Seasonal Rainfall Forecasting with Multimodel Climate Ensembles

PREPARE Drought and Flood Early Warning for Pacific Islands Training Workshop
Nadi, Fiji, 15-20 July 2024

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NOAA/CPC/International Desks

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All models are wrong, *but some are useful*

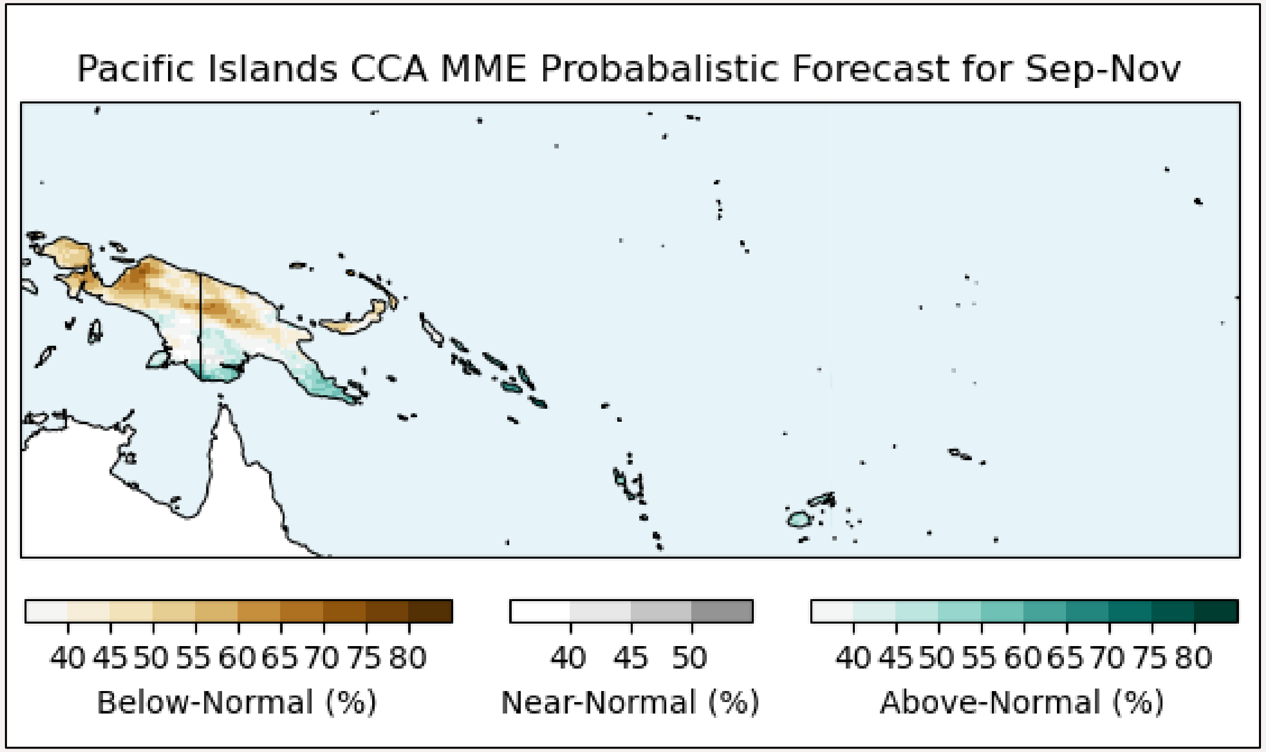
Earth system is complex and chaotic, no model will have a perfect representation of future conditions

We can **improve** the **usefulness of a prediction by**

(1) **Choosing a more attainable forecast type** for a model (e.g. tercile-based probabilities)

(2) **Combining forecast models** to aggregate different assumptions about the earth system

(3) **Bias-correcting** our raw model outputs using statistical relationships



Common Models / Rainfall Data Products Used at the CPC International Desk

Monitoring Products	Subseasonal Forecasts	Seasonal Forecasts
CMORPH 0.25' rainfall data	GFS (1 member, many variables)	**NMME - North American Multimodel Ensemble** -NOAA NCEP CFSv2 -NOAA GFDL SPEAR -NASA GEOSv5 -NCAR CSM4 and/or CESM1 -Canadian Models (GEM5-NEMO, CanCM4i)
CHIRPS 5km rainfall data	GEFS (31 members, a few variables)	C3S Multimodel Ensemble (European models) -ECMWF SEAS 51 -UK Met Office Glosea6 -Meteo France System 8 -German DWD System 21 -Italian CMCC System 35 -Canadian Models (GEM5-NEM, CanCM4i) -NOAA CFSv2
CMAP		
CPC Unified Gauge		
RFEv2		

Several techniques can correct raw forecasts

- **Canonical Correlation Analysis (CCA)** – spatial pattern matching using linear correlations
- Logistic Regression (LR) **–** probability of a binary outcome (probability of above or below normal) based on one or more predictor variables, applied separately for each tercile
- **Extended Logistic Regression (ELR)** – nonlinear ensemble calibration that extends Logistic Regression and is applied across all terciles simultaneously
- Probabilistic Output Extreme Learning Machine (POELM) – nonlinear advanced machine learning approach (neural network with a single hidden layer)
- **Extended Probability Output Extreme Learning Machine (EPOELM)** – combines ELR and POELM approaches, useful for non-exceedance forecasts for any threshold value after fitting

Considerations for applying these techniques

- Grid by grid vs. spatial pattern matching
- Need for examining nonlinear vs. linear relationships
- Choosing predictor variables, e.g. SSTs or Precip

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How comfortable do you feel with using CCA as a bias correction technique?

