Weather Typing as a Potential Tool to Analyze Tropical-Extratropical Interactions

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Outline

1. Available states of the dynamical system
2. Weather types
3. Lab Example: NE North America
4. Tropical-Extratropical interactions and intra-seasonal predictability
5. Summary

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Available states of the system

A Nonlinear Dynamical Perspective on Climate Prediction

T. N. PALMER

European Centre for Medium-Range Weather Forecasts, Shinfield Park, Reading, United Kingdom

(Manuscript received 7 October 1997, in final form 26 February 1998)

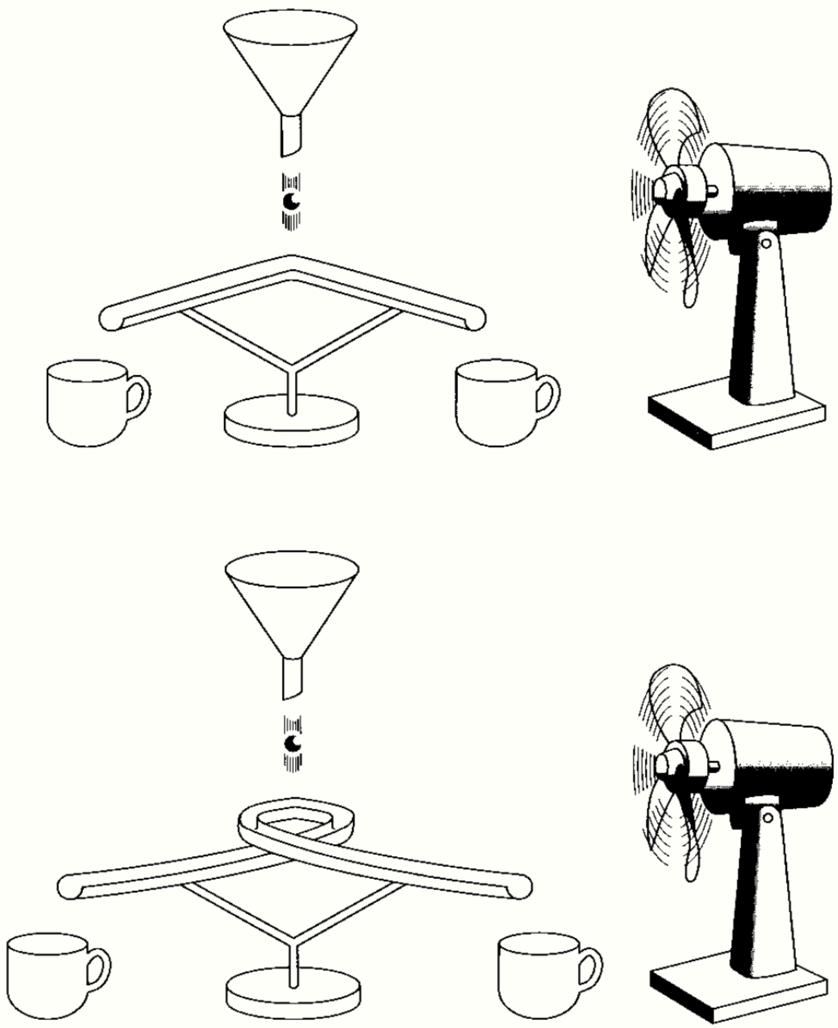
ABSTRACT

A nonlinear dynamical perspective on climate prediction is outlined, based on a treatment of climate as the attractor of a nonlinear dynamical system *D* with distinct quasi-stationary regimes. The main application is toward anthropogenic climate change, considered as the response of *D* to a small-amplitude imposed forcing **f**.

The primary features of this perspective can be summarized as follows. First, the response to **f** will be manifest primarily in terms of changes to the residence frequency associated with the quasi-stationary regimes. Second, the geographical structures of these regimes will be relatively insensitive to **f**. Third, the large-scale signal will be most strongly influenced by **f** in rather localized regions of space and time. In this perspective, the signal arising from **f** will be strongly dependent of *D*'s natural variability.

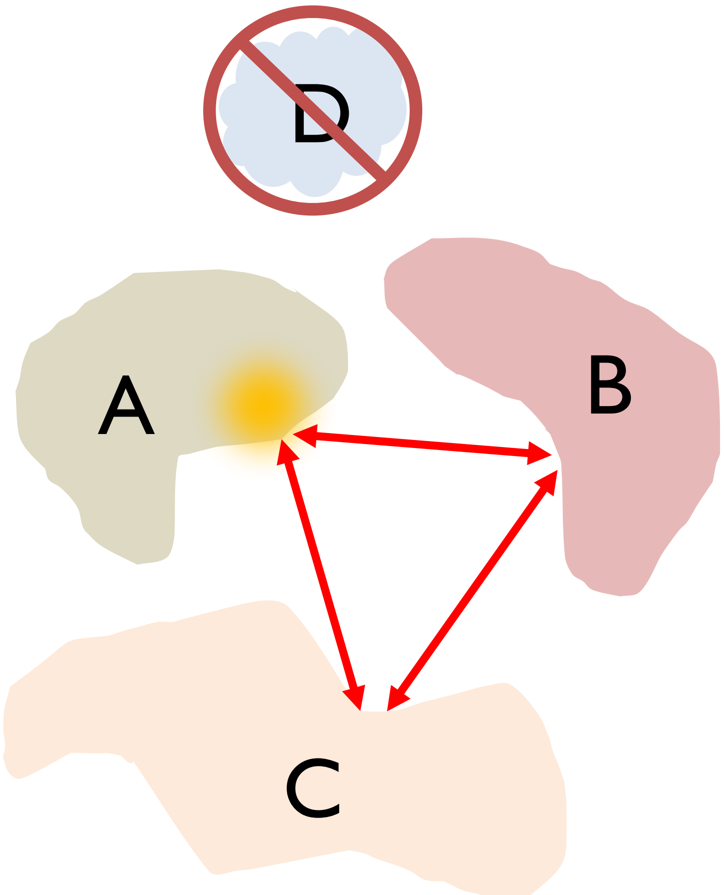
A theoretical framework for the perspective is developed based on a singular vector decomposition of *D*'s tangent propagator. Evidence for the dyamical perspective is drawn from a number of observational and modeling studies of intraseasonal, interannual, and interdecadal variability, and from climate change integrations. It is claimed that the dynamical perspective might resolve the apparent discrepancy in global warming trends deduced from surface and free troposphere temperature measurements.

A number of specific recommendations for the evaluation of climate models are put forward, based on the ideas developed in this paper.



Palmer, 1999 (J Clim)

Available states of the system



Available physical states and transitions

AB
ABC
ABA
BBC
CAC
...

Events are described in terms of sequences of available states

Muñoz et al., 2017 (J Clim)

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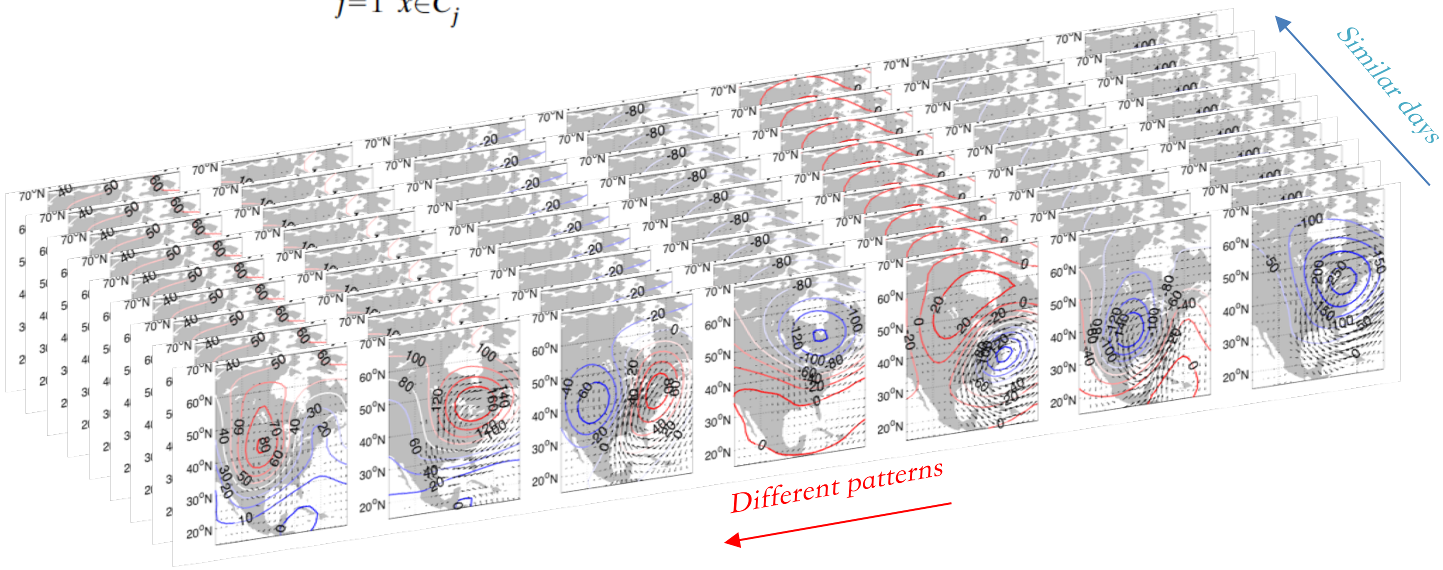
Weather types via *k-means*

Minimize the function:

$$W(P) = \sum_{j=1}^{N} \sum_{x \in C_j} d^2(X, Y_j),$$



Anomaly correlation coefficients

$$\mathrm{ACC}\,(P_i, Q_j) = \frac{\sum_{n=1}^{N} p'_n q'_n}{\sqrt{\sum_{N=1}^{N} (p'_n)^2 \sum_{n=1}^{N} (q'_n)^2}},$$

centroids

$$p'_n = p_n - \frac{\sum_{n=1}^{N} p_n}{N}, \quad \text{and}$$

$$q'_n = q_n - \frac{\sum_{n=1}^{N} q_n}{N},$$

- Assess classifiability using statistics (e.g., Michelangeli et al., 1995) and physics
- Daily transitions, duration, sub-seasonal and seasonal (and decadal, and$\cdots$) statistics
- Spatial patterns
- Link to climate drivers

