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II. Országos HUN-REN Cloud Találkozó | 2025.11.13. | Budapest

#### Acknowledgement

My visit at the **Bjerknes Centre for Climate Research**, Bergen, Norway was funded by a research mobility stipend of the *Hungarian University of Agriculture and Life Sciences* (MATE) in the framework of the **Pannónia Scholarhip** programme. I was also supported by the University's **Research Excellence Programme** (KKP).



**BIG THANKS, MATE!** 

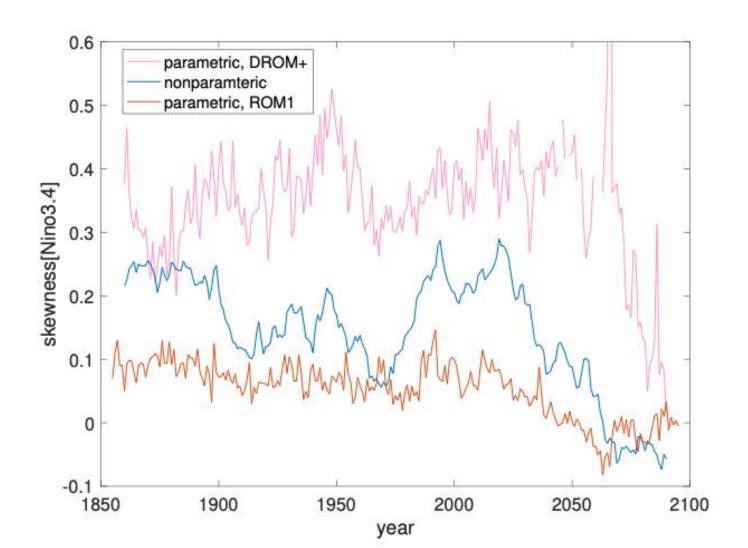
## Motivation: a study of the forced change of ENSO skewness (asymmetry)

Model: CESMv2

Initial condition Large Ensemble data: CESM2-LE (Rodgers et al. ESD 2021)

ROM1 underestimates CESM2 skewness

CESM2 underrepresents true ENSO skewness



#### **Recharge Oscillation Models (ROMs)**

ROM1

$$\frac{dT}{dt} = (a_{1,TT} + A\cos(\Omega t - \Phi))T + a_{1,Th}h + a_{2,TT}T^2 + \sqrt{2D_T}(1 + bT)\xi_T,$$
(1a)

$$\frac{\mathrm{d}h}{\mathrm{d}t} = a_{1,hT}T + a_{1,hh}h + \sqrt{2D_h}\xi_h,\tag{1b}$$

DROM+ 
$$(i = 1, 2)$$
  $d = 1, ..., D$ 

$$\frac{\mathrm{d}x_i}{\mathrm{d}t} = a_i^j x_j + f_{il}(x_j, t; \hat{c}_i^l) + \sigma_i^{\xi} (1 + b_i x_i) \xi_i(t), \tag{2}$$

$$x_{i(n+1)} \approx a_i^{jd} x_{j(n-d)} + f_{il}(x_{jn}; c_i^l) + \sqrt{2D_i \Delta t} (1 + b_i x_{in}) \xi_{in},$$
 (3)

#### **XROM** (i = 1, ..., 10) $\xi_i(t)$ are red noise (**d** = **0**)

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Article Published: 26 June 2024

#### Explainable El Niño predictability from climate mode interactions

Sen Zhao, Fei-Fei Jin ☑, Malte F. Stuecker, Philip R. Thompson, Jong-Seong Kug, Michael J. McPhaden, Mark A. Cane, Andrew T. Wittenberg & Wenju Cai

