Winter precipitation scenarios for the Western United States: bridging subseasonal and seasonal forecasts

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In Memoriam
Lisa Goddard
1966-2022

Outline

1. Context
2. The Approach
3. Subseasonal-to-seasonal (s2s) Scenarios
4. Discussion

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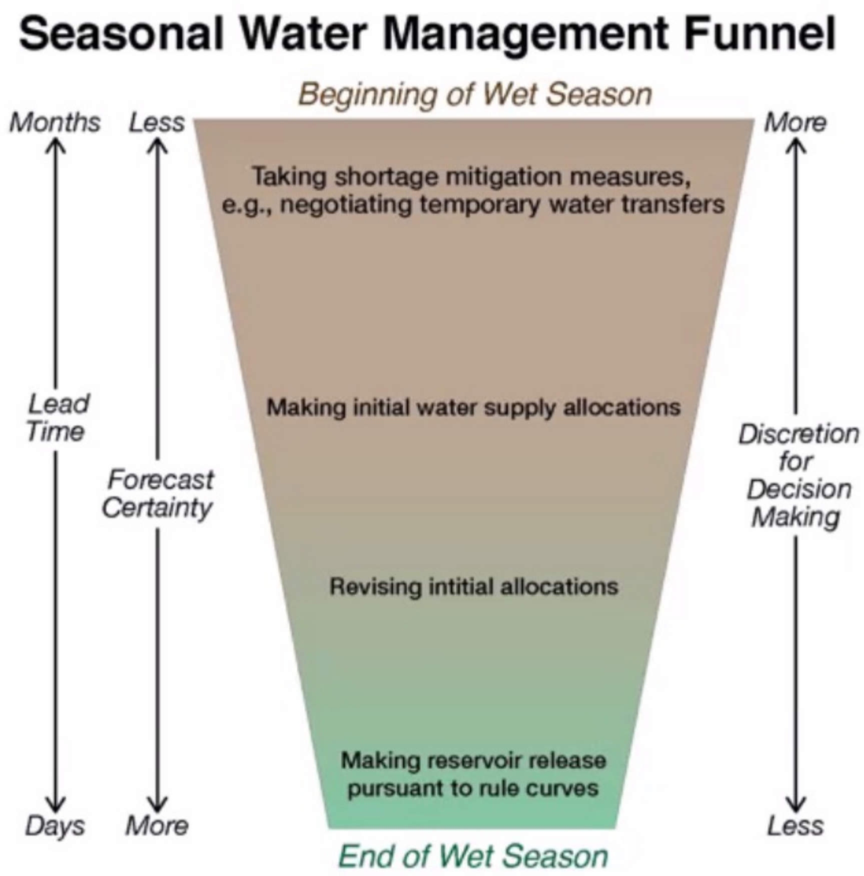
Water Resources Management

The Demand
(or part of it)



(Courtesy of Jeanine Jones)

1. Total rainfall is important but also how it is distributed in time (onset, demise, duration, frequency, intensity).
2. Multiple lead times are important: subseasonal, seasonal, interannual (e.g., 2-yr is key because of storage capacity).
3. Understandable, reliable forecasts.
4. Link to experience/common sense management practices (*context*).

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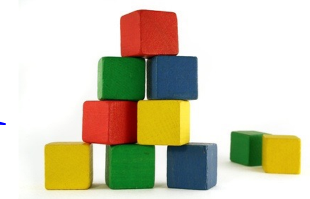
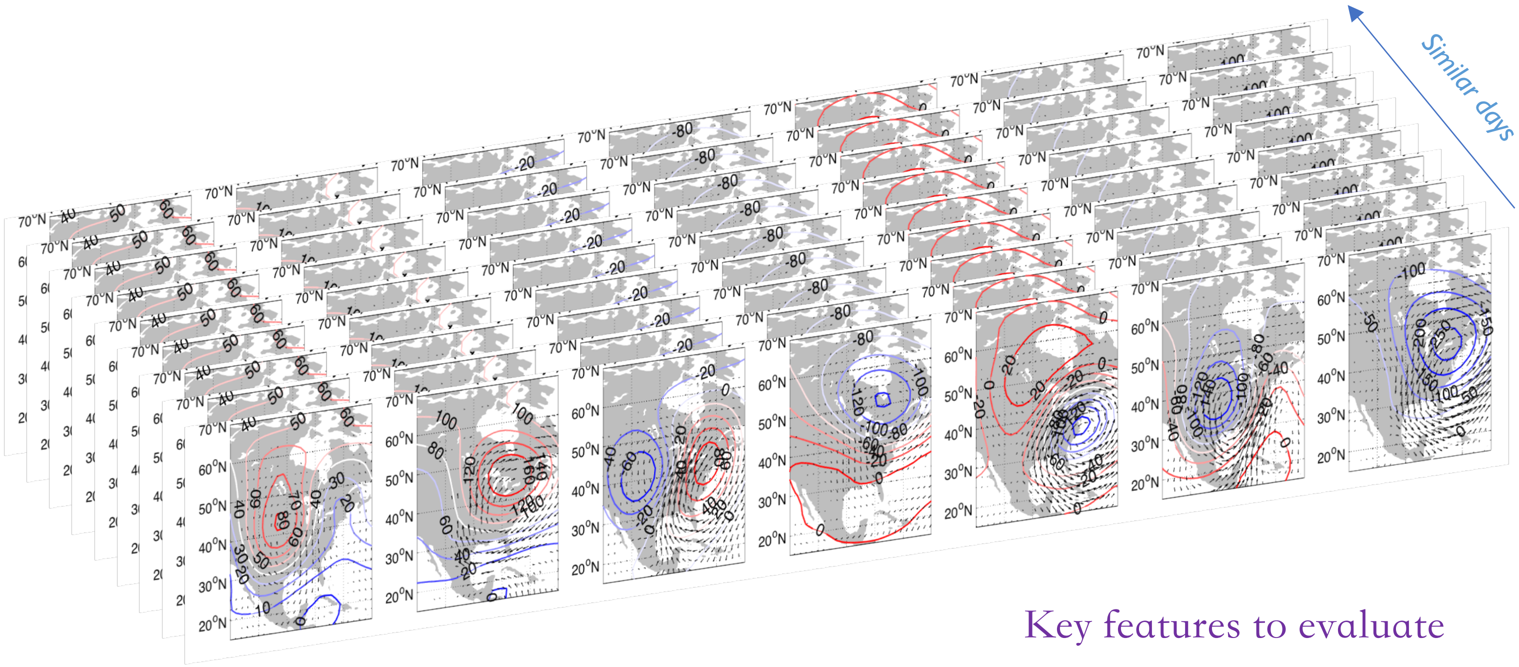
A Flow-Dependent Approach



Building blocks!



Minimize the function:

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

Key features to evaluate

- Shape, location and magnitude of spatial patterns
- Daily transitions, duration, sub-seasonal and seasonal (and decadal, and$\cdots$) statistics
- Link to climate drivers

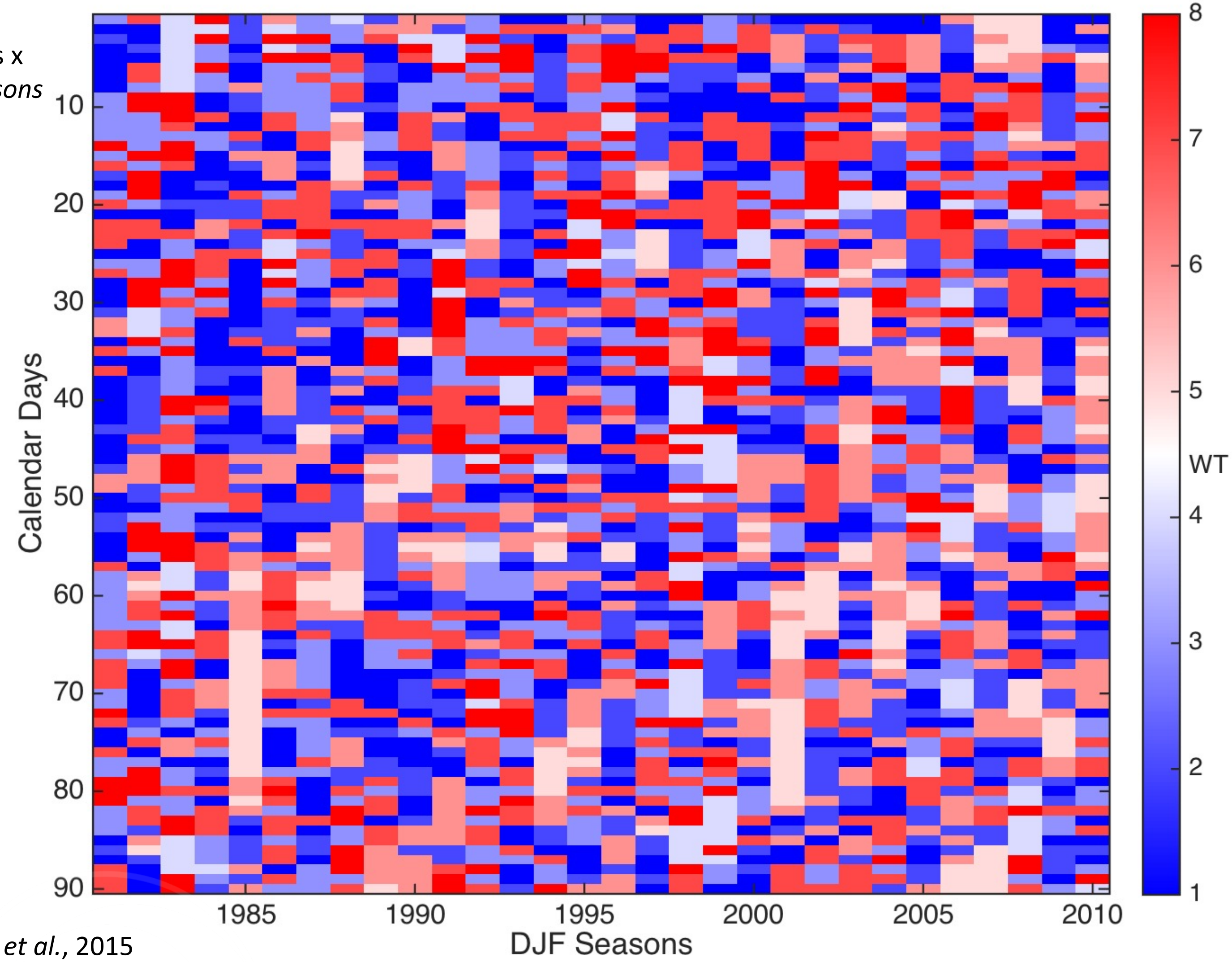
Michelangeli *et al.* (1995); Robertson and Ghil (1999); Robertson *et al.* (2015); Muñoz *et al.* (2015, 2016, 2017; in prep)

Klee and his exploration of color sequences

Paul Klee (1879-1940)

Klee diagram

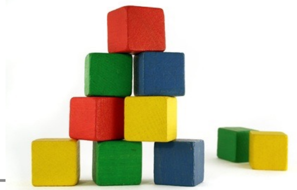
WTs:
90 days x
30 seasons

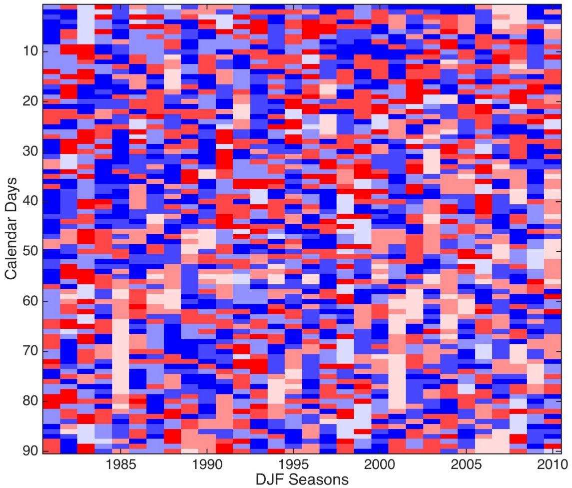


Muñoz *et al.*, 2015

Paul Klee (1879-1940)

Can we identify "typical years"?

