

ENSO Precipitation and Temperature Forecasts in the NMME: Composite Analysis and Verification

Li-Chuan Chen^{1,2}, Huug van den Dool², Emily Becker², and Qin Zhang²

ESSIC/CICS-MD, University of Maryland, College Park
 Climate Prediction Center/NCEP/NOAA





ENSO Impacts



- Strong influence on the seasonal P and T patterns around the globe and over the U.S.
- Improved P and T forecast skill in climate models can be attributed to the known impacts of ENSO signals.

ENSO Prediction

Questions:

- Can climate models predict the onset of ENSO events?
- If an ENSO event is in progress, can climate models adequately predict its impacts on P and T patterns?





ENSO Composites

- The composite analysis is conducted using the 1982-2010 hindcasts from the CFSv2, CanCM3, CanCM4, FLOR, GEOS5, and CCSM4 models.
- Composite years are selected based on the historical Ocean Nino Index (ONI).
- If the seasonal ONI just prior to the date the forecasts were initiated indicates a warm or cold ENSO episode, the forecasts are selected for the composite analysis.
- The composites apply to monthly mean conditions in November, December, January, February, and March, respectively, as well as to the five-month aggregates (NDJFM) resembling the winter conditions.

Selected ENSO years used in the model composites (1982-2010)

Month	nth Nov		Dec		Jan		Feb		Mar	
ENSO	Warm	Cold	Warm	Cold	Warm	Cold	Warm	Cold	Warm	Cold
	1982	1985	1982	1983	1982	1983	1983	1984	1983	1984
	1986	1988	1986	1985	1986	1984	1987	1985	1987	1985
	1987	1998	1987	1988	1987	1988	1988	1989	1988	1989
	1991	1999	1991	1995	1991	1995	1992	1996	1992	1996
Veere	1997	2000	1994	1998	1994	1998	1995	1999	1995	1999
rears	2002	2007	1997	1999	1997	1999	1998	2000	1998	2000
	2004	2010	2002	2000	2002	2000	2003	2001	2003	2001
	2009		2004	2007	2004	2007	2005	2006	2005	2006
			2006	2010	2006	2010	2007	2008	2007	2008
			2009		2009		2010	2009	2010	2009
Total No. of years	8	7	10	9	10	9	10	10	10	10

Anomaly Composites

- For each model, monthly ensemble P and T forecasts are first computed by the equally weighted mean of all member forecasts.
- The P (or T) anomalies for a given start and lead times are then calculated by the differences between the ensemble P (or T) forecasts and the lead-specific model climatology derived from the hindcast average of all members excluding the forecast year.
- The P (or T) composites for the El Nino and La Nina events are simply the average of the ensemble P (or T) anomaly maps of selected years.
- The NMME composites are the equally weighted mean of the six models' composites.

NMME Composites

Observed Composites



a) Obs b) NMME 70N 60N 50N 40N -30N 20N 10N 120W 105W 90W 75W 165% 150W 135₩ 120W 10⁵₩ 90W 75¥ d) CanCM3 e) CanCM4

La Nina Composites for NDJFM P Anomaly

9



70N

60N

50N

40N

30N

20N

10N

165W

150W

135₩



La Nina Composites for NDJFM T Anomaly







Verification Scores (Anomaly Composites)

Anomaly Correlation Coefficient (ACC)

$$ACC = \frac{\sum_{i=1}^{n} (w_i \times Xm_i \times Xo_i)}{\sqrt{\sum_{i=1}^{n} (w_i \times Xm_i^2) \times \sum_{i=1}^{n} (w_i \times Xo_i^2)}}$$

Root-Mean-Square Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} w_i (Xm_i - Xo_i)^2}{\sum_{i=1}^{n} w_i}}$$

where Xm_i is the model anomaly (either P or T) at grid *i*, Xo_i is the observed anomaly at grid *i*, *n* is the total number of land grid points within the North American domain, and *w* is the weighting coefficient based on the latitude (*y*) of grid *i*, that is,

$$w_i = \cos(y_i)$$



ACC

0.74

0.69

NDJEM

0.69

0.59

NDJFM

0.8

0.7

0.6

0.5

0.4

- 0.3

-0.2

- The skill generally is higher for NMME composites, as well as NDJFM composites.
- Predictive skill varies with month. All models, as well as NMME, have greater ACC for February composites.
- Most models have slightly better skill in predicting El Nino P and T patterns than La Nina patterns.
- CFSv2 performs better in predicting P patterns under ENSO conditions than other models.