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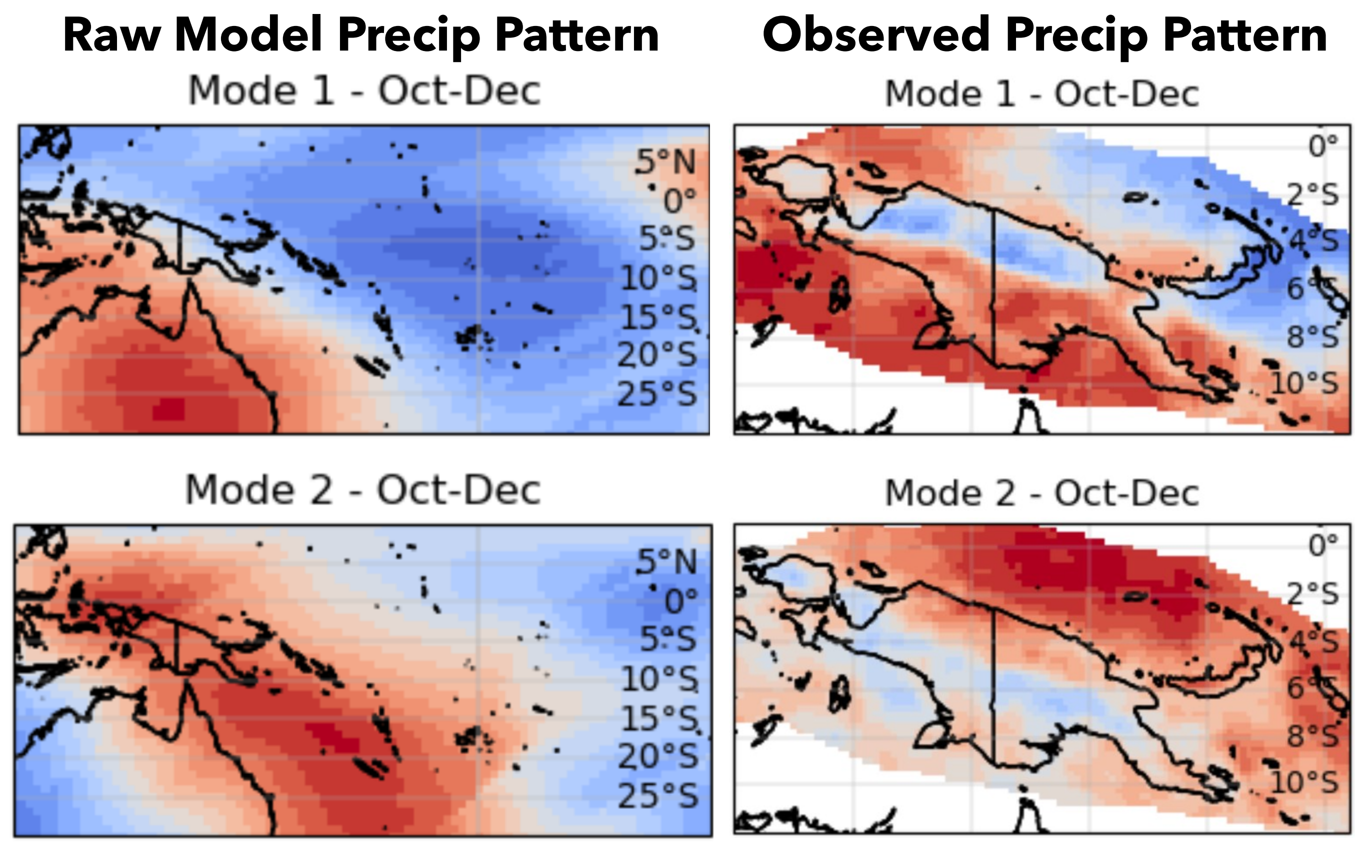
CCA corrects the pattern of the spatial bias and downscales raw model forecasts to the predictand resolution

