Seasonal forecasting skill of the National Multimodel Ensemble (NMME) over southeastern United States

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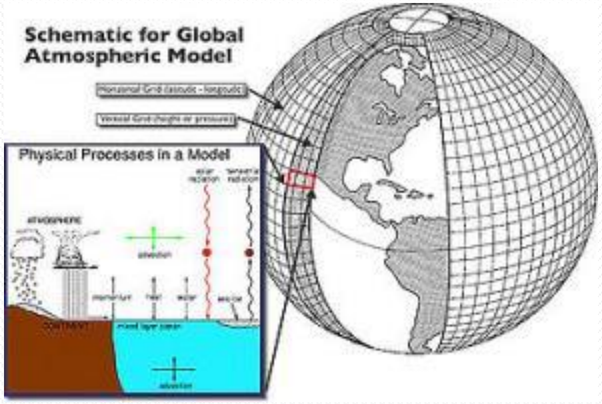
Background

- Seasonal climate forecasts can be used to reduce the damages caused by climate variability
- Seasonal forecasts can be made by general circulation models (GCMs)
    - Statistical downscaling
    - Multimodel ensemble
- National Multimodel Ensemble (NMME)



Objectives

1. Evaluate the skill of **NMME** models to forecast the El Nino - Southern Oscillation (**ENSO**)

2. Evaluate the skill of the downscaled seasonal precipitation (**P**) and temperature (**T**) for the **NMME** models in the SEUS

3. Evaluate the skill of the downscaled **CFSv2** forecasts of reference evapotranspiration (**ETo**) and relevant variables in the SEUS:

- Temperature (maximum, minimum and mean)
- Solar radiation
- Wind speed

NMME historical forecast (hindcast) dataset

No.	Model	Abbr.	Members	Period	Lead Month
1	NCEP-CFSv1	CFSv1	15	1981-2009	0-8
<u>2</u>	<u>NCEP-CFSv2</u>	<u>CFSv2</u>	<u>24</u>	<u>1982-2010</u>	<u>0-9</u>
3	COLA-RSMAS-CCSM3	CCSM3	6	1982-2010	0-11
4	IRI-ECHAM4p5-AnomalyCoupled	ECHAM-Anom	12	1982-2010	0-7
5	IRI-ECHAM4p5-DirectCoupled	ECHAM-Dir	12	1982-2010	0-7
6	GFDL-CM2p1	GFDL	10	1982-2010	0-11
7	NASA-GMAO (incomplete)	GMAO	10	1982-2010	0-8
8	NASA-GMAO-062012 (incomplete)	GMAO-062012	12	1982-2010	0-8
9	GFDL-CM2p1-aer04 (incomplete)	GFDL-aer04	10	1982-2010	0-11

Forecast evaluation

- Brier Skill Score (**BSS**) is used to evaluate the accuracy of **probability forecast**

$$BSS = 1 - \frac{BS_{forecast}}{BS_{climatology}}$$

$$BS = \frac{\sum_{i=1}^{N}(p_i - o_i)^2}{N}$$

- BSS is used to determine how many of the forecast members correctly forecasted the correct tercile compared to climatology (which is 33%)

-∞ to 1

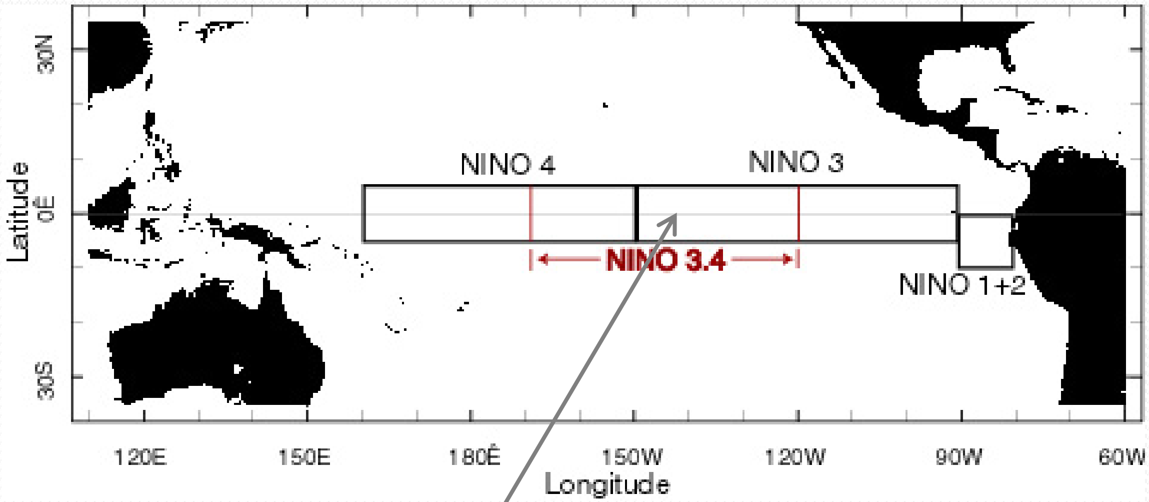
- Mean square error skill score (**MSESS**) is used to evaluate the accuracy of **deterministic forecast**

