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California Institute of Technology

Center for Western Weather and Water Extremes

Forecasting Ridging on S2S timescales

WSWC, San Diego
May 23 2019

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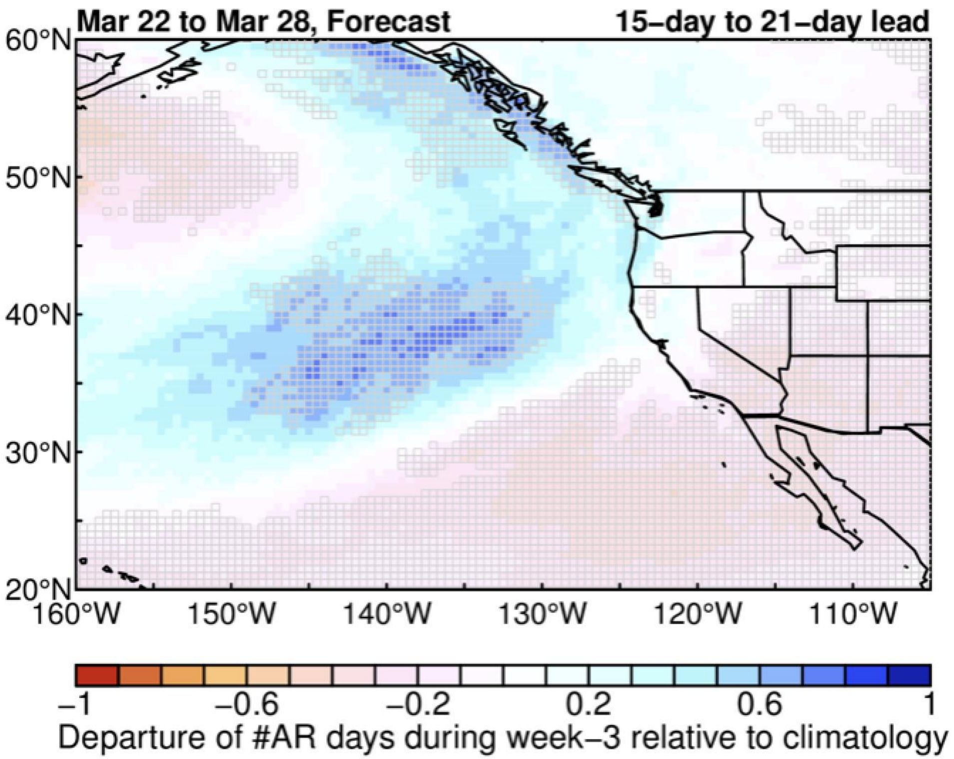
Motivation

- JPL/CW3E/DWR has been working on assessing and implementing operational forecast products for atmospheric rivers (ARs)

- This approach is now being extended to forecasting **atmospheric ridging events** (i.e. conditions associated with rainfall deficits)

- **Test hypothesis that ridges are more predictable than ARs**

EXPERIMENTAL week3: ECMWF (51-member)



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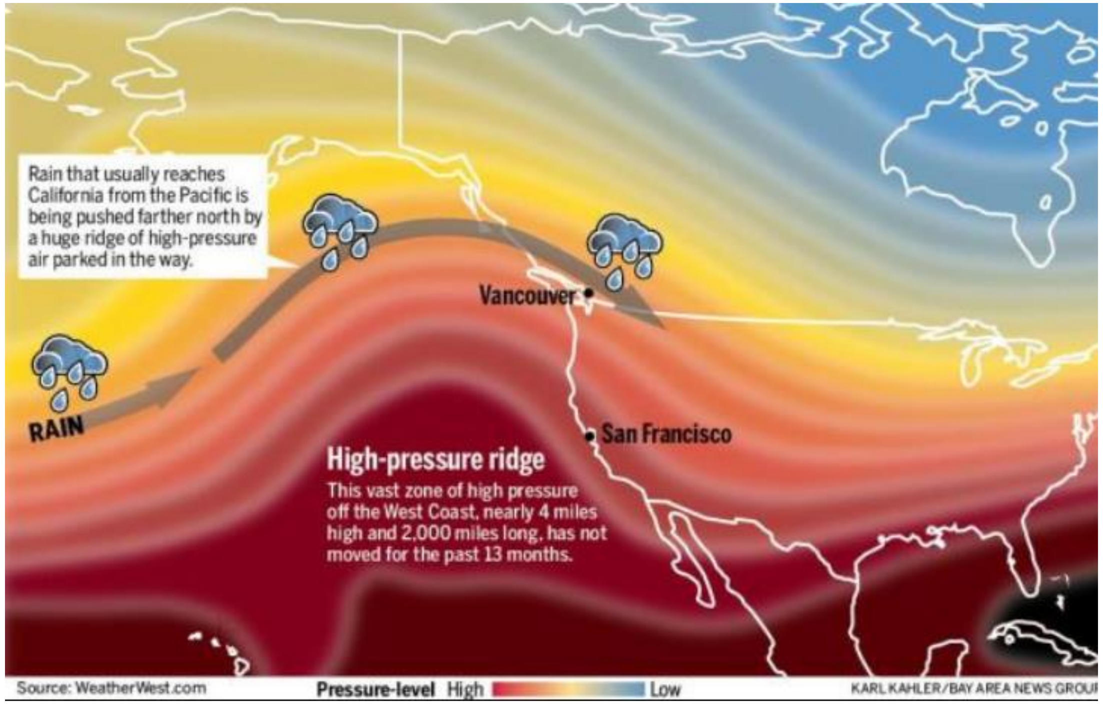
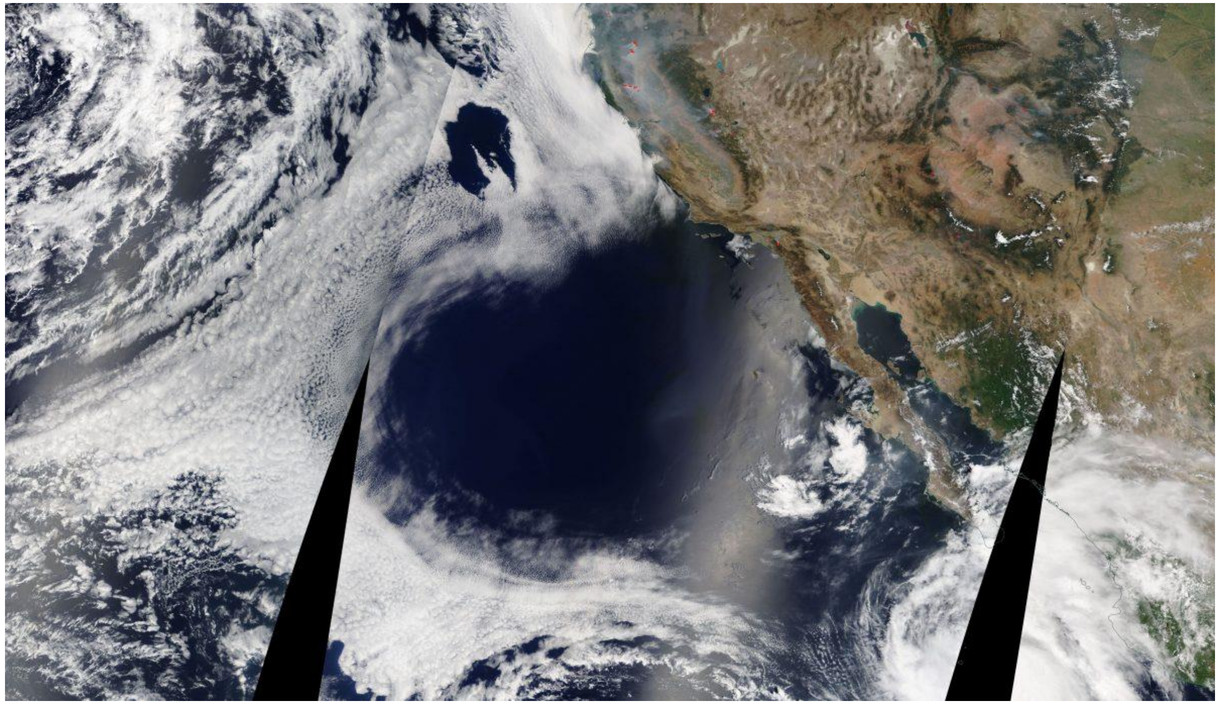
Winter ridge events influence where and how it rains

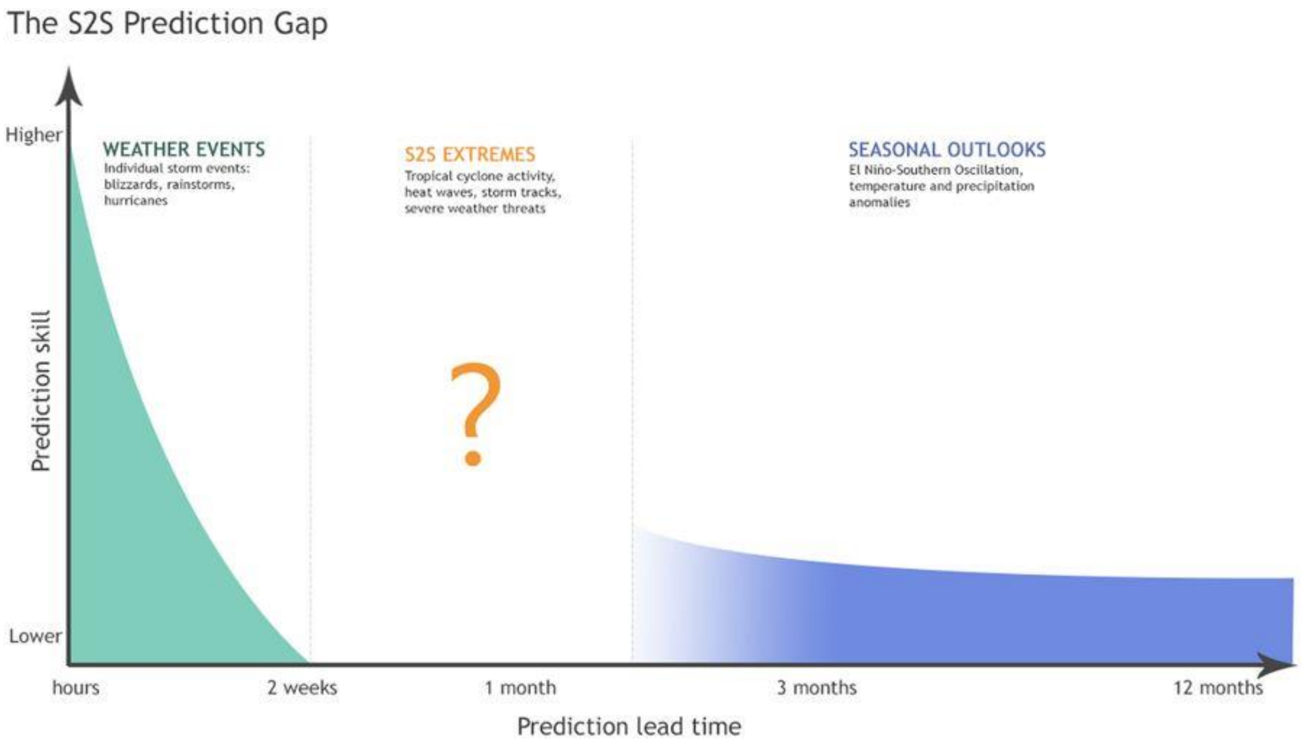
- Ridging events often occur (and sometimes persist) in winter off the west-coast of USA
- These ridge events divert important rain-bearing systems away from California