Probability Composites

- For each model, P (or T) forecasts for a given start and lead times are classified into three categories (A, N, B) based on the terciles derived from the hindcasts of all members excluding the forecast year.
- The classification applies to each individual member forecast, and the number of ensemble members that fell into the three categories under the El Nino and La Nina conditions are counted for the selected ENSO years.
- The probability of occurrence for each category under the warm (or cold) ENSO condition is then calculated by dividing the total number of counts by the product of the number of the selected ENSO years and the number of ensemble members.
- The NMME composite is the combination of all six models by adding all counts in each category from the six models together.
- The NDJFM composite is the combination of all five winter months.

El Nino Composites for NDJFM P Probability







El Nino Composites for NDJFM T Probability







Verification Scores (Probability Composites)

Probability Anomaly Correlation (PAC)

$$PAC = \frac{\sum_{i=1}^{n} w_i (Am_i \times Ao_i + Nm_i \times No_i + Bm_i \times Bo_i)}{\sqrt{\sum_{i=1}^{n} w_i (Am_i^2 + Nm_i^2 + Bm_i^2) \times \sum_{i=1}^{n} w_i (Ao_i^2 + No_i^2 + Bo_i^2)}}$$

Root-Mean Probability Score (RMPS)

$$RMPS = \sqrt{\frac{\sum_{i=1}^{n} w_i [(Am_i - Ao_i)^2 + (Nm_i - No_i)^2 + (Bm_i - Bo_i)^2]}{\sum_{i=1}^{n} 3w_i}}$$

where *Am*, *Nm*, and *Bm* are the probability anomalies of the above, near, and below normal categories from the model composite, respectively, and *Ao*, *No*, and *Bo* are the probability anomalies of the above, near, and below normal categories from the observed composite, respectively

PAC

- The skill for NMME and NDJFM composites are generally greater than individual model and month.
- February tends to have higher skill than other months for both P and T composites under either EI Nino or La Nina conditions.
- PAC shows larger scores for P composites than T composites under both El Nino and La Nina conditions.

