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Understanding Relative Skill of Experimental S2S Forecasts: Winter 2021-2022 Review

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2022 Western States Water Council Meeting; 18 May 2022

Partnering Institutions: Center for Western Weather and Water Extremes, Scripps Institution of Oceanography at UC San Diego; Jet Propulsion Laboratory, California Institute of Technology

Sponsoring Agency: Department of Water Resources, State of California

Key Collaborators: IRI, Environment Canada, ECMWF, NASA Goddard Space Flight Center, Ucla, NCAR

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Outline

- Overview of DWR-sponsored CW3E-JPL S2S partnership
- Overview of Winter 2021-2022 observations and review of S2S forecasts
- S2S forecasting methods and skill metrics: take-home messages
- Future directions

DWR supports a CW3E-JPL S2S Partnership, with key collaborating institutions

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CW3E S2S Advisory Panel

***F. Martin Ralph**[1] (Co-Chair), ***Duane Waliser**[2] (Co-Chair), Dan Cayan[1], Bruce Cornuelle[1], Art Miller[1]

**denotes DWR co-PI*

S2S Prediction Team

Mike DeFlorio (CW3E S2S Team Lead)[1], Alphan Altinok[2], Patrick Broxton[4], Christopher Castellano[1], Will Chapman[7], Jason Cordeira[1], Luca Delle Monache[1], Sasha Gershunov[1], Peter Gibson[8], Alexander Goodman[2], Bin Guan[6,2], Kristen Guirguis[1], Xianan Jiang[6,2], Julie Kalansky[1], Brian Kawzenuk[1], Wen-shu Lin[1], Ángel Muñoz[3], Cody Poulsen[1], Colin Raymond[2], Andrew Robertson[3], William Scheftic[4], Agniv Sengupta[1], Bohar Singh[3], Aneesh Subramanian[5], Frederic Vitart[6], Jiabao Wang[1], Jing Yuan[3], Xubin Zeng[4], Zhenhai Zhang[1]

Affiliations: [1]CW3E, SIO-UCSD; [2]NASA JPL/CalTech; [3]IRI; [4]U. Arizona; [5]University of Colorado Boulder; [6]UCLA; [7]NCAR; [8]NIWA; [9]ECMWF

Overview of Subseasonal Research and Experimental Forecast Products

Forecast Product	Lead(s)	Predictands	Lead Times	Development stage	Associated Publication(s)
Weeks 1-3 AR activity outlooks	Mike DeFlorio[1]	AR frequency	Subseasonal	Public	DeFlorio et al. 2019a,b (Cli. Dyn., JGR-A)
Weeks 1-6 ridging outlooks	Peter Gibson[5]	Z500/ridge types	Subseasonal	Public	Gibson et al. 2020a,b (J. Clim., JGR-A)
Weeks 1-4 AR intensity outlooks	Zhenhai Zhang[1]	AR intensity	Subseasonal	Research/Internal	Zhang et al. 2022 (in prep)
Weeks 1-6 AR/IVT anomaly outlooks	Chris Castellano[1]	Total IVT and AR frequency	Subseasonal	Research/Internal	Castellano et al. 2022 (in prep); Wang et al. 2022 (in revision)
Weeks 1-6 weather regime outlooks	**Andy Robertson[3], Juan Ying[3], Bohar Singh[3], Ángel Muñoz[3]**	**Circulation regimes**	**Subseasonal**	**Public**	**Robertson et al. 2020 (MWR)**

[1] *CW3E/SIO-UCSD;* [2] *NASA JPL;* [3] *IRI;* [4] *University of Arizona;* [5]*NIWA*

Green = subseasonal lead times
Bold = new WY2021-2022 product

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Overview of Seasonal Research and Experimental Forecast Products

Forecast Product	Lead(s)	Predictors	Lead Times	Development stage	Associated Publication(s)
North Pacific circulation regimes (NP4 modes)	Kristen Guirguis[1], Alexander Gershunov[1], Tamara Shulgina[1]	Z500/SST	Subseasonal to seasonal	Research/Internal	Guirguis et al. 2020 (GRL); Guiguis et al. 2022 (in prep)
Seasonal precipitation anomaly (next three months and JFM)	Alexander Gershunov[1], Tamara Shulgina[1], Kristen Guirguis[1]	Pacific SST	Seasonal	Public	Gershunov and Cayan 2003
Seasonal precipitation anomaly clusters (NDJ and JFM)	Peter Gibson[1], Will Chapman[1], Alphan Altinok[2], Luca Delle Monache[1], Mike DeFlorio[1]	Tropical SSTs, VP200, U200, Z500	Seasonal	Public	Gibson et al. 2021 (Nat. Commun. Earth Environ.)
Seasonal precipitation	Agniv Sengupta, Duane Waliser	Global SST	Seasonal	Research/Internal	Sengupta et al. 2022 (in prep)
Seasonal SWE, precipitation, and temperature forecasts	**Xubin Zeng, Patrick Broxton, William Scheftic**	**N/A (based on dynamical ensembles)**	**Seasonal**	**Internal**	**Scheftic et al. 2022 (in prep)**
Odds of water year normal precipitation	Mike Dettinger[1]	Historical precipitation obs	Seasonal	Public	Experimental only

[1] CW3E/SIO-UCSD; [2] NASA JPL; [3] IRI; [4] University of Arizona

Blue = seasonal lead times
Bold = new WY2021-2022 product

CW3E-JPL and DWR participation in WMO S2S Project Real-time Pilot Initiative

Projects participating in the S2S Real Time Pilot Initiative:

Project ID No.	Name	Project Focus	Sector	User Partners
1	Sea Ice Prediction Network Phase 2	Improve understanding of Arctic sea ice and predictability	Agriculture, Forestry & Fishing Sector	Modelling centres; Shipping industry; Resource management; Defence; Marine mammal subsistence hunting
		To provide sub-seasonal to seasonal forecasts		

Bulletin of the American Meteorological Society

Early Online Release

Advances in the application and utility of subseasonal-to-seasonal predictions

Christopher J. White[1], Daniela I. V. Domeisen[2], Nachiketa Acharya[3], Elijah A. Ade...

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Published-online: 22 Nov 2021

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Page(s): 1–57

applications project

- Our parti... internati... ...e

CW3E/JPL/DWR co-authors: DeFlorio, Gibson, Waliser, Ralph, Anderson, Delle Monache

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Overview of Winter 2021-2022 Observations and Seasonal Predictions

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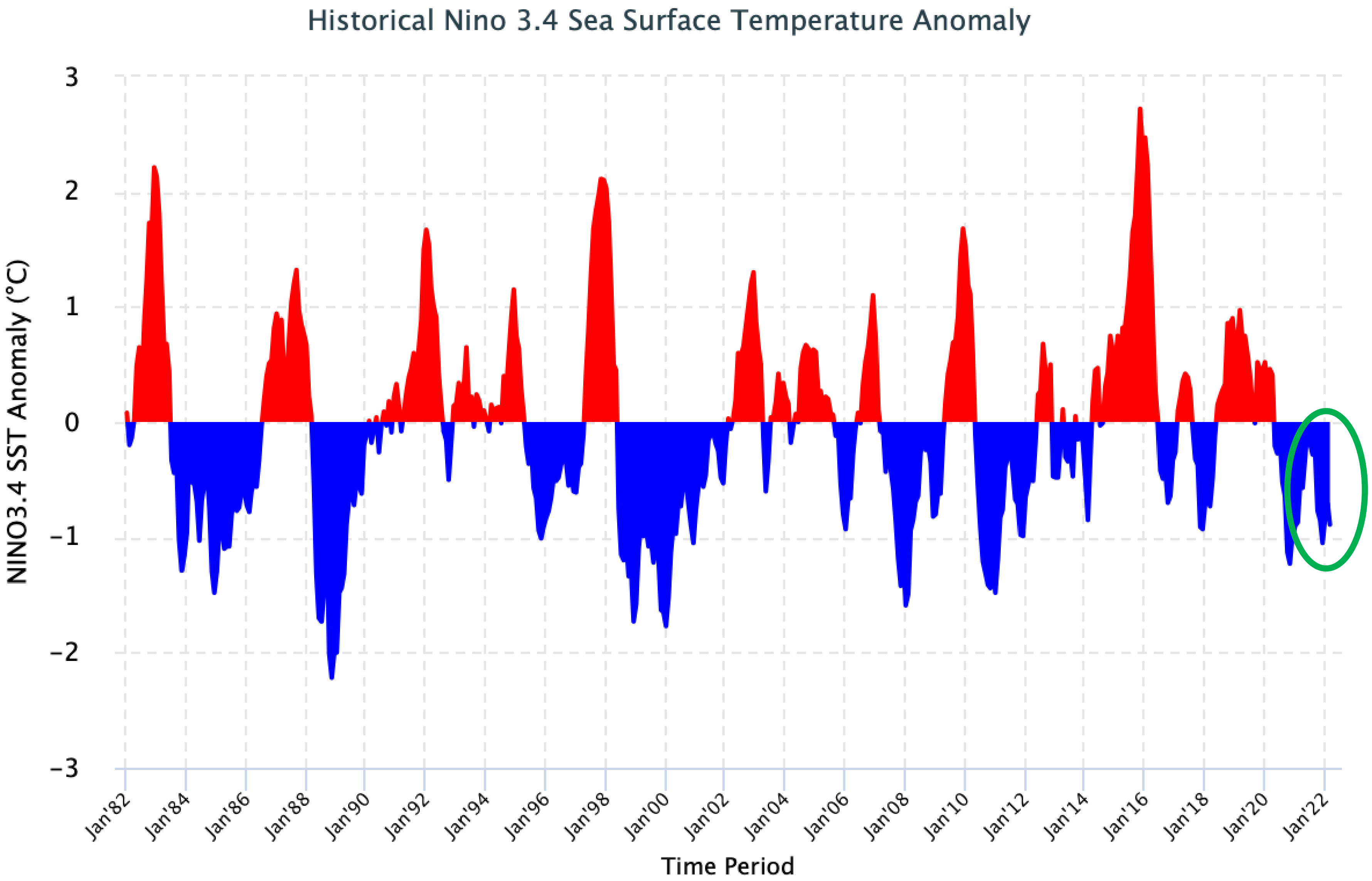
Persistent La Niña Pattern throughout Winter 2021-2022