Muñoz et al., 2017 (J Clim)

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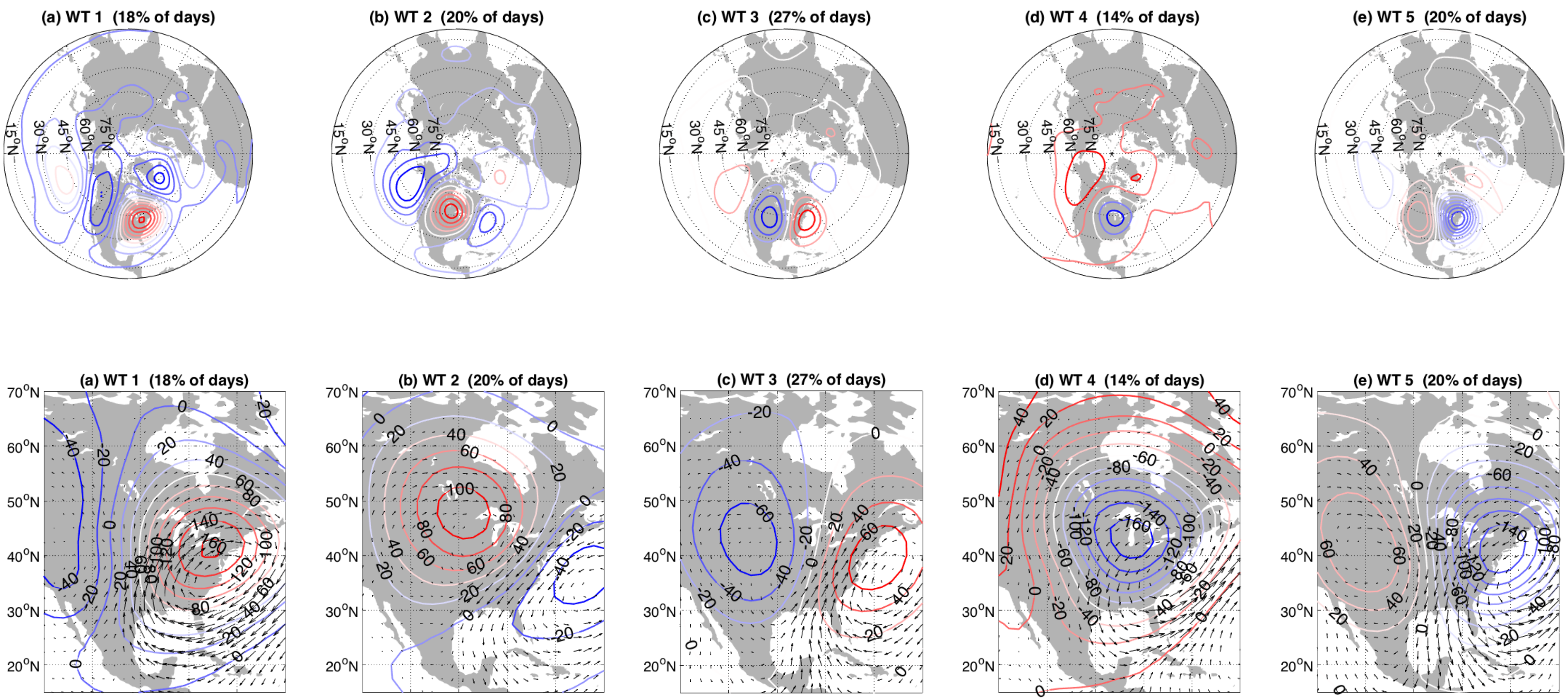
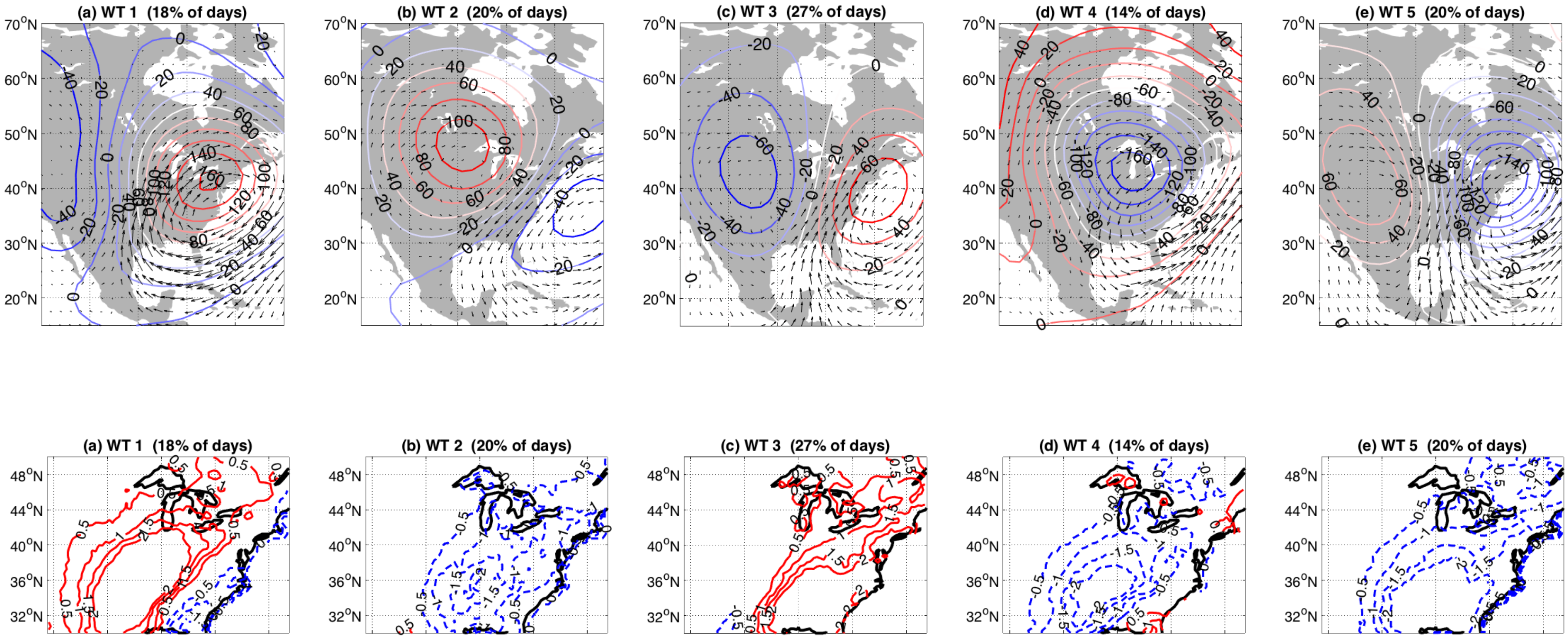
Lab Example: NE North America

