Center for Western Weather and Water Extremes
SCRIPPS INSTITUTION OF OCEANOGRAPHY AT UC SAN DIEGO

DEPARTMENT OF WATER RESOURCES
STATE OF CALIFORNIA

Jet Propulsion Laboratory
California Institute of Technology

Seasonal Forecasting of Western U.S. Precipitation Using Machine Learning Models

*Peter Gibson[1], Will Chapman[1], Alphan Altinok[2], Luca Delle Monache[1], **Mike DeFlorio**[1], Duane Waliser[2]*

[1]Center for Western Weather and Water Extremes, Scripps Institution of Oceanography, UCSD
[2]NASA Jet Propulsion Laboratory/California Institute of Technology

SCRIPPS INSTITUTION OF OCEANOGRAPHY

Center for Western Weather and Water Extremes
SCRIPPS INSTITUTION OF OCEANOGRAPHY AT UC SAN DIEGO

DEPARTMENT OF WATER RESOURCES · STATE OF CALIFORNIA

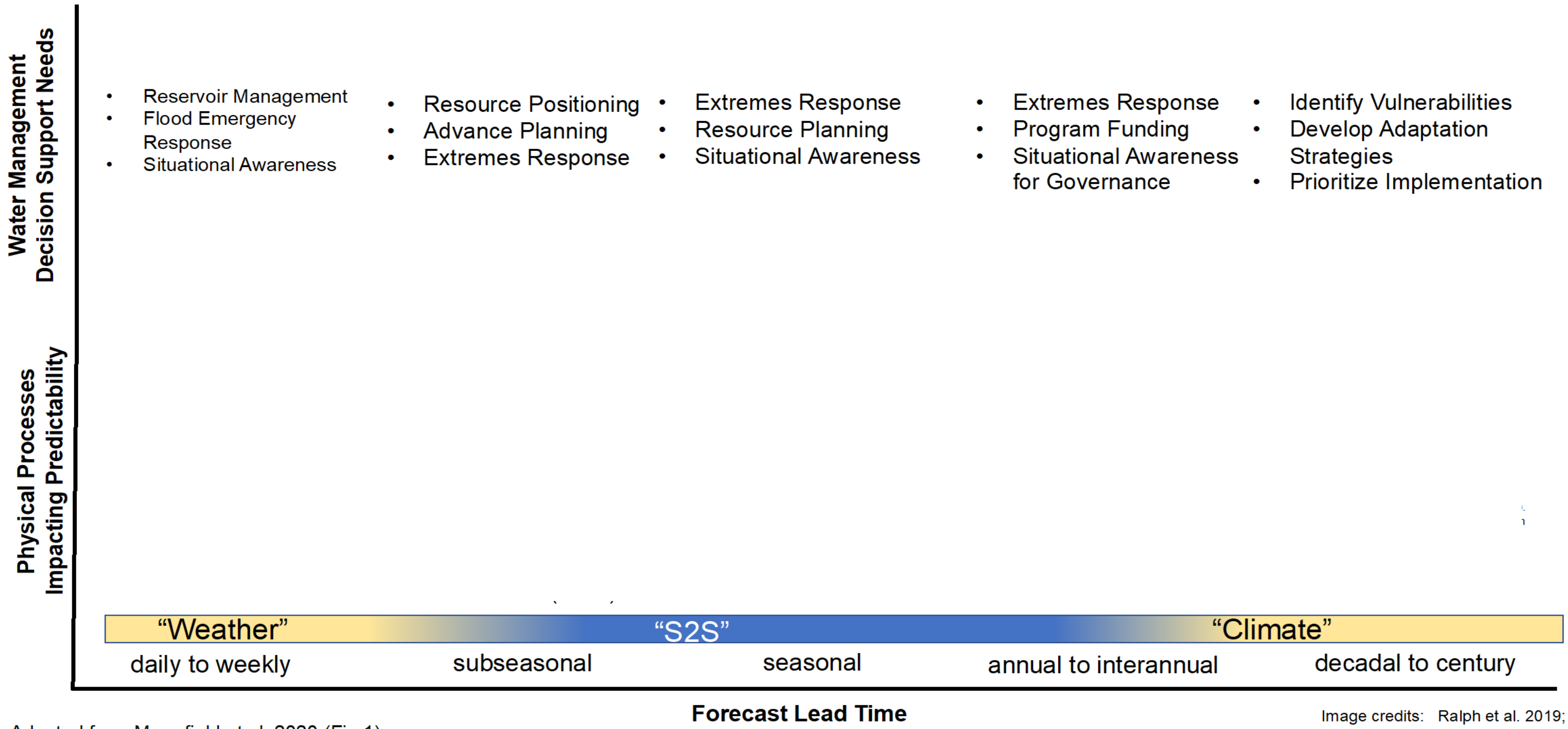
Jet Propulsion Laboratory
California Institute of Technology