IRI/CPC

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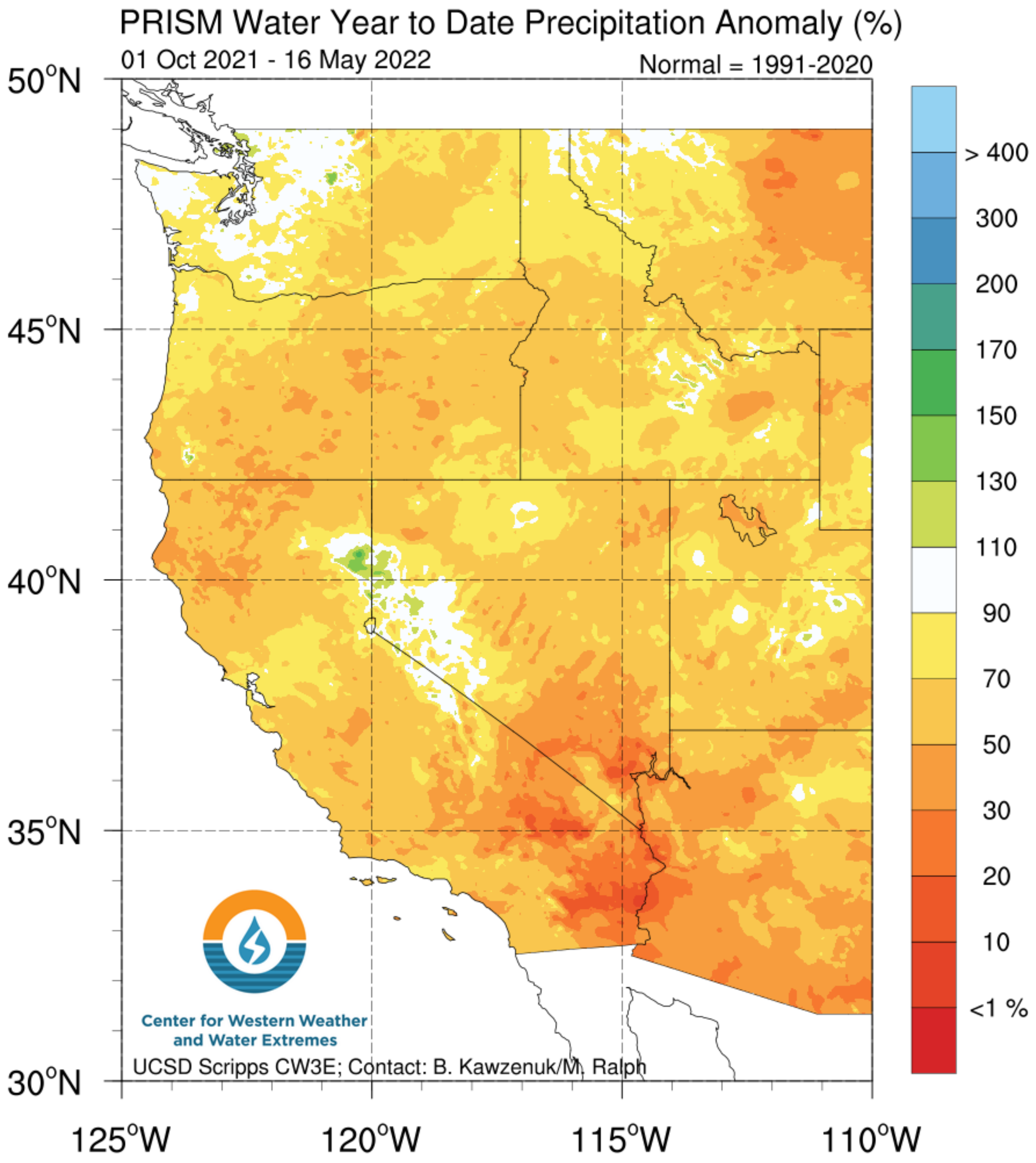
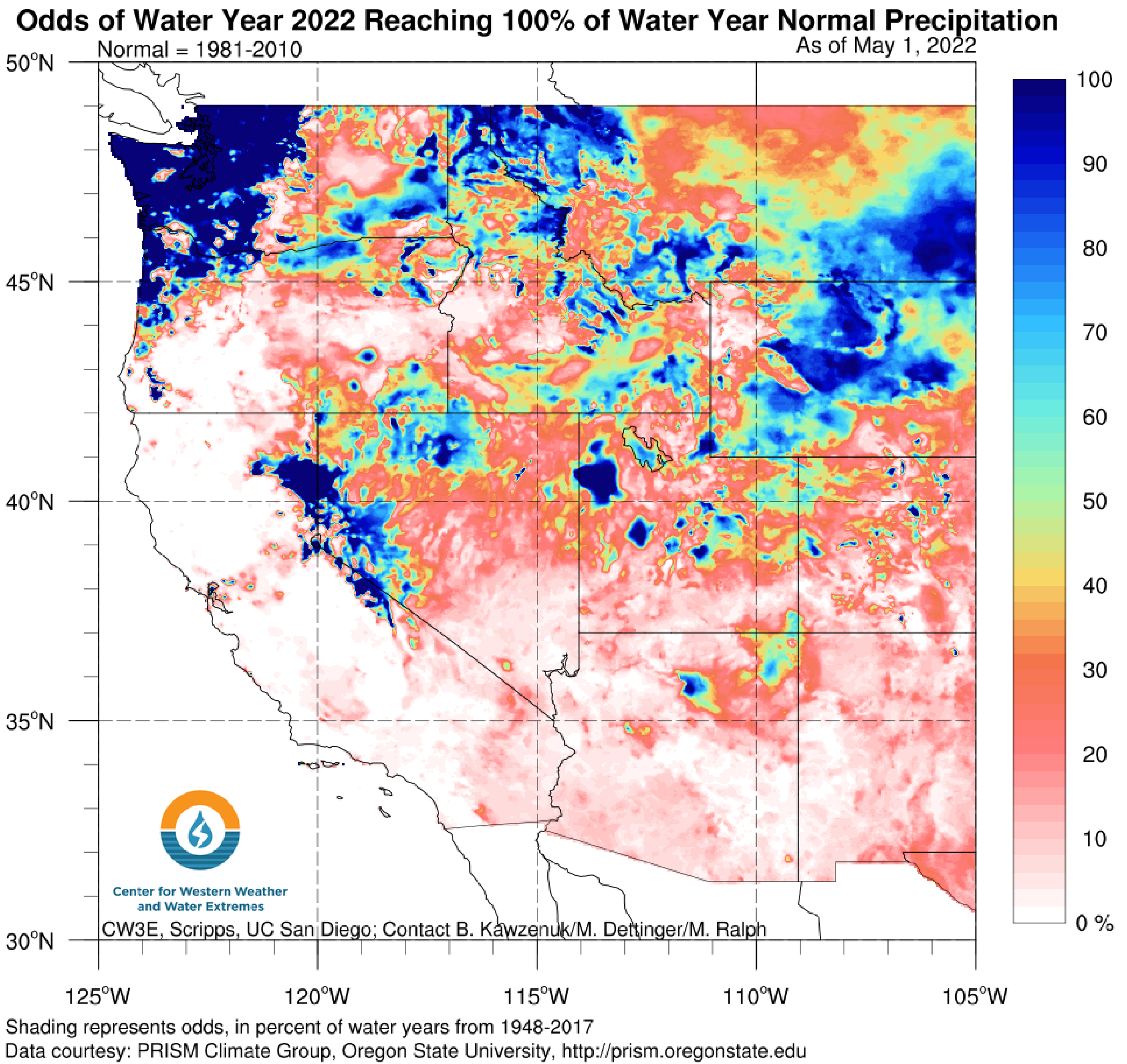
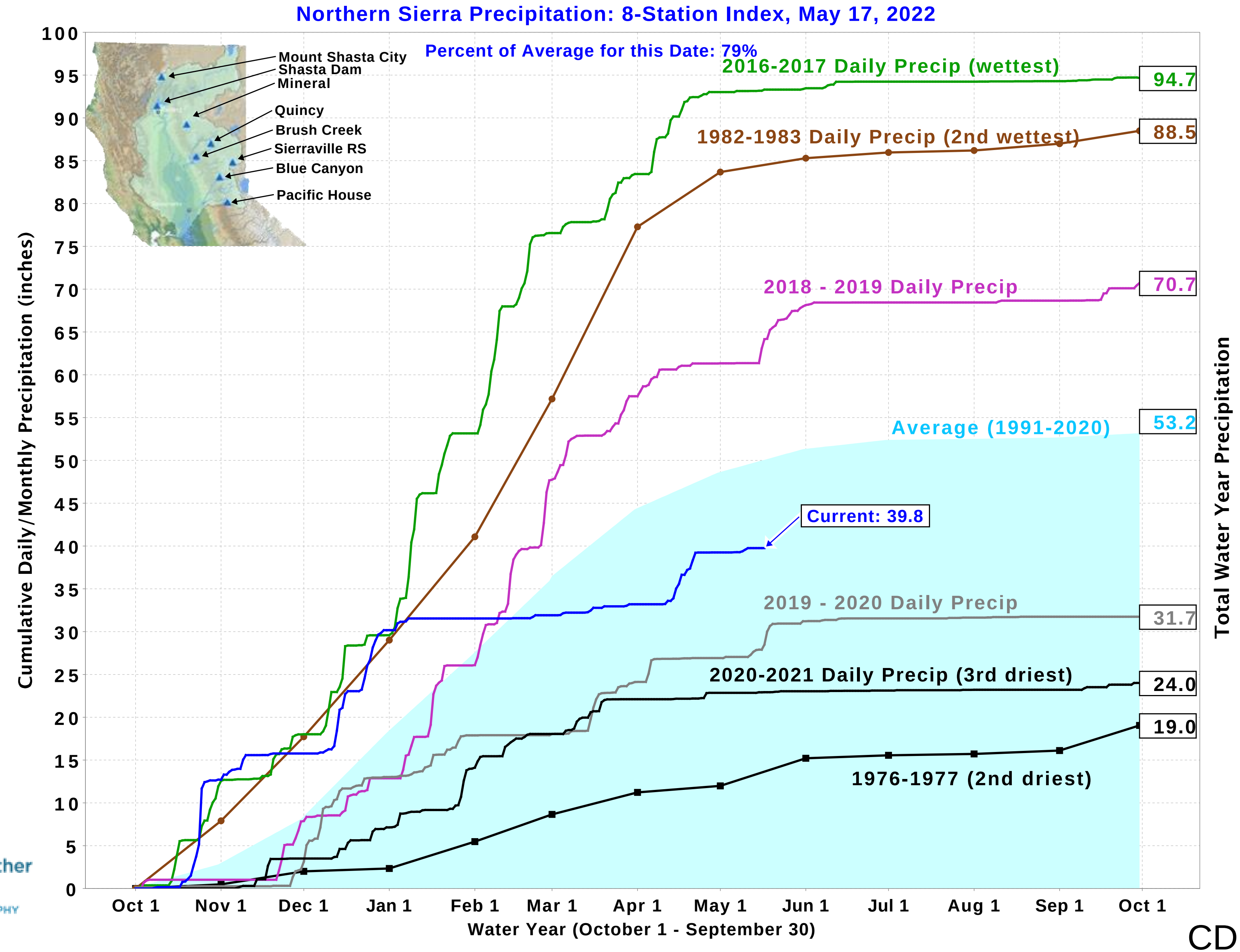
Water Year to Date Precipitation Relative to Normal - Anomaly (as of 16 May 2022)