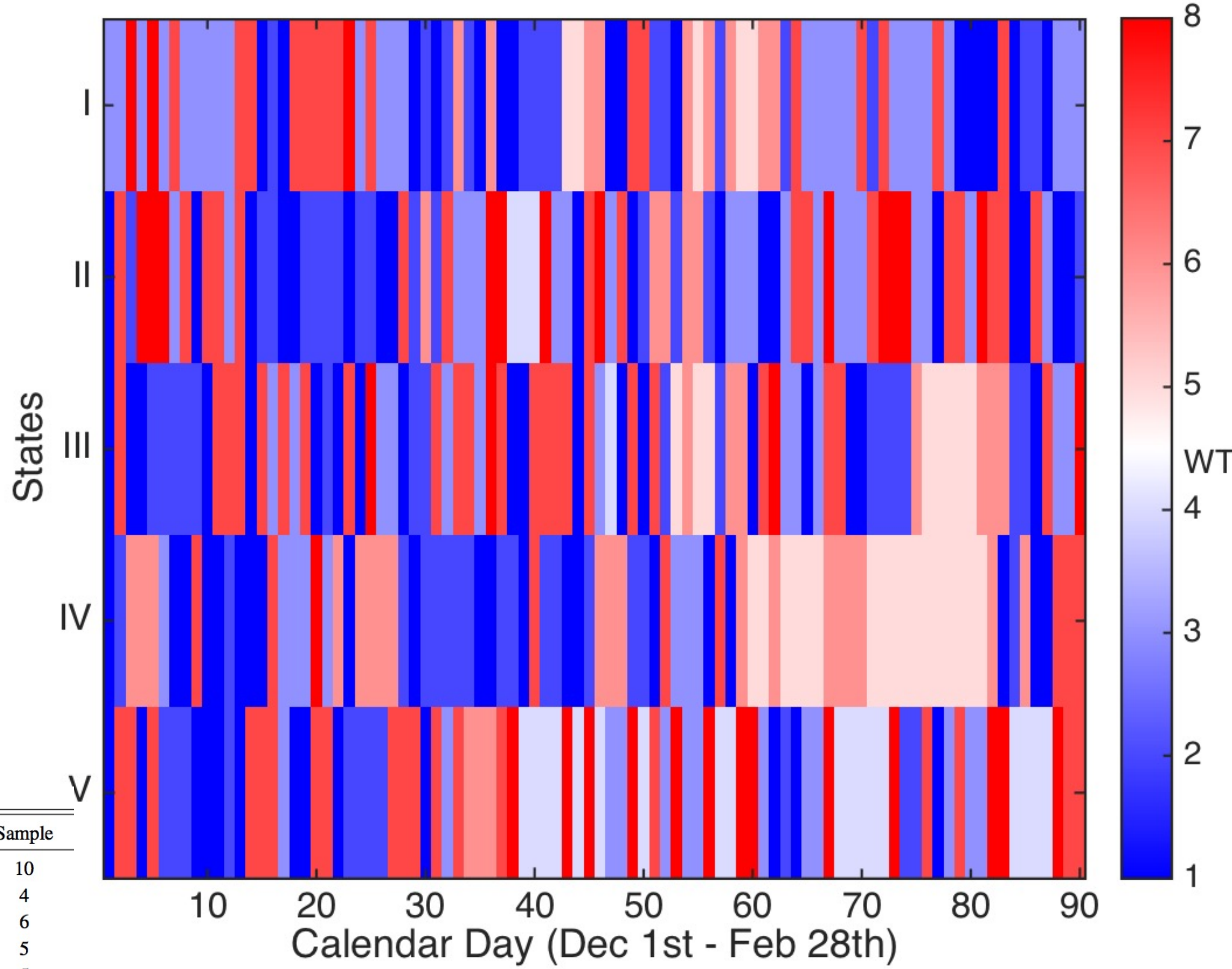




Categorical classification algorithm (Hamming distance), repeated multiple times

k-medoids

States = particular sequences of WTs

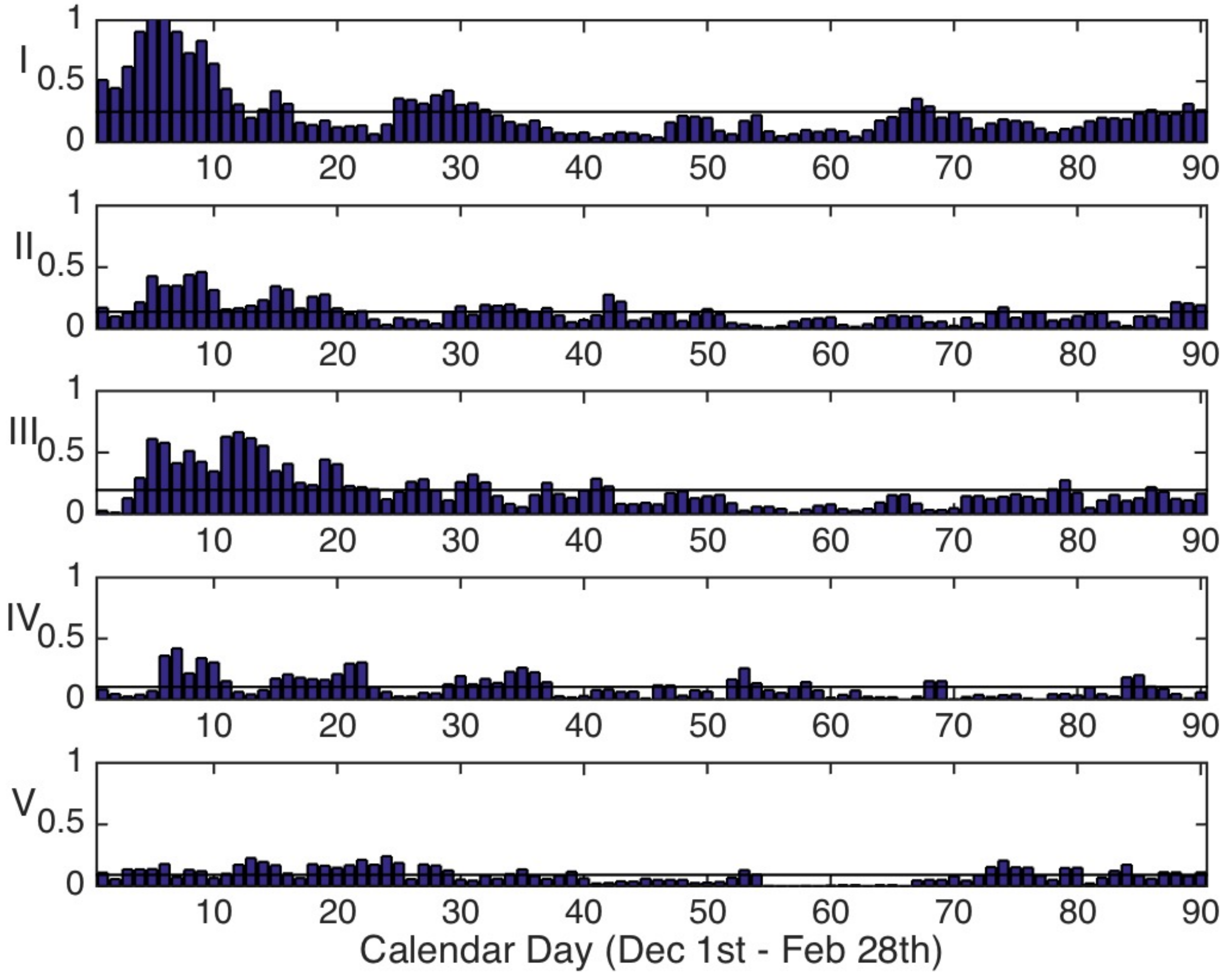


s2s state	Years	Sample
I	1981, 1982, 1984, 1986, 1987, 1988, 1990, 1995, 2004, 2010	10
II	1989, 1993, 1997, 2000	4
III	1991, 1994, 1996, 1999, 2002, 2006	6
IV	1985, 2001, 2003, 2007, 2009	5
V	1983, 1992, 1998, 2005, 2008	5

Muñoz *et al.*, 2015, 2016

s2s extreme rainfall *scenarios*

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



22.5 days/season

12.4 days/season

17.6 days/season

9.3 days/season

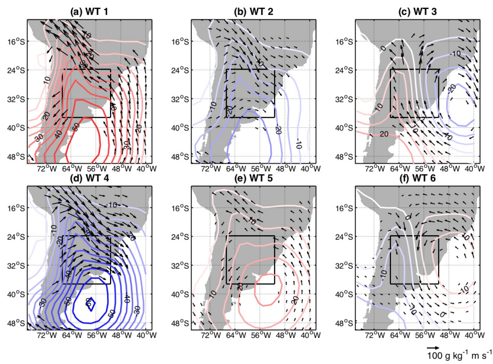
8.1 days/season

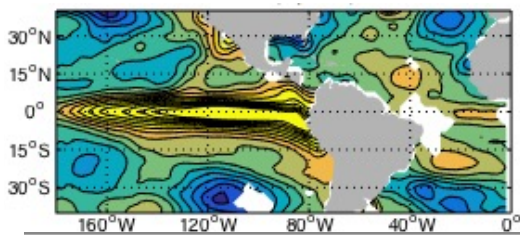
Interested in a particular week/month?

