July 11, 2006, National Centers for Environmental Prediction Environmental Modeling Center (EMC) Seminar

Predictability of Coupled GCMs: NCEP CFS, CliPAS, and DEMETER

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Motivations and Objectives

❖ To understand the predictability of coupled models focusing on error growth

❖ To investigate the CGCMs behaviors in a long simulation and in short-term forecast

❖ NCEP CFS, CliPAS and DEMETER
→ 12 coupled GCMs having 5-9 months integrations starting from 3-15 different observed initial conditions for 2-12 calendar months in the common 23 years from 1981 to 2003: Large number of integrations from the variety of initial states gives us a better chance to examine the overall skill of coupled GCMs.
→ CFS, SINTEX, SNU, and UKMO GCMs, that have both forecasts and long run dataset, is perfect candidate to investigate the influence of model ability on forecast.

➢ Focusing on tropical Pacific SST

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Contents

1 Overall assessment of CGCMs' performance

ENSO forecast skill of 12 CGCMs

→ Influence of amplitude of SST anomalies on the forecast skill

→ ENSO phase-locking on seasonal cycle and forecast skill

2 Error growth and its implication on seasonal predictability

→ Characteristics of error growth in NCEP CFS

→ Theoretical approach: "Lorenz curve" and error growth

3 Influence of model deficiency on forecast skill

as a cause of decreasing predictability with respect to lead time

→ Models' coupled mode behavior in long run

Model Description and Experimental Design

CLIPAS

5 CGCMs

- 1981 – 2004
- 4 case of initial time (Feb, May, Aug, Nov)
- 3-15 member
- 5-9 months duration

DEMETER

7 CGCMs

- 1980 – 2001
- 4 case of initial time (Feb, May, Aug, Nov)
- 9 ensemble member
- 6 months duration

	Lead month	run	Period	AGCM	OGCM
FRCGC SINTEX	6	9	82-04	ECHAM 4 T106 L19	OPA 8.2 2x2 L31
NASA	5	3	80-04	NSIPP 1 2x2.5 L34	Poseidon V4 1/3x1 L40
SNU	6	6	60-01	SNU T42 L21	MOM 2.2 1/3x1 L32
UH	6	10	83-03	ECHAM 4 T31 L19	UH Ocean 1x2 L2
NCEP CFS	9	15	81-03	GFS T62 L64	MOM 3 1/3x5/8 L27

12 calendar months case during 23 years (1981-2003) with 9 months forecast

	AGCM	OGCM
CERFACS	ARPEGE T63 L31	OPA 8.2 2.0x2.0 L31
ECMWF	IFS T95 L40	HOPE-E 1.4x0.3-1.429 L29
INGV	ECHAM 4 T42 L19	OPA 8.1 2.0x0.5-1.5 L31
LODYC	IFS T95 L40	OPA 8.2 2.0x2.0 L31
Meteo-France	ARPEGE T63 L31	OPA 8.0 192-152, L31
MPI	ECHAM-5 T42 L19	MPI-IM1 2.5x0.5-2.5 L23
UK Met Office	HadAM3 2.5x3.75 L19	GloSea OGCM 1.25x0.3-125 L40

Analyzed Dataset

CLIPAS 5 models

- 1980-2001 climatology removed
- analyzed during 22-year

DEMETER 7 models

- 1980-2001 climatology removed
- analyzed during 22-year

Forecast

SST anomalies

Observation

HadSST 1.1 from Hadely center (Rayner et al. 2003)

→ 4 case of initial time (Feb, May, Aug, Nov) is investigate for 10 GCMs except NASA, UH having only May and Nov cases.

➢ For ENSO predictability, our study will focus on the tropical Pacific by analyzing Nino indices