Odds of WY2022 Reaching 100% of WY Normal (as of 1 May 2022)



Northern Sierra 8-Station Index: 17 May 2022



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CDEC

S2S Quantities of Interest, Methods, and Lead Times

Lead times investigated for S2S predictability of atmospheric rivers, ridges/blocking, or precipitation floods

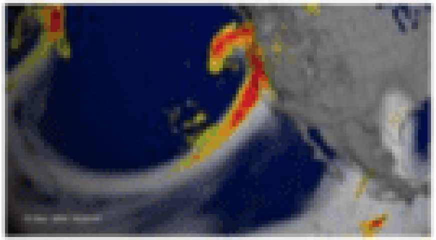
		Machine Learning	
	A	B	C
6–12 months (water year/annual)		X	
3–6 months (seasonal)	X	X	X
4–12 weeks (long-range subseasonal)	X	X	X
2–4 weeks (short-range subseasonal)	X	X	

S2S Methods

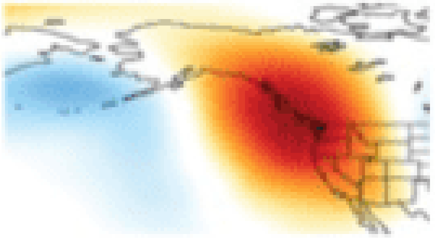
A = dynamical ensemble methods
B = statistical/traditional methods
C = neural network/deep learning methods

S2S quantities of interest

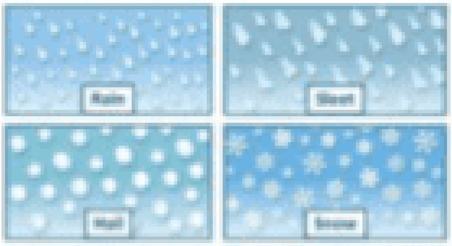
Atmospheric Rivers



Ridges/Blocking

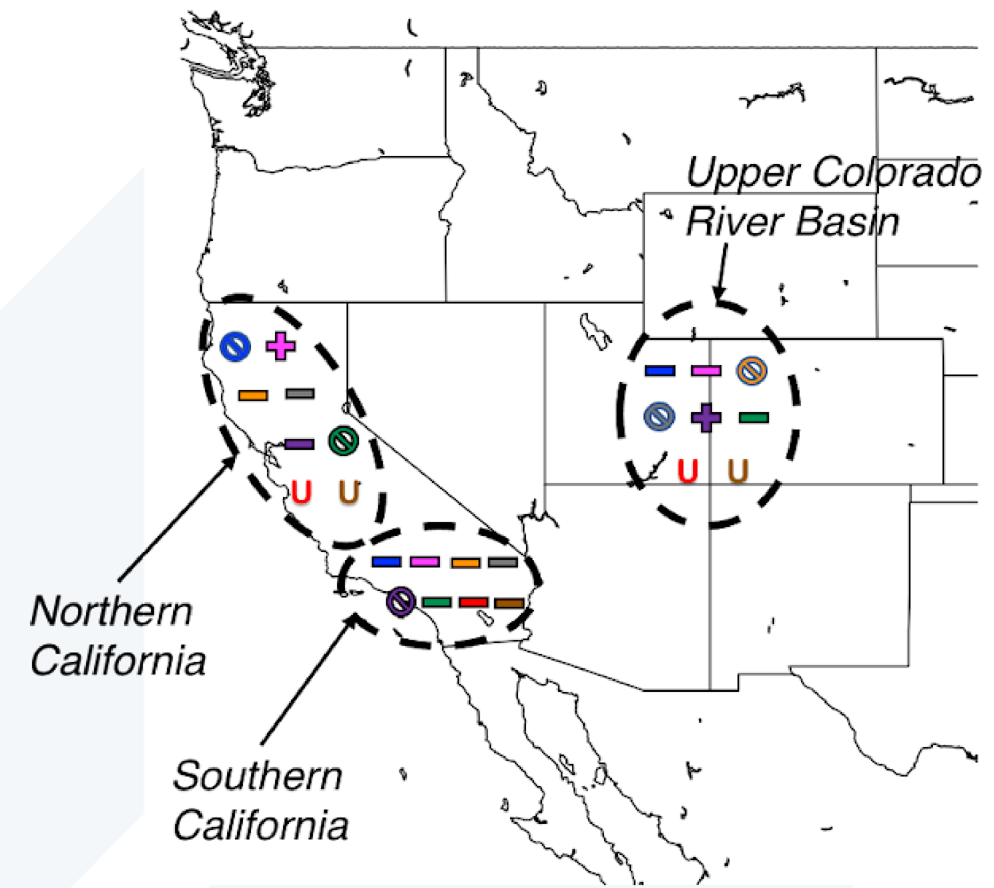


Precipitation/Floods



DeFlorio, Ralph, Waliser, Jones & Anderson (EOS, 2021)

