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Multi-model assessment of global atmospheric river synoptic and S2S prediction skill: hindcast analysis and real-time experimental forecasting efforts

Mike DeFlorio

NASA Jet Propulsion Laboratory/California Institute of Technology

Co-authors/collaborators: Duane Waliser (JPL/UCLA), Alexander Goodman (JPL), Bin Guan (JPL/UCLA), F. Martin Ralph (SIO-CW3E), David Lavers (ECMWF), Frédéric Vitart (ECMWF), Aneesh Subramanian (SIO-CW3E), Jason Cordeira (Plymouth State University)

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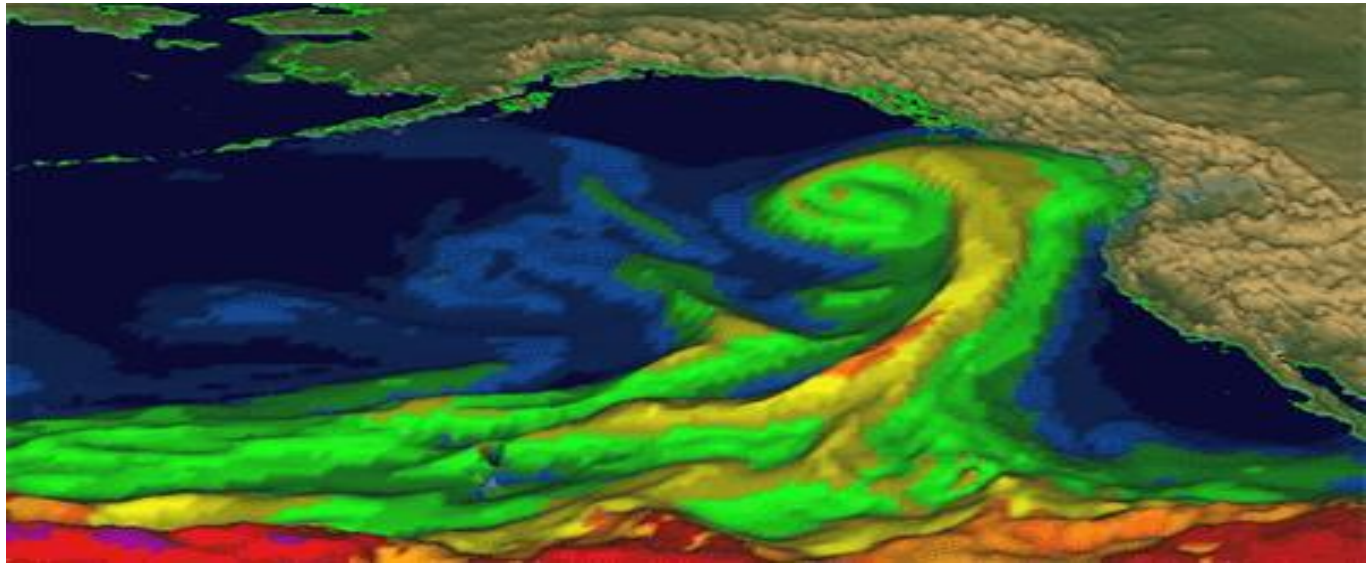
Contains key figures/concepts from:

1. DeFlorio et al. 2018a, **Global assessment of atmospheric river prediction skill**, J. Hydromet. (in press)
2. DeFlorio et al. 2018b, **Global evaluation of atmospheric river subseasonal prediction skill**, Clim. Dyn. (in revision)
3. Guan and Waliser 2015, **Detection of atmospheric rivers: Evaluation and application of an algorithm for global studies**, J. Geophys. Res., **120**, 12514-12535.

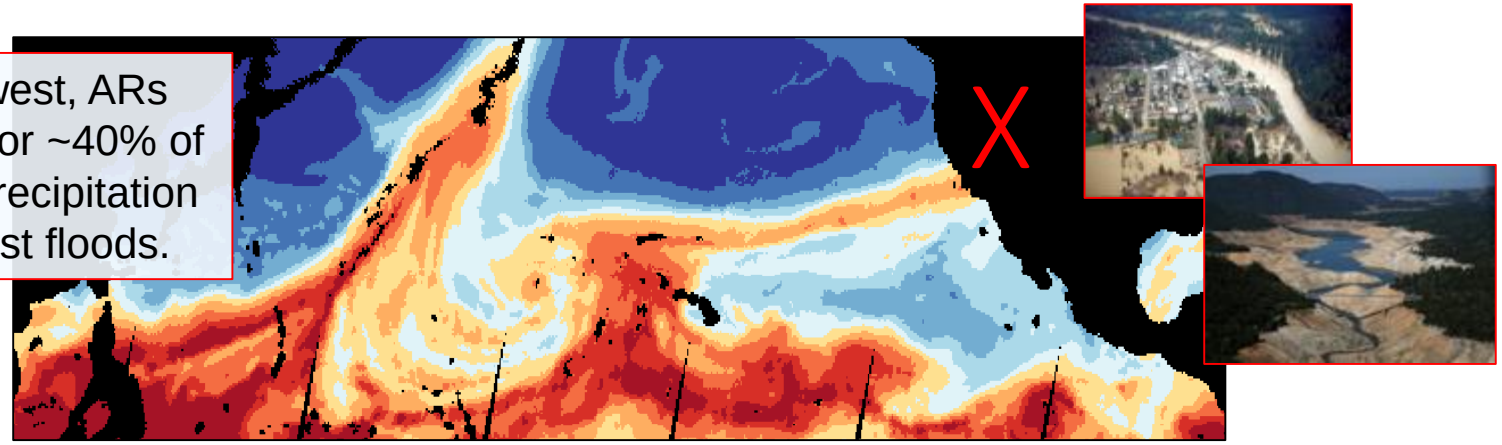
Atmospheric rivers and their associated flood and hazard risks occur globally and influence climate and water extremes.



NOAA ESRL

Over 90% of poleward moisture transport at midlatitudes is by ARs that take up only ~10% of the zonal circumference (Zhu and Newell 1998).

In the west, ARs account for ~40% of annual precipitation and most floods.



Key Research Question

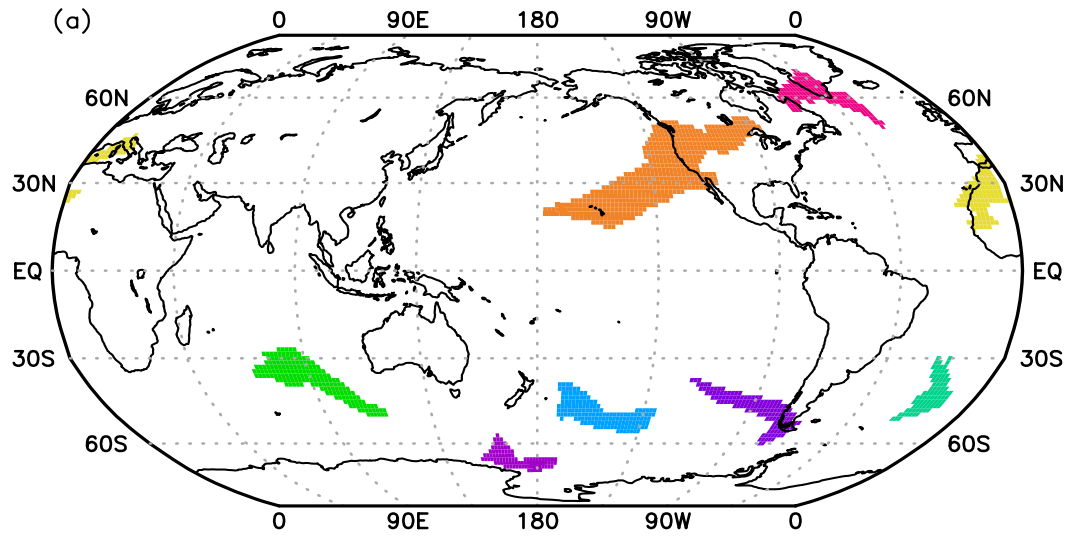
What is the limit of global subseasonal (1-week to 1-month) prediction skill of 2-week AR occurrence, and how does it vary as a function of season, region, and certain large-scale climate conditions?

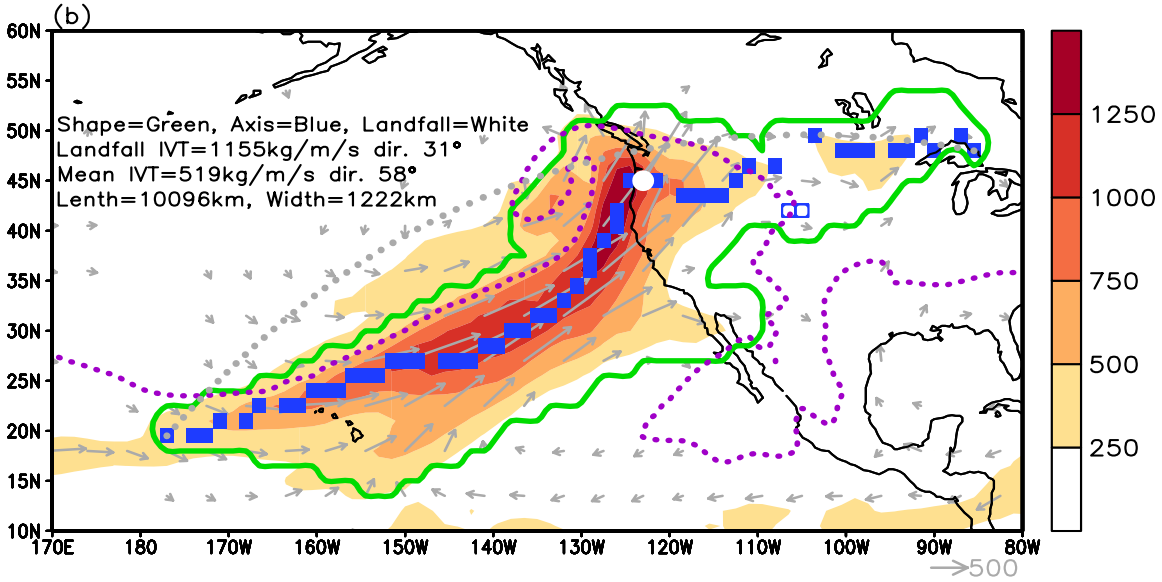
Key Applications Question

Can present-day S2S forecast systems provide benefit to CA water resource management decision makers?