0.8

0.7

0.4

-0.2

17

a) P_El Nino									b) P_L	a Nin	a	
CFSv2 -	0.39	0.39	0.41	0.54	0.36	0.69	CFSv2 -	0.44	0.31	0.28	0.53	0.23	0.61
CanCM3 -	0.31	0.34	0.24	0.25	0.21	0.55	CanCM3 -	0.38	0.32	0.15	0.33	0.21	0.51
CanCM4 -	0.35	0.33	0.30	0.41	0.30	0.58	CanCM4 -	0.27	0.32	0.18	0.42	0.19	0.52
FLOR -	0.31	0.29	0.24	0.41	0.28	0.55	FLOR -	0.38	0.27	0.23	0.38	0.14	0.54
GEOS5 -	0.29	0.31	0.22	0.38	0.23	0.52	GE0S5 -	0.29	0.33	0.17	0.40	0.15	0.49
CCSM4 -	0.30	0.24	0.29	0.30	0.17	0.48	CCSM4 -	0.35	0.30	0.25	0.36	0.07	0.48
NMME -	0.41	0.40	0.36	0.52	0.37	0.65	NMME -	0.46	0.38	0.27	0.53	0.22	0.61
	Nov	Dec	Jan	Feb	Mar	NDJFM		Nov	Dec	Jan	Feb	Mar	NDJFM
		(;) T_E	El Nino	0				d	I) T_L	a Nin	a	
CFSv2 -	0.10	0.23) T_E 0.22	0.29	0.32	0.27	CFSv2 -	0.15	0.18	0.17	a Nin 0.29	a 0.26	0.25
CFSv2 - CanCM3 -	0.10	0.23 0.15	<pre>>) T_E 0.22 0.20</pre>	0.29 0.28	0.32	0.27	CFSv2 - CanCM3 -	0.15	0.18 0.19	0.17 0.09	a Nin 0.29 0.24	a 0.26 0.22	0.25
CFSv2 - CanCM3 - CanCM4 -	0.10	0.23 0.15 0.14) T_E 0.22 0.20 0.13 	0.29 0.28 0.30	0.32	0.27 0.25 0.23	CFSv2 - CanCM3 - CanCM4 -	0.15	0.18 0.19 0.23) T_L 0.17 0.09 0.17 	a Nin 0.29 0.24 0.25	0.26 0.22 0.11	0.25 0.23 0.20
CFSv2 - CanCM3 - CanCM4 - FLOR -	0.10 0.10 0.16	0.23 0.15 0.14 0.18) T_E 0.22 0.20 0.13 0.22 	0.29 0.28 0.30 0.27	0.32 0.24 0.23 0.23	0.27 0.25 0.23 0.23	CFSv2 - CanCM3 - CanCM4 - FLOR -	0.15 0.12 0.11 0.11	0.18 0.19 0.23 0.19) T_L 0.17 0.09 0.17 0.23 	a Nin 0.29 0.24 0.25 0.31	a 0.26 0.22 0.11 0.15	0.25 0.23 0.20 0.25
CFSv2 - CanCM3 - CanCM4 - FLOR - GEOS5 -	0.10 0.10 0.16 0.10	0.23 0.15 0.14 0.18 0.21) T_E 0.22 0.20 0.13 0.22 0.17 	0.29 0.28 0.30 0.27 0.27	0.32 0.24 0.23 0.23 0.23	0.27 0.25 0.23 0.23 0.25	CFSv2 - CanCM3 - CanCM4 - FLOR - GEOS5 -	0.15 0.12 0.11 0.11	0.18 0.19 0.23 0.19 0.15) T_L 0.17 0.09 0.17 0.23 0.18 	a Nin 0.29 0.24 0.25 0.31 0.30	a 0.26 0.22 0.11 0.15 0.11	0.25 0.23 0.20 0.25 0.22
CFSv2 - CanCM3 - CanCM4 - FLOR - GEOS5 - CCSM4 -	0.10 0.10 0.16 0.10 0.12	0.23 0.15 0.14 0.18 0.21 0.19) T_E 0.22 0.20 0.13 0.22 0.17 0.26 	 0.29 0.28 0.30 0.27 0.27 0.28 	0.32 0.24 0.23 0.23 0.24 0.24	0.27 0.25 0.23 0.23 0.25 0.25	CFSv2 - CanCM3 - CanCM4 - FLOR - GEOS5 - CCSM4 -	0.15 0.12 0.11 0.11 0.14	d 0.18 0.19 0.23 0.19 0.15 0.22) T_L 0.17 0.09 0.17 0.23 0.18 0.12 	 a Nin 0.29 0.24 0.25 0.31 0.30 0.25 	 a a<	0.25 0.23 0.20 0.25 0.22
CFSv2 - CanCM3 - CanCM4 - FLOR - GEOS5 - CCSM4 - NMME -	 0.10 0.10 0.16 0.10 0.12 0.17 0.15 	0.23 0.15 0.14 0.18 0.21 0.19) T_E 0.22 0.20 0.13 0.22 0.17 0.26 0.23 	 Nind 0.29 0.28 0.30 0.27 0.27 0.27 0.28 0.31 	0.32 0.24 0.23 0.23 0.24 0.24 0.24	0.27 0.25 0.23 0.23 0.25 0.25 0.25	CFSv2 - CanCM3 - CanCM4 - FLOR - GEOS5 - CCSM4 - NMME -	0.15 0.12 0.11 0.11 0.14 0.09 0.16	d 0.18 0.19 0.23 0.19 0.15 0.22) T_L 0.17 0.09 0.17 0.23 0.18 0.12 0.20 	 a Nin 0.29 0.24 0.25 0.31 0.30 0.25 0.31 	 a a<	0.25 0.23 0.20 0.25 0.22 0.22

RMPS

- Consistent with PAC's findings.
- NMME has higher skill in predicting P patterns than T patterns under both El Nino and La Nina conditions.
- NDJFM composite would provide a better prediction for an independent new ENSO case in any given month.