Synthesizing Experimental Seasonal Precipitation Forecasts during Winter 2021-22



Methods	Forecast Period	Organization(s)	Nor Cal	So Cal	Upper Colo
Machine Learning based Forecast (Gibson et al.)	Jan-Mar	Jet Propulsion Laboratory, California Institute of Technology; Center for Western Weather and Water Extremes	⊘	−	−
CCA Seasonal Precipitation Forecast (Gershunov et al.)	Jan-Mar	Center for Western Weather and Water Extremes, Scripps Institution of Oceanography at UC San Diego	+	−	−
Univ. of Arizona Hybrid Seasonal Forecast (Zeng et al.)	Nov-Mar		−	−	⊘
Evolution-centric Statistical Forecast (Sengupta et al.)	Nov-Mar	Jet Propulsion Laboratory, California Institute of Technology	−	−	⊘
IRI Forecast based on Weather Regimes (Robertson et al.)	Nov-Mar	IRI	−	⊘	+
NOAA ESRL Seasonal Forecast (Switanek et al.)	Nov-Mar	NOAA	⊘	−	−
NMME Seasonal Forecast	Jan-Mar	The North American Multi-Model Ensemble	U/−	−	U
NOAA CPC Operational Outlook	Jan-Mar	NOAA	U	−	U/−

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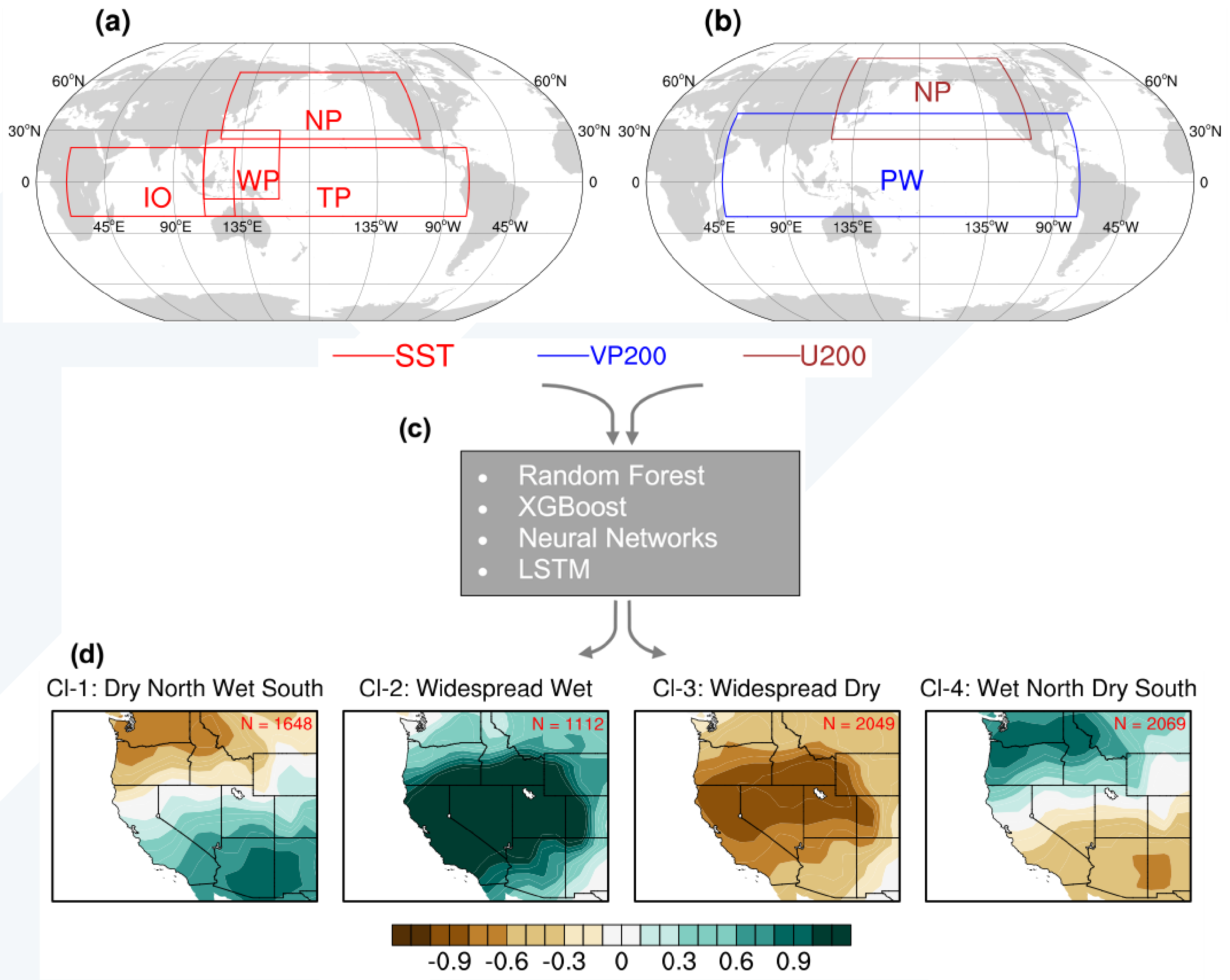
IRI

- ✚ Above Normal
- ▬ Below Normal
- ⊘ Normal
- U Uncertain/Equal Chances

DeFlorio et al. 2022 (BAMS, in prep)

Credit: A. Sengupta, M. DeFlorio, D. Waliser, F. M. Ralph, A. Robertson, X. Zeng, J. Jones

Seasonal Machine Learning Precipitation Clusters Outlook: Methodology



(a) SST predictors
(b) Atmosphere predictors
(c) ML models
(d) Predictands

ML models trained on ~3500 winter seasons from CESM-LENS → greatly increases sample size for seasonal prediction

Predicting NDJ and JFM clusters

Citation: Gibson, P.B., Chapman, W.E., Altinok, A., Delle Monache, L., DeFlorio, M.J, & Waliser, D.E. (2021). Training machine learning models on climate model output yields skillful interpretable seasonal precipitation forecasts. *Communications Earth & Environment*, 2,159.

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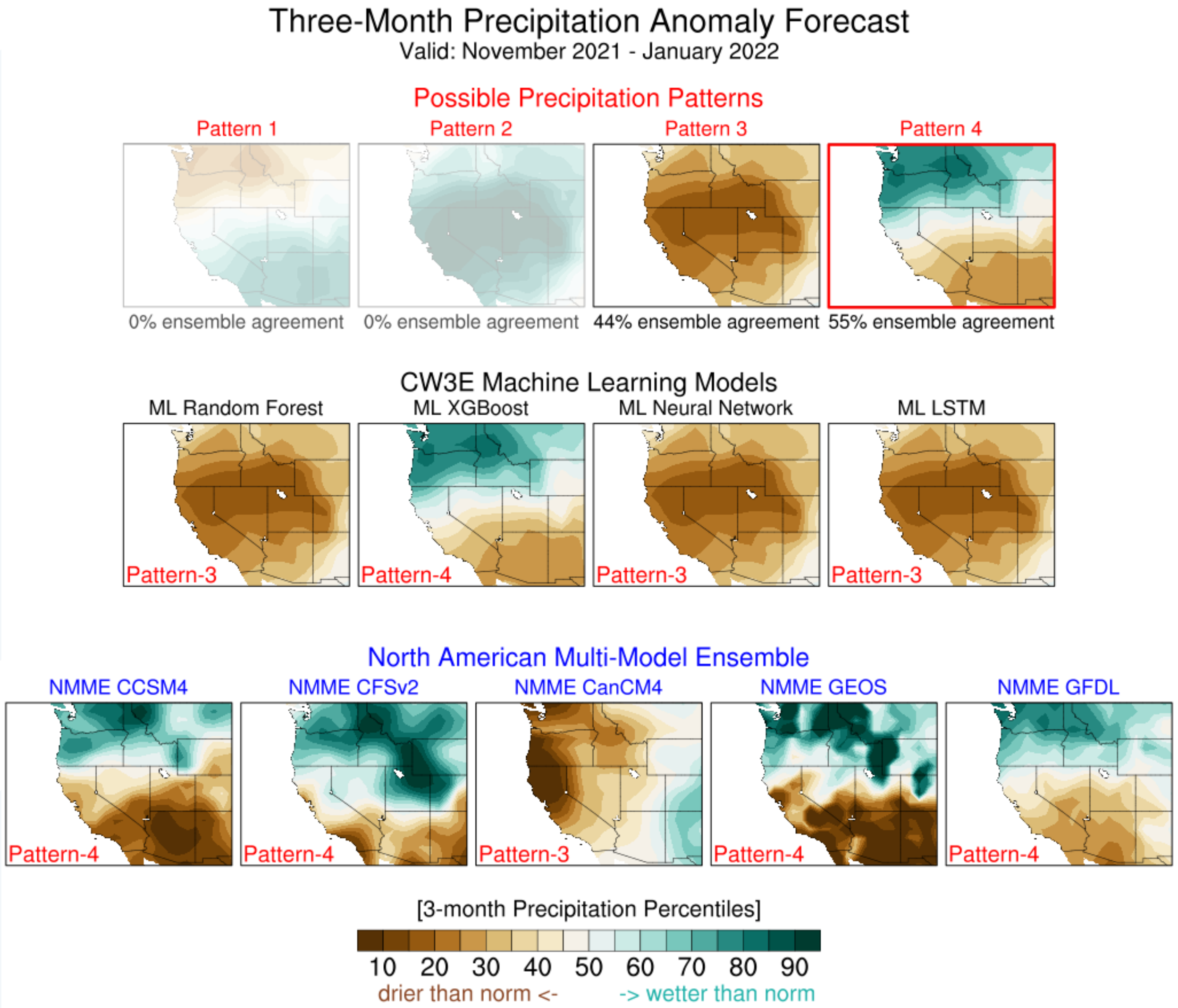
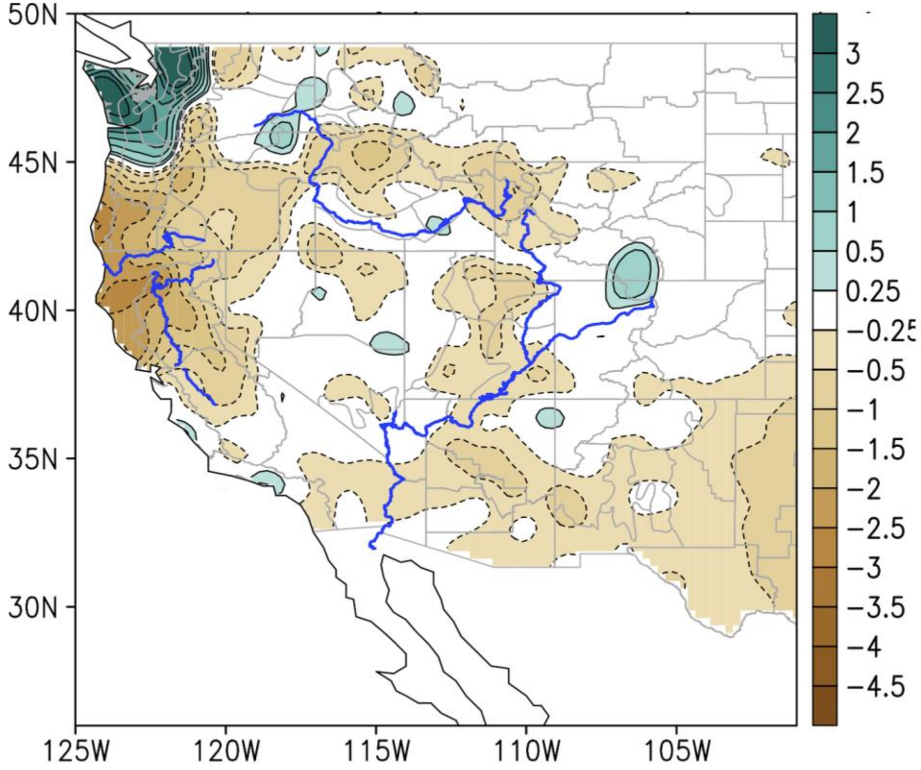
Verification of Seasonal ML Forecast: WY2022 NDJ

