Global Prediction Skill of Atmospheric Rivers

Seasonal Variability and Relationship to ENSO Phase

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Atmospheric rivers (and their associated flood and hazard risks) occur globally.

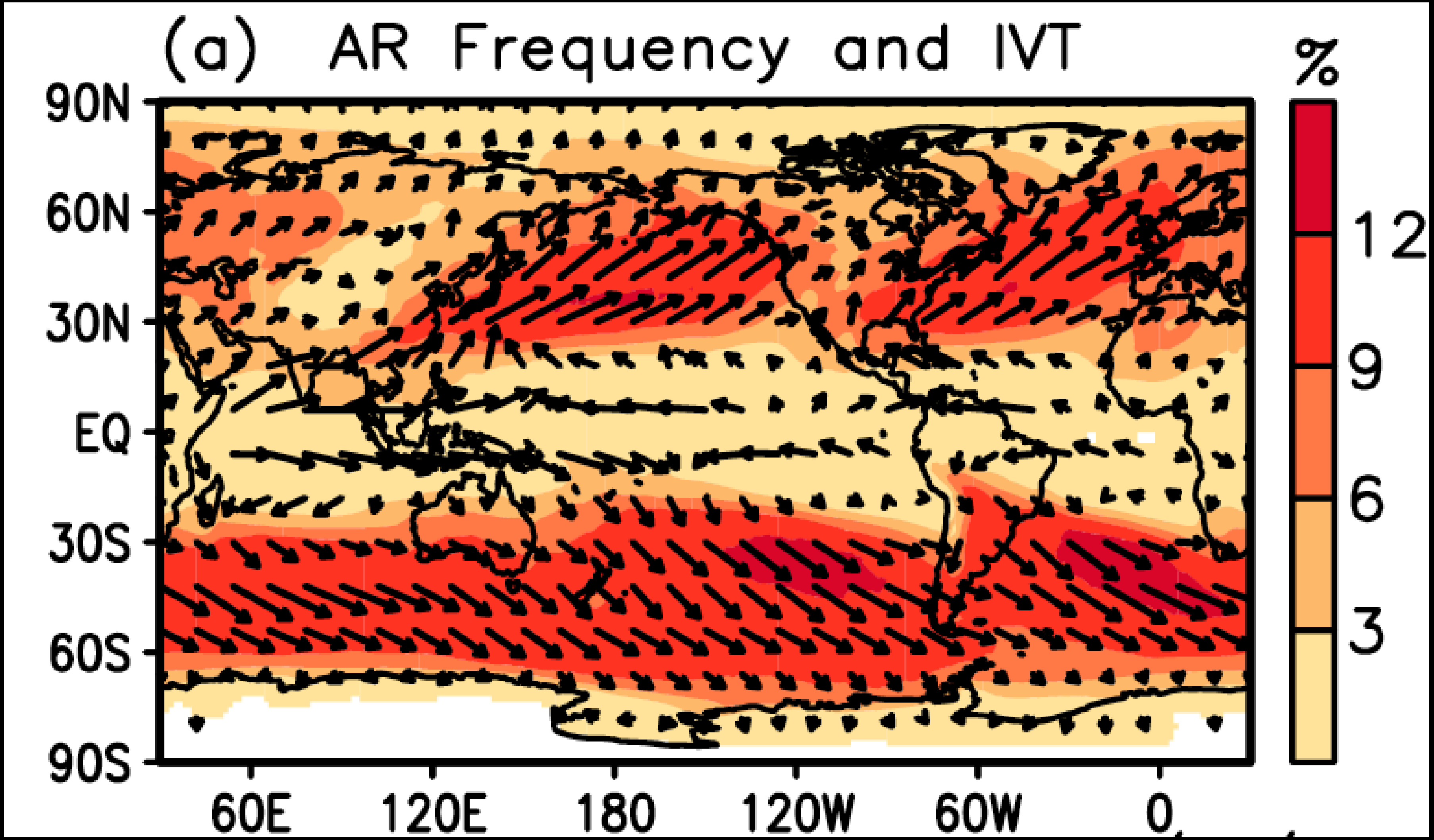


Fig 7a, Guan and Waliser 2015

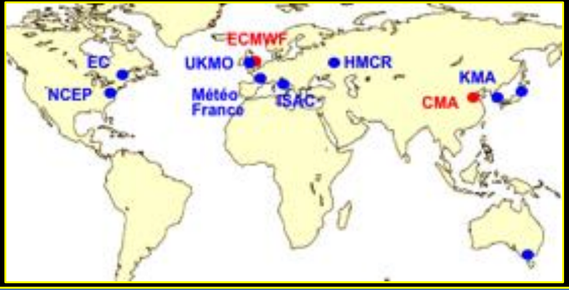
Motivation for this study:

There is a need for rigorous global assessment of AR prediction skill and predictability on subseasonal timescales to improve model development, weather forecasting, and water resources management.

The S2S database: our toolbox for assessing global AR prediction skill and predictability

- Suite of real-time forecasts and several decades of hindcasts from 11 operational forecast models
- Maximum lead time ranging from 32 days to 60 days
- Hindcast ensemble size ranging from 1 to 33
- Variety of forecasting configurations and other model parameters (heterogeneity amongst models)
    - opportunity for S2S-related research to suggest optimal future configurations for weekly to monthly forecasts

The S2S Database: a joint WCRP-WWRP Project



	Time-range	Resol.	Ens. Size	Freq.	Hcsts	Hcst length	Hcst Freq	Hcst Size
ECMWF	D 0-46	T639/319L91	51	2/week	On the fly	Past 20y	2/weekly	11
UKMO	D 0-60	N216L85	4	daily	On the fly	1996-2009	4/month	3
NCEP	D 0-44	N126L64	4	4/daily	Fix	1999-2010	4/daily	1
EC	D 0-32	0.6x0.6L40	21	weekly	On the fly	1995-2014	weekly	4
CAWCR	D 0-60	T47L17	33	weekly	Fix	1981-2013	6/month	33
JMA	D 0-34	T319L60	25	2/weekly	Fix	1981-2010	3/month	5
KMA	D 0-60	N216L85	4	daily	On the fly	1996-2009	4/month	3
CMA	D 0-45	T106L40	4	daily	Fix	1886-2014	daily	4
CNRM	D 0-32	T255L91	51	Weekly	Fix	1993-2014	2/monthly	15
CNR-ISAC	D 0-32	0.75x0.56 L54	40	weekly	Fix	1981-2010	6/month	1
HMCR	D 0-63	1.1x1.4 L28	20	weekly	Fix	1981-2010	weekly	10

