# Skillful Prediction of Seasonal Mean United States Precipitation Based on Past Global Sea Surface Temperatures

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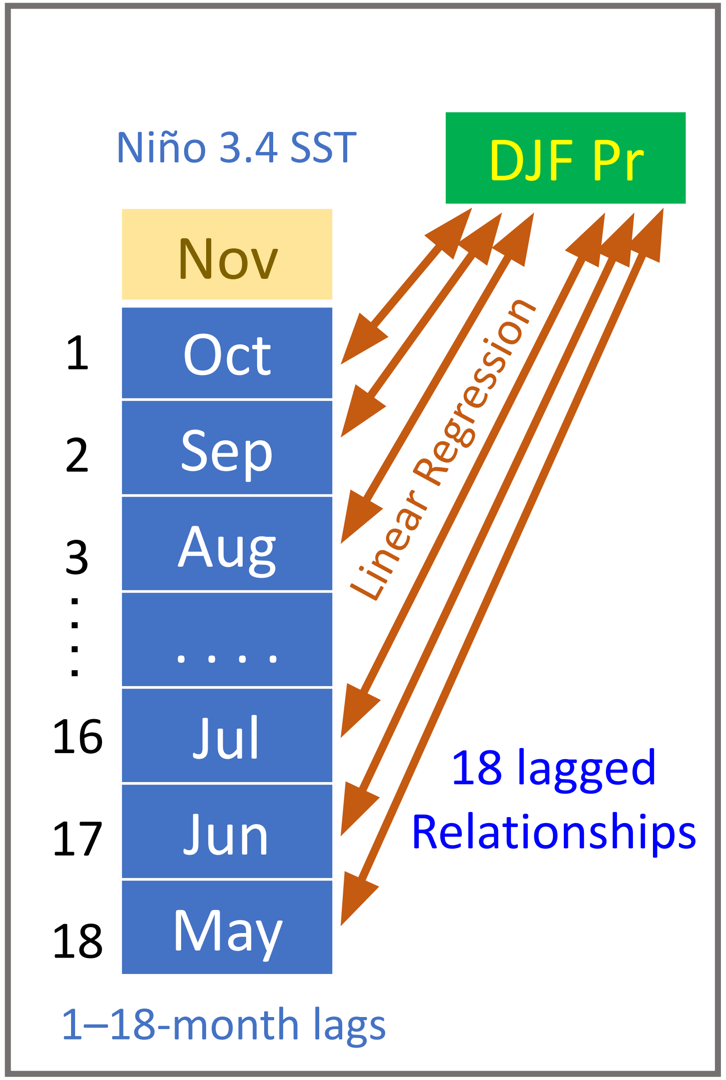
# Background

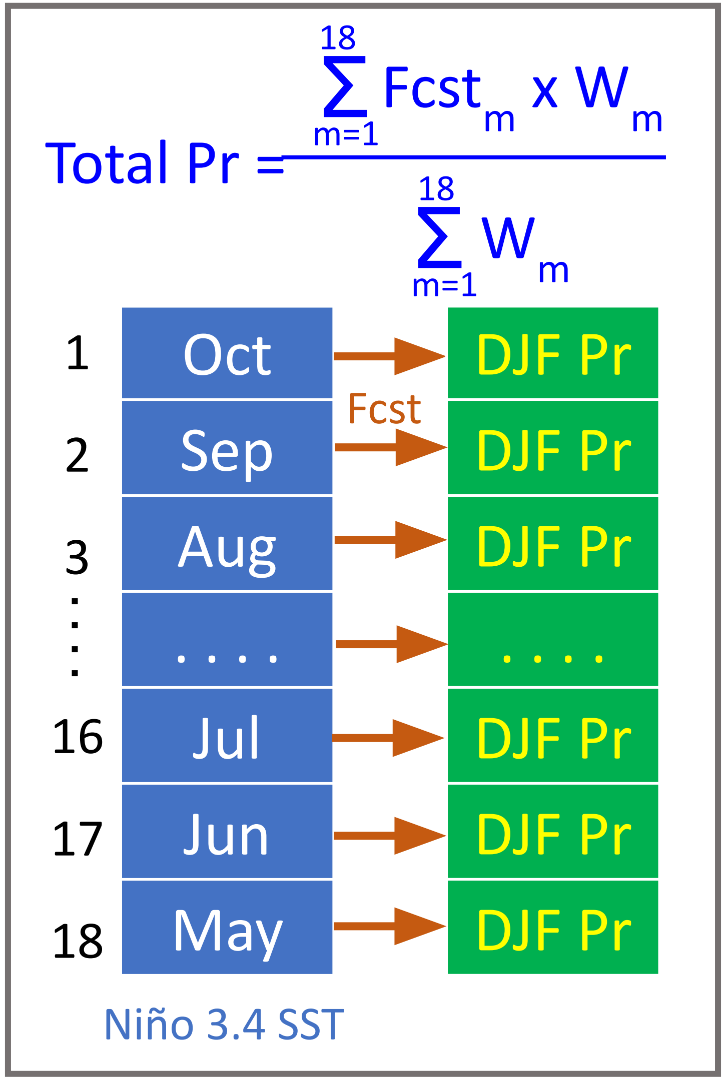
- Switanek et al. (2020)
  CLSST model
- Wang et al. (1999)
  SVD-based model

→ SVD-CLSST model

# Combined-Lead SST (CLSST) Model (Switanek et al. 2020)




Calibration Period




$$\text{Total Pr} = \frac{\sum_{m=1}^{18} Fcst_m \times W_m}{\sum_{m=1}^{18} W_m}$$

Validation Period

Weights:

$$W_m = \begin{cases} AC & \text{if } AC > 0 \\ 0 & \text{if } AC < 0 \end{cases}$$

Anomaly correlation (AC) skill assessed over the calibration period for each SST lag (m).