A global, objective algorithm for AR identification

(Guan and Waliser 2015)

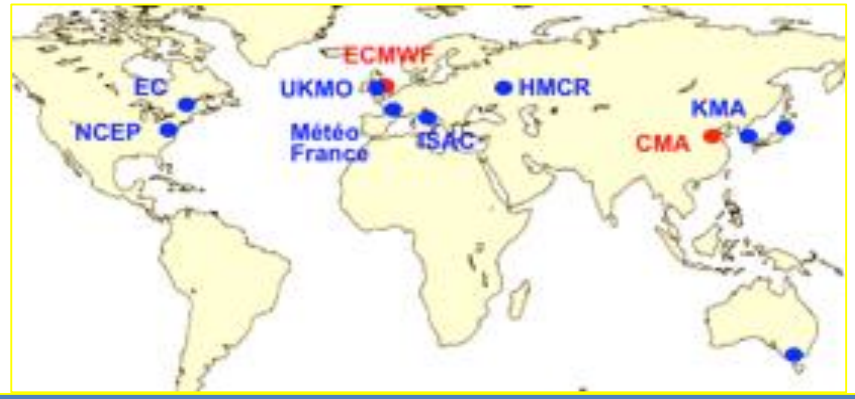




- Based on Integrated Vapor Transport (IVT) fields and a number of common AR criteria (e.g. Ralph et al. 2004)
- Applied to global hindcast/forecast systems and reanalysis datasets
- Code and databases available at: https://ucla.box.com/ARcatalog
- Databases include AR Date, $IVT_{x,y}$, Shape, Axis, Landfall Location, etc.
- Used for GCM evaluation (Guan and Waliser 2017), climate change projections (Espinoza et al. 2017, submitted), & forecast skill assessment (DeFlorio et al. 2018a and 2018b, in press, in revision)

The S2S Project Database (s2sprediction.net)

- 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)
  - “dataset of opportunity”



	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

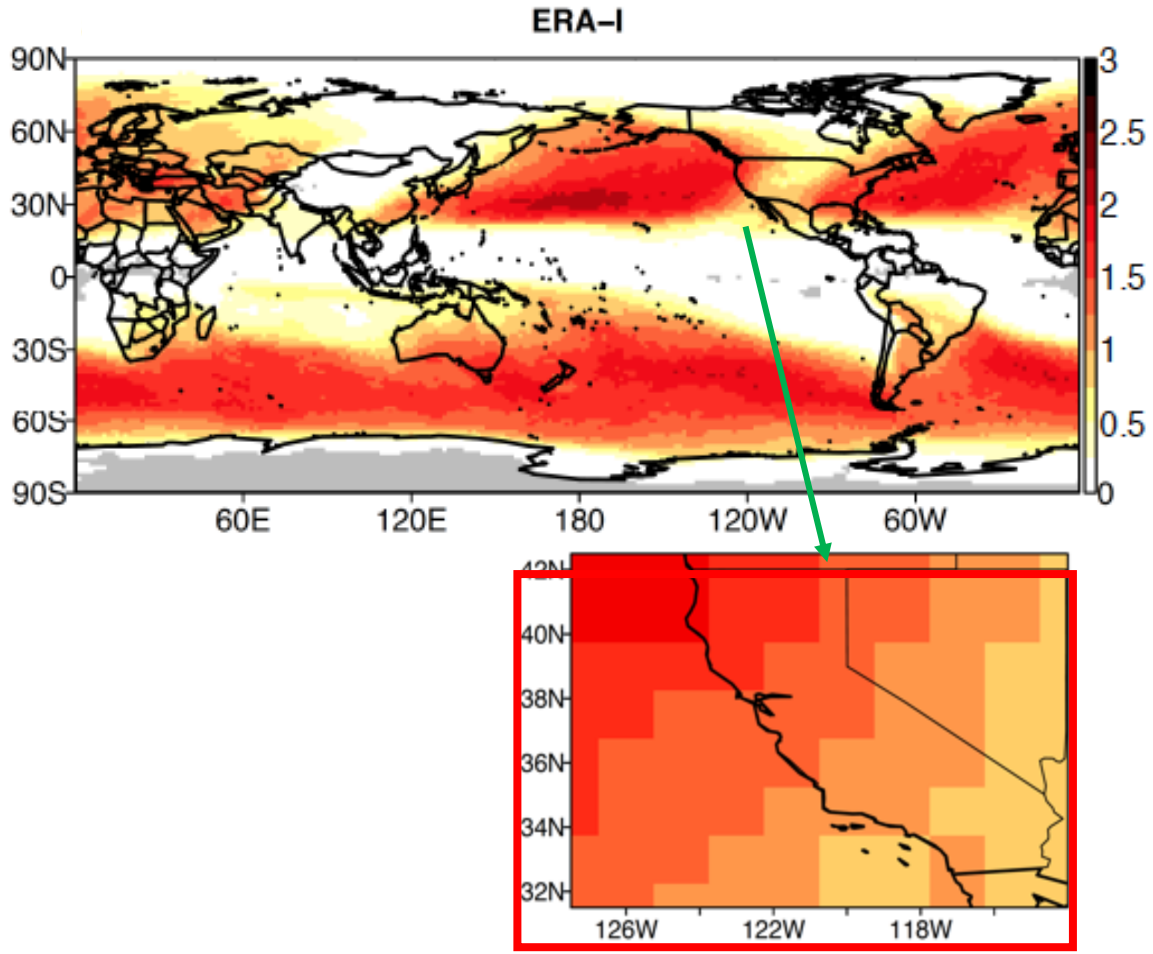
Vitart et al. 2017

Goal: use objective identification algorithm to assess global AR subseasonal prediction skill at lead times of 1-week to 1-month using S2S hindcast data

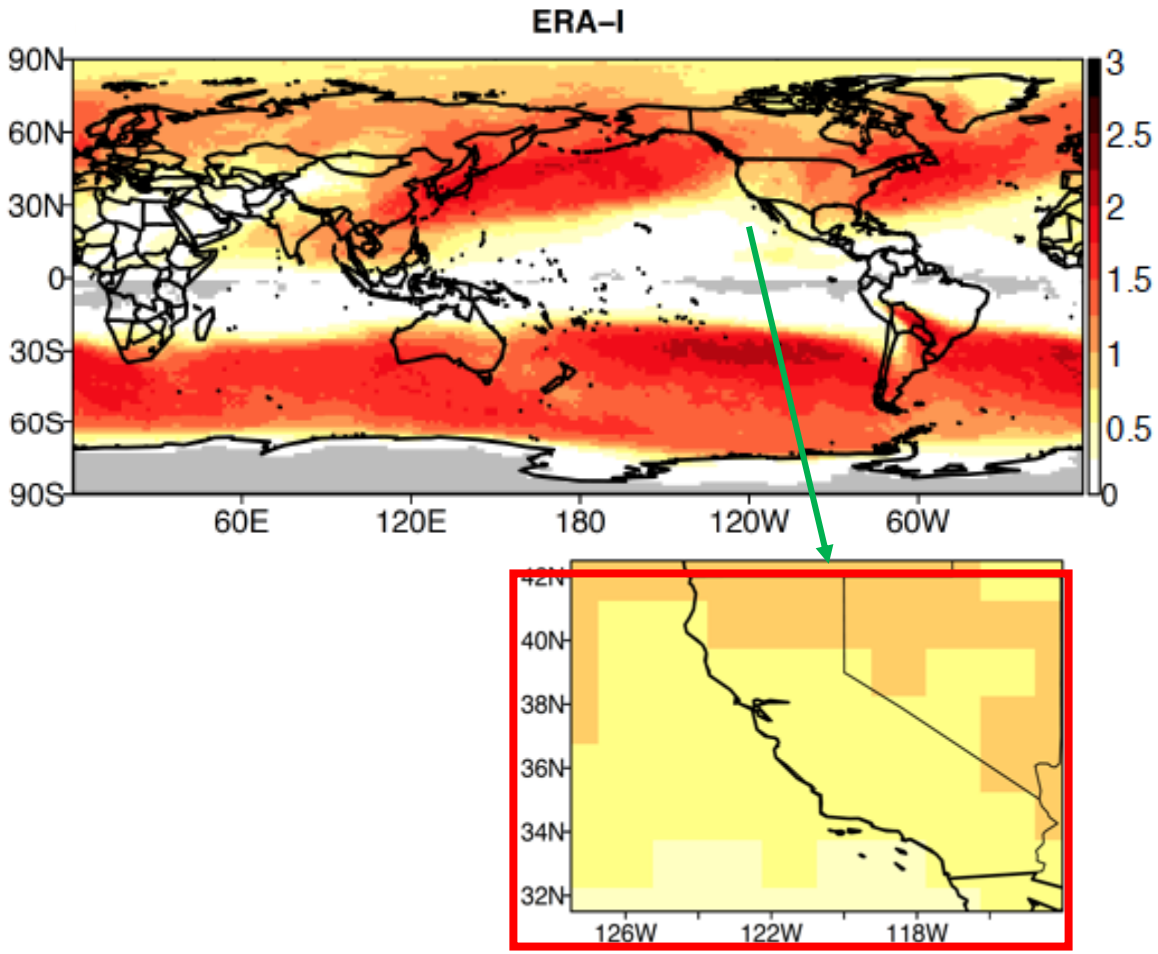
DeFlorio et al. 2018b, **Global evaluation of atmospheric river subseasonal prediction skill**, Clim. Dyn. (in revision)

AR occurrence climatology (#AR days per two weeks; “AR2wk”)