DJF 1981-2010

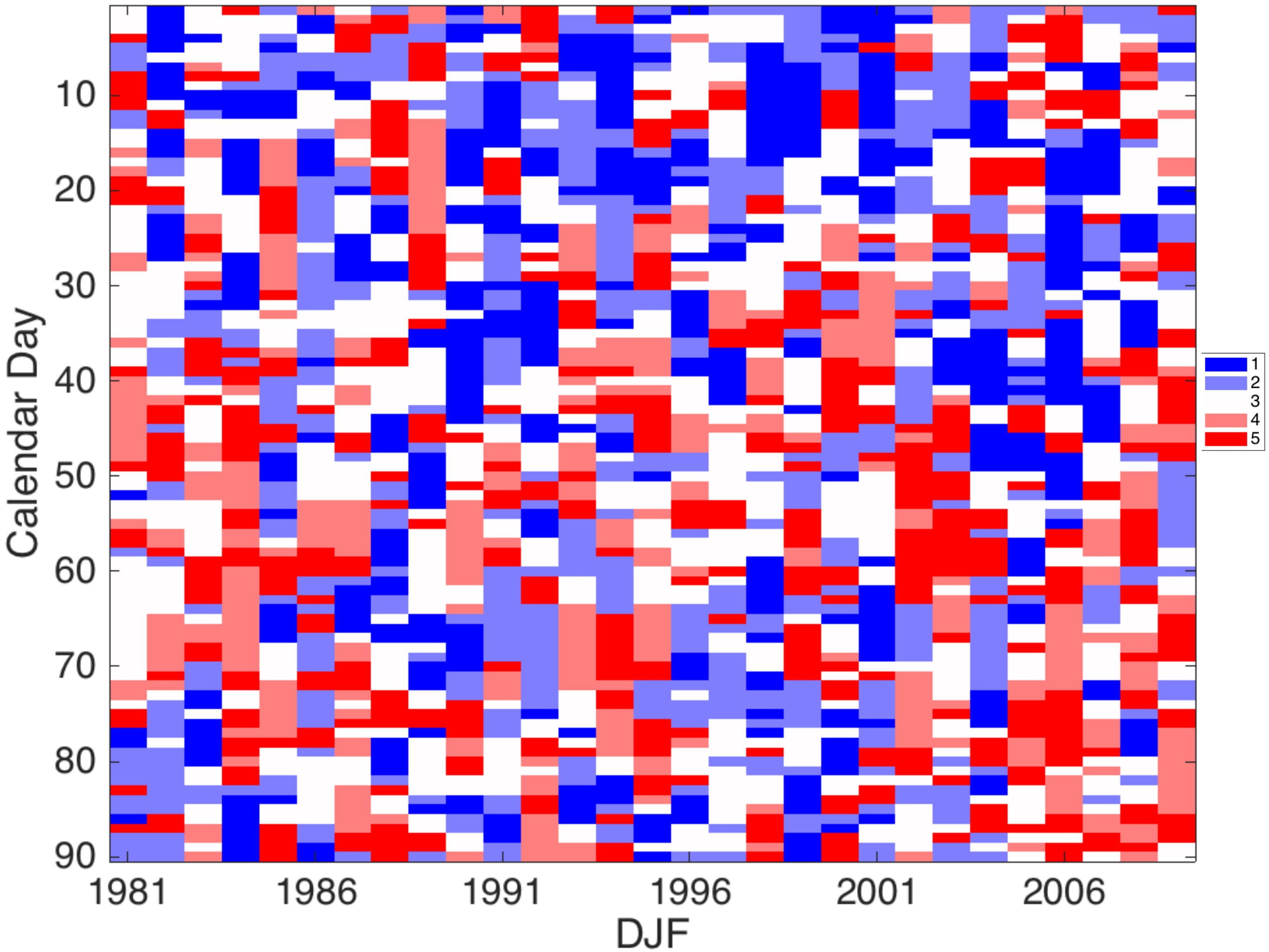


Lab Example: NE North America

DJF 1981-2010

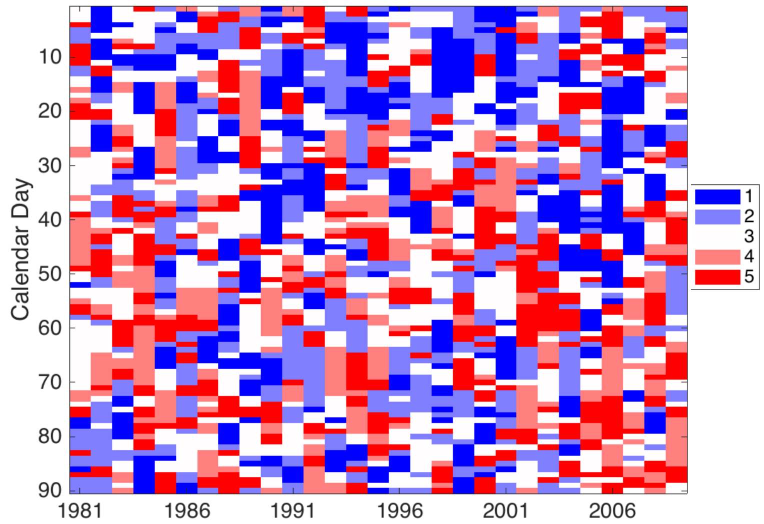


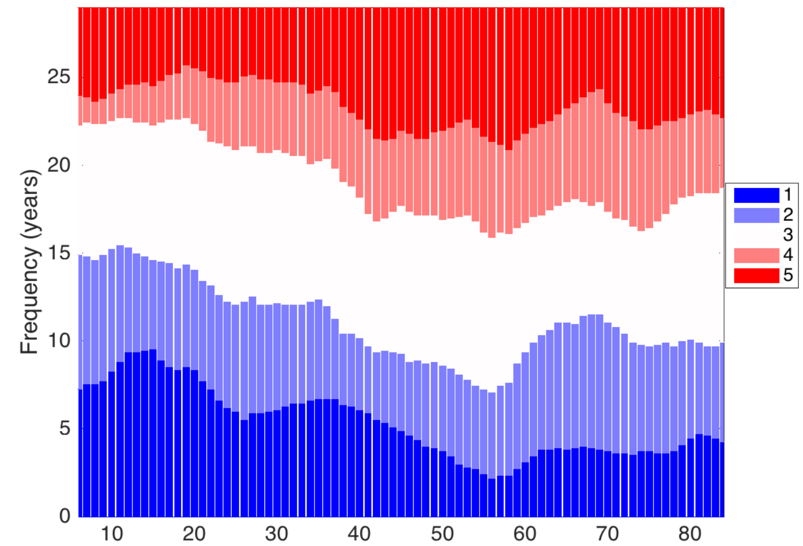
Lab Example: NE North America

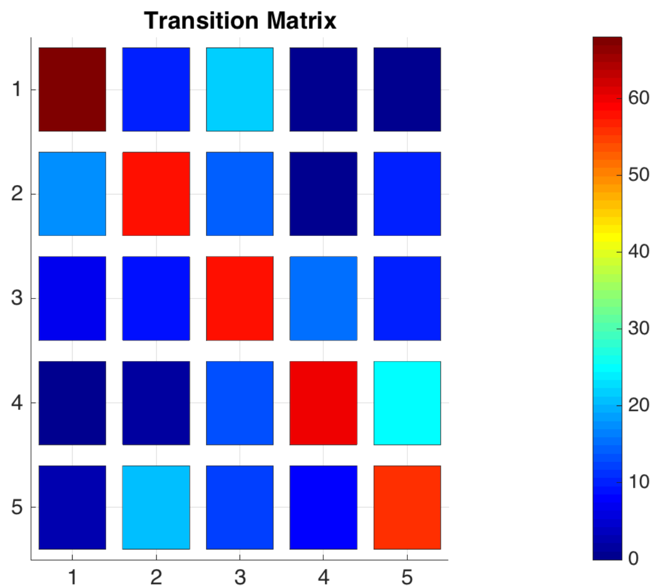


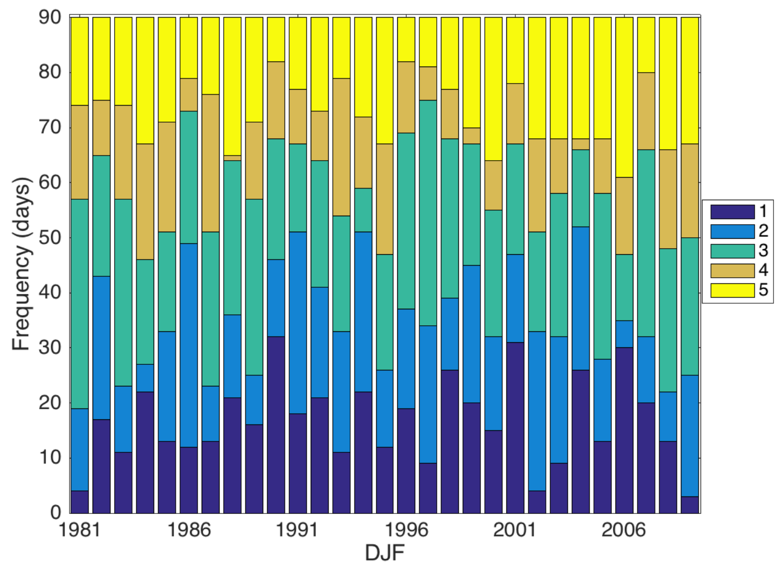
Paul Klee (1879-1940)

Lab Example: NE North America



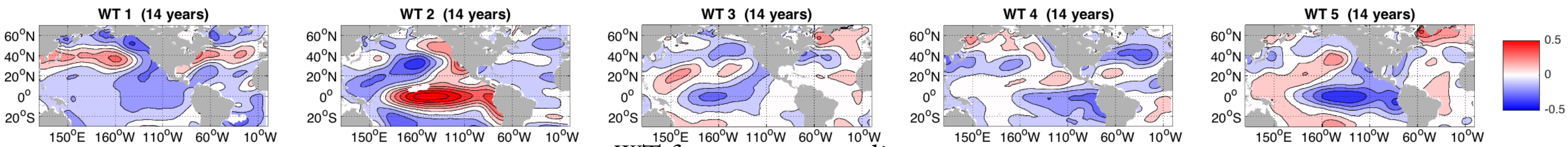




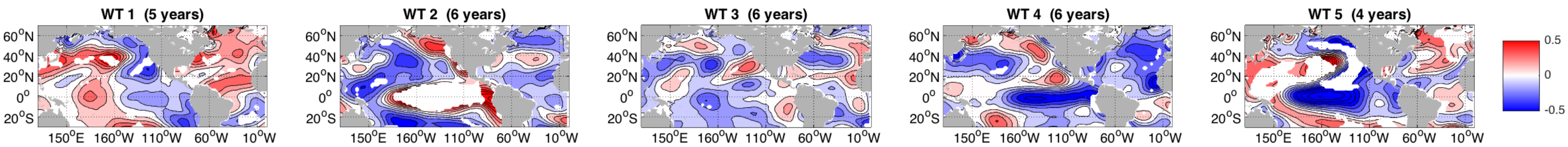


Lab Example: NE North America

DJF SST anomalies (composites)

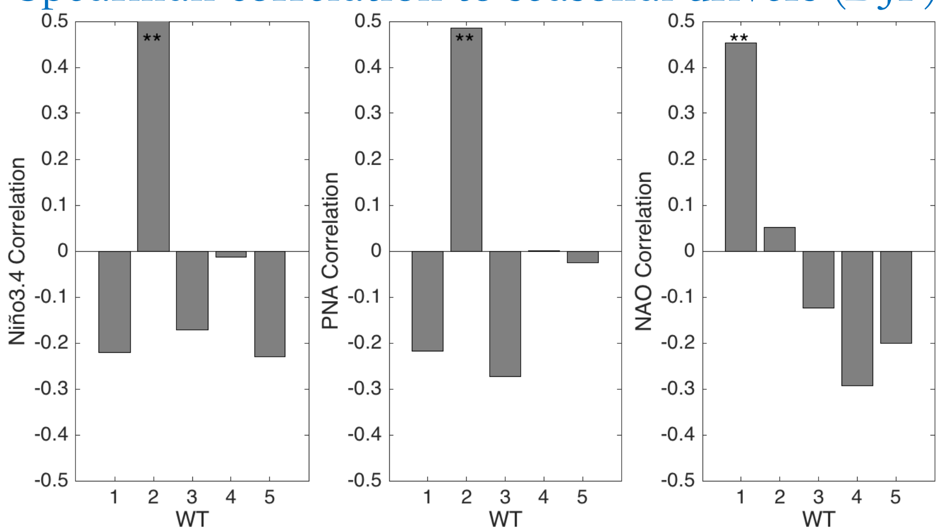


WT frequency = median



WT frequency = 80th pctl

Spearman correlation to seasonal drivers (DJF)



