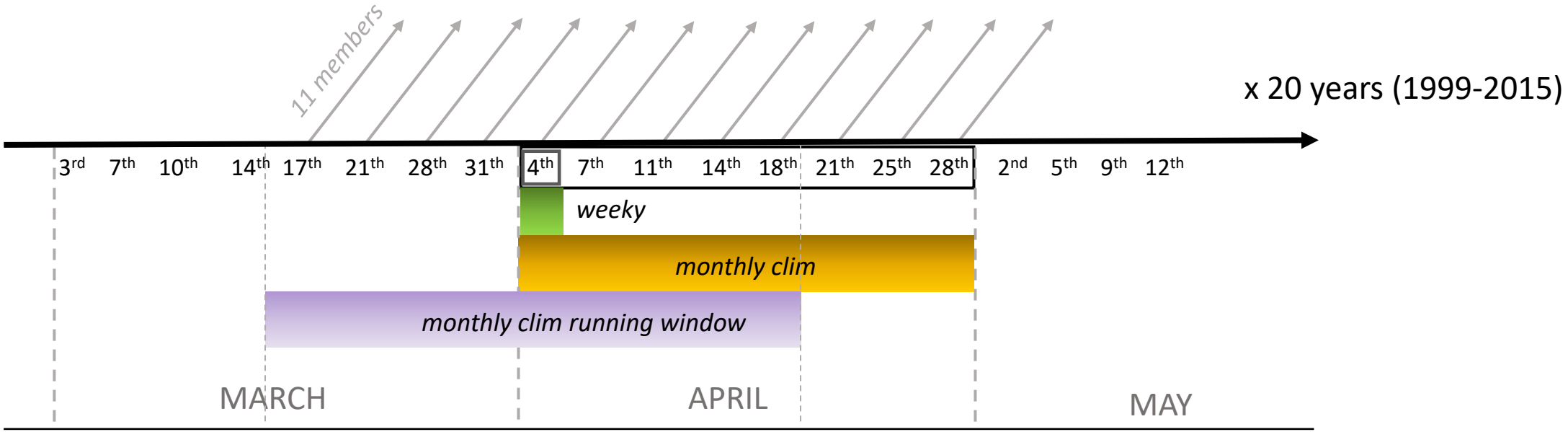
Choices in sample size for the skill score and definition of climatology



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

Climatology used for:
- Reference for anomalies
- Benchmark forecast
- Bias adjustment