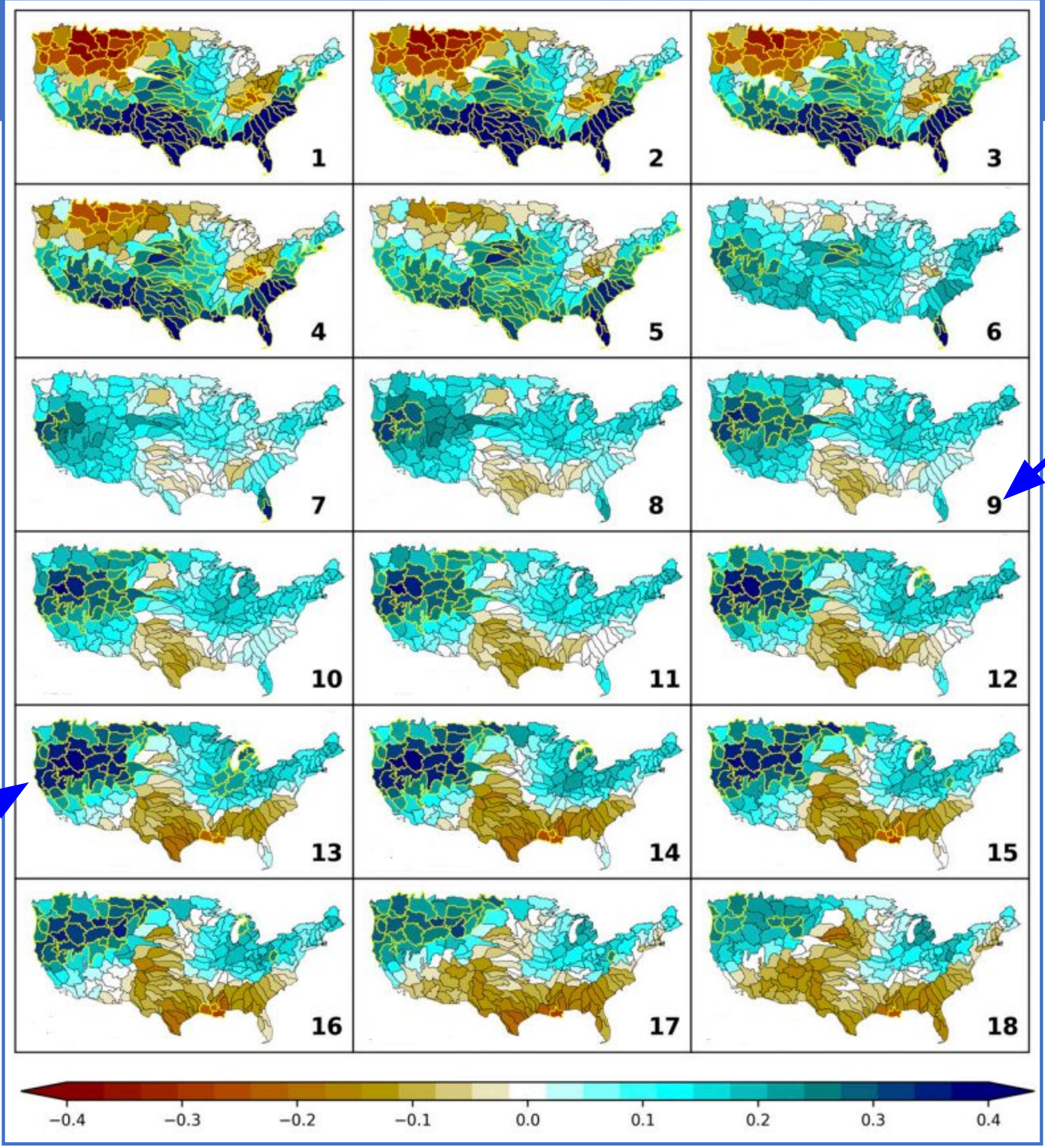
Unique Features

1) Predictive information from SSTs up to 18 months prior

2) Contributions optimized through weighting

# Lag Correlation

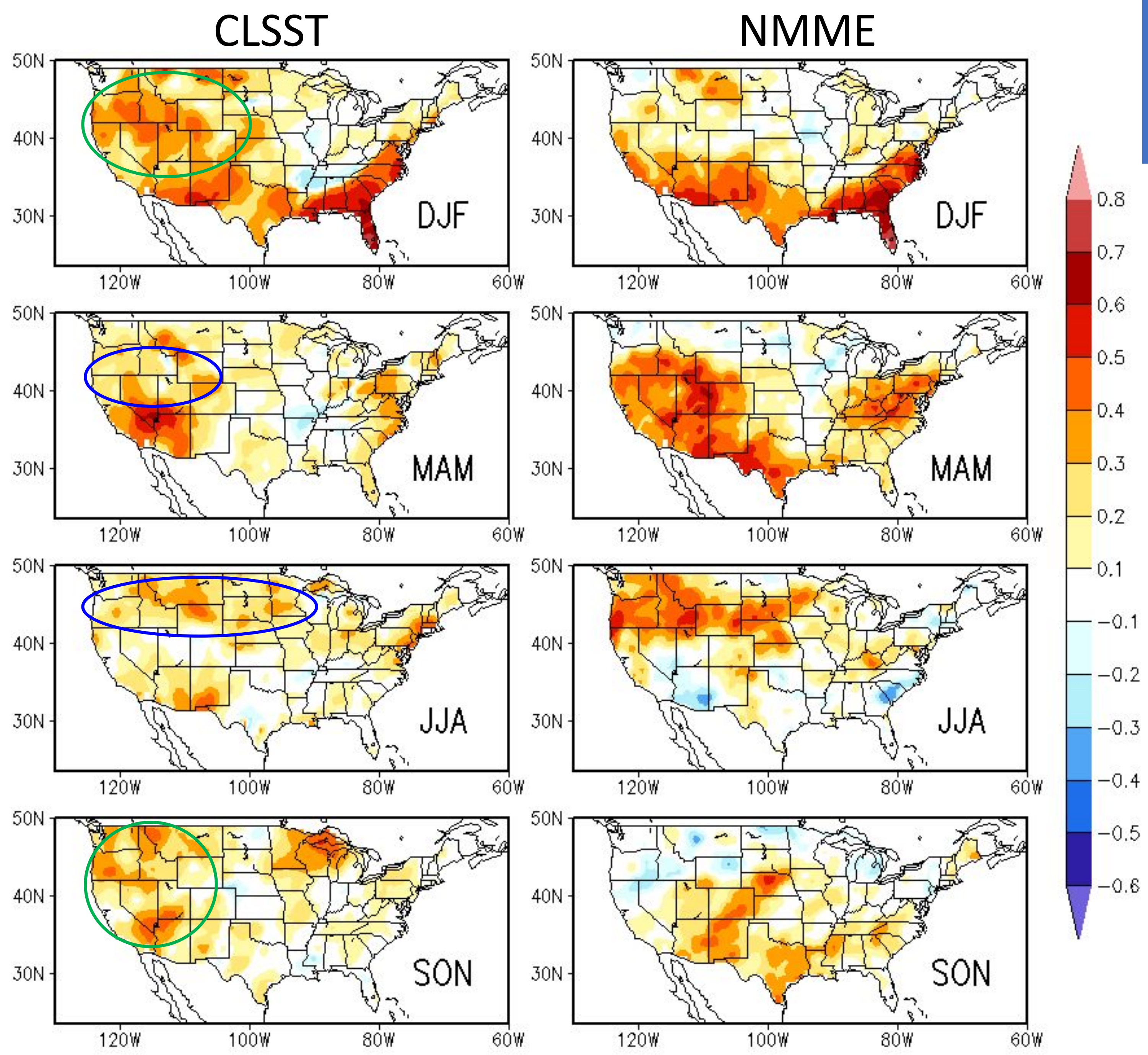
Cold Season Precipitation
vs.
Niño 3.4 SST
(Previous 1–18 months)




Months of SST Lags

Strong correlation in the western U.S.