0.21

0.18

0.15

0.12

0.09

0.06

0.03

Mar

NDJFM

Feb

Jan

Dec

Nov

 NMME has comparable skill (in terms of accuracy) in predicting El Nino and La Nina patterns, for both P and T composites.

	C	i) P_E	El Nin	0		b) P_La Nina						
0.119	0.106	0.102	0.104	0.102	0.054	CFSv2 -	0.112	0.117	0.122	0.108	0.116	0.062
0.133	0.120	0.117	0.118	0.111	0.061	CanCM3 -	0.129	0.128	0.127	0.123	0.116	0.066
0.130	0.121	0.124	0.114	0.115	0.068	CanCM4 -	0.140	0.126	0.143	0.122	0.137	0.075
0.124	0.111	0.112	0.107	0.110	0.060	FLOR -	0.116	0.118	0.120	0.118	0.122	0.063
0.129	0.117	0.125	0.123	0.124	0.069	GEOS5 -	0.130	0.121	0.136	0.126	0.142	0.075
0.129	0.117	0.111	0.118	0.115	0.065	CCSM4 -	0.125	0.121	0.116	0.121	0.129	0.067
0.118	0.104	0.101	0.098	0.099	0.053	NMME -	0.110	0.111	0.115	0.106	0.111	0.058
Nov	Dec	Jan	Feb	Mar	NDJFM		Nov	Dec	Jan	Feb	Mar	NDJFM
		c) T_E	El Nine	0				d	I) T_L	a Nin	a	
0.190	0.183	0.185	0.192	0.179	0.165	CFSv2 -	0.187	0.184	0.188	a Nin 0.190	a 0.185	0.163
0.190	0.183 0.192	0.185 0.188	0.192 0.184	0.179	0.165	CFSv2 - CanCM3 -	0.187	0.184 0.185	0.188 0.190	a Nin 0.190 0.194	a 0.185 0.190	0.163
0.190	0.183 0.192 0.196	 C.185 O.188 O.207 	 C Nine 0.192 0.184 0.191 	0.179 0.190 0.204	0.165 0.166 0.175	CFSv2 - CanCM3 - CanCM4 -	0.187 0.192 0.194	d 0.184 0.185 0.182) T_L 0.188 0.190 0.194 	a Nin 0.190 0.194 0.199	a 0.185 0.190 0.225	0.163 0.164 0.174
0.190	0.183 0.192 0.196 0.186	 c) T_E 0.185 0.188 0.207 0.186 	0.192 0.184 0.191 0.187	0.179 0.190 0.204 0.193	0.165 0.166 0.175 0.168	CFSv2 - CanCM3 - CanCM4 - FLOR -	0.187 0.192 0.194 0.186	0.184 0.185 0.182 0.183) T_L 0.188 0.190 0.194 0.183 	a Nin 0.190 0.194 0.199 0.184	a 0.185 0.190 0.225 0.205	0.163 0.164 0.174 0.164
0.190 0.193 0.190 0.190 0.189 0.191	0.183 0.192 0.196 0.186 0.193	 c) T_E 0.185 0.188 0.207 0.186 0.204 	0.192 0.184 0.191 0.187 0.205	0.179 0.190 0.204 0.193 0.202	0.165 0.166 0.175 0.168 0.175	CFSv2 - CanCM3 - CanCM4 - FLOR - GEOS5 -	0.187 0.192 0.194 0.186 0.190	d 0.184 0.185 0.182 0.183 0.183) T_L 0.188 0.190 0.194 0.183 0.203 	a Nin 0.190 0.194 0.199 0.184 0.195	a 0.185 0.190 0.225 0.205 0.217	0.163 0.164 0.174 0.164 0.174
0.190 0.193 0.190 0.189 0.191 0.187	0.183 0.192 0.196 0.186 0.187	 c) T_E 0.185 0.188 0.207 0.186 0.204 0.185 	 Nine 0.192 0.184 0.191 0.187 0.205 0.195 	0.179 0.190 0.204 0.193 0.202 0.187	0.165 0.166 0.175 0.168 0.175 0.168	CFSv2 - CanCM3 - CanCM4 - FLOR - GEOS5 - CCSM4 -	0.187 0.192 0.194 0.186 0.190 0.191	d 0.184 0.185 0.182 0.182 0.183 0.183) T_L 0.188 0.190 0.194 0.194 0.183 0.203 0.189 	 a Nin 0.190 0.194 0.199 0.184 0.195 0.192 	a 0.185 0.190 0.225 0.205 0.217 0.195	0.163 0.164 0.174 0.164 0.174