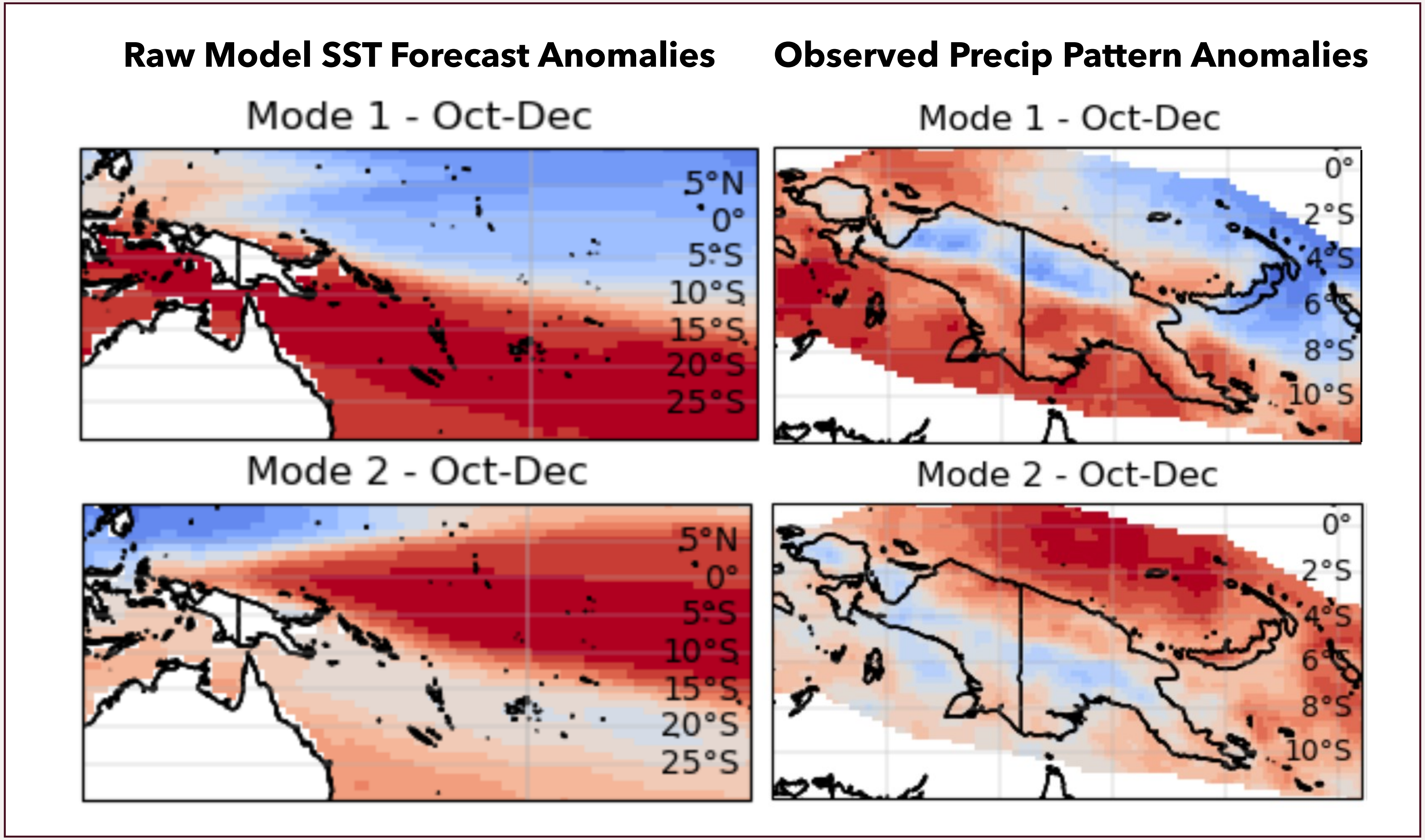
Key CCA Steps

1. **Estimate spatial pattern** with a principle component (PC) analysis
2. **Correlate PCs**
3. **Find combinations** between principle components **with maximum correlation**



Example: Comparing the Spatial Pattern of Rainfall Anomalies

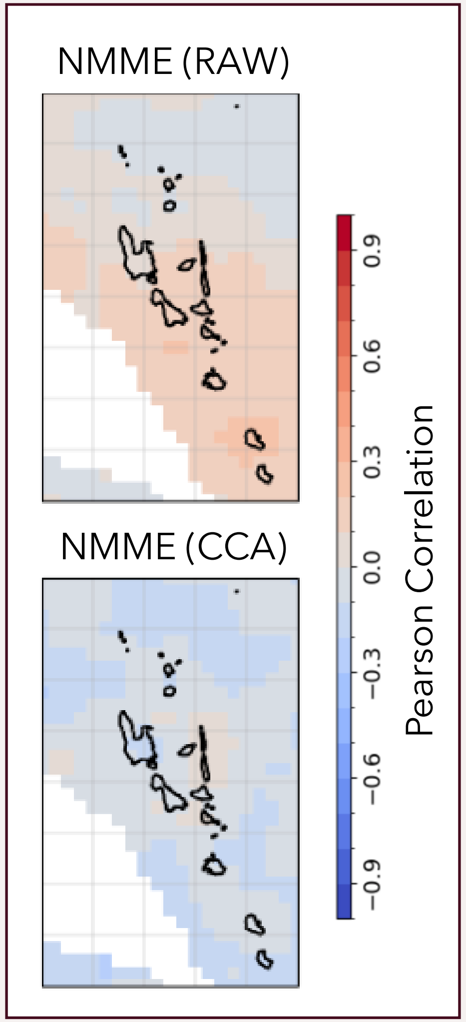
Diving More Deeply into CCA
Possibilities of Driving Precip Forecasts with SST



Verification is KEY - Skillfulness of Bias Correction Varies Spatially and Seasonally

- **CCA** is **often better over large zones but** can be **sensitive to** the **spatial extent** used to train a model **and** the **time of year**

- **Grid-based techniques** (ELR, EPOELM in this session) can **better account for nonlinear relationships**, **but require more data** to be useful **and often perform worse in small zones** where there are fewer grid cells to train a model (e.g. small islands)



Example of Bias Correction Not Helping Over Vanuatu
Model Initialized October, Predicting Dec-Feb

Step by Step Verification/Consolidated Ensemble Generation Process using CMORPH 0.25′ rainfall data

1. **We train and verify our model using hindcast data** – prior forecasts over a historical period
2. **We expand our dataset years** because CMORPH data is only available from 1998-2022 (25 years). To expand our dataset, we train our data over 3 seasons at a time

EXAMPLE: Model is initialized this month, 1st of July, 2024, for a one-month lead forecast (August-October, ASO), we pull hindcast data from July-Sep, Aug-Oct, and Sep-Nov for 25 available years (75 data points to train/test our model performance)

3. **We split training/testing years.** When we train the model using CCA we dump out X number of years (e.g. 5), but will randomly pull the test years 75 times.
4. **We apply a skill score** (e.g. Pearson or GROCS) to comparatively examine how the raw and bias-corrected forecasts compared
5. **We generate a consolidated ensemble** that combines different bias correction techniques, weighted by their skill (e.g. GROCS)

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How comfortable are you with applying the Generalized Receiver Operating Characteristic Score (GROCS) as a verification score for forecasts?