*Nature* **630**, 891–898 (2024) | Cite this article

11k Accesses | 48 Citations | 159 Altmetric | Metrics

#### "Climate mode interaction" = Teleconnection

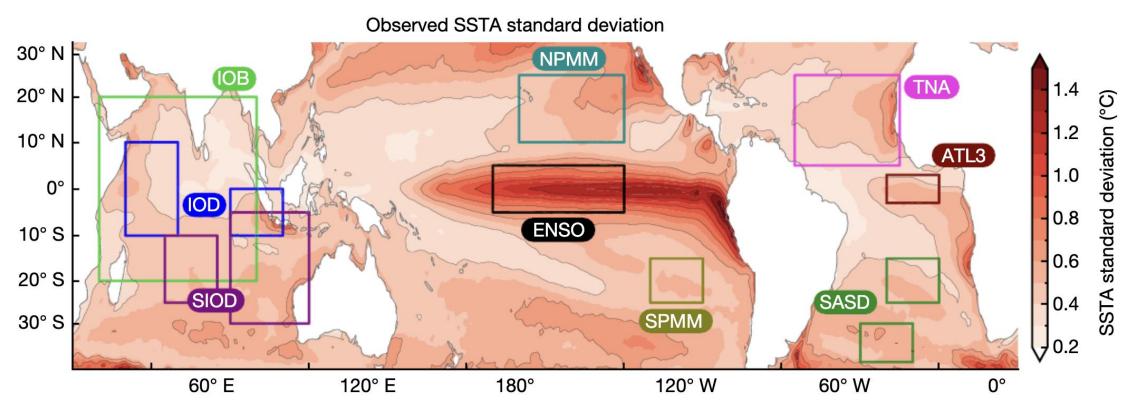
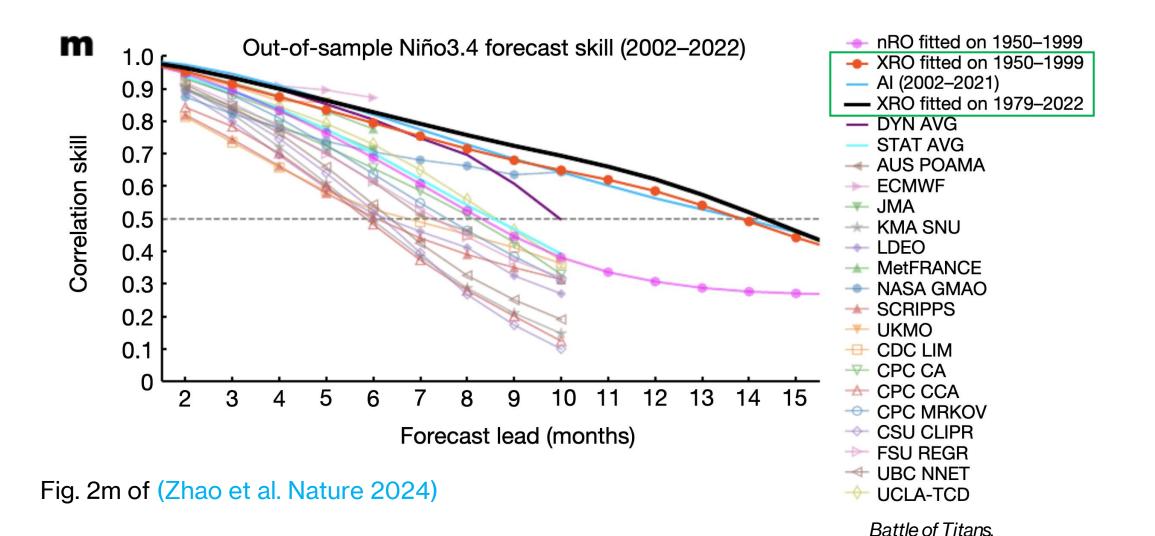


Fig. 1a of (Zhao et al. Nature 2024)

#### Zhao et al. (Nature 2024) vs Ham et al. (Nature 2019)



#### **XDROM+**

npj | climate and atmospheric science

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nature > npj climate and atmospheric science > articles > article

Article Open access Published: 22 July 2025

### **Enhanced El Niño predictability from climate mode interactions**

<u>Tamás Bódai</u> ⊠

npj Climate and Atmospheric Science 8, Article number: 278 (2025) Cite this article

**781** Accesses Metrics

#### Recap: Slight (3) changes XROM -> XDROM+

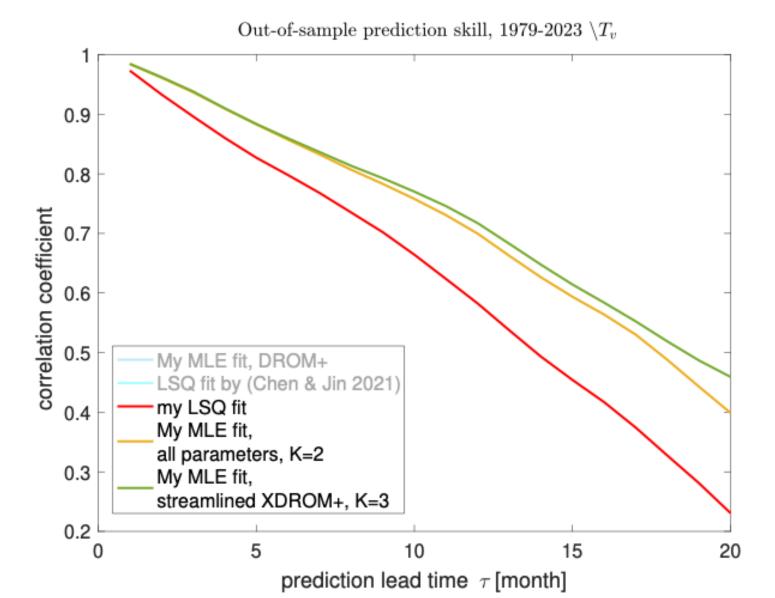
- 1. D: delay variables instead of red noise, to correctly represent coarse-graining
- 2. +: Add state-dependence for the noise in the first eq. (i = 1)
- 3. +: Add seasonal modulation of both the (a) additive noise magnitude and the (b) (multiplicative) state dependent noise magnitude.

Further coarse-graining: XDROM+ -> DROM+: i = 1, ..., I, I = 10 -> 2

Wait! Can this improve forecast skill if we have a large enough (but not too large) memory, *D*?