DWR Seasonal Forecasting Team Objective

- Improve understanding of seasonal predictability of western U.S. precipitation
- Produce experimental S2S prediction products to better support water management over the western U.S.

Motivation: Western U.S. water managers need better S2S forecasts of precipitation

From Days to Decades: Lead-Dependent Water Management Decisions Impacted by Multi-Scale Weather and Climate Variability



Adapted from Merryfield et al. 2020 (Fig 1).

Image credits: Ralph et al. 2019; NOAA; NOAA; Josef Friedhuber

DeFlorio, M. J., F. M. Ralph, D. E. Waliser, J. Jones, and M. L. Anderson (2021), Better subseasonal-to-seasonal forecasts for water management. *EOS, 102*, https://doi.org/10.1029/2021EO159749.

Seasonal Forecasting Using Machine Learning Models

- Skilful seasonal forecasts of precipitation over the Western US would be immensely valuable for water resource managers leading up to and during drought
- However, operational dynamical forecast models have relatively low skill in this region
- Can developments in machine learning improve seasonal forecast skill here?
- A barrier to using machine learning is the severely limited observational record (1-sample per season), whereas machine learning models typically require very large datasets for training
- To circumvent this, we train ML models on very long climate simulations (as opposed to observations directly), giving several thousand years of physically consistent data to train on

Methodology and Data Used

Methods & Data:

- We trained various ML models on output from the CESM-LENS climate model database.
- ML models tested were: Random Forests, XGBoost, neural networks and LSTMs
- After training on the climate model dataset, the ML models were tested for making predictions on the observed dataset (1980-2020) which wasn't used in training