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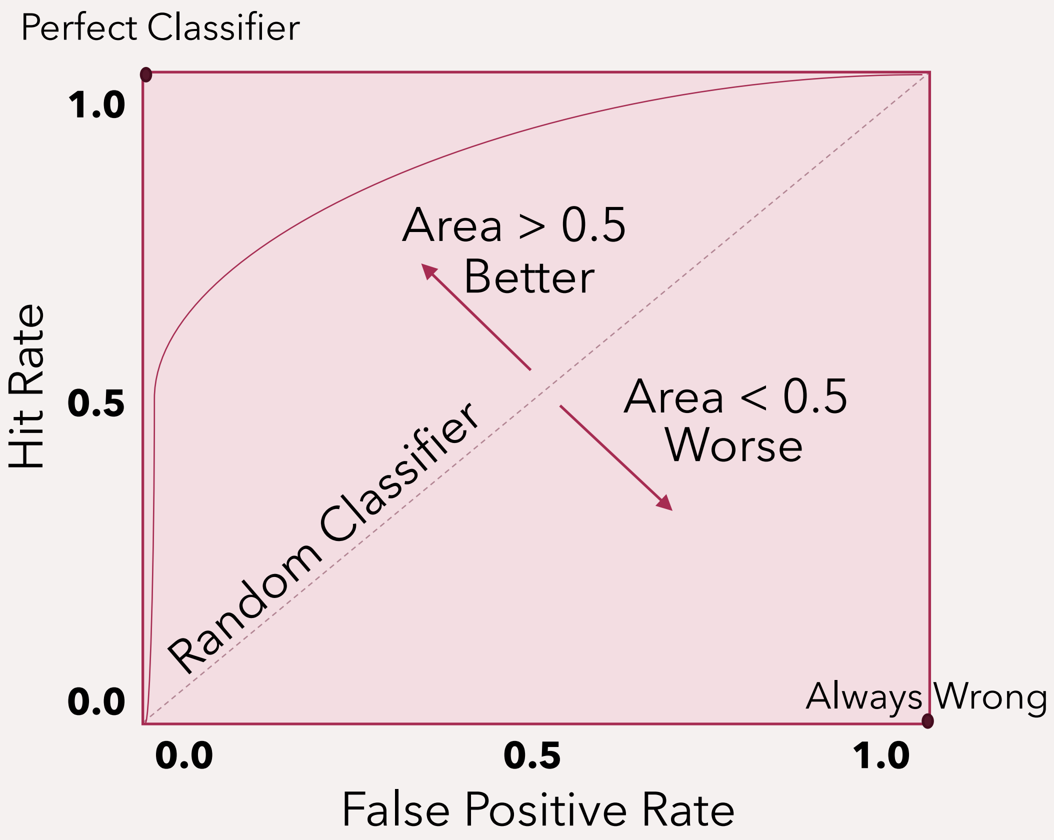
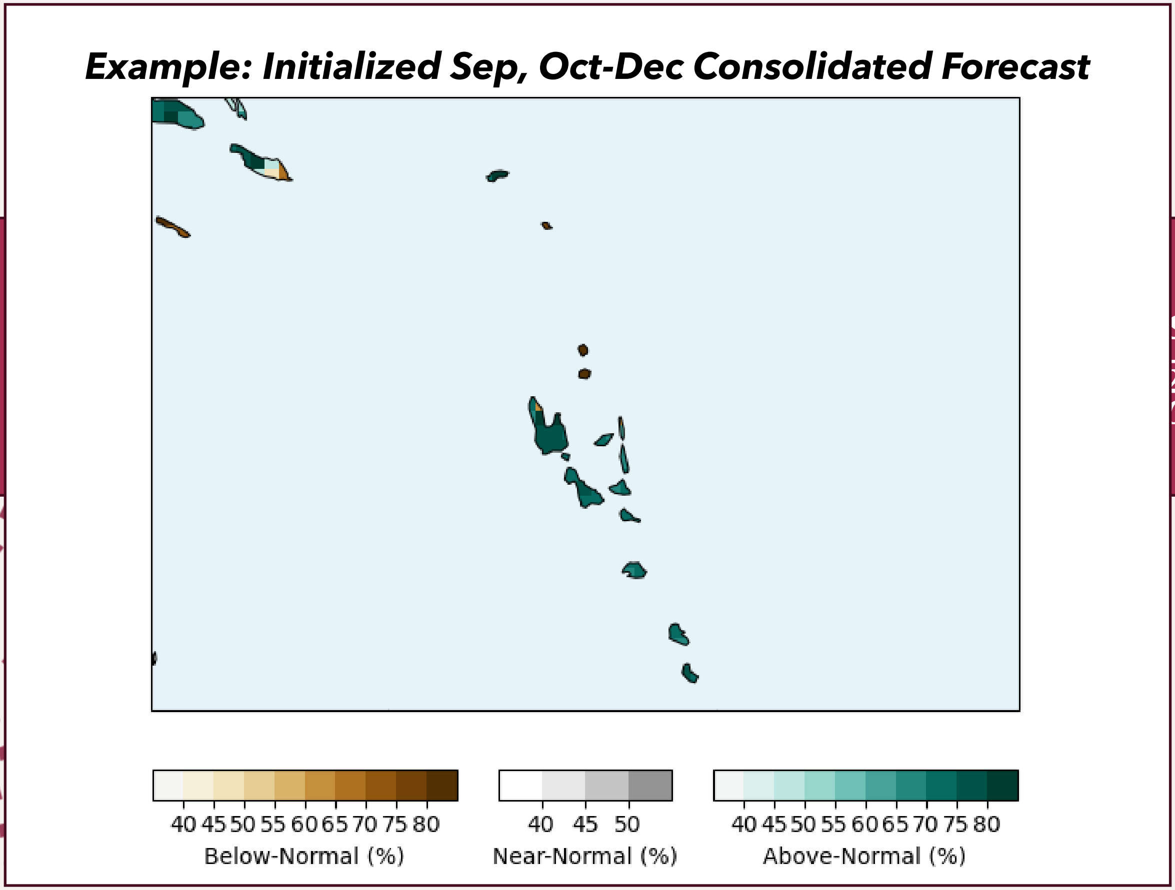
Verification Metric Used in Today's Session: Generalized Receiver Operating Characteristic Score (GROCS)