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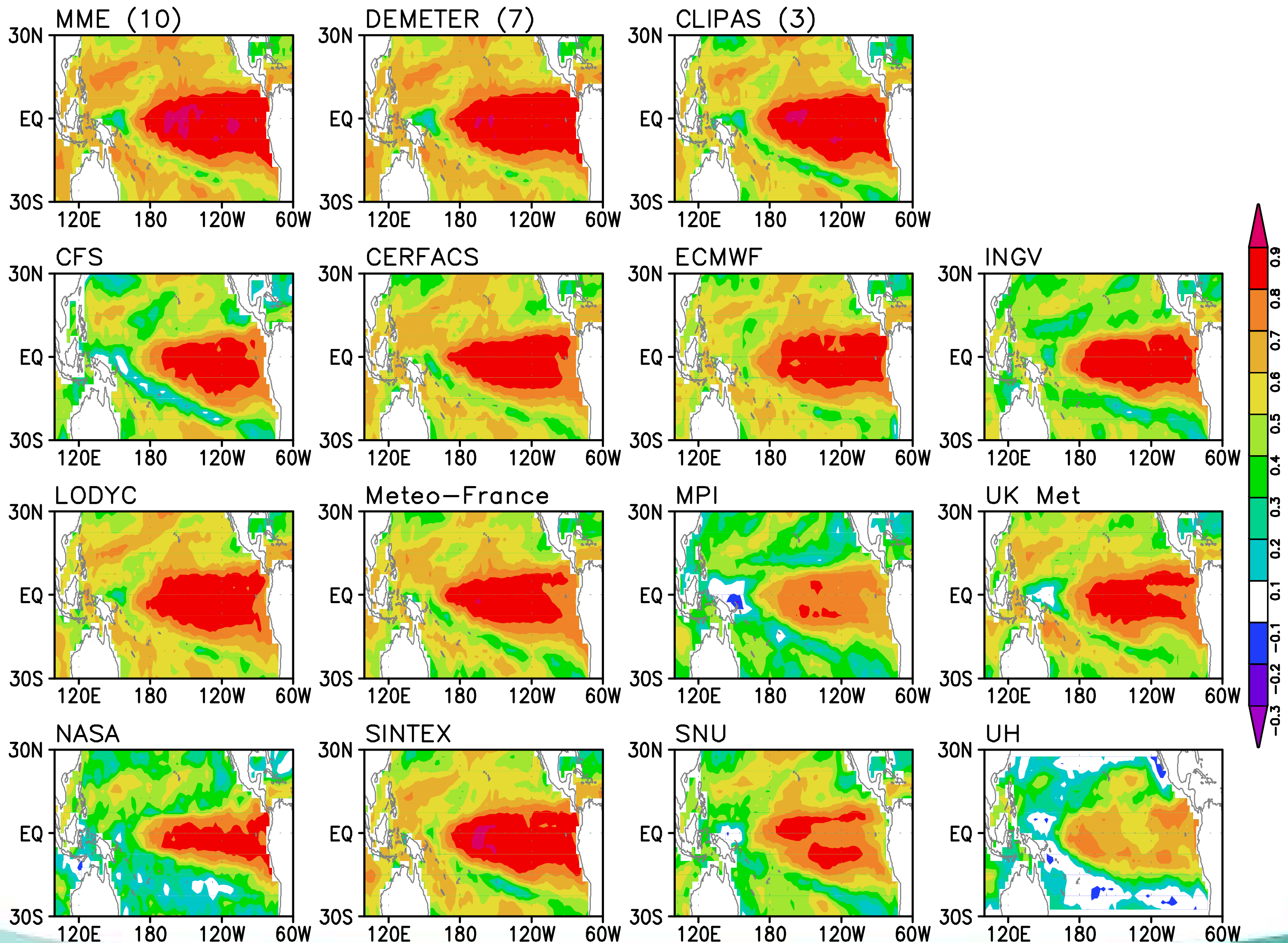
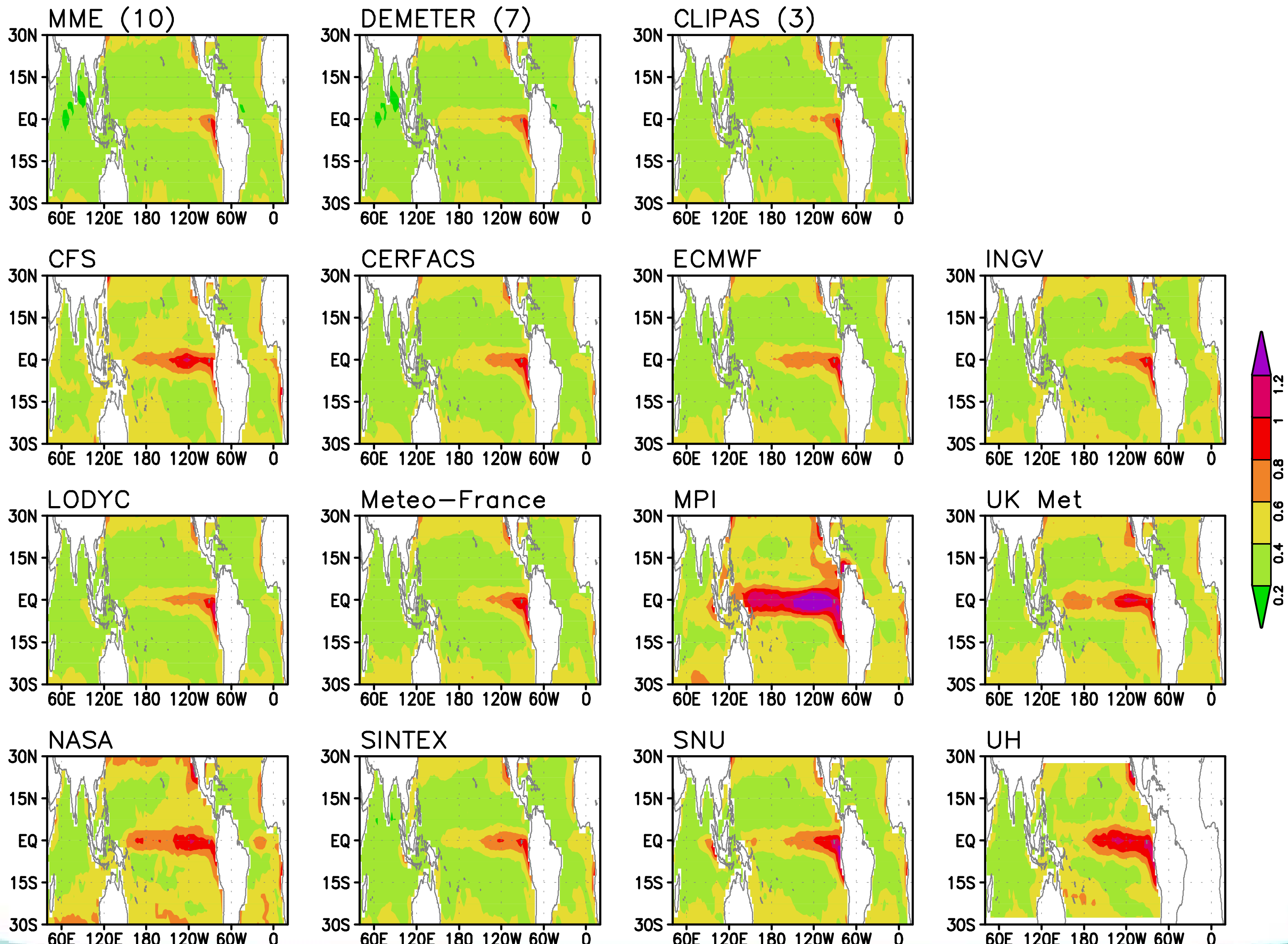
Overview of ENSO Predictability