Muñoz *et al.*, 2015, 2016

The general picture: s2s scenarios

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



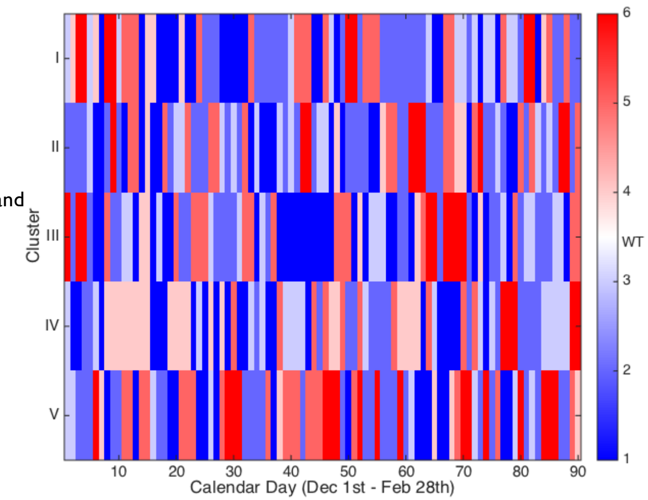


Predictor

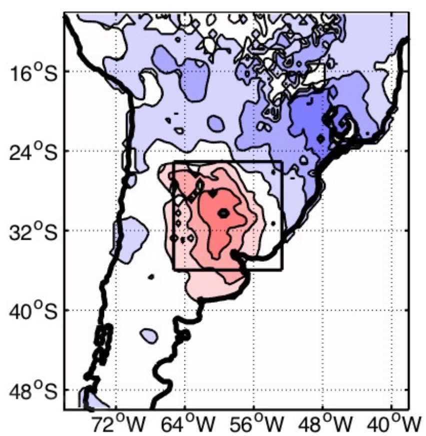
Predictand

Multinomial logistic model

s2s states



s2s extreme rainfall scenario

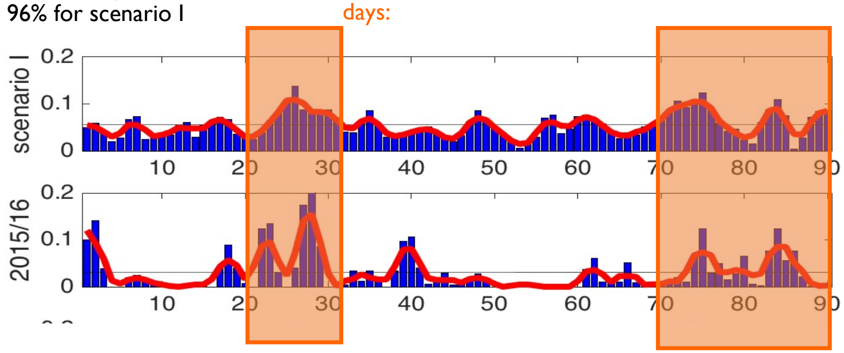


Spatial distribution

Forecast DJF '16

96% for scenario I

Extremes more likely during these days:



Temporal distribution

s2s state's probabilities

Selection: 95^{th}, 99^{th},…

Composite analysis/analogs

Moron et al 2015

Muñoz et al 2016

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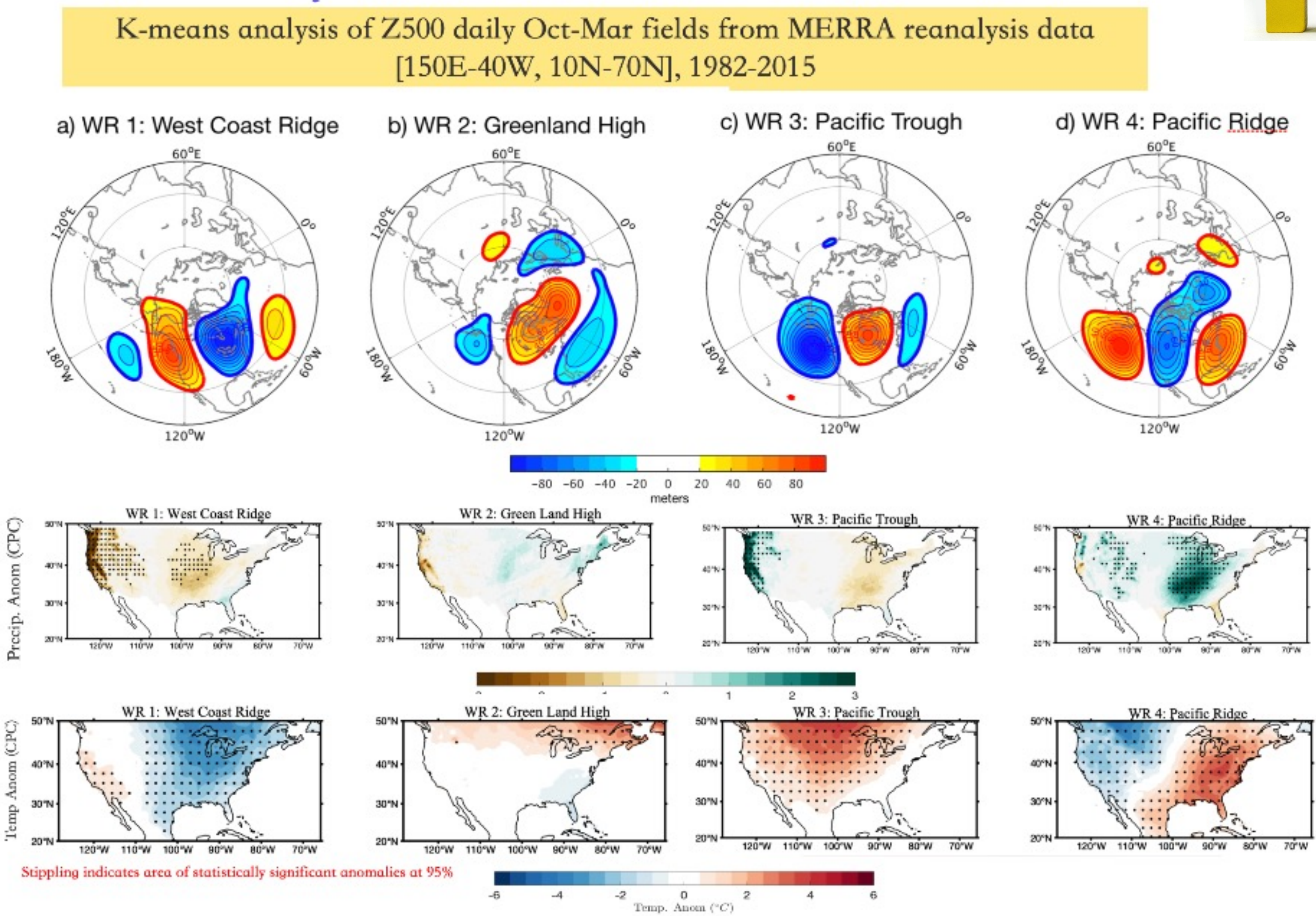
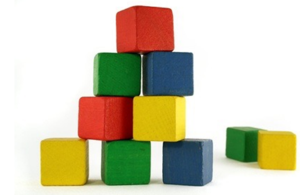
Weather Types and their "impacts"