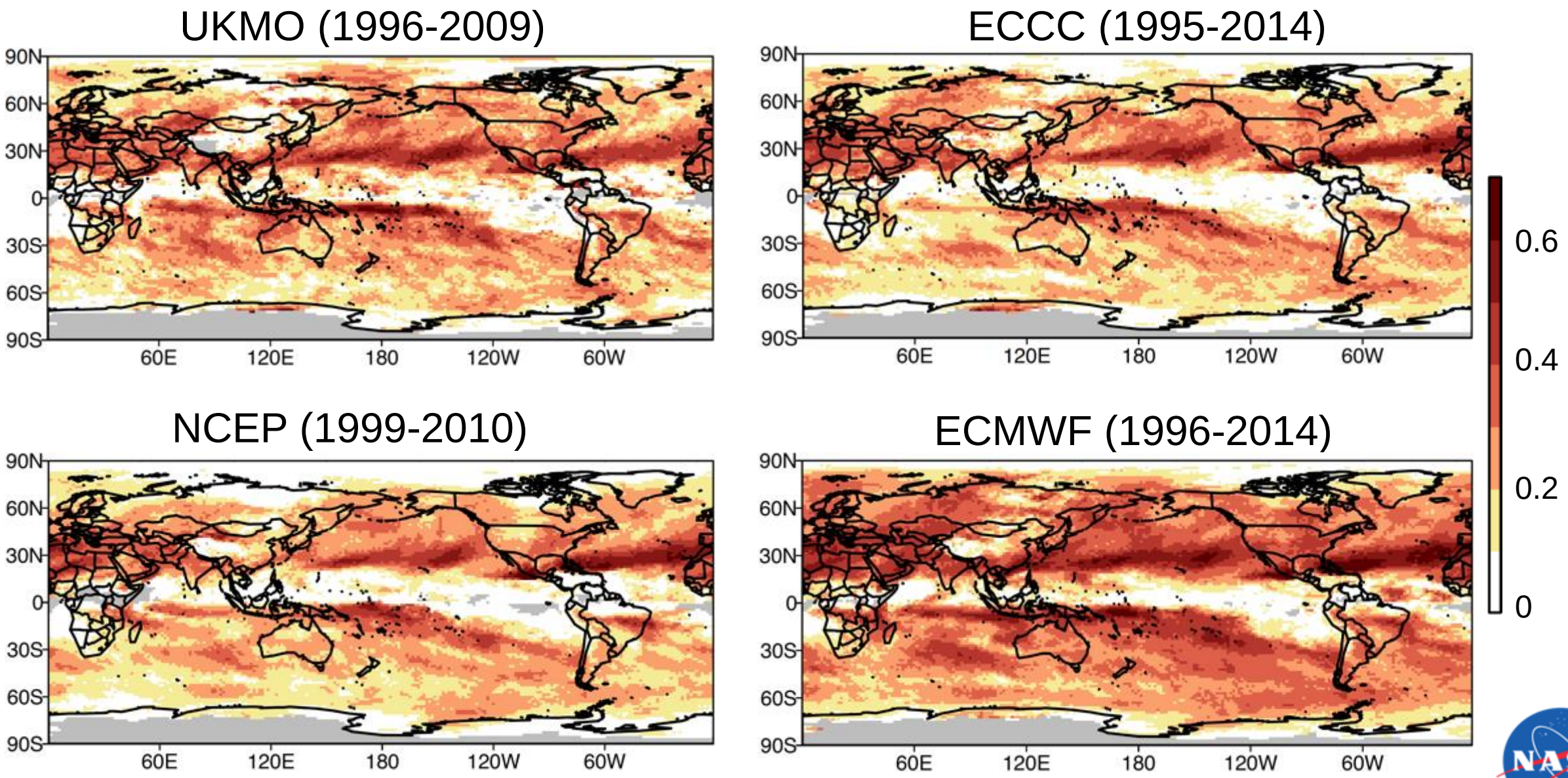
NDJFM



MJJAS

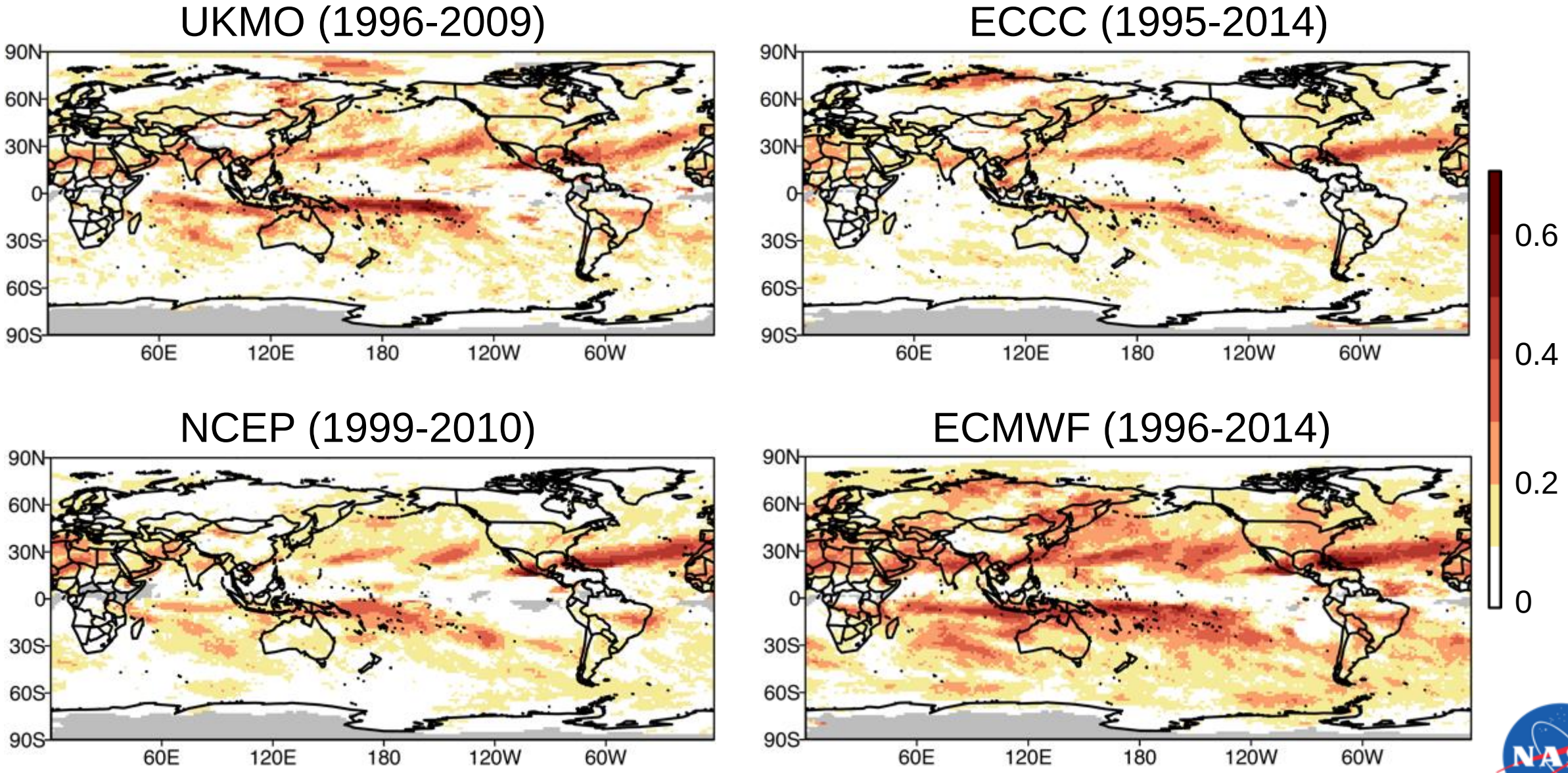


NDJFM AR2wk Forecast skill: 7d-21d lead window



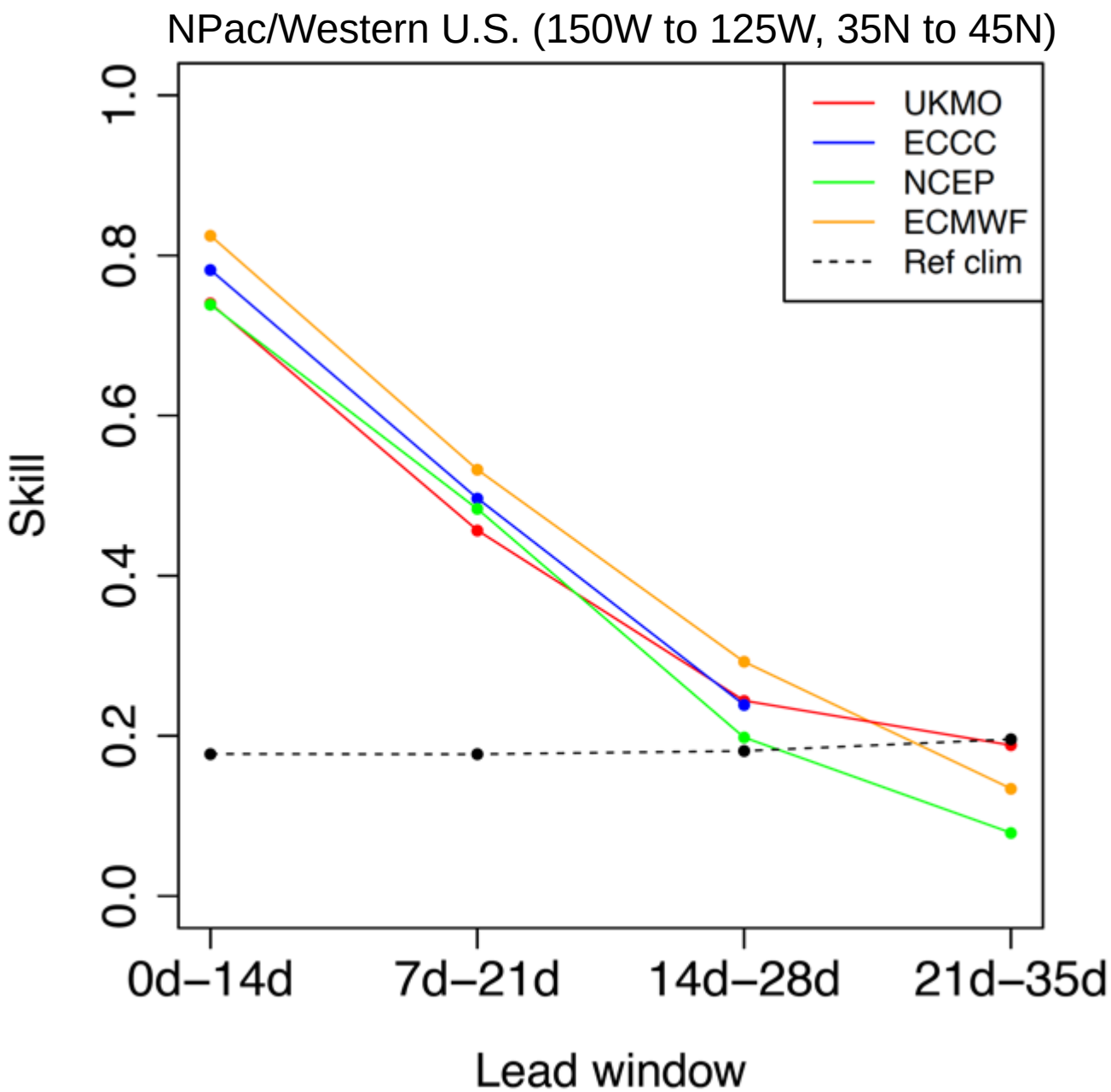
Note: forecast skill is defined as the anomaly correlation of AR2wk for ERA-I and each model

