Multivariate correction and statistical disaggregation for seasonal multi-model ensemble forecast applications

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Outline

- Seasonal Forecasting, NMME, and SERVIR
- Seasonal Forecasting Challenges
- Addressing these challenges
- Limitations and advantage of model adjustment
- Alternative Approach: Multivariate regression of forecast errors
- Results
- Summary

SERVIR and Seasonal Forecasting

- SERVIR is a joint NASA-USAID project to bring Earth observations to use in decision-making systems in SERVIR hub regions: East Africa, Hindu-Kush Himalaya, and Mekong

- Our project was selected to serve the SERVIR Applied Science Team through development and evaluation of downscaled seasonal forecasts for use in impact models to be applied in different SERVIR hub regions
  - Stephanie Granger/ Jet Propulsion Laboratory / ***East Africa*** *Drought and Agricultural Productivity Assessment and Prediction System*
  - Faisal Hossain / University of Washington/ *Early Warning, Mapping, Post-Disaster Visualization System for Water Resources of Low-Lying Deltas of the* ***Hindu Kush-Himalayan Region***
  - Juan Valdes / Univ Arizona / *Water Resource Projections on Medium Range to Decadal Scales for Selected Basins in* ***Africa***

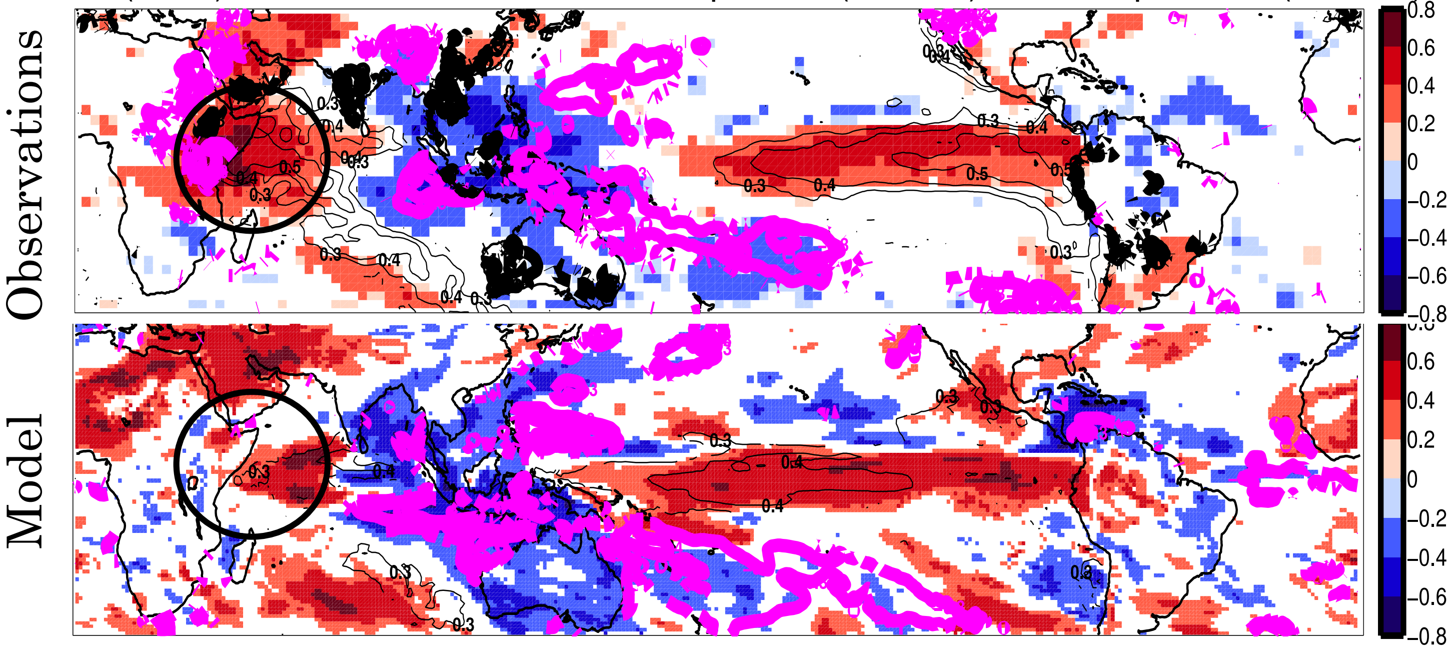
- Seasonal Forecasts: Provided by the North American Multimodel Ensemble (NMME)
  - 9 models contributing operationally , ~100 ensembles
  - Precipitation, sea surface temperature, and 2-m air temperature are the only variables across all operational models
  - Hindcast archive covering 1982-2010
    - Available at 1^{o}x1^{o}, Monthly resolution @ IRI (**http://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/**)