$$MSESS = 1 - \frac{MSE_{forecast}}{MSE_{climatology}}$$

-∞ to 1

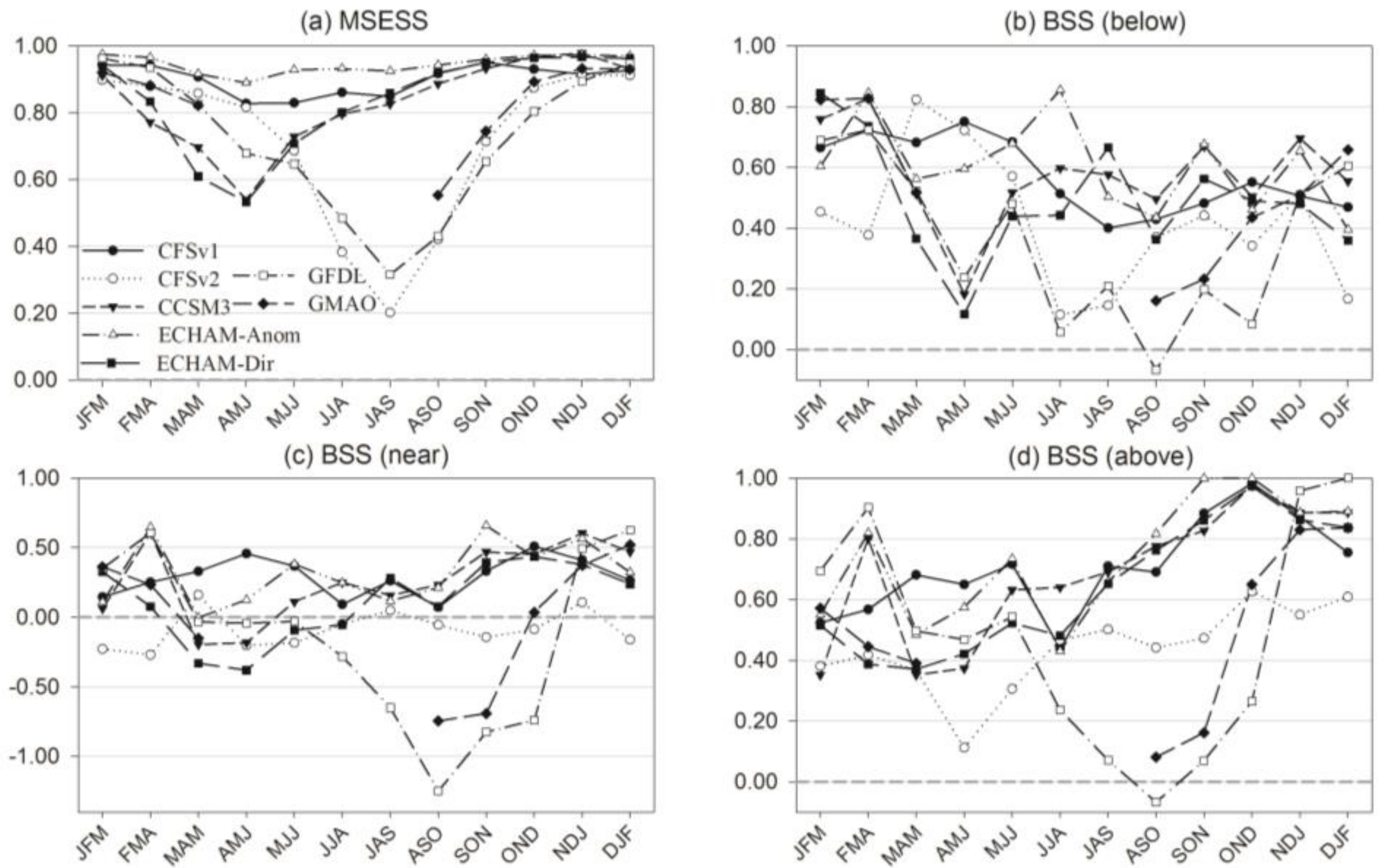
Objective 1: Skill of the ENSO forecast

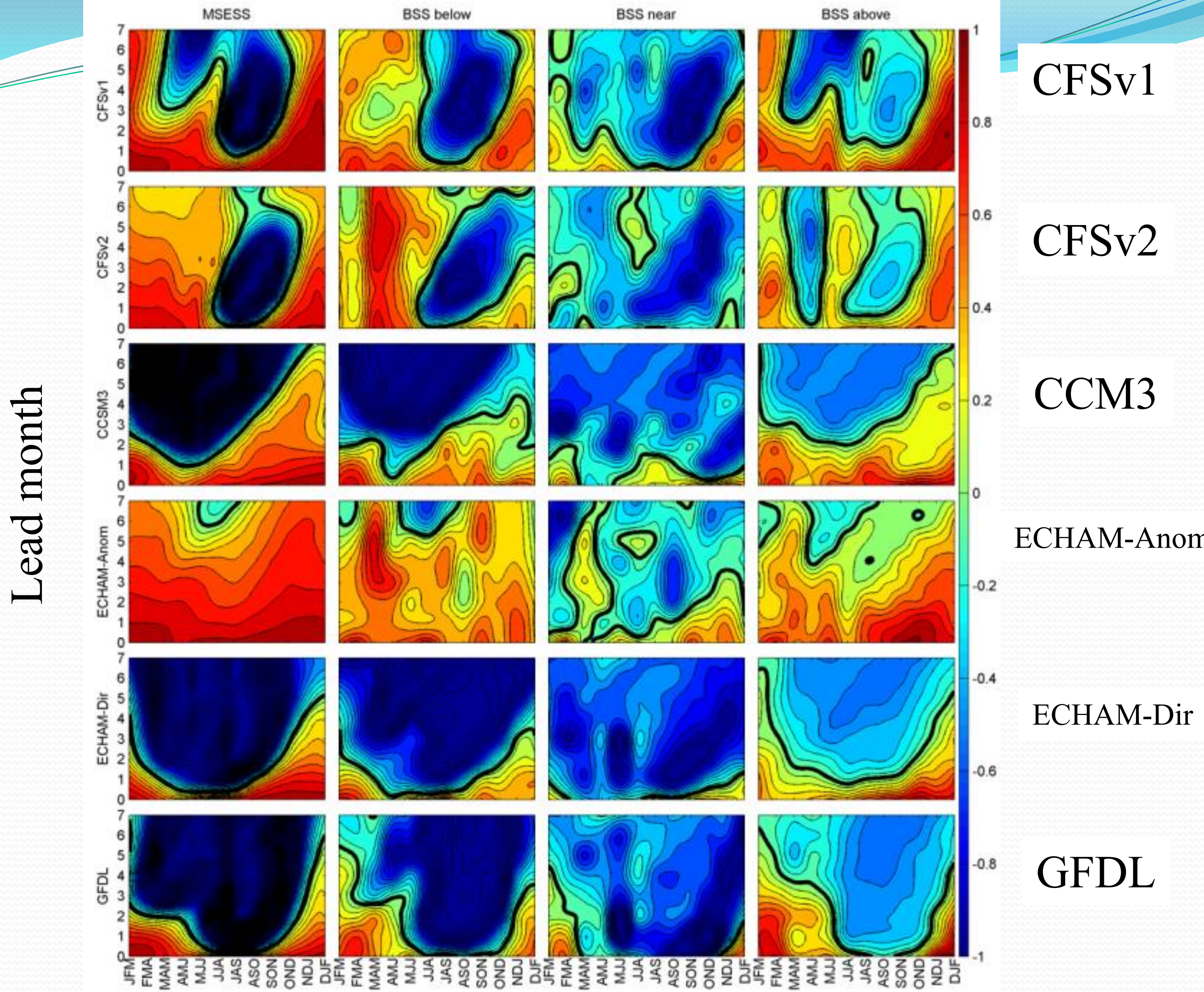
Evaluate against observations



Calculate the spatial average of the **SST** in this region for each NMME model

Skill of the ENSO forecast in different seasons at lead 0



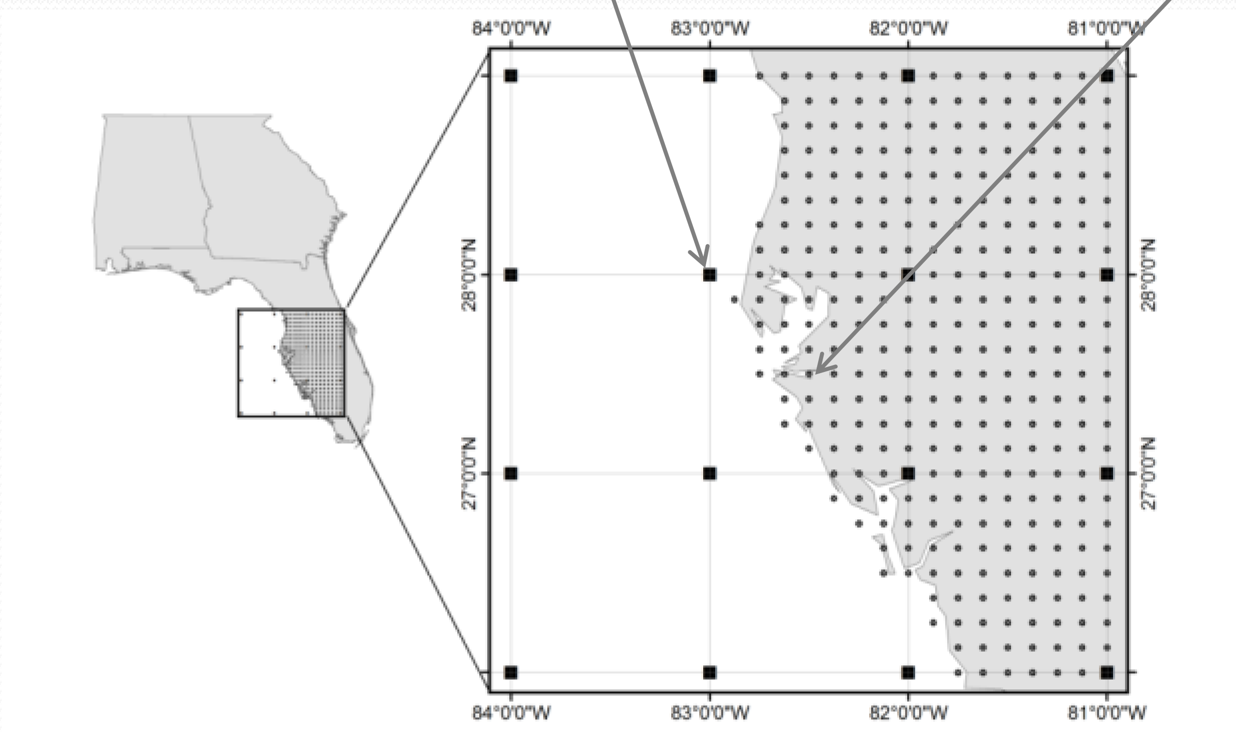


Lead month
MSESS
BSS below
BSS near
BSS above
CFSv1
CFSv2
CCSM3
ECHAM-Anom
ECHAM-Dir
GFDL
CFSv1
CFSv2
CCM3
ECHAM-Anom
ECHAM-Dir
GFDL
JFM
FMA
MAM
AMJ
MJJ
JJA
JAS
ASO
SON
OND
NDJ
DJF
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1

Objective 2: Skill of the downscaled P and T forecast of NMME

NMME grid point ~100-km

NLDAS-2 grid point ~12-km



Forcing dataset of **NLDAS-2** were used as surrogate of observations for statistical downscaling and forecast verification

Statistical downscaling methods

- Model output statistics (MOS): Corrects systematic errors of the NMME output
  - Spatial disaggregation (**SD**)
  - Spatial disaggregation with bias correction (**SDBC**)
- Perfect prognosis (PP): Establishes statistical model using large-scale and local-scale observed data (**SST in Nino3.4** and **P, T**) and apply this model to the NMME output
  - Linear regression (**LR**)
  - Locally weighted polynomial regression (**LWPR**) (nonparametric nonlinear regression)
- Direct interpolation (**INTP**) of the raw output as a benchmark
- Leave-one-out cross validation was conducted