FORECAST



-ML model predictions use October 2021 (and earlier) data
-NMME models are initialized in early October 2021
*Possible precipitation patterns identified in Gibson et al. 2021

OBSERVED



Nov–Jan 2021-22 Precip Anomaly (mm/day) from NOAA CPC-Unified RT gauge-based dataset

Base period: 1981–2010; major rivers are outlined in blue.

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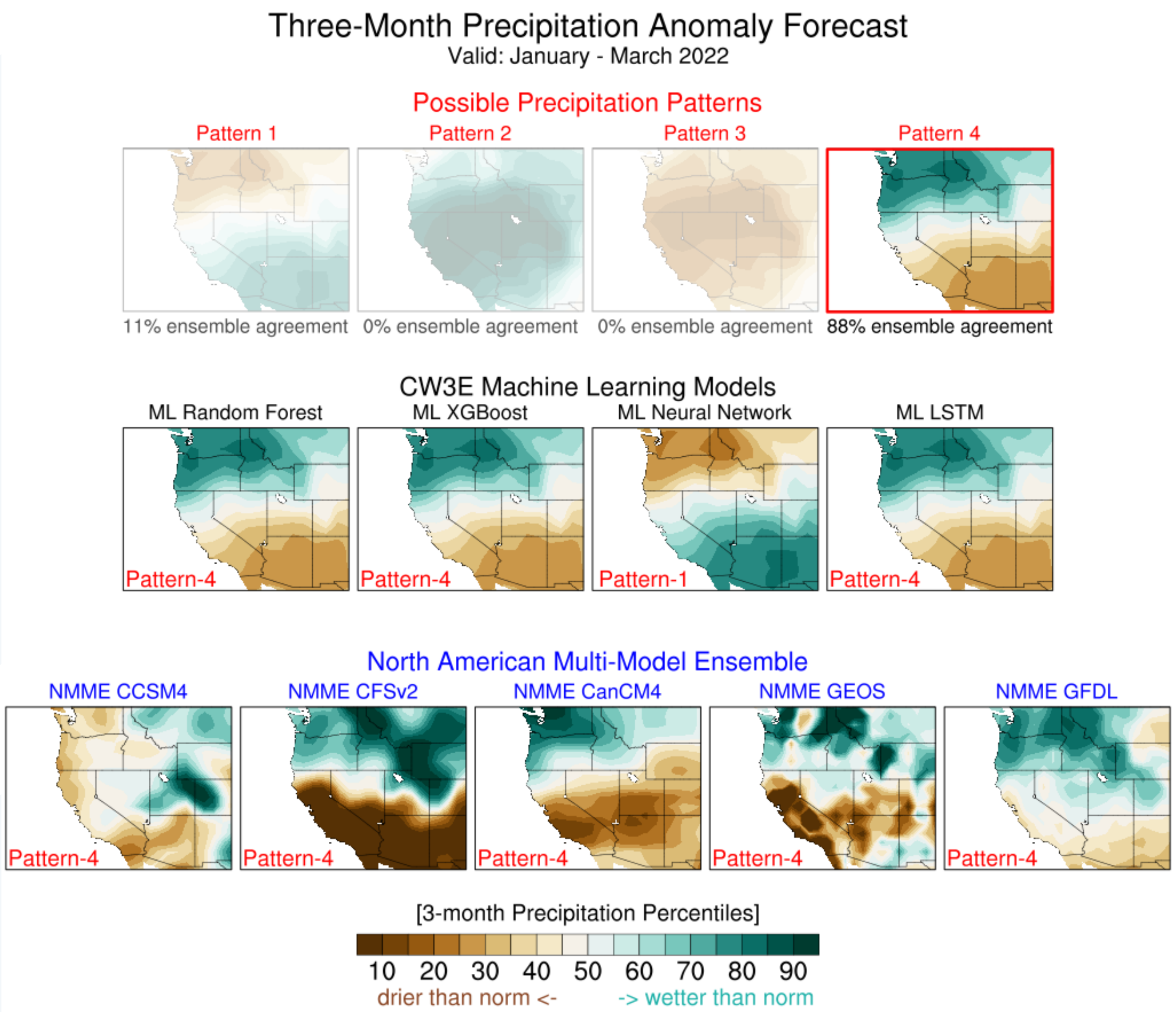
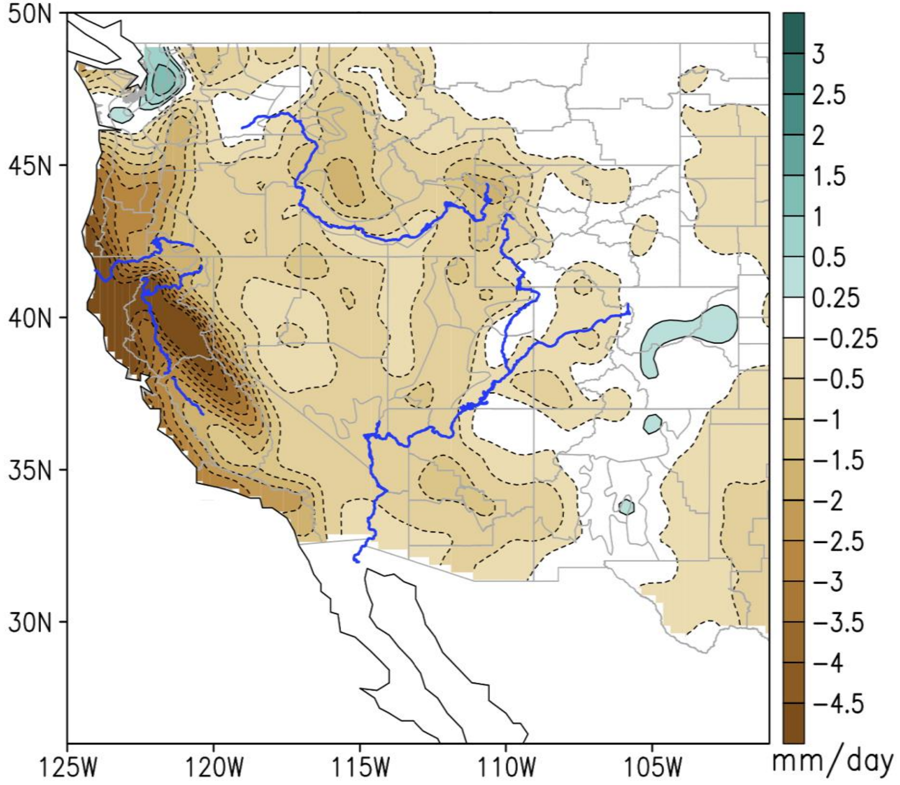
Verification of Seasonal ML Forecast: WY2022 JFM

FORECAST



-ML model predictions use December 2021 (and earlier) data
-NMME models are initialized in early January 2022
*Possible precipitation patterns identified in Gibson et al. 2021

OBSERVED



Jan–Mar 2022 Precip Anomaly (mm/day) from NOAA CPC-Unified RT gauge-based dataset

Base period: 1981–2010; major rivers are outlined in blue.