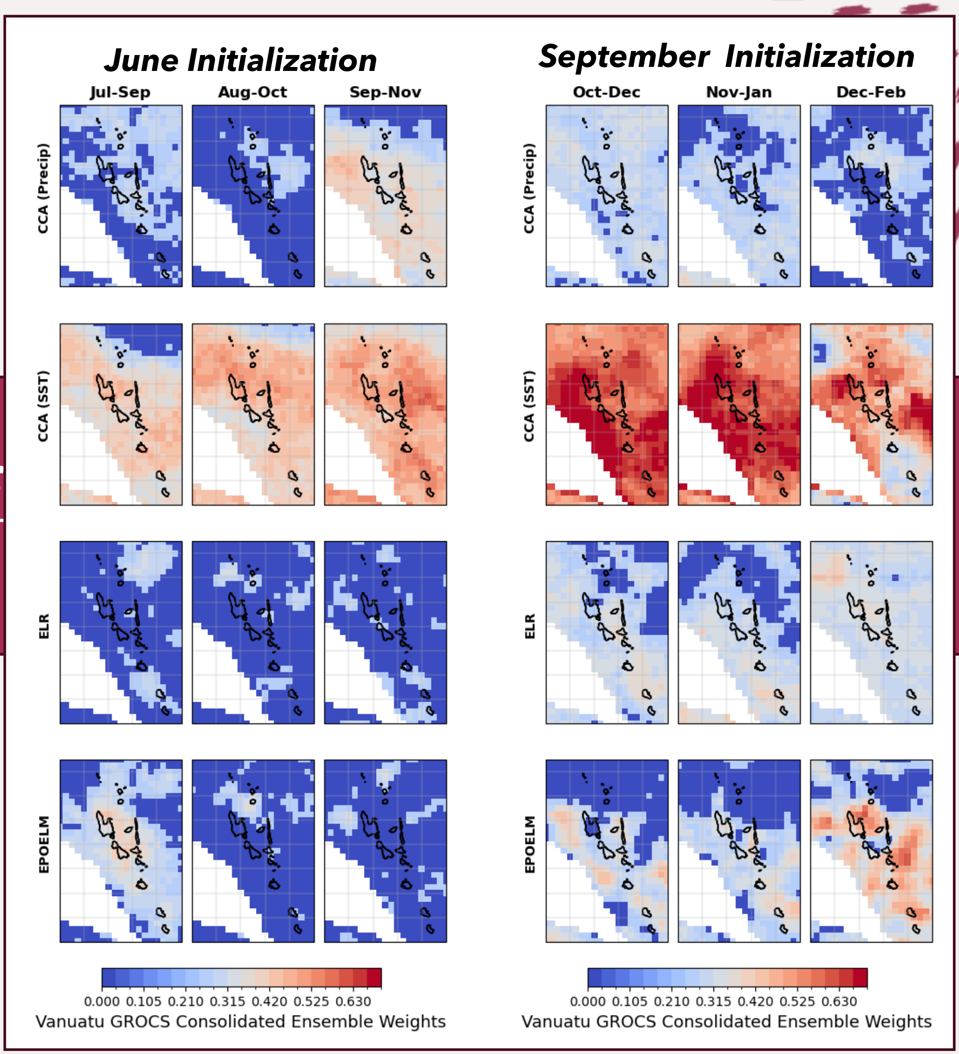
- **Receiving Operating Characteristic Curve – ROC:** visualization of the ability of a forecast to discriminate between binary classes (e.g. False Positive, Hit Rate, Misses)
- **Generalized ROC:** ROC applied to probabilistic forecasts, degree of correct probabilistic forecast discrimination between all forecast categories (e.g. below-normal, normal, and above normal)