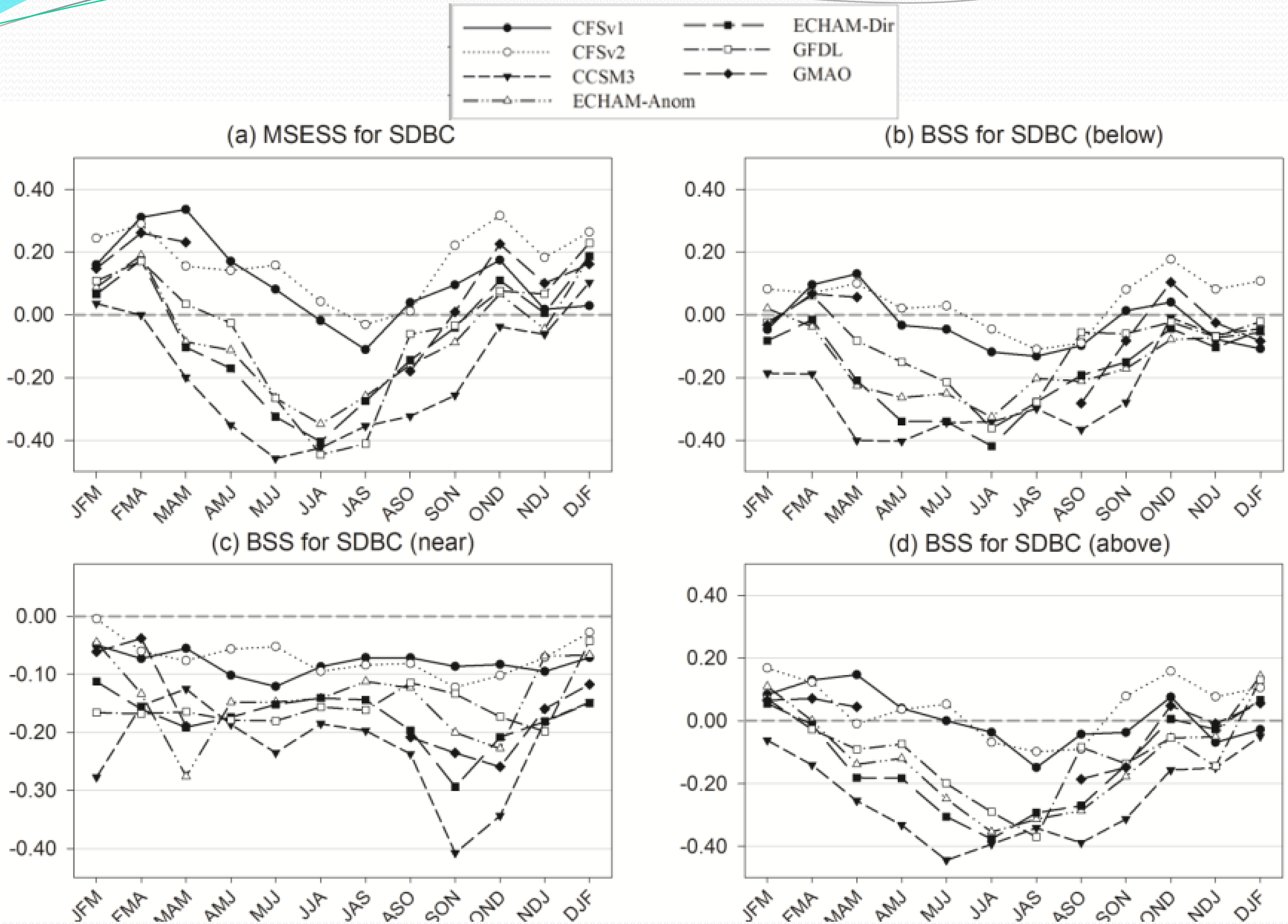
Overall mean of precipitation forecasting skills for NMME models at lead 0

SS	Methods	Models										
		CFSv1	CFSv2	CCSM3	ECHAM-Anom	ECHAM-Dir	GFDL	GFDL-aer04	GMAO	GMAO-062012	MeanEns	SuperEns
MSESS	INTP	-0.426	-0.094	-1.040	-0.677	-0.710	-0.872	-1.522	-0.063	-0.694	-0.229	-0.133
	SD	0.110	0.164	0.003	0.020	0.018	0.051	-0.139	0.163	0.086	0.147	0.161
	SDBC	0.107	**0.167**	-0.194	-0.069	-0.076	-0.046	-0.260	0.120	0.035	0.042	0.166
	LR	0.145	0.127	**0.142**	0.150	0.145	**0.136**	-	**0.169**	-	0.142	0.152
	LWPR	**0.165**	0.136	0.140	**0.171**	**0.158**	0.132	-	0.166	-	**0.161**	**0.171**
BSS Below	INTP	-0.205	-0.095	-0.938	-0.628	-0.642	-0.713	-0.729	-0.205	-0.365	-0.295	-0.133
	SD	-0.049	0.021	-0.349	-0.198	-0.205	-0.148	-0.259	-0.086	-0.106	-0.293	-0.013
	SDBC	-0.031	**0.042**	-0.243	-0.156	-0.185	-0.106	-0.263	-0.034	-0.066	-0.105	0.036
	LR	0.032	0.017	0.029	0.034	0.033	**0.022**	-	**0.038**	-	0.026	0.037
	LWPR	**0.040**	0.021	**0.039**	**0.048**	**0.040**	**0.021**	-	0.035	-	**0.036**	**0.047**
BSS Near	INTP	-0.151	-0.109	-0.329	-0.230	-0.230	-0.274	-0.253	-0.207	-0.237	-0.201	-0.056
	SD	-0.107	-0.107	-0.787	-0.294	-0.307	-0.317	-0.264	-0.312	-0.292	-0.922	-0.136
	SDBC	-0.080	-0.069	-0.223	-0.141	-0.175	-0.153	-0.177	-0.158	-0.167	-0.201	-0.041
	LR	-0.025	-0.024	-0.035	-0.028	-0.028	-0.027	-	-0.030	-	-0.034	-0.020
	LWPR	-0.025	-0.024	-0.035	-0.027	-0.028	-0.028	-	-0.031	-	-0.033	-0.019
BSS Above	INTP	-0.373	-0.141	-0.426	-0.318	-0.326	-0.330	-0.537	-0.182	-0.395	-0.219	-0.075
	SD	-0.011	0.027	-0.291	-0.152	-0.159	-0.132	-0.282	-0.026	-0.070	-0.168	0.025
	SDBC	0.009	**0.044**	-0.252	-0.124	-0.138	-0.106	-0.269	-0.007	-0.041	-0.066	0.054
	LR	0.035	0.023	0.031	0.038	0.037	**0.029**	-	**0.052**	-	0.031	0.042
	LWPR	**0.052**	0.032	**0.041**	**0.054**	**0.045**	**0.029**	-	**0.051**	-	**0.044**	**0.056**

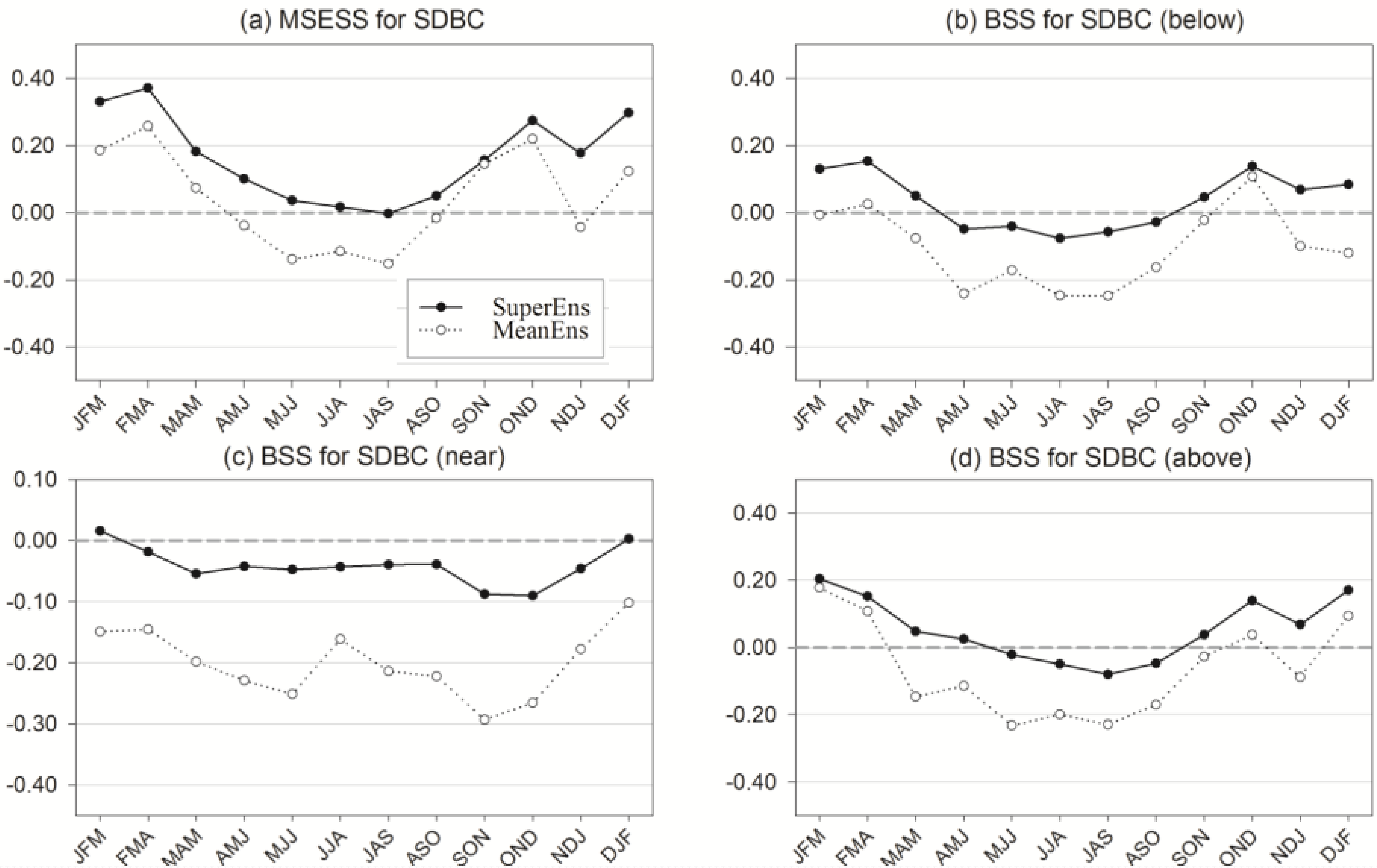
Overall mean of temperature forecasting skills for NMME models at lead 0