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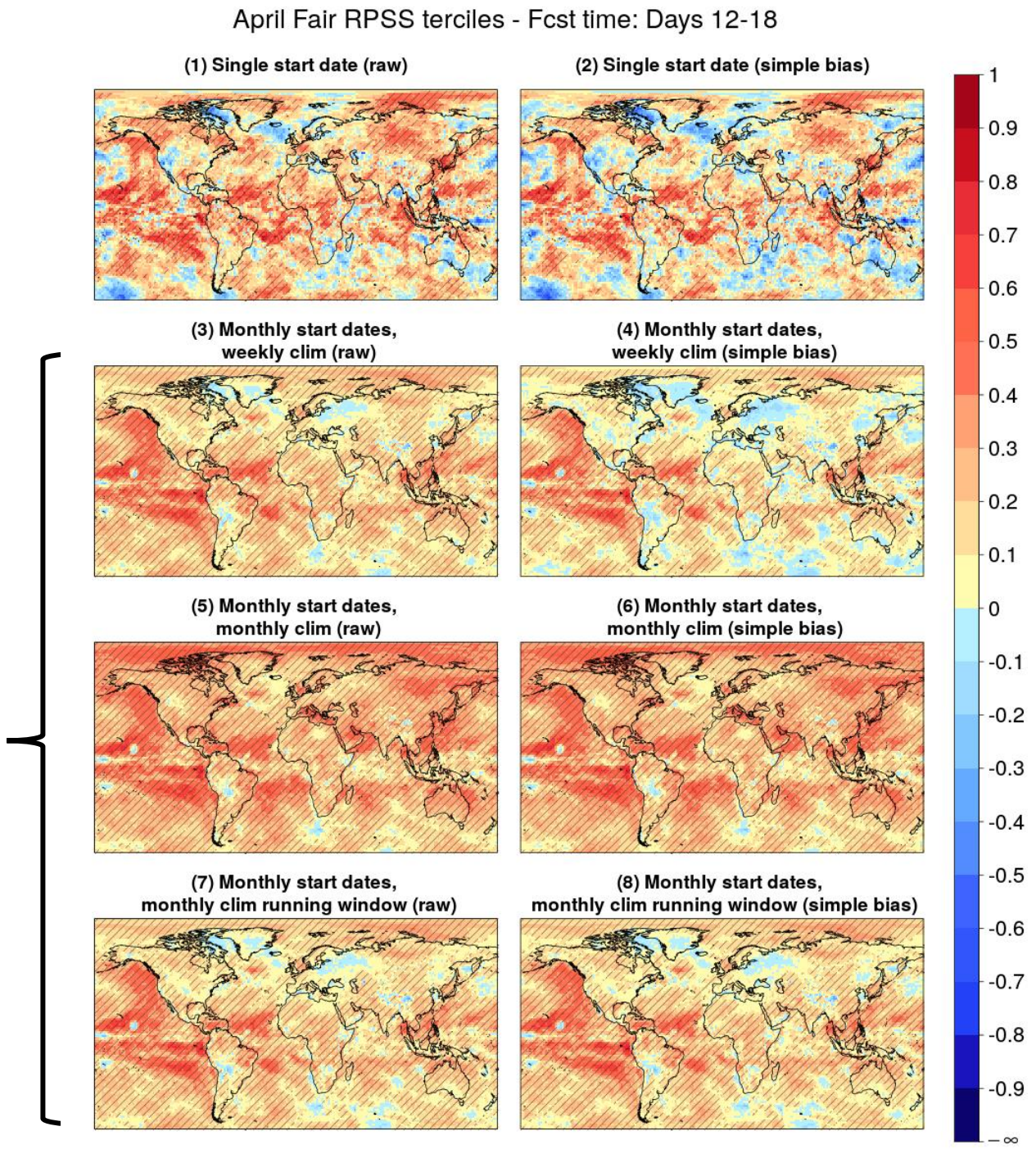
8 Verification setups

Methodology	Skill score	Climatology	Bias correction
1	**Single start date** (1 start date)	**Weekly** (1 start date)	Raw
2	**Single start date** (1 start date)	**Weekly** (1 start date)	Simple bias adjustment
3	**Monthly** (concatenating 8/9 start dates)	**Weekly** (1 start date)	Raw
4	**Monthly** (concatenating 8/9 start dates)	**Weekly** (1 start date)	Simple bias adjustment
5	**Monthly** (concatenating 8/9 start dates)	**Monthly** (8/9 start dates)	Raw
6	**Monthly** (concatenating 8/9 start dates)	**Monthly** (8/9 start dates)	Simple bias adjustment
7	**Monthly** (concatenating 8/9 start dates)	**Monthly running window** (9 start dates)	Raw
8	**Monthly** (concatenating 8/9 start dates)	**Monthly running window** (9 start dates)	Simple bias adjustment

Same hindcast, 4 ways to perform forecast quality assessment (fair RPSS)
Var: 2m temperature



Concatenating startdates
8/9*20 yrs
data-obs pairs

Single start date:
Too noisy to compute skill score (20 data-obs pairs)

Weekly climatology
Simple bias adjustment degrades skill

Monthly climatology
Apparently good skill but ...
(... next slide)

Monthly climatology running window
More robust climatology for bias adjustment – less degradation

