Earth Sciences Department



Barcelona Supercomputing Center Centro Nacional de Supercomputación

On causality, sources of predictability, and bridging predictions across timescales

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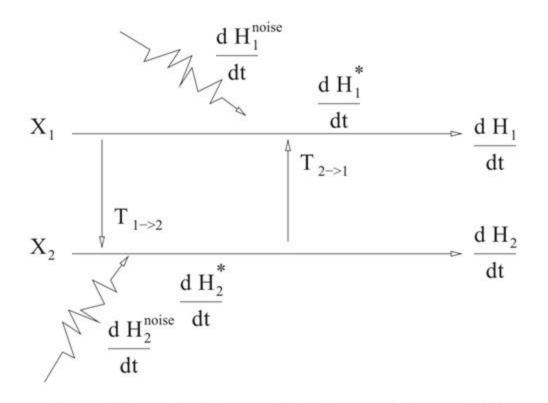
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Outline

- 1. Liang-Kleeman causality framework (brief)
- 1. Identifying sources of predictability at intraseasonal to seasonal timescales
- 1. Bridging predictions across timescales
- 1. Further work on the topics



Quick Intro to Liang-Kleeman Causality



The temporal evolution of the total marginal entropy of X_1 can be disjointly decomposed in terms of the change rate of the marginal entropy without any influence from X_2 and a term involving the influence of X_2 :

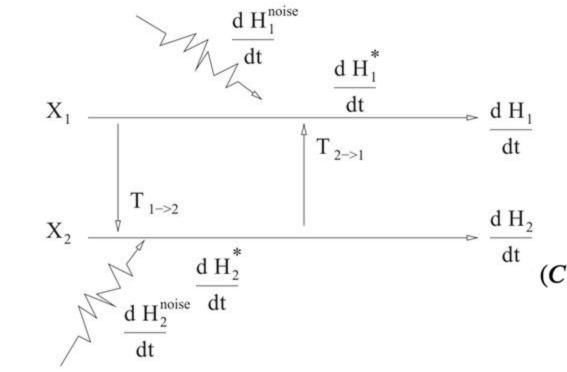
FIG. 1. Schematic of the marginal entropy evolutions and information flows in the system of (X_1, X_2) .

San Liang, 2015, 2016

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What is the rate information flow from, say, X_1 to X_2 ?

Quick Intro to Liang-Kleeman Causality



$$T_{2 \to 1} = \frac{C_{12}}{C_{11}} \hat{a}_{12}$$

$$\hat{a}_{12} = \frac{C_{11}C_{2\dot{1}} - C_{12}C_{1\dot{1}}}{\det C}$$

 $(C)_{ij}$ are the elements of the sample covariance-crosscovariance matrix

 C_{ii} is the sample crosscovariance of X_i and X_j .

FIG. 1. Schematic of the marginal entropy evolutions and information flows in the system of (X_1, X_2) .

San Liang, 2015, 2016

BSC Barcelona Supercomputing Center Centro Nacional de Supercomputación $T_{2\to 1} = \frac{r}{1 - r^2} (r'_{2,d1} - rr'_{1,d1}).$

Obviously, two uncorrelated events (r = 0) must be noncausal $(T_{2\rightarrow 1} = 0)$; in other words, causation implies correlation. The converse, however, does not hold; i.e., correlation does not imply causation.