Lab Example: NE North America

Link to MJO

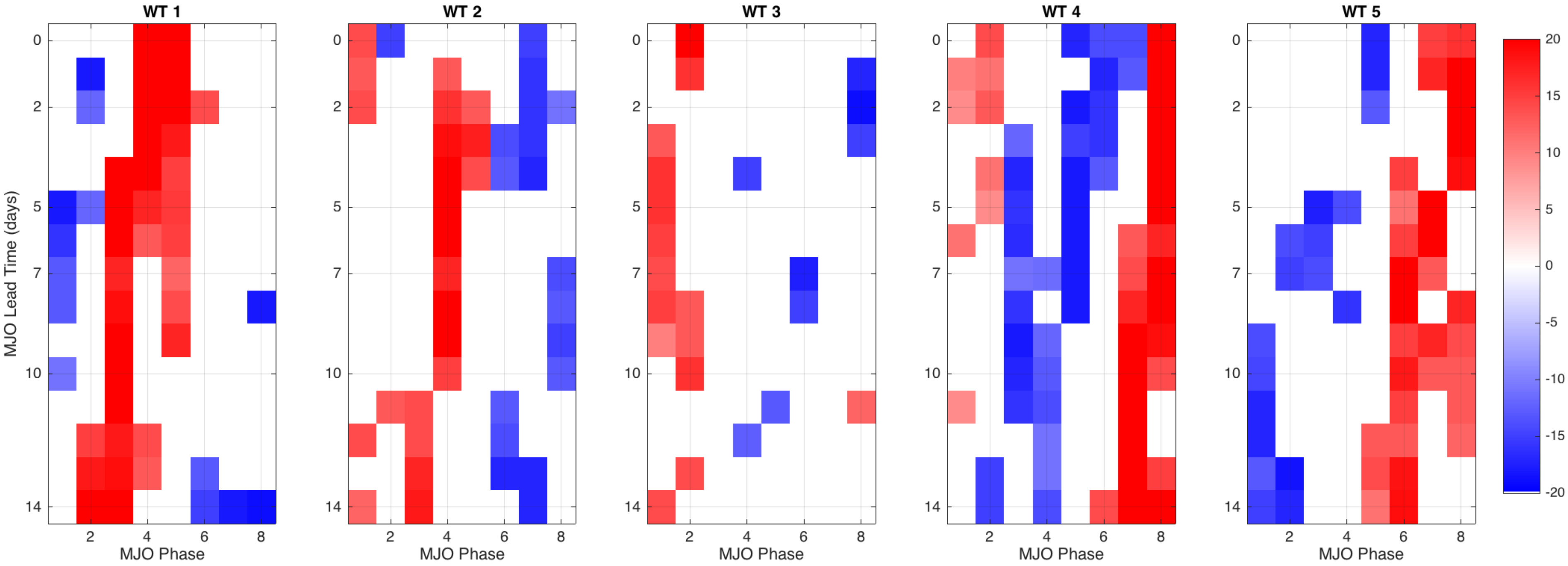


FIG. 10. Anomalous percentage of occurrence (see color bar) of each WT for each phase of the MJO (DJF 1979–2010). The ordinate gives the number of days that the MJO phase precedes each WT, from 0 (simultaneous) to 14 days. Colored tiles are significant at $p < 0.05$ confidence level, obtained using a bootstrapping method resampling 1000 times.

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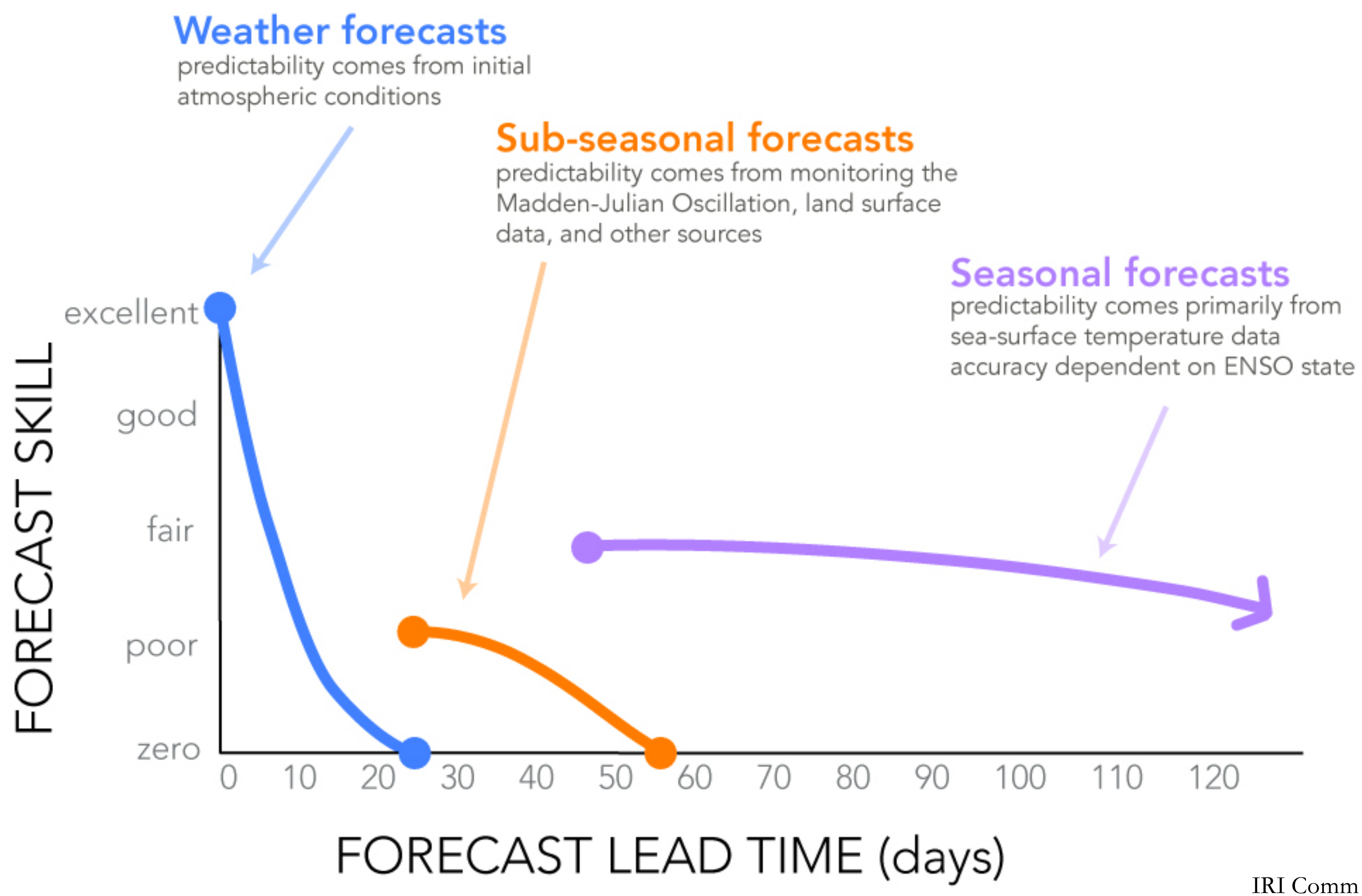
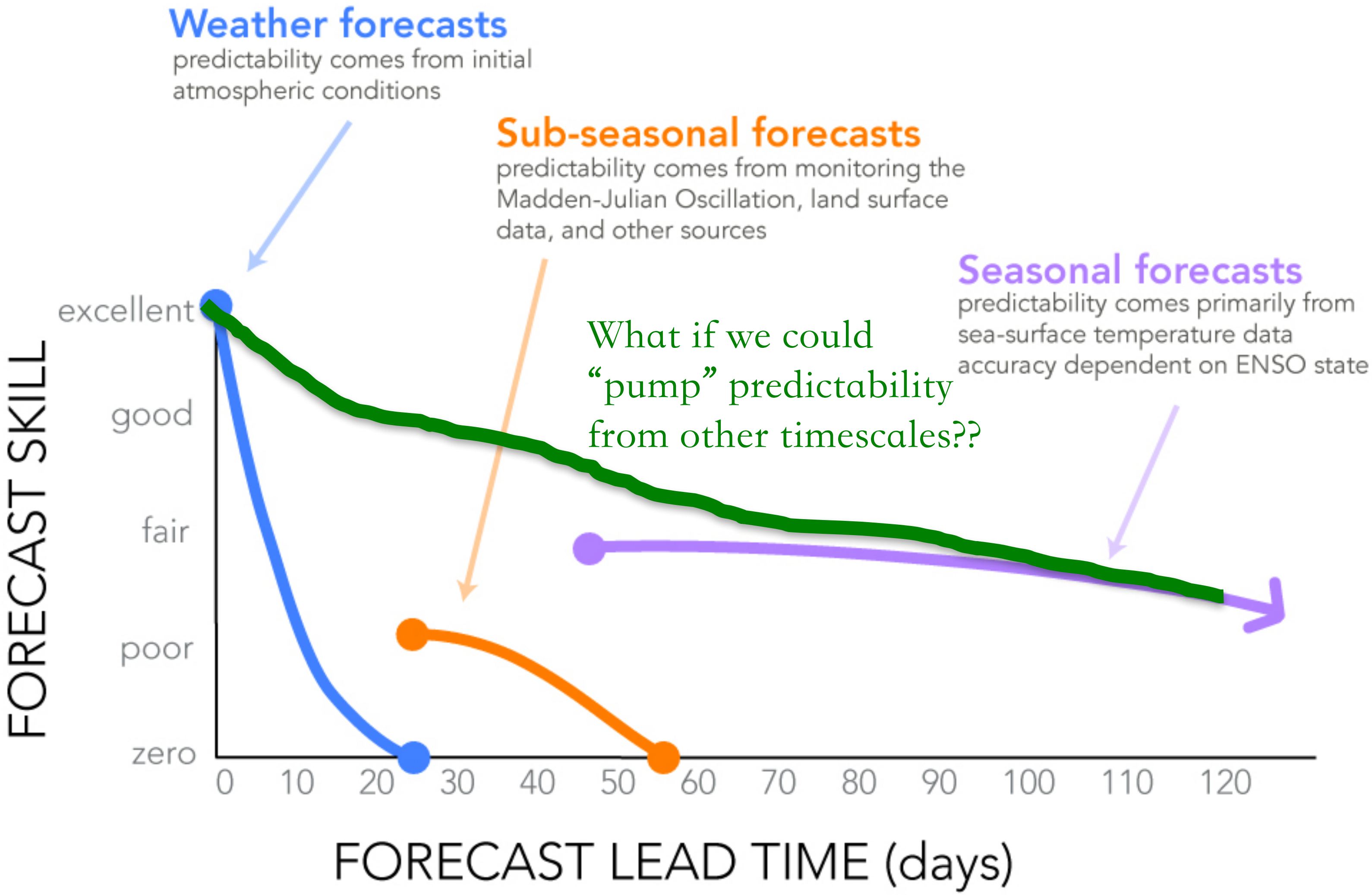
Interactions and predictability