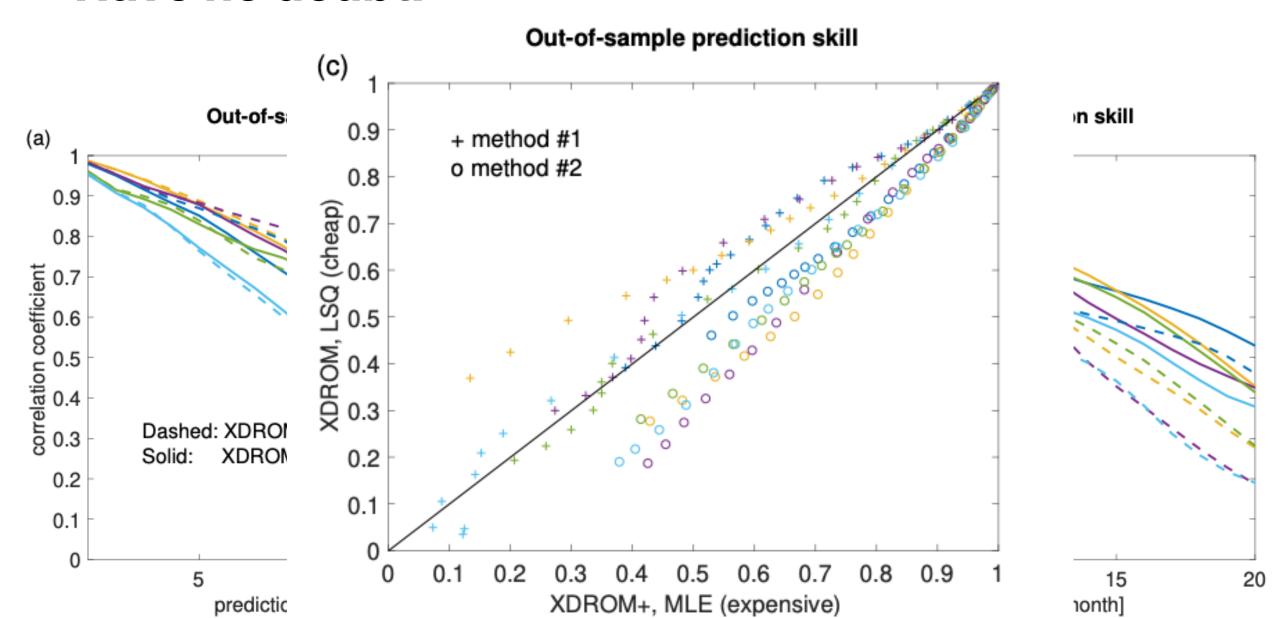






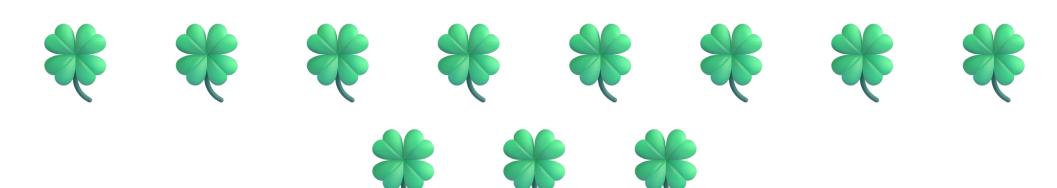
The overfitting is "BENIGN". (Bartlett et al. PNAS 2020)

#### Have no doubt!

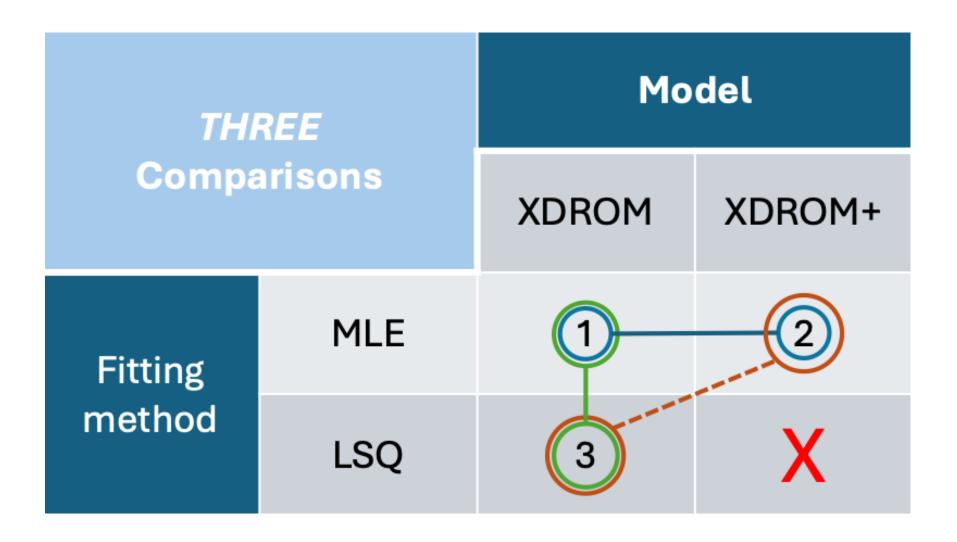




# We DO have 46 years of reliable satellite data!



#### Rank of skills for (valid) scenarios



Altogether 3 comparisons of 2 scenarios wrt. skill:

- -- C1
- C2
- C3

- C3 implies: MLE is better than LSQ
- C2 implies: there is no ENSO noise state dependence
- Note: these two inferences can be made also by C1 & C2