(Switanek et al. 2020)



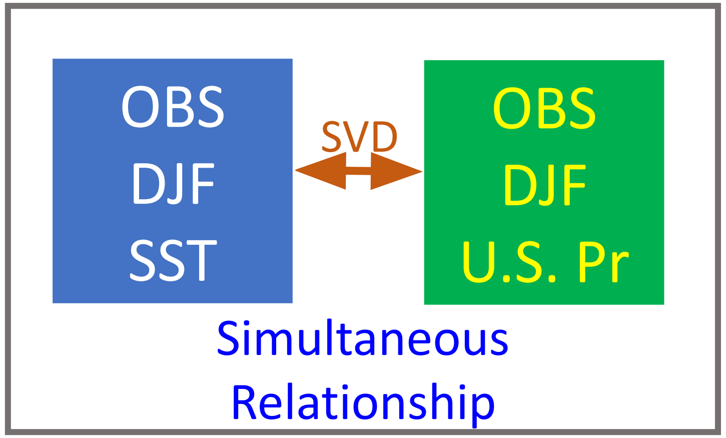

# Forecast Skill CLSST vs. NMME

**AC Skill (1982–2021)**
**Seasonal Precipitation**

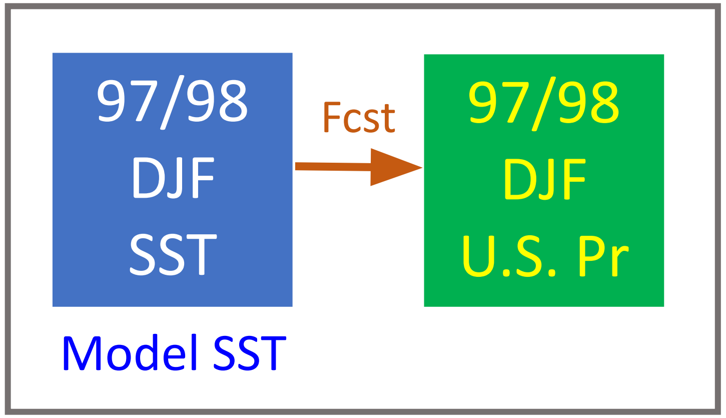
**CLSST Model**

- Better skill for DJF and SON in western U.S.
- Predictors: Niño 3.4 SST
  - Limited source of predictability
- Additional sources?
  - Using global SSTs