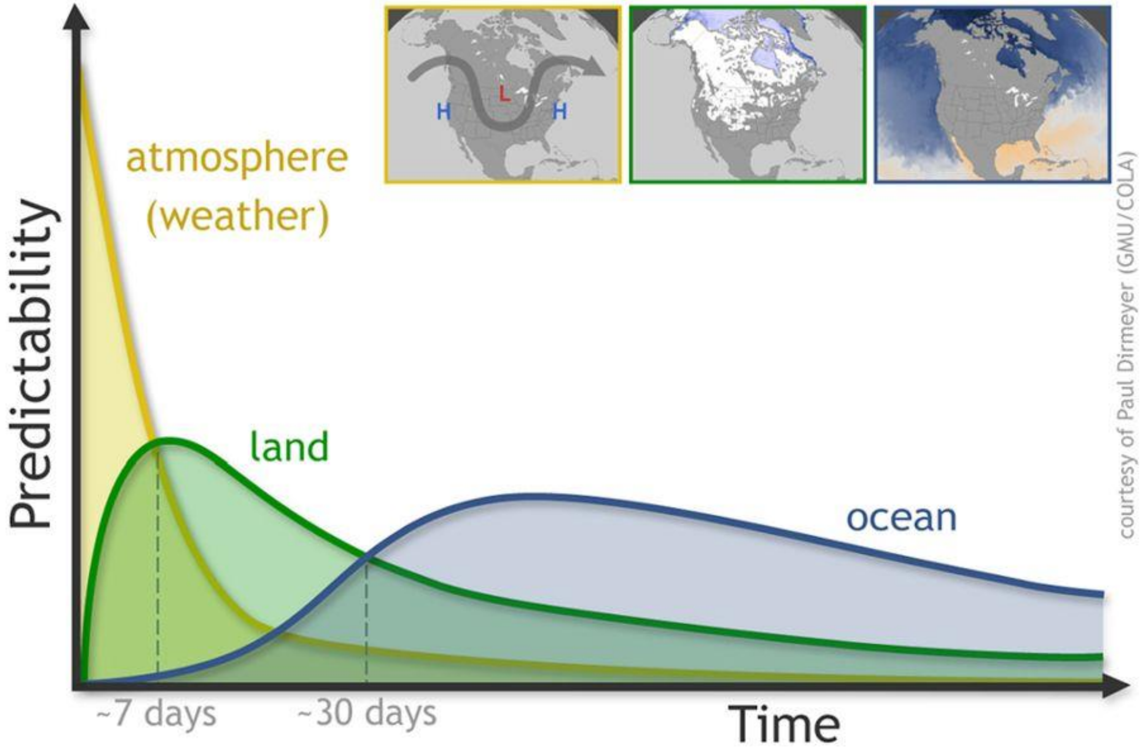


From NASA Terra satellite – August 7 2018

S2S: A major challenge and opportunity for the weather/climate research community

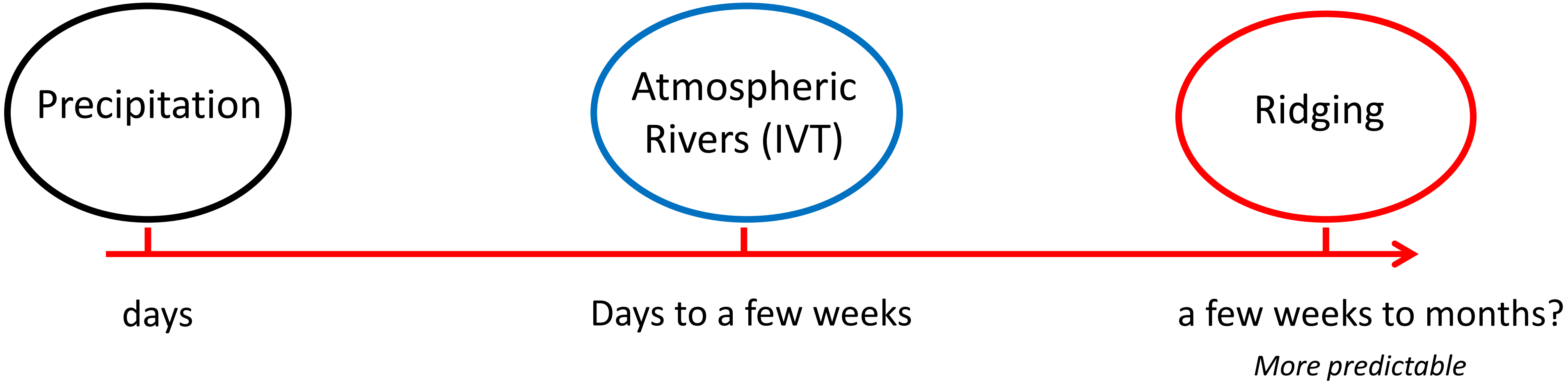


Adapted from: iri.columbia.edu/news/qa-subseasonal-prediction-project



Mariotti et al. (2018), Nature

A working hypothesis ….



Deterministic forecast: How much rain will fall on May 22nd?

Probabilistic forecast: What is the probability of above-average rainfall over a certain time-period?

What is a ridge?

Requirements:

- Should be relatively easy-to-understand so stakeholders can use/implement
- Must be relevant to water resources/drought
- Must be applicable to different observational datasets and weather models
- Must not be too computationally expensive (else will be difficult to implement operationally)