SS	Methods	Models										
		CFSv1	CFSv2	CCSM3	ECHAM-Anom	ECHAM-Dir	GFDL	GFDL-aer04	GMAO	GMAO-062012	MeanEns	SuperEns
MSESS	INTP	-3.370	-2.316	-2.494	-2.839	-2.770	-2.216	-133.070	-0.903	-2.273	-2.478	-3.991
	SD	0.143	0.367	-0.198	-0.384	-0.421	-0.663	-1.441	0.313	**0.253**	0.167	0.195
	SDBC	0.150	**0.379**	-0.436	-0.133	-0.154	-0.161	-0.683	**0.350**	0.190	**0.190**	**0.258**
	LR	0.175	0.085	0.096	0.098	0.090	**0.092**	-	0.096	-	0.093	0.104
	LWPR	**0.229**	0.129	**0.169**	**0.187**	**0.162**	0.079	-	0.094	-	0.170	0.180
BSS Below	INTP	-1.157	-0.877	-0.785	-0.272	-0.264	-0.595	-0.963	-0.413	-0.638	-0.113	-0.049
	SD	0.012	0.196	-0.407	-0.186	-0.187	-0.188	-0.457	**0.159**	0.125	-0.042	0.103
	SDBC	0.043	**0.216**	-0.360	-0.133	-0.150	-0.158	-0.440	0.143	**0.144**	0.019	**0.135**
	LR	0.008	-0.005	0.004	0.008	0.007	-0.002	-	0.007	-	0.001	0.011
	LWPR	**0.046**	0.043	**0.047**	**0.068**	**0.045**	-0.003	-	0.009	-	**0.050**	0.063
BSS Near	INTP	-0.322	-0.246	-0.236	-0.220	-0.212	-0.269	-0.431	-0.213	-0.282	-0.212	-0.169
	SD	-0.117	-0.083	-0.437	-0.111	-0.125	-0.240	-0.270	-0.103	-0.181	-0.436	-0.052
	SDBC	-0.080	-0.048	-0.248	-0.125	-0.161	-0.304	-0.279	-0.164	-0.146	-0.221	-0.031
	LR	-0.041	-0.024	-0.038	-0.030	-0.031	-0.030	-	-0.034	-	-0.036	-0.022
	LWPR	-0.045	-0.026	-0.039	-0.033	-0.033	-0.036	-	-0.046	-	-0.037	-0.022
BSS Above	INTP	-0.301	-0.268	-0.362	-0.719	-0.700	-0.459	-1.350	-0.115	-0.284	-0.102	-0.107
	SD	0.007	0.158	-0.285	-0.214	-0.230	-0.307	-0.485	**0.164**	0.083	-0.098	0.076
	SDBC	0.018	**0.173**	-0.269	-0.216	-0.241	-0.295	-0.439	0.152	**0.099**	-0.033	**0.096**
	LR	-0.001	-0.016	-0.011	-0.006	-0.011	-0.014	-	-0.004	-	-0.012	-0.001
	LWPR	**0.040**	0.019	**0.038**	**0.055**	**0.040**	**0.009**	-	0.011	-	**0.043**	0.054

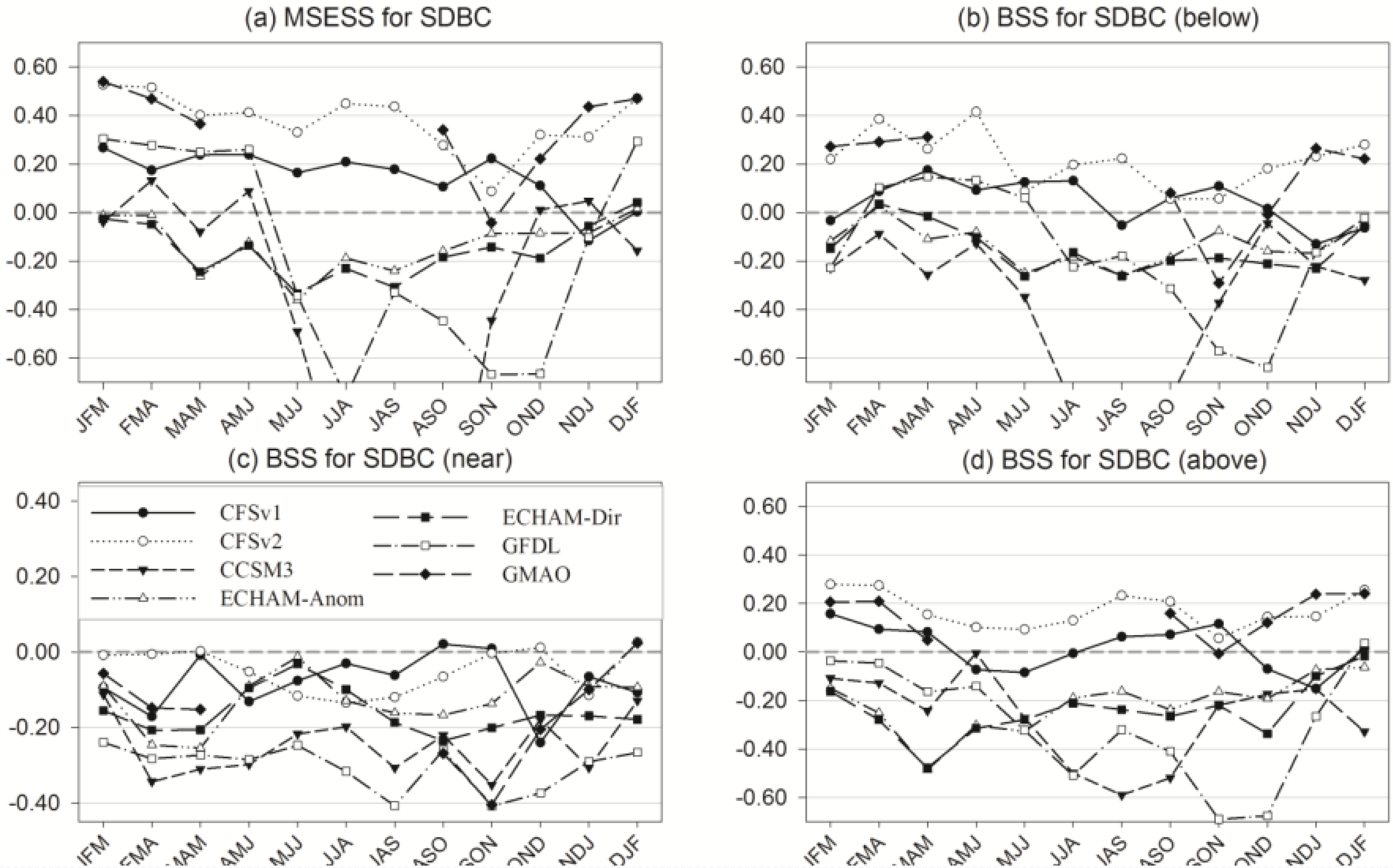
SDBC: Precipitation forecasting skills for NMME models in different seasons at lead 0



SDBC: Precipitation forecasting skills for NMME ensembles in different seasons at lead 0

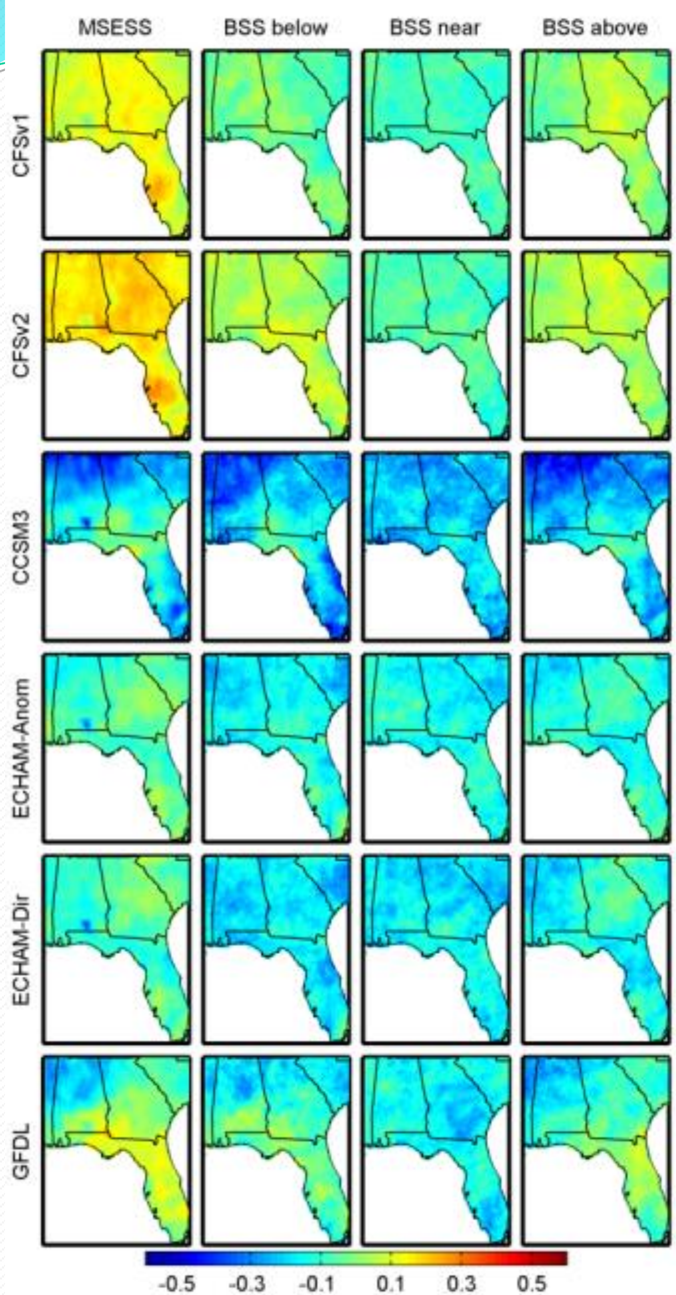


SDBC: Temperature forecasting skills for NMME models in different seasons at lead 0