- ❑ **ENSO forecast skill of 12 CGCMs**
- ❑ **Influence of amplitude of SST anomalies on the forecast skill**
- ❑ **ENSO phase-locking on seasonal cycle and forecast skill**

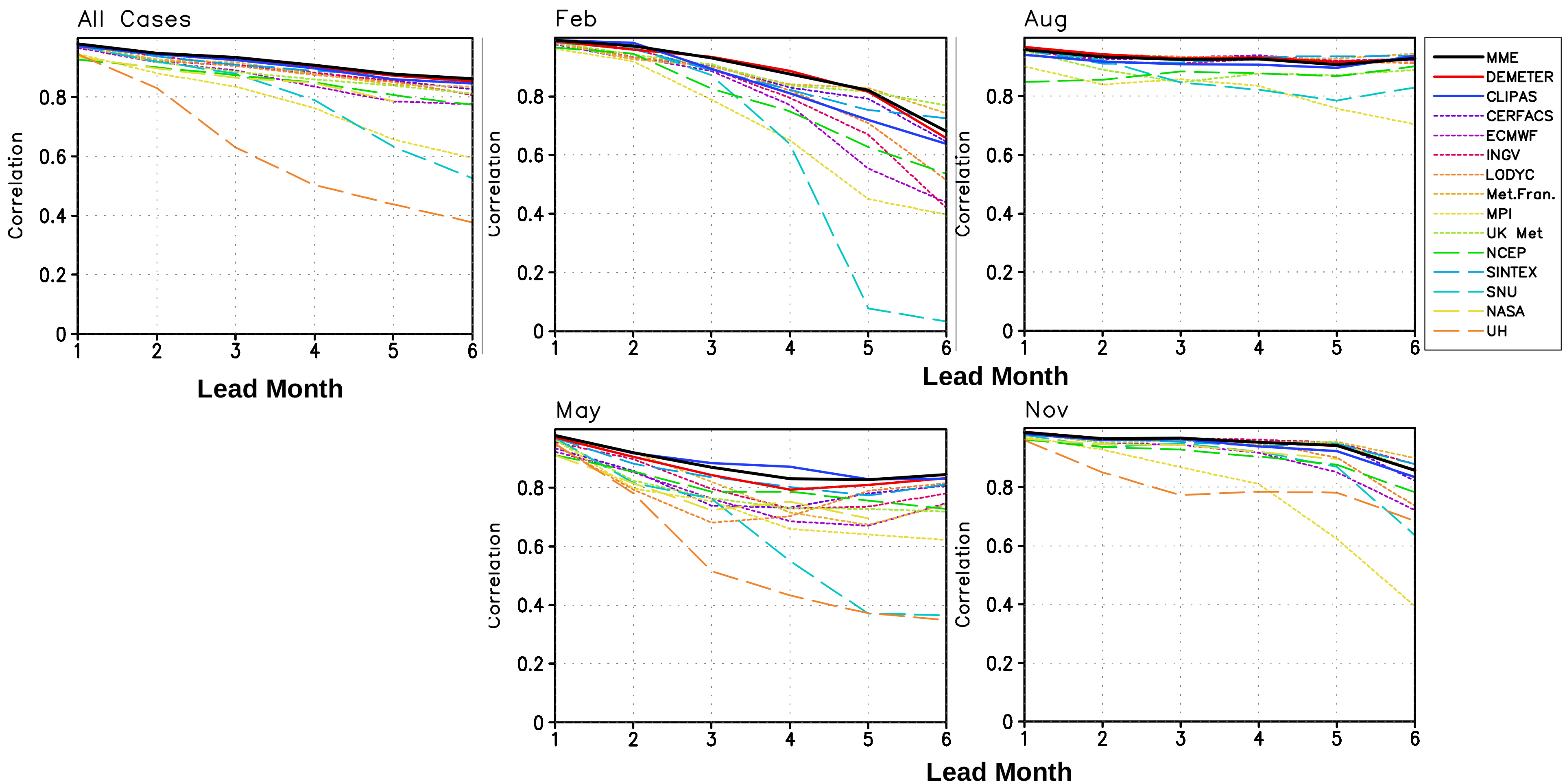
Correlation of SST anomalies during 1980-2001 (1st season)