# SVD-Based Model (Wang et al. 1999)

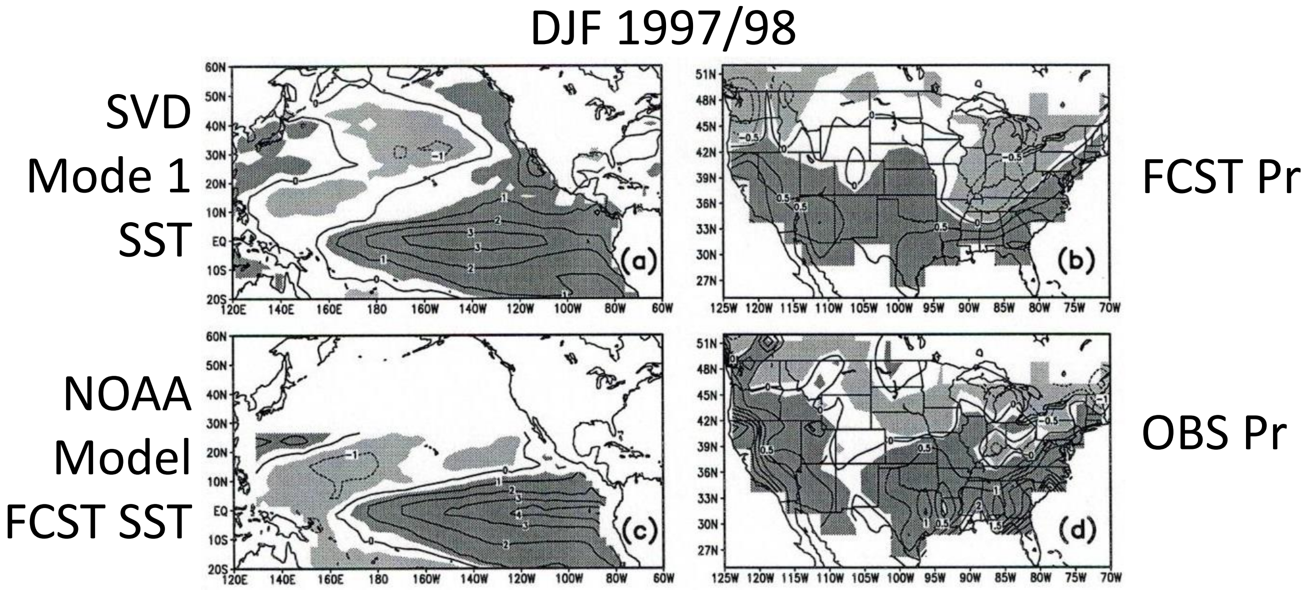



Calibration Period



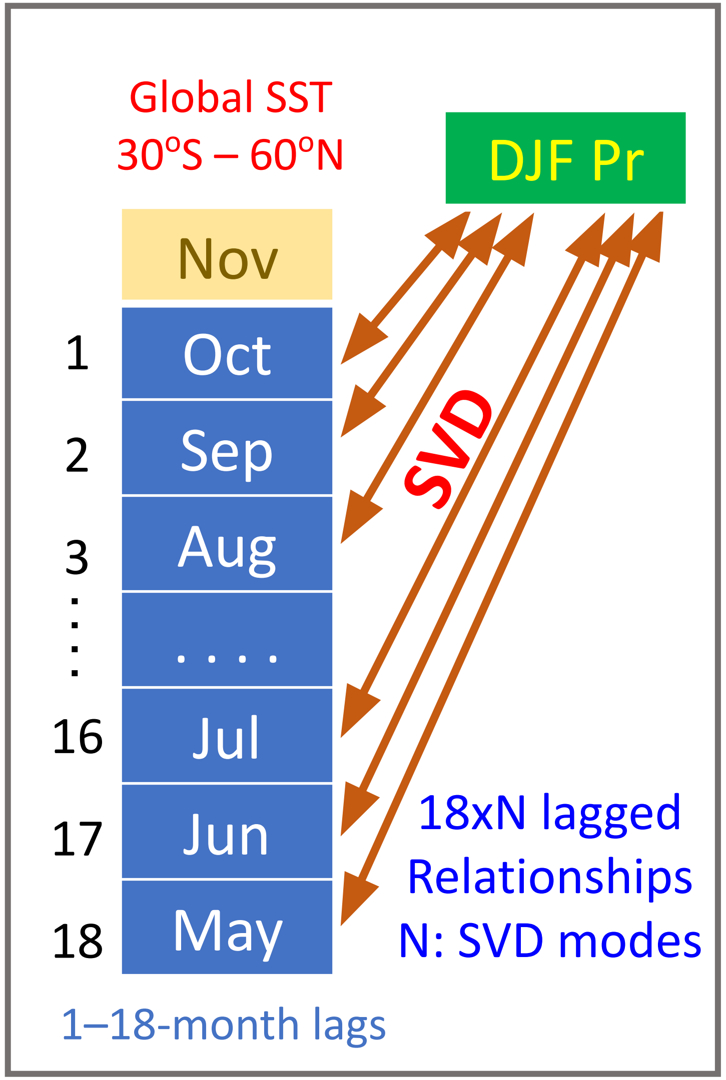

Validation Period

- SVD: Relationship between SST and U.S. precipitation
- Model predicted SST projected onto the SVD SST pattern
  - SST projection coefficient
  - Corresponding precipitation coefficient
  - Precipitation forecast

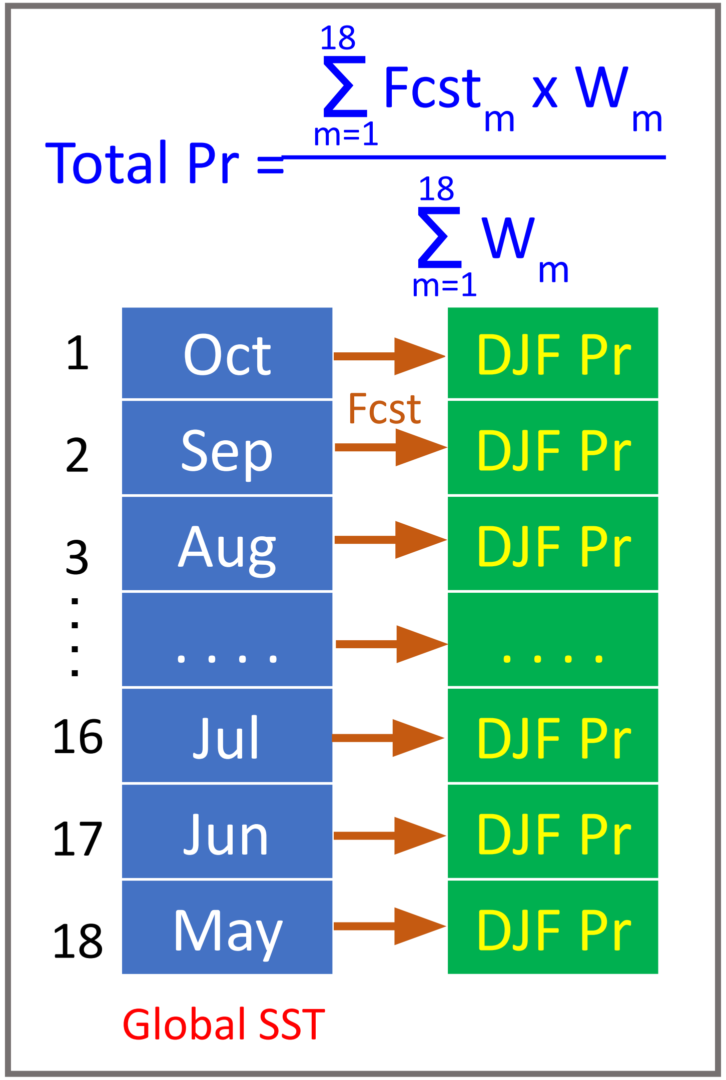



(Wang et al. 1999)

# SVD-CLSST Model




Calibration Period




Validation Period

Weights:

W = AC x |AC|

- Putting more weight on high ACs
- Including negative ACs

Unique Features Retained

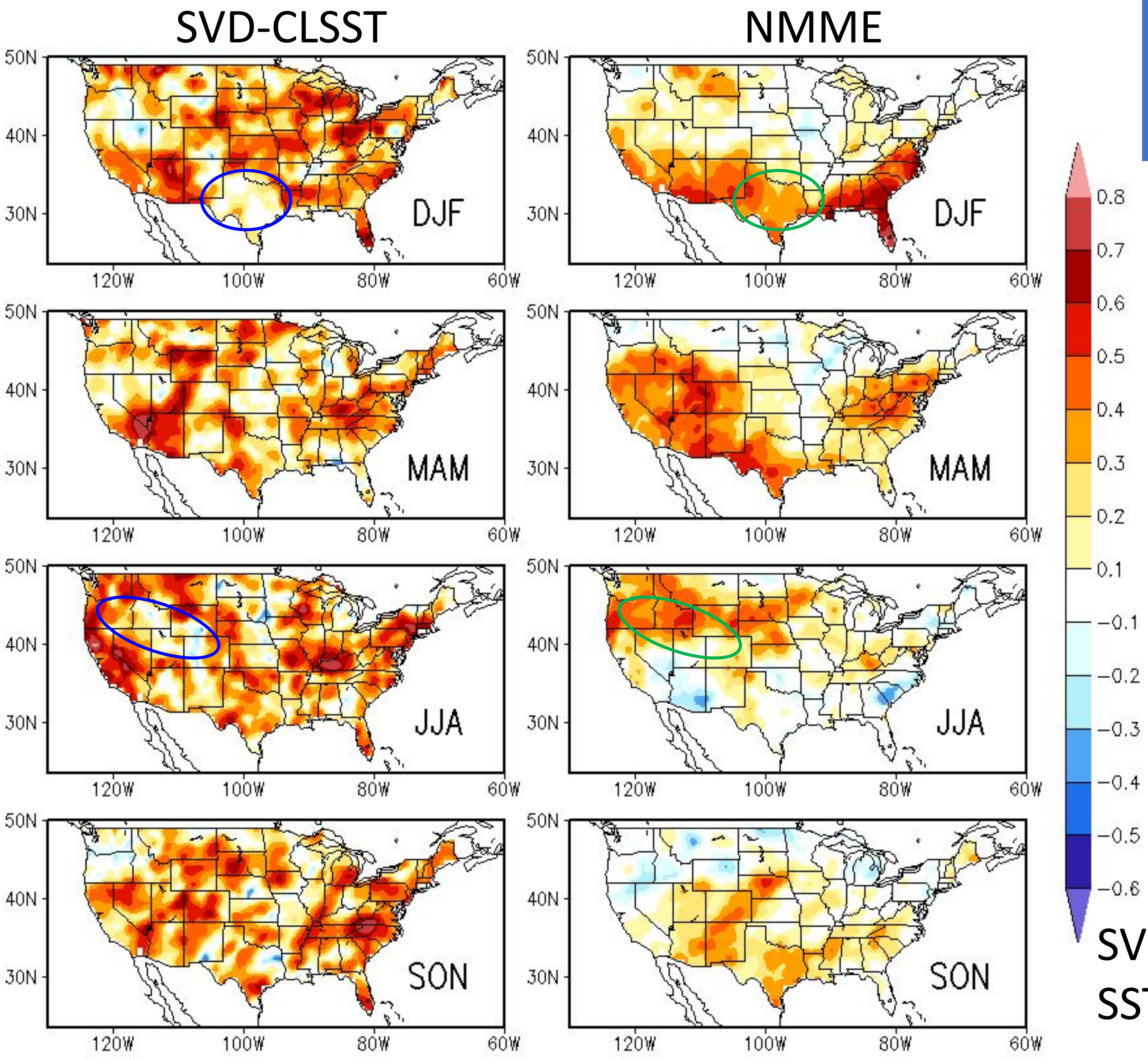
1) Predictive information from SSTs up to 18 months prior

2) Contributions optimized through weighing

# Results

- Skill assessment of the SVD-CLSST model
- Comparison with NMME
- NMME and SVD-CLSST merged forecast