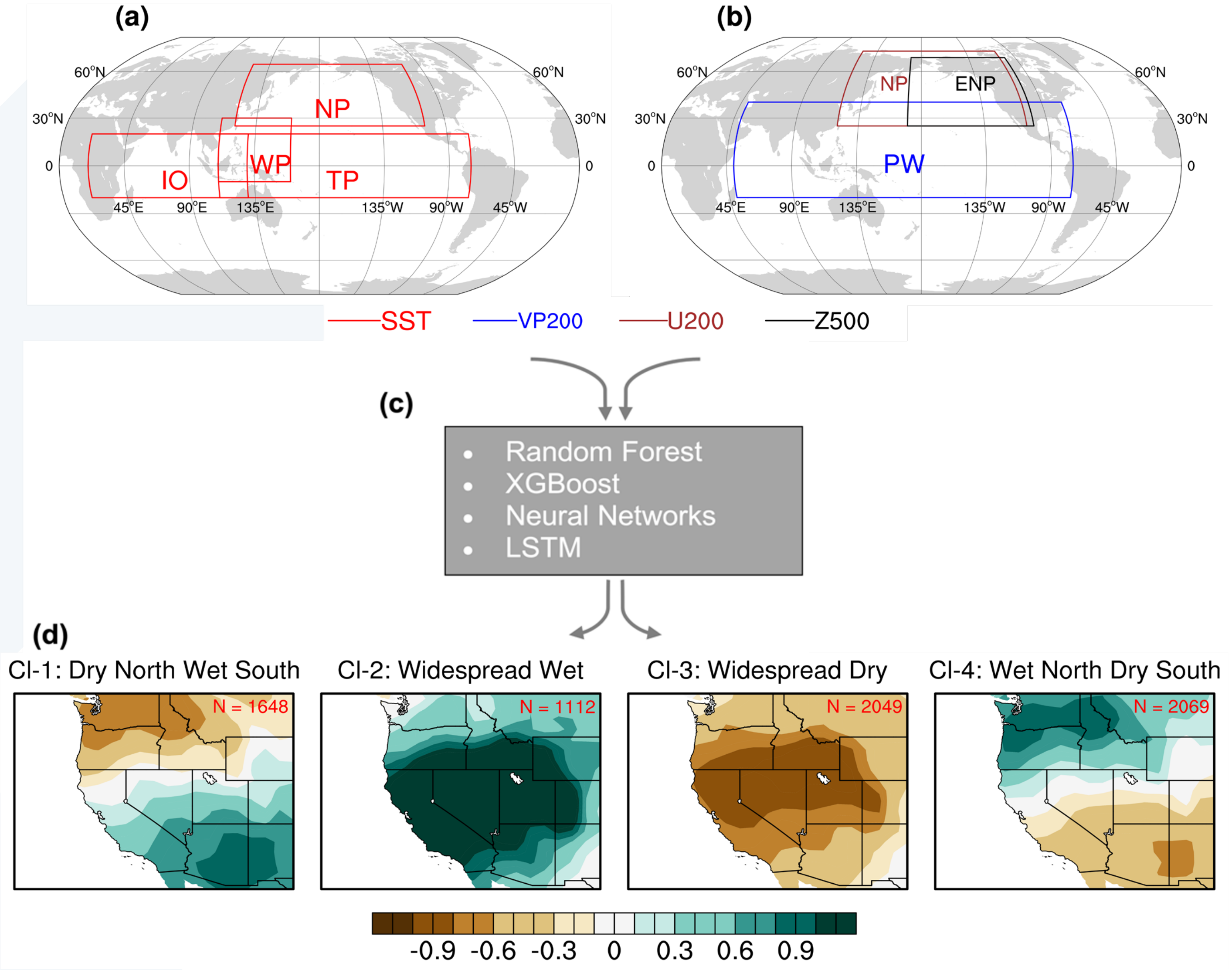


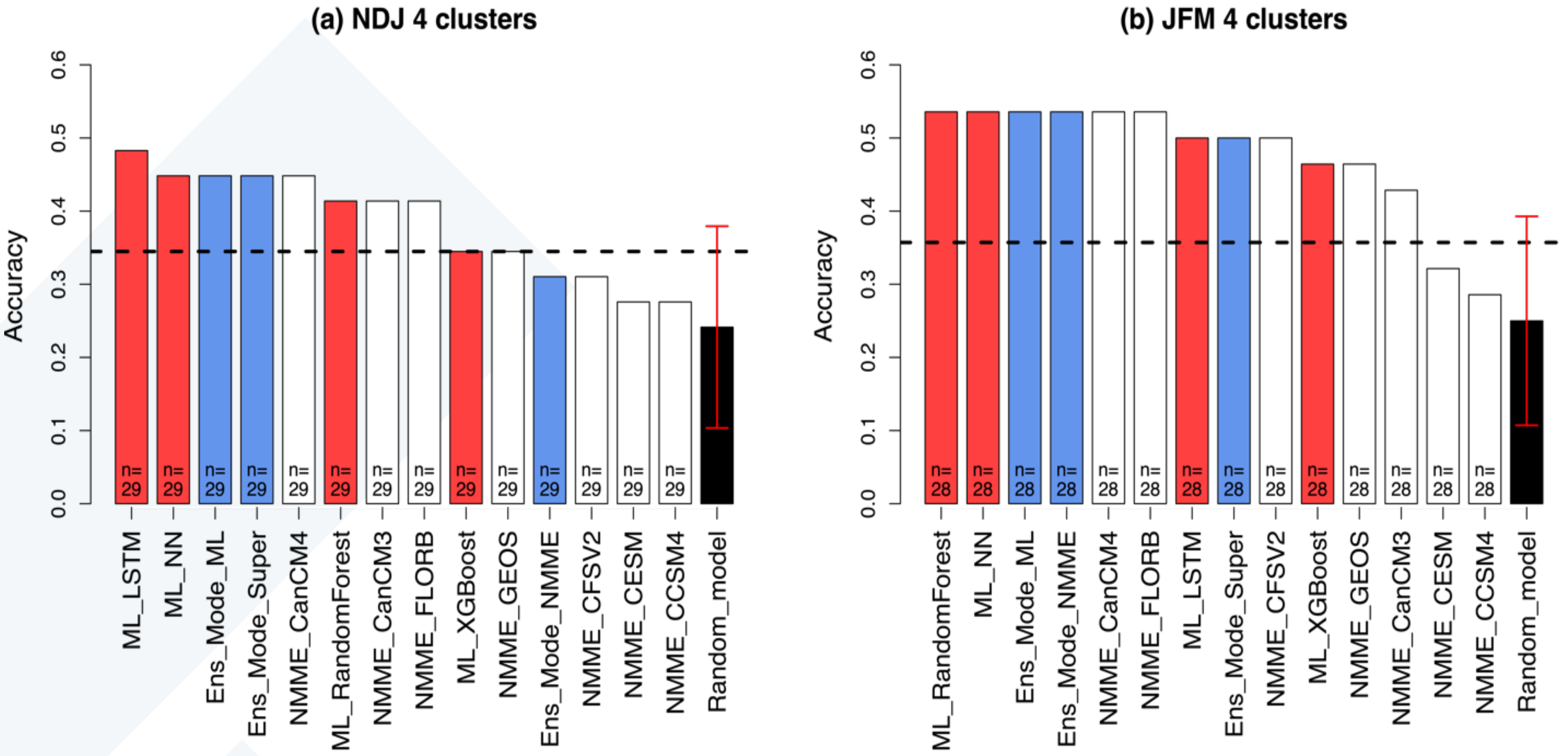
Figure: Machine learning trained on key predictor variables derived from the CESM-LENS climate model dataset. (Top): the different remote predictor variables and regions used in training; (Middle): the 4 ML models used in seasonal prediction; (Bottom): the target clusters to be predicted, which characterize broad spatial patterns of precipitation anomalies across the Western US

Gibson et al. 2021, Nature Comm.

Accuracy of ML Models in Predicting Precipitation Patterns

Results (accuracy):

- We found that ML models trained in this way can compete with the top operational dynamical forecast models and outcompete several other models.
- These results suggest ML models used alongside existing operational approaches may help improve seasonal forecasting skill.



ML models **NMME models** **Ensemble models**

Figure: Accuracy of machine learning models (red), NMME models (white), and ensemble models (blue) for NDJ (panel a) and JFM (panel b) seasons. Accuracy is defined as the proportion of correct predictions. The sample size (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 $5^{th}/95^{th}$ percentile of the random prediction accuracy. The Ensemble models (blue) are based on the ensemble mode cluster prediction across their respective groups, with Ens_mode_Super based on the ensemble mode across all models

Gibson et al. 2021, Nature Comm.