- AST members require these seasonal forecasts to be downscaled to daily time scales and higher spatial resolution — the classic "downscaling" problem with a few wrinkles:
  - *Produced on an operational schedule*
  - *Available for all months… even in months of low seasonal predictability*
  - *Approach must be easily adaptable to multiple regions, or preferably treat multiple regions at once*

Seasonal Forecasting Challenges

- Variability in seasonal predictability and model skill
- Local systematic errors in model climatology
- Non-local/Spatial systematic errors such as misrepresentation of covariant relationships (e.g. SST-forced teleconnections)
- Reliability -> ensembles may be under/over-dispersive leading to unreliable forecasts

Short (OND) Rain Teleconnections – Precipitation (shaded) and Temperature (contour)



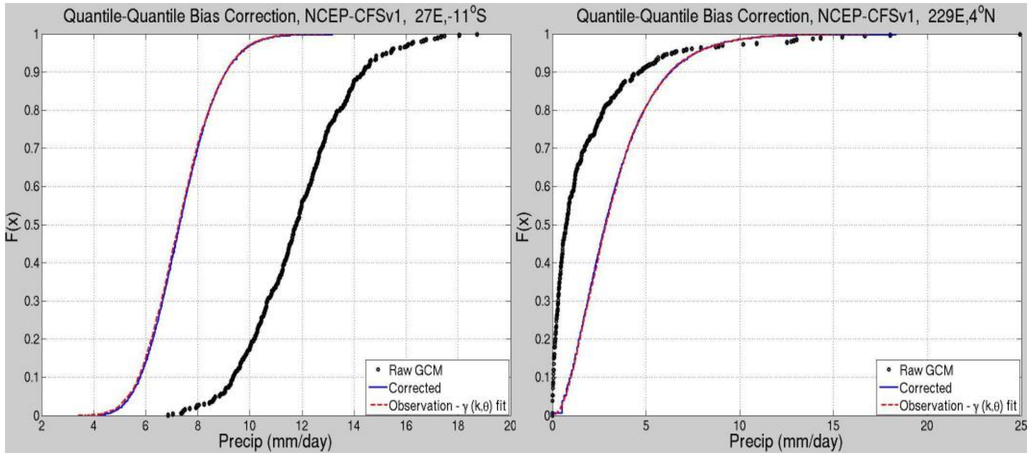
Addressing Forecasting Challenges

Predictability and Model Skill

- Use a multi-model ensemble approach to improve skill

Model Space vs. Observational Space

- Calibration: Correct systematic errors in model climatology
  - Mean and/or variance adjustment:
$$g = a * x + b$$
  - Quantile-quantile mapping (i.e. CDF-matching):
$$g = F_{obs}^{-1}(F_{model}(x))$$



- Multivariate regression: Correct non-local errors; also can be used for spatial downscaling
  - CCA/MCA/RDA seeks coupled relationships between model forecasts and model observations:
$$G = A * X$$

Reliability

- Re-calibration: Adjust ensemble members such that they are statistically indistinguishable from the observations
$$g_{i,j} = \alpha * \mu_i + \beta * \epsilon_{i,j}$$