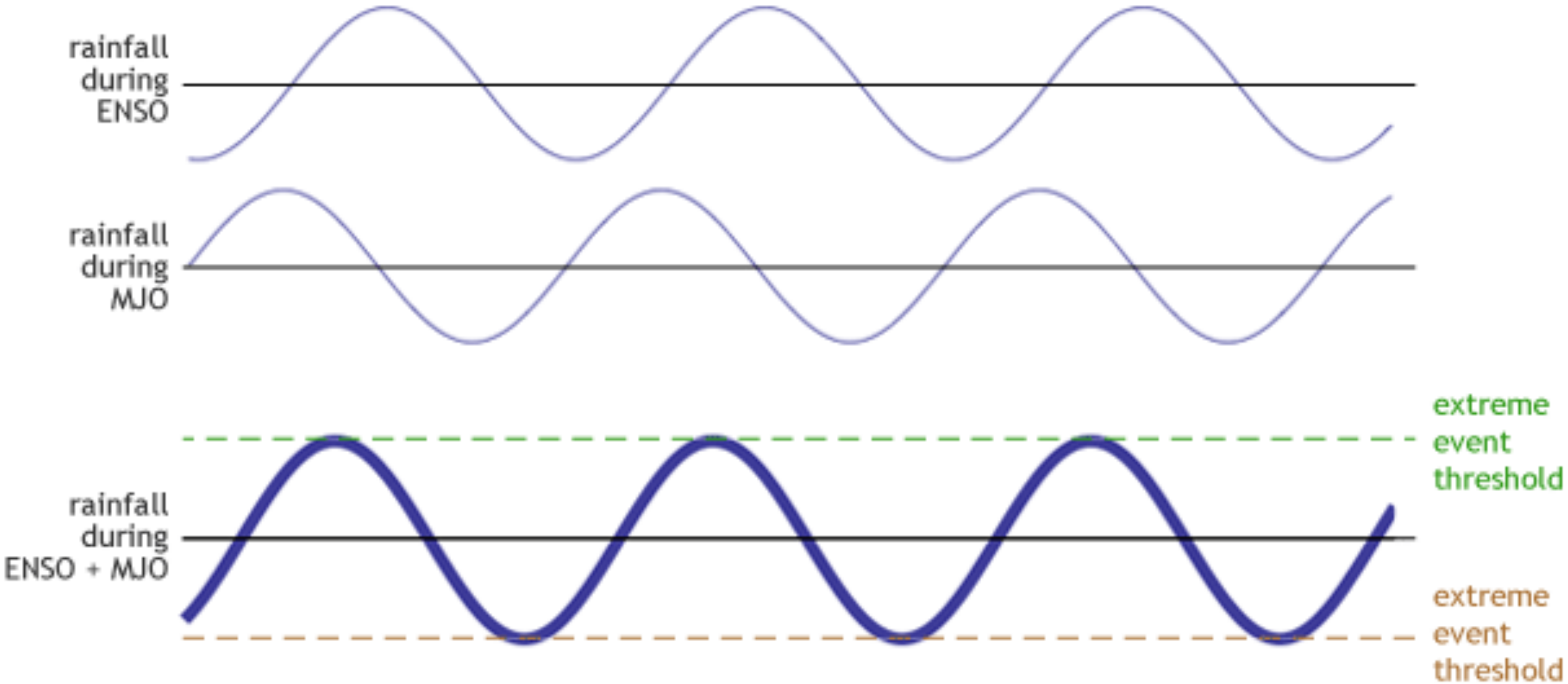


IRI Comm Team

Interactions and predictability

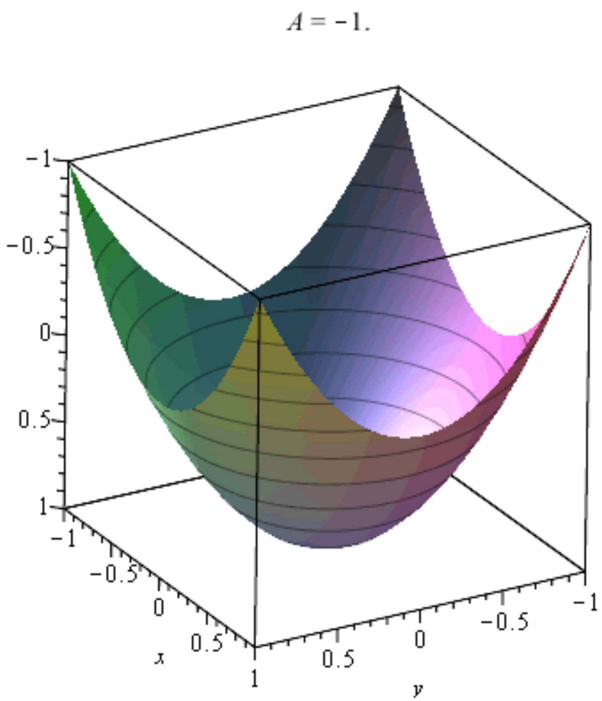


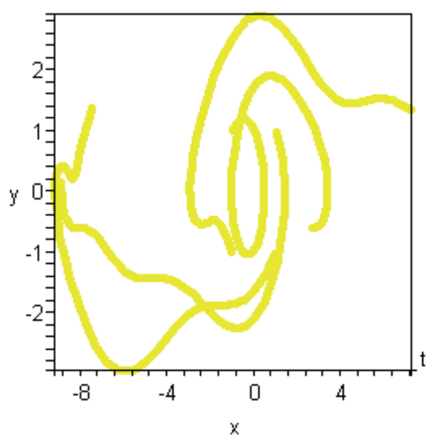
Interactions and predictability

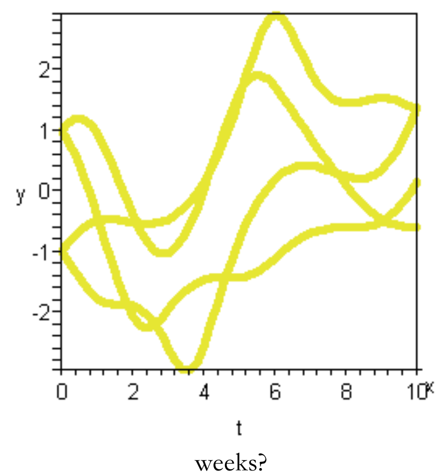


NOAA's ENSO Blog, Jan 2017 (Muñoz)

Interactions and predictability







The basins of attraction in the phase space are modified by the interaction of different climate drivers (e.g., ENSO + MJO)

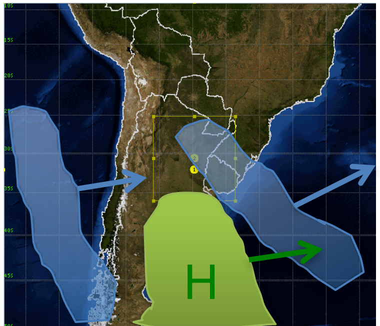
As a result, certain trajectories in the phase space tend to be visited more frequently by the system.

Which implies some predictability in the temporal evolution of the variable of interest.

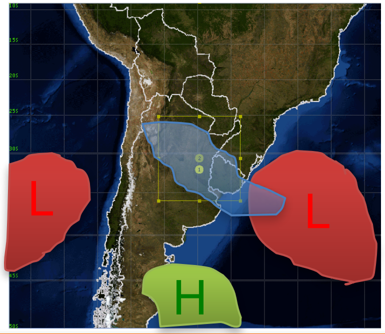
Putting the pieces together

Seasonal drivers

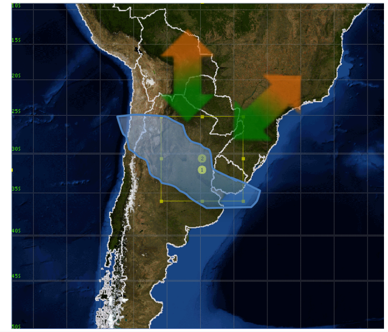
SAM



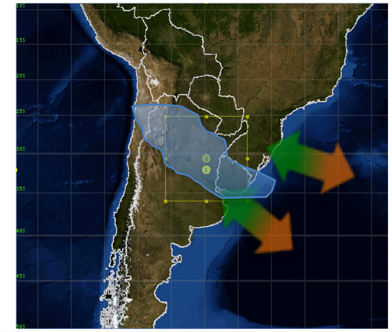
ENSO



AMM

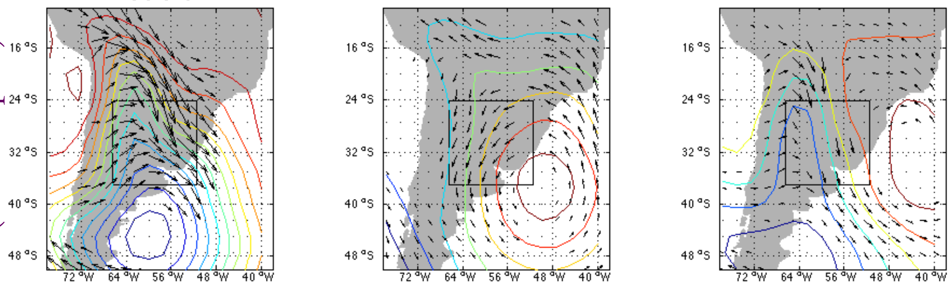


SAD



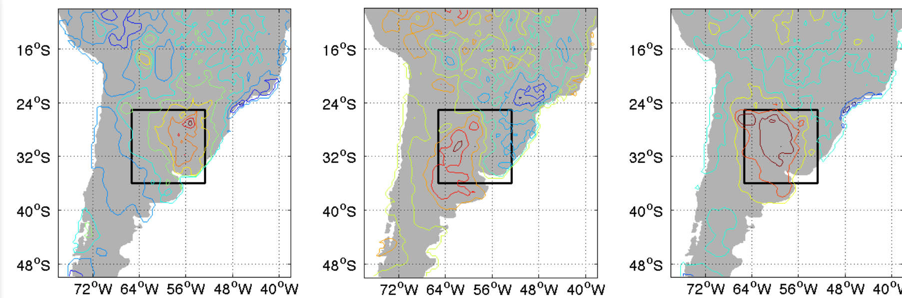
(3 Examples)