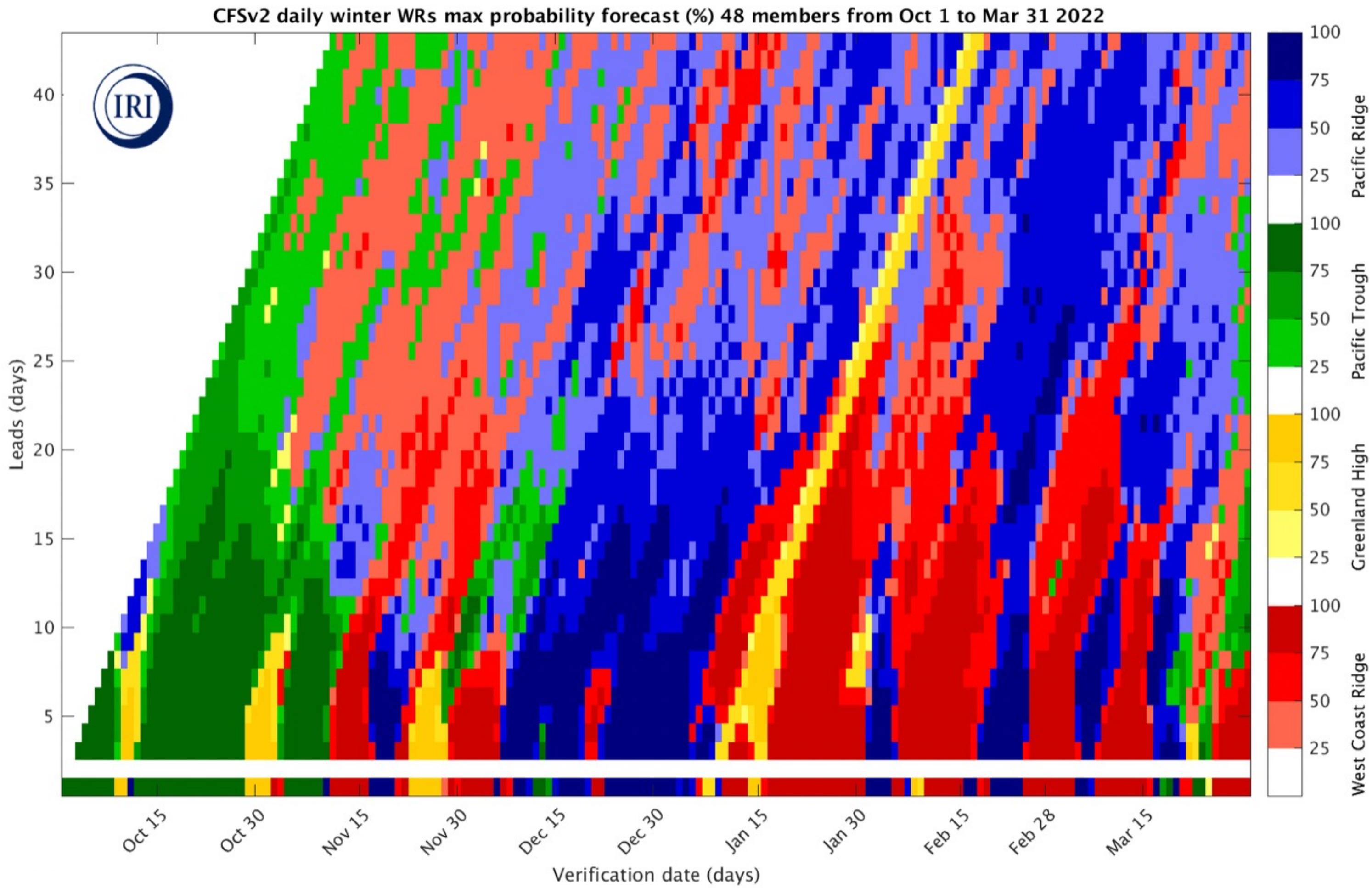


Robertson et al (2020); see also Andy's presentation tomorrow

Weather Types and their impacts

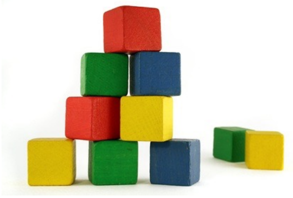


Forecasts at daily resolution

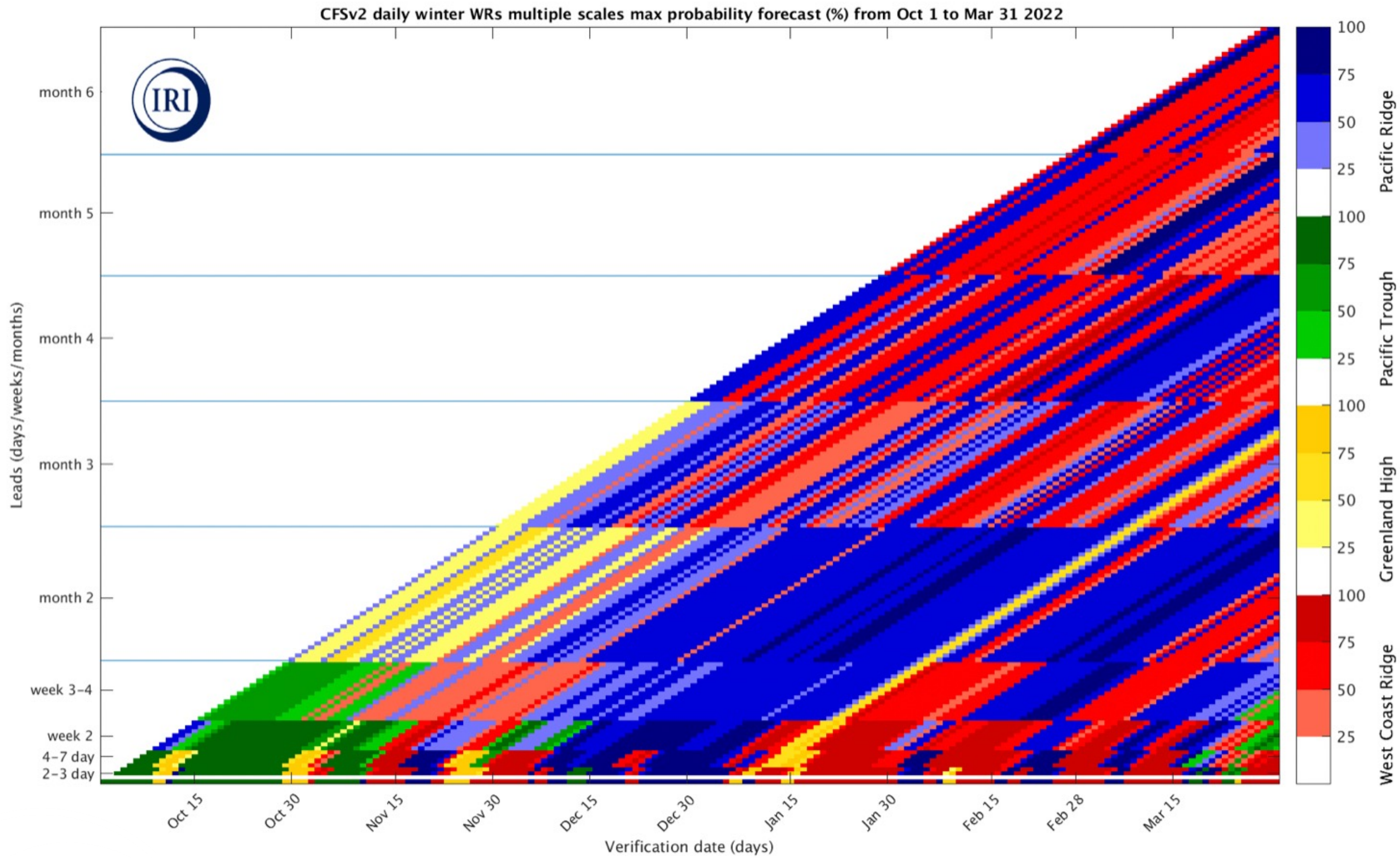


Robertson et al (2020)

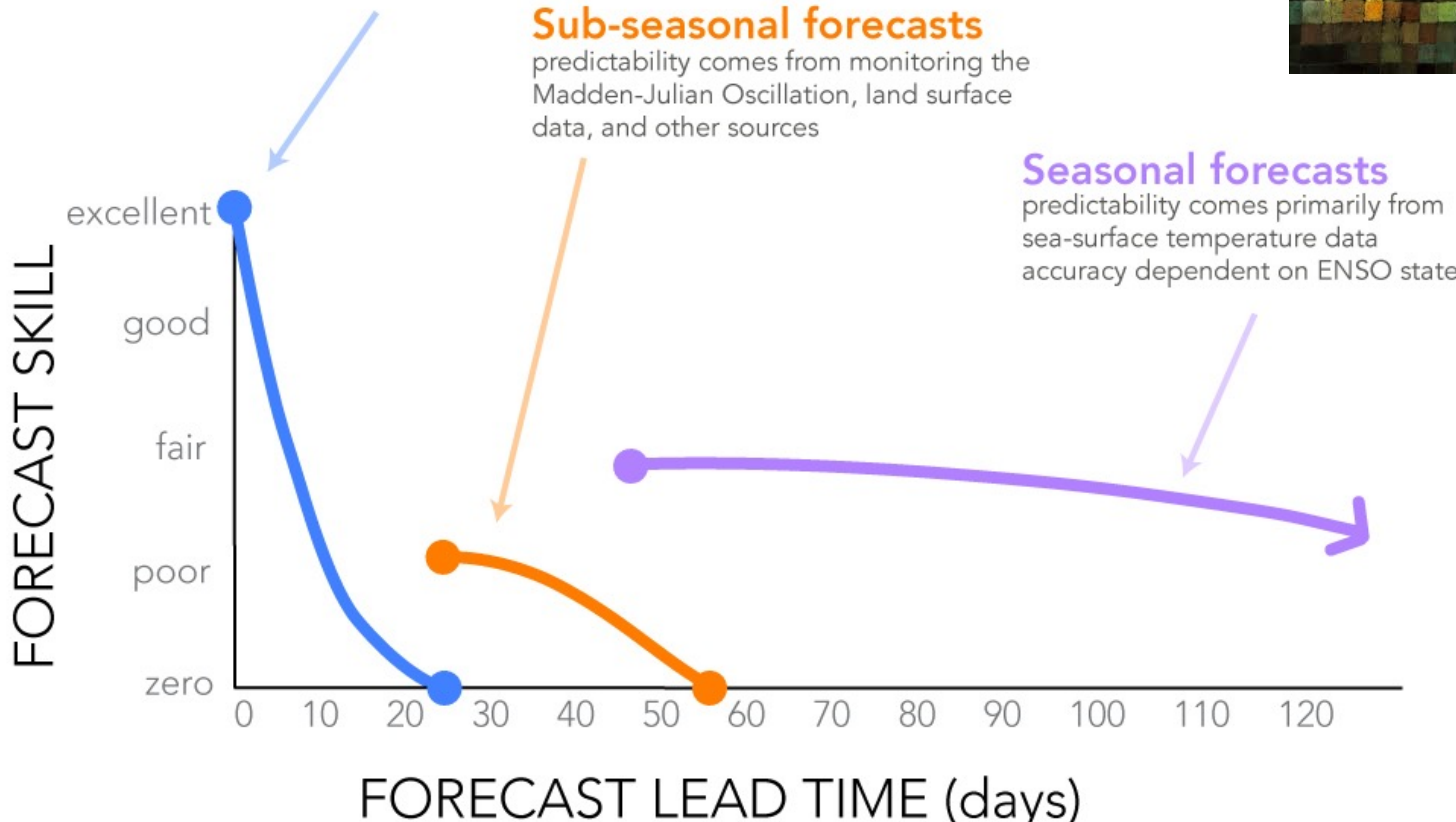
Weather Types and their impacts



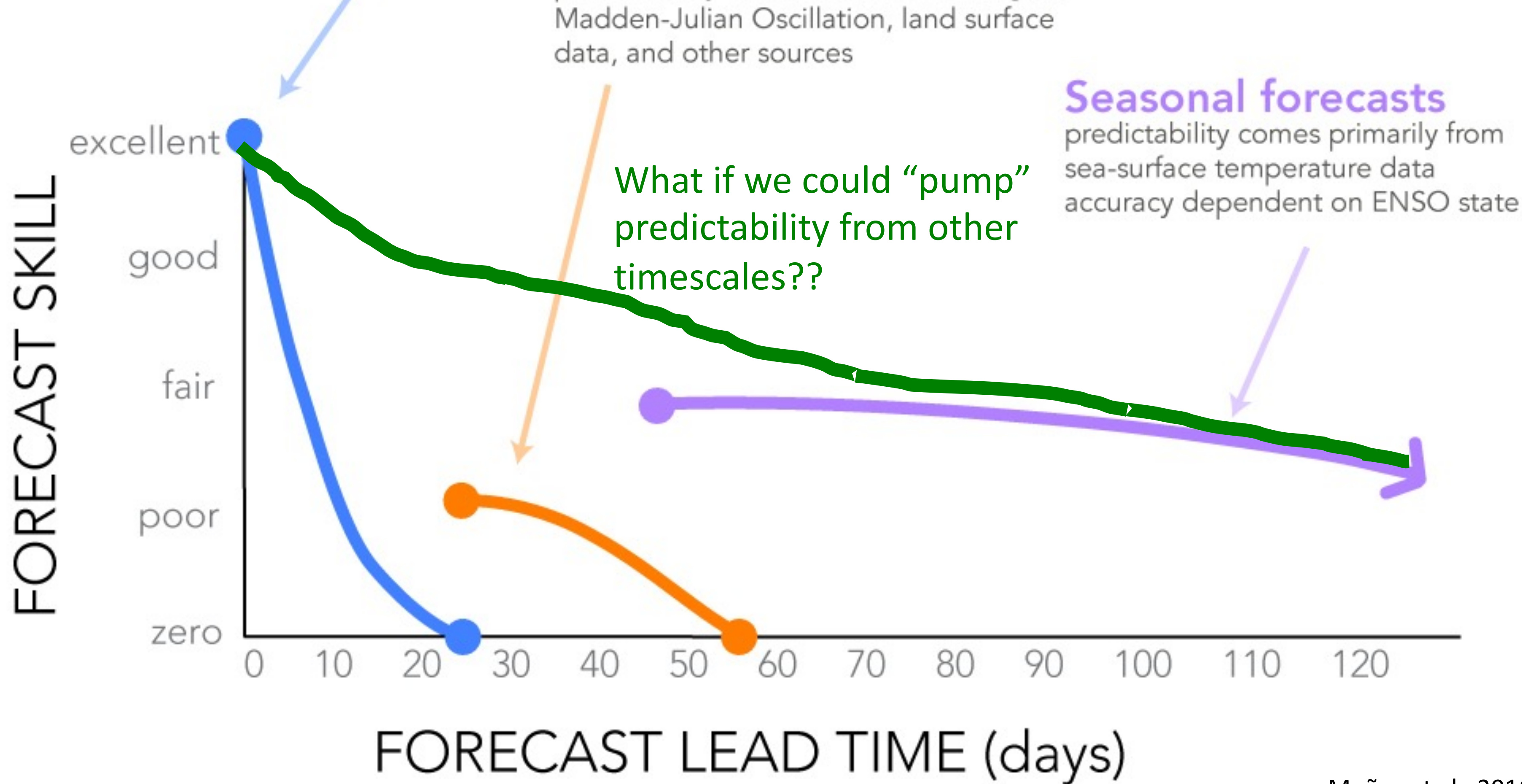
Six-month seamless forecasts



Robertson et al (2020)