Model adjustments – Limitations and Advantages

Q-Q Mapping / Bias Correction

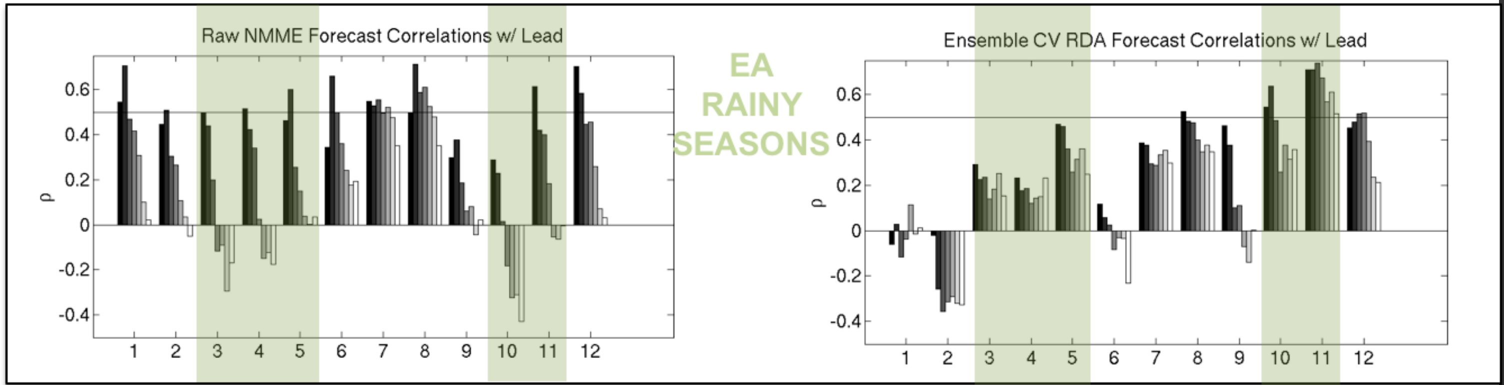
- **Rank-preserving transformation**, *(-) thus unable to improve the probabilistic skill (e.g. as measured by RPSS), (+) does not destroy the skill either*
- **Local,** *(-) thus unable to correct systematic errors in covariant relationships, (+) easy to apply globally*

Given the ease of application and its ability to maintain skill, we have used Q-Q Mapping as part of a BCSD (bias correction and statistical disaggregation) approach to generate our Version-1 downscaled seasonal forecasts for the SERVIR AST
Available via chirps.nsstc.nasa.gov

Multivariate Regression

- **Non-local,** *(+) can potentially improve predictive skill of forecasts through inclusion of additional information, (-) typically many more predictors than samples to train (e.g. all tropical ocean SST grid points)*
- **State-dependent,** *(+) uses paired hindcast information to establish relationships and implement time-dependent regression estimates, (-) small hindcasts (~30yrs) limit number of conditional states, (-) some states simply don't have much signal/predictability (at least in a linear sense)*

- Both of these issues introduce classic problems in regression that can lead to overfitting and poor performance of regression estimates



Multivariate Correction – Formulation and Issues

$\boldsymbol{X} = \boldsymbol{A} * \boldsymbol{F} + \mathbf{E}$ — $\boldsymbol{X}$, observation anomaly; $\boldsymbol{F}$, raw forecast anomaly; $\mathbf{E}$, random error

$\widehat{\boldsymbol{X}} = \boldsymbol{A} * \boldsymbol{F}$ — $\widehat{\boldsymbol{X}}$, predicted anomaly

$\mathbf{A} = \boldsymbol{C}_{\boldsymbol{XF}} \boldsymbol{C}_{\boldsymbol{FF}}^{-\mathbf{1}}$

$\boldsymbol{A}$, Least squares regression coefficient matrix;
$\boldsymbol{C}_{\boldsymbol{XF}}$, covariance between raw forecast and observations;
$\boldsymbol{C}_{\boldsymbol{FF}}$, raw forecast covariance matrix

$\mathbf{A} = \boldsymbol{P}_{\boldsymbol{X}} \boldsymbol{S} \boldsymbol{Q}_{\boldsymbol{F}}^{\boldsymbol{T}}$