<u>ROC Visualized</u>



Using GROCS to generated a consolidated weighted ensemble forecast



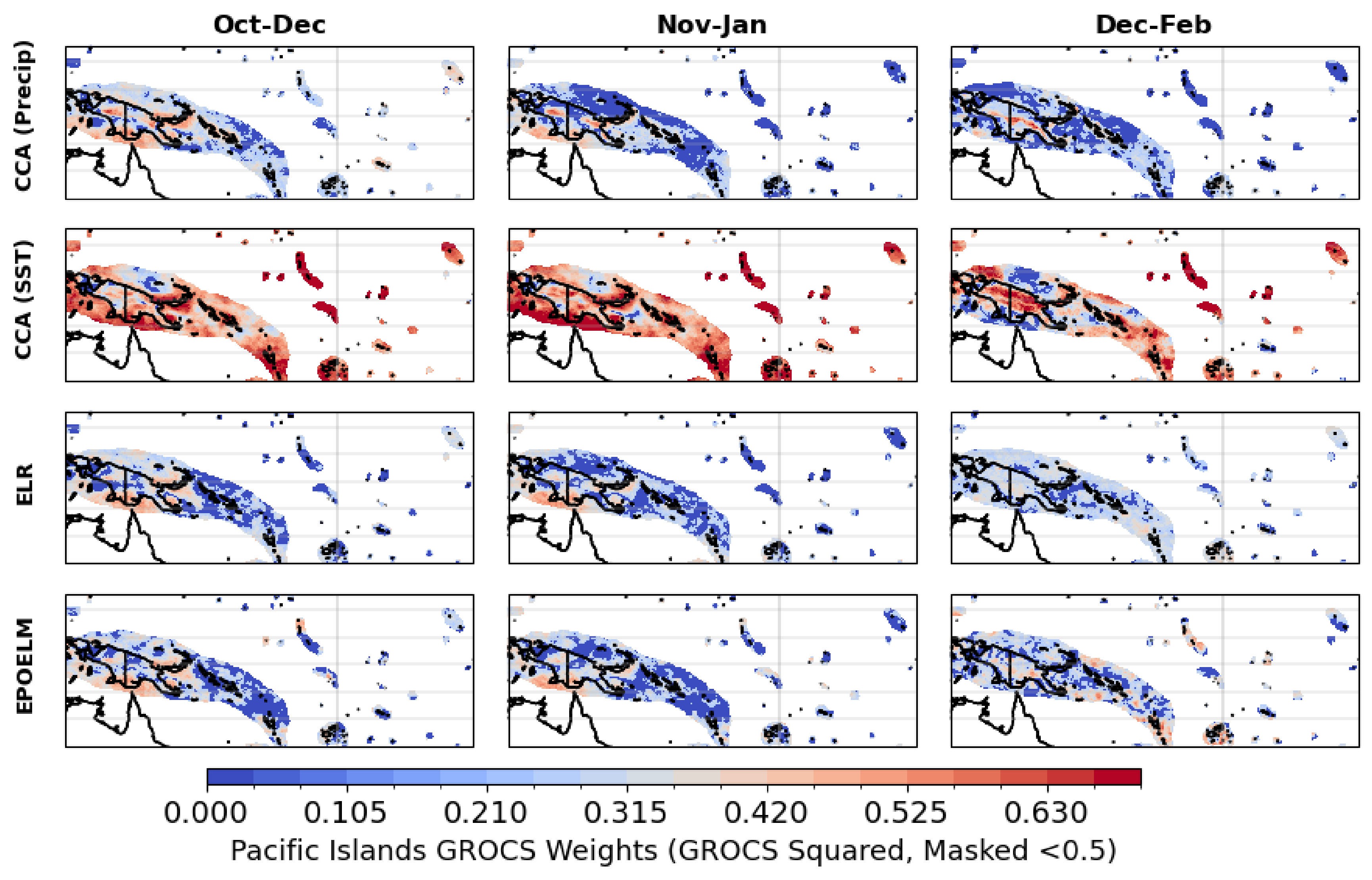


Consolidated Probabilistic Forecast (After masking GROCS < 0.5) =

$$\frac{prob(CCA{-}SST\ fcst) * GROCS^2_{CCA-SST} + prob\ (CCA{-}Precip\ fcst) * GROCS^2_{CCA-Precip} + prob(ELR\ fcst) * GROCS^2_{ELR} + prob(EPOELM\ fcst) * GROCS^2_{EPOELM}}{GROCS^2_{CCA-SST} + GROCS^2_{CCA-Precip} + GROCS^2_{ELR} + GROCS^2_{EPOELM}}$$