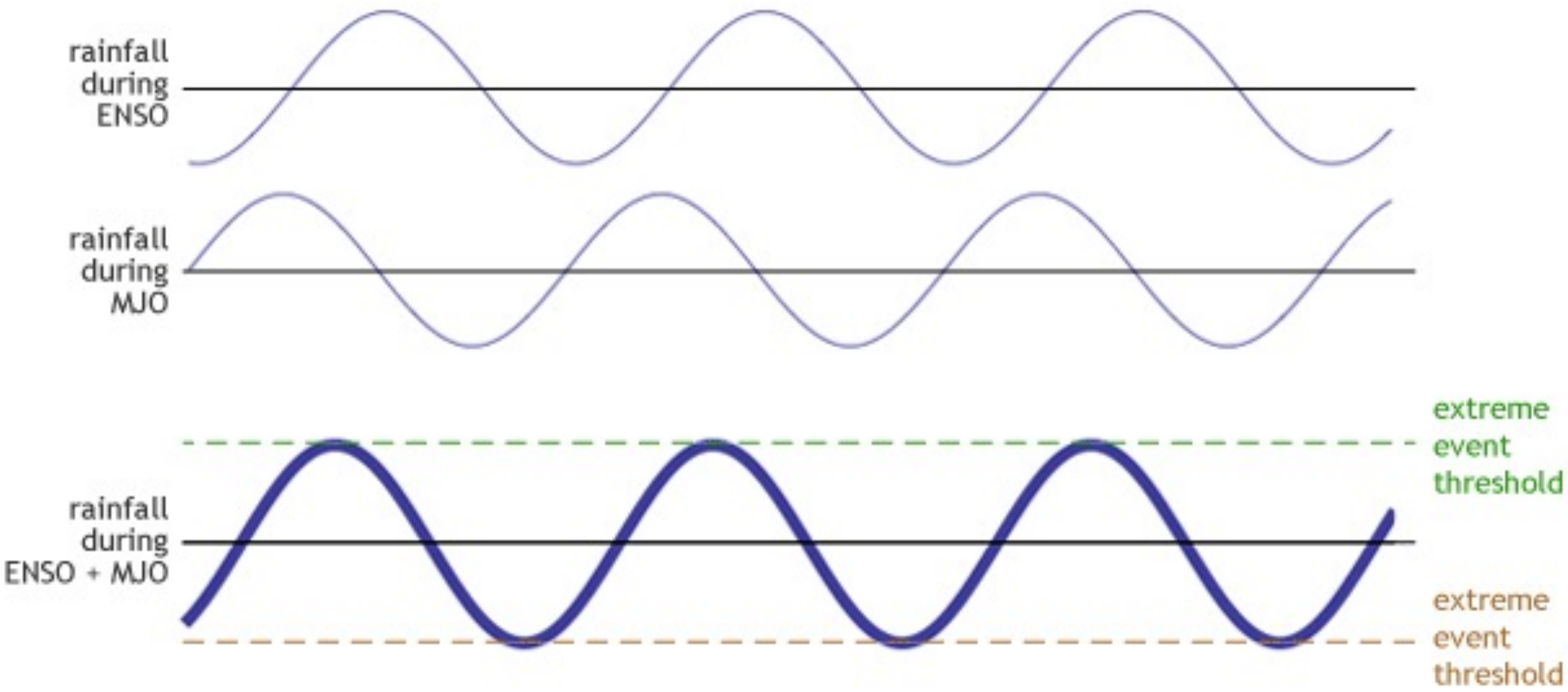


IRI Media team



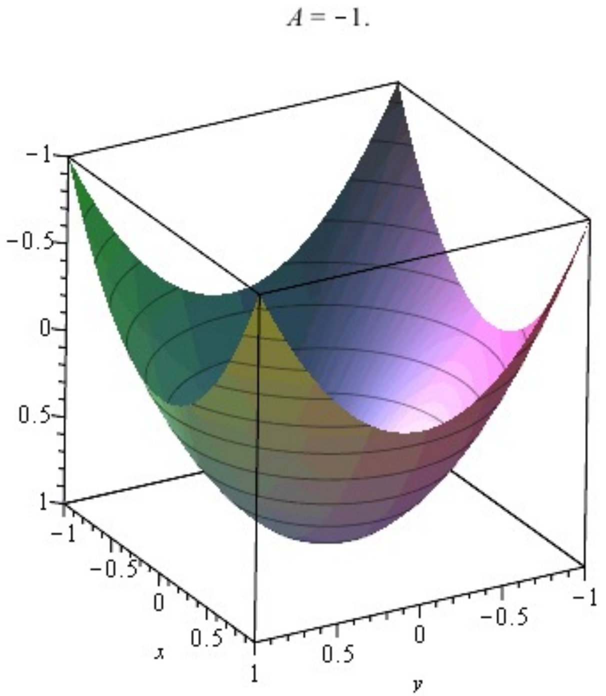
Muñoz et al., 2016

Cross-timescale Interference: orchestrating climate rhythms

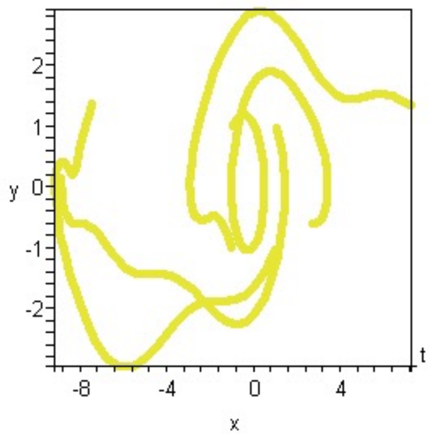


NOAA's ENSO Blog, Jan 2017 (Muñoz)

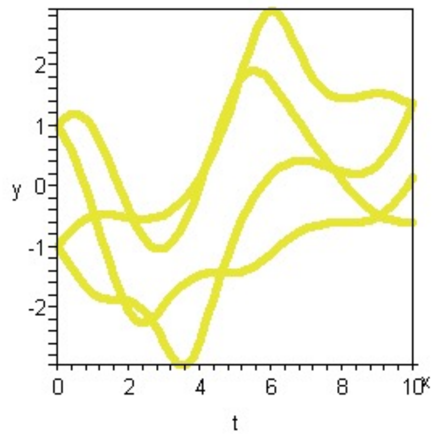
X-timescale interference and pre-conditioning



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



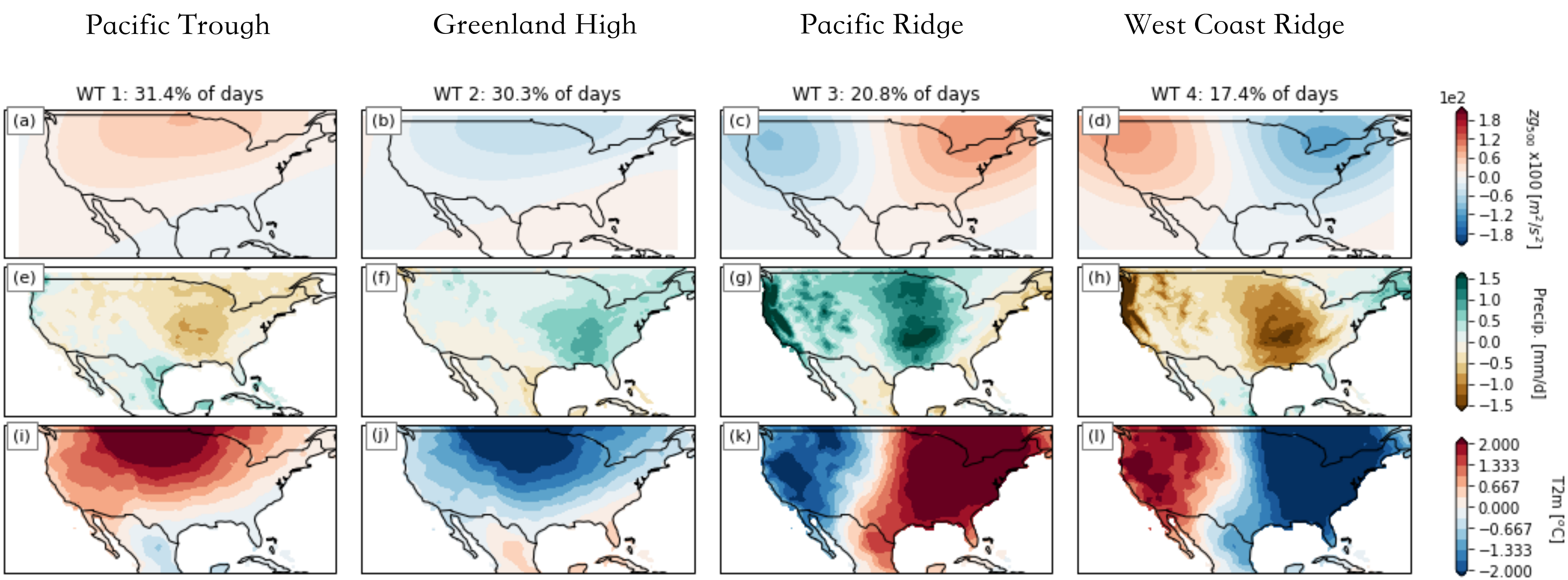
As a result, certain trajectories in the phase space tend to be visited more frequently by the system.