RMSE of SST anomalies during 1980-2001 (1st season, 2-4 lead month



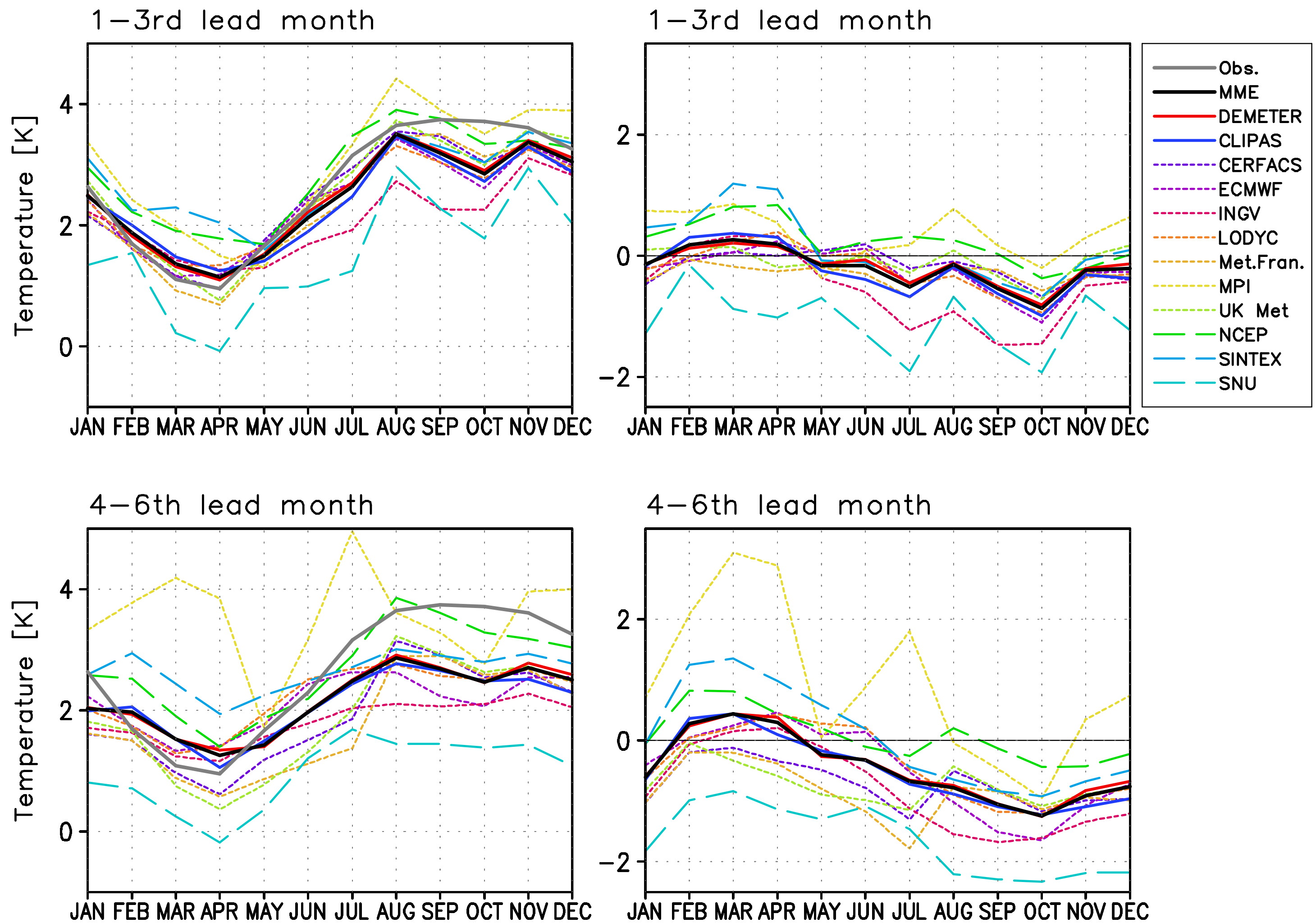
Forecast Skill of NINO 3.4 Index with respect to Initial Time