WT4 WT5 WT6



Vertically-integrated moisture advection

WT4 WT5 WT6

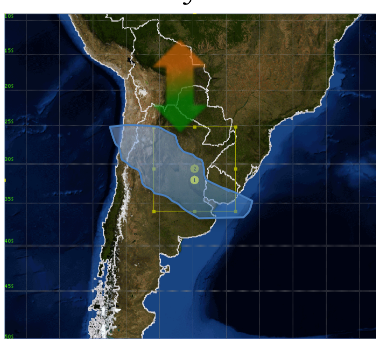


Rainfall patterns

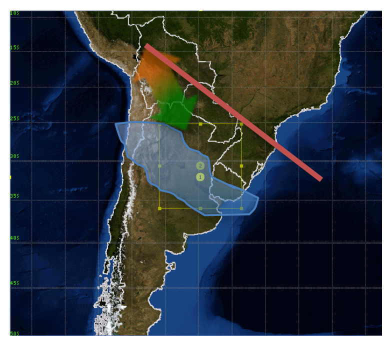
Sub-seasonal drivers

Could the WT contain all the information needed to make good forecasts of extreme events?

MJO



SACZ

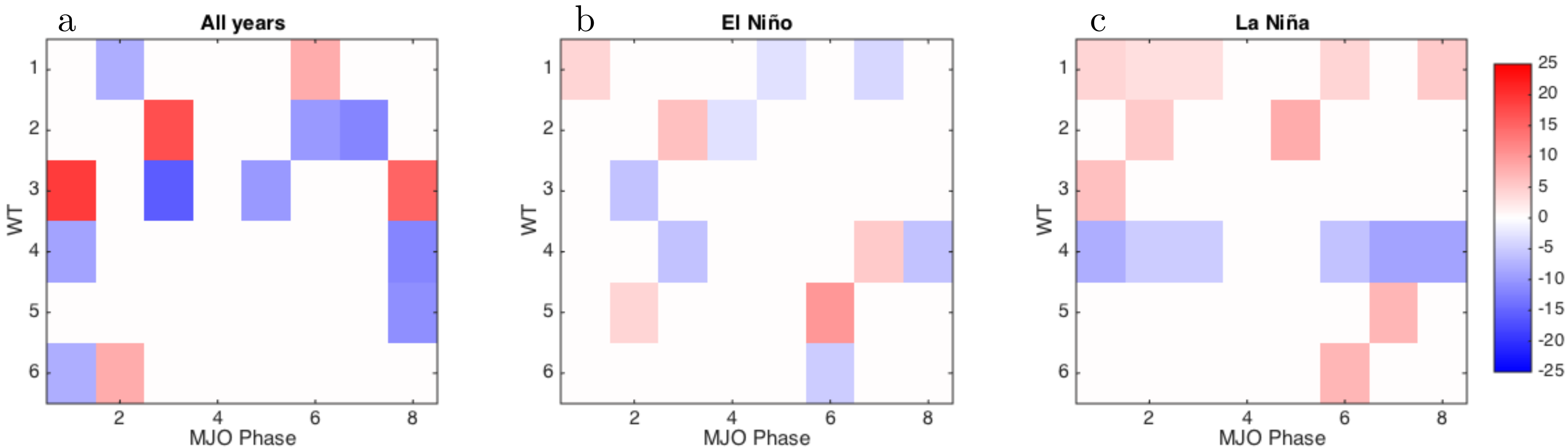


Different drivers interacting at different temporal and spatial scales, but their impacts are represented by only 6 weather types

Muñoz et al., 2015

Interactions and predictability

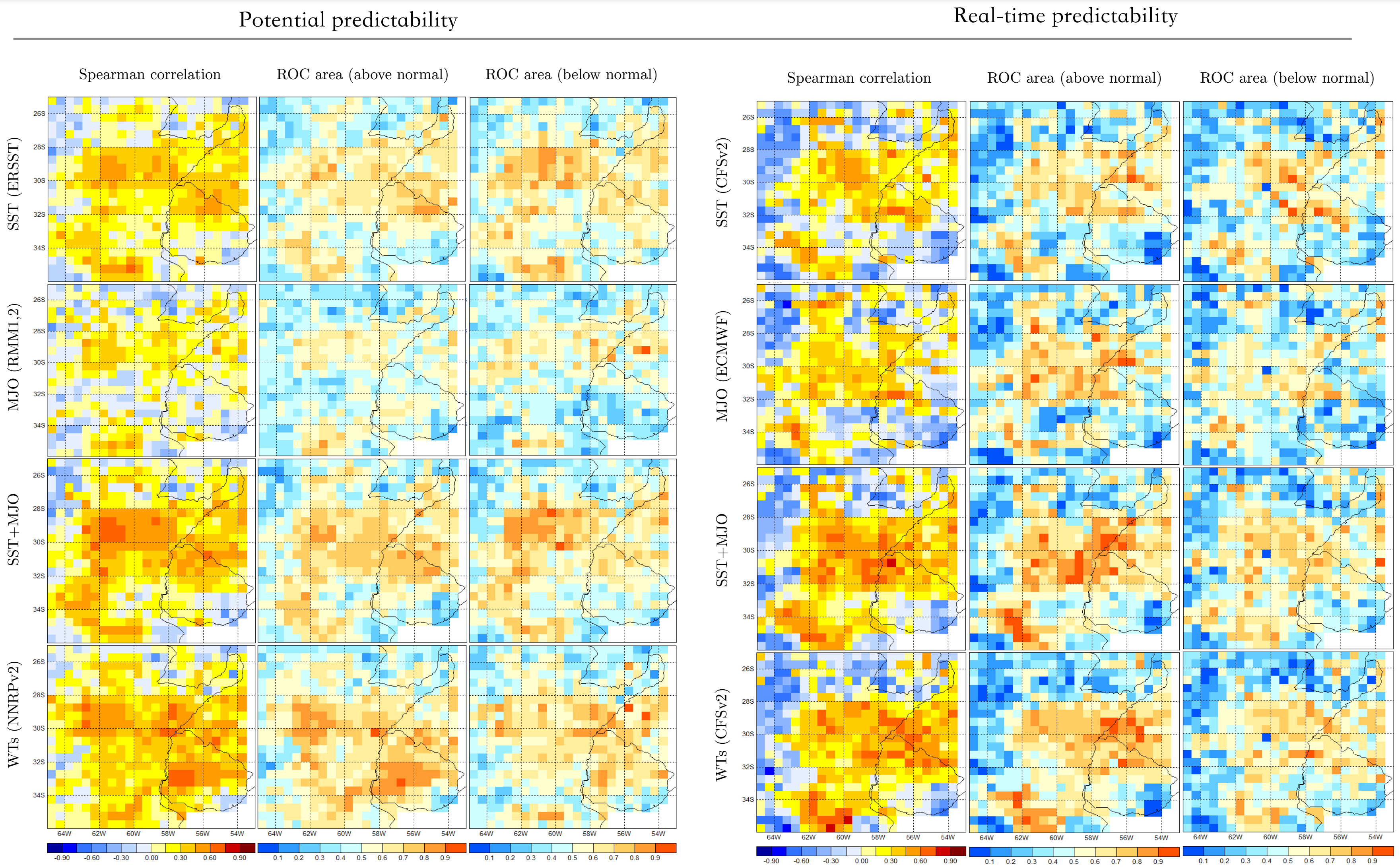
+ Are climate drivers independent?
+ Entanglement of climate drivers (s2s states?)
+ Forecast skill enhancement
+ A way to subseasonal-to-seasonal forecasts?



Anomalous percentage of occurrence (see color bar) of each weather type for each phase of the MJO for all DJF seasons (1981-2010; panel a), El Niño events (b) and La Niña events (c). Region: South Eastern South America.