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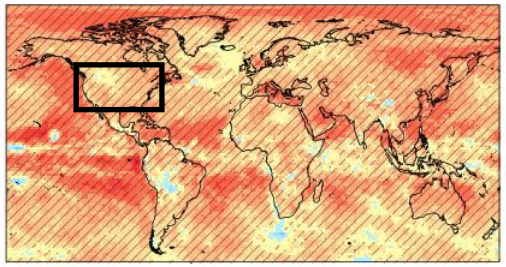
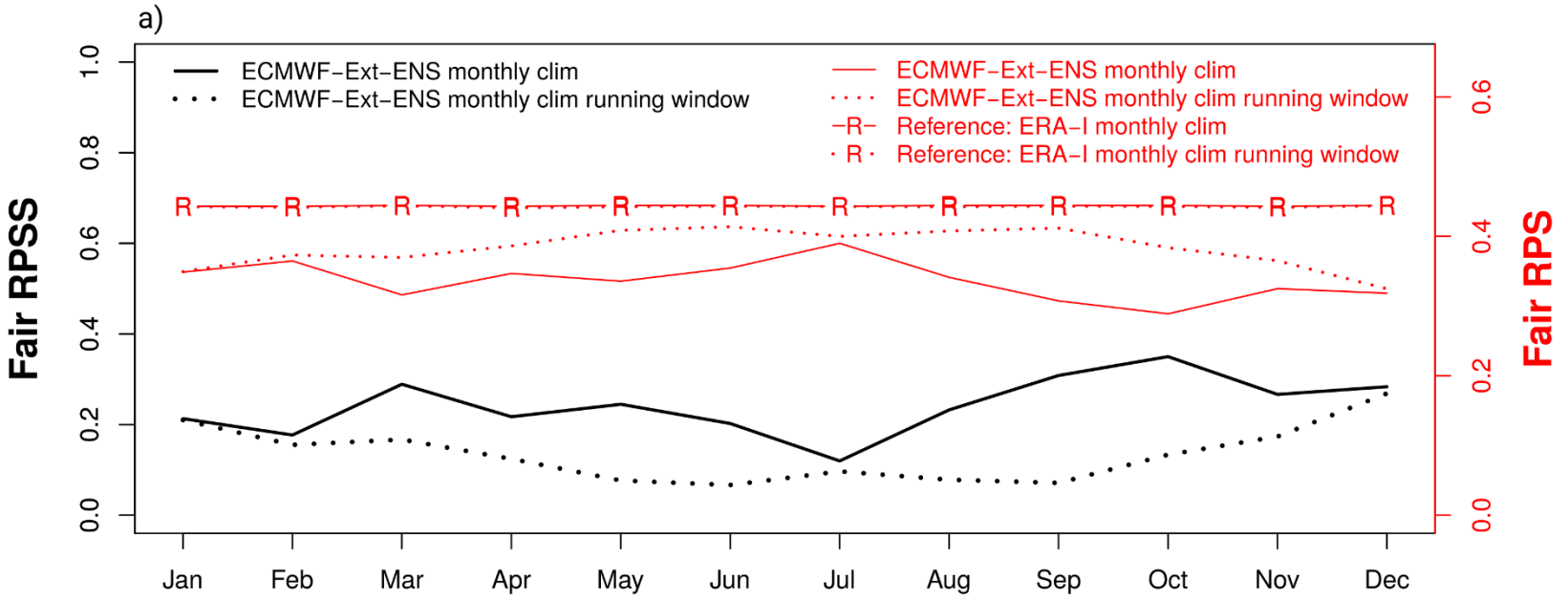
Annual evolution for a region in North America, for forecast days 12-18