- ❑“all cases” means anomaly correlation coefficients including four cases (*N=88*).
- ❑ Overall skill shows gradual decline with respect to lead month
- ❑ Feb and May IC cases show fast drop of skills than Aug and Nov cases.
- ❑ Multi-model ensembles show better skill than individual model.
- ❑ MPI(yellow dot) and SNU(blue dash) show lower skill than other GCMs.

Annual Cycle of West-East Gradient of SST (NINO4 minus NINO3)

Climatological Annual Cycle | **Difference from Obs.**



- ❑ From the first 3 months, SNU show weak annual cycle.
- ❑ While MPI show rapid drop of skill after 4 to 6 lead month comparing with other models.
- ❑ These wrong climatology may have an influence on anomaly forecast field.

Sources of Forecast Error

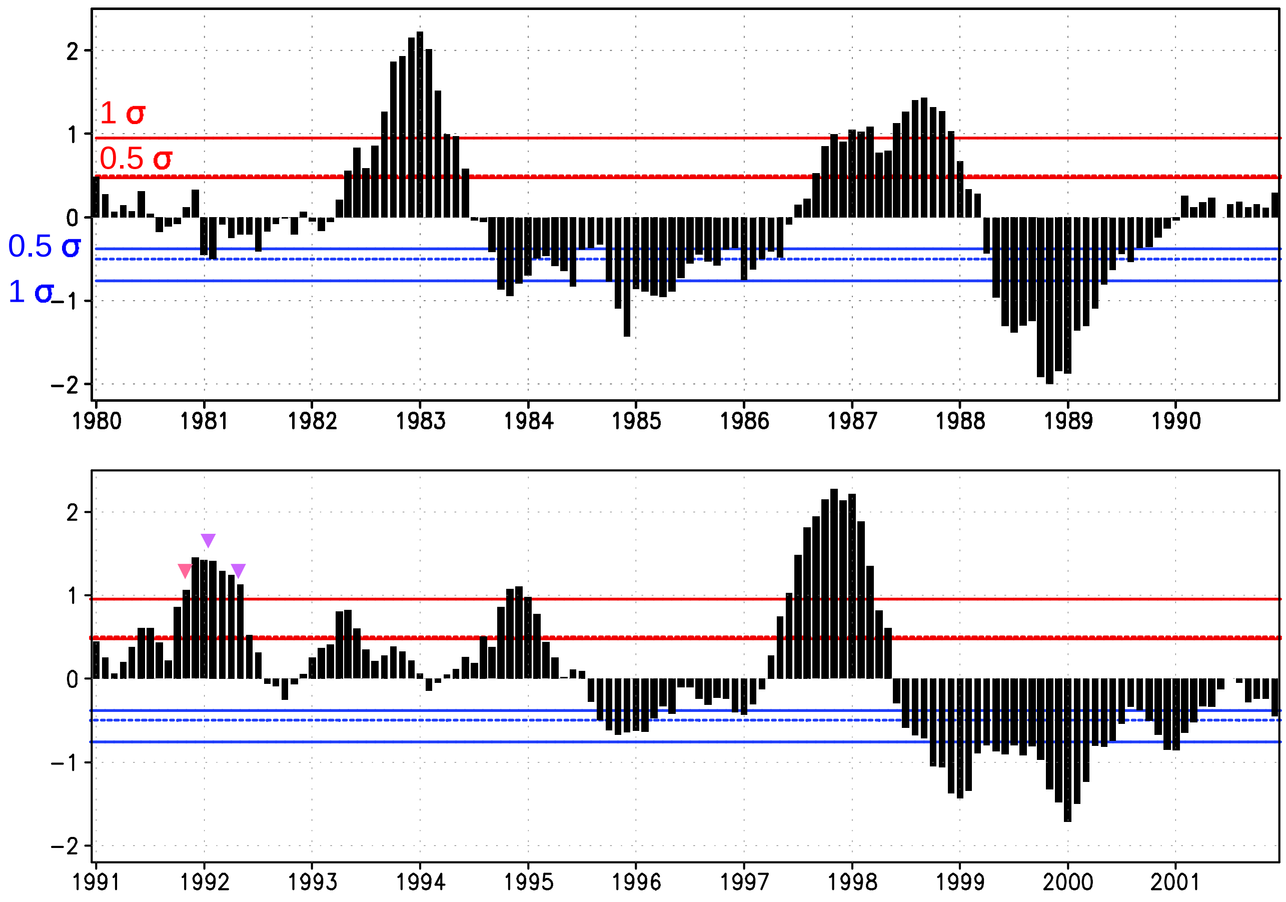
Forecast Error

❑ From amplitude and phase of ENSO
→ amplitude of SST anomalies with respect to ENSO phase