Vitart et al. 2016

Detecting ARs in observations & operational models

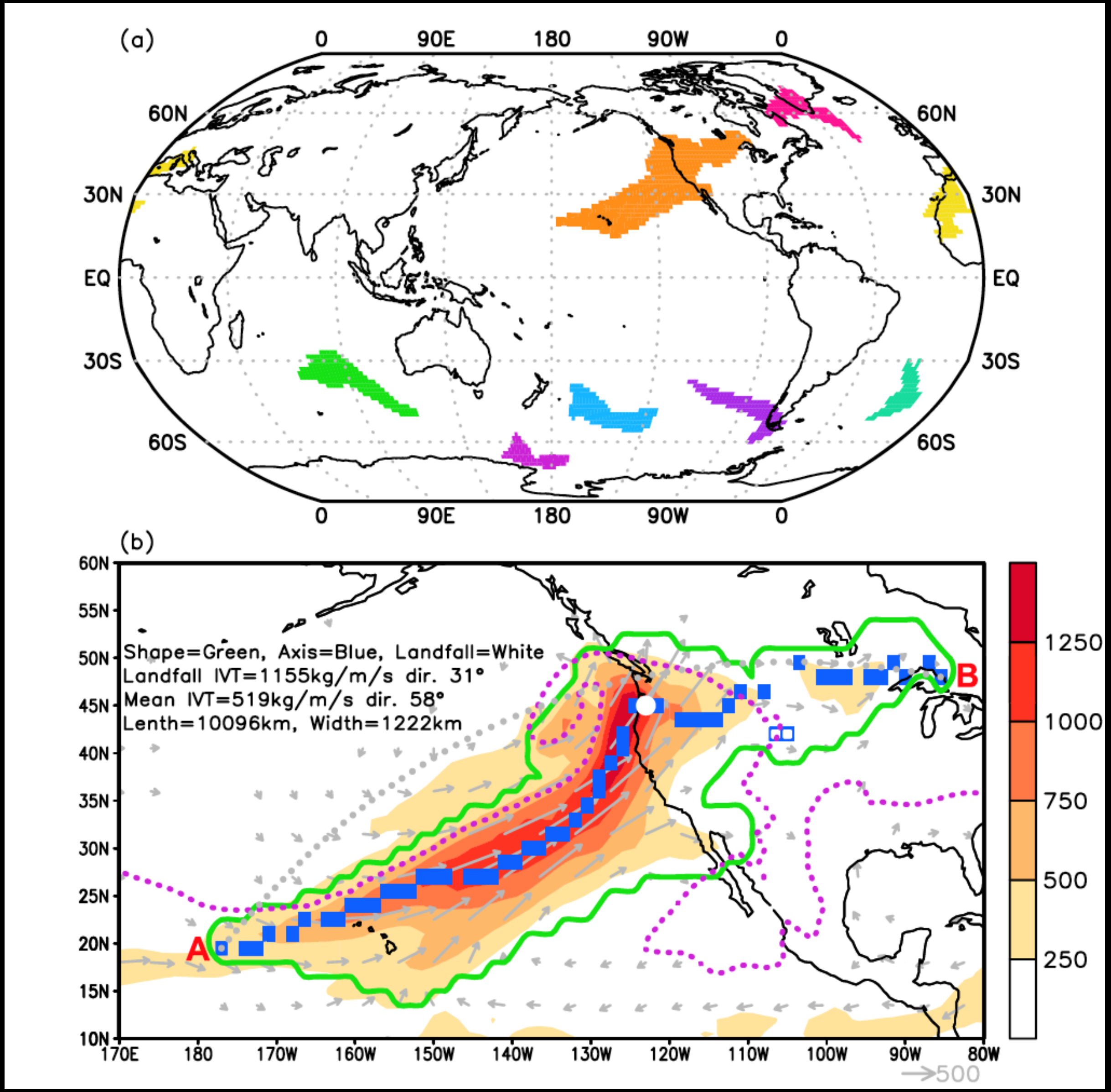


Fig 2, Guan and Waliser 2015

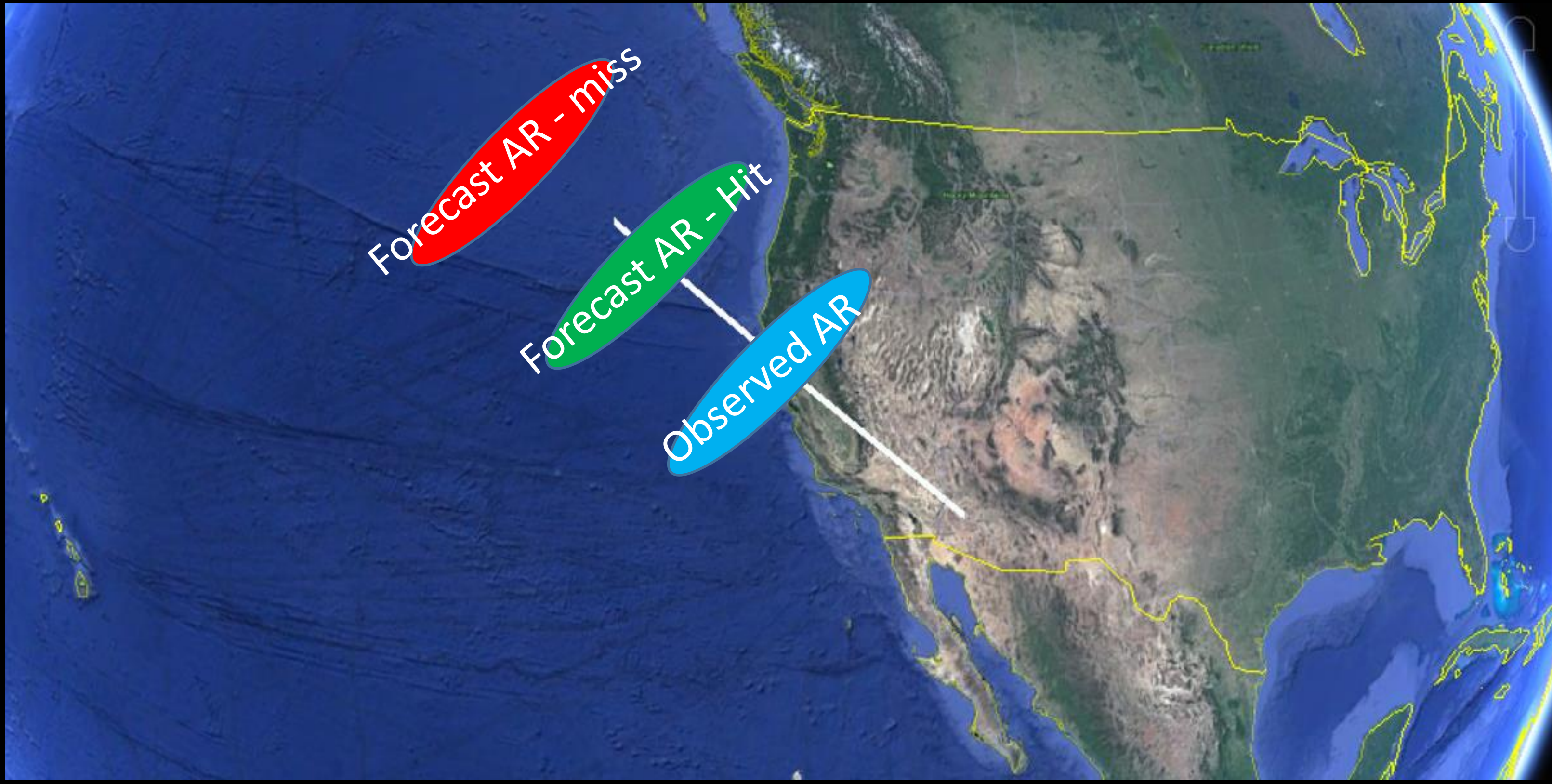
- We compute IVT values for each hindcast ensemble member.
- We apply the Guan and Waliser 2015 detection algorithm to the ensemble hindcasts of IVT for all lead times.
- We compare the locations of the detected ARs in the hindcasts with observations to determine "hit" rates.
- We aggregate statistics of hit rates to examine lead-time, spatial, seasonal, climate variation, and other sensitivities.