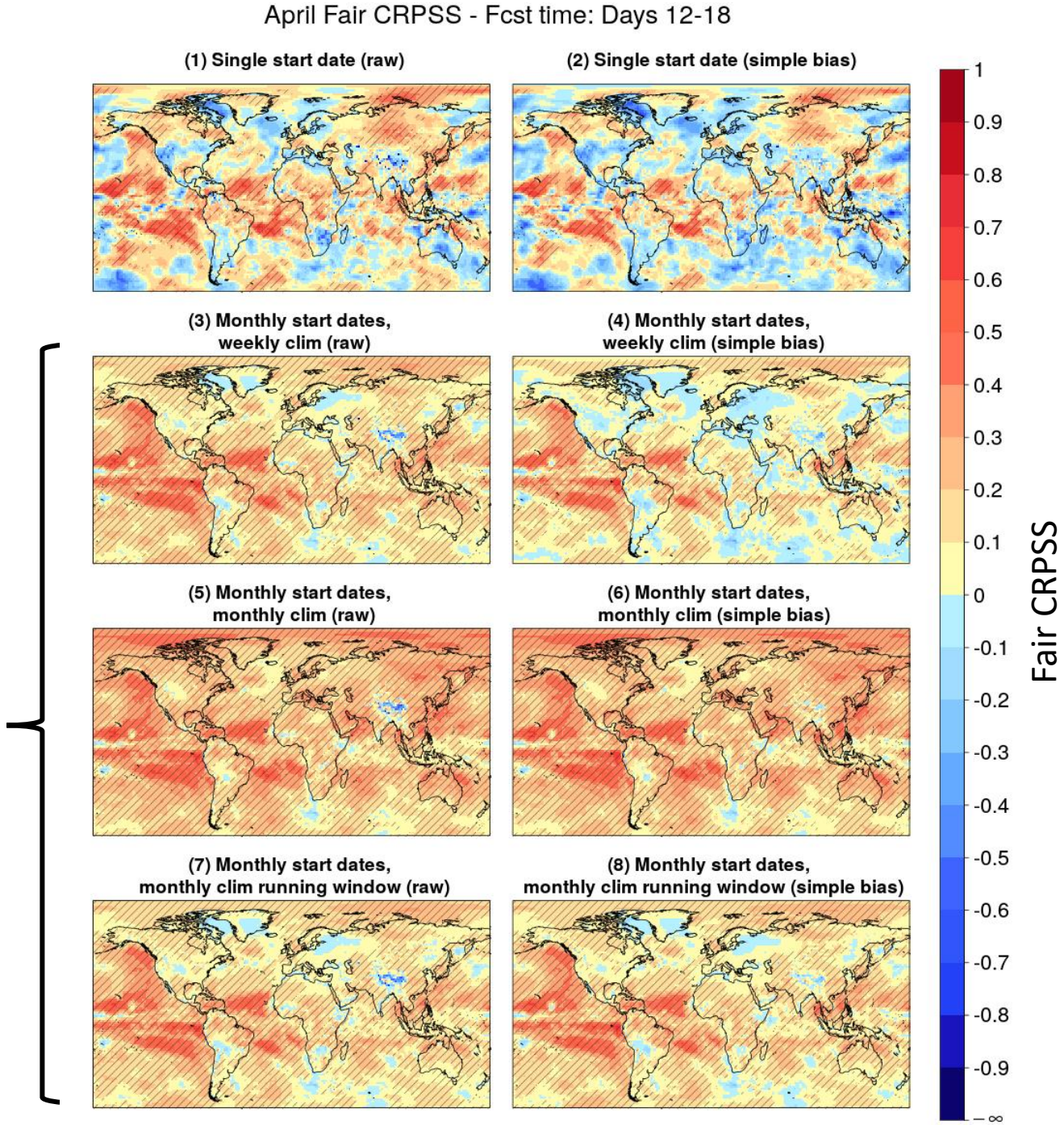




$$SS = 1 - \frac{S_{fcst}}{S_R}$$

Same hindcast, 4 ways to perform forecast quality assessment (fair CRPSS)
Var: 2m temperature

Concatenating startdates
8/9*20 yrs
data-obs pairs



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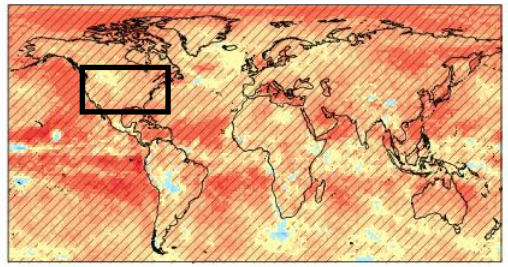