ENOSO MOJIH

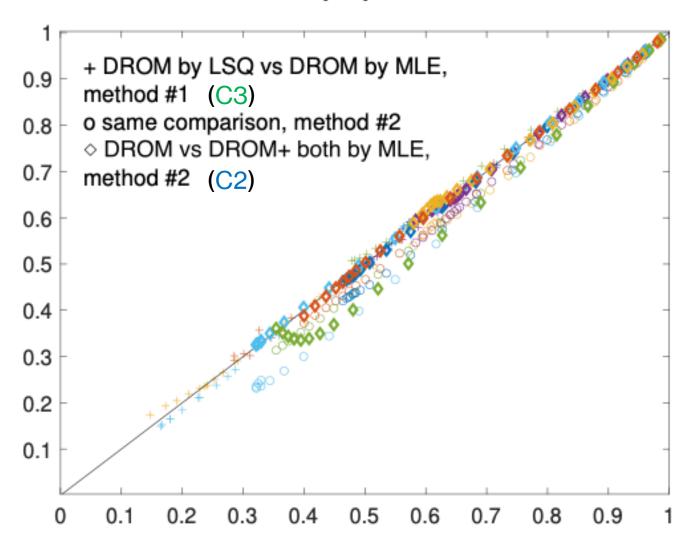
- C3 implies: MLE is better than LSQ
- C2 implies: there is **no** ENSO noise state dependence
- Note: these two inferences can be made also by C1 & C2



#### Really? Wait! How about CGCMs?

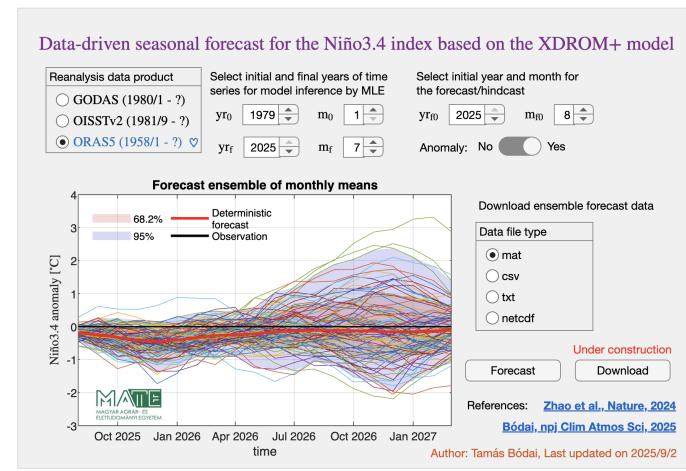
#### Out-of-sample prediction skill

Using 6 member of the CESM2-L



#### My operational ENSO forecast service

- A Matlab web app: http://bodaimatlab.zapto.org:9988/
  - Susceptible to: power cuts; laziness; high demand (nahh! get over yourself!).
- Check out the service by Sen Zhao: <a href="https://senzhao.netlify.app/climate/xro/">https://senzhao.netlify.app/climate/xro/</a>
  - (But only if mine is unavailable.)



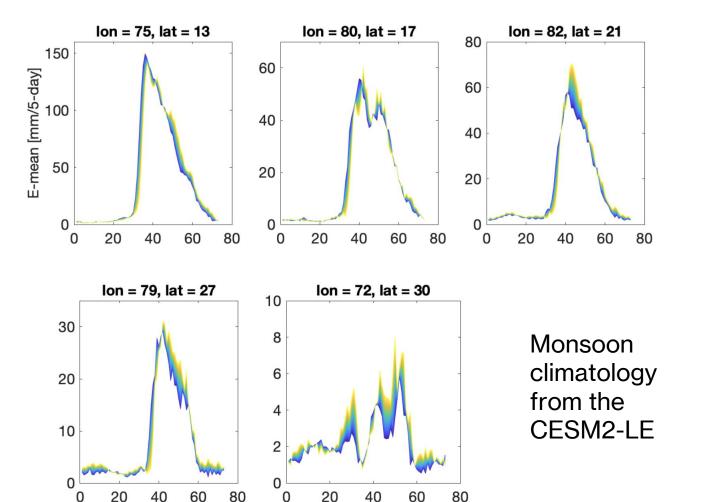
#### What I've been doing in Bergen

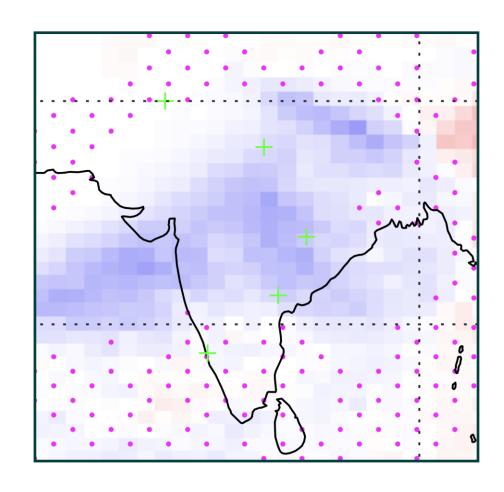
- Developing a forecast service for the Indian summer monsoon.
  - Go regional / local!
- Forecasting monthly means, with a couple of months lead time.
- Backbone is the XDROM+.
  - I.e., it is a cheap skate data-driven forecast system, riding on the backs of expensive data acquisition missions, reanalysis products (CHIRPS, ORA5S).
  - We can have any seasonal / "extended range" forecast skill thanks only to the thermal inertia of the ocean.



Okay, but can you show us something?