Accuracy of ML Models in Predicting Precipitation Patterns

Results (accuracy):

- The widespread wet cluster pattern (cluster-2) was found to be the most challenging cluster to forecast

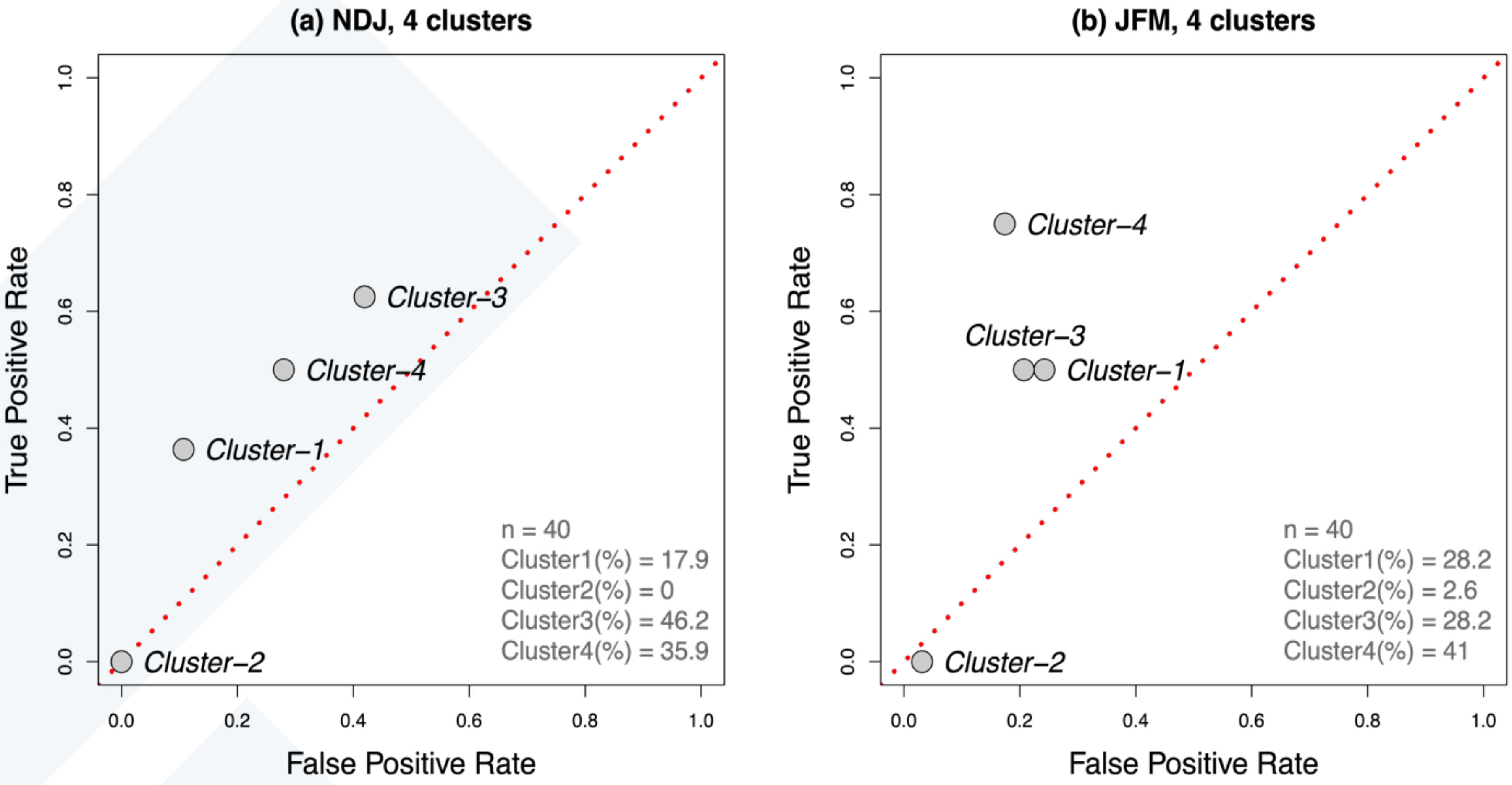


Figure: ROC diagram for cluster predictions of NDJ season (panel a) and JFM season (panel b) from the Random Forest model on the test dataset (years 1980-2020). The percentage of predictions assigned to each cluster is given in the bottom right of each plot.

Gibson et al. 2021, Nature Comm.