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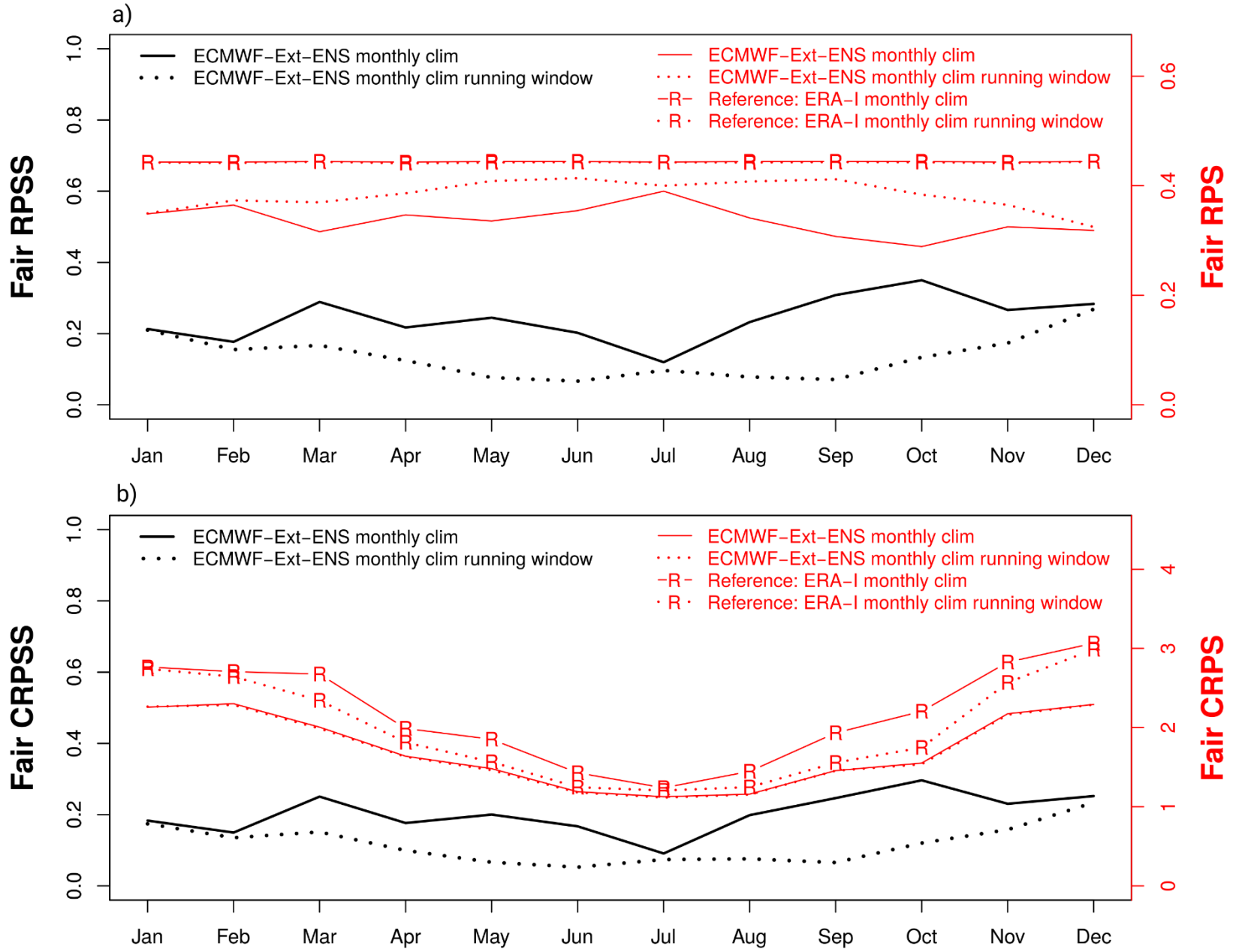

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Conclusions

- SAMPLE SIZE: One single start date is not enough for a robust skill score with a 20 years hindcast. Concatenating several start dates is a good approach to increase the sample size and produce robust skill scores

- BIAS ADJUSTMENT: The reference climate distribution to bias adjust weekly averages should span a longer period than one week

- CLIMATOLOGY: The aggregation period to compute the climatology should be centered around the target week. Using a calendar month to compute climatology can lead to “artificial skill” when computing skill scores.

--> It is fundamental to carefully document all verification procedures !

Thank you, Questions?

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