Our method for global assessment of AR prediction skill

- S2S hindcast data
  - ECMWF (1995-2014)
  - HMCR (1995-2010)
- Observations
  - ERA-I data (used to initialize hindcasts)

Goal: produce global maps of AR prediction skill (and predictability)

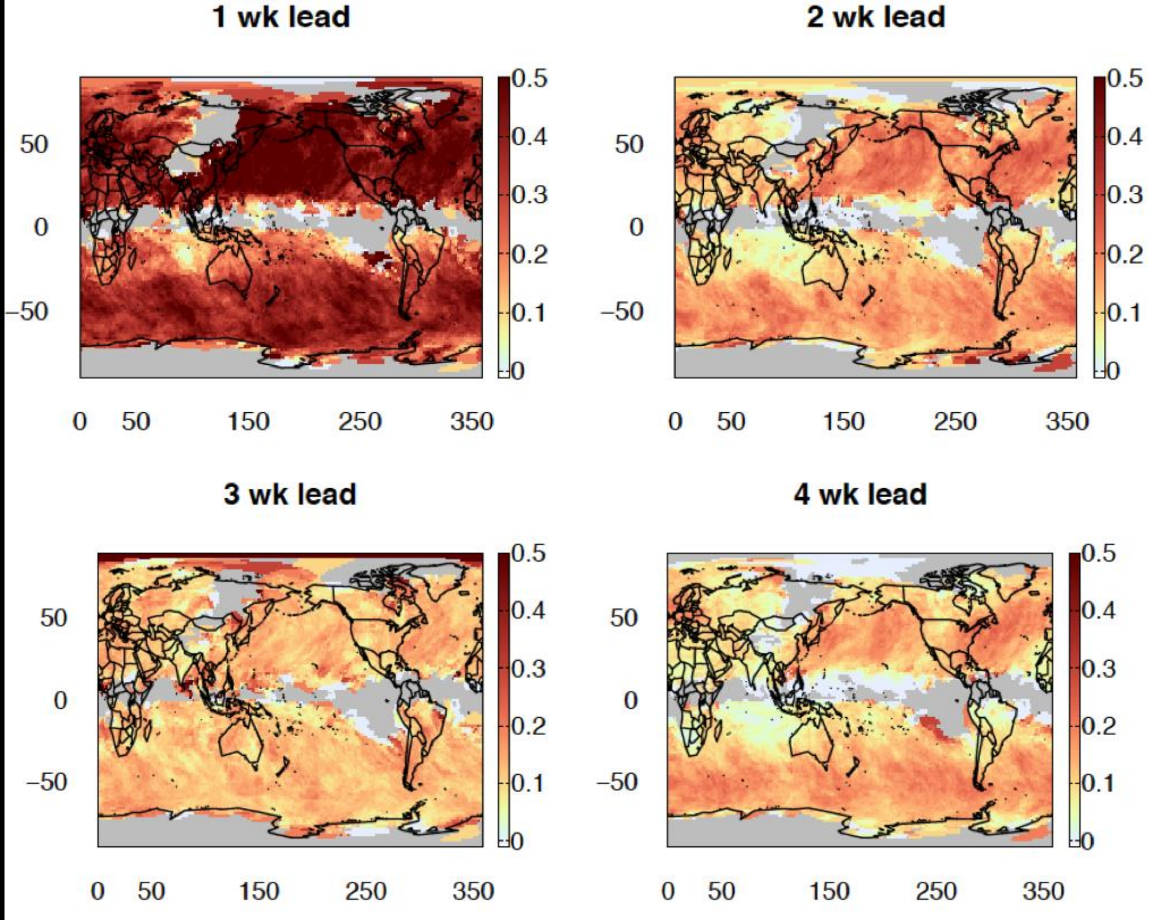
"1000km" AR hit threshold



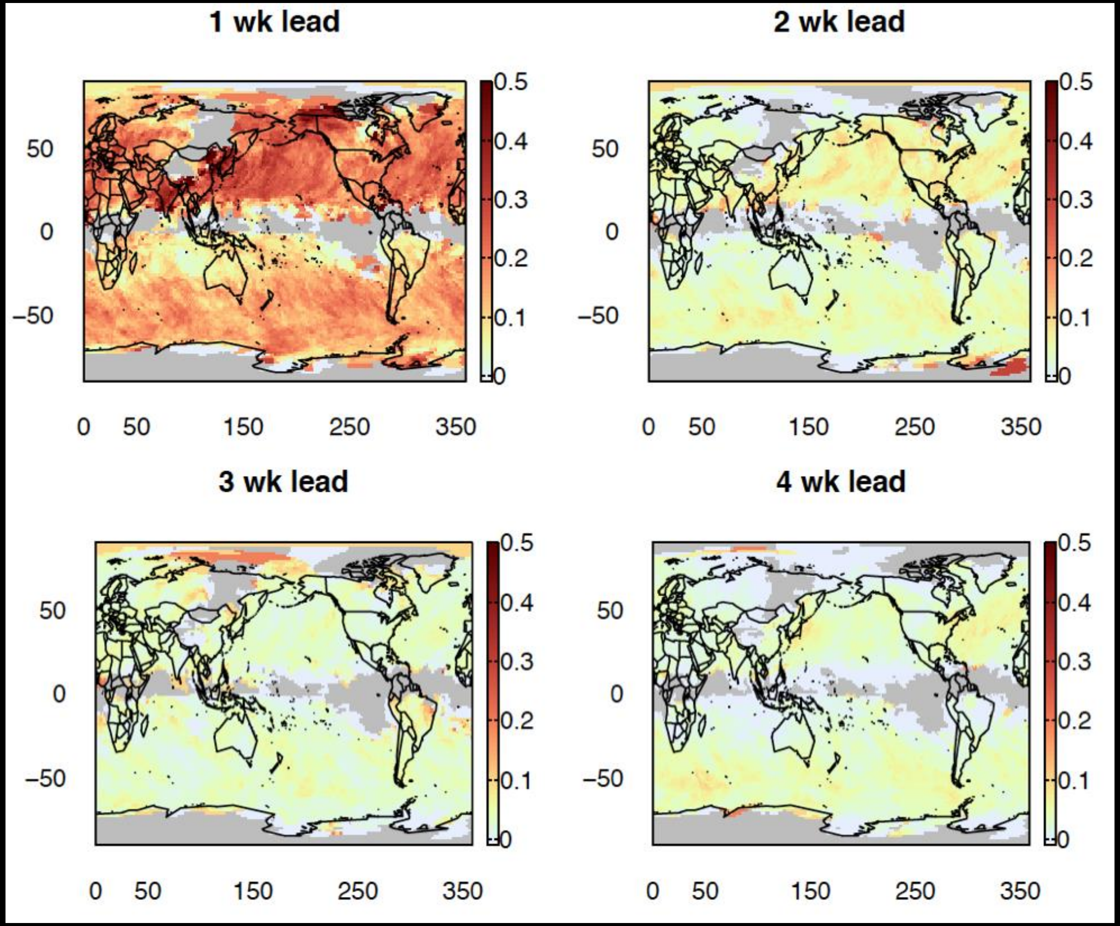
How does AR prediction skill vary as a function of forecast lead time, hit threshold distance, S2S model choice, and season?