Interpretability: Which variables impact seasonal predictability of western U.S. precipitation most strongly?

Results (interpretability):

- We implemented various 'interpretable ML' approaches to try and understand why the ML makes a particular forecast
- These included: variable importance plots, partial dependence plots, ALE plots and LIME modeling
- In general, we found that ENSO-related SST variability is the largest contributor to seasonal forecast skill
- Variability in SST in Western tropical Pacific, and Velocity Potential variables also contribute to skill beyond ENSO

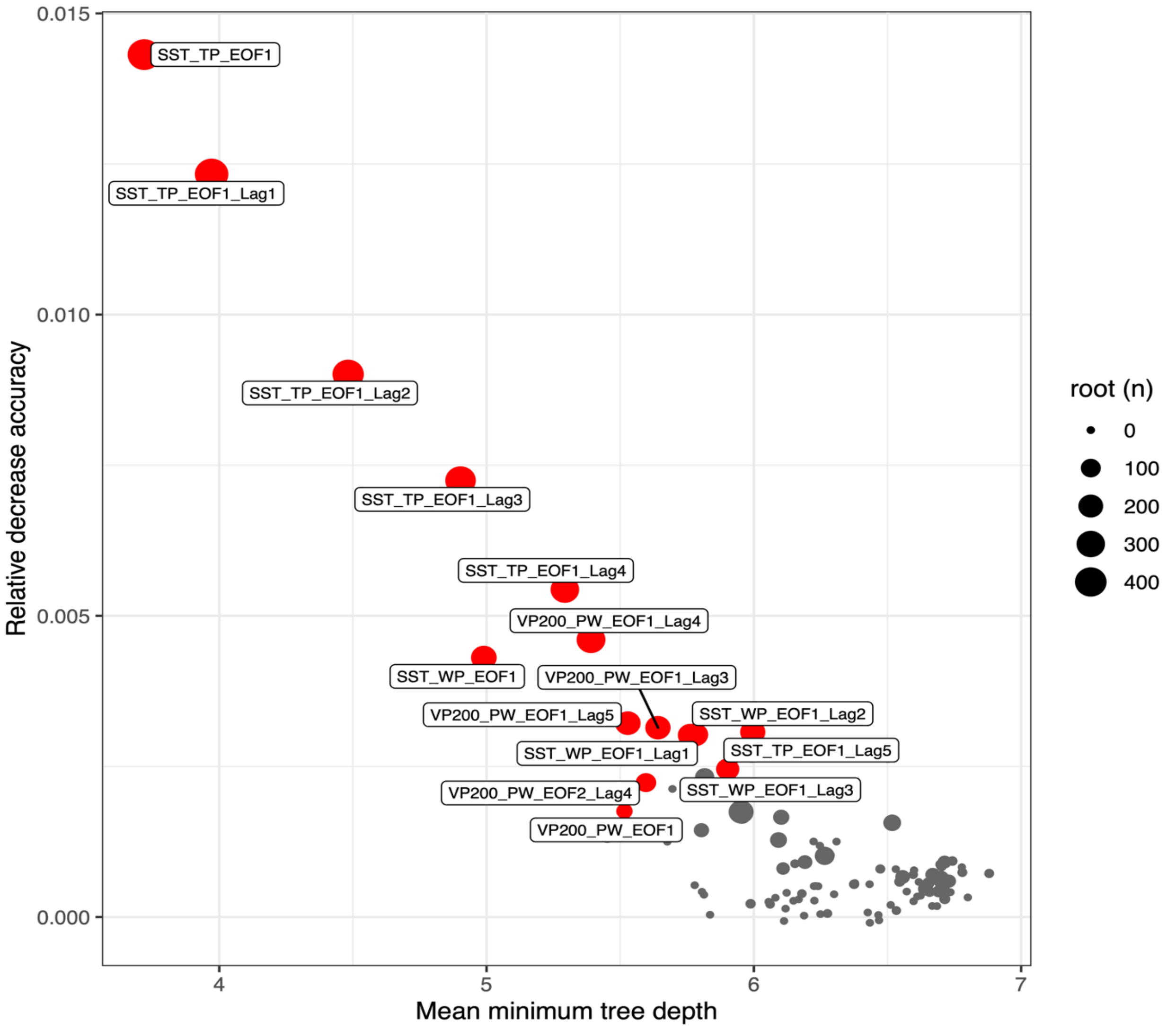