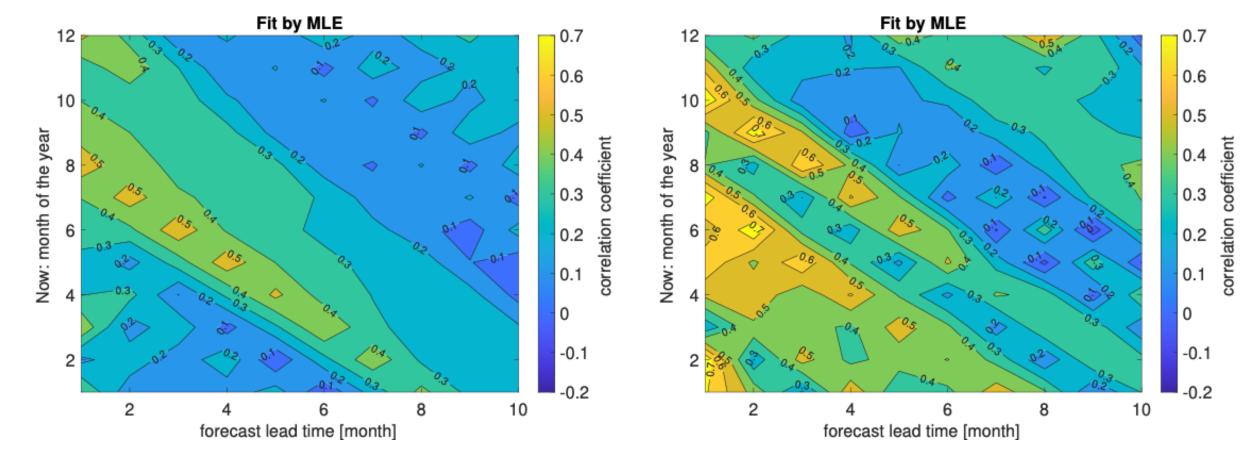
## Nice. Glad you had a good time! Any diagrams, though?



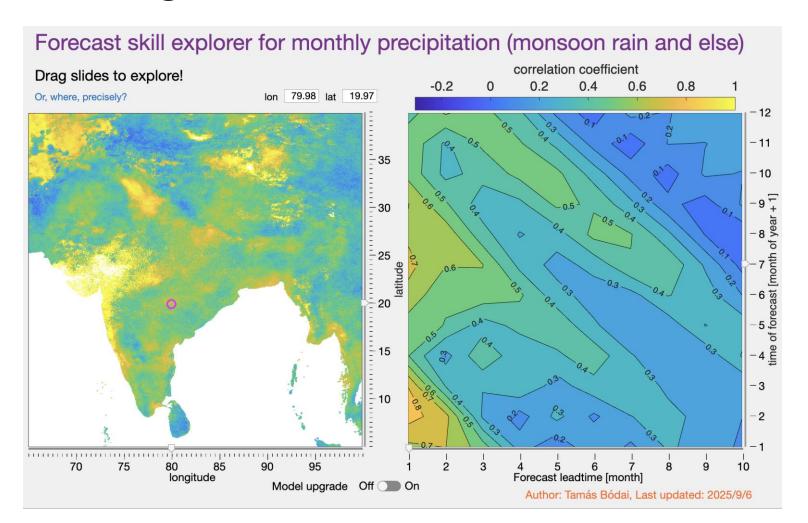


## I think you have had these figures for a long time...

- Guilty as charged!
- But...



#### Dude, you have to submit a report about your trip! No-one will care how much you worked if you don't have something to show for!



#### Comparison

Home > Climate Dynamics > Article

## Skill of Indian summer monsoon rainfall prediction in multiple seasonal prediction systems

Published: 19 September 2018

Volume 52, pages 5291-5301, (2019) Cite this article

Access provided by Hungarian University of Agriculture and Life Sciences, Magyar Agrar-es

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**Climate Dynamics** 

Aims and scope →

Submit manuscript →

Shipra Jain , Adam A. Scaife & Ashis K. Mitra

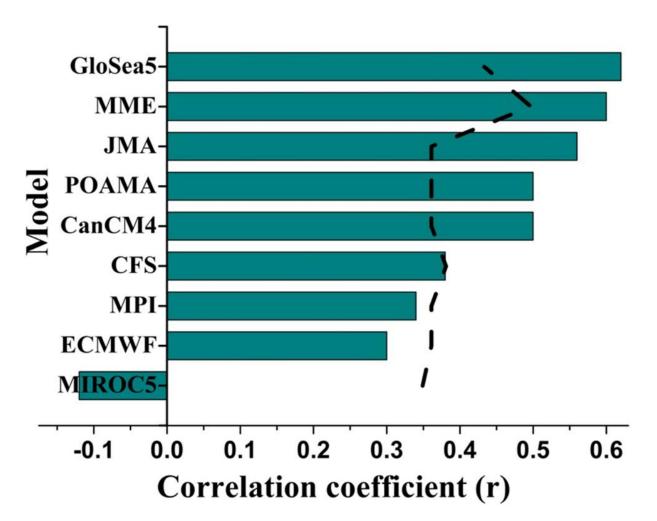
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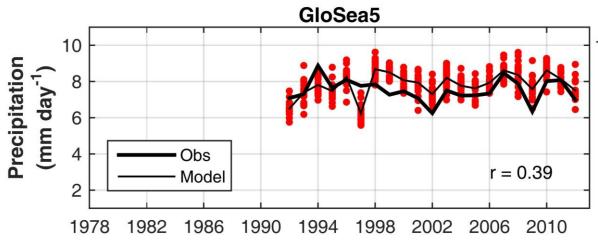
#### Comparison for forecasting JJA rain on 1 May