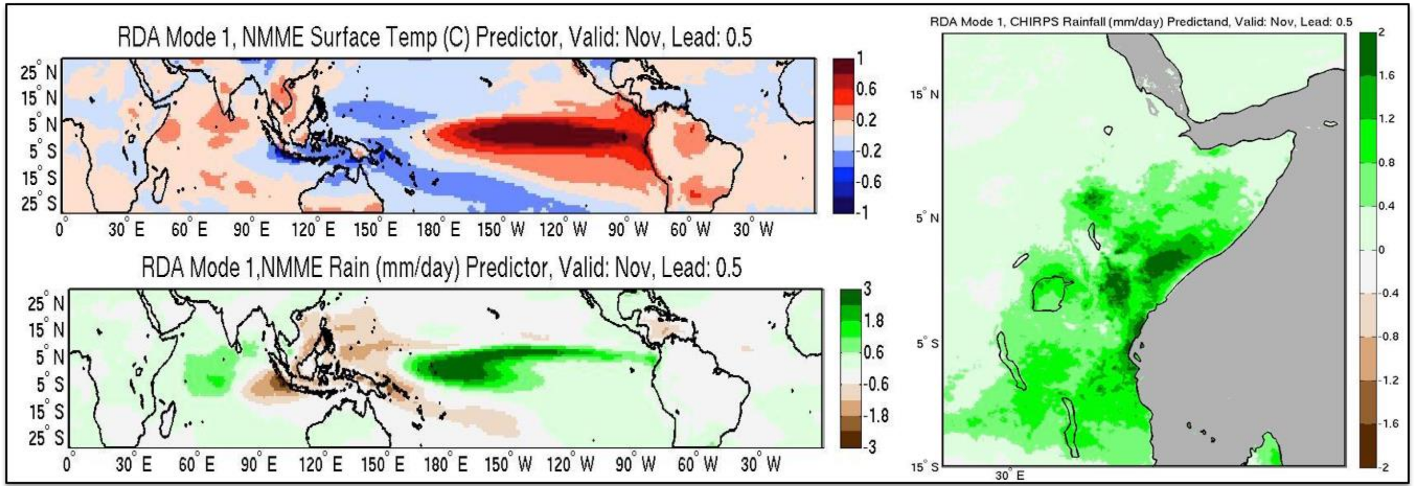
Following Tippett et al. (2008)

$\boldsymbol{P}_{\boldsymbol{X}}$, projection pattern into observational space
$\boldsymbol{S}$, diagonal (scaling) matrix, (e.g. canonical correlations)
$\boldsymbol{Q}_{\boldsymbol{F}}$, projection pattern for raw forecast space

Formalism can be used for different multivariate techniques (e.g. CCA, MCA, RDA, PPA)

Particularly for seasonal forecasting, problems of multiplicity & multicollinearity must be addressed.

- The general approach is to operate in a significantly reduced subspace through limitation of the coupled patterns included in regression.
- Consequently, a much reduced fraction of variance may be able to be successfully recovered



Multivariate Correction as a “Replacement” prediction

- Where the loading patterns in observations are small, MVR will tend to produce near-climatological predictions.
- While this is preferable in an area where there is low-skill in the context of the MVR, it is possible that you are removing skill that *WAS present in the raw seasonal forecasts*.

$$\boldsymbol{\widehat{X}} = \boldsymbol{F_{RAW}}$$

$$\boldsymbol{\widehat{X}} = \boldsymbol{P_X S}(\boldsymbol{Q_F^T F_{RAW}})$$

- This problem is compounded in particular by the necessity to use a very reduced set of modes that may or may not project strongly, or recover a significant amount of variability, in your region of interest.
- Thus we are left with the challenge of understanding how to blend the good with the bad. That is how can we work towards correcting the systematic (nonlocal) errors when we can robustly identify them while at the same time not destroying the potential skill found in the raw seasonal forecast.

Multivariate Correction as an "Error Replacement" prediction

- Rather than focusing on the structure of the relationship between observations and the model forecast, we can instead focus on the structure of errors in forecast.

$$\boldsymbol{X(t)} = \boldsymbol{F_i(t)} + \boldsymbol{\Delta_i}(\mathbf{t})$$
$$\boldsymbol{\Delta_i}(\mathbf{t}) = \mathbf{X}(\mathbf{t}) - \boldsymbol{F_i(t)}$$