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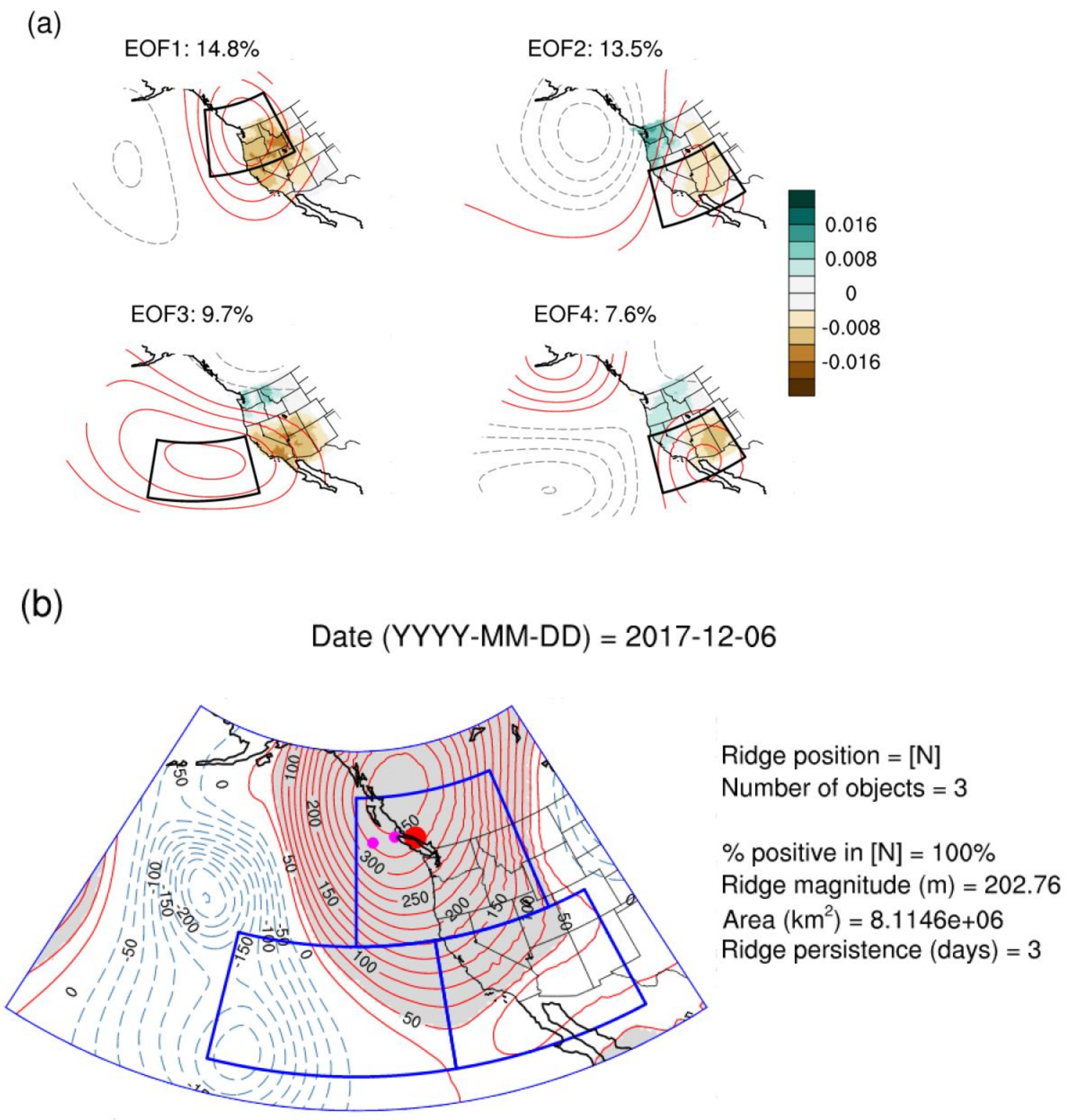
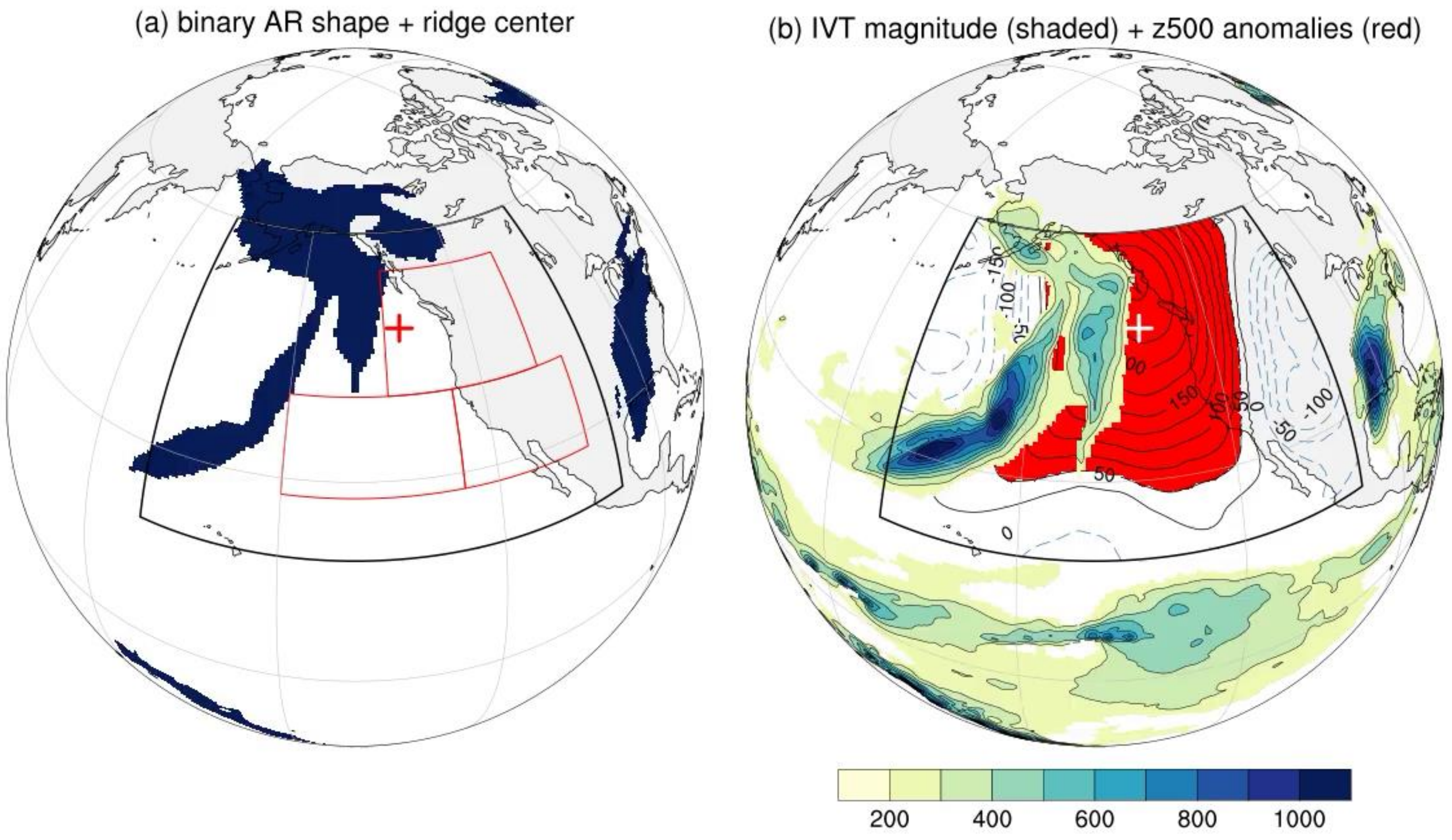
Ridge detection algorithm

- Applied on daily z500 anomalies from MERRA-2
- Reports the *magnitude, extent, location, persistence* of large z500 anomalies > 50m
- Outputs information with respect to 3 regions: N,S,W
- Ridge occurrence is 'counted' for region if anomaly covers > 50% of domain

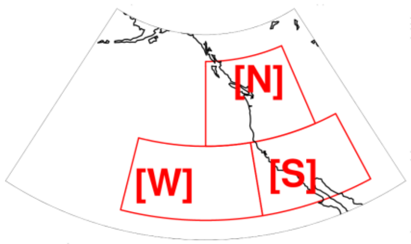


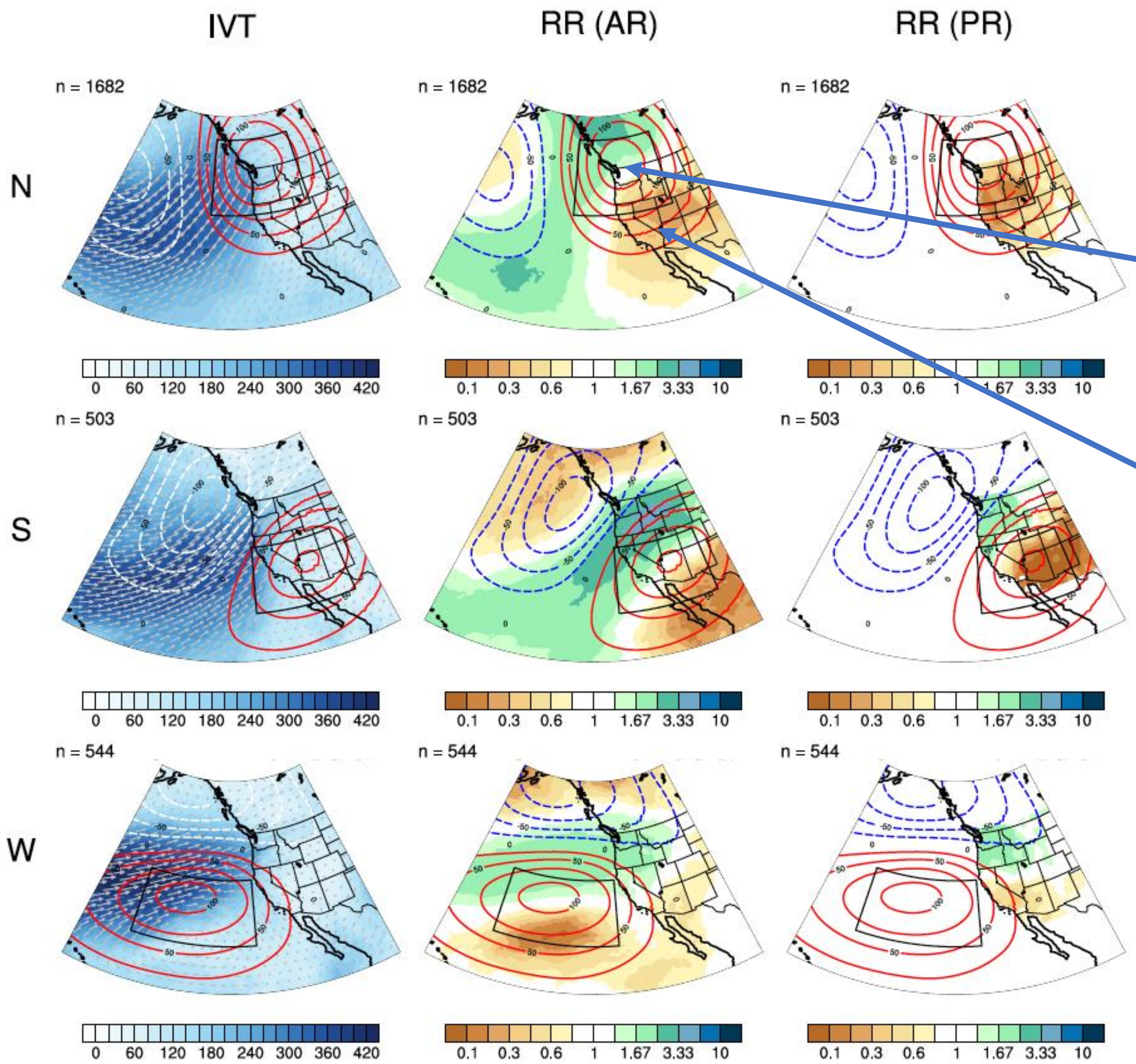
Tracking ridge events and AR events concurrently