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

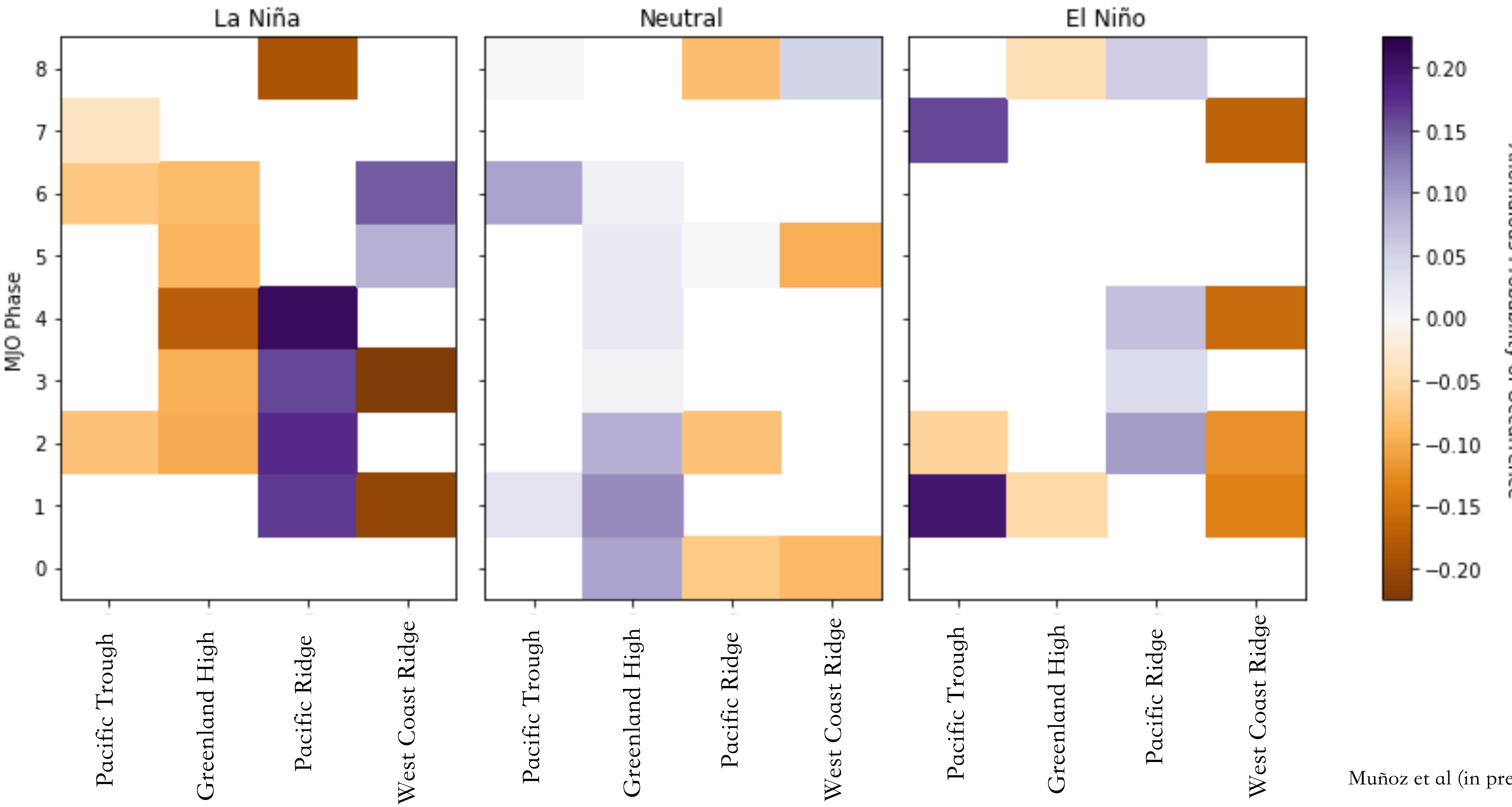
Muñoz et al (2015, 2016, 2017)

Weather Types and their impacts

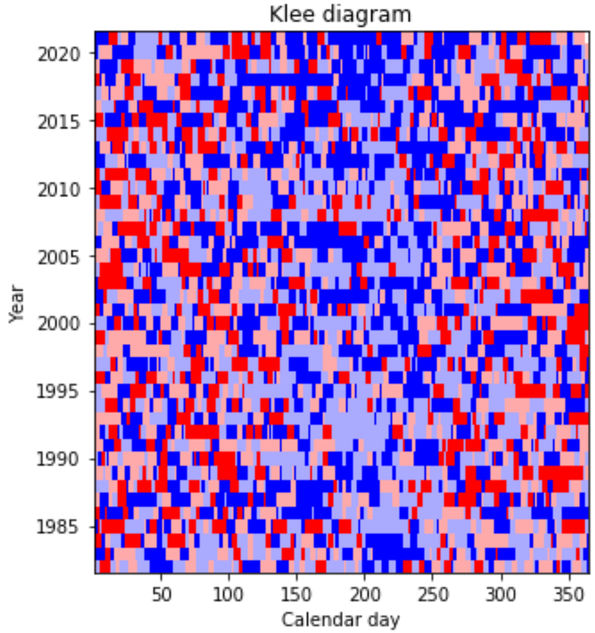


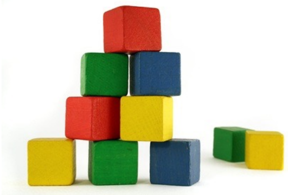
Muñoz et al (in prep)

Cross-timescale Interference

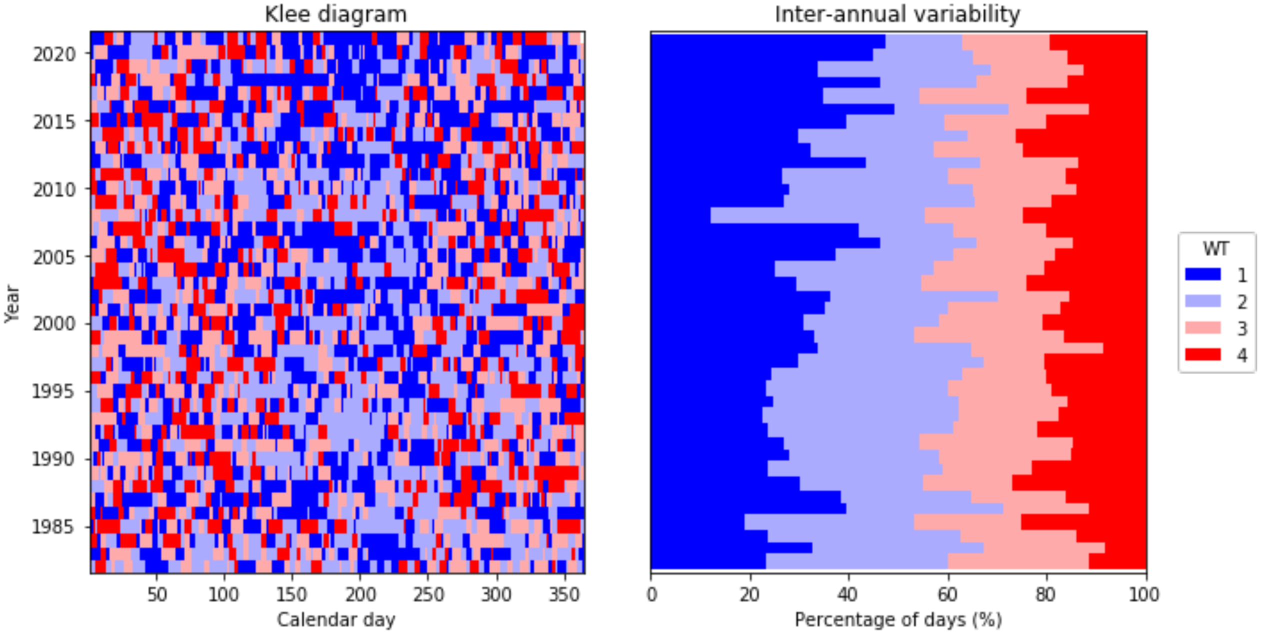


Muñoz et al (in prep)