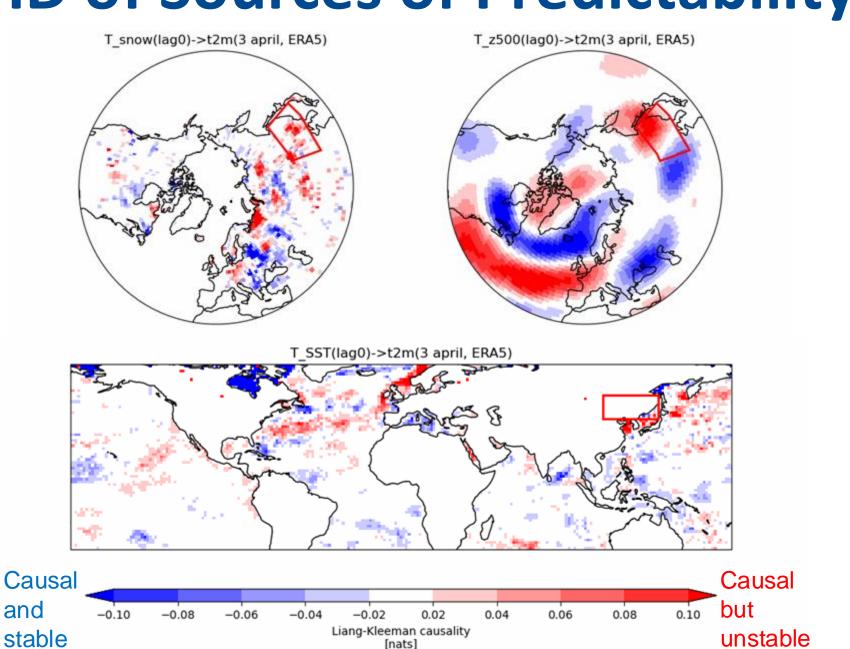
Causal ID of Sources of Predictability

LK causality between (snow, z500 and SST), and t2m over the China box, using **ERA5** data.

(colors indicate statistically significant values, p<0.05)

Ardilouze, Materia and Muñoz (2024); Ardilouze, Muñoz, Materia (in prep)





Using Causality in Model Diagnostics

- Work driven by our previous research (e.g., Materia et al., 2019)
- Multi-model ensemble approach, but analysis also for each independent model (and members!)
- 4 models: ECMWF, CNRM, BoM (Australia) and HMCR (Russia)
- 10 members each = 40-member ensemble
- Model selection driven by ensemble size, common reforecast period and the availability of snow cover data (not provided by the UK model, for example)

Ardilouze, Materia and Muñoz (2024); Ardilouze, Muñoz, Materia (in prep)



Materia, S., Muñoz, Á. G., Álvarez-Castro, M. C., Mason, S. J., Vitart, F., & Gualdi, S. (2019). Multi-model subseasonal forecasts of spring cold spells: potential value for the hazelnut agribusiness. Weather and Forecasting. https://doi.org/10.1175/waf-d-19-0086.1

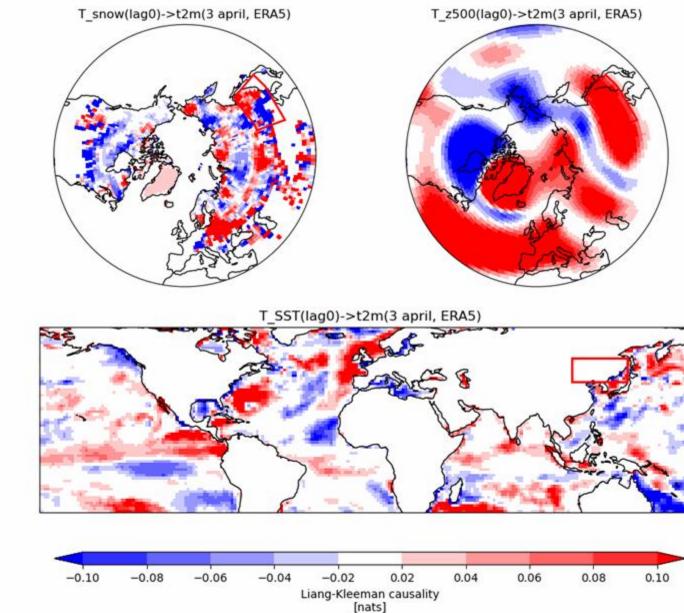
Using Causality in Model Diagnostics

LK causality between (snow, z500 and SST), and t2m over the China box, for the **multimodel ensemble and ERA5**

(colors indicate statistically significant values, p<0.05)

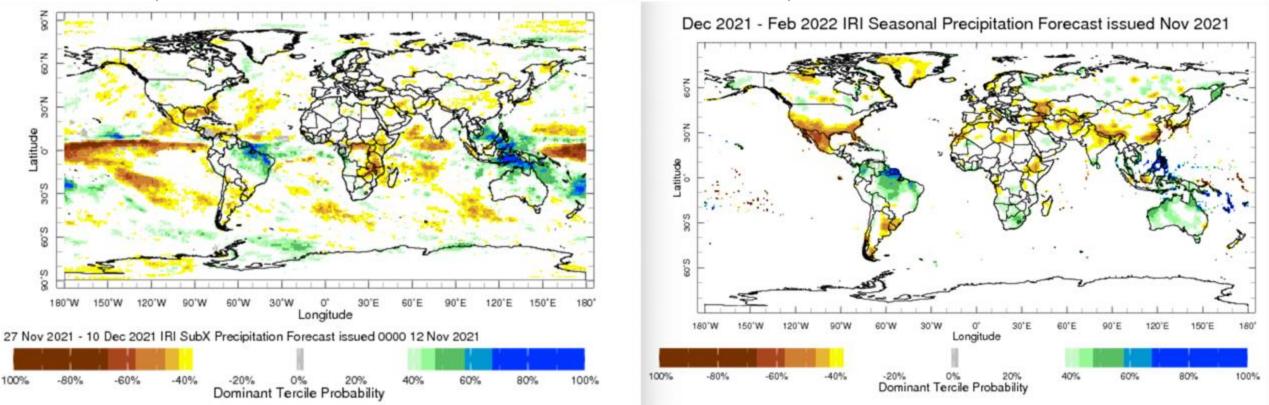
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Merging Prediction Systems: The Problem