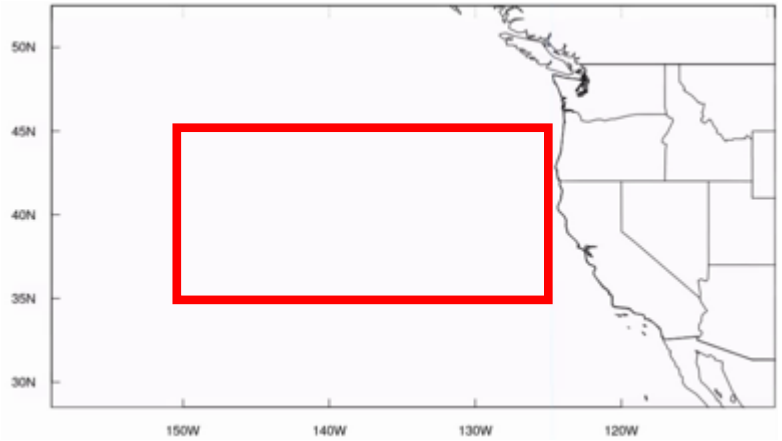
NDJFM AR2wk Forecast skill: 14d-28d lead window



Note: forecast skill is defined as the anomaly correlation of AR2wk for ERA-I and each model

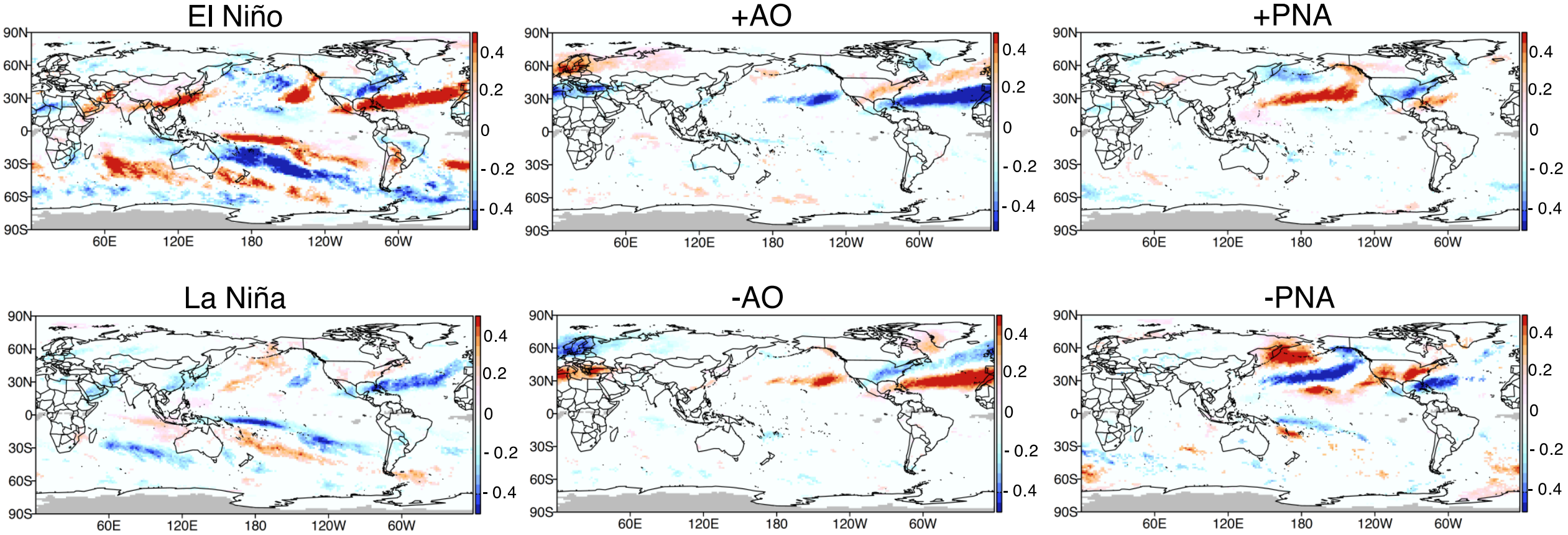
NDJFM AR2wk Forecast Skill vs. Lead: comparison to reference skill



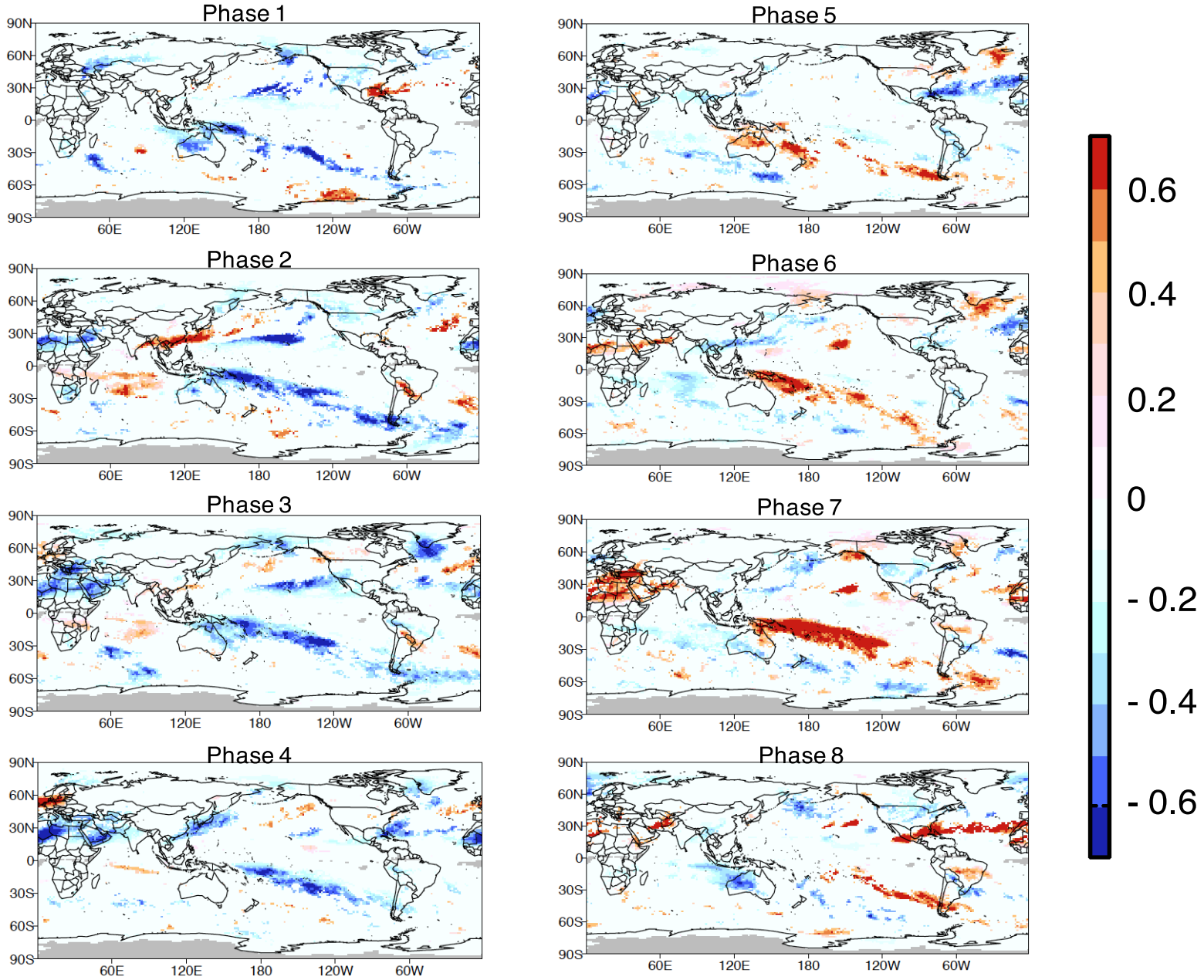


Reference skill is defined as the correlation between ”total” observed AR2wk (observed AR2wk anomaly + observed AR2wk monthly climatology value) and observed AR2wk monthly climatology

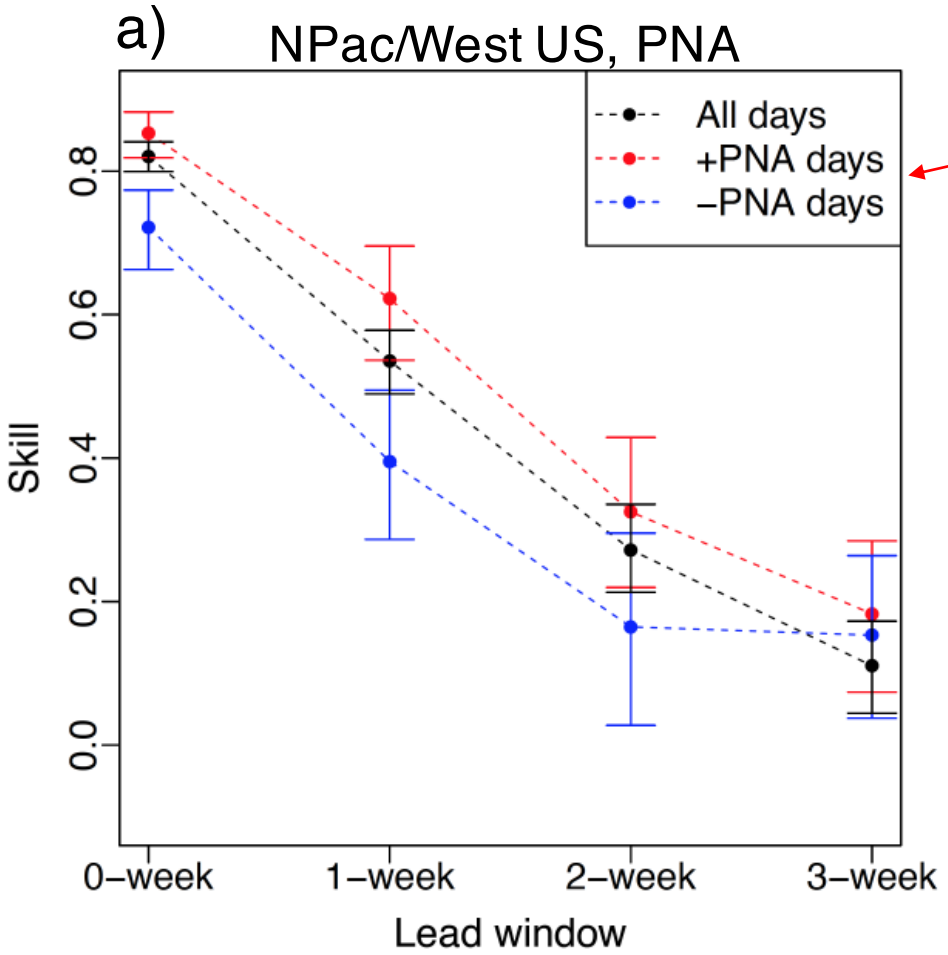
NDJFM AR2wk Occurrence Anomalies: ENSO, AO, and PNA, ERA-I



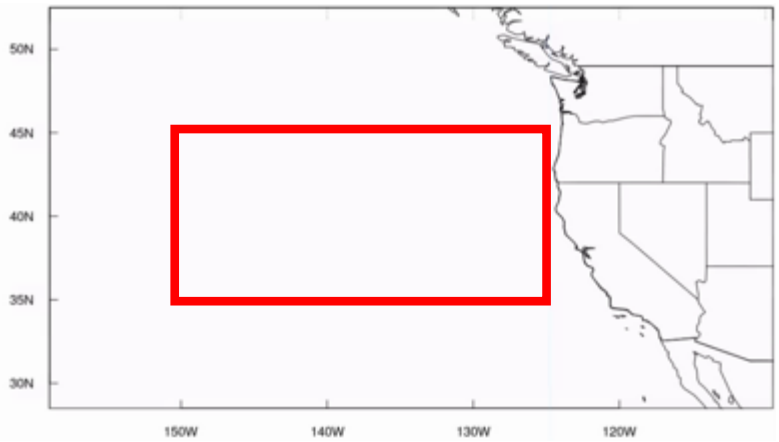
NDJFM AR2wk Occurrence Anomalies: MJO, ERA-I



NDJFM AR2wk Occurrence ECMWF Forecast Skill: PNA Composite

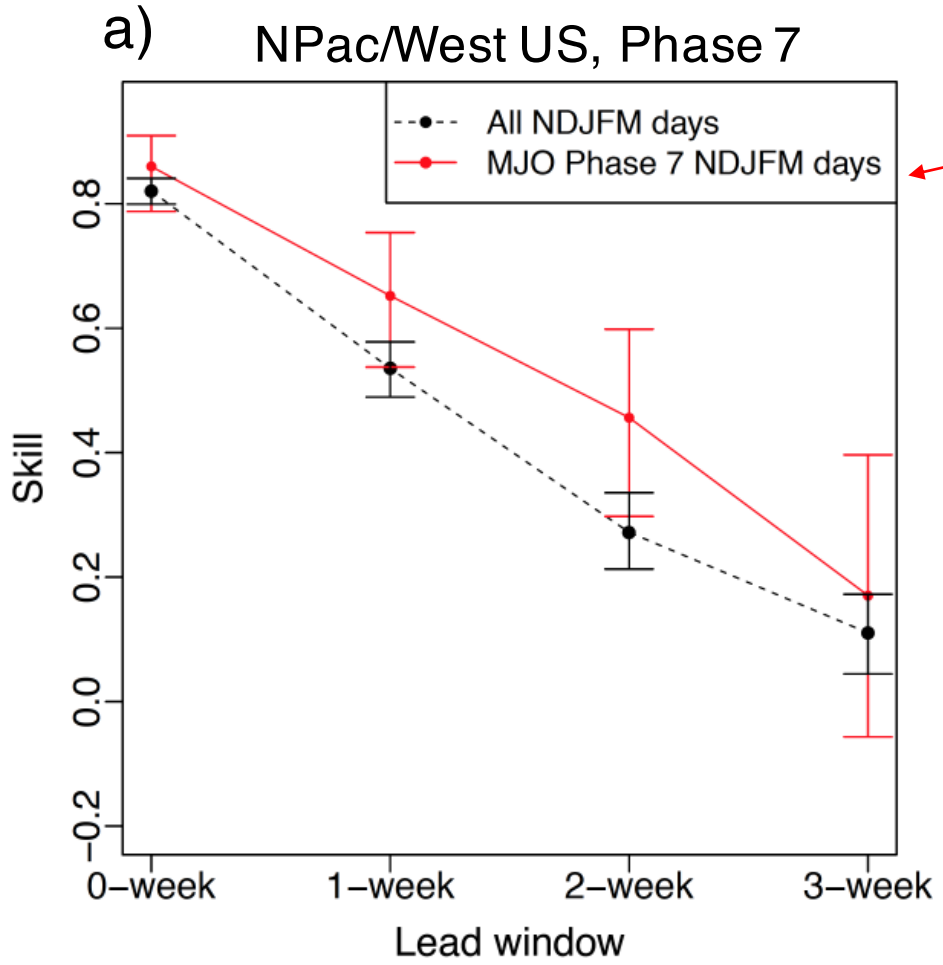


Relative to state of PNA at time of hindcast initialization

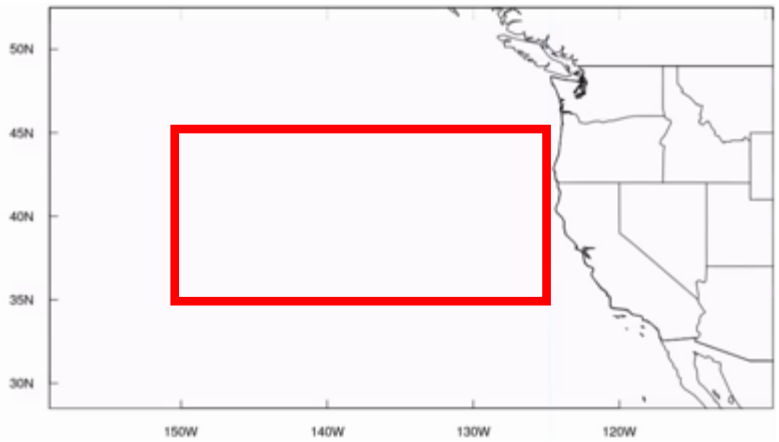


Also: higher ratio of hits relative to false alarms during +PNA conditions relative to –PNA conditions for individual AR events at 3d, 7d, 10d lead times (DeFlorio et al. 2018a, J. Hydromet., in press)

NDJFM AR2wk Occurrence ECMWF Forecast Skill: MJO Phase Composite



Relative to state of MJO at time of hindcast initialization



Experimental synoptic and S2S AR forecasting for winter 2017-18 and 2018-19

Mike DeFlorio,
Duane Waliser,
Alex Goodman

Bin Guan

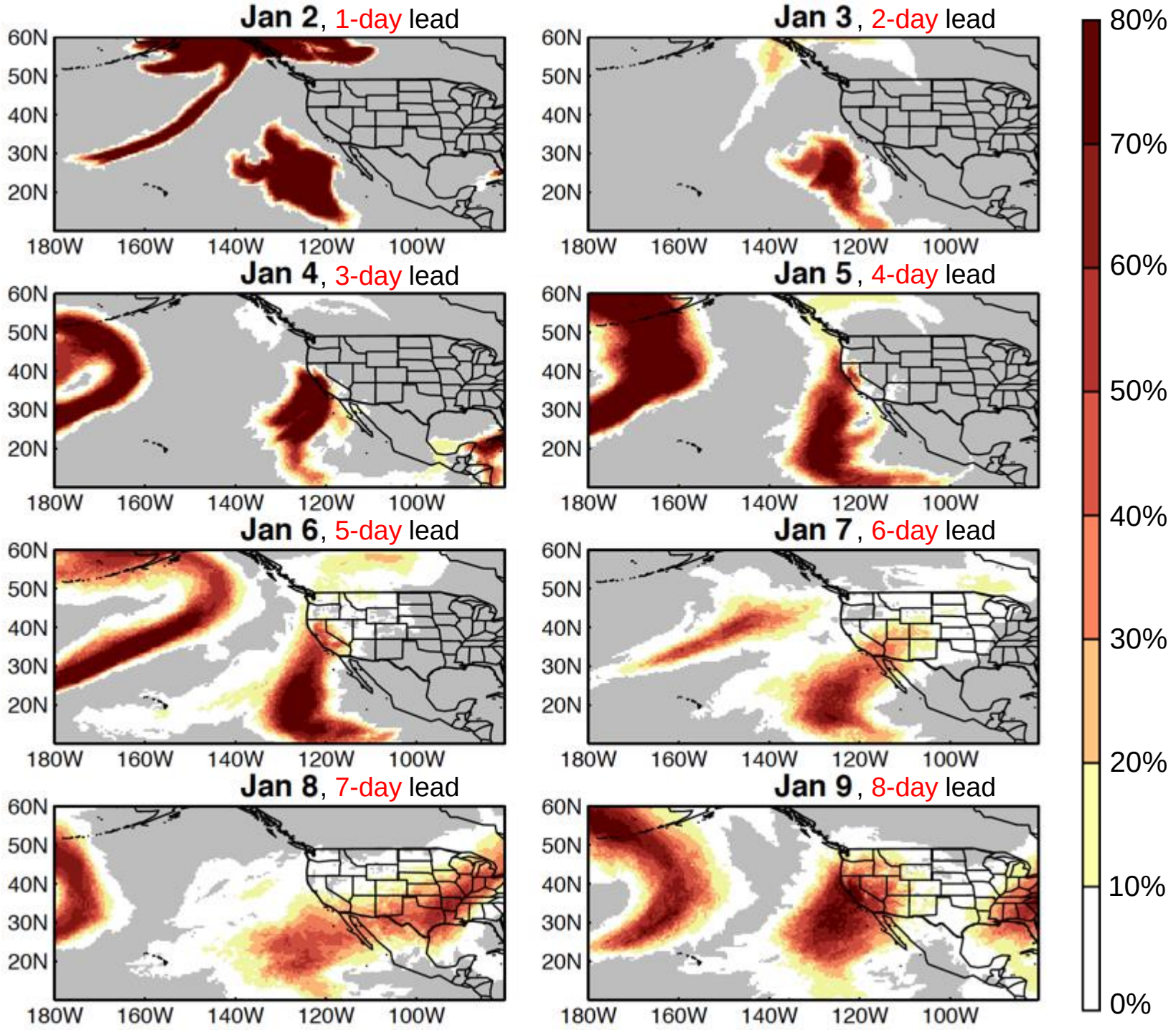
Marty Ralph
Aneesh Subramanian
Alexander Gershunov

Frédéric Vitart

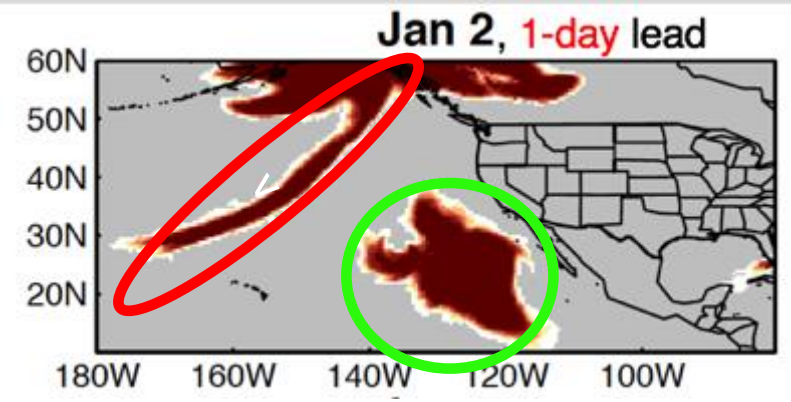
Jay Cordeira

Jeanine Jones

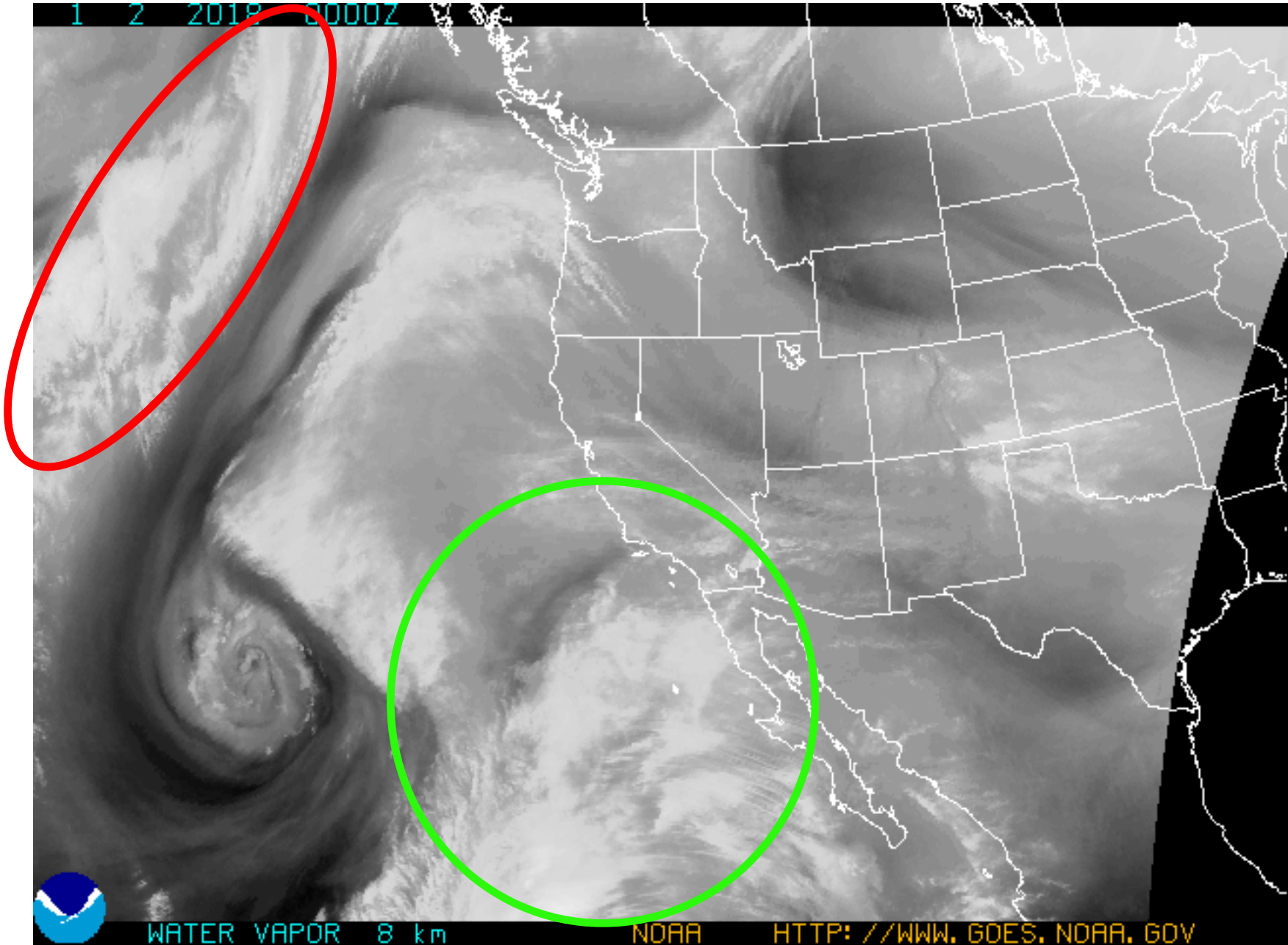
Probability of AR occurrence (chance of an AR occurring any time during each day), ECMWF January 1, 2018 00Z forecast, 1-day to 8-day lead