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Historical Skill (Past Years, 1982-2010)

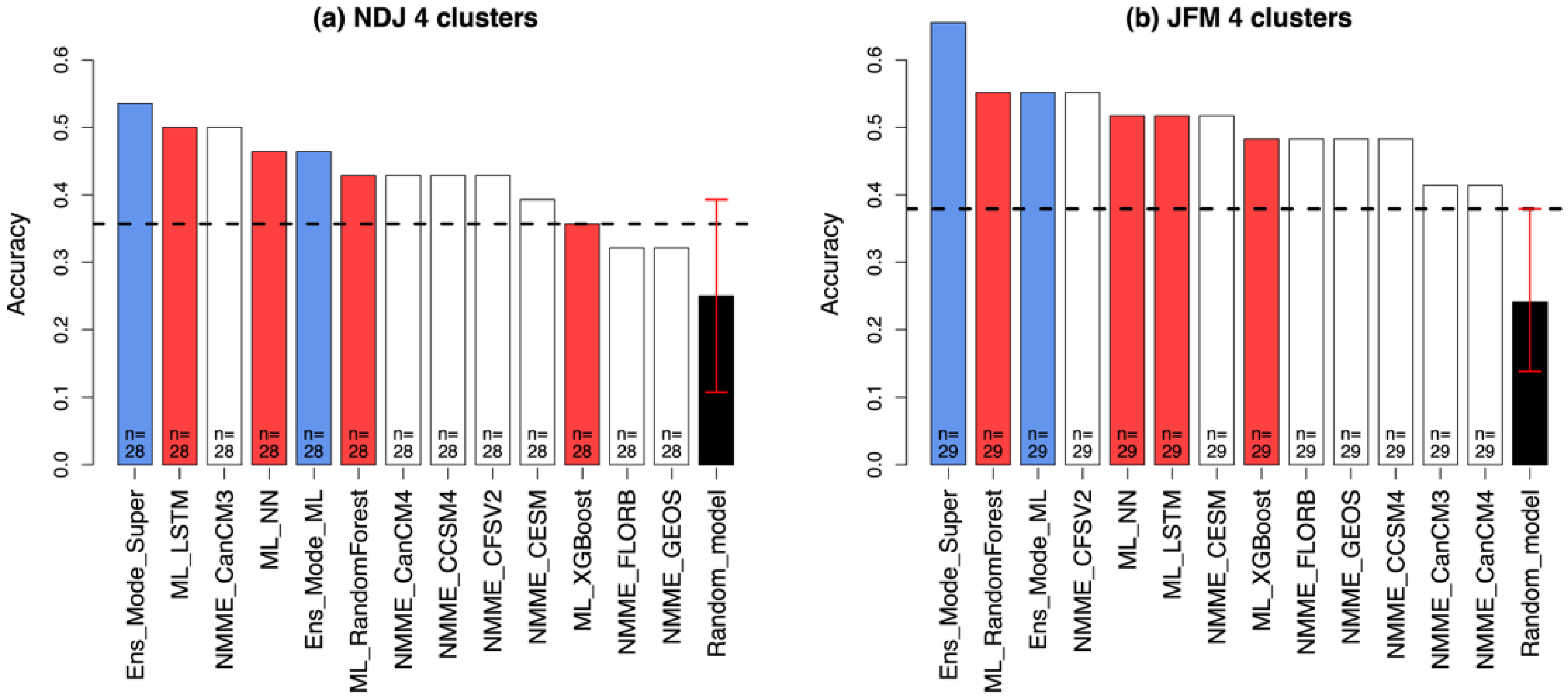

Figure 2: Accuracy of Machine learning models (red), NMME models (white), and Ensemble models (blue) for NDJ and JFM seasons. Accuracy here is defined as the proportion of correct predictions. The sample size (i.e. number of predictions made) is given at the base of each bar. Baseline skill is defined here in two ways: (1) the horizontal line defined by the frequency of the most common cluster; (2) A random model prediction repeated 1000 times with bars showing the 5th/95th percentile of the random prediction accuracy. Here accuracy is computed across overlapping years between all models in the test set, refer to Supplementary Material Figure S11 for accuracy across all years.

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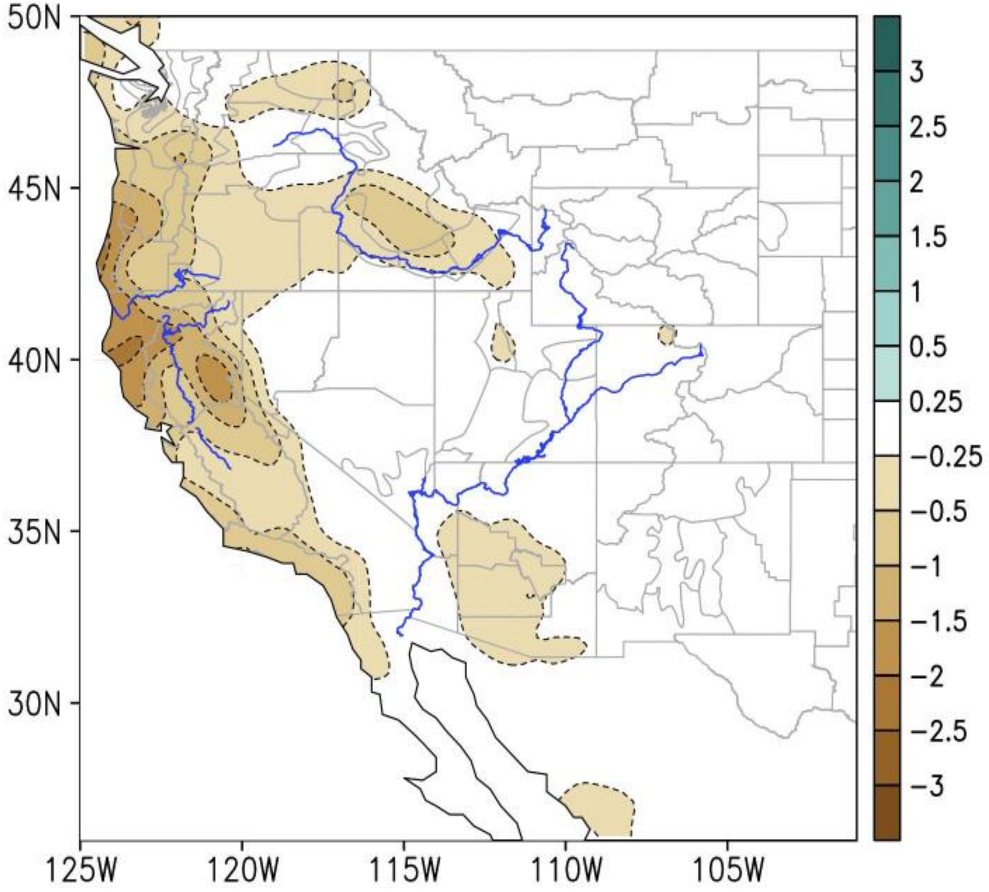
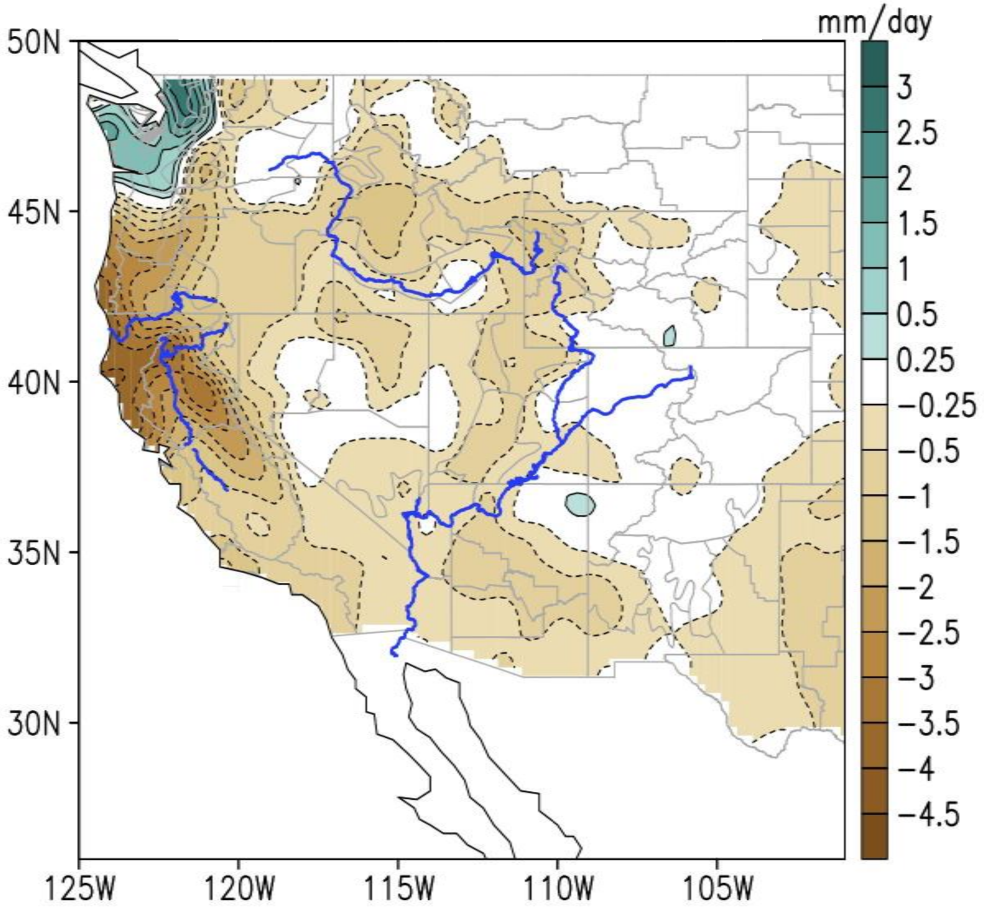
Seasonal Evolving-SST approach: Experimental NDJFM 21-22 Forecast