# Forecast Skill SVD-CLSST vs. NMME




**AC Skill (1982–2021)**
**Seasonal Precipitation**

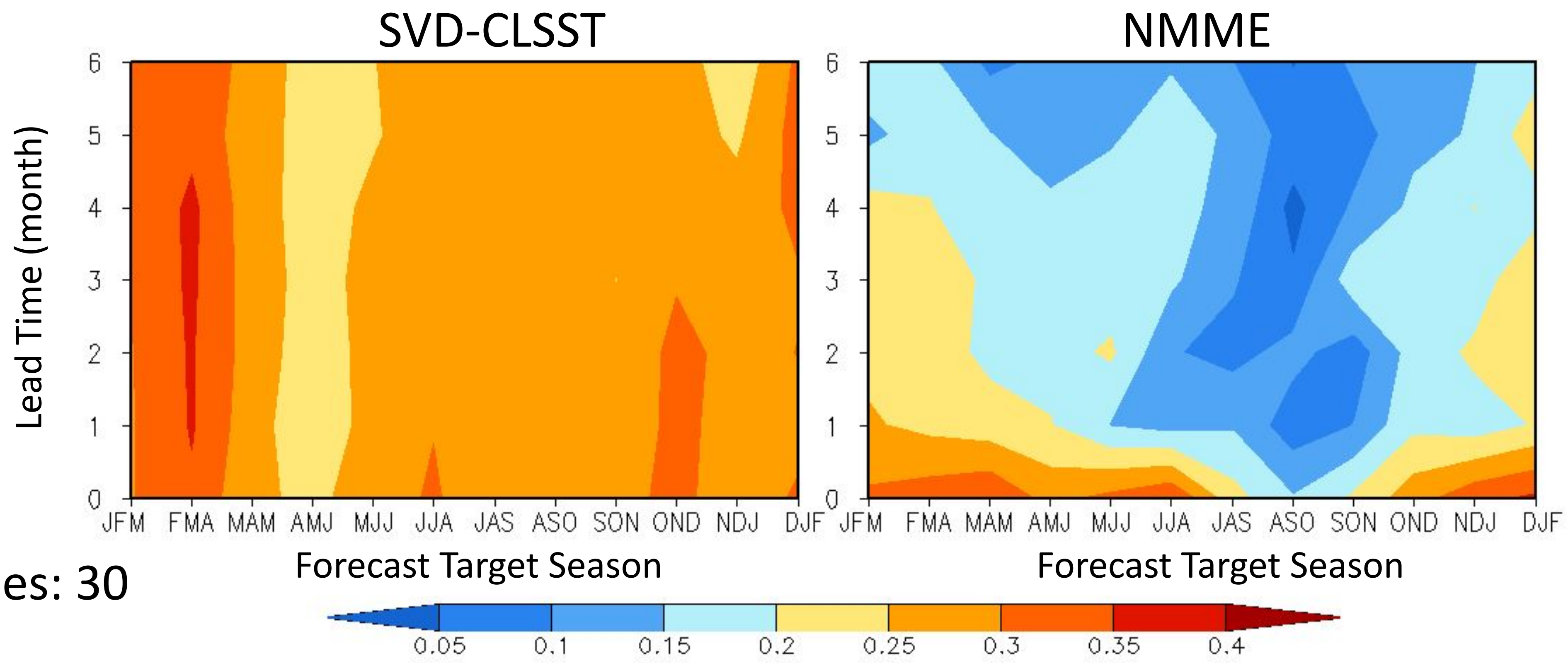
## SVD-CLSST Model

- Leave-5-yr-out cross validation
- Overall better skill
- More spatially homogeneous
- Lower skill in certain regions where NMME has higher skill