❑ From observation
→ Imperfect initial condition

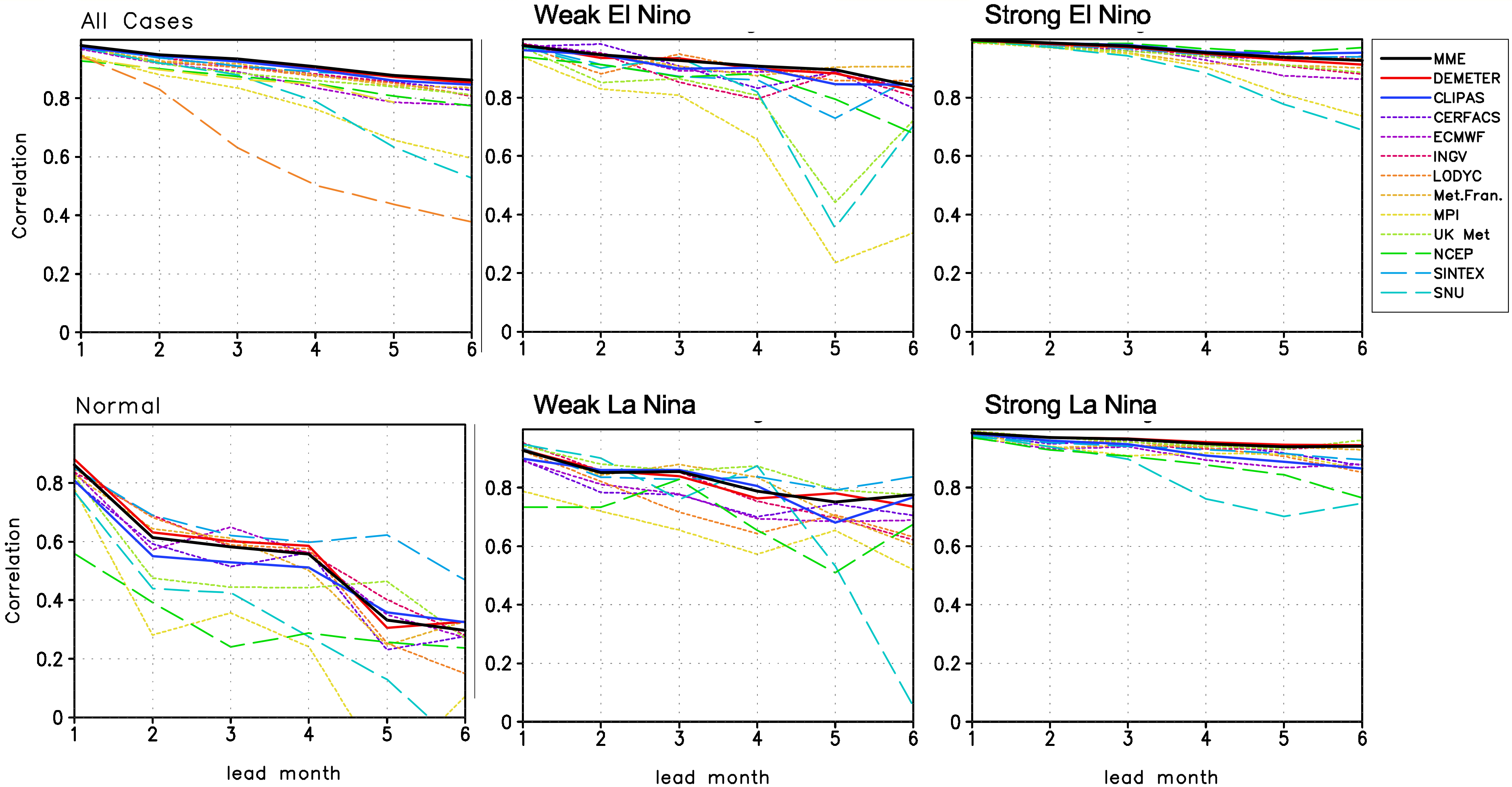
❑ From model errors
→ mean error, phase shift, different amplitude, and wrong seasonal cycle, etc