Figure: The 15 most important predictor variables are highlighted in red. SST_TP_EOF1 is the first EOF of tropical Pacific SST (i.e. December value) and SST_TP_EOF1_Lag1 is the additional 1-month lag of the first EOF of tropical Pacific SST (November value).

Gibson et al. 2021, Nature Comm.

CW3E/JPL Seasonal ML Precipitation Outlook: November 2021 – January 2022

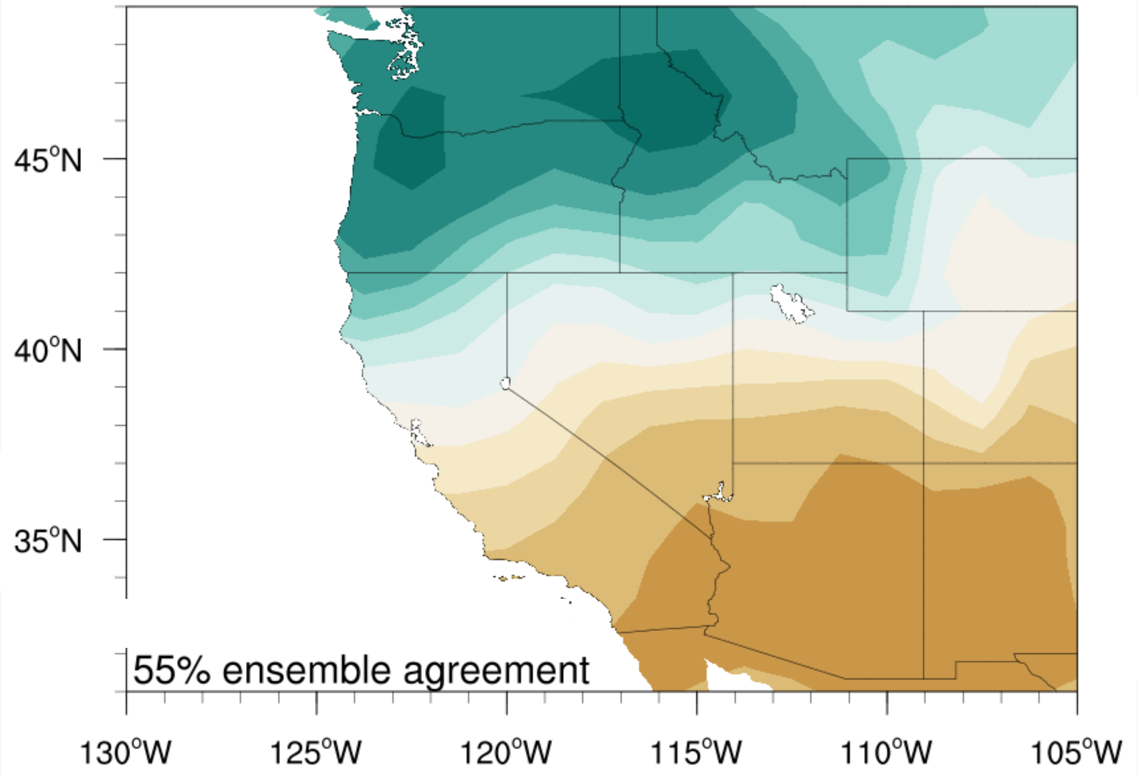
- Drier than normal conditions favored for southwest during NDJ
- Northern California could see near normal or drier than normal conditions during NDJ

Center for Western Weather and Water Extremes
SCRIPPS INSTITUTION OF OCEANOGRAPHY AT UC SAN DIEGO