CFSv2

CanCM3

CanCM4

FLOR

GEOS5

CCSM4

NMME

CFSv2

CanCM3

CanCM4

FLOR

GEOS5

CCSM4

NMME

Feb

Jan

Mar

NDJFM

Dec

Nov

Benefits of Probability Composites

- They unify P and T composites through the use of probability as unit.
- They directly provide probability distribution information for three category outcomes (as used in operational seasonal prediction at CPC).
- By using the tercile thresholds, each count is treated and contributed equally and thus the effect of outliers is reduced.
- They are less sensitive to the sample used and thus give a more robust estimate of the ENSO impacts.
- Because both the model and observed composites are derived with respect to their own distributions, we bypass the question whether the model and observation have the same distribution.

Summary

- NMME predicts ENSO P patterns well during wintertime. All models are reasonably good. CFSv2 performs particularly well. This result gives us confidence in NMME P forecasts during an ENSO episode and models' ability in simulating teleconnections.
- There are some discrepancies between the NMME and observed composites for T forecasts. The differences are mainly contributed by the GEOS5, CanCM4, and FLOR models.
- For both P and T composites, predictive skill under ENSO conditions is greater for NMME, as well as NDJFM. February tends to has higher skill than other winter months.
- For anomaly composites, most models have better skill in predicting El Nino patterns than La Nina patterns.
- For probability composites, all models have better skill in predicting P patterns than T patterns.

The North American Multi-Model Ensemble

Thank you and questions

NMME ENSO webpage:

http://www.cpc.ncep.noaa.gov/products/NMME/enso/

Contact: lichuan.chen@noaa.gov

NMME The North American Multi-Model Ensemble

- NMME is an experimental multi-model seasonal forecasting system consisting of coupled climate models from U.S. modeling centers and Canadian Meteorological Centre, aimed at improving intraseasonal to interannual prediction capability.
- The multi-model ensemble approach has proven effective at quantifying prediction uncertainty due to uncertainty in model formulation, and has proven to produce better forecast quality (on average) than any single model ensemble.
- CTB NMME documents:

http://www.cpc.ncep.noaa.gov/products/ctb/nmme/

CPC NMME forecasts:

http://www.cpc.ncep.noaa.gov/products/NMME/



c) T_El Nino CFSv2 -0.54 0.44 0.50 0.60 0.57 CanCM3 0.46 0.55 0.72 0.42 0.76 Can CanCM4 0.52 0.72 1.03 0.65 1.13 0.62 Can FLOR -0.57 0.42 0.52 0.73 0.56 0.89 0.63 GEOS5 -0.56 0.68 1.19 0.94 0.95 CCSM4 0.50 0.59 0.68 0.89 0.75 0.50 NMME 0.43 0.53 0.69 0.50 0.80 0.38 Feb NDJFM Dec Jan Mar Nov

	d) T_La Nina										
CFSv2 -	0.58	0.68	0.60	0.59	0.66	0.34					
CanCM3 -	0.49	0.57	0.73	0.69	0.73	0.32					
CanCM4 -	0.67	0.56	0.95	0.73	1.22	0.58					
FLOR -	0.58	0.77	0.71	0.55	1.01	0.48					
GEOS5 -	0.55	0.79	1.23	0.81	1.31	0.75					
CCSM4 -	0.81	0.61	0.60	0.70	0.91	0.49					
NMME -	0.54	0.61	0.68	0.57	0.95	0.45					
	Nov	Dec	Jan	Feb	Mar	NDJFM					

0.8

0.7

0.4

0.2

RMSE

- Similar to ACC results.
- The skill generally is higher for NMME composites, as well as NDJFM composites.