1 Jan 1985



Likelihood (Relative risk) of AR occurrence given Ridge occurrence

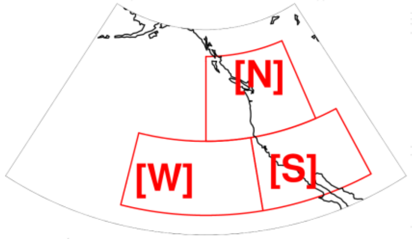




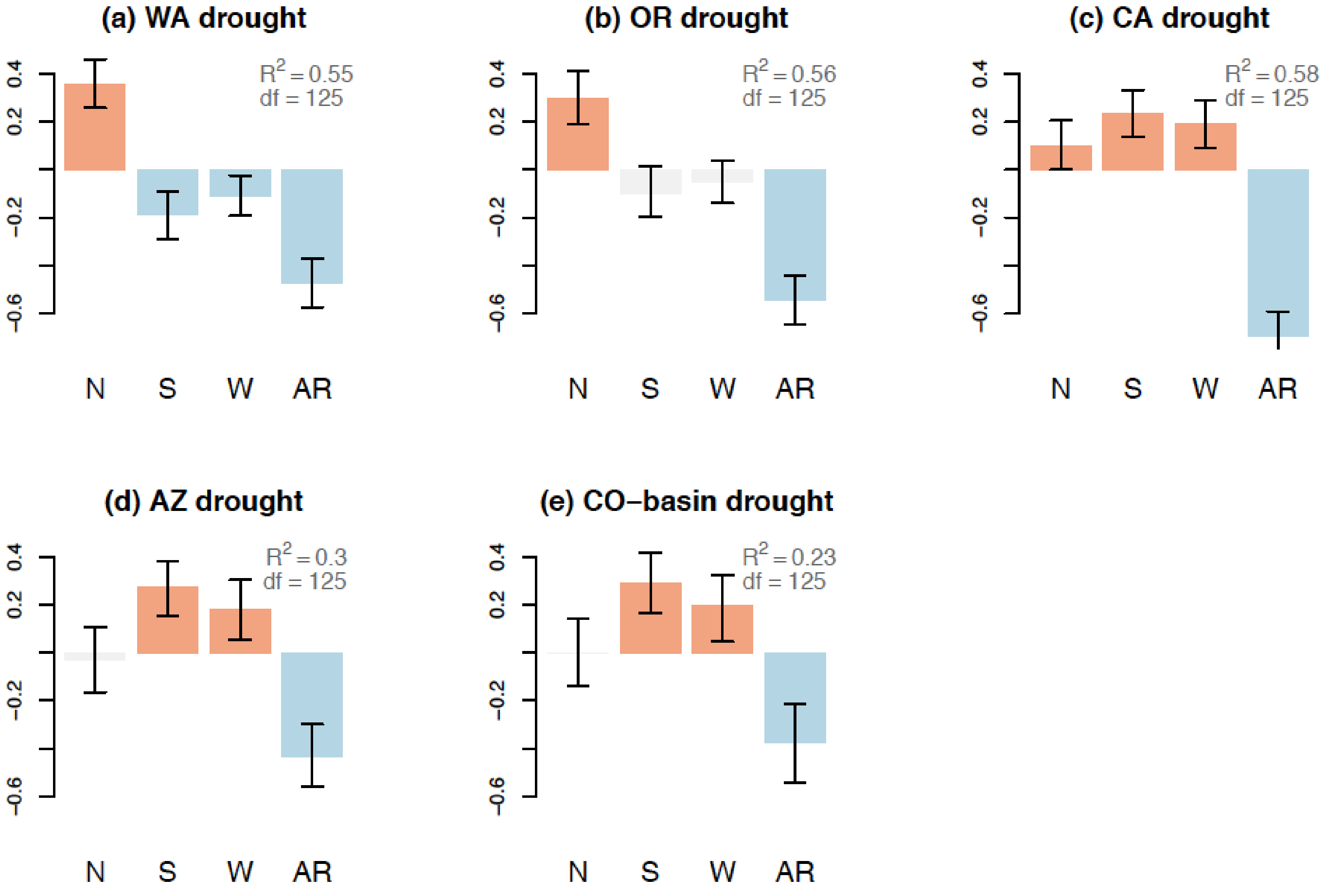
When ridging occurs here

=

Less chance of AR here



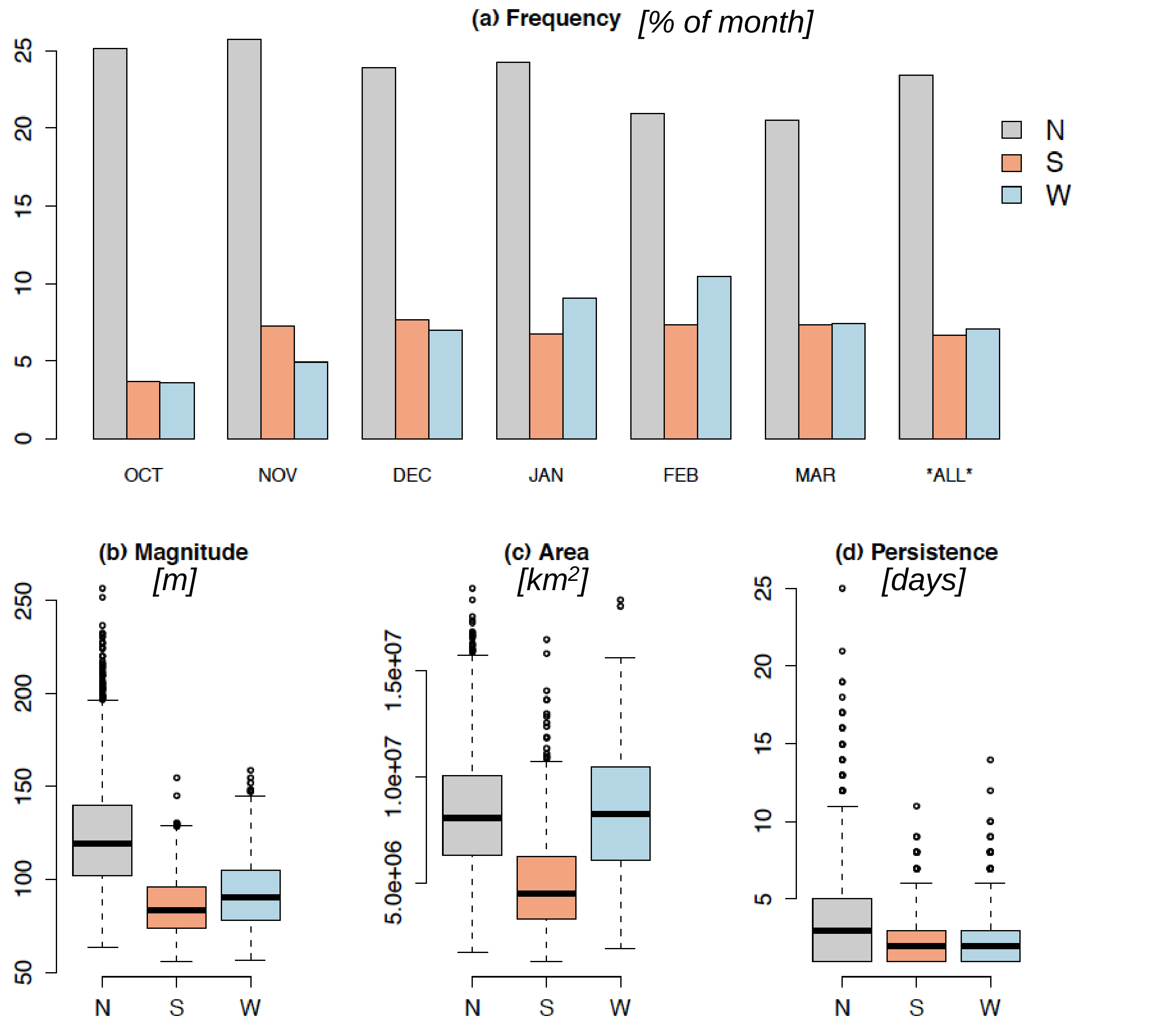
Ridge frequency in a month versus drought (SPI-3, by region)



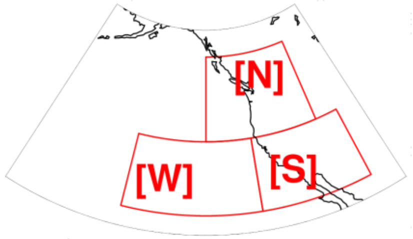
- In WA, OR and CA, the N ridge is much more frequent during periods of meteorological drought
- S and W ridge types are more important for AZ and CO-basin

General ridge characteristics

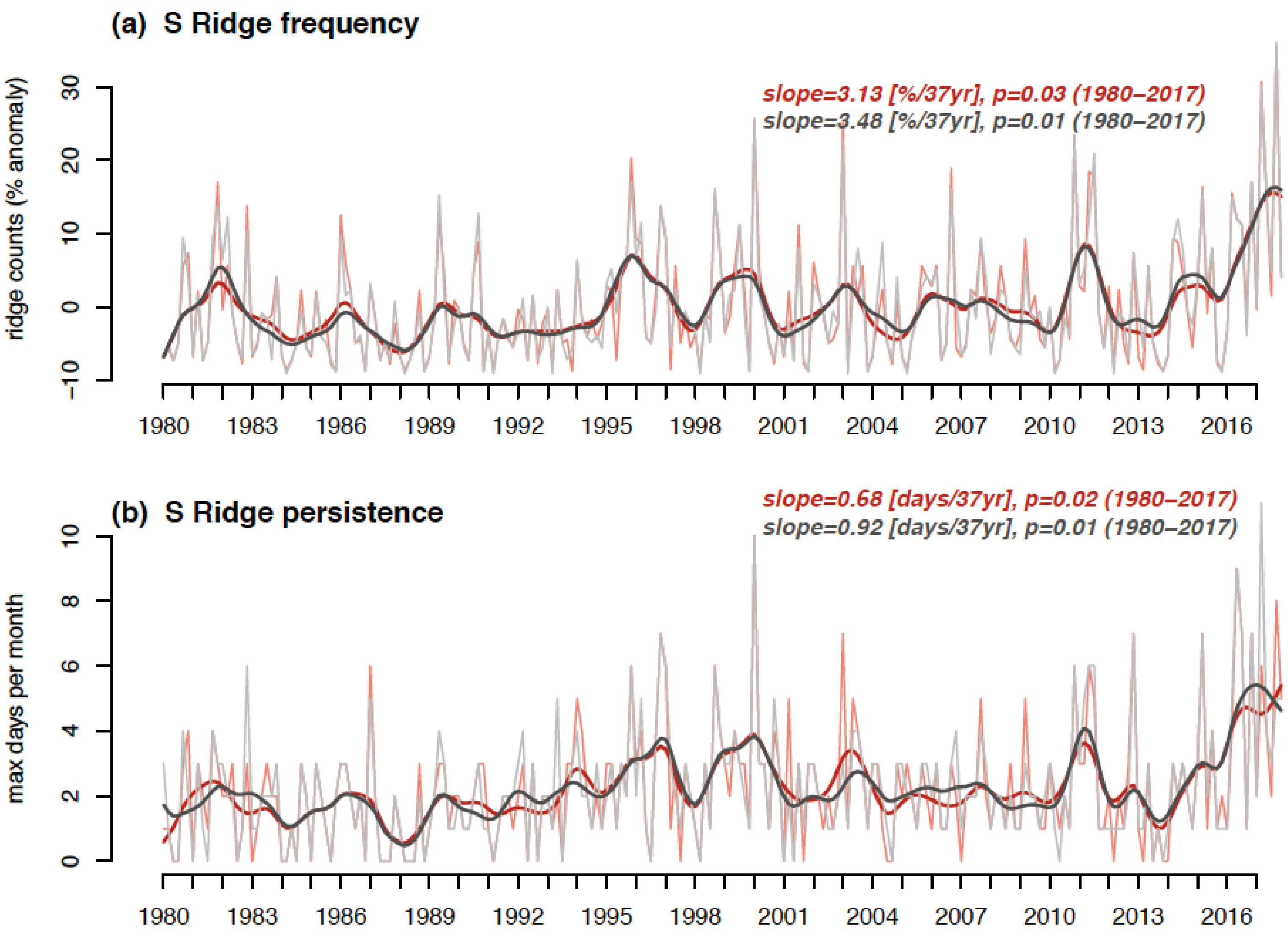
- A reasonable amount of within season variability for frequency over ONDJFM months
- N Ridge tends to be larger and more persistent