a) SubX calibrated subseasonal rainfall forecast



Muñoz et al, 2023



(a) SubX multi-model, calibrated subseasonal rainfall forecast system, targeting Nov 27, 2021 to Dec 10, 2021 (weeks 3-4). b) NMME calibrated seasonal rainfall forecast system, targeting Dec 2021 to Feb 2022. There are clear similarities in the regions of above-normal (green) and below-normal (brown) dominant tercile probabilities of rainfall at the two scales, both impacted by La Niña conditions, highlighting physical bridging

b) NMME calibrated seasonal rainfall forecast

How can we bridge predictions?

•Stitching

e.g. Wetterhall and DiGiuseppe (2018); Beford et al (2020)

Constraining

e.g. Beford et al (2020, 2022); Mahmood et al (2021)

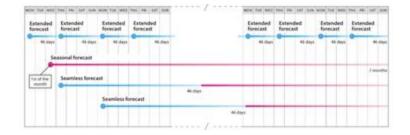
•Weighting

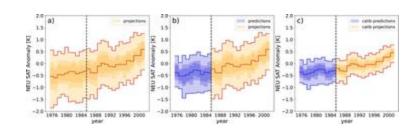
e.g. Ford et al. (2018); Dirmeyer et al (2018, 2020)

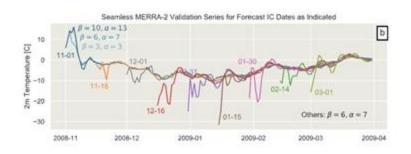
Causal-flowing (X_{it}/Cross-it)

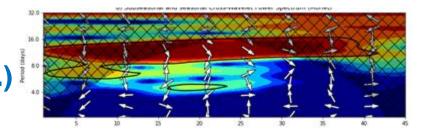
BSC

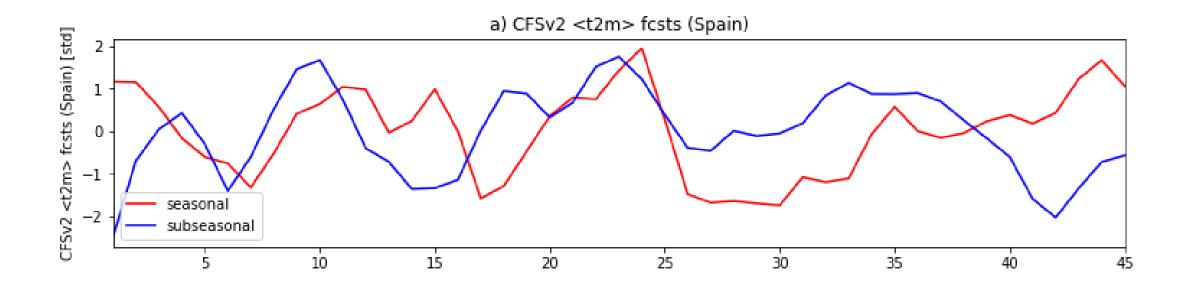
Barcelona Supercomputing e.g. this work (Muñoz et al., 2023, 2024; in prep.)