Over land only

Just one model

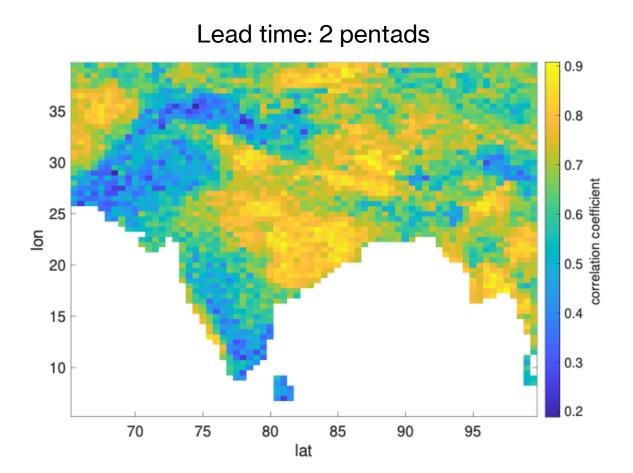


**For my model: r = 0.837** 

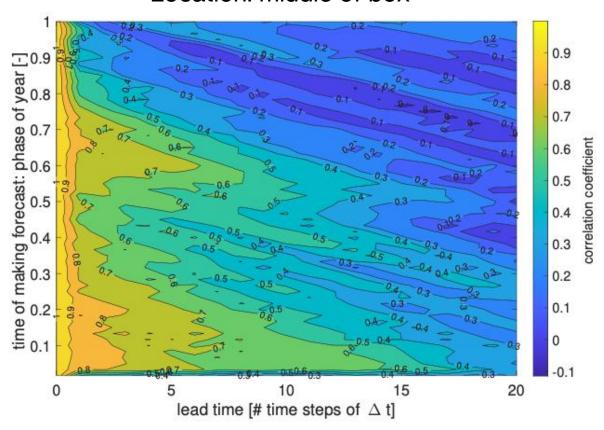
**Sample** r is callculated over years 1992-2007

For the full data period (1981-2022): r = 0.711

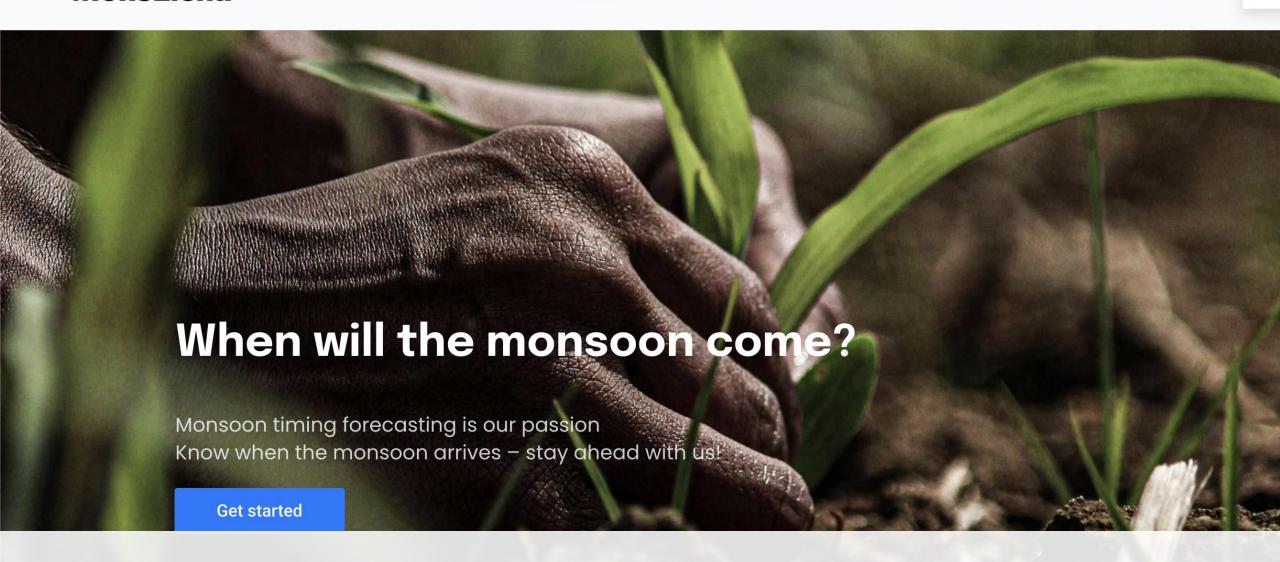
#### Treat also pentads!



#### Location: middle of box







### A crowded space

#### A crowded space



#### **UC Berkeley News**

Campus news

### Al revolutionizes weather prediction to help farmers in India

Co-developed by UC Berkeley's William Boos, an artificial intelligence-based weather model delivered a timely prediction of a stalled monsoon this season, helping farmers decide when to plant their crops.

#### By Robert Sanders



India's Ministry of Agriculture and Farmer Welfare delivered regular forecasts via cellphone to some 38 million farmers across northeastern India at the start of the 2025 summer monsoon season. For the first time, these forecasts provided up to four weeks' advance notice of the start of the continuous rainy season, allowing the farmers to better time the planting of crops with the onset of the rains.

### And it's going to be even more crowded

#### Scientists Must Join Forces to Solve Forecasting's Predictability Desert

To strengthen societal resilience to worsening natural hazards, siloed Earth system science communities must collaborate to understand conditions that favor skillful subseasonal-to-seasonal forecasts.