DJF AR prediction skill: ECMWF 1995-2014

1000 km threshold

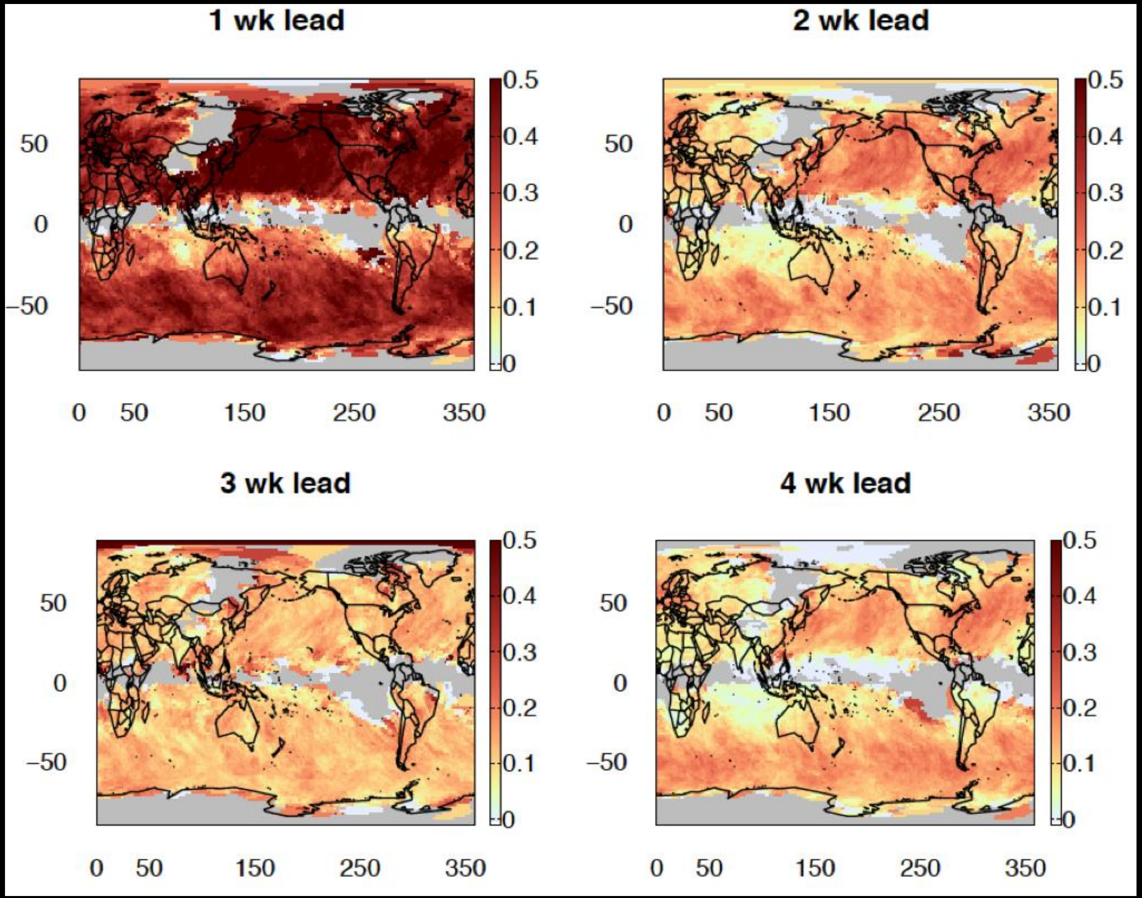


500 km threshold

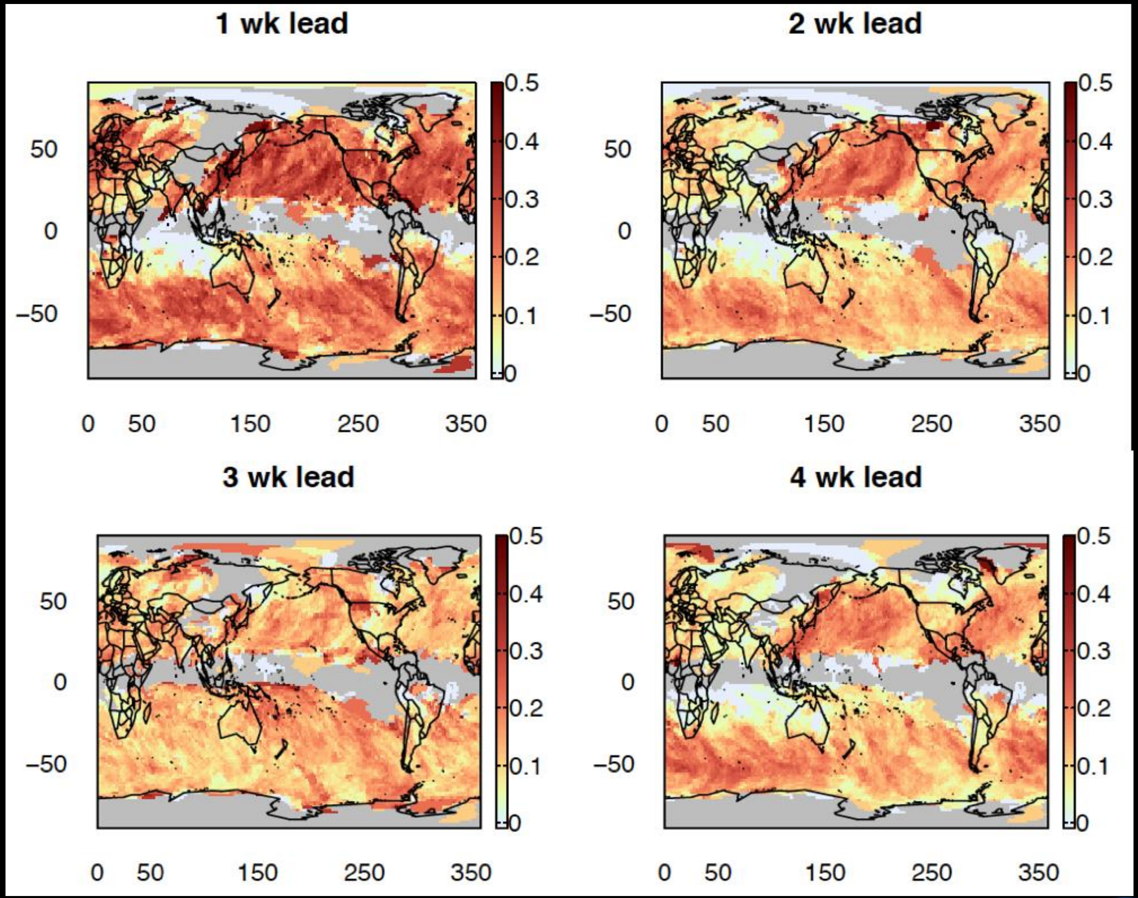


Model dependence: DJF ECMWF 1995-2014 vs. HMCR 1995-2010

ECMWF

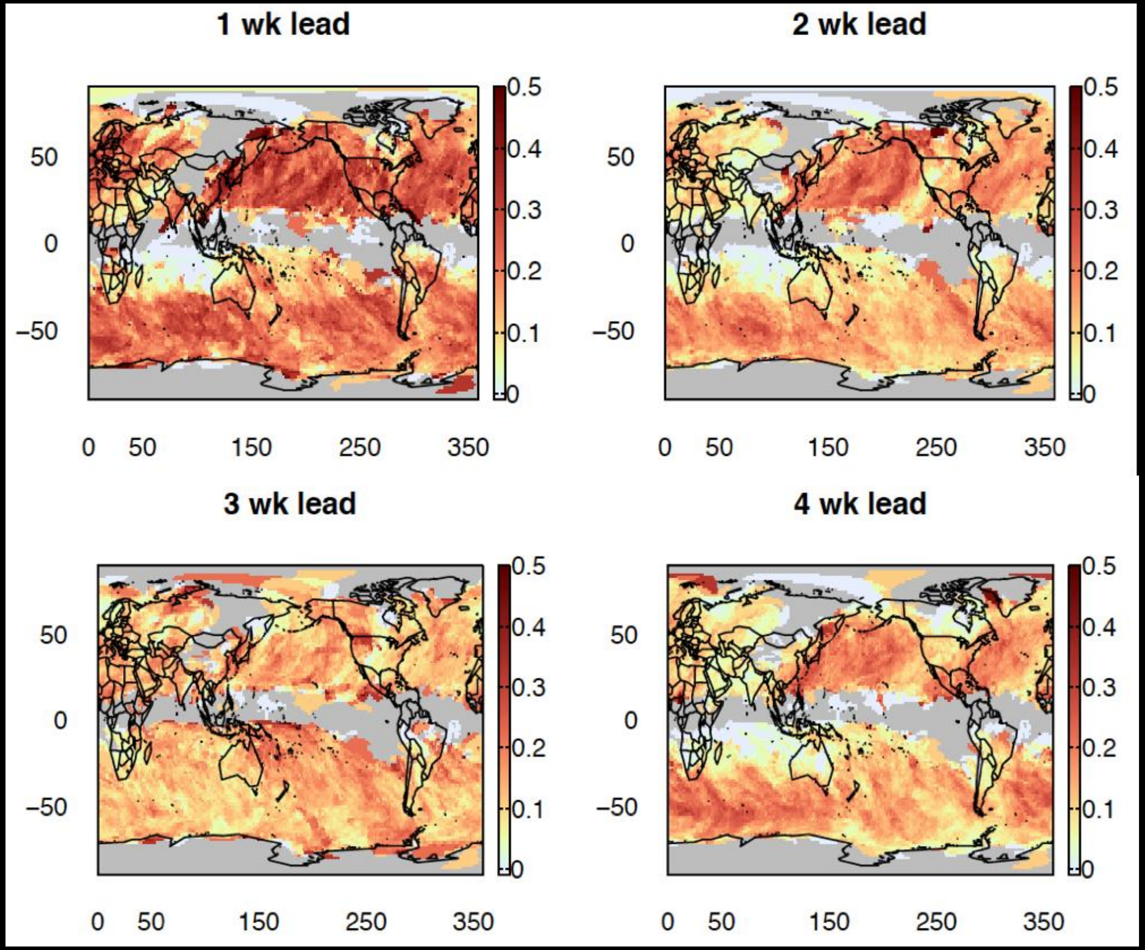