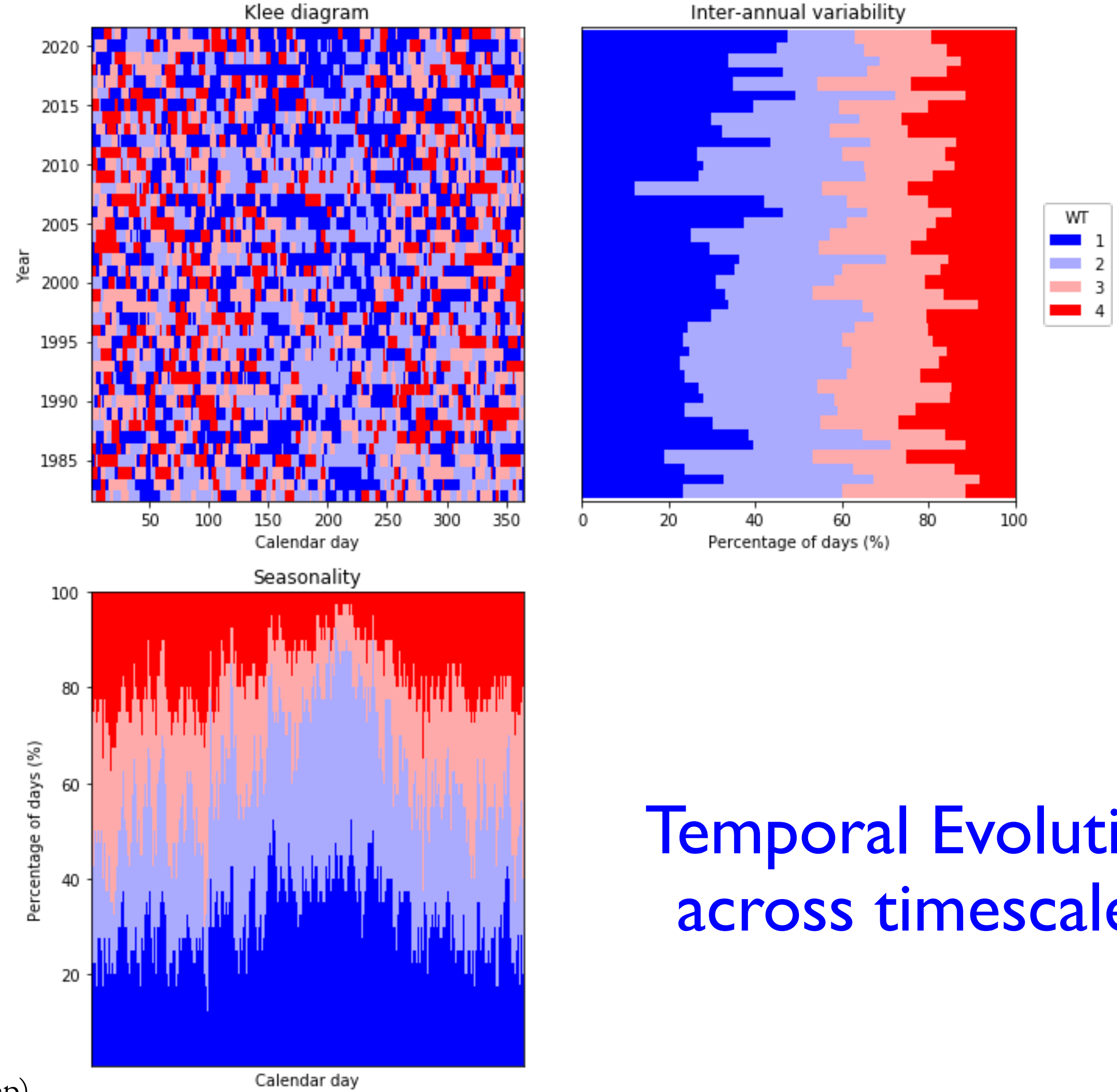




Temporal Evolution across timescales



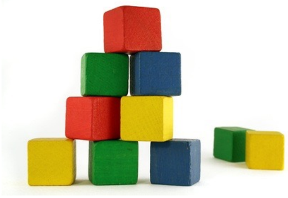
Temporal Evolution across timescales

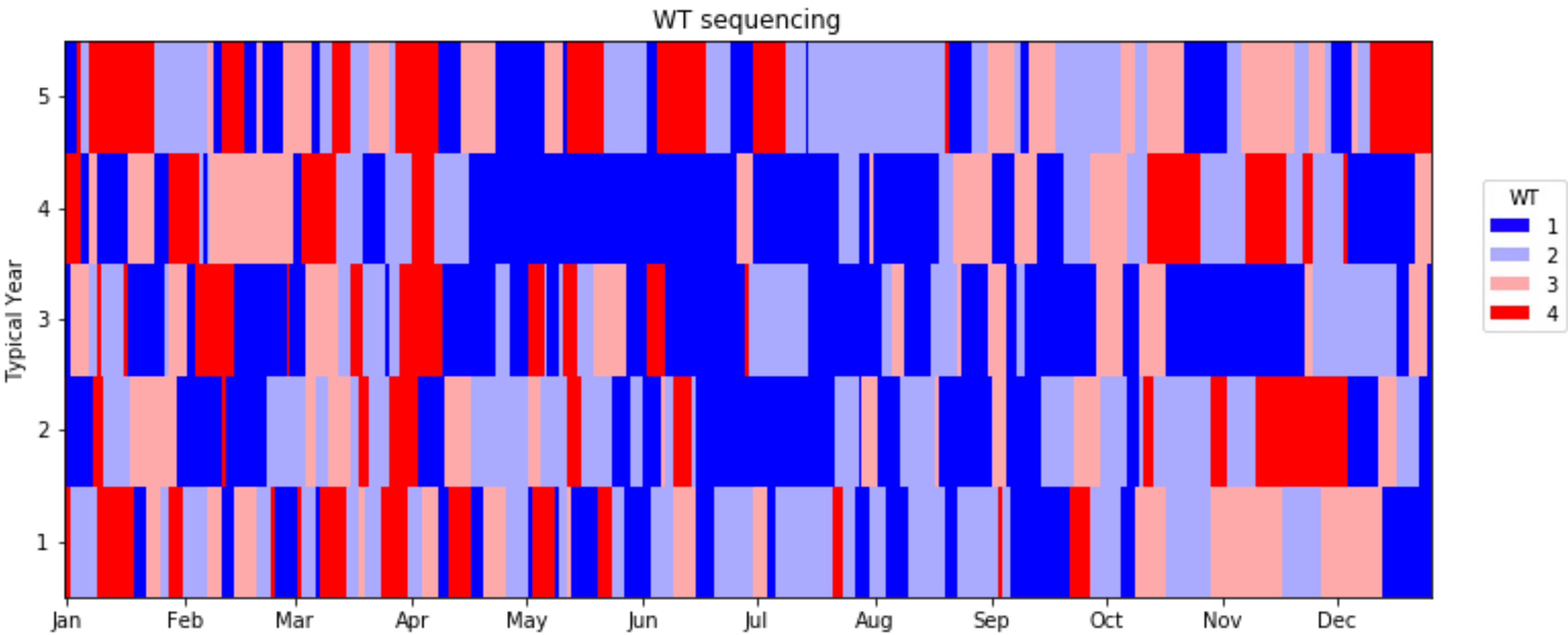


Temporal Evolution across timescales

Muñoz et al (in prep)

S2S Scenarios:
(circulation-based analog years)





Muñoz et al (in prep)

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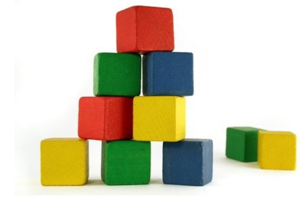
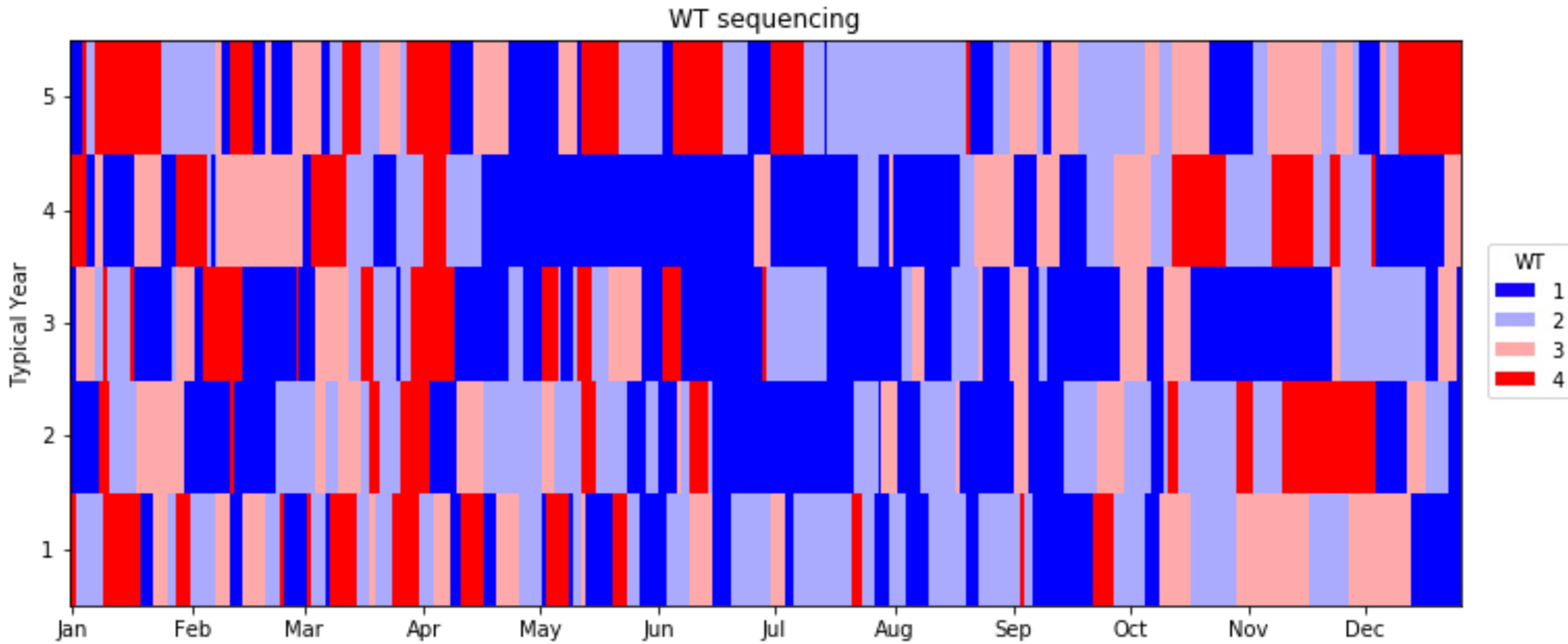
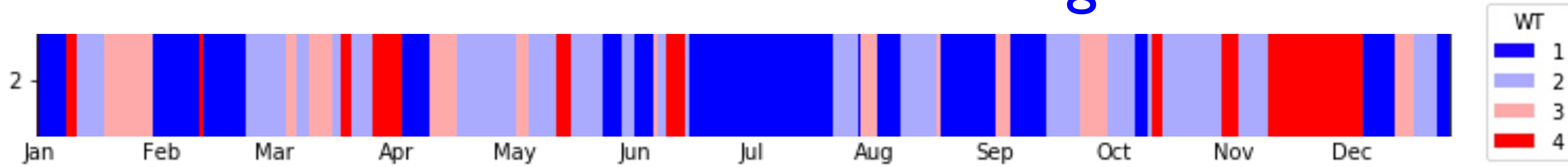




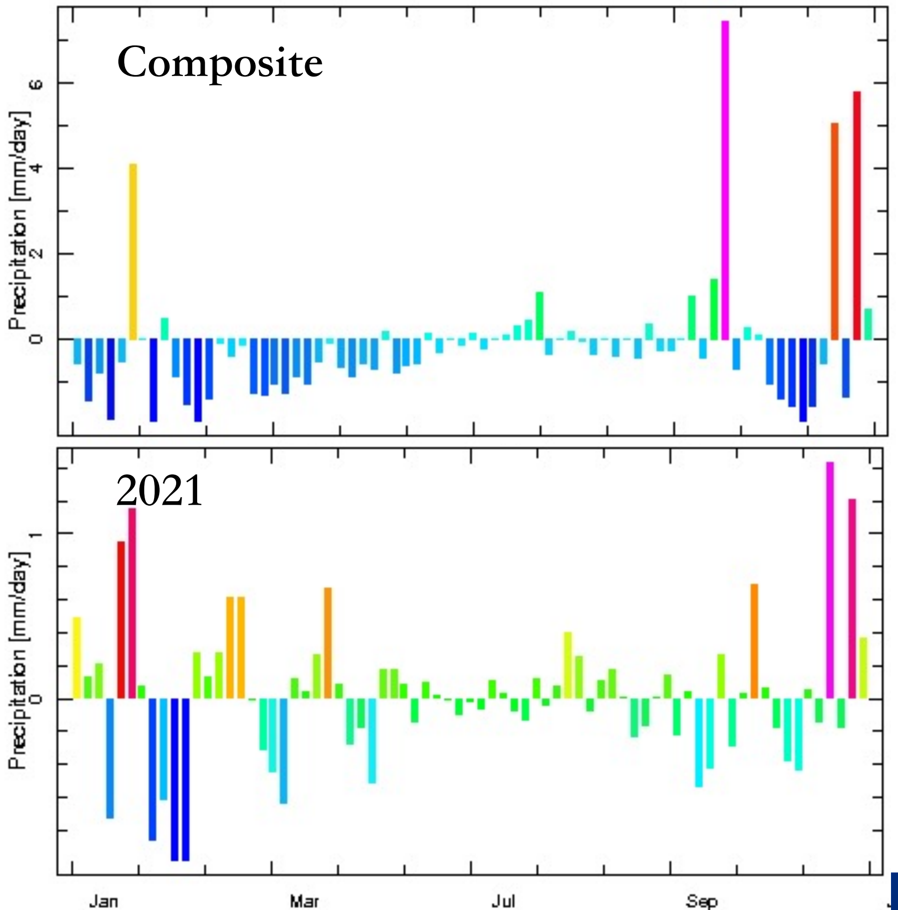
Typical Year	
1	1984,1992,1993,1994,2001,2009,2010,2011,2014,2020
2	1983, 1990, 1991, 1995, 1997, 2002, 2003, 2008, 2012, 2021
3	1982, 1986, 1987, 1988, 1989, 2005, 2007, 2015, 2016
4	1996, 1998, 2006, 2013, 2017, 2018, 2019
5	1985, 1999, 2000, 2004

Muñoz et al (in prep)

Type 2 Year
Western US Rainfall Average



Rainfall



Muñoz et al (in prep)

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Concluding Remarks

- This research is trying to provide additional guidance tools to forecasters.
- There are events that cannot be explained without interference or cross-timescale interference.
- A weather type approach is useful to understand the physical process and to identify potential predictors at different timescales (WTs, SST+MJO,…).
- Extreme rainfall events may occur due to mono-timescale climate drivers (e.g., SST fields) or due to cross-timescale interferences.
- Cross-timescale Interference Conjecture:

  + Climate drivers at different timescale are not completely independent (entanglement).