By Jadwiga H. Richter and Everette Joseph

17 October 2025















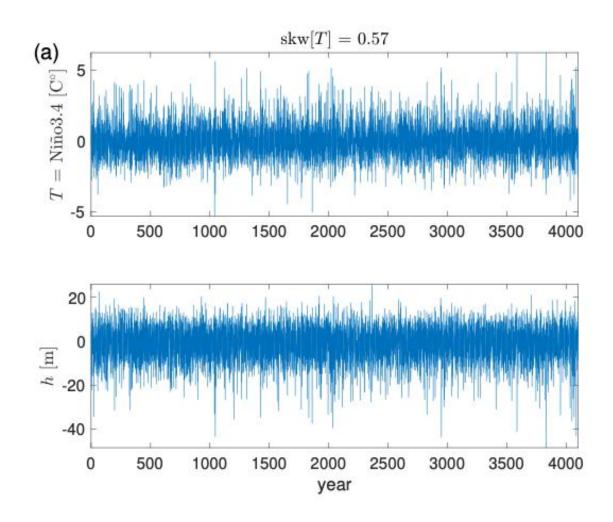
## Thank You! Takk!

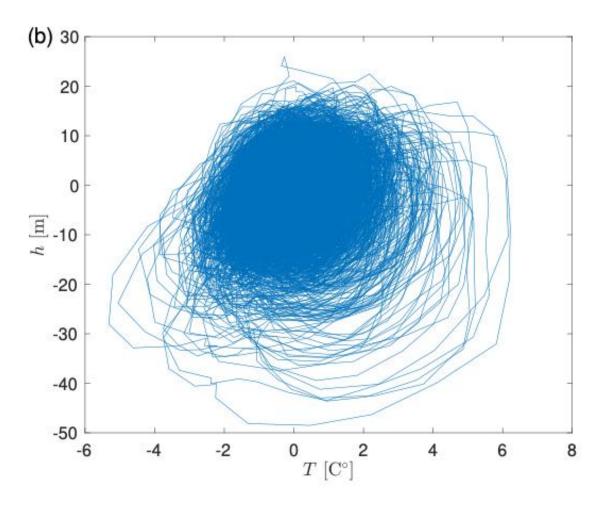
Köszönöm!