2021-22 Nov-Mar **Forecasted**
Seasonal Precipitation Anomalies



2021-22 Nov-Mar **Observed**
Seasonal Precipitation Anomalies



For historical skill – see Agniv's talk later today

Observations from NOAA CPC-Unified RT gauge-based dataset
NOAA NCEI Climate Divisions outlined in grey
Major western rivers in blue; Base period for precipitation anomalies: 1981-2010

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Key Take Home Messages: Seasonal Outlooks

1. Historical skill assessment is a requirement in meaningfully interpreting any single seasonal forecast. Due to sampling variability, the skill of seasonal forecasts should be interpreted differently from the skill of a subseasonal prediction system across an extended winter season.

2. Increasing sample size of model training period (either through using longest available and reliable observations [e.g., Sengupta et al. (in prep)], or novel large ensemble methods [e.g., Gibson et al. 2021]) is especially key for seasonal prediction of western U.S. precipitation, which we know is influenced by interannual-to-multidecadal modes of climate variability.

3. Demonstrating plausible/testable connections between predictor variables and seasonal anomalies in western U.S. precipitation through specific physical mechanisms/pathways increases confidence in such seasonal prediction systems.

Example of a subseasonal experimental forecast

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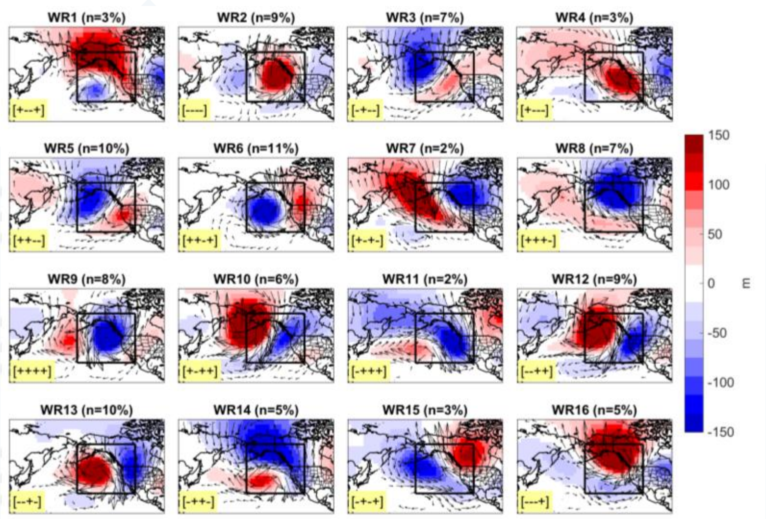
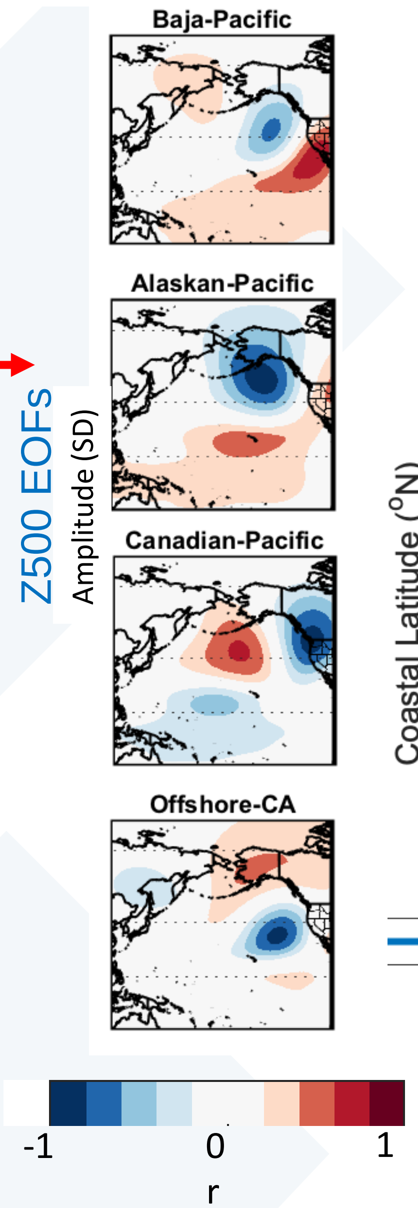
Historical Weather Regimes: 1949-2017



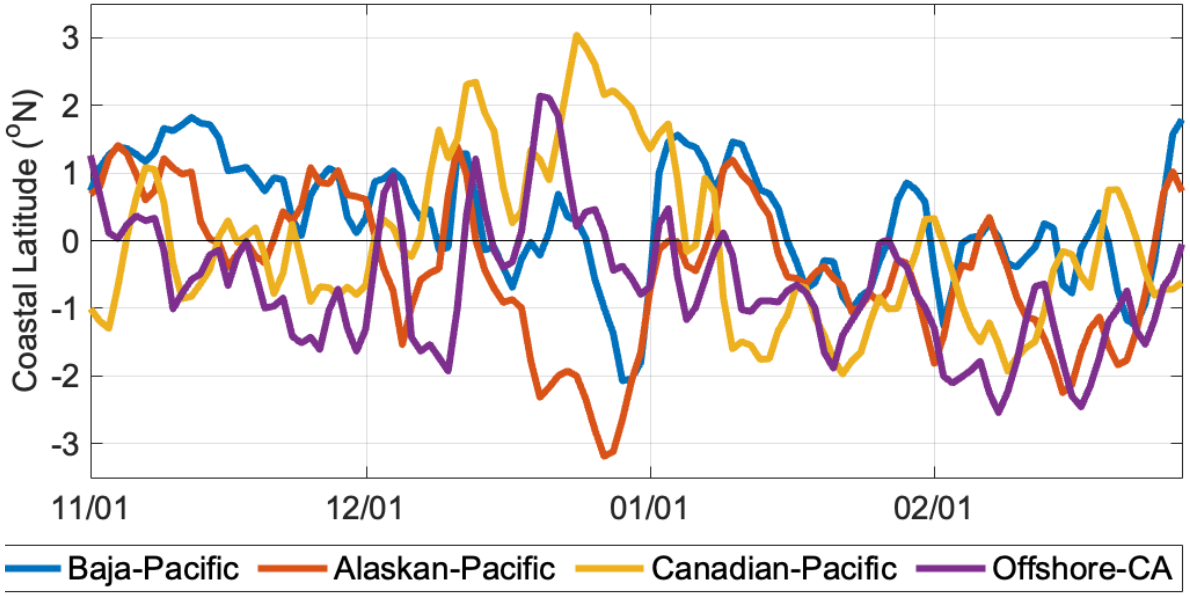
- Historically linked to:
  - AR Landfalls
  - California precipitation
  - Damaging California Floods
  - Sierra Snowpack
  - Temperature
  - Santa Ana Winds
  - California Wildfires

NP4 Modes



The NP4 modes fluctuate over the course of the season and different mode phase combinations produce distinct weather patterns.