SVD modes: 30
SST lags: 1–18 months

# How does the AC skill change with lead time?

CONUS Averaged AC Skill Seasonal Precipitation 1982–2021



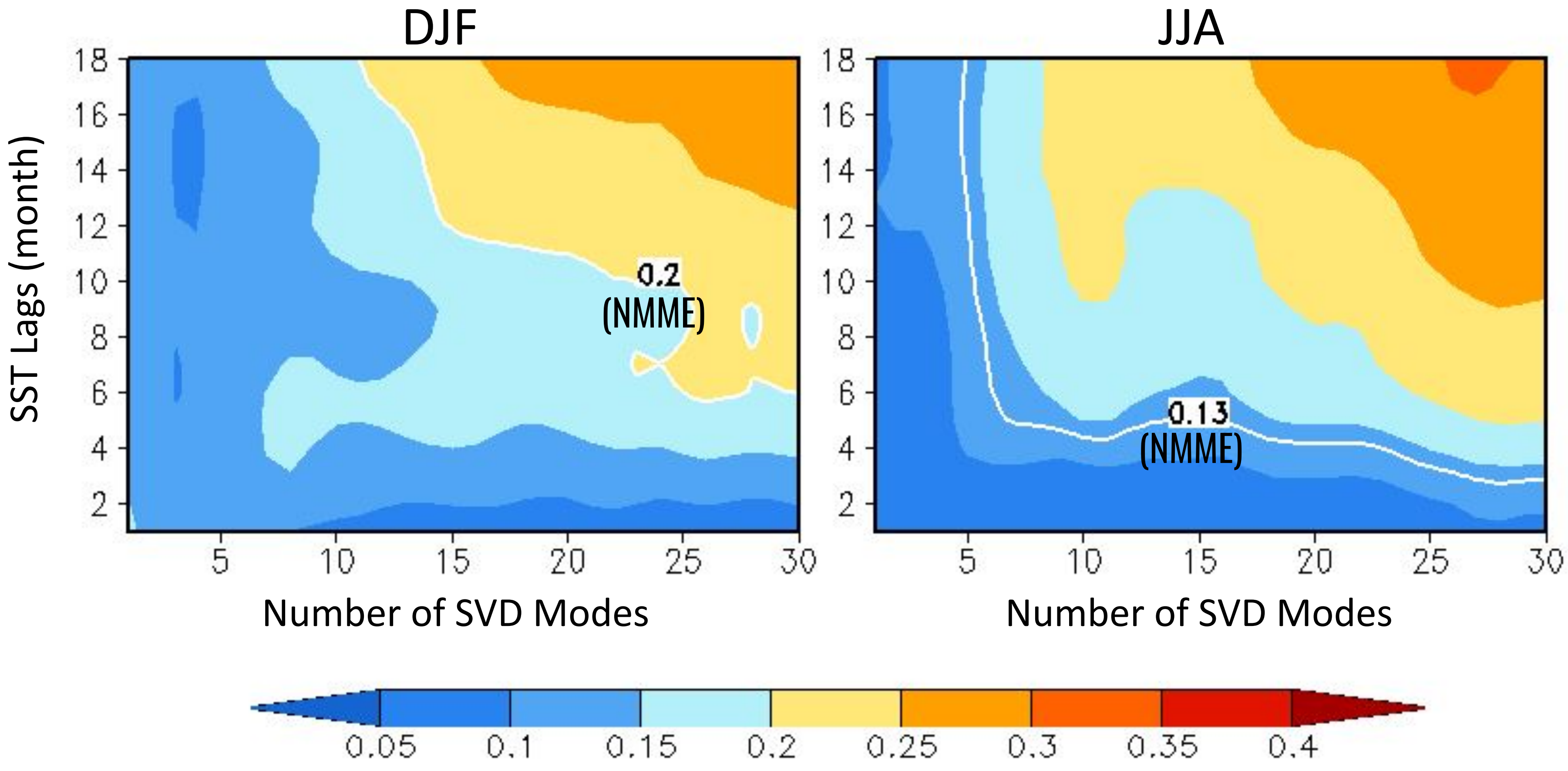

SVD modes: 30
SST lags:
1–18 months

- Weak seasonality
- No significant decrease with lead time

- Strong seasonality
- Decrease in skill with lead time

# CONUS Averaged AC Skill

- Number of SVD modes
- Number of SST lags

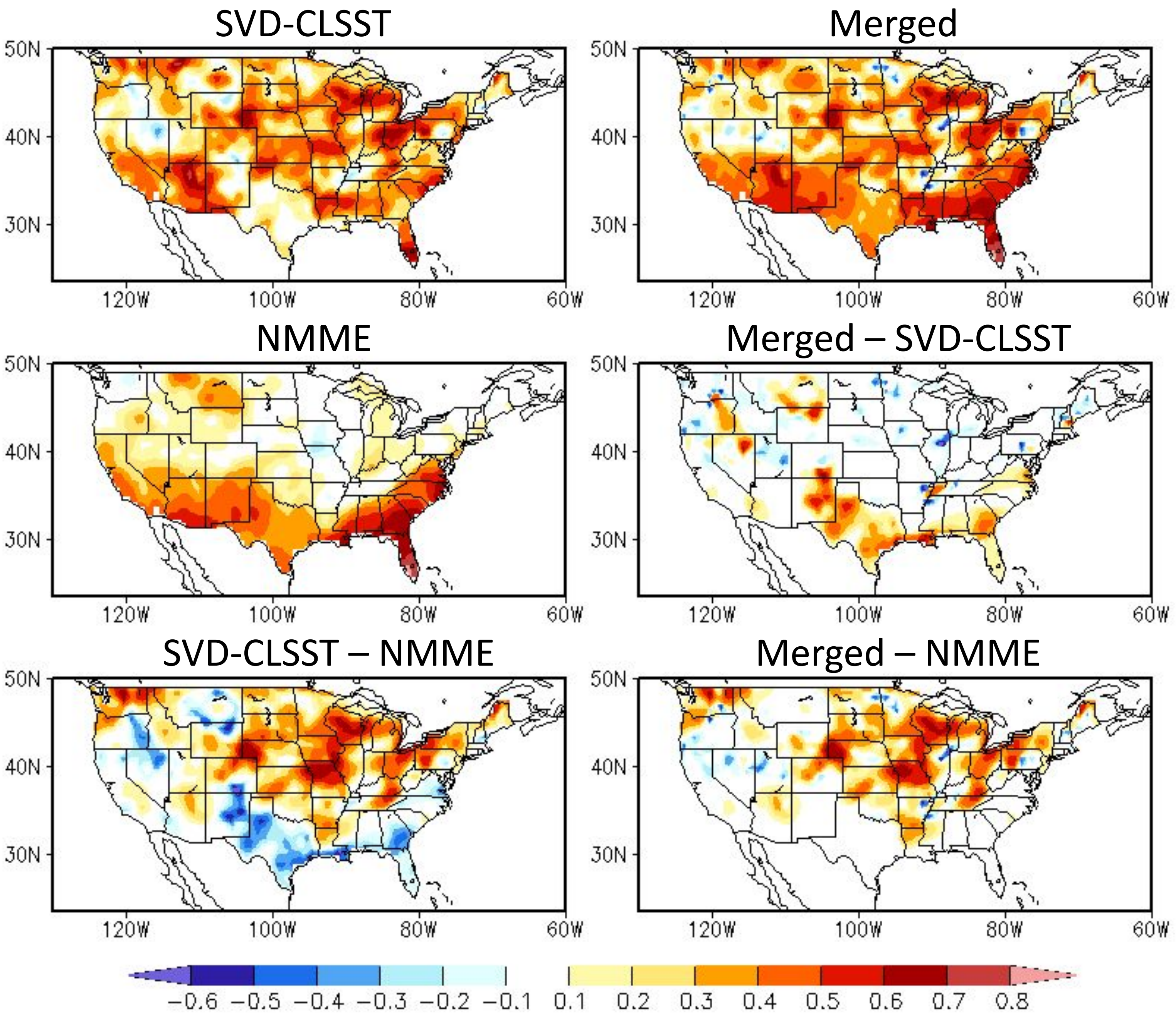



Skill increases with number of SVD modes and SST lags used.

1-month lead forecast

White contour: NMME AC skill

# Merged SVD-CLSST and NMME Forecast: DJF




**AC Skill for DJF Pr 1982–2021**

1-month lead forecast

SVD modes: 30

SST lags: 1–18 months

Merged forecast of dynamical model (D) and statistical model (S):

$FCST_{merged}$ =

$(FCST_D \times W_D + FCST_S \times W_S) / (W_D + W_S)$

W = AC x |AC|

# Summary

- The SVD-CLSST model exhibits superior skill compared to NMME, offering a spatially more homogenous distribution of high skill levels.
- Forecast skill tends to rise with an increase in the number of SVD modes and SST lags (predictors) used.
- The merged forecast provides valuable supplementation to NMME in areas where NMME demonstrates lower skill levels.

# Future Work

- Understanding physical processes responsible for the lagged SVD relationships between global SST and U.S. precipitation.
- Potential application of precipitation from the SVD-CLSST model for drought prediction.