$\boldsymbol{i}$**,** index for forecast ensemble member

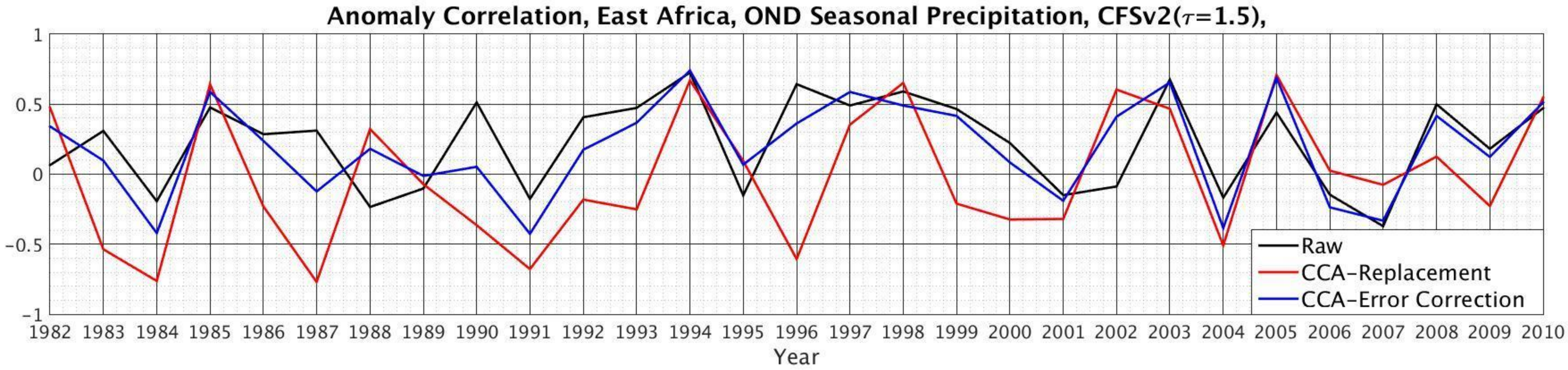
- Seek a multivariate regression estimate of the error field to be used for "correcting" the error in a state/time-dependent manner

$$\boldsymbol{\mu_\Delta}(\mathbf{t}) = \boldsymbol{A} * \widetilde{\boldsymbol{F_i(t)}} + \boldsymbol{E(t)}$$
$$\widetilde{\boldsymbol{\Delta_i}(\mathbf{t})} = \boldsymbol{A} * \widetilde{\boldsymbol{F_i(t)}}$$
$$\widetilde{\boldsymbol{X_i(t)}} = \boldsymbol{F_i(t)} + \boldsymbol{A} * \widetilde{\boldsymbol{F_i(t)}}$$

$\widetilde{\boldsymbol{F(t)}}$**,** set of predictors from available forecasts

- Where the loading patterns in observations are small, the predicted error correction should tend towards "climatology," or near-zero values such that the final prediction tends towards the original model prediction
- Further, you could potentially severely restrict the correction factor by thresholding the projection coefficients so that corrections are only implemented when your model projects strongly onto the projection pattern (in forecast space) that is coupled to some well-associated error pattern
- In short, this rearrangement is more of an effort to use the hindcasts to identify predictable error patterns themselves, and then remove them when we expect them to be present.

Results



- The new MVR strategy generally out-performs the traditional "replacement" approach
- It does primarily but hedging more closely to the raw forecast prediction
- However, the new approach still shows only limited improvement, ***for this model, season, and lead time***, over the raw forecast

Summary

- As with long-term climate projections, bias correction and downscaling — either statistical or dynamical — is a necessity for seasonal climate forecasts for those using impact models

- Bias correction involves both calibration of systematic errors in the model climatology as well as recalibration of ensemble forecasts to ensure reliability

- Calibration can be (and has) been implemented in a variety of ways
  - simple linear scaling and shifting,
  - full distribution-matching (i.e. Quantile-quantile mapping)
  - Multivariate correction using some form of multivariate regression

- Multivariate correction is typically implemented in a “replacement” approach. Because of the need to significantly truncate the space in which the regression is performed, with a complementary loss of variance, MVR approaches often result in near-climatological, low-skill predictions even though the original model forecasts may have shown some non-negligible skill

- We have implemented a new approach to the correction in which we attempt to estimate the systematic error component outright and then “adjust” the model forecast to account for the predicted error component.

- The new approach tends to outperform the MVR-“replacement” approach. However, it does not necessarily outperform the raw predictions skillful models.