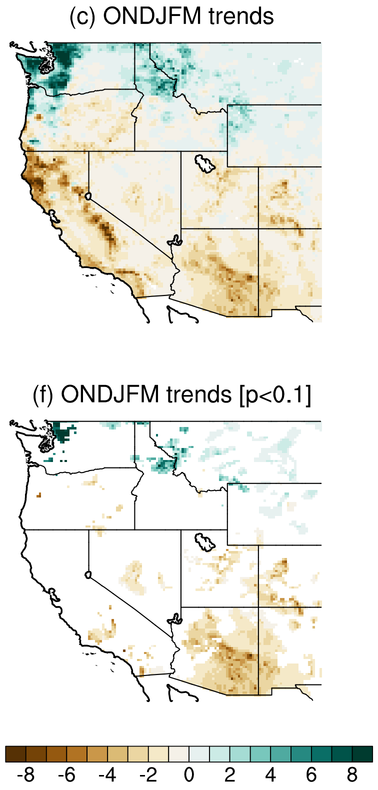


Trends in ridging frequency?

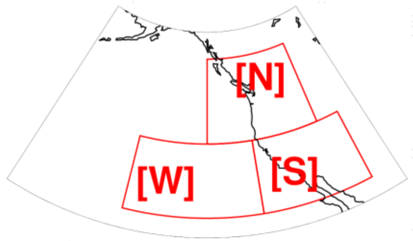


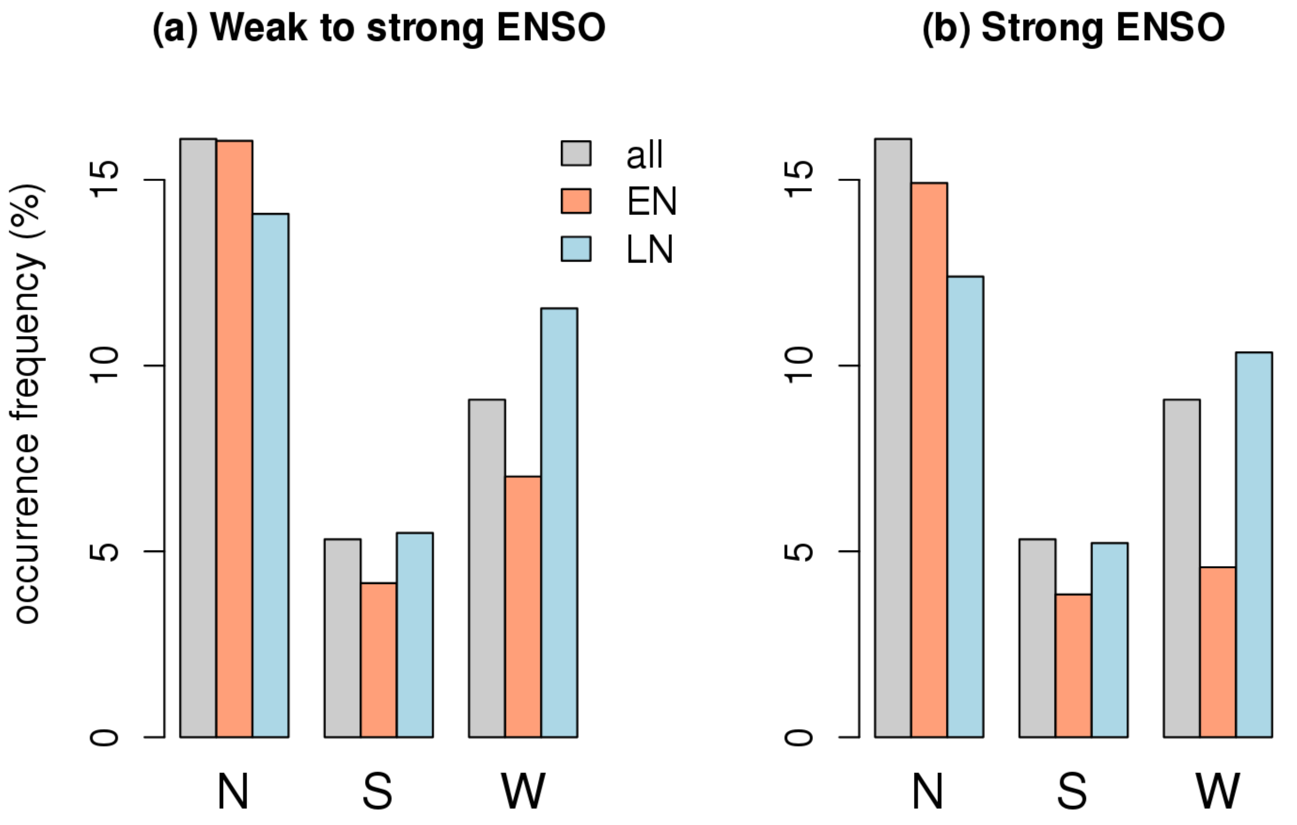
A slight upward trend in S Ridge frequency and persistence (mostly over last decade)



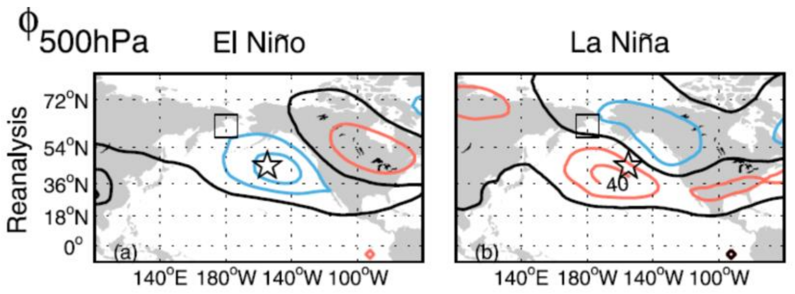


ENSO association with Ridge frequency





- ENSO impact is mainly through influencing the W Ridge frequency
- Relationship with how La Nina favors drier conditions (on average in SWest)



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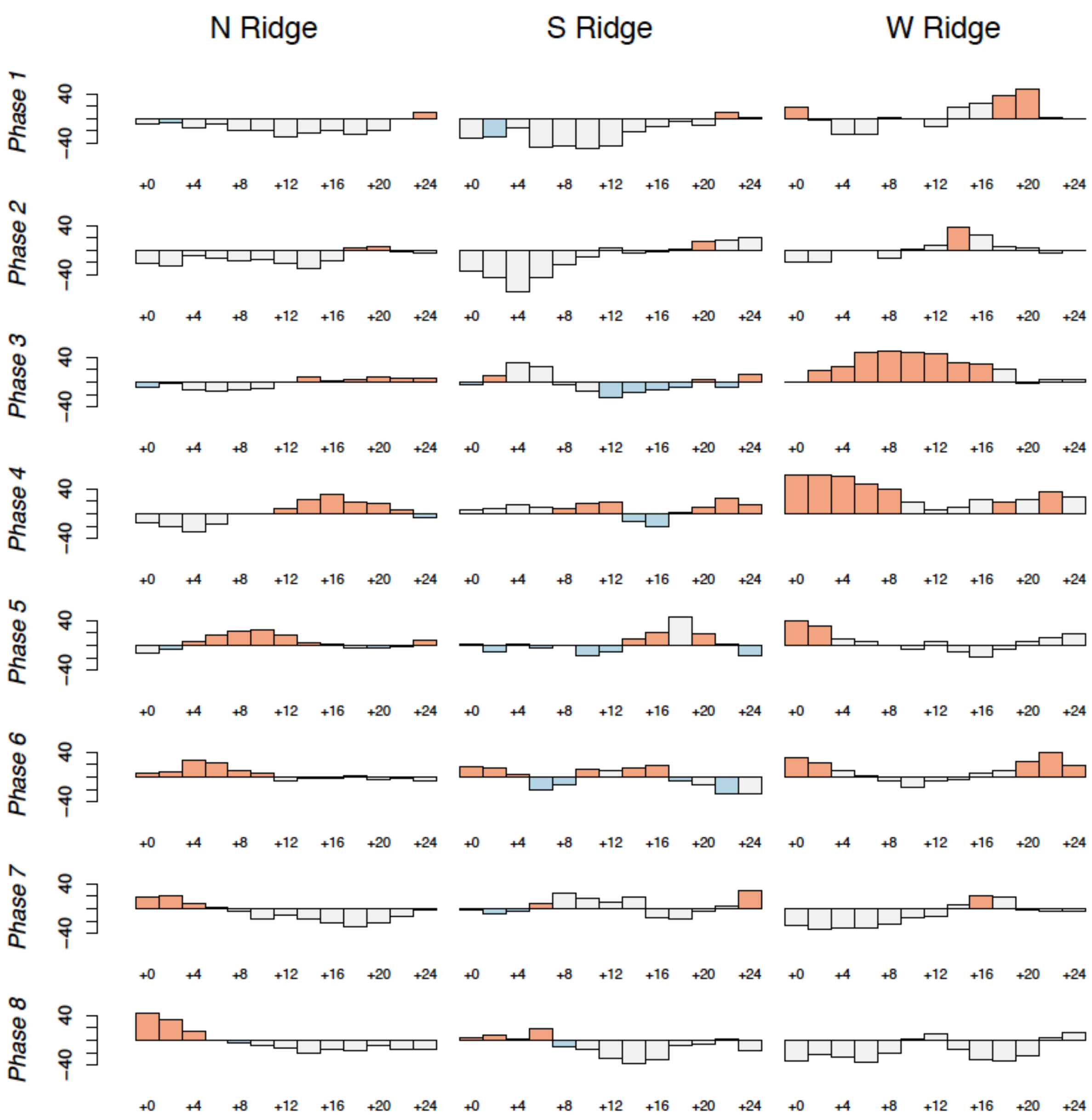
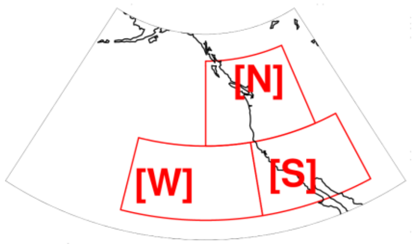
MJO association with Ridge frequency