  + Models considering cross-timescale interference provide forecasts with higher skill.
- It is possible to build forecast models to predict subseasonal-to-seasonal (s2s) states (typical years or "circulation-based analogs"). And from there there are different ways to produce s2s extreme rainfall scenarios.

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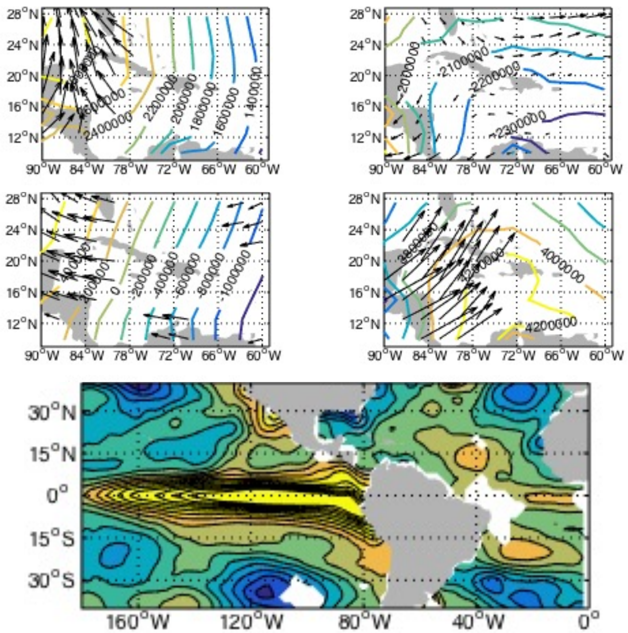
The general picture: Caribbean

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

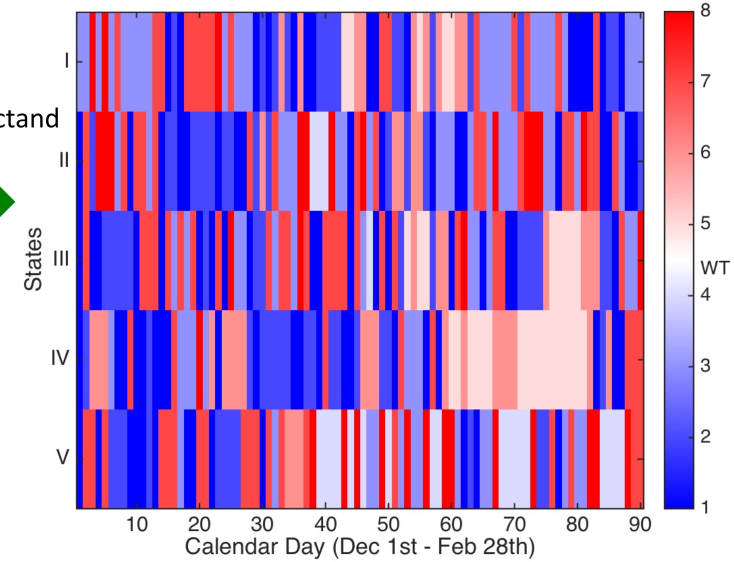


Predictor

Predictand

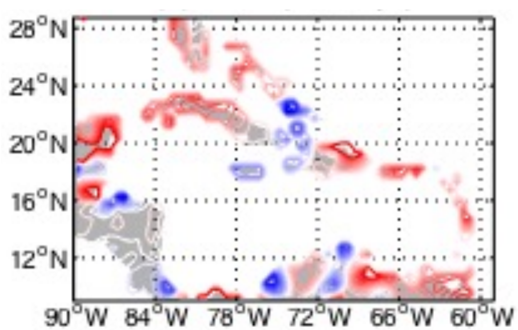
Multinomial logistic model

s2s states



s2s state's probabilities

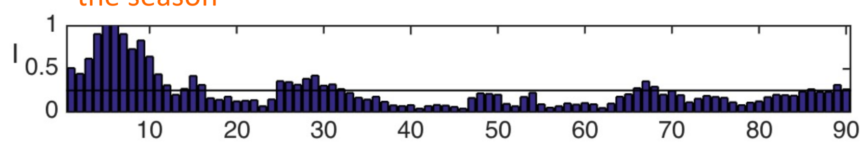
s2s extreme rainfall scenario



Spatial distribution

More extremes during first 10 days of the season

Example
most likely scenario(s): I



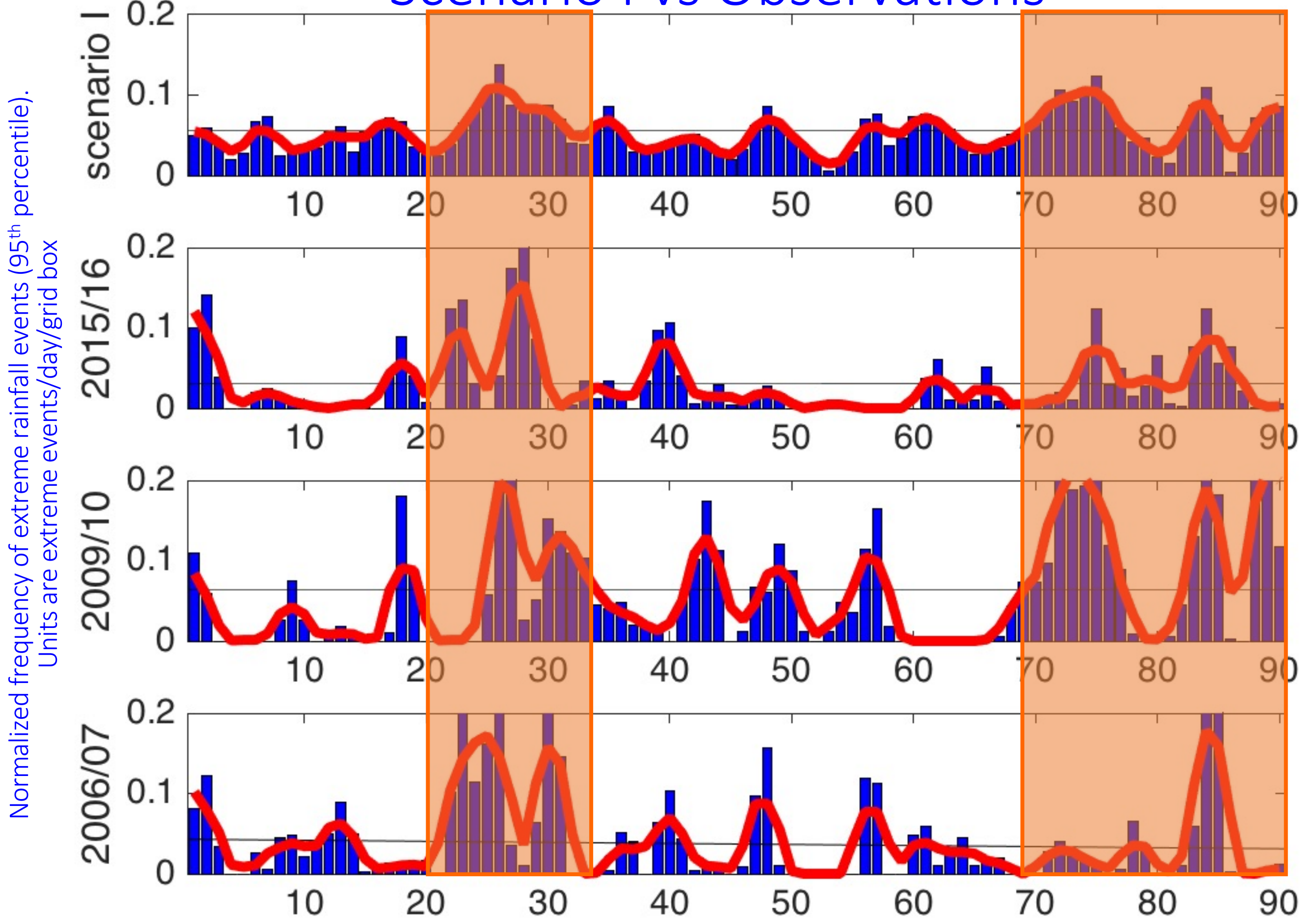
Temporal distribution

Selection: 95th, 99th,...

Composite analysis/analogs

Muñoz et al., (2015, 2016)

Scenario I vs Observations



Muñoz et al 2016

Cross-validation (3-yr window)

TABLE 3. Cross-validated forecasted probabilities (in %) for each scenario, and observed category. Results are shown for the best-guess multinomial logistic model. Probabilities have been rounded to the closest integer.

Predictor: frequency of WTs
Predictand: s2s states

Year	I	II	III	IV	V	Observed	Hit(1)/Miss(0)
1981	36	64	0	0	1	I	0
1982	68	17	1	7	7	I	1
1983	0	0	1	0	99	V	1
1984	43	48	3	0	7	I	0
1985	0	0	0	100	0	IV	1
1986	13	2	24	0	61	I	0
1987	95	4	0	0	1	I	1
1988	82	10	2	6	0	I	1
1989	49	49	1	0	1	II	1
1990	61	38	0	0	0	I	1
1991	27	0	21	0	52	III	0
1992	8	0	0	0	92	V	1
1993	65	14	1	0	20	II	0
1994	60	17	12	0	11	III	0
1995	72	5	8	0	15	I	1
1996	88	5	1	0	5	III	0
1997	54	44	1	0	1	II	0
1998	0	0	41	0	59	V	1
1999	1	0	42	0	56	III	0
2000	81	12	3	0	4	II	0
2001	0	0	0	100	0	IV	1
2002	10	2	30	0	57	III	0
2003	82	2	3	13	0	IV	0
2004	93	1	3	0	3	I	1
2005	81	6	4	0	9	V	0
2006	1	0	43	0	56	III	0
2007	0	0	0	100	0	IV	1
2008	5	0	58	0	37	V	0
2009	6	8	0	86	0	IV	1

Skill metrics:
Kendall's $\tau = 0.371^{*}$
Hit score = 48.27%
HSS = 0.353

* statistically significant value at $p<0.05$