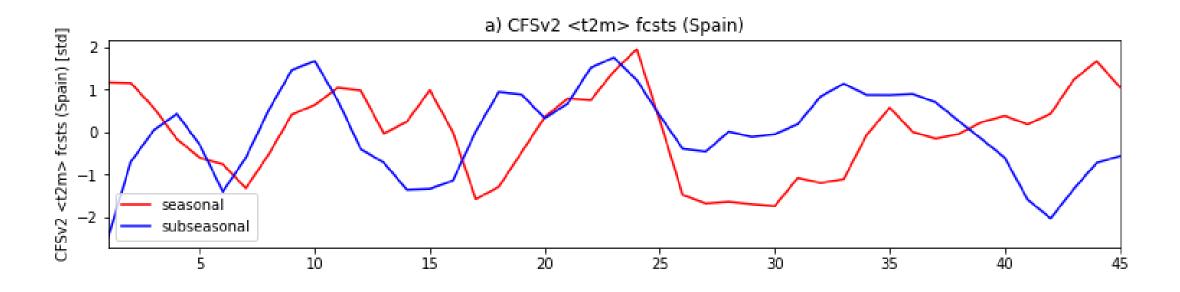




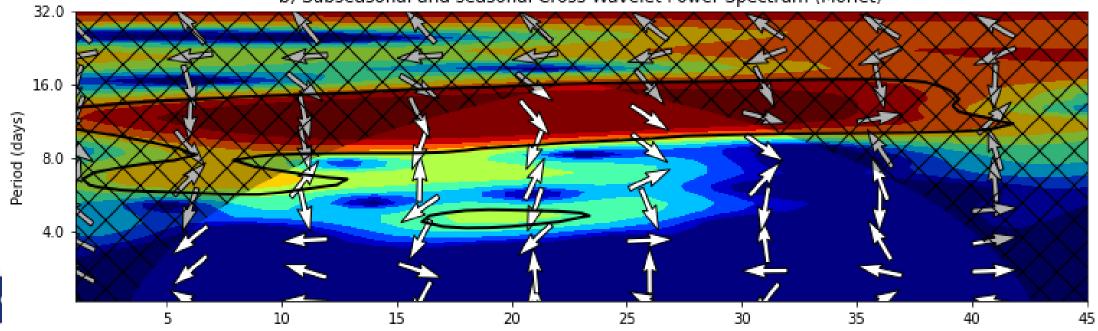


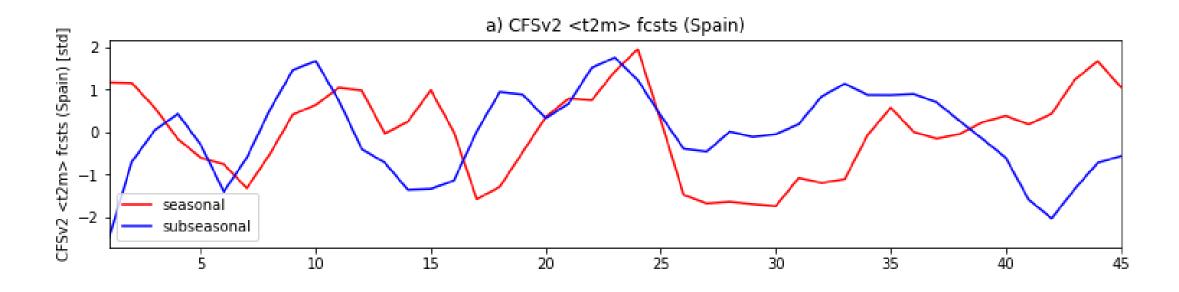




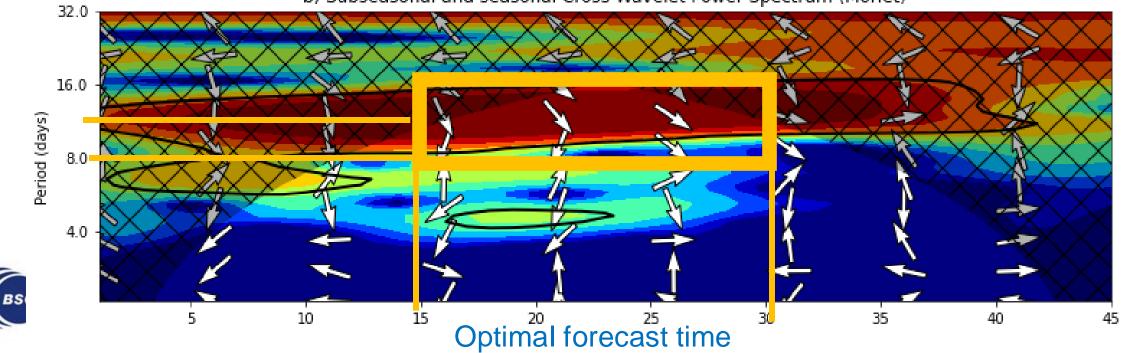


b) Subseasonal and seasonal Cross-Wavelet Power Spectrum (Morlet)





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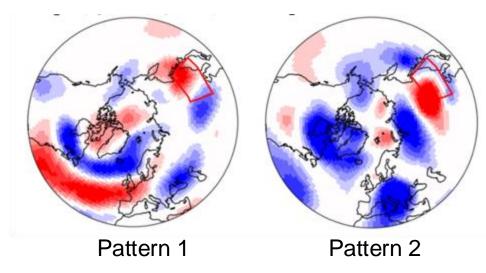


Optimal period

Ongoing research (ask us more later about it)

- 1. Causal patterns (linear vs non-linear)
- 1. Causal pattern regression
- 1. Causality and predictive skill





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