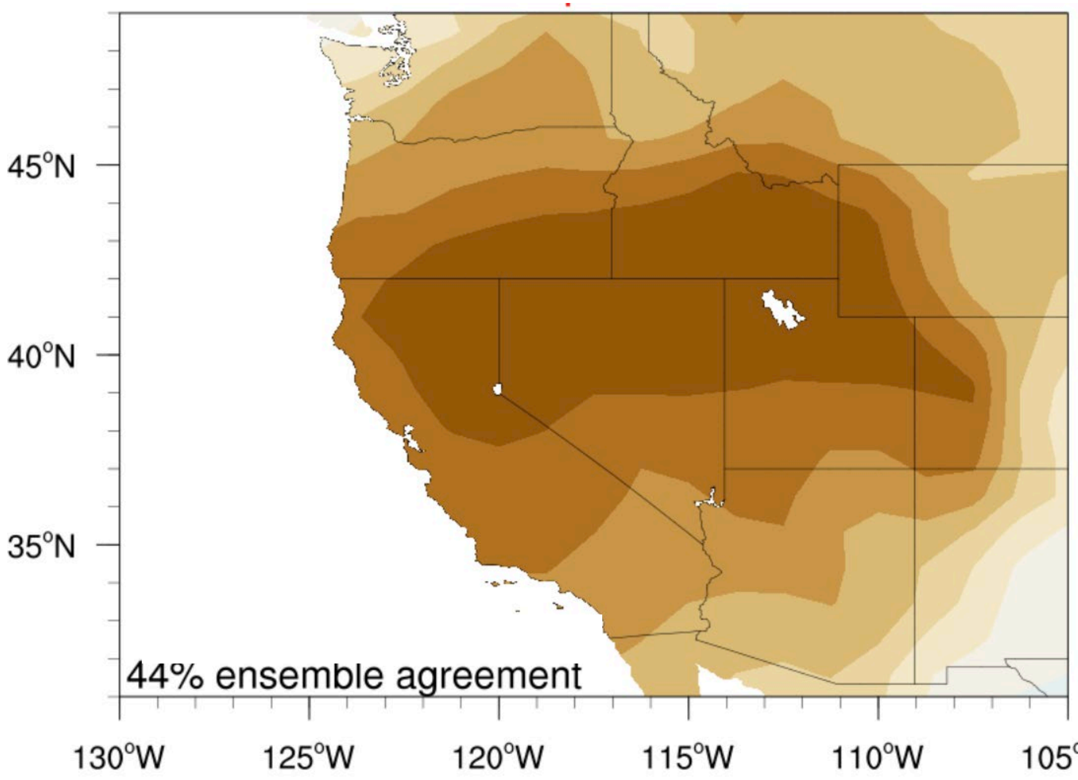
Jet Propulsion Laboratory
California Institute of Technology

Machine Learning Model NDJ Forecast

55% chance for wet Pac NW, dry SW



45% chance for widespread dry



Skill assessment: Gibson et al. 2021

Summary: NDJ 2021-2022 Seasonal ML Forecast

- Broad agreement across machine learning models for drier than normal wintertime precipitation in the Southwest US
  - consistent with emerging La Niña in tropical Pacific

- More uncertainty in forecast for Northern California. Some models favor normal conditions, while others predict drier or wetter than normal conditions.

Summary: CW3E-JPL S2S Team Effort

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.

Center for Western Weather and Water Extremes
SCRIPPS INSTITUTION OF OCEANOGRAPHY AT UC SAN DIEGO

DEPARTMENT OF WATER RESOURCES • STATE OF CALIFORNIA

NASA Jet Propulsion Laboratory
California Institute of Technology

Center for Western Weather and Water Extremes

SCRIPPS INSTITUTION OF OCEANOGRAPHY AT UC SAN DIEGO

cw3e.ucsd.edu

Thank you!

mdeflorio@ucsd.edu

Photo credit of Lake Mead: Oakley Originals