HMCR

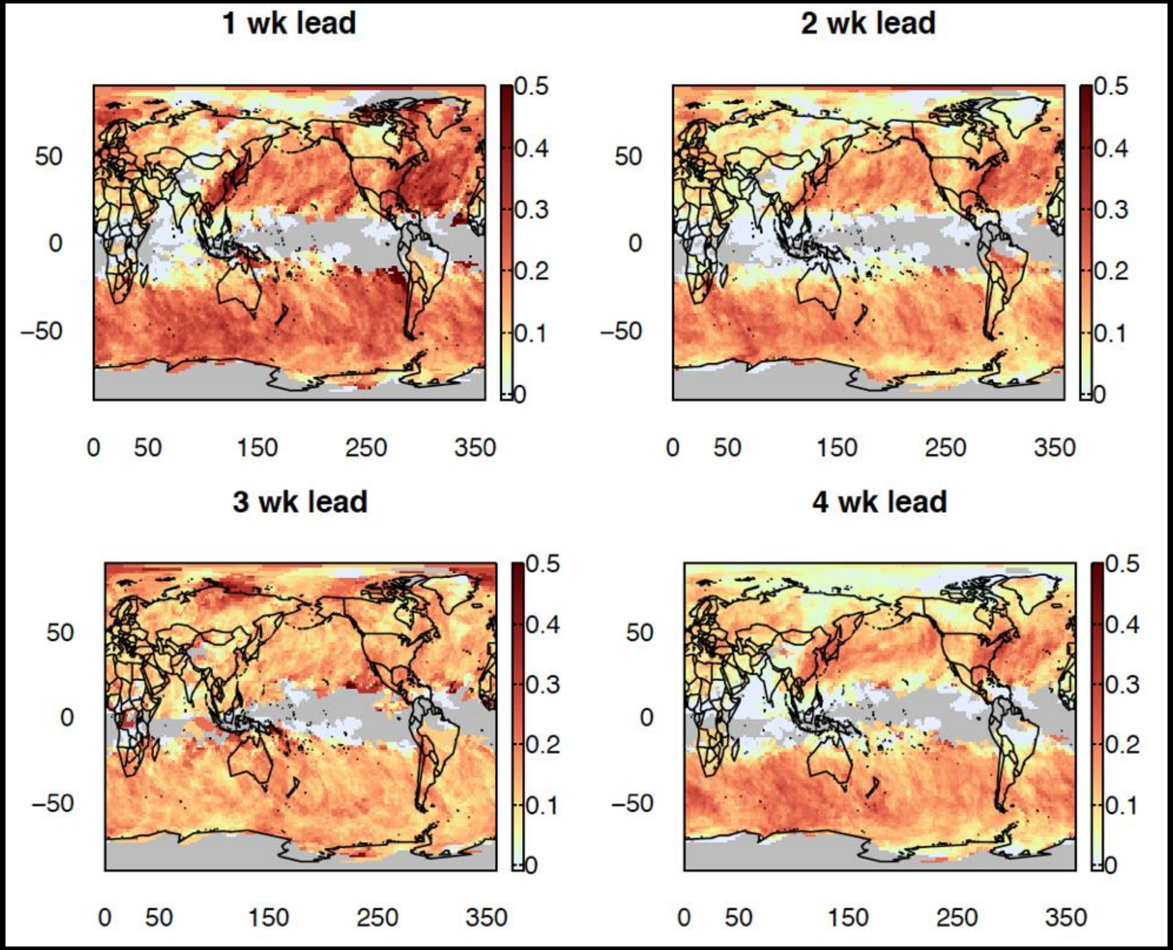


Seasonal dependence: DJF vs. MAM, HMCR

DJF

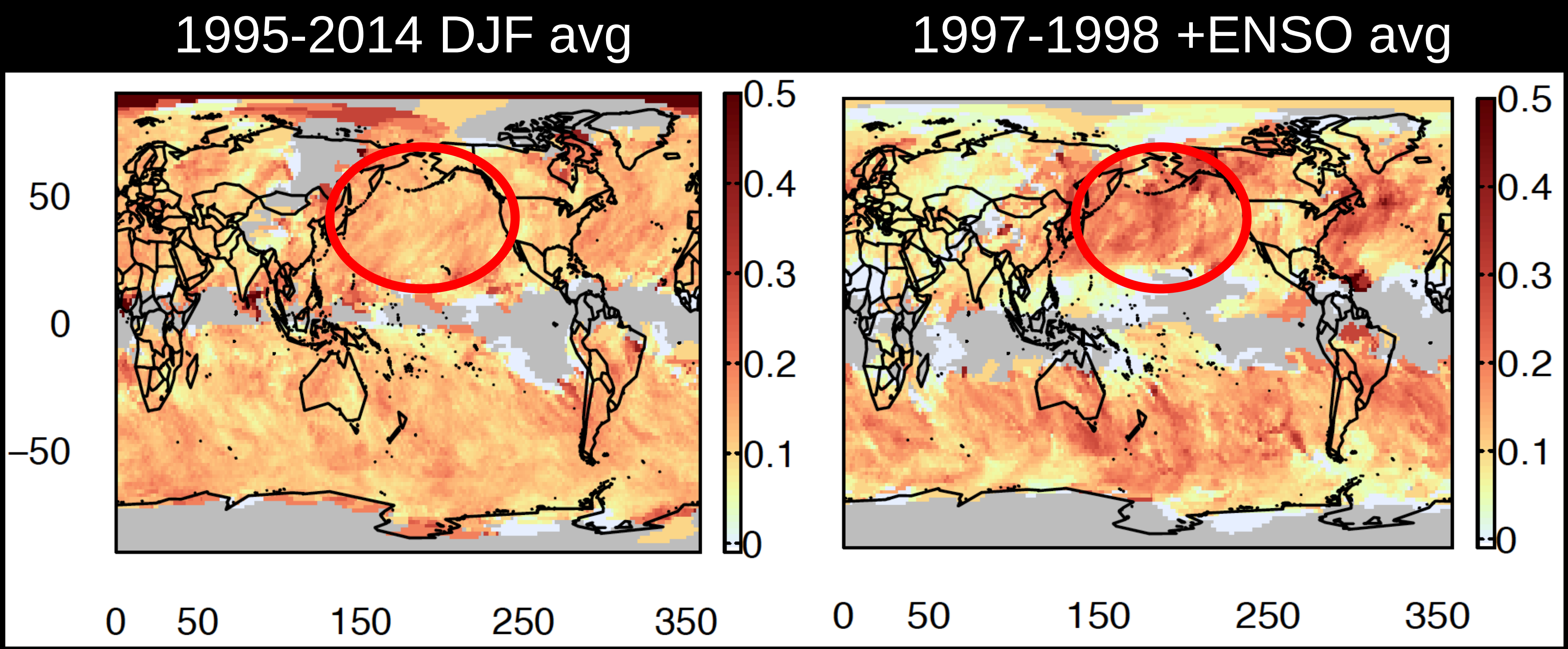


MAM



Can we exploit higher than average skill at longer lead times during certain phase regimes of large scale climate variability?

3-week lead AR skill: ECMWF Apr 1997 – Feb 1998 average hindcasts (strong El Niño conditions)



45% 3-week lead skill increase in North Pacific during El Niño season relative to climatology (average between 150E-240E, 30N-60N).