### Feel free to find me on Linked in

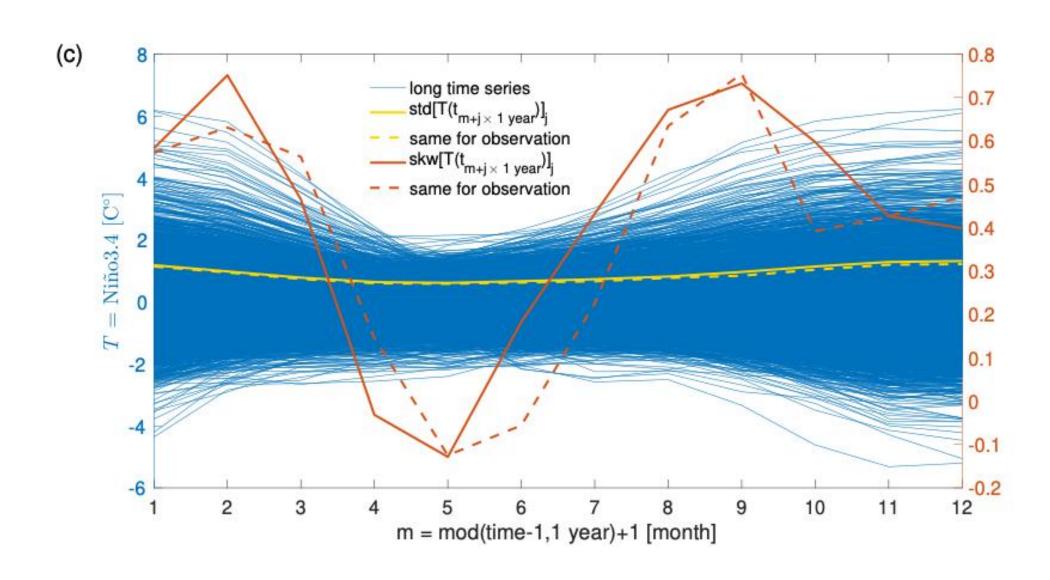


#### Authenticity of the X(D)ROM(+)



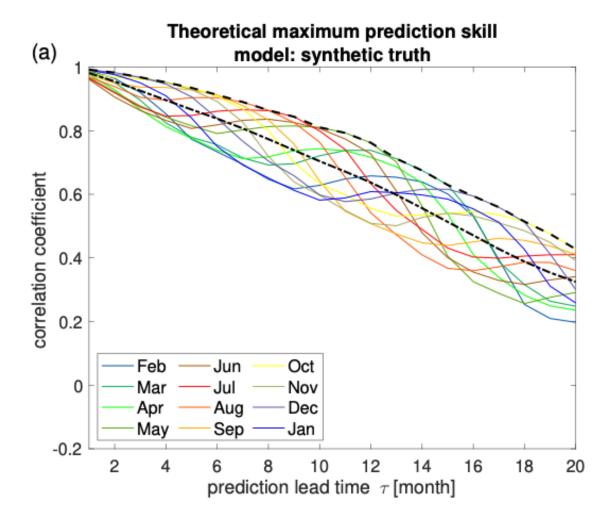


### Authenticity of the X(D)ROM(+)

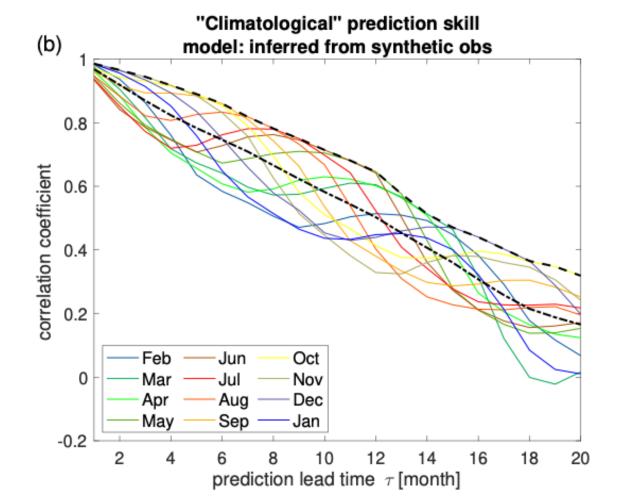


#### Theoretical maximum and climatological skill

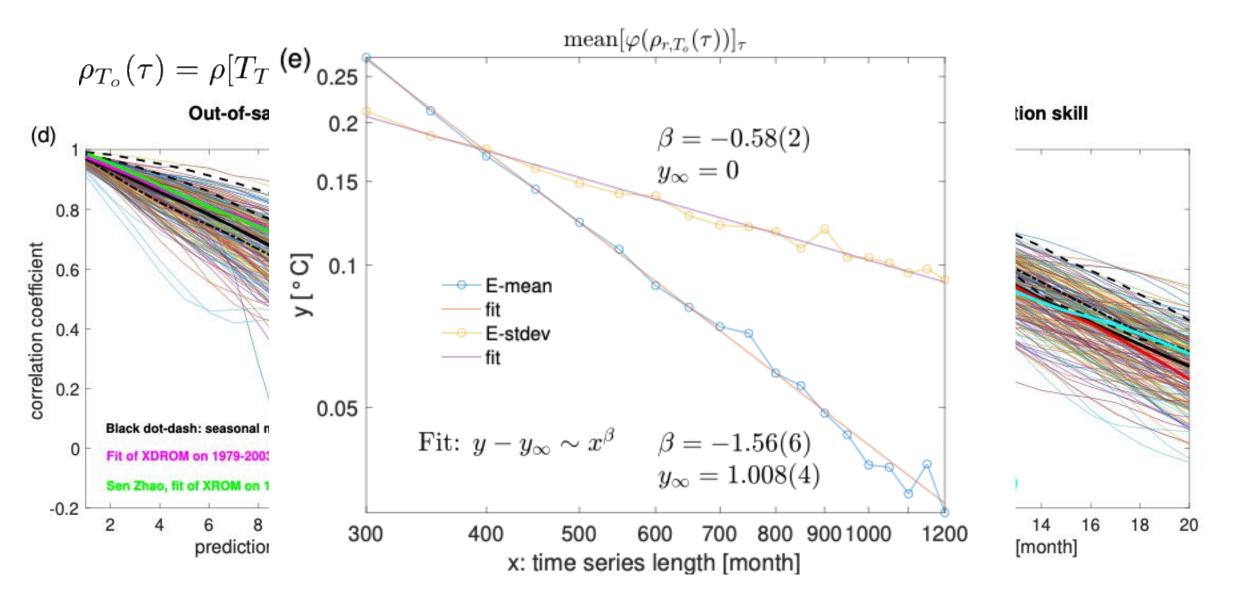
$$\rho_{max}(\tau) = \rho[T_{r,p}(t_t + \tau), T_{r,t}(t_t + \tau)]_r$$



$$\rho_{T_t, max}(\tau) = \rho[T_{r, T_t, p}(t_t + \tau), T_{r, t}(t_t + \tau)]_r$$



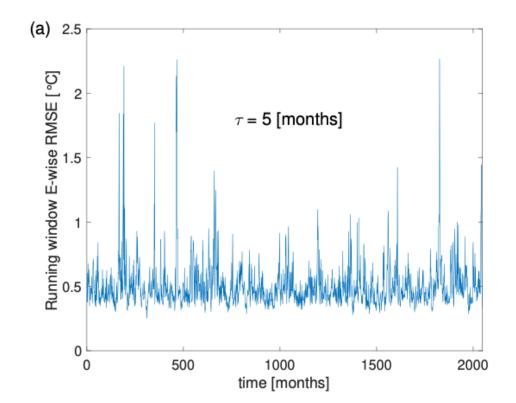
#### **Apparent skill**

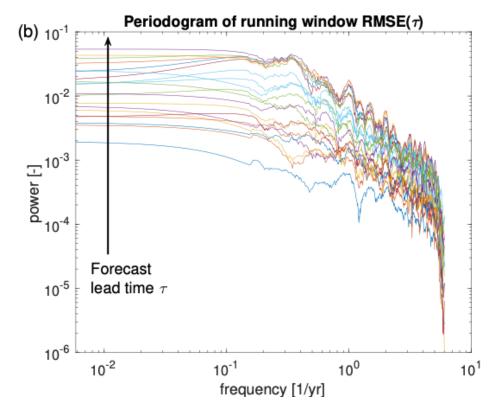


#### **True skill**

- It cannot be a correlation coefficient
- Rather an ensemble-wise RMSE:

$$REMSE_{T_o}(\tau) = RMSE[T_{r,T_o,p}(t_f + \tau), T_{r,t}(t_f + \tau)]_r, \ t_f = \max[T_o]$$





## The apparent skill is not indicative of the true skill...

...as the true skill has hardly any persistence. Also:

