Experimental S2S AR Activity Outlooks: Hindcast Skill Assessment and Case Study for 2019 Russian River Flooding Event

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Contains key figures/concepts from:

- 1. DeFlorio et al. 2018, **Global assessment of atmospheric river prediction skill**, J. Hydromet., **19**, 409-426, doi:https://doi.org/10.1175/JHM-D-17-0135.1.
- 2. DeFlorio et al. 2019a, **Global evaluation of atmospheric river subseasonal prediction skill**, Clim. Dyn., doi:10.1007/s00382-018-4309-x.
- B. DeFlorio et al. 2019b, Experimental Subseasonal-to-Seasonal (S2S) Forecasting of Atmospheric Rivers in a Multi-Model Framework over the Western United States, in prep.
- 4. Guan and Waliser 2015, **Detection of atmospheric rivers: Evaluation and application of an algorithm for global studies**, J. Geophys. Res., **120**, 12514-12535.





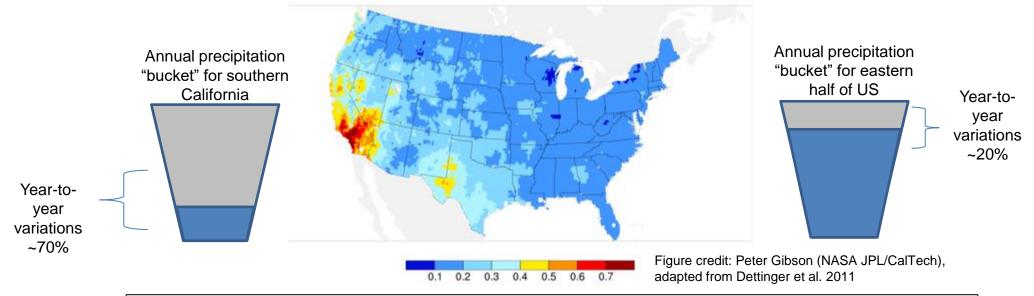


Outline

- Projection of ARs onto western U.S. annual precipitation
- Overview of multi-model S2S hindcast skill assessment of AR activity
- Review of February 25-27 Russian River flooding event
- Experimental outlooks for Russian River flooding event and forecast evaluation
- Summary
- Development of seasonal precipitation forecasts over the western U.S. and future directions

Precipitation is uniquely variable year-to-year in the western U.S.

Ratio of Year-to-Year Variation in Precipitation over Average Precipitation



Caption: Map shows the ratio of the year-to-year variability in precipitation divided by the long-term mean precipitation (based on TRMM, 1998-2016). Thus, the eastern half of the country vary rarely experiences a significant variation from their typical precipitation totals (~1-1.5 m), about +/- 20% of the mean. Uniquely, in southern California, the year-to-year variations are nearly as big as the total annual precipitation (~0.2-0.3 m), i.e. +/- 70% of the mean.

Relative to the rest of the U.S., central and southern California experiences the largest year to year swings in annual precipitation totals relative to its average values.



Calculation using Tropical Rainfall Measuring Mission (TRMM) data, as originally performed by Dettinger et al. 2011 with station data





Variance of western U.S. annual precipitation strongly linked to atmospheric rivers

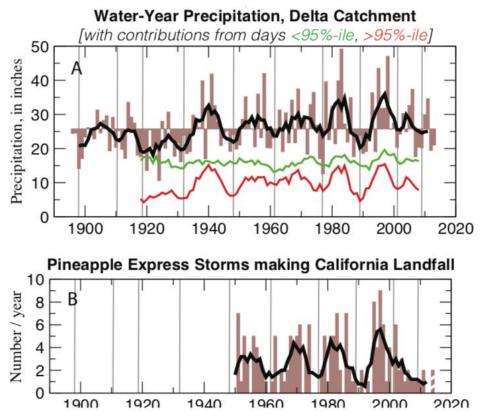
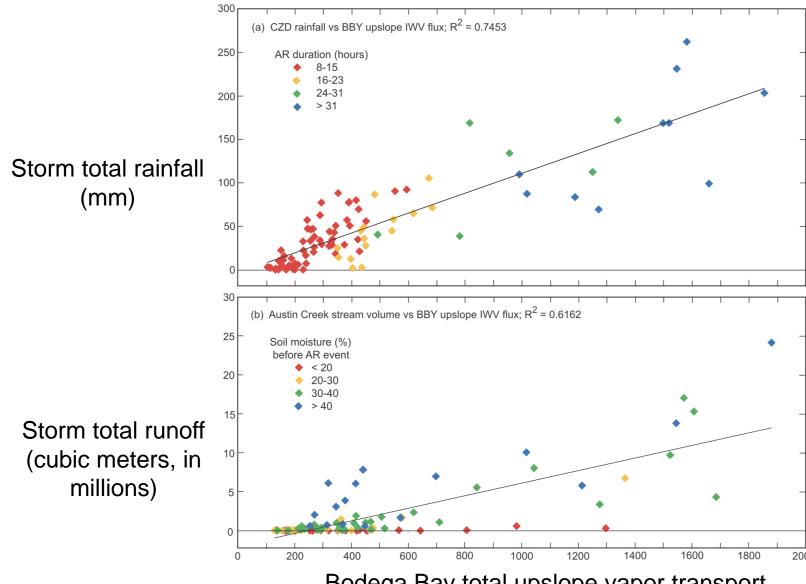


Figure 1 (A) Water-year precipitation totals (brown bars and black curve) in the Delta's catchment, 1895—present based on updated monthly Abatzoglou et al. (2009) data, and 5-year moving averages of contributions to these totals from the wettest 5% of wet days (days with precipitation > 95th percentile; red curve) and all other wet days (< 95th percentile; green curve) based on updated daily Hamlet et al. (2005) data, 1916–2010, and (B) numbers of pineapple-express storms making landfall between 35°N and 42.5°N per water year (using counts from Dettinger et al. 2011, updated through March 2014). Heavy curves are 5-year moving averages in both frames; vertical grey lines are approximate centers of persistent droughts in upper panel.

Dettinger and Cayan 2014







Vapor transport (associated with ARs) directed up the mountain slope contribute 74% of the variance in storm-total rainfall across the events, and 61% of the variance in storm-total runoff volume.

Bodega Bay total upslope vapor transport (associated with ARs)







Key Research Question





What is the limit of global subseasonal-to-seasonal (S2S) (here, 1-week to 1-month) prediction skill of atmospheric river occurrence, and how does it vary as a function of season, region, and certain large-scale climate conditions?

Key Applications Question



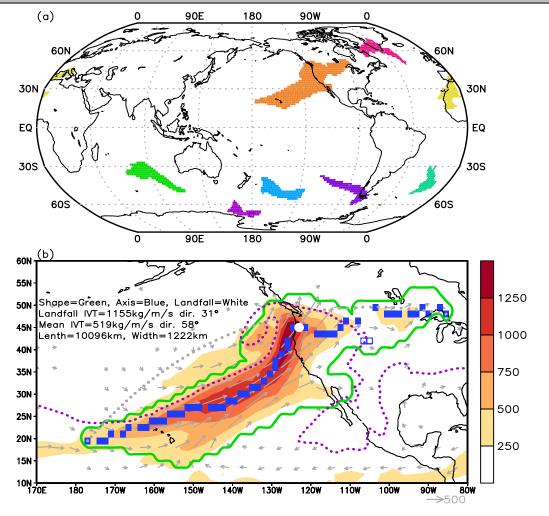


Can present-day subseasonal-toseasonal (S2S) forecast systems provide benefit to western U.S. water resource management decision makers?



A global, objective algorithm for AR identification

(Guan and Waliser 2015)



- AR detection involves thresholding 6-hourly fields of ERA-I IVT based on the 85th percentile specific to each season and grid cell and a fixed lower limit of 100 kg/ms and checking for the geometry requirements of length >2000 km, length/width ratio >2, and other considerations indicative of AR conditions
- Applied to global hindcast/forecast systems and reanalysis datasets (code and databases available at: https://ucla.box.com/ARcatalog)
- Parameter space AR Date, IVT_{x,y}, Axis, Landfall Location, etc.
- Used for GCM evaluation (Guan and Waliser 2017), comparison to dropsonde data (Ralph et al. 2017, Guan et al. 2018), climate change projections (Espinoza et al. 2018), extratropical and polar vapor transport (Nash et al. 2018), & hindcast/forecast skill assessment (DeFlorio et al. 2018, 2019a; and DeFlorio et al. 2019b [in prep])

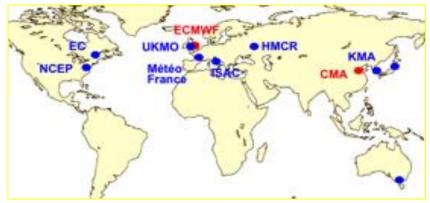




The S2S Project Database (s2sprediction.net)



- 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	Hests	Hest length	Host Freq	Hest Ste
ECHWF	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	- 5
HMCR	D 0-63	1.1x1.4 L28	20	weekly	Fix	1981-2010	weekly	10

Vitart et al. 2017





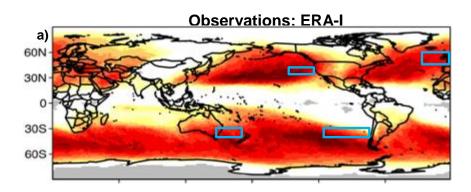


Global Evaluation of Atmospheric River Subseasonal Prediction Skill

Michael J. DeFlorio¹, Duane E. Waliser^{2,3}, Bin Guan^{2,3}, F. Martin Ralph¹, and Frederic Vitart⁴; (*Climate Dynamics* 2019) ¹UCSD/SIO/CW3E, ²NASA JPL/CalTech, ³UCLA, ECMWF⁴



Global climatology of wintertime AR1wk, 1996-2015

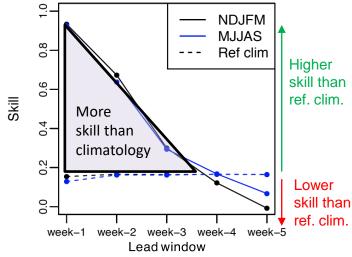




AR1wk is largest in midlatitude storm track regions

Does ECMWF AR1wk skill exceed climatological skill? Is AR1wk skill modulated by large-scale climate mode activity?

NPac/West U.S. (150W to 125W, 35N to 45N)



 (left) ECMWF AR1wk occurrence forecast skill (ACC) outperforms a reference forecast based on monthly climatology of AR1wk occurrence at week-3 (14d-20d) lead over the North

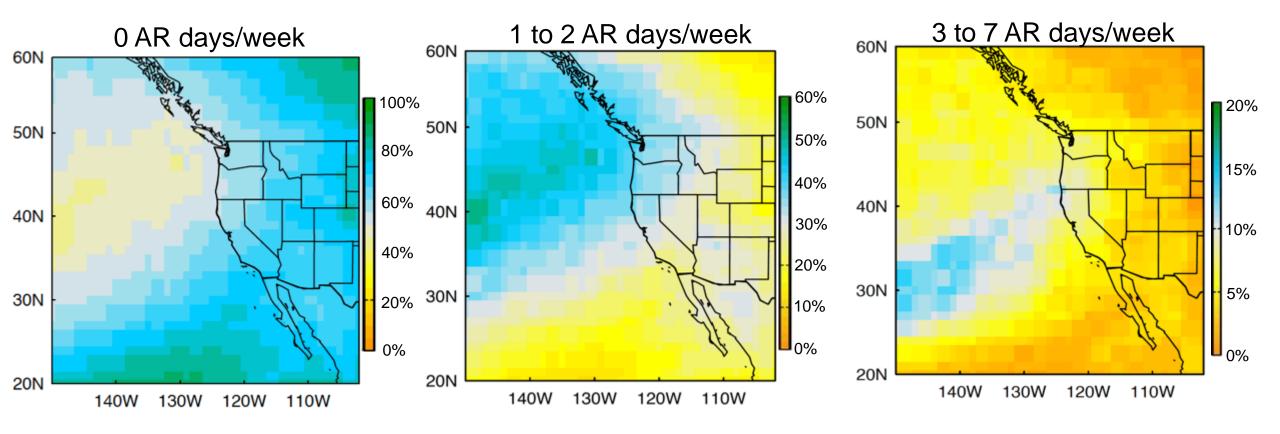






Michael J. DeFlorio¹, Duane E. Waliser^{2,3}, F. Martin Ralph¹ et al. (2019, in prep) ¹UCSD/SIO/CW3E, ²NASA JPL/CalTech, ³UCLA





ERA-I NDJFM 1996-2015 average number of AR days per week ("AR1wk") for 0, 1-2, 3-7 AR days/week



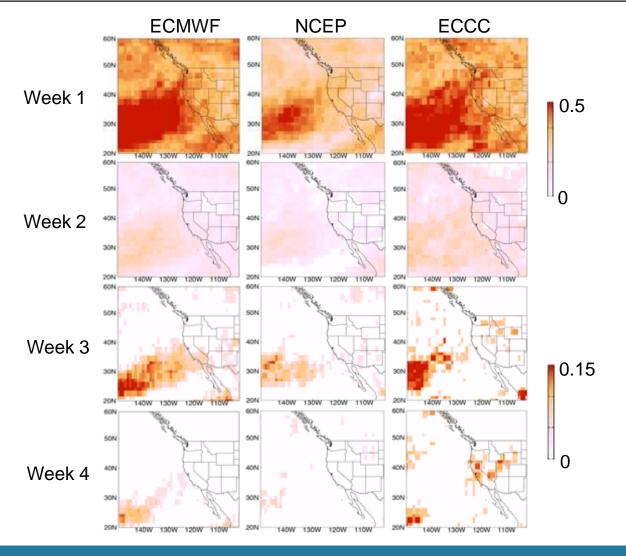




Michael J. DeFlorio¹, Duane E. Waliser^{2,3}, F. Martin Ralph¹ et al. (2019, in prep) ¹UCSD/SIO/CW3E, ²NASA JPL/CalTech, ³UCLA



AR1wk NDJFM Brier Skill Scores: "0 AR days/week" category



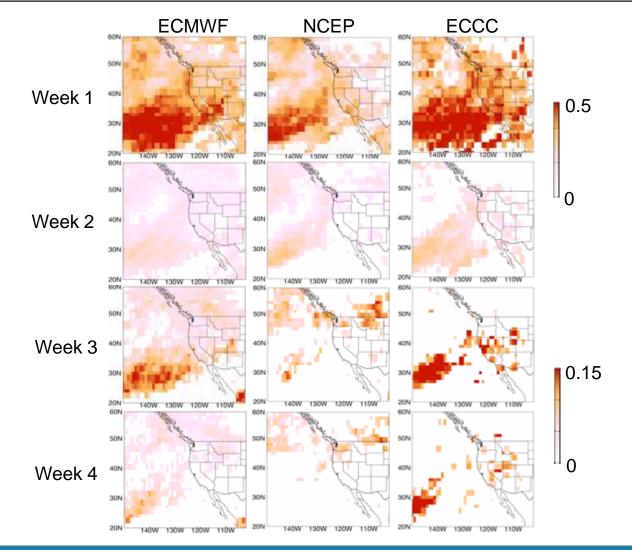




Michael J. DeFlorio¹, Duane E. Waliser^{2,3}, F. Martin Ralph¹ et al. (2019, in prep) ¹UCSD/SIO/CW3E, ²NASA JPL/CalTech, ³UCLA



AR1wk NDJFM Brier Skill Scores: "3 to 7 AR days/week" category



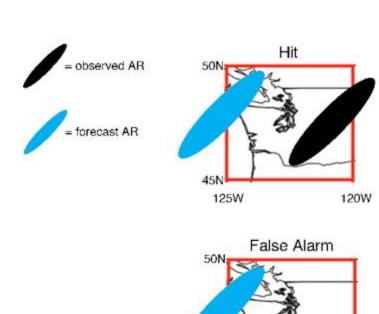






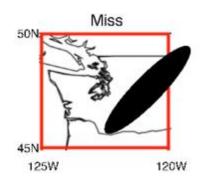
Michael J. DeFlorio¹, Duane E. Waliser^{2,3}, F. Martin Ralph¹ et al. (2019, in prep) ¹UCSD/SIO/CW3E, ²NASA JPL/CalTech, ³UCLA

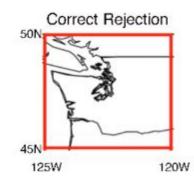


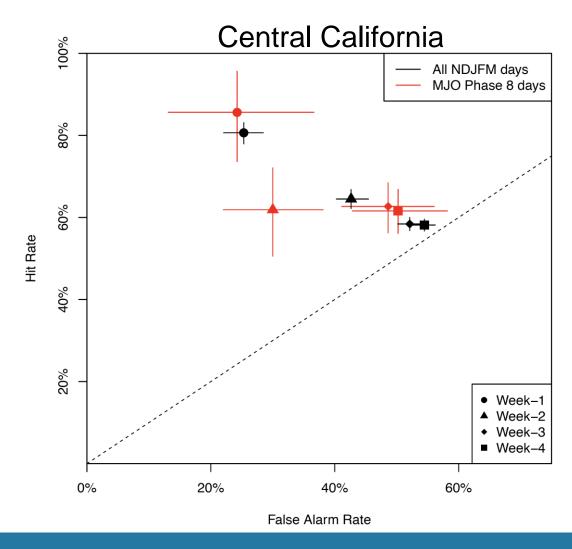


125W

120W







Summary of multi-model AR activity hindcast skill assessment

- NCEP hindcast system underperforms relative to other hindcast systems in predicting categorical AR occurrence at all lead times, especially between 150W-130W, 25-40N.
- Hindcast systems are more skillful in predicting no AR (0 AR days/week) or high AR (3 to 7 AR days/week) conditions relative to medium AR (1 or 2 AR days/week) conditions.
- There are isolated areas of skill at week-3 over the 150W-125W, 25N-35N regions in the ECMWF and ECCC hindcast systems in the 0 and 3-7 AR days/week categories. These results suggest that "western" ridges (if deficit of ARs is associated with ridging event) and high AR activity periods with southwest-to-northeast orientation are more predictable than "northern" ridges or west-to-east/northwest-to-southeast oriented high AR activity conditions.
- Generally no skill at week-4, except over the 150W-140W, 20N-30N regions in ECMWF/ECCC
- Increased prediction skill over Central California at week-2 lead time at 95% confidence level in composites of ECMWF hindcasts initialized during strong MJO Phase 8 conditions.
 - Evidence for decreased prediction skill over Central California at week-3,4 lead time, but not at 95% confidence level
 - Other mode/region skill modulations are quantified in manuscript









Flooding on Laguna de Santa Rosa inundated downtown Sebastopol. Fire department helping residents evacuate flooded areas. Photo: N. Oakley

Flooding in the Barlow shopping area in downtown Sebastopol. Photo: N. Oakley





Sonoma County placed evacuation orders on 24 areas (http://nixle.us/ASDYN).

Summary provided by B.Kawzenuk, C. Hecht, F. Cannon, L. Dehaan, J. Kalansky, N. Oakley, D. Reynolds, E. Sumargo, A. Wilson, F. M. Ralph



AR Summary: 25-27 Feb 2019

For California DWR's AR Program

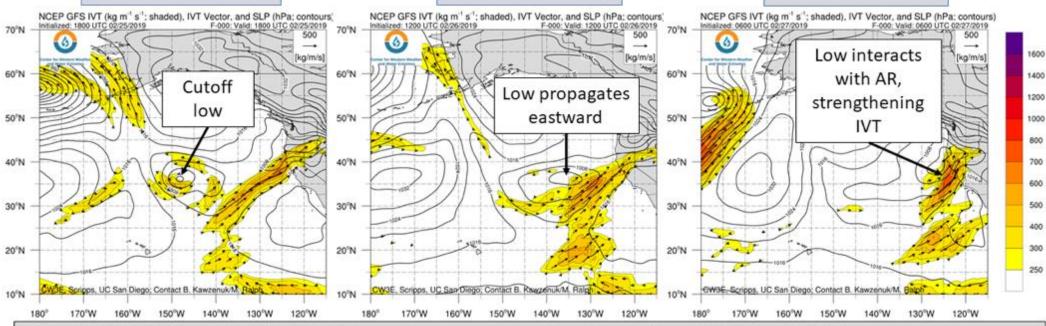
NCEP GFS Analysis



06 UTC 27 February

18 UTC 25 February

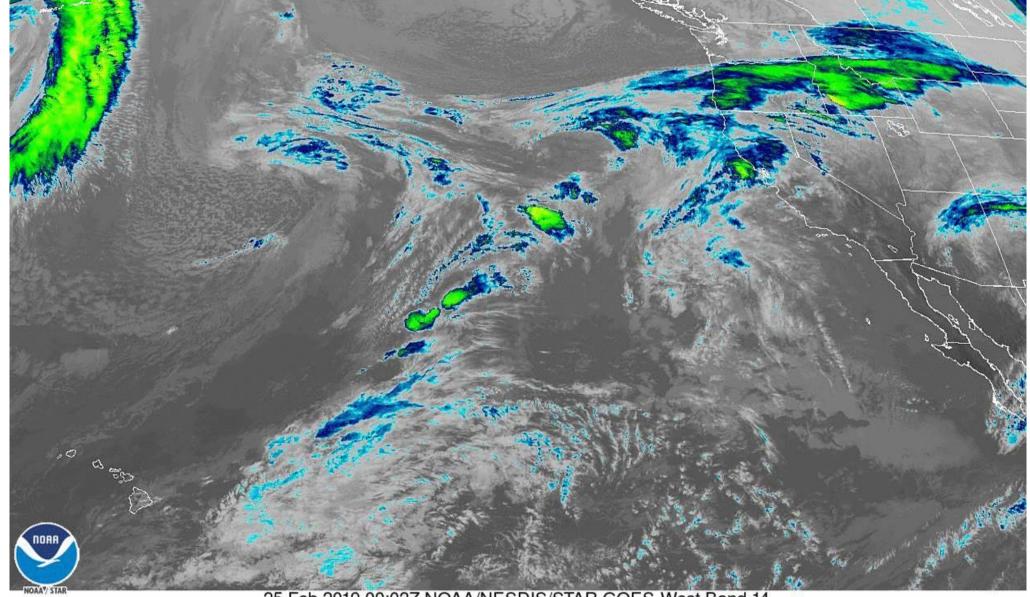
12 UTC 26 February



- A cutoff low in the central East Pacific began to propagate eastward beginning on 25 February 2019
- · As the low propagated eastward, it began to interact with the AR that was impacting Northern California
- The interaction between the eastward propagating low and the landfalling AR resulted in an intensification of IVT within the AR, a cyclonic rotation of the IVT orientation, and ultimately resulted in the AR stalling over Northern California
- The cyclonic rotation of the AR to a more south/southwesterly orientation may have led to a more favorable IVT orientation to topography for upslope more flux, enhancing precipitation over the coast

Summary provided by B.Kawzenuk, C. Hecht, F. Cannon, L. Dehaan, J. Kalansky, N. Oakley, D. Reynolds, E. Sumargo, A. Wilson, F. M. Ralph





25 Feb 2019 00:02Z NOAA/NESDIS/STAR GOES-West Band 14

What did our experimental S2S AR outlooks predict for this event?

Experimental Multi-Model Atmospheric River Forecast*

Week-3: issued on February 7, 2019; Week-2: issued on February 14, 2019; Week-1: issued on February 21, 2019

Contents:

Slide 1: "week-3" - US west coast weather/precipitation forecast for week 3 considering the number of atmospheric river days predicted to occur in the given forecast week.

Novelty – an S2S forecast presented only in terms of AR likelihood - specifically for week 3, an extended/long-range or "subseasonal" prediction

Slides 2-3: "Weather" - Typical presentation of US west coast weather/precipitation forecast over lead times of 1 to 14 days considering only the likelihood of an atmospheric river (AR) occurring on a given forecast day. *Novelty – a weather forecast presented only in terms of AR likelihood.*

Ensemble Forecast Systems Used

ECMWF (European Centre for Medium-Range Weather Forecasts) forecast system NCEP (National Centers for Environmental Systems) forecast system ECCC (Environment and Climate Change Canada) forecast system



*This is an experimental activity for the 2017-18 and 2018-19 winters. Methodologies and hindcast skill are documented in DeFlorio et al. (2018,2019a,2019b). Further validation of the real-time forecast results is required and underway. This phase of the research includes gathering stakeholder input on the presentation of information – feedback is welcome.





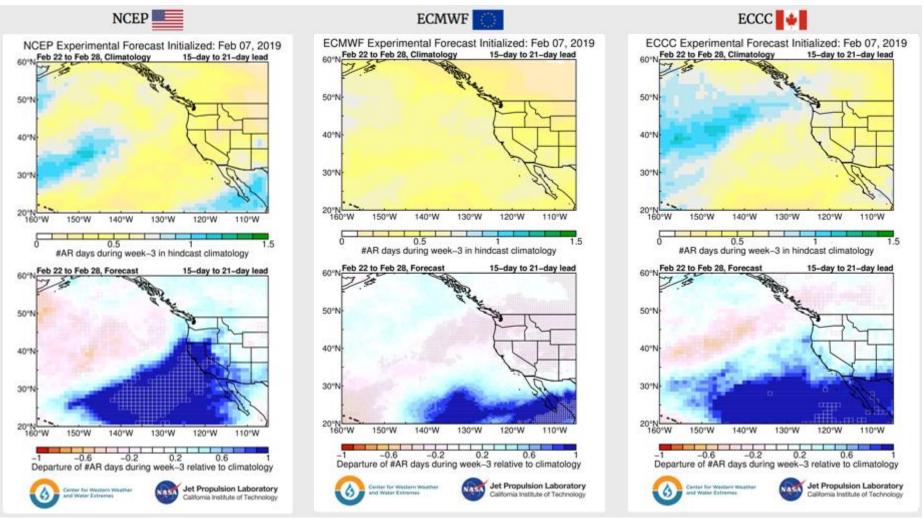


EXPERIMENTAL AR FORECAST

Week-3 (15-day to 21-day lead)

Hindcast Climatology

Forecast Minus Climatology



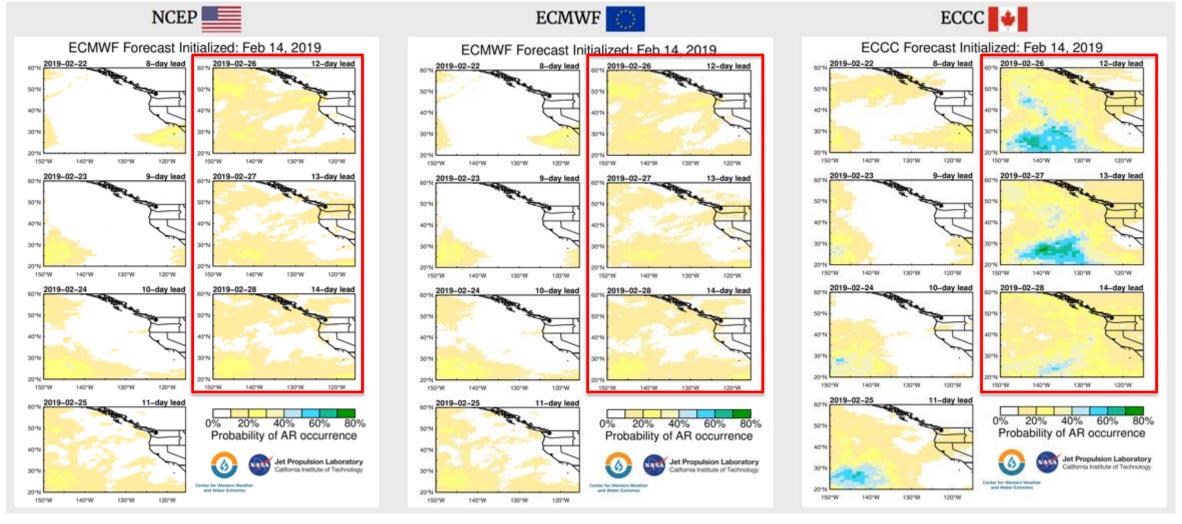
Experimental AR forecast issued on Thursday, February 7, 2019 by M. DeFlorio, D. Waliser, M. Ralph, A. Goodman, B. Guan, A. Subramanian, and Z. Zhang for an Experimental AR Forecasting Research Activity sponsored by California DWR





EXPERIMENTAL AR FORECAST

Week-2 (8-day to 14-day lead)



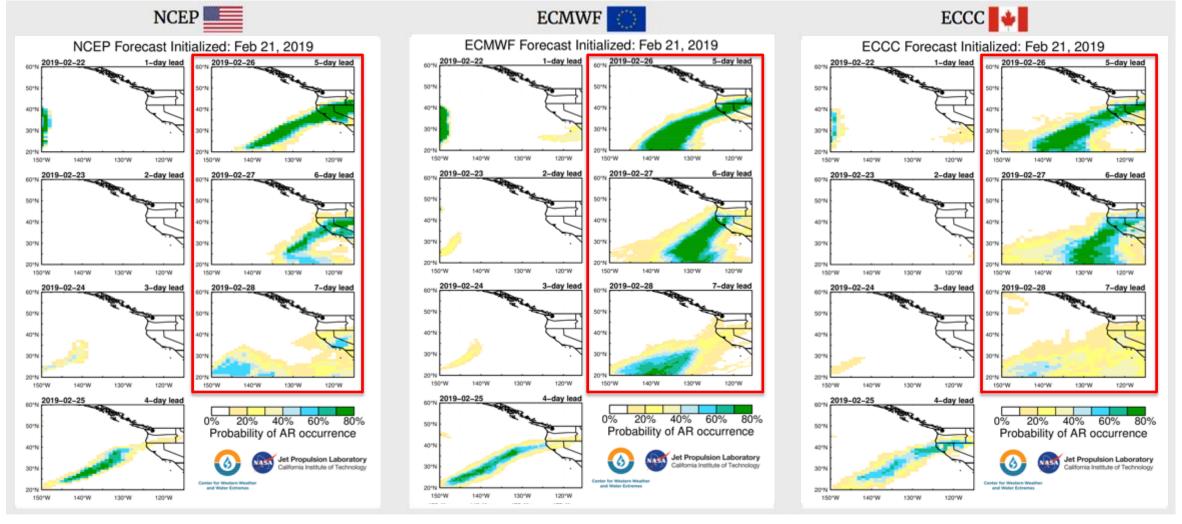
Experimental AR forecast issued on Thursday, February 14, 2019 by M. DeFlorio, D. Waliser, M. Ralph, A. Goodman, B. Guan, A. Subramanian, and Z. Zhang for an Experimental AR Forecasting Research Activity sponsored by California DWR





EXPERIMENTAL AR FORECAST

Week-1 (1-day to 7-day lead)



Experimental AR forecast issued on Thursday, February 21, 2019 by M. DeFlorio, D. Waliser, M. Ralph, A. Goodman, B. Guan, A. Subramanian, and Z. Zhang for an Experimental AR Forecasting Research Activity sponsored by California DWR





Verification of Week 1-3 AR Outlook for Russian River 2018-2019 Winter

From 2018 October to 2019 March AR outlook issued every Thursday (22 weeks/forecasts)

Forecast and Verification Data

NCEP	16 ensemble members
ECCC	21 ensemble members
ECMWF	50 ensemble members
CLIM (baseline)	Climatology of 31 winters (1979-2009) from CFSR
CFSv2 (OBS)	CFSv2 reanalysis from NCEP



Russian River
2 grid cells
(1×1 degree
resolution)

(More reanalysis data will be added as reference for the verification)

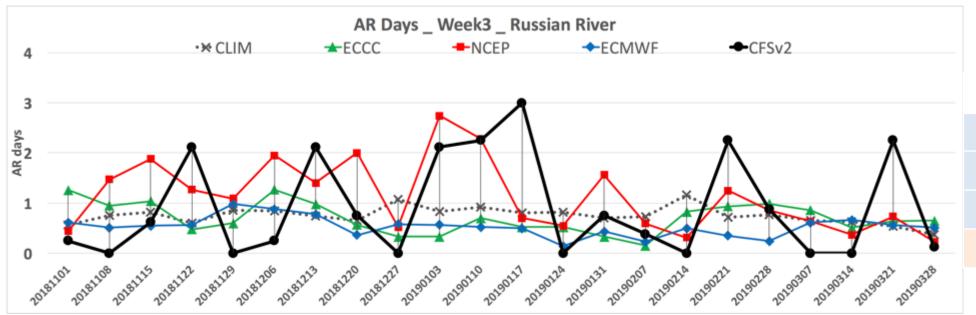




AR occurrence at Russian River Week-3 [15-21day lead]

2018-2019 winter (22 forecasts issued every Thursday)

(AR occurrence: number of AR days per week)



	CORR	RMSE	
ECCC	-0.02	1.09	
NCEP	0.16	1.06	
ECMWF	0.04	1.09	
CLIM	-0.01	1.12	

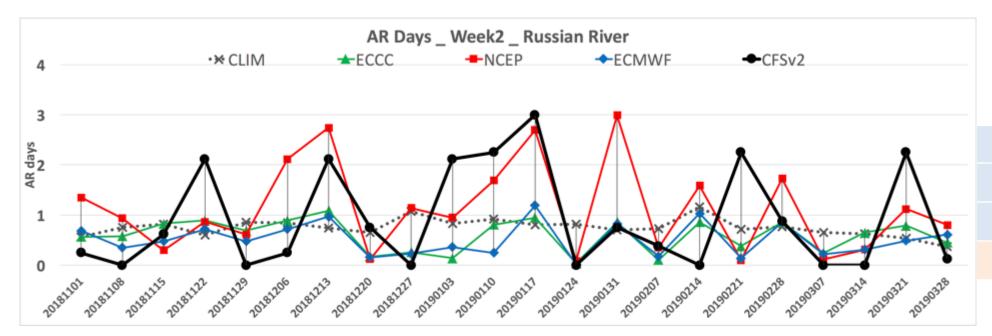
Forecasted Weeks



AR occurrence at Russian River Week-2 [8-14day lead]

2018-2019 winter (22 forecasts issued every Thursday)

(AR occurrence: number of AR days per week)



	CORR	RMSE
ECCC	0.34	0.99
NCEP	0.35	1.04
ECMWF	0.27	1.04
CLIM	-0.01	1.12

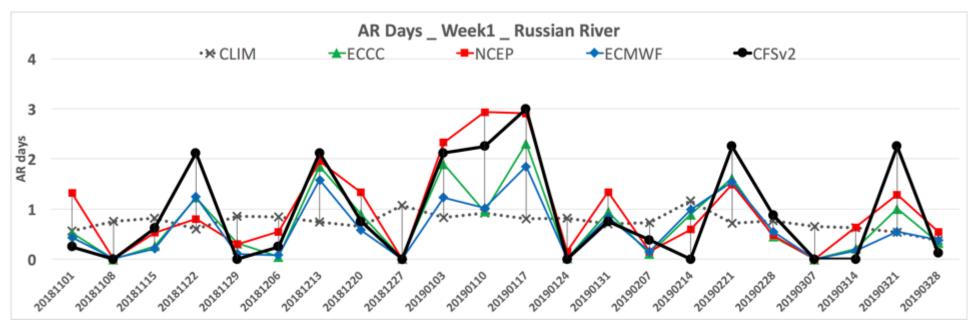
Forecasted Weeks



AR occurrence at Russian River Week-1 [1-7day lead]

2018-2019 winter (22 forecasts issued every Thursday)

(AR occurrence: number of AR days per week)



	CORR	RMSE
ECCC	0.88	0.55
NCEP	0.83	0.56
ECMWF	0.86	0.66
CLIM	-0.01	1.12

Forecasted Weeks

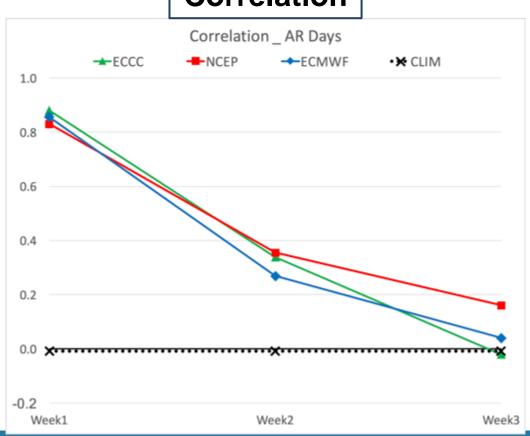


Verification of AR Occurrence in 2018-2019 Winter (22 weeks/forecasts)

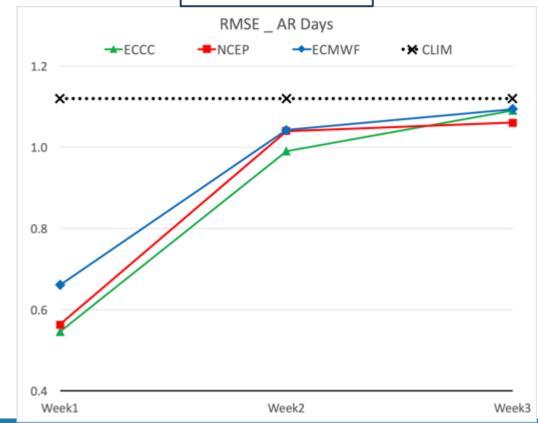
Correlation and RMSE of AR Occurrence for Russian River the changes with lead time (week1 - week3)

Statistics also computed for **AR-related IVT**





RMSE



Summary

- Atmospheric rivers occur globally and influence weather and water extremes.
- Total amount of annual California precipitation is uniquely variable from year to year and is strongly influenced by occurrence or absence of atmospheric rivers.
- S2S (here, week 3-4) forecasting of atmospheric rivers represents a critical decision-making time window for water resource managers.
- Real-time experimental AR occurrence forecasting effort using ECMWF, NCEP, and ECCC data is ongoing (CW3E/JPL partnership), with engagement from NCEP and addition of NASA GMAO data forthcoming
 - Pilot S2S Project for Applications
- NCEP and ECCC ensemble systems predicted above average AR activity for California at week-3 lead for Russian River flooding event. The signal diminished during week-2, but reemerged at 5-6 day lead time.
 - NCEP GEFS performed best during WY 2018-2019 over Russian River region at week-3 lead time in predicting AR activity and AR-related IVT. However, NCEP GEFS has least skill among three ensemble systems at week-3 lead over longer hindcast record.





Development of Statistically-Based Seasonal Prediction of Precipitation over the Western U.S.

Tamara Shulgina, Alexander Gershunov, Kristen Guirgius, Marty Ralph

Predictand: Precipitation (PR): 1949 – 2012, 1/16°× 1/16°, [20-

52N, 125-110W]

Predictor: Sea Surface Temperature (SST, NOAA Extended

Reconstructed SST V4): 1948-2011, 2°× 2°, [20S-

64N, 260-100W]

Method: Canonical Correlation Analysis (CCA) (Model

training period: 1950 – 2012 (63 years)

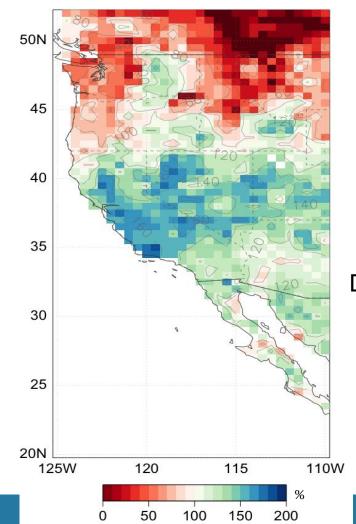
Experimental Seasonal Forecast of January-March 2019 precipitation anomalies over the western US via December 2018 SST

Prediction of total precipitation anomalies, January-March, 2019

CCA prediction approach:

Predictor: December Pacific SST [20S – 65N] Predictand: JFM precipitation anomalies (%)

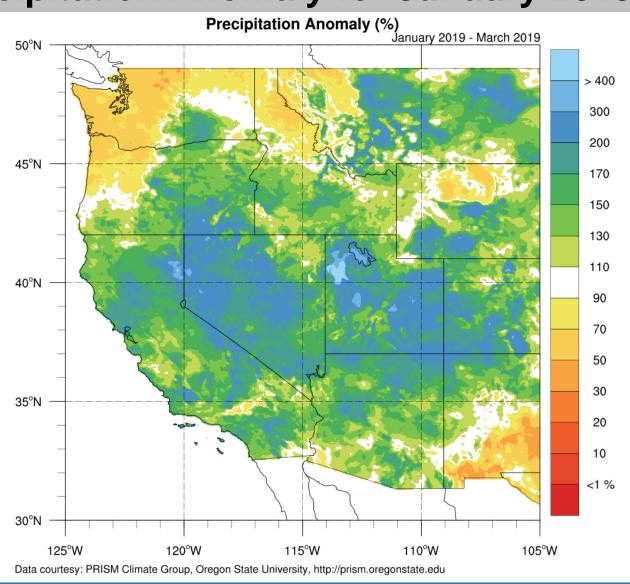
Model training period: 1950 – 2012



**EXPERIMENTAL
SEASONAL
FORECAST IN
DECEMBER 2018 OF
JFM 2019
PRECIPITATION
BASED ON PACIFIC
SST**



Observed Precipitation Anomaly for January 2019 – March 2019





Future directions

- Implement post-processing methods into multi-model experimental forecast product pipeline
 - Bias correction
 - Superensemble prediction
- Continue development of experimental seasonal precipitation forecasting model using Canonical Correlation Analysis based on Pacific SST and other variables
- Extension of Chapman et al. (2019) methodology to S2S timescales and in combination with Analog Ensemble methodology