NP4 Mode Amplitude WY2022



Guirguis et al. 2022 (in prep)

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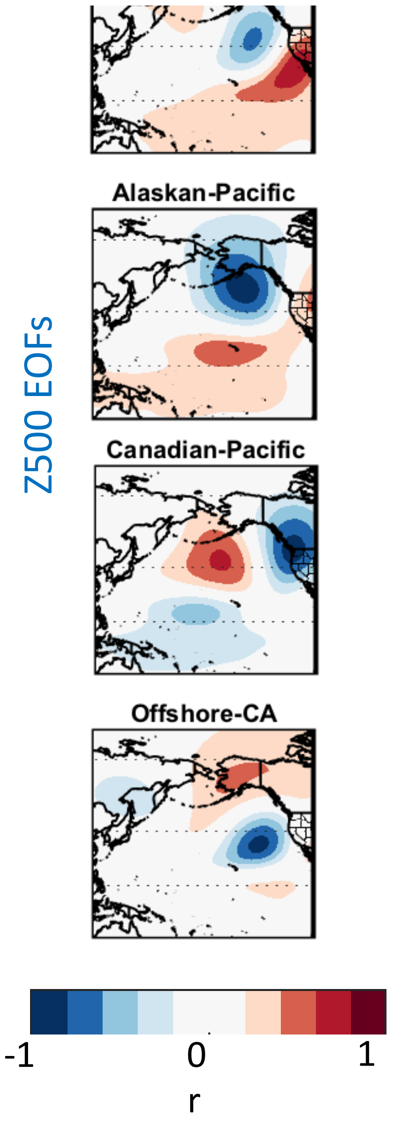
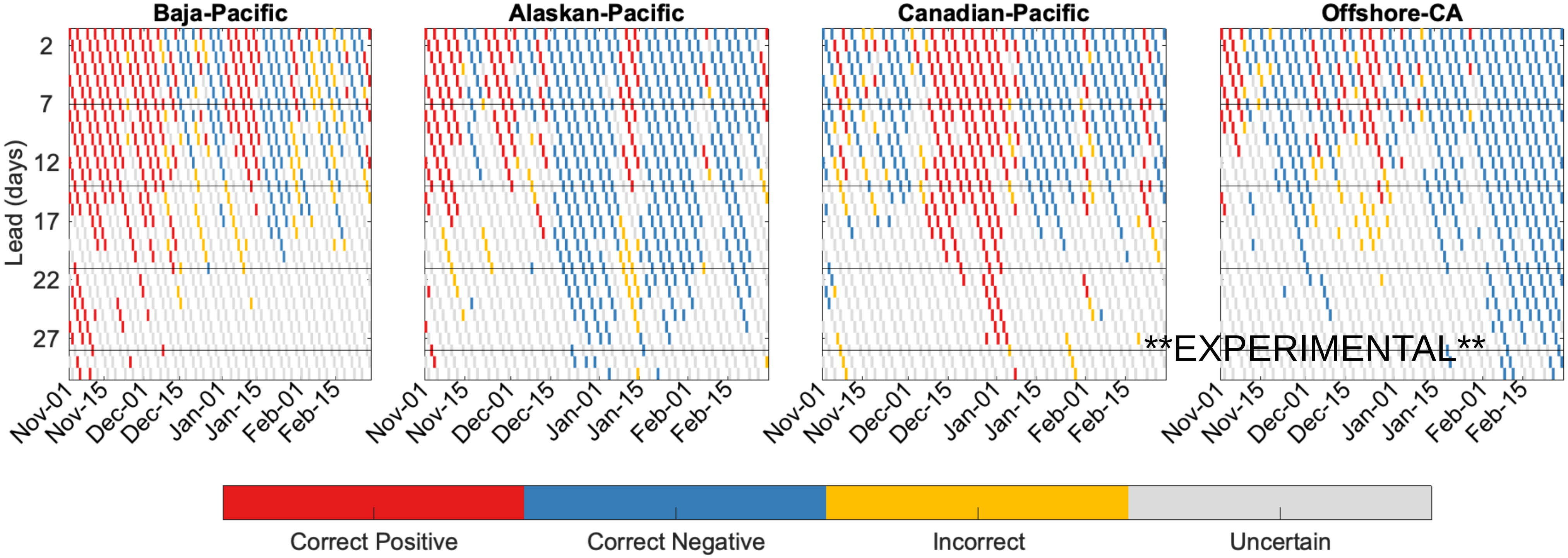
Skill Metric: Classification (Chance of Correct/Incorrect Sign of NP4 Mode Forecast)

NP4 Modes



Validated NP4 Phase Forecasts for WY2022 from ECMWF



91% Correct

9% Incorrect

Guirguis et al. 2022 (in prep)

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Key Take-Home Messages: Subseasonal Outlooks

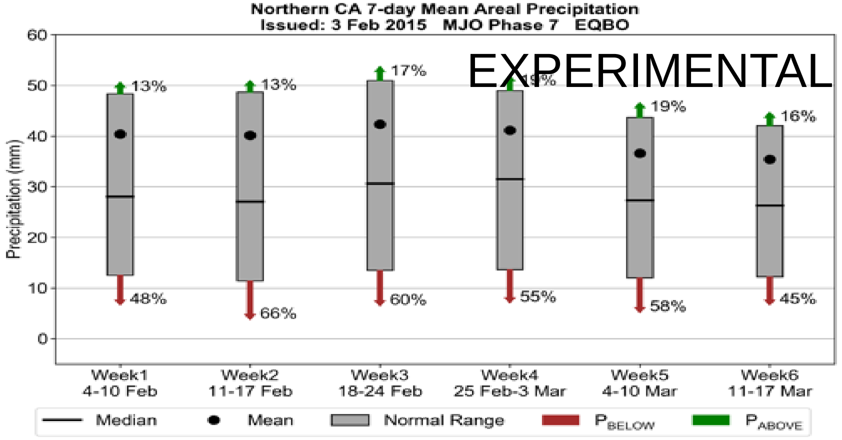
1. Due to much larger intraseasonal sample size (weekly or bi-weekly forecasts over 5-6 months), skill metrics for subseasonal outlooks computed over the entire extended winter season can be more insightful and interpretable than a skill metric computed for only a handful seasonal predictions within a given season.

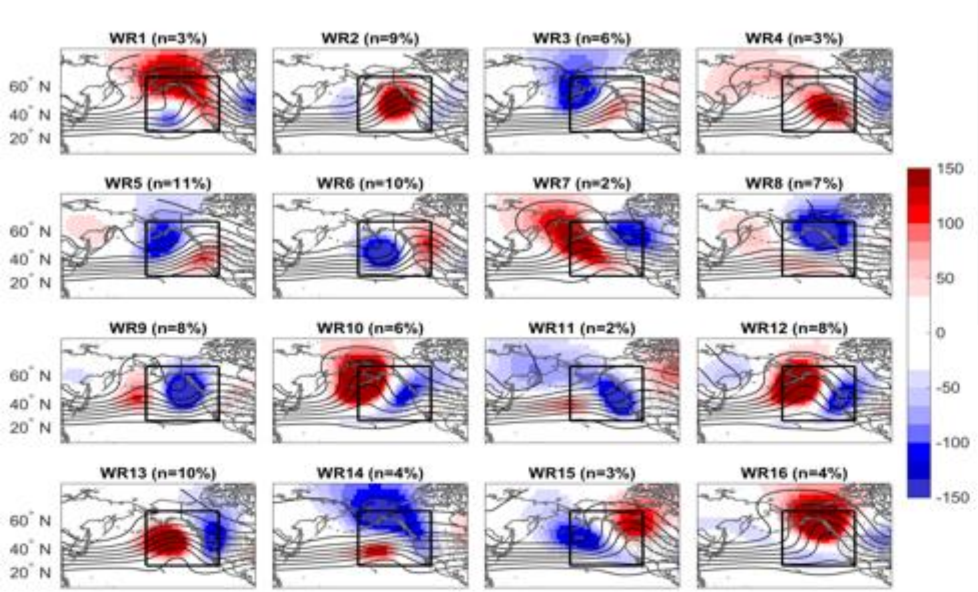
2. Uncertainty in dynamical model output can be supplemented with statistical forecasts based on historical data to increase lead time and/or confidence.

3. Categorical prediction (i.e., predicting sign of NP4 modes) is viable, and can yield higher relative skill than deterministic prediction in the subseasonal prediction range (note: these methods are not mutually exclusive to these lead times).

CW3E S2S Forecast Products: Future Directions

- Experimental subseasonal forecast product predicting probability of above or below normal precipitation and AR occurrence based on MJO/QBO phase (Castellano et al. 2022 (in prep); Wang et al. 2022 (in revision))





- Experimental subseasonal forecast product predicting probability weather regimes important for western U.S. AR landfalls and extreme precipitaton (Guirguis et al. 2022, in prep)

- Launching of CW3E Seamless Experimental S2S Forecasting Tool from 1-week to 6-month lead time (DeFlorio et al. 2022 [BAMS, in prep])

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Summary

The western U.S. region, and in particular California, experiences the highest interannual variability of wintertime precipitation in the country relative to average conditions.

In addition, water managers across the western U.S. are in need of more skillful predictions of precipitation at S2S lead times.

This combination, along with increasing demand by other end users in the applications community for more skillful longer-lead precipitation forecasts, has led to increased international investment for S2S research, with a focus on better understanding of physical mechanisms related to predictability, and an end goal of creating experimental S2S forecast products to meet end user needs.

California Department of Water Resources has funded a research and operations partnership led by the Center for Western Weather and Water Extremes and the NASA Jet Propulsion Laboratory to create experimental S2S forecast products for precipitation, atmospheric rivers, and ridging.

These experimental S2S products are necessarily supported by peer-reviewed hindcast skill assessments, and are designed in tandem with DWR stakeholders to best meet their needs.

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cw3e.ucsd.edu/s2s_forecasts

Thank you!

mdeflorio@ucsd.edu

Photo credit of Lake Mead: Oakley Originals