Can we exploit higher than average skill at longer lead times during very active AR periods (which often contribute significantly to annual precipitation)?

Winter 2010 case study: an exceptionally active AR year over the Sierra Nevada region

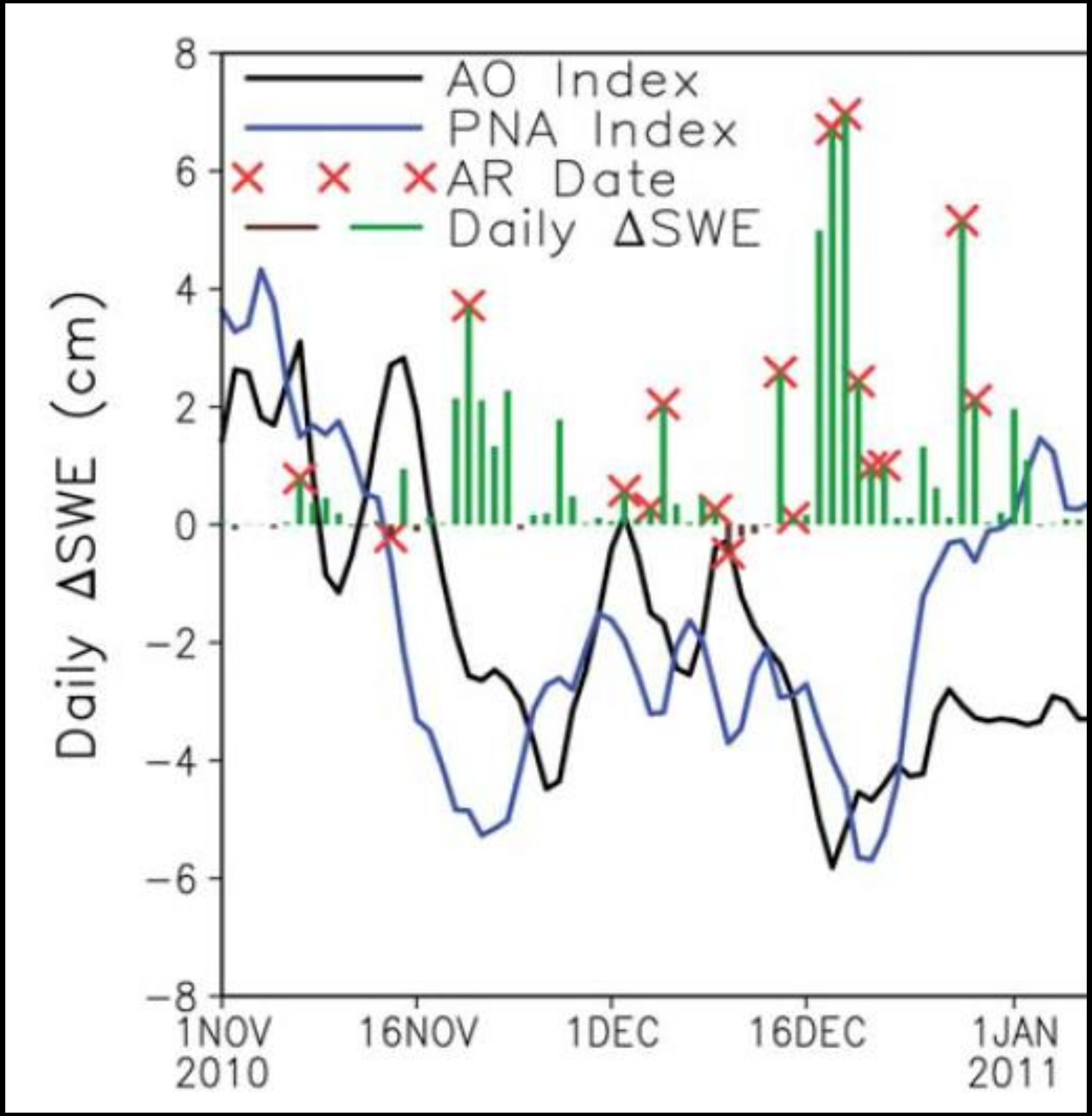
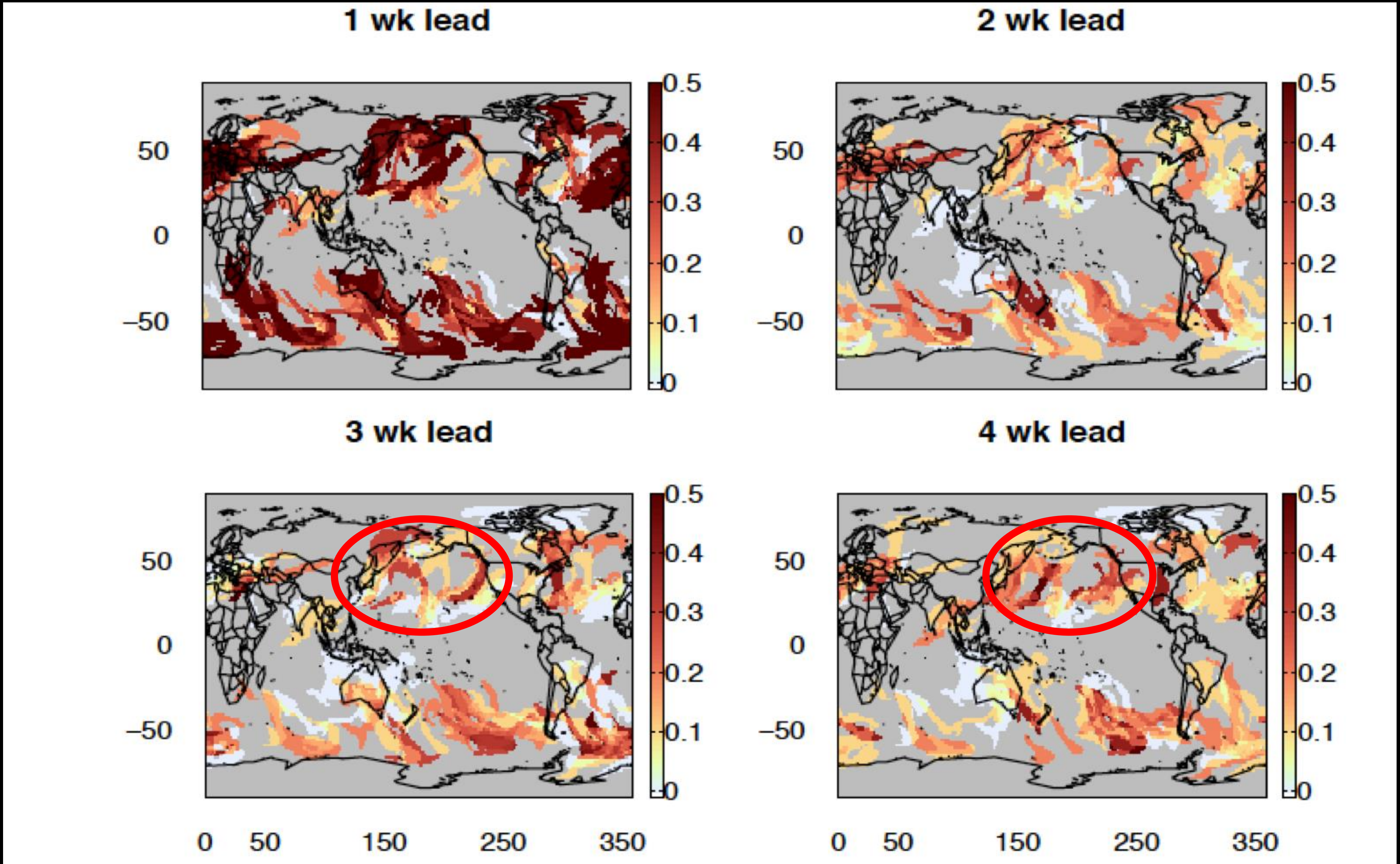