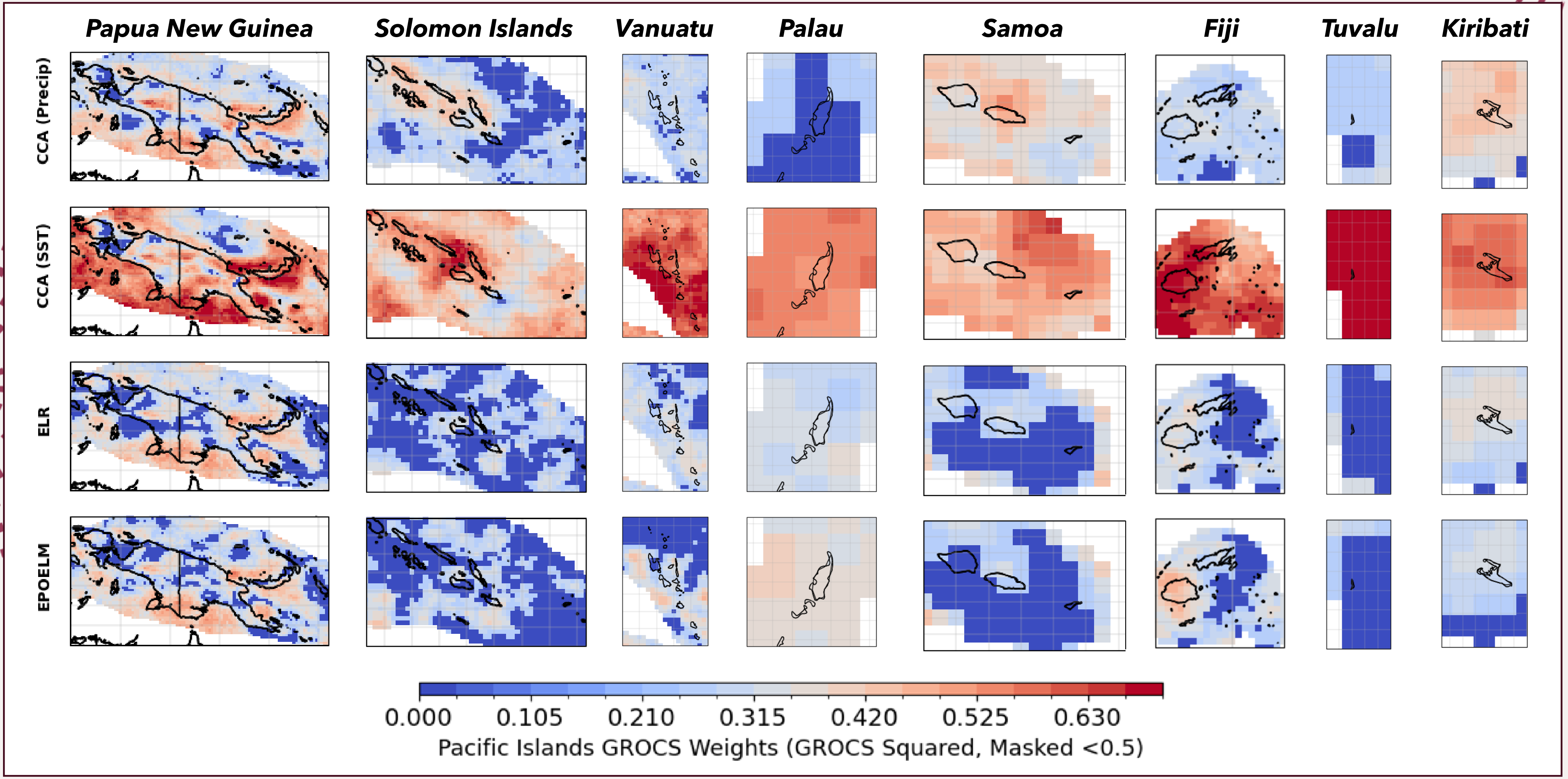
An Intercomparison of Methods

CCA, ELR, and EPOELM, initialized Sep for Oct-Dec Prediction



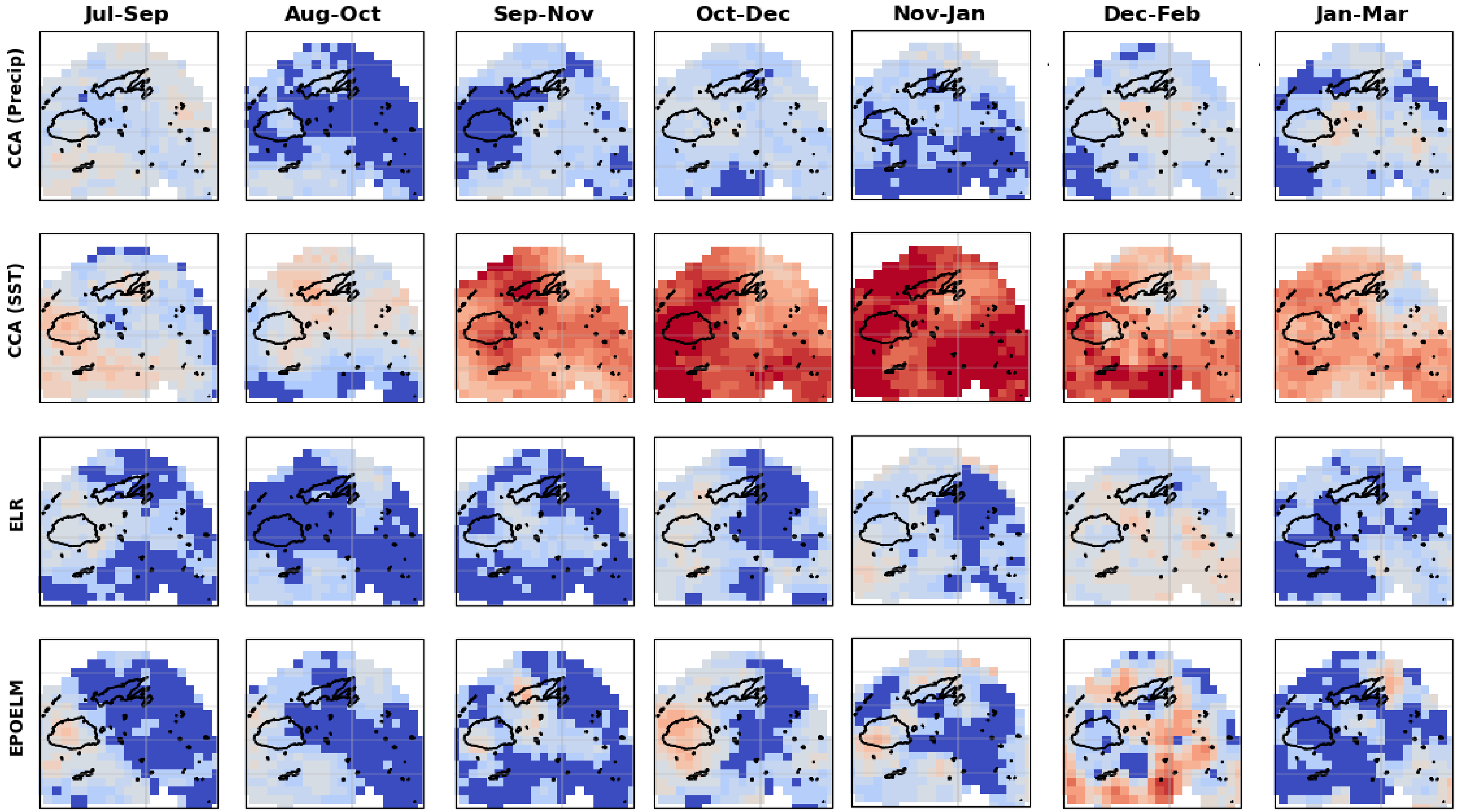
Spatial Intercomparison of Methods

CCA, ELR, and EPOELM … initialized Sep for Oct-Dec Prediction



Seasonal Intercomparison of Methods

CCA, ELR, and EPOELM … seasonal skill comparison in Fiji



Model Initialized One Month Ahead of Season (Same Scale as Prior Slide)