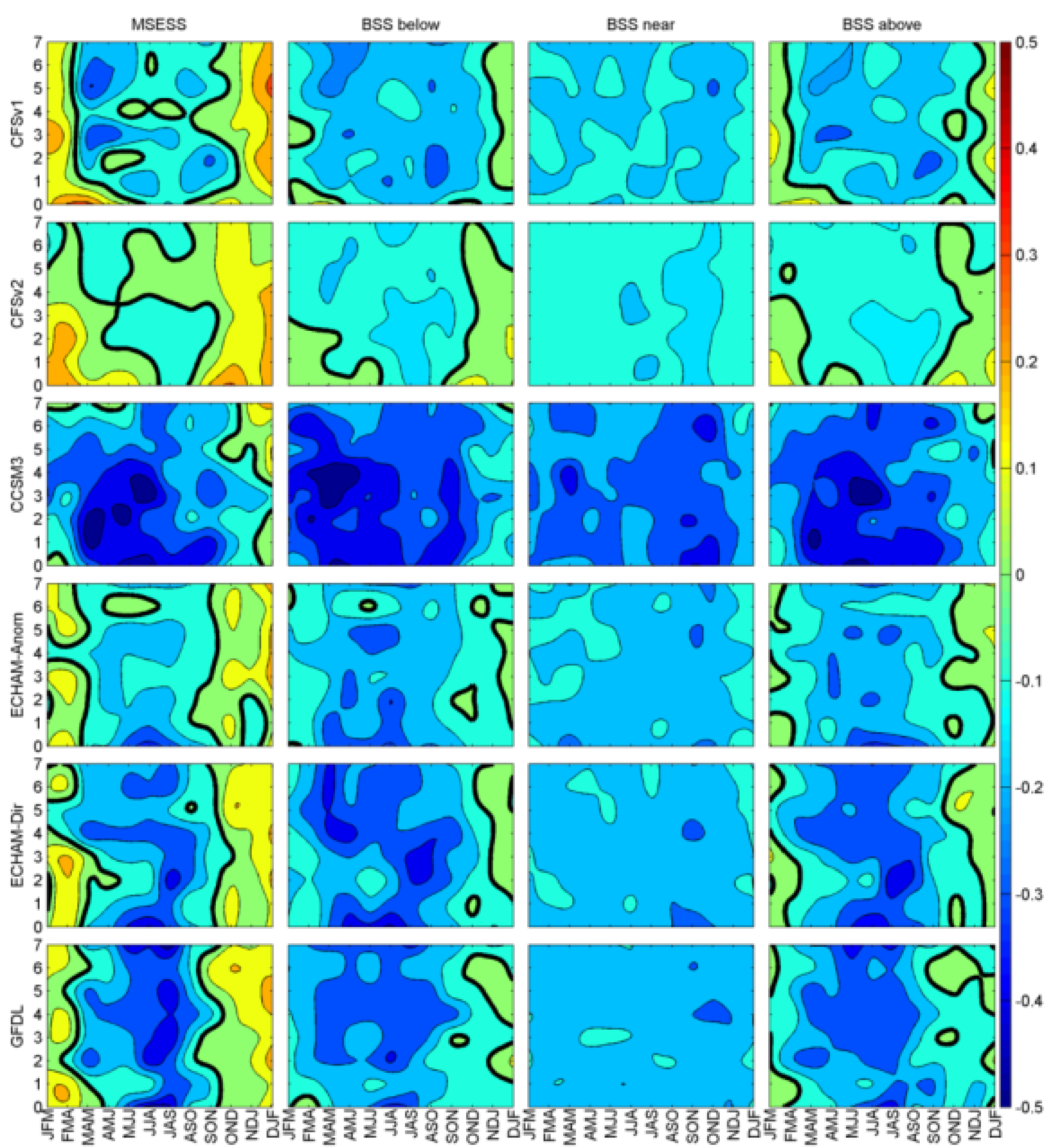


Precipitation

SDBC: lead 0



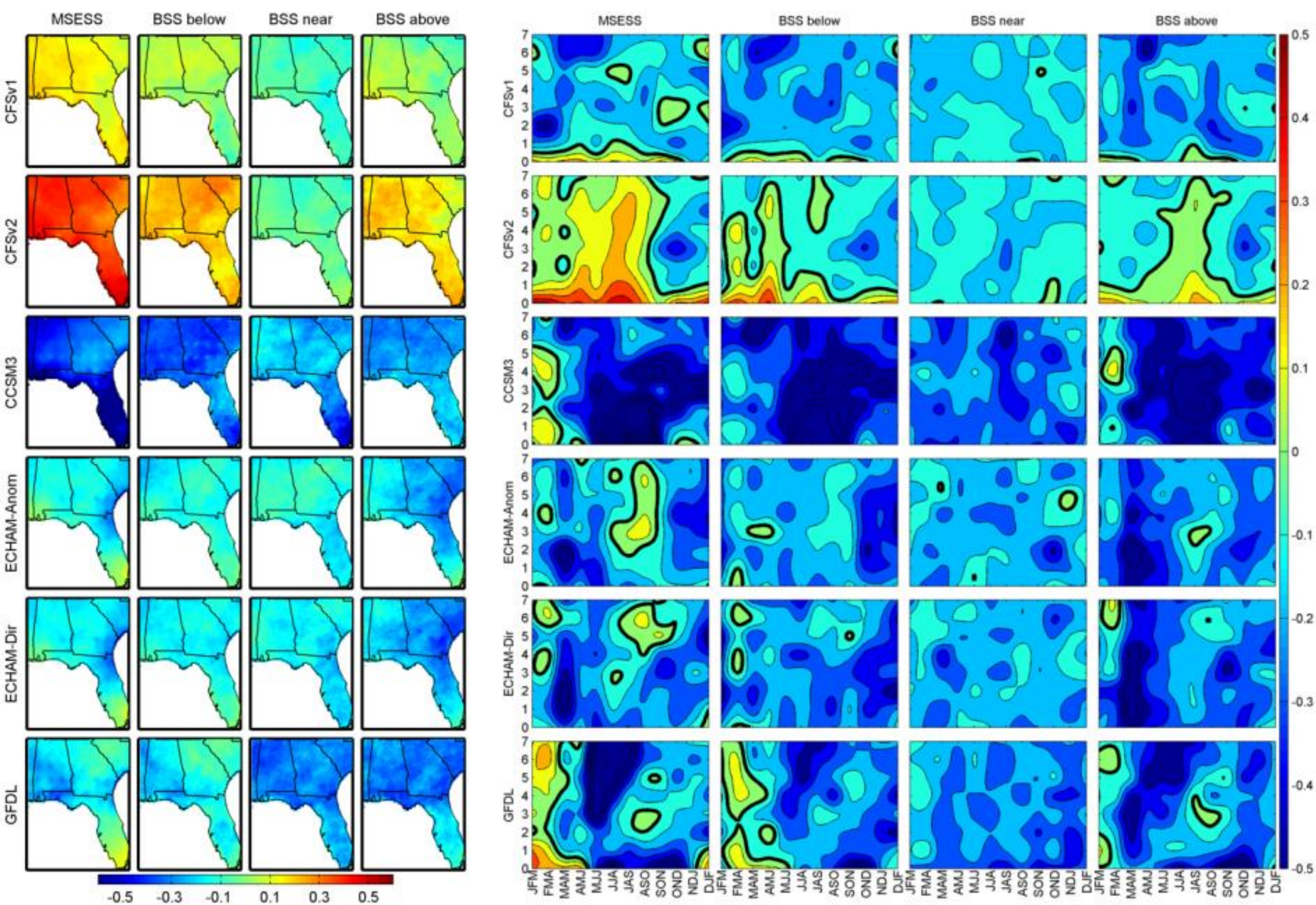
SDBC: lead 0 to 7



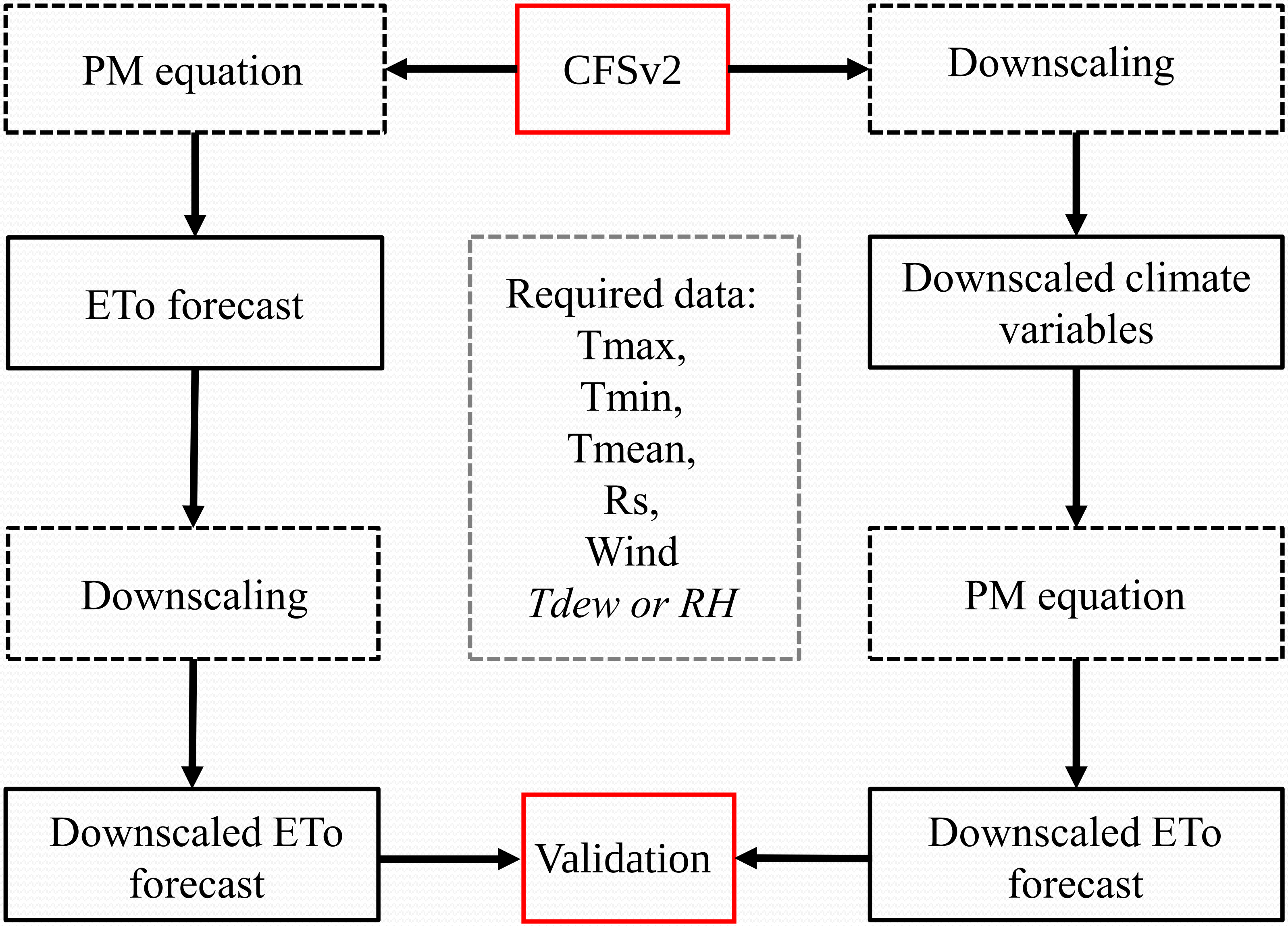
Temperature

SDBC: Lead 0

SDBC: Lead 0 to 7



Objective 3: Skill of the downscaled CFSv2 ETo forecast



Overall mean skills in lead 0

Variables	SD				SDBC			
	MSESS	BSS			MSESS	BSS		
		Below	Near	Above		Below	Near	Above
Tmean	0.367	0.196	-0.083	0.158	0.379	0.216	-0.048	0.173