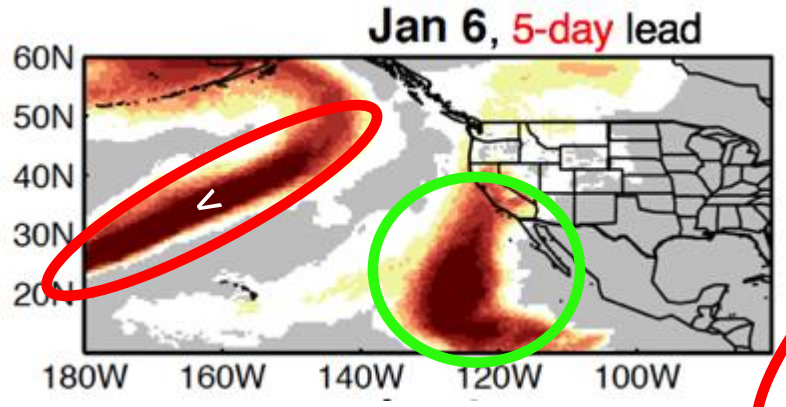
Jan 2 00Z AR Forecast



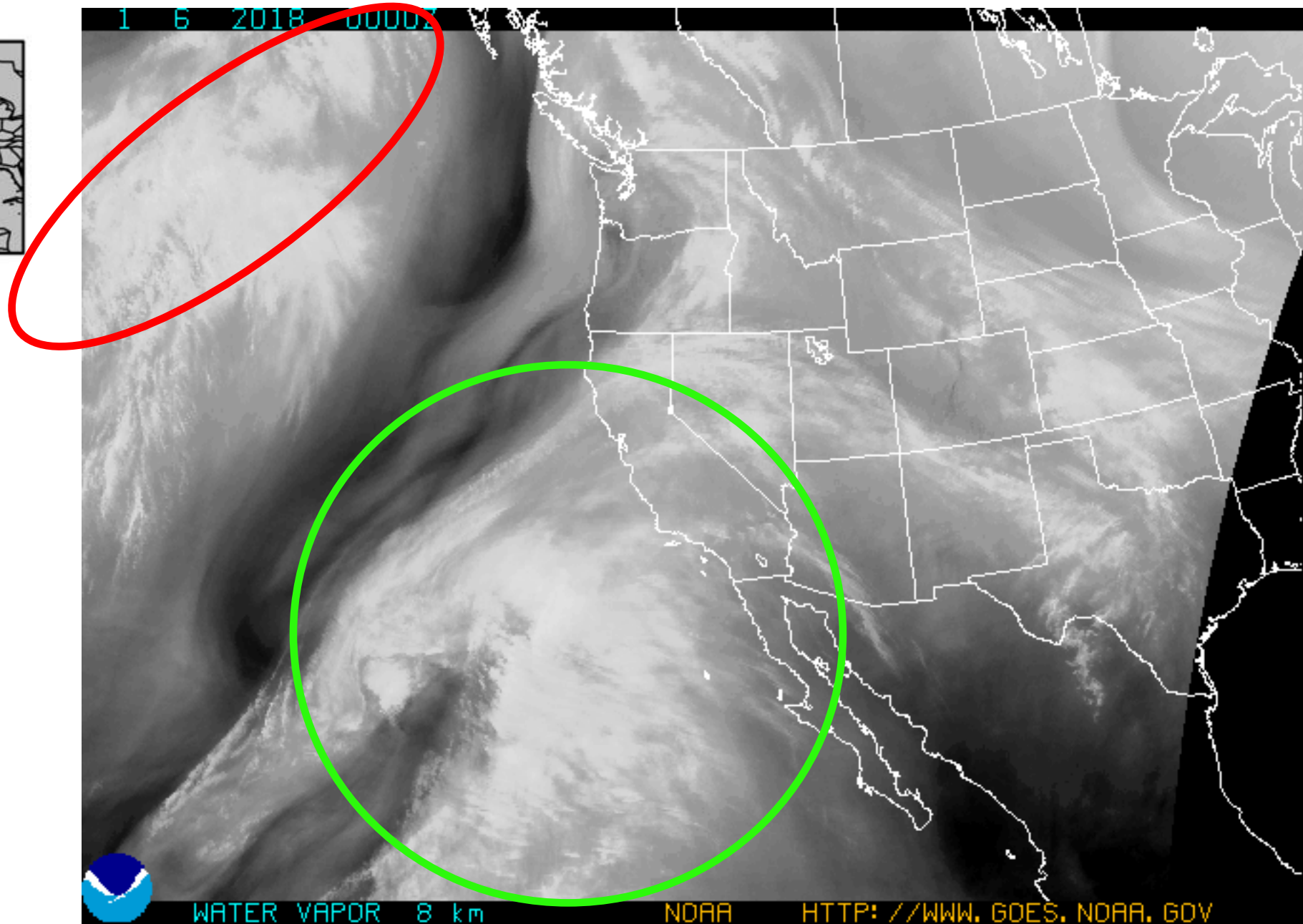
Jan 2 00Z GOES Water Vapor Channel



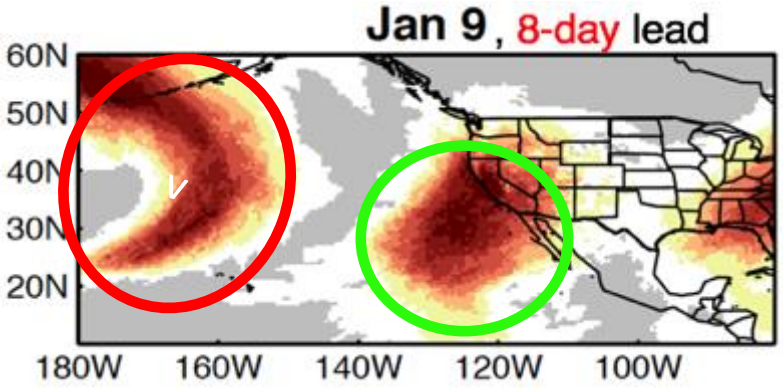
Jan 6 00Z AR Forecast



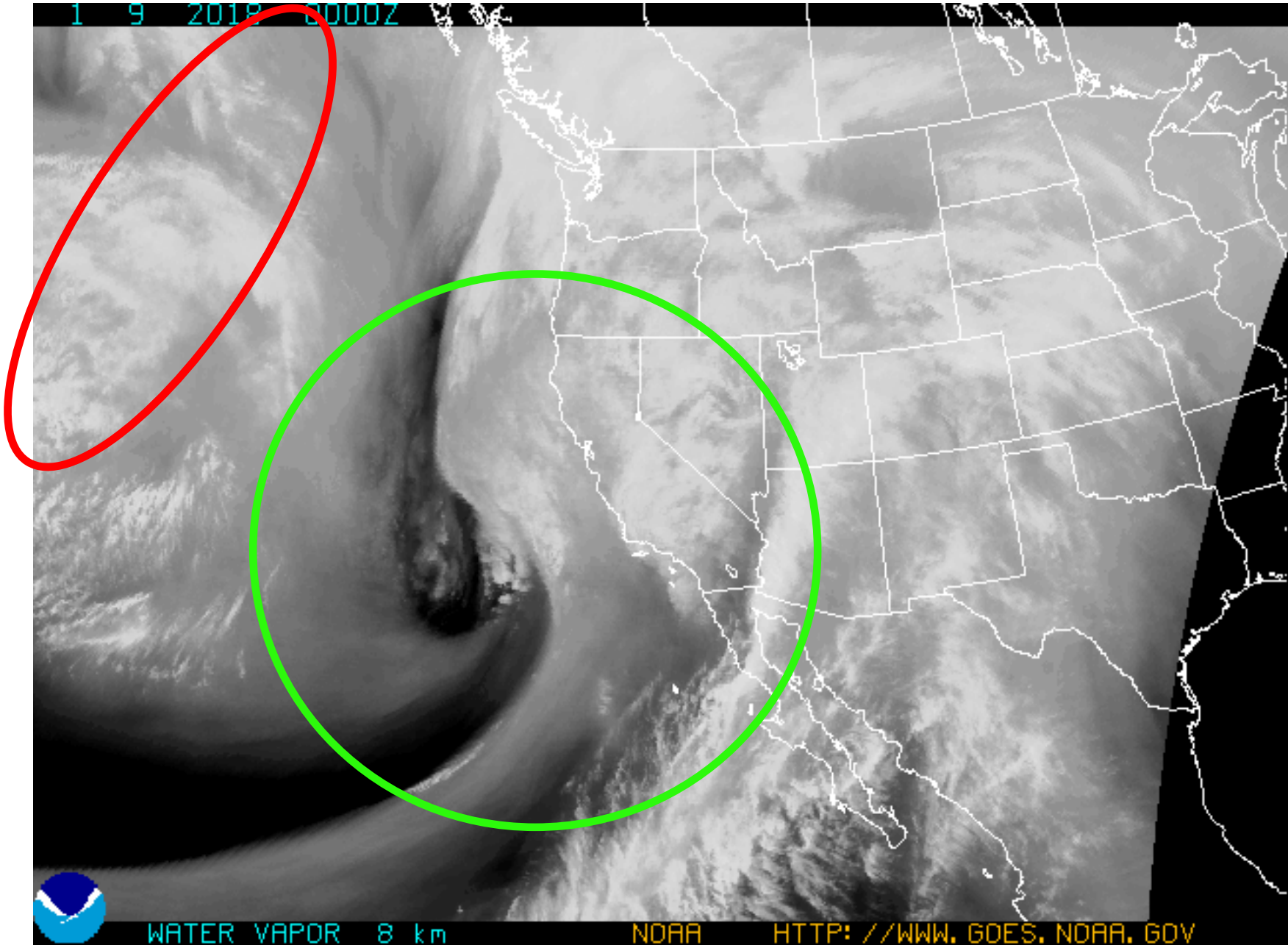
Jan 6 00Z GOES Water Vapor Channel



Jan 9 00Z AR Forecast

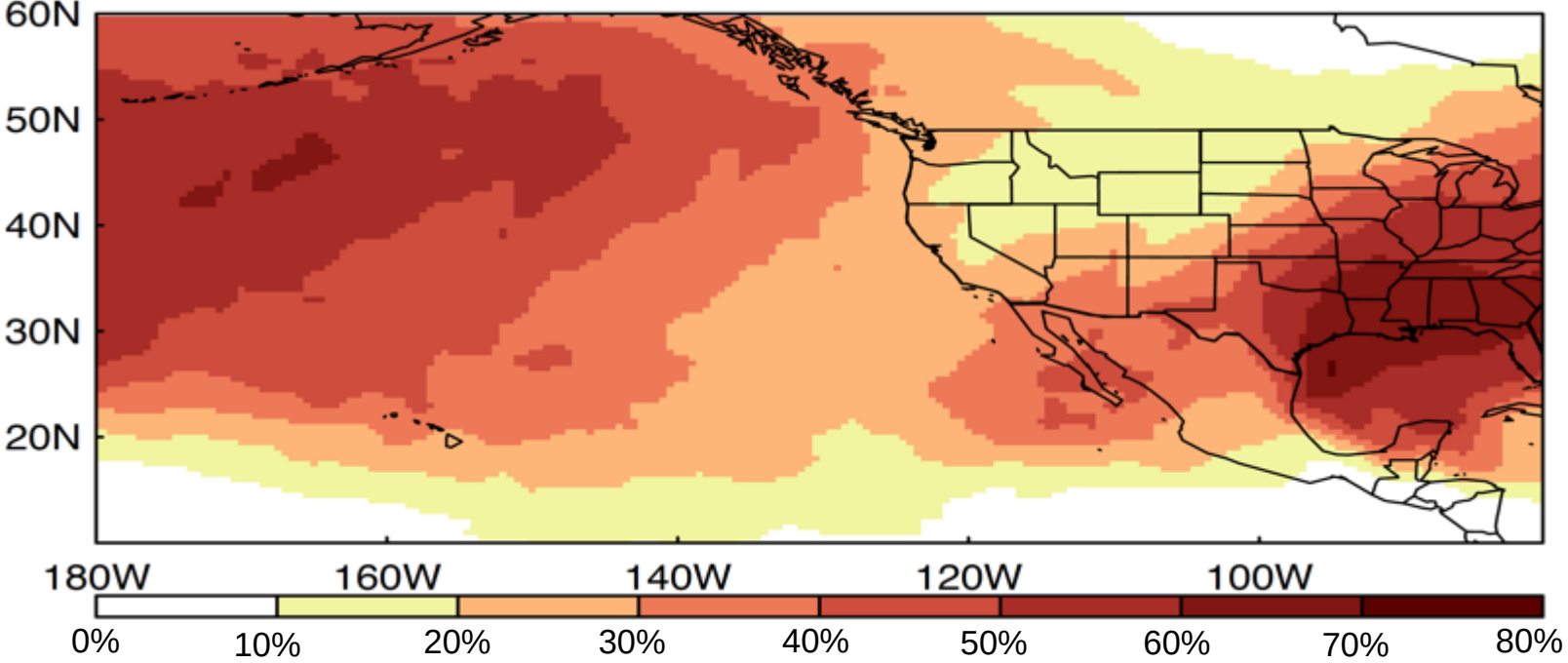


Jan 9 00Z GOES Water Vapor Channel



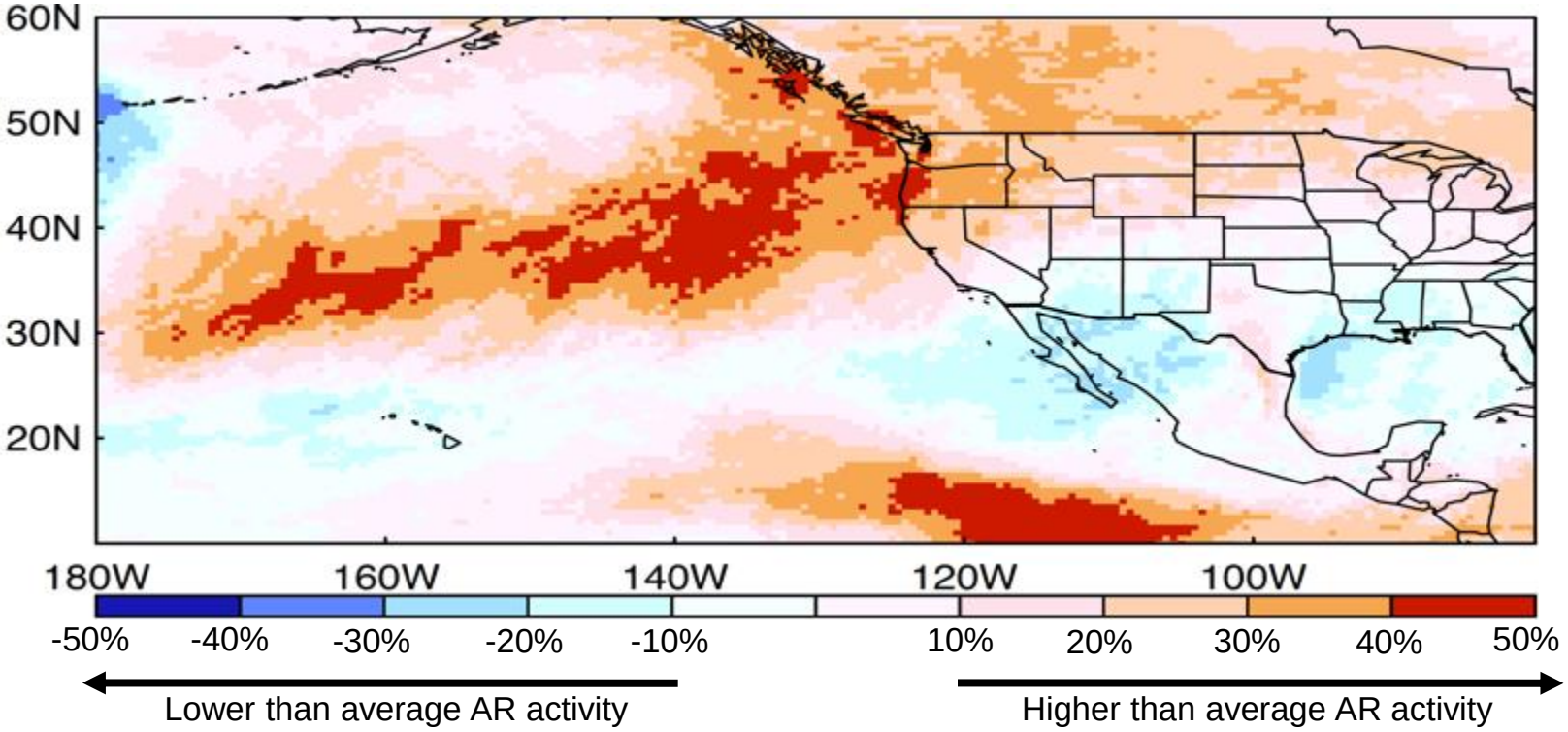
AR Occurrence Climatology

- Chance of an AR occurring sometime during a week-long period in mid-January
- Climatology based on all week-3 ECMWF forecasts from 1996-2015 for mid-January



AR Occurrence Forecast Relative to Climatology

- Week 3 ECMWF forecast valid for Jan 16-22, 2018
- Values shown are forecast minus climatology (top)
- ECMWF ensemble forecast includes 51 members

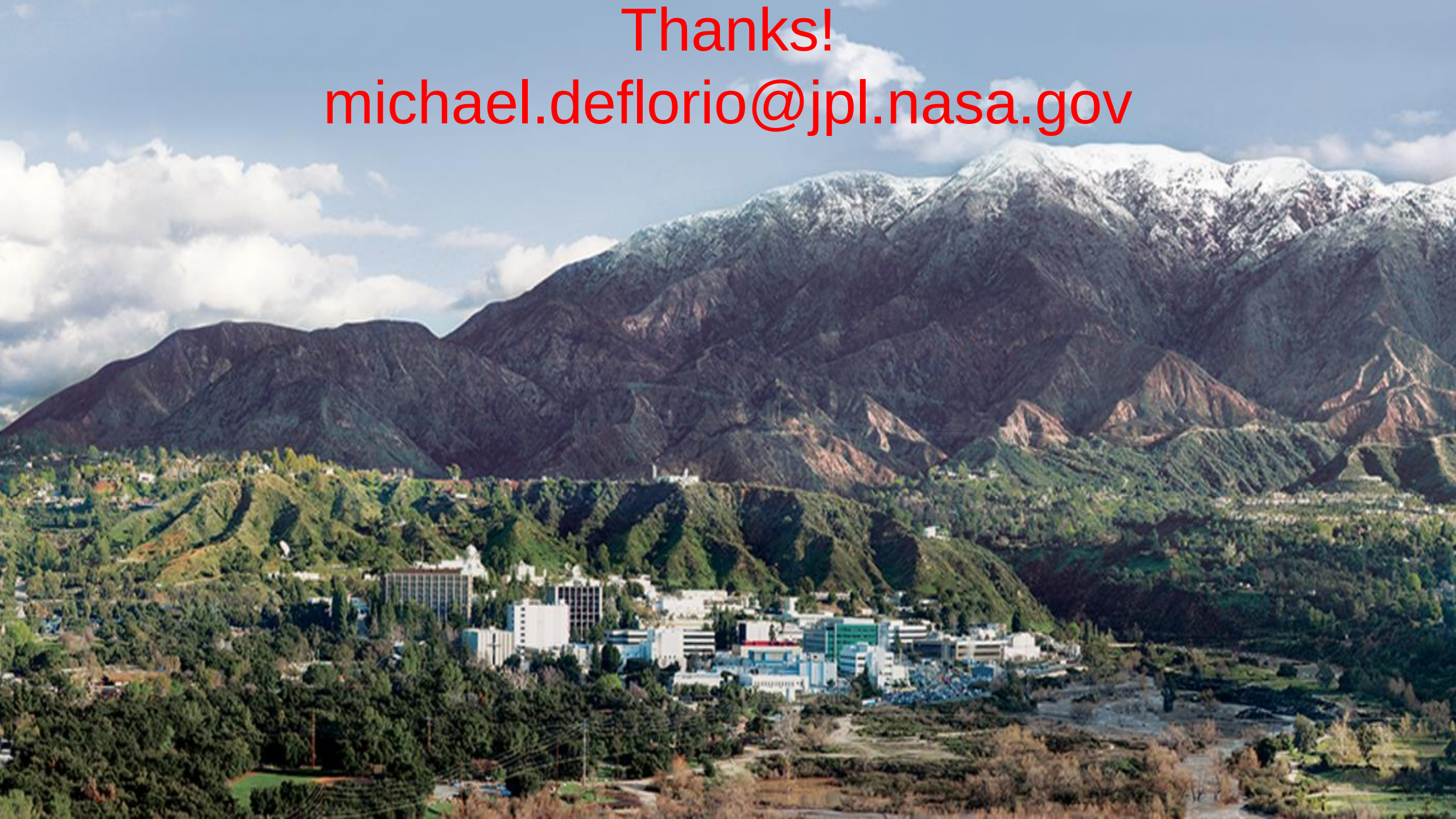


Summary: synoptic and subseasonal AR prediction skill

- Subseasonal (1-week to 1-month lead time) AR prediction skill evaluated globally for the first time in multi-model S2S framework (DeFlorio et al. 2018b, in revision)
  - Skill metric = correlation between observed and model “number of ARs occurring in a two week window” (AR2wk, or AR occurrence)
- ECMWF forecast system is generally most skillful model in 7-21 day and 14-28 day lead windows
- Observed AR occurrence and prediction skill are sensitive to large scale climate mode variability
- Higher prediction skill over the North Pacific/Western U.S. region:
  - at 0-week and 1-week lead time during +PNA relative to –PNA (robust synoptic and subseasonal result)
  - at 1-week and 2-week lead time during MJO phase 7 relative to “all days” forecast (but not quite at 95% confidence)

Ongoing and future research plans

- Global analysis of entire S2S model suite
- Multi-model (ECMWF, ECCC, NCEP) experimental week-3 S2S forecasting (collaboration with CW3E; S. Gershunov, A. Subramanian, F. M. Ralph) for winter 2017-18 and 2018-19
  - CA-DWR sponsored
  - Proposed S2S Project applications pilot study
- Joint consideration of statistical and dynamical approaches, optimizing conditional AR skill estimation parameters
- Distinguishing ARs (and their prediction skill) from other baroclinic systems that produce extreme precipitation

Thanks!

michael.deflorio@jpl.nasa.gov