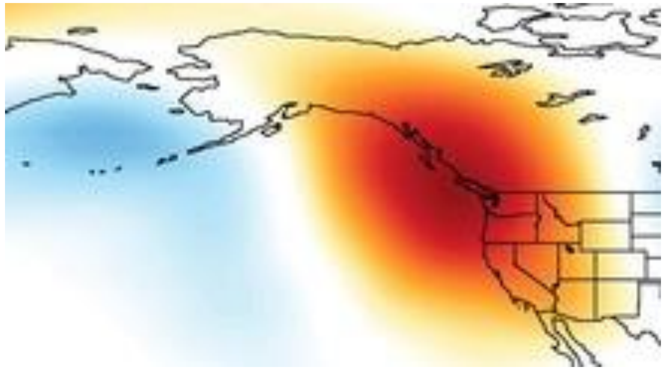
Potential for MJO to offer probabilistic ridge prediction out to S2S

- MJO phase 4-5 for N and N Ridge
- MJO phase 1-3 (+6) for W Ridge

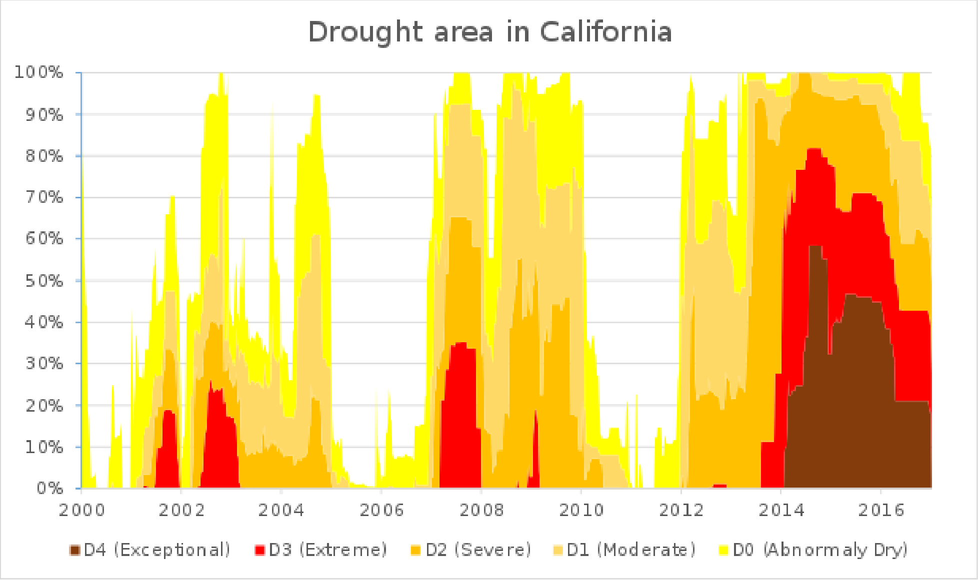




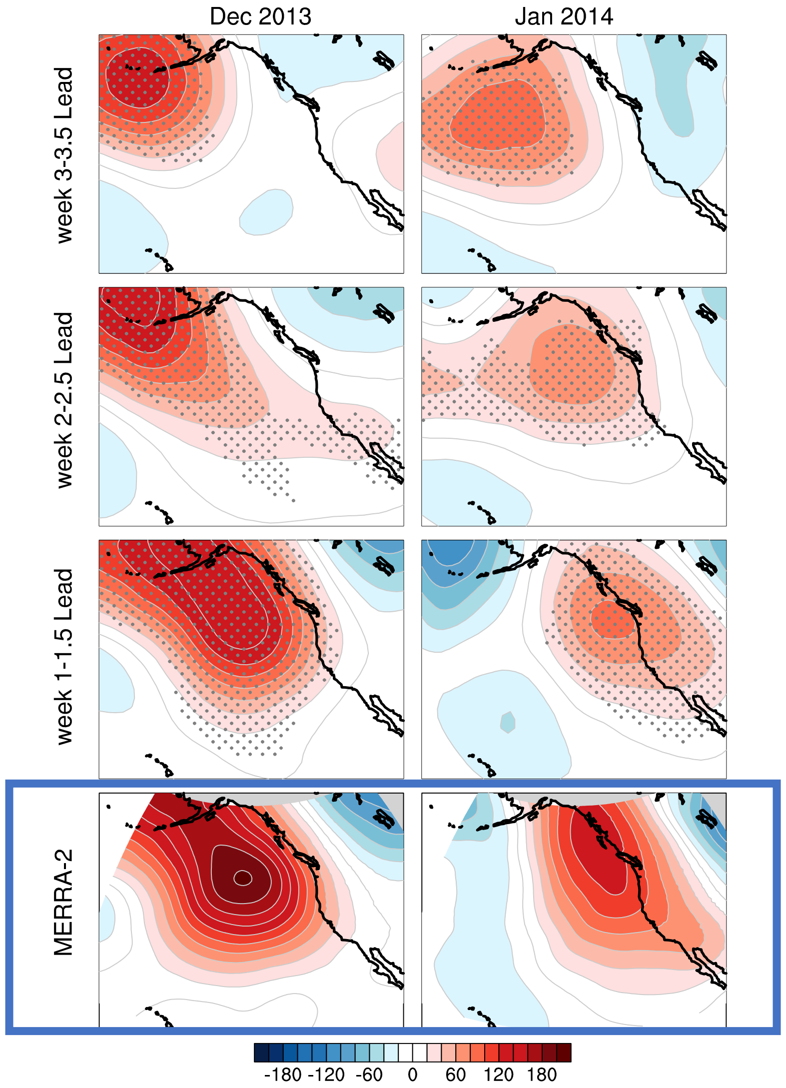
Case Study of ECMWF skill



The ‘**Ridiculously Resilient Ridge**’ January 2014 (90-day running mean 500mb geopotential height anomaly)



ECMWF (wk1,2,3) z500 anomaly prediction of RRR (dots >90% directional argeement)



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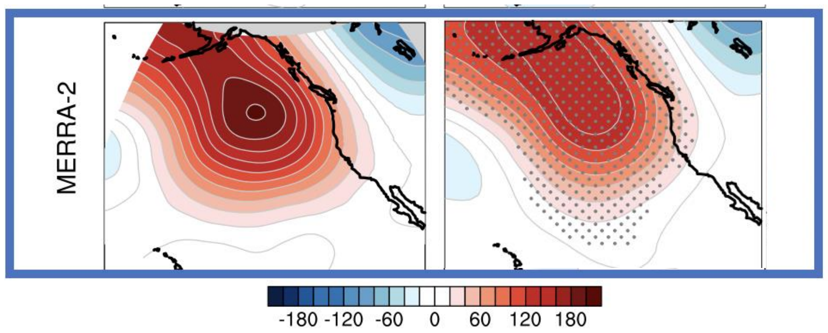
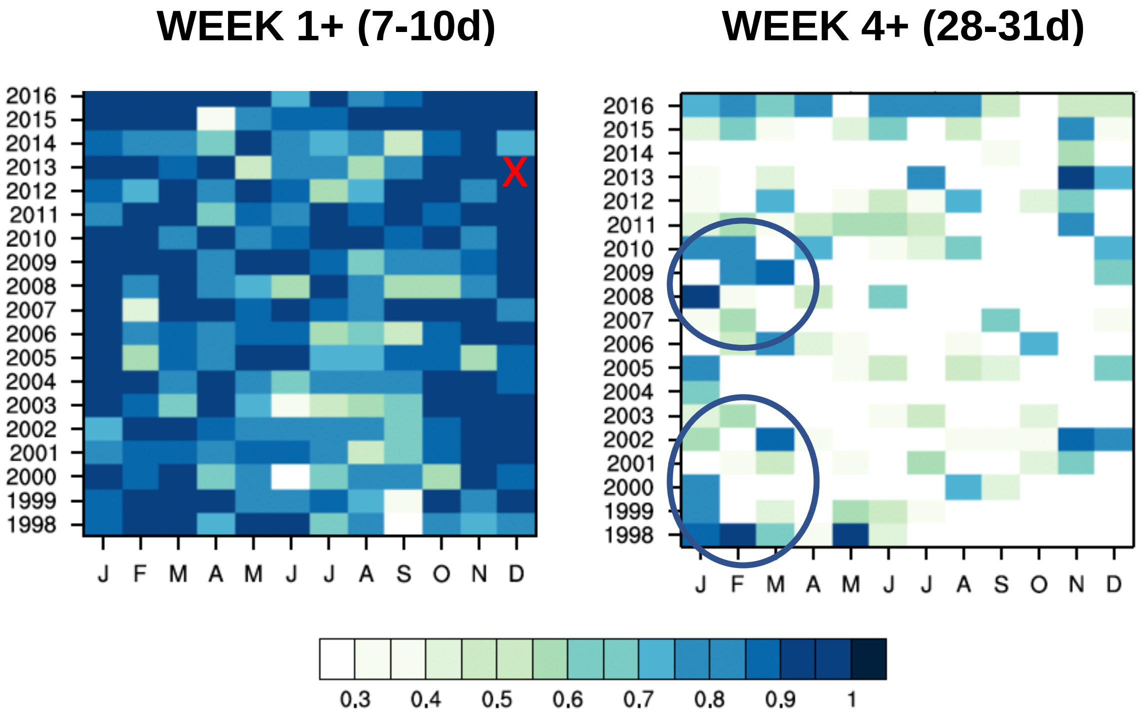
ECMWF skill – all years



r>0.9

- As expected week1+ skill is very good (weather forecast skill)
- There are some select months where the week 3 and 4 forecast is fairly good (ACC > 0.7)



Ongoing work

- Quantify hindcast **prediction skill** from other S2S/SubX ensemble of models
- Can prediction skill be improved through post-processing/**Machine Learning** by combining models and observations is a more optimal way?