Tmax	0.410	0.177	-0.165	0.218	0.443	0.254	-0.053	0.261
Tmin	0.148	0.012	-0.111	-0.038	0.145	0.020	-0.086	-0.025
Rs	0.027	-0.092	-0.120	-0.071	-0.020	-0.083	-0.094	-0.053
Wind	-0.172	-0.100	-0.081	-0.115	-0.055	-0.095	-0.081	-0.111

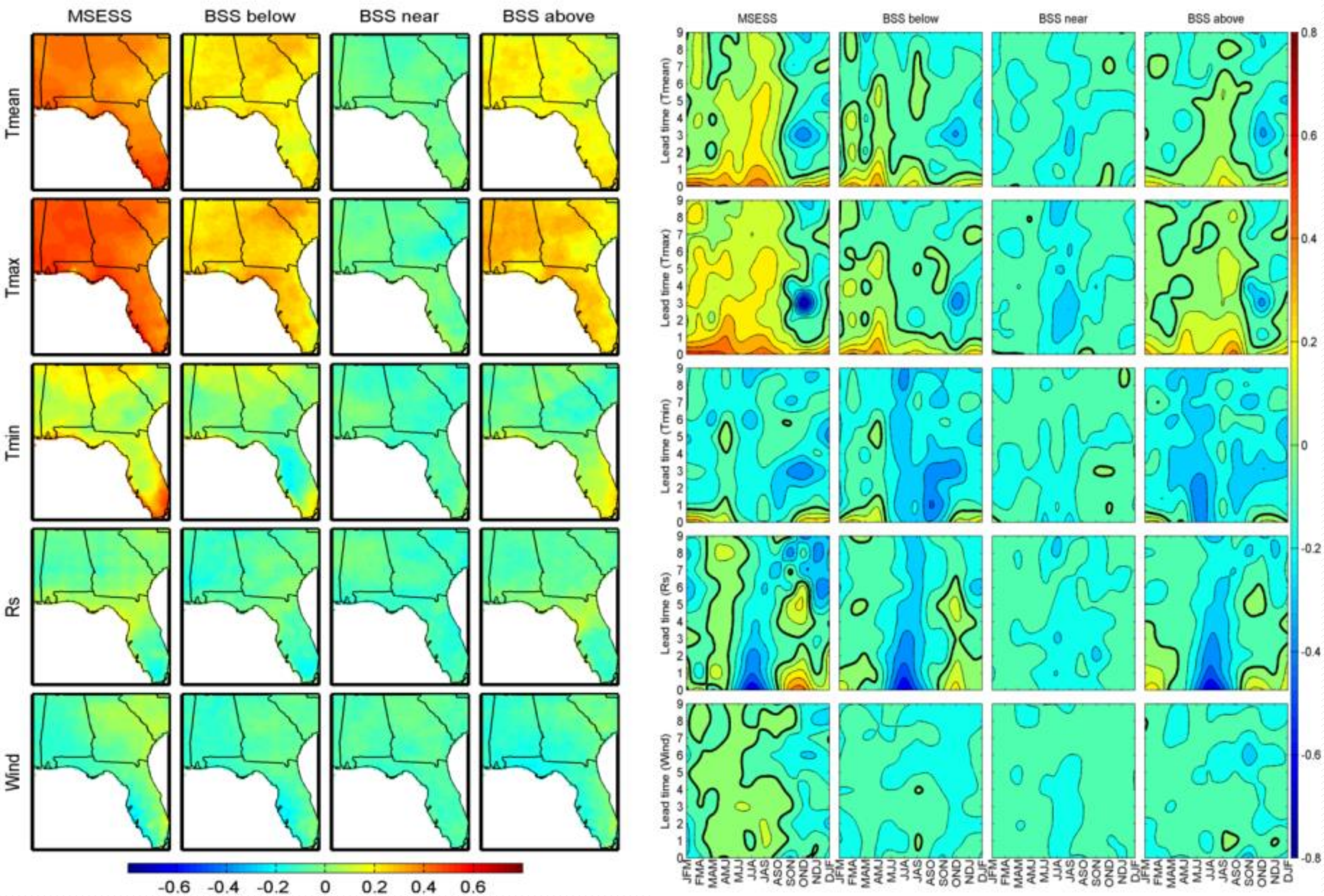
Variables	SD				SDBC			
	MSESS	BSS			MSESS	BSS		
		Below	Near	Above		Below	Near	Above
ETo1*	0.156	-0.070	-0.353	-0.033	0.052	-0.002	-0.089	0.034
ETo2**	**0.188**	-0.089	-0.334	**0.043**	**0.216**	-0.006	-0.212	**0.099**