Definition of each case in NINO 3.4 Index



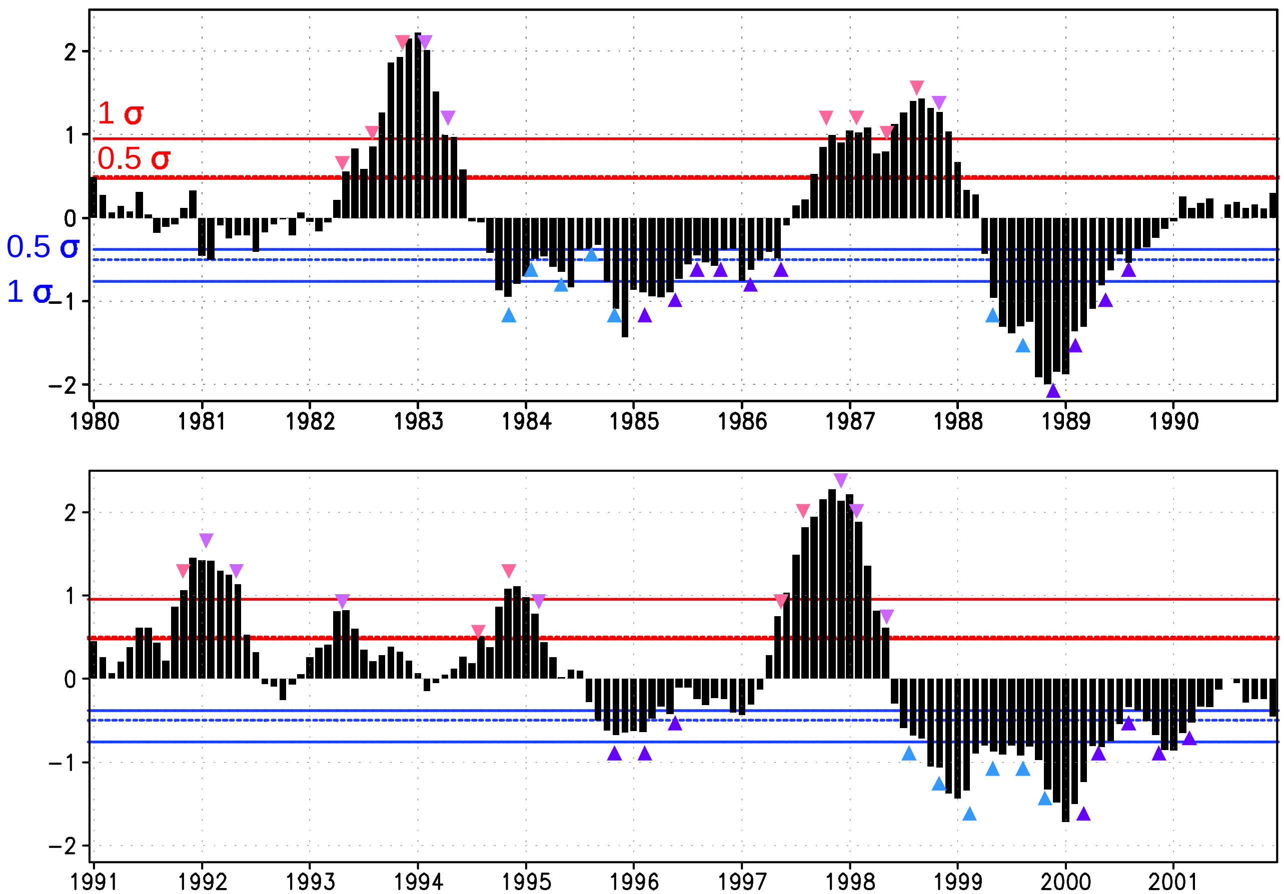
- ❑ **Standard deviation is calculated separately for warm and cold anomalies to consider the asymmetry**
  - ✓ **Forecast skill with respect to SST intensity of target time**
  - ✓ **Forecast skill with respect to ENSO phase of initial time**

Forecast Skill of NINO3.4 with respect to SST Intensity of Target Time



- Normal case shows fast drop of skill with respect to lead month and 1st month skill is also very low.
- Strong ENSO case with SST anomalies more than one standard deviations, shows higher skill till 6th month.
- While weak ENSO case shows moderate skill and gradual drop with respect to lead month.

Definition of ENSO Phase in NINO 3.4 Index



- Based on 0.5 standard deviation, normal, growth, decaying phase is distinguished during 1980-2001.
- Standard deviation is calculated separately for warm and cold anomalies to consider the asymmetry.