Fig 5, Guan et al. 2013

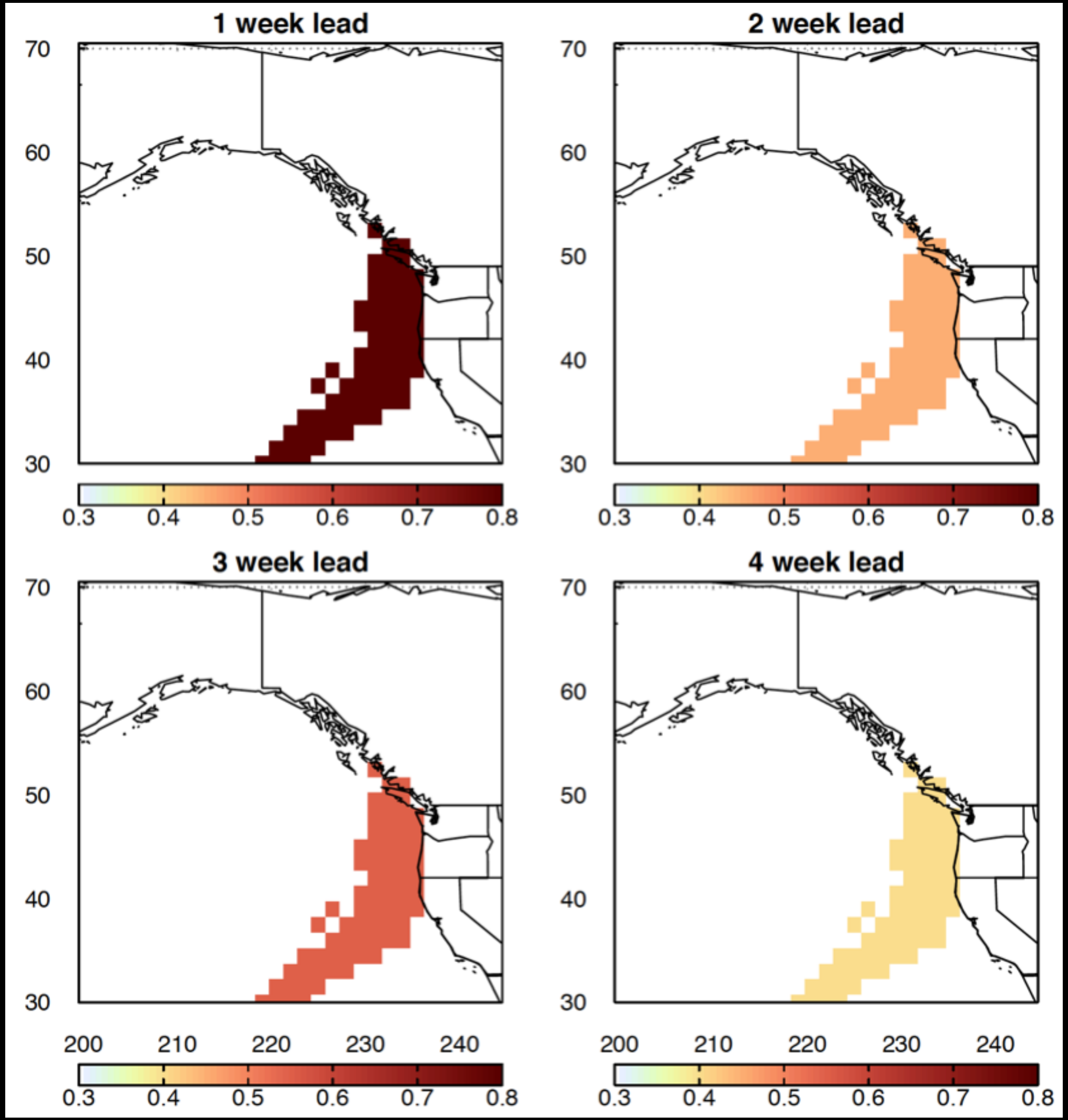
High frequency of ARs associated with very snowy conditions and negative AO/PNA phase locking during December 2010.

Nov 2 – Dec 3 2010 ECMWF AR prediction skill



Regional application: landfalling AR on December 3, 2015 during El Niño

- Previous examples use fixed ECMWF hindcast date
  - here, we fix observed date (to focus on a particular observed AR event of interest) and assess skill of 1 week, 2 week, 3 week, and 4 week lead hindcasts



Summary and preliminary conclusions

- wrote an algorithm and developed flexible methodology for calculating prediction skill of AR events in operational forecast models
- prediction skill generally decreases with more stringent AR distance threshold
  - moderate-to-high prediction skill at 1 week lead even with reduced 500-km distance threshold, especially over climatologically active AR regions (e.g. N. Pacific)
- generally higher prediction skill at 1-2 week leads in DJF relative to MAM
- potential increase of 3-4 week skill relative to climatology during strong El Niño and La Niña events and anomalously active AR winters
  - will add more ENSO events and examine phase locking of different climate modes to try to exploit predictability and prediction skill at longer leads
- our global methodology allows for targeted regional prediction skill estimates of particular observed AR events
- currently expanding methodology to utilize a dozen S2S operational models, and to estimate predictability of ARs

Thanks! Stay tuned...

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