Goals of Today's Practical Session

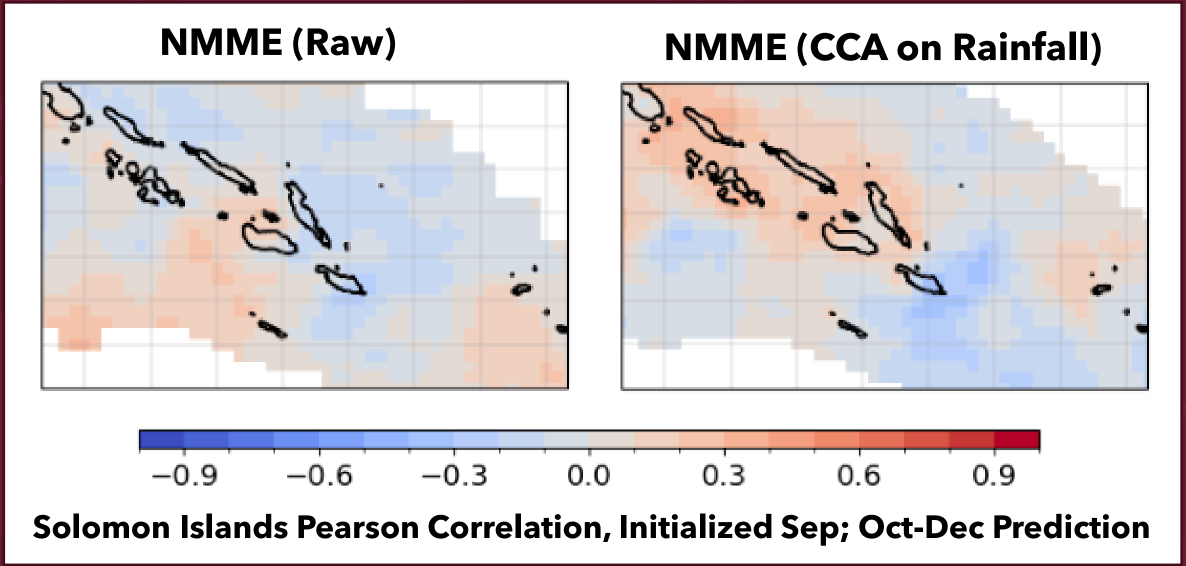
Use — **Use CCA to bias correct an NMME forecast**

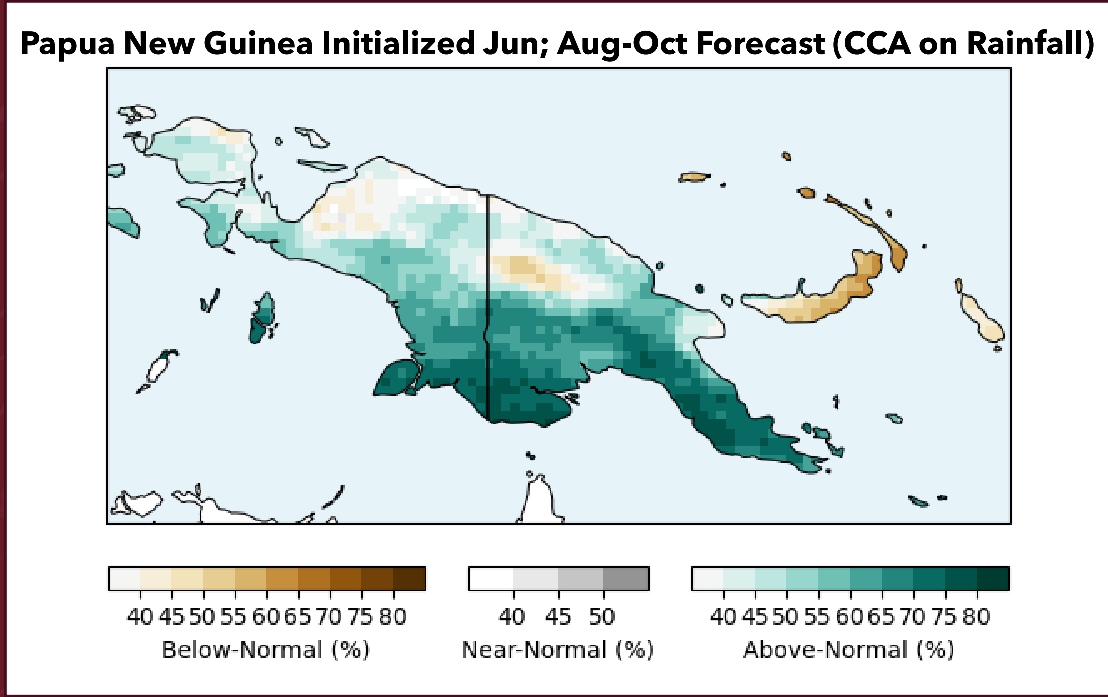
Compare — **Compare** the **CCA approaches** to see how **driving forecasts with SSTs vs rainfall** affects forecast performance

Consider — **Consider seasonal variability** of the correction techniques

Consider — **Consider spatial variability** of the above correction techniques

Predict — **Predict seasonal rainfall** by generating a probabilistic tercile forecast using a bias correction technique of choice





Example Plots