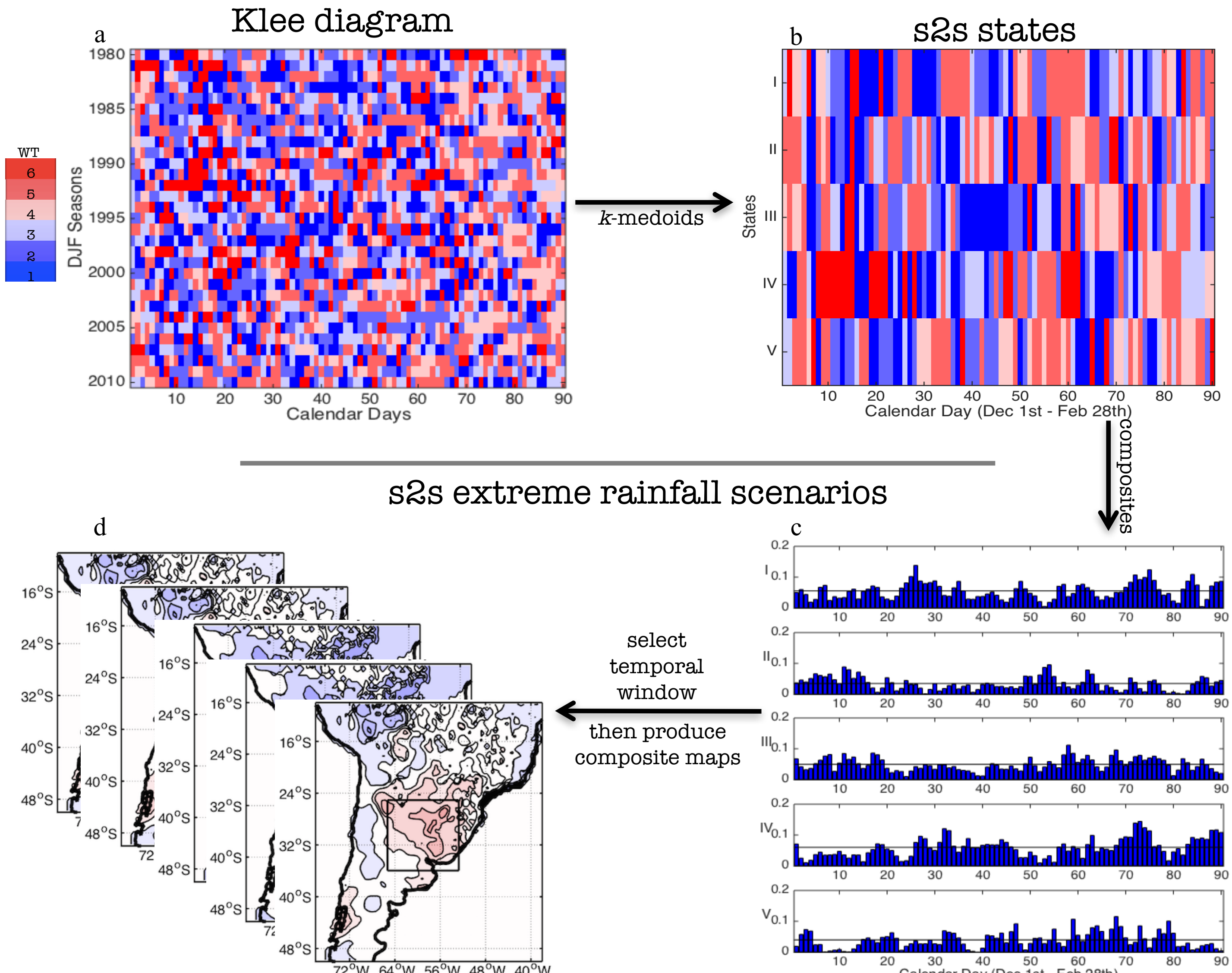
Muñoz et al. 2015, 2016

XTSI and seasonal skill



Muñoz *et al.* (2016, J. Clim)

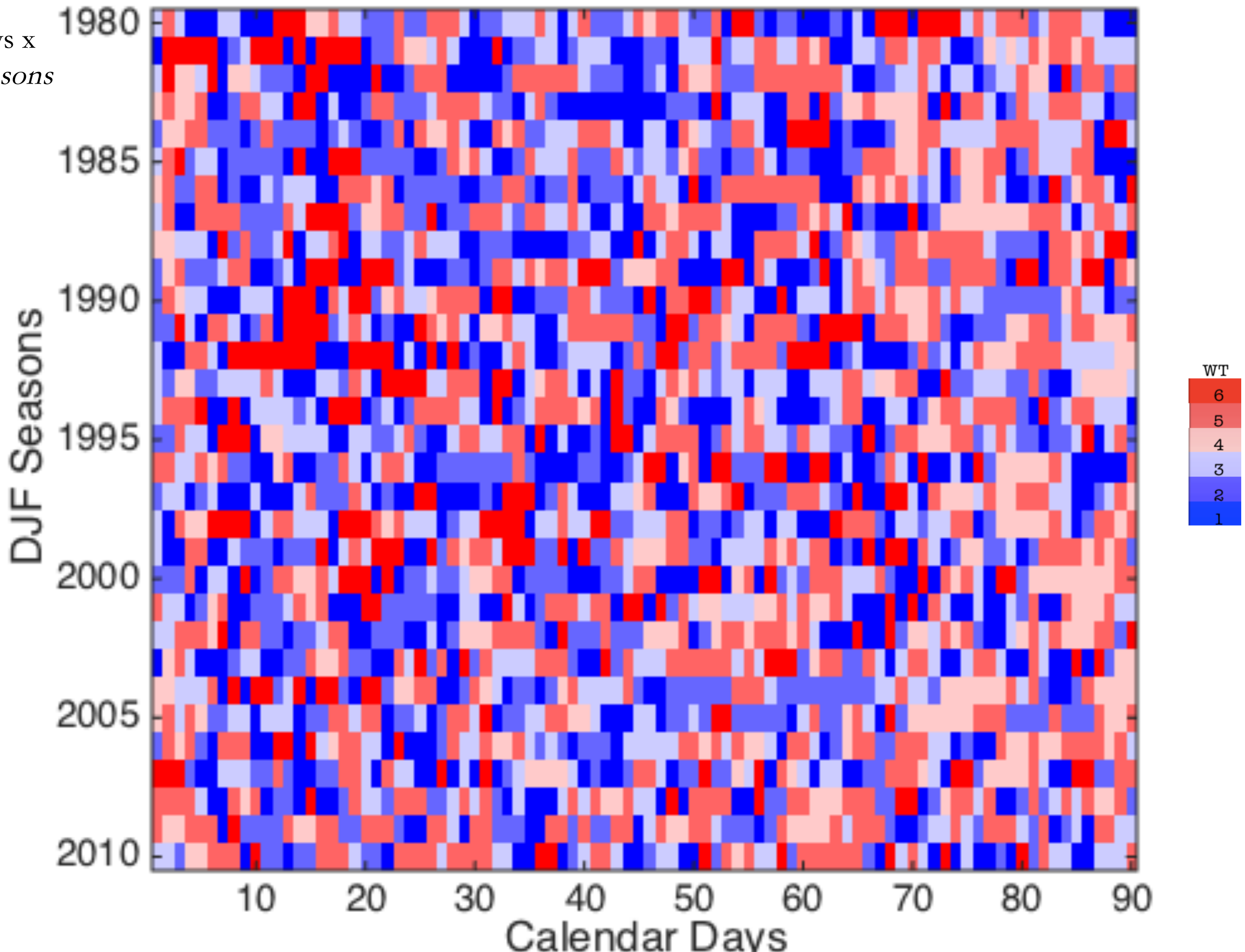
Extracting s2s extreme rainfall scenarios



Muñoz *et al.* (2016, J. Clim). See also: Moron *et al* 2013 (J. Clim)

Extracting s2s extreme rainfall scenarios

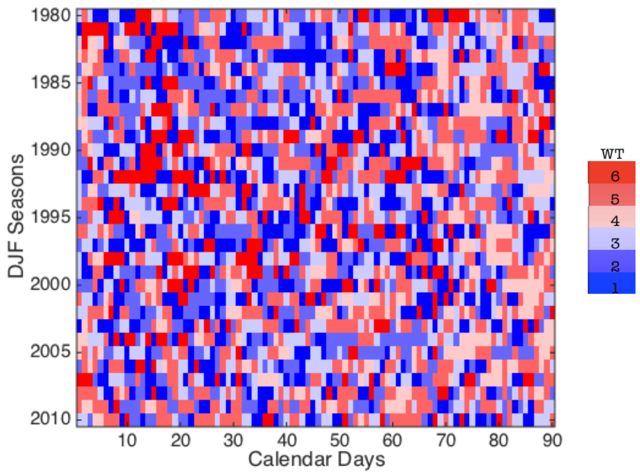
WTs:
90 days x
31 seasons



Muñoz *et al.*, 2015, 2016

Paul Klee (1879-1940)

Extracting s2s extreme rainfall scenarios

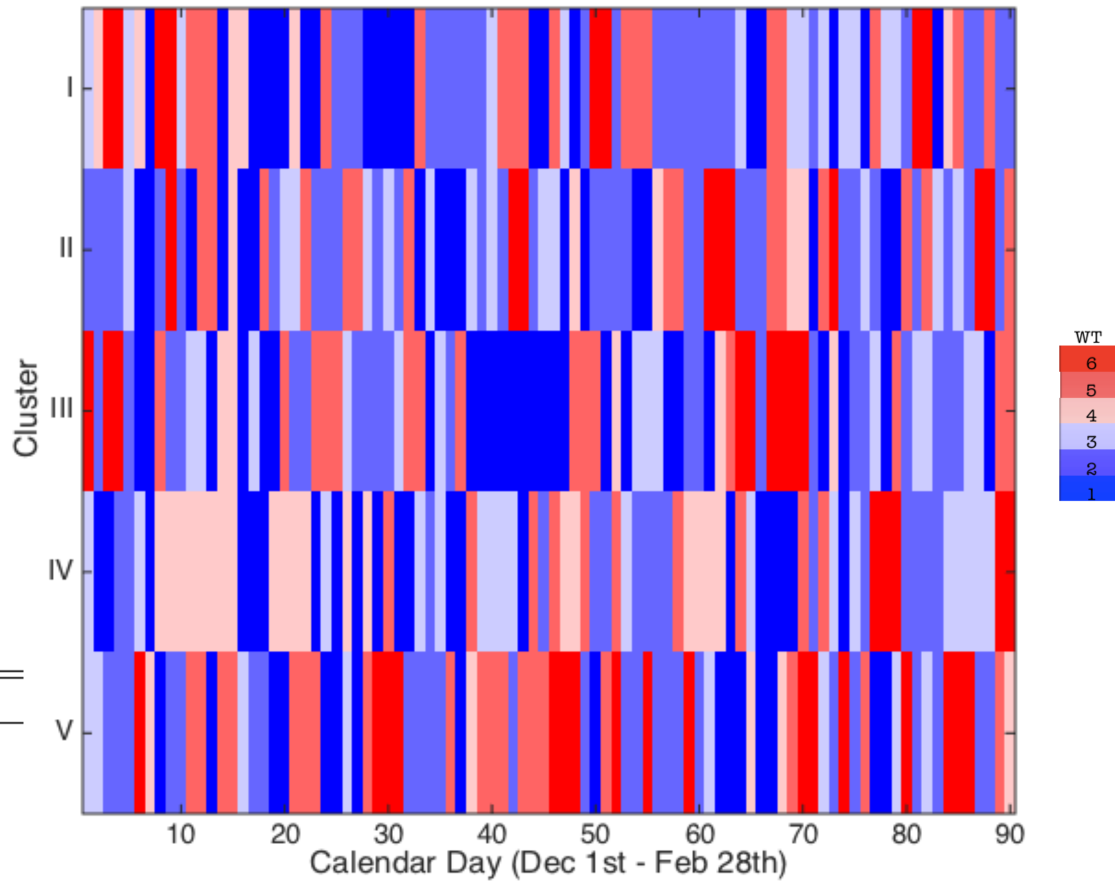


Categorical classification algorithm (Hamming distance), repeated multiple times

k-medoids

s2s state	Years	Sample
I	1982, 1986, 1996, 1998, 2003, 2007, 2009, 2010	8
II	1989, 1991, 1995, 1997, 2006, 2008	6
III	1980, 1983, 1985, 1988, 1990, 1993, 1994, 2005	8
IV	1981, 1984, 1987, 1992, 2004	5
V	1999, 2000, 2001, 2002	4