Machine Learning

Dermatology > General Dermatology

The Artificial Brain as Doctor

— AI equals dermatologists in identifying lesions

by Lisette Hilton, Dermatology Times
January 15, 2018

Stanford Deep Neural Network (130,000 images) – classification of malanoma

- “Ruler” or “no ruler” identified as most important predictor
- AI can guide us, but we also need to guide AI very closely.
- We still need to use our knowledge of the system

Summary

- There are different ‘flavors’ of ridging that impact W/SW United States differently
- They influence ARs, precipitation and drought likelihood
- We are currently investigating model skill at predicting ridges over different time-periods and spatial scales
- We are currently investigating different ways to improve model prediction skill

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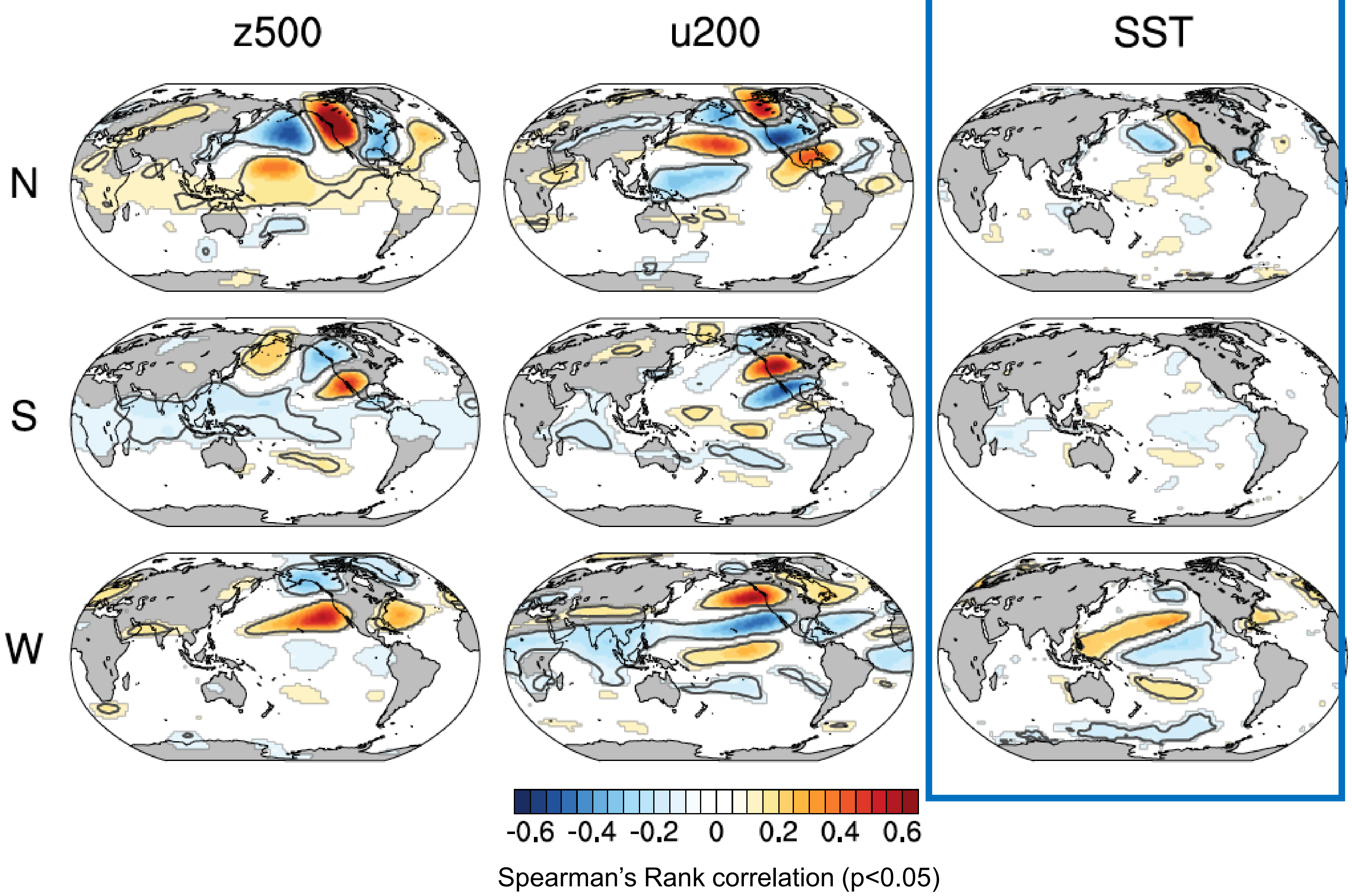
Drivers of monthly frequency variability?

- N ridge is strongly related to a PNA-like/pattern wave-train from the tropics
- S ridge related to a mid-latitude wave train with little relationship to tropics
- W ridge La-Nina/PDO like



nature
International journal of science

Review Article | Published: 02 September 2015

The quiet revolution of numerical weather prediction

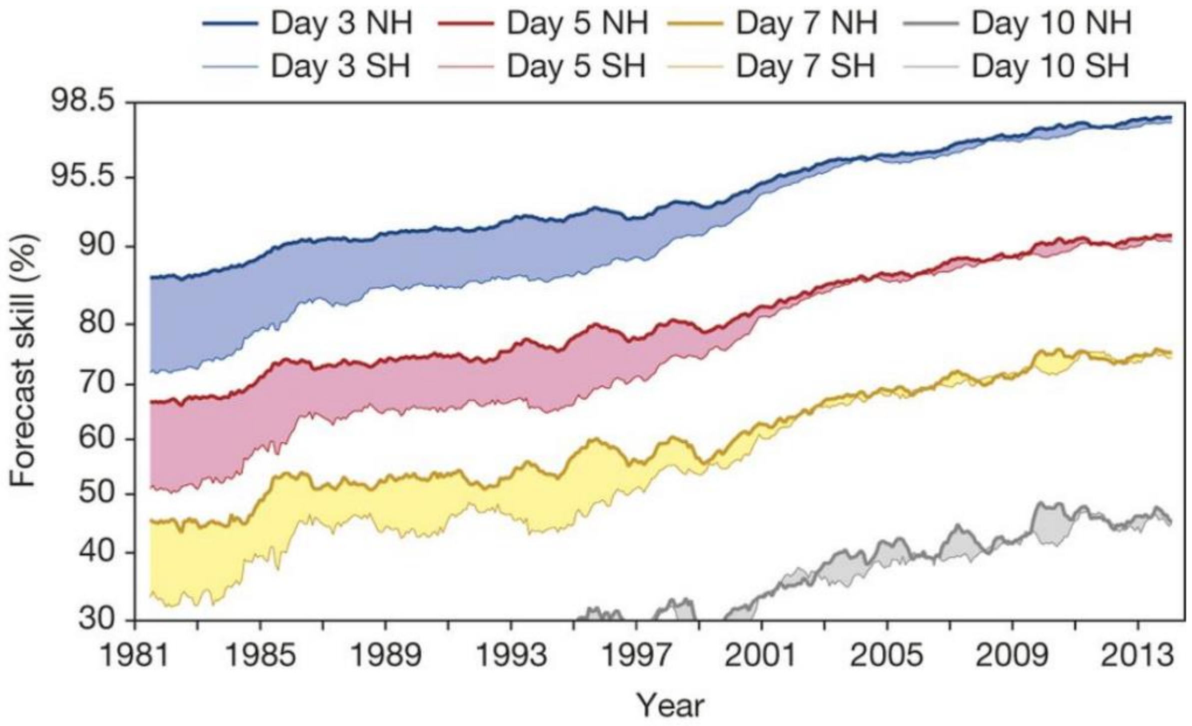
Peter Bauer, Alan Thorpe & Gilbert Brunet

Nature **525**, 47–55 (03 September 2015) | Download Citation

- Numerical weather prediction skill has increased fairly consistently/linearly since the 80’s
- “As a computational problem, global weather prediction is comparable to the simulation of the human brain and of the evolution of the early Universe”

Figure 1 : A measure of forecast skill at three-, five-, seven- and ten-day ranges, computed over the extra-tropical northern and southern hemispheres.