* ETo was calculated using the CFSv2 variables before downscaling

** ETo was calculated using the downscaled CFSv2 variables

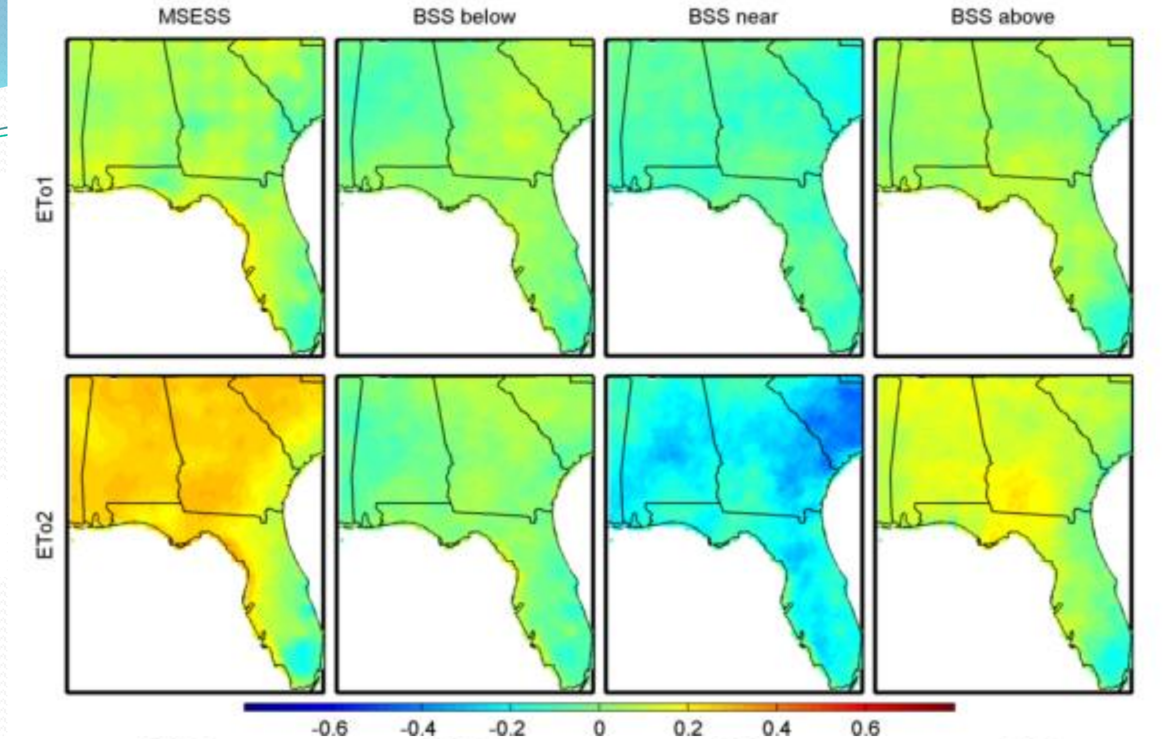
CFSv2 variables

Lead 0 | Lead 0 to 9



ETo1

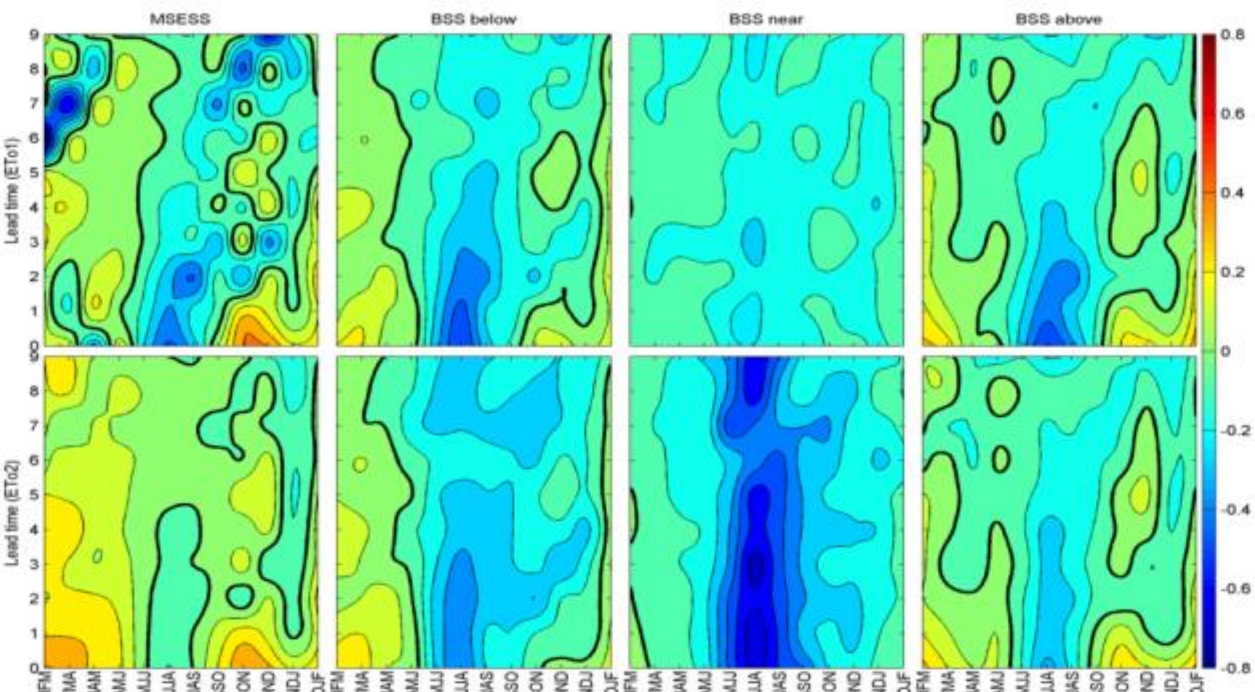
ETo2



Lead 0

ETo1

ETo2



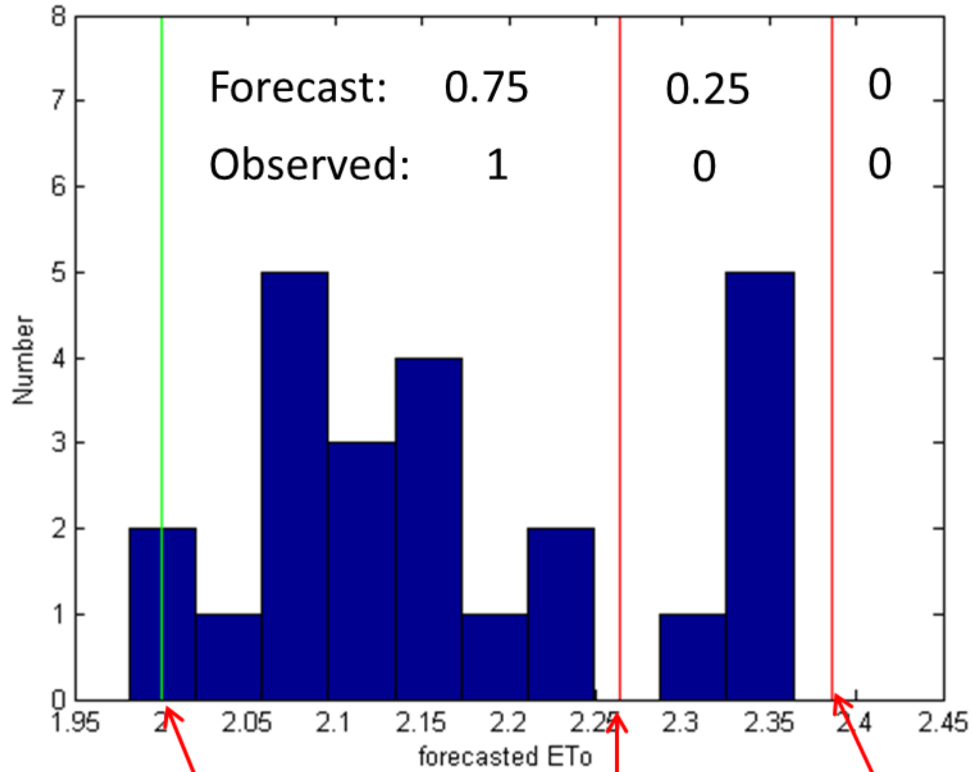
Lead 0 to 7

Summary

1. Most of the NMME models showed high skill on forecasting ENSO
2. The forecasting skill of P and T for NMME was improved through different statistical downscaling methods
3. The skill is higher in cold seasons than warm seasons
4. The LR and LWPR methods did better than the SD and SDBC methods for downscaling P but worse than the SD and SDBC for downscaling T
5. In the first lead, CFSv2 model achieved the highest skill on forecasting T with the SDBC method; the ECHAM model and the multimodel ensemble forecasts achieved the highest skill on forecasting P with the LWPR method
6. CFSv2 showed great potential on forecasting seasonal ETo