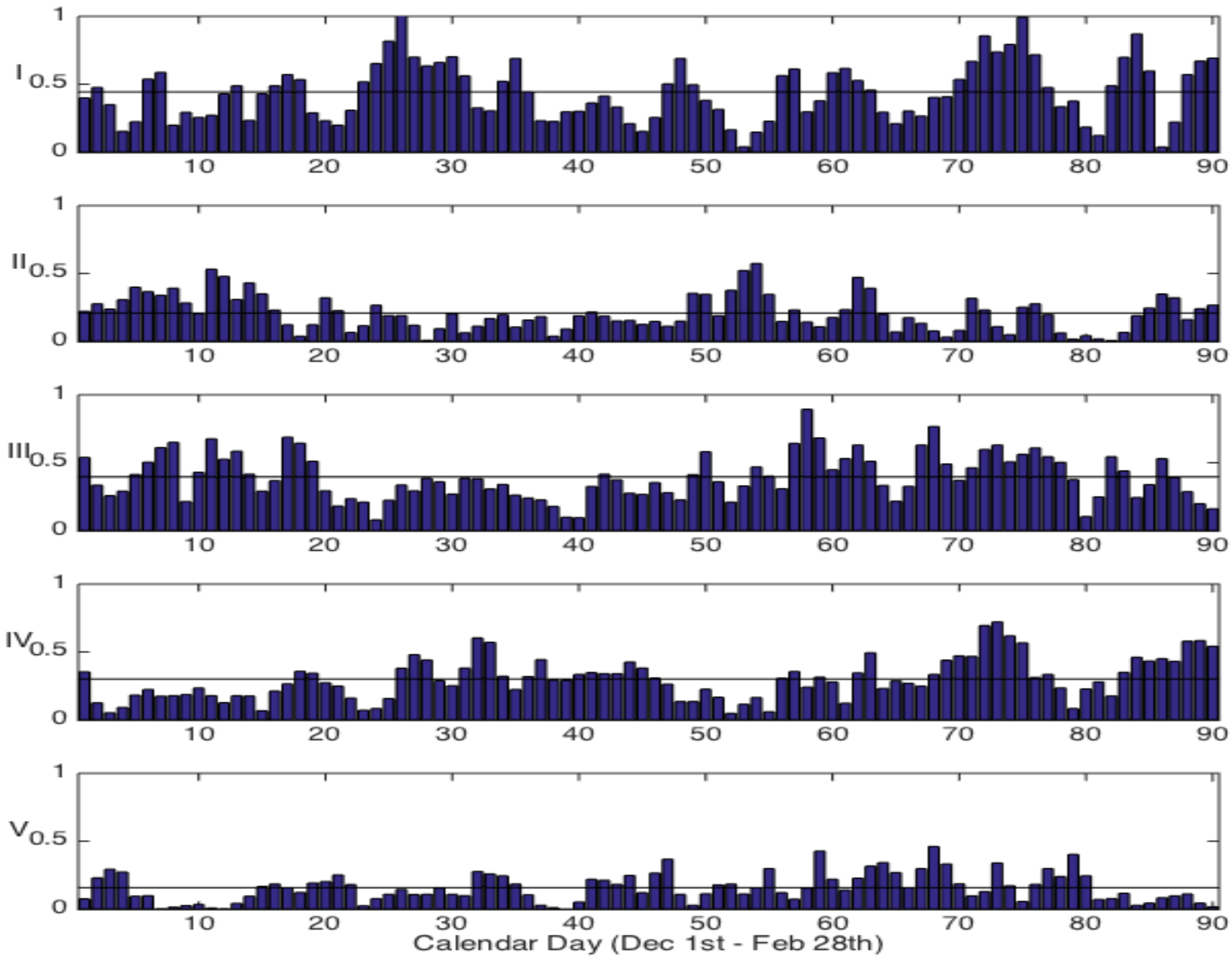
States = representative sequences of WTs



Muñoz *et al.*, 2015, 2016

Extracting s2s extreme rainfall scenarios

Frequency of days exceeding the 95th percentile (per grid box)



39.6 days/season

18.9 days/season

36.0 days/season

27.0 days/season

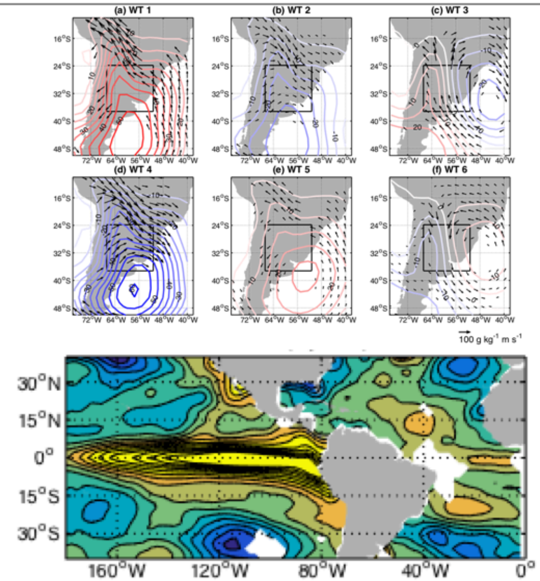
14.4 days/season

Interested in a particular week/month?

Muñoz *et al.*, 2015, 2016

S2S extreme rainfall scenarios: Summary

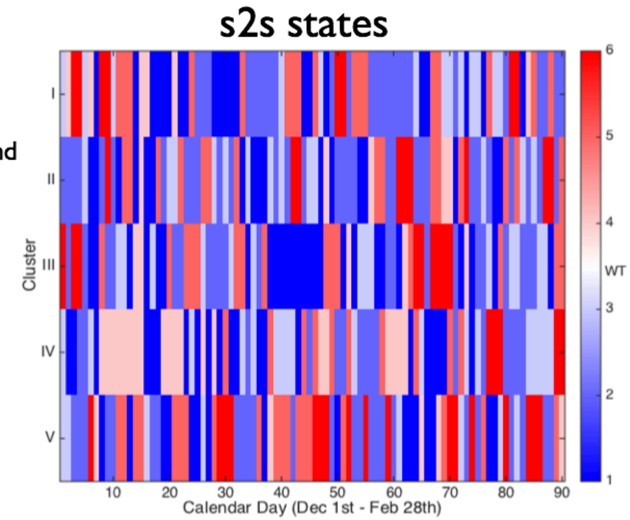
WTs sequences/frequencies for next season (GCM), or observed SST+MJO phases



Predictor

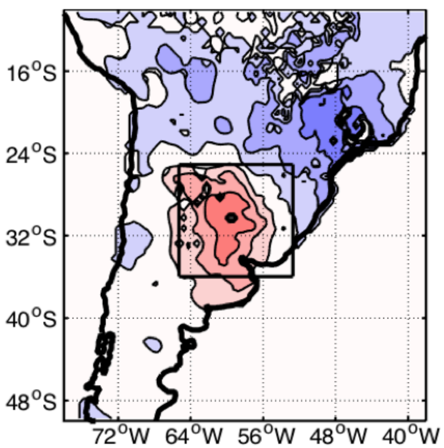
Predictand

Multinomial logistic model



s2s state's probabilities

s2s extreme rainfall scenario

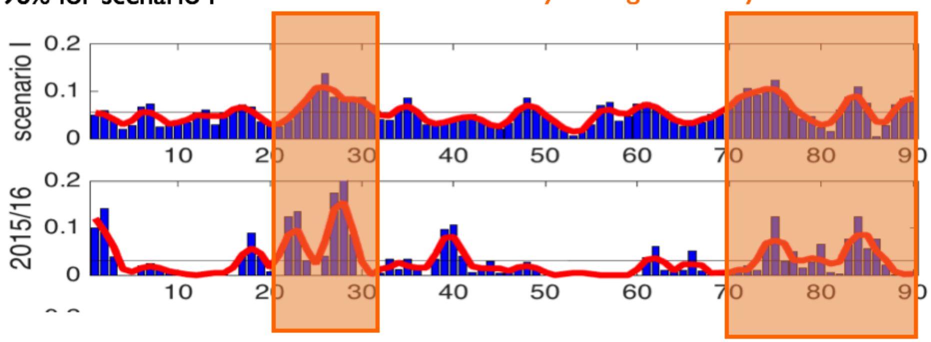


Spatial distribution

Forecast DJF '16

96% for scenario I

Extremes more likely during these days:



Temporal distribution

Selection: 95th, 99th,…

Composite analysis/analogs

Muñoz *et al.* (2016, J. Clim)

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Summary

+ The forecast skill of extreme rainfall frequency in South East South America for the DJF season is improved when the interference of predictors at different timescales is considered.

+ Attributed to mechanisms of climate variability acting at one timescale that contribute to predictability at other timescales.

+ Seasonal forecasts of frequency of daily rainfall exceeding the 95th-percentile are, at regional scale, significantly more skillful when cross-timescale predictors are used, compared to models employing SST fields alone or when model rainfall is used.

+ Subseasonal-to-seasonal scenarios for extreme rainfall events can be built based on probability forecasts of seasonal sequences of weather types. (Another method: Moron *et al* 2013, J. Clim).

+ The cross-validated predictions show Hit Scores ~50% (climatological: 20%). The model is better for state I (extremely wet season), followed by state III (wet), worse for state V (dry), which tends to be confused with state II. (Muñoz et al., 2016)