From: The quiet revolution of numerical weather prediction



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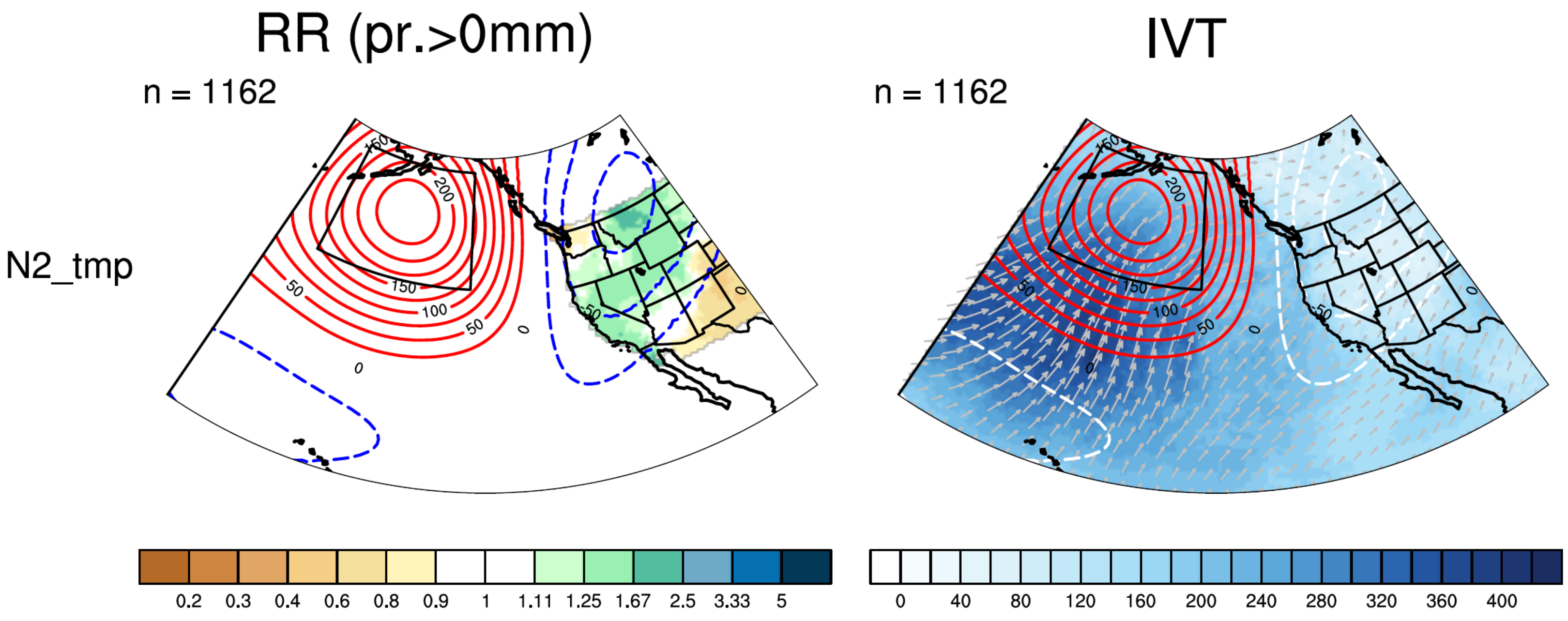
Supplementary Slides



- Evidence that the ridge related to EOF1 is a 'wet type' not relevant to W-SW drought

Supplementary Slides

Extreme ridge event occurrences

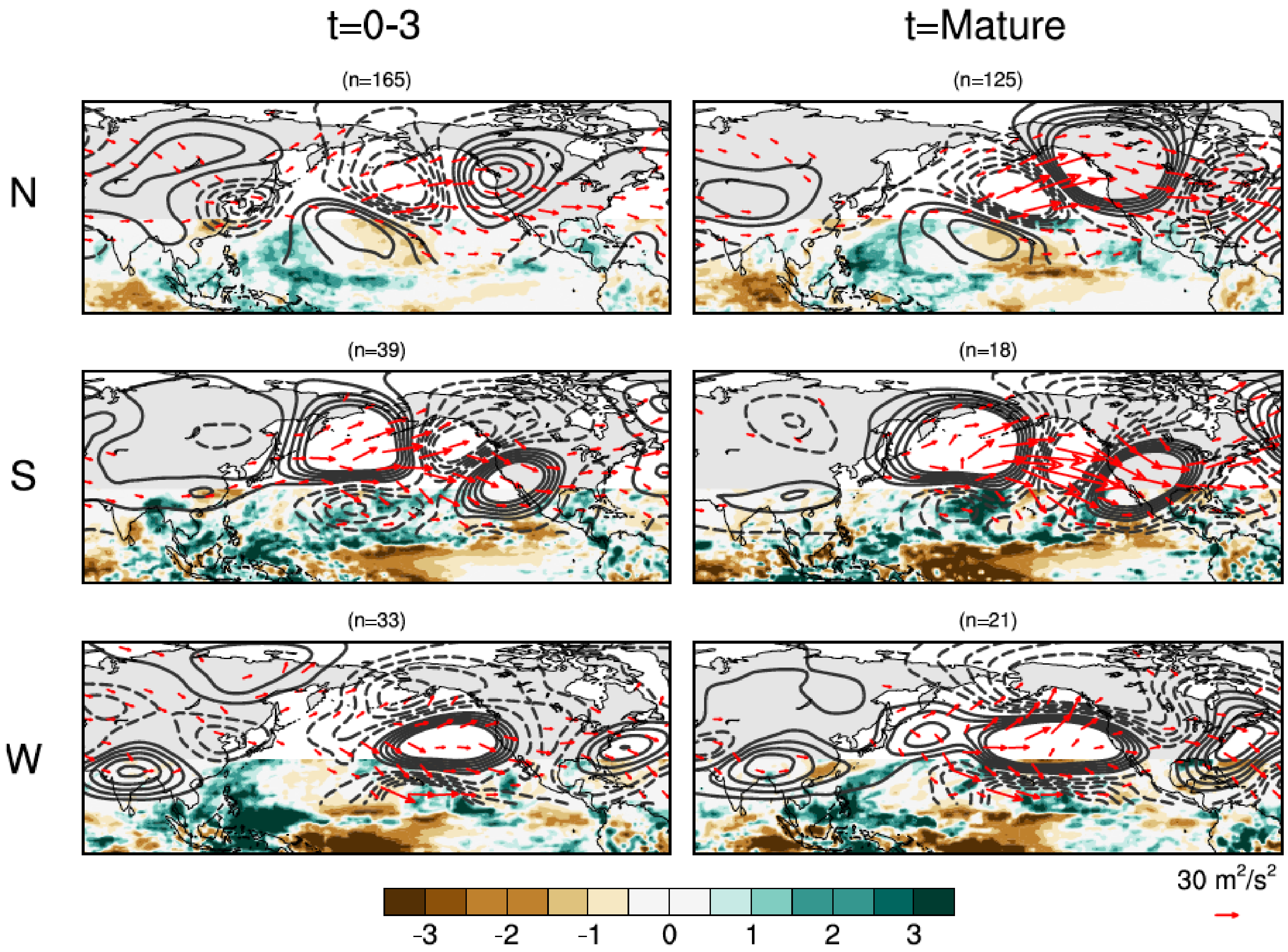
- Find days where ridge exceeds the 90th percentile of magnitude and persists for 3+ days
- Analyze composites of wave activity flux, tropical precipitation, velocity potential
- Analyze composites w.r.t onset (t=0), first 3 days (t=0-3), maturity (t=time of 90th percentile)

$$\mathbf{W} = \frac{p}{2|\mathrm{U}|}\begin{pmatrix} U(\psi_x'^2 - \psi'\psi_{xx}') + V(\psi'_x\psi'_y - \psi'\psi_{xy}') \\ U(\psi'_x\psi'_y - \psi'\psi_{xy}') + V(\psi_x'^2 - \psi'\psi_{yy}' \end{pmatrix}$$

- WAF = Vector quantity that describes the approximate path of a Rossby wave packet

Supplementary Slides

Extreme ridge event occurrences



- Contours are 250hPa stream function anomalies
- Arrows are Wave activity Flux
- Shading are daily precip anomalies

Supplementary Slides

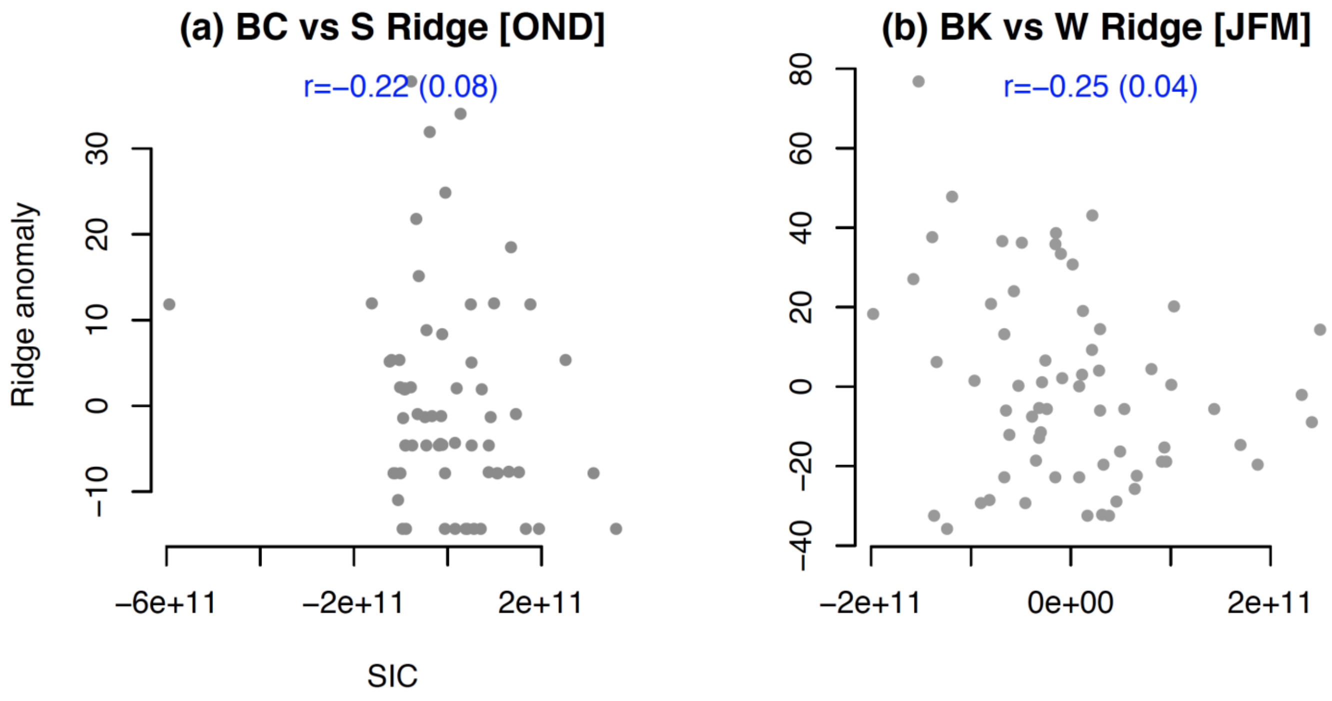


Figure S5: Scatterplot of sea ice concentration anomalies (SIC) (see section 2.1) and ridging anomalies (% frequency) for the Bering/Chukchi region (BC) and Barents/Kara region (BK) over months OND and JFM. Only the strongest correlations are shown here from all ridge types and seasons examined. Pearson's r (p-value) are shown in blue.