Additional Information

Brier Score (BS) of Forecast



Observed value of Jan 2010

Terciles got from all observations of Jan over all the years

Ensemble Forecast:
Jan 2010, 24 members

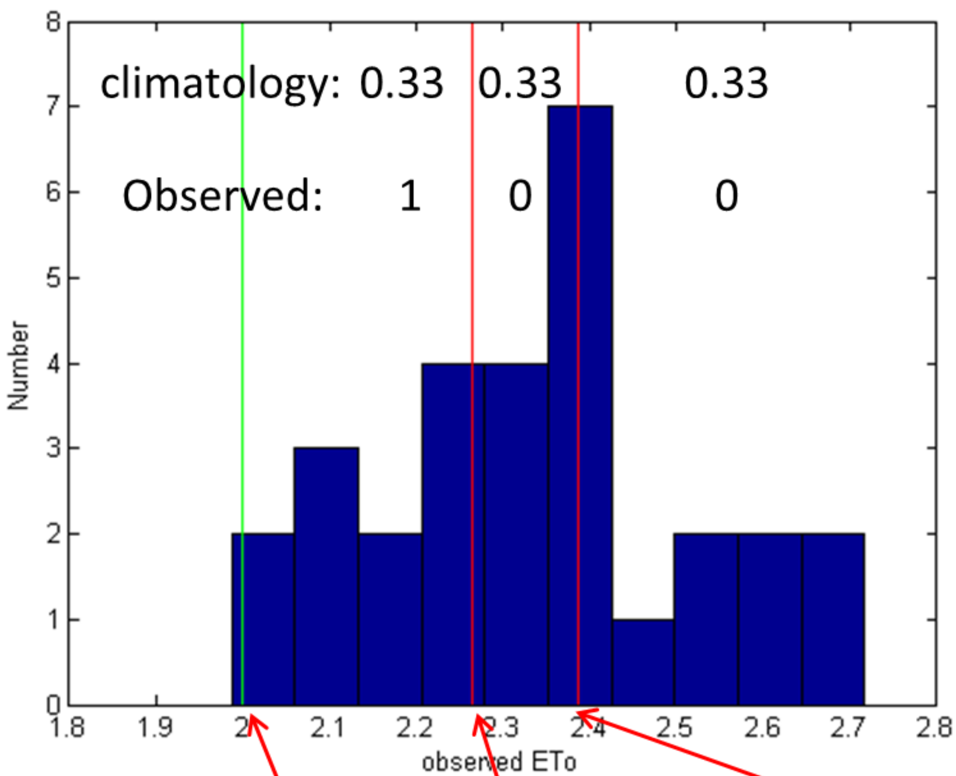
Lower tercile BS$_f$:

$$BS_f = \frac{1}{n}\sum_1^n \left(p_j^f - I_j^o\right)^2$$

$$= (0.75-1)^\wedge 2$$

$$= 0.0625$$

Brier Score (BS) of Climatology



Observed value of this year

Terciles of all the observations of this month over all the years

Obs: Jan, 1982-2010

Lower tercile BSc:

$$BS_c = \frac{1}{n}\sum_1^n \left(p_j^c - I_j^o\right)^2$$

= (0.33-1)^2

= 0.449

To calculate Lower tercile BSS:

$$BSS = 1 - \frac{BS_f}{BS_c}$$

$$= 1- 0.0625/0.449$$

$$= 0.861$$

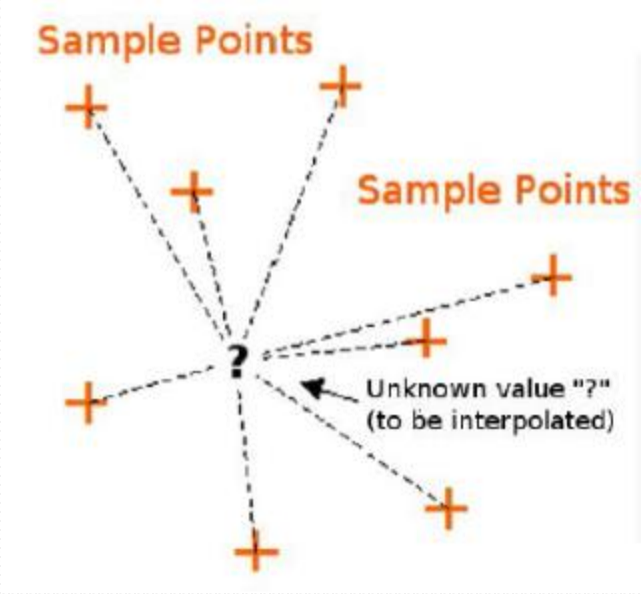
- Similarly, we can calculate BSS in other terciles
- Deterministic forecast was calculated by **ensemble mean**
- Replacing the BS with MSE, we can calculate MSESS
- The BSS is a very conservative evaluation metrics of probabilistic forecast (Stefanova and Krishnamurti, 2002)

MOS downscaling methods

- **SD**
  - Spatially interpolate the anomalies of the NMME forecasts using inverse distance weighting (IWD) and then add to the climatology of the NLDAS-2
- **SDBC**
  - Spatially interpolate the anomalies of the NMME forecasts using IWD
  - Quantile mapping bias correction of the anomalies using the anomalies of NLDAS-2 and add the bias corrected anomalies to the climatology of the NLDAS-2

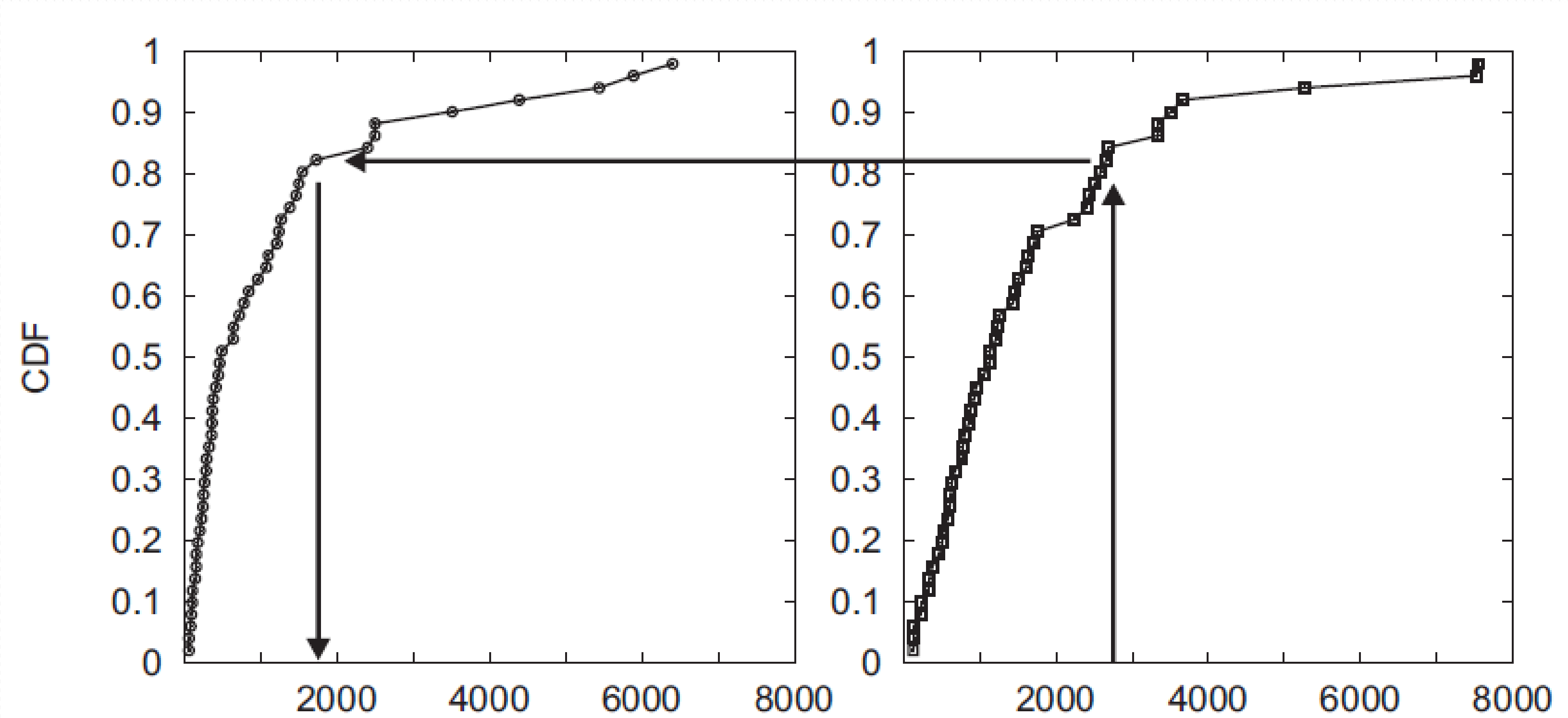
MOS downscaling methods

- IDW estimates values at a point by weighting the influence of nearby data the most, and more distant data the least.
- Procedure:
  - Compute distances of the unknown points to all the points in the dataset
  - Compute the weight of each point. Weighting function is the inverse power of the distance.
  - Estimated value is the weighted average



MOS downscaling methods

- Quantile mapping bias correction technique



Observations

Forecasts

(Hashino et al., 2007)

- Leave-one-out cross validation

PP downscaling methods

- **LR:** $Y_{ij} = a_{ij} + b_{ij} X_{ij} + e_{ij}$ *i*: season; *j*: grid
  - Fit *linear regression models* for X (the observed SST in Nino3.4 region) and Y (the P or T2M of NLDAS-2) for each season and each grid point
  - Apply these *linear regression models* to the NMME SST in Nino3.4 region to predict the P or T2M for each season and each grid point
  - Estimate regression residuals
  - Generates 10 random numbers from regression residuals by assuming normal distribution with mean 0 and standard deviation of regression residuals
  - Calculate ensemble forecast by adding 10 generated numbers to the predicted value

PP downscaling methods

- **LWPR:** $Y_{ij} = f(X_{ij}) + e_{ij}$ *i*: season; *j*: grid
  - Fit *locally weighted polynomial functions (f)* for X (the observed SST in Nino3.4 region) and Y (the P or T2M of NLDAS-2) for each season and each grid point
  - Apply these functions to the NMME SST in Nino3.4 region to predict the P or T2M for each season and each grid point
  - Estimate regression residuals
  - Generates 10 random deviates from regression residuals by assuming normal distribution with mean 0 and standard deviation of local regression residuals
  - Calculate ensemble forecast by adding 10 generated numbers to the predicted value