▼ El Nino decay
▼ El Nino develop
▲ La Nina develop
▲ La Nina decay

	El Nino		La Nina		Normal
	growth	decay	growth	decay	
Case	13	10	13	19	33
Feb	87	82,92,95,98	84,99	81,85,86,89,96,00,01	80,82,88,90,91,93,94,97
May	82,87,97	83,92,93,98	84,88,99	85,86,89,96,00	80,81,90,91,94,95,01
Aug	82,87,91,94,96		84,88,98,99	85,89,00	80,81,83,86,90,92,93,95,96,01
Nov	82,86,91,94	87,97	83,84,98,99	85,88,95,00	80,81,89,90,92,93,96,01

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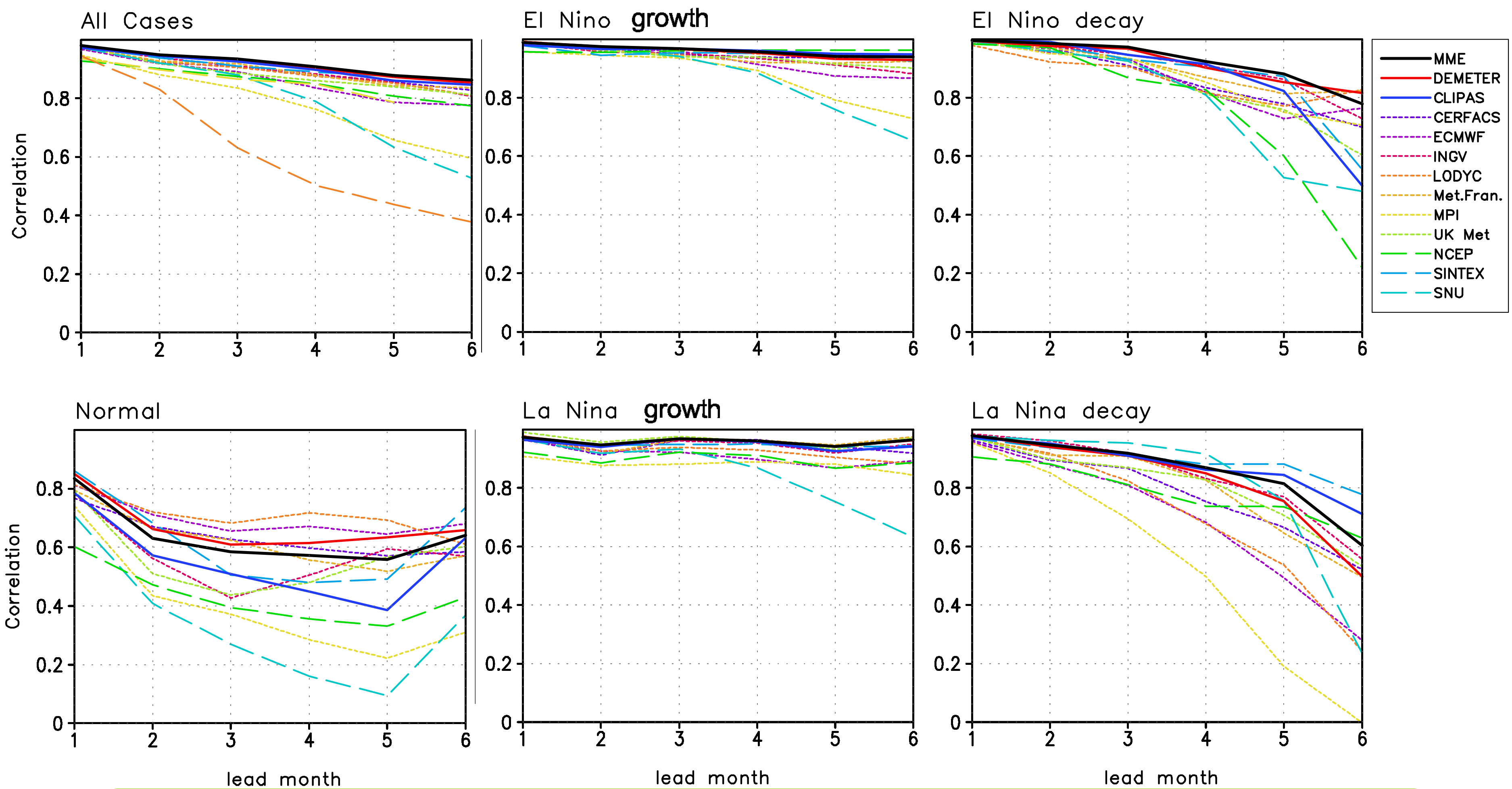
Forecast Skill of NINO3.4 with respect to ENSO Phase of Initial Time



- Growth phase of both warm and cold events is more predictable than decay phase.
- Normal events are far less predictable than warm and cold events.
- Therefore, fast drop of skill in February and May cases can be explained since it includes more decaying phase having lower skill than growth phase.

Error Growth and its Implication on Seasonal Predictability

- **Structure of error growth in NCEP CFS**
- **Theoretical approach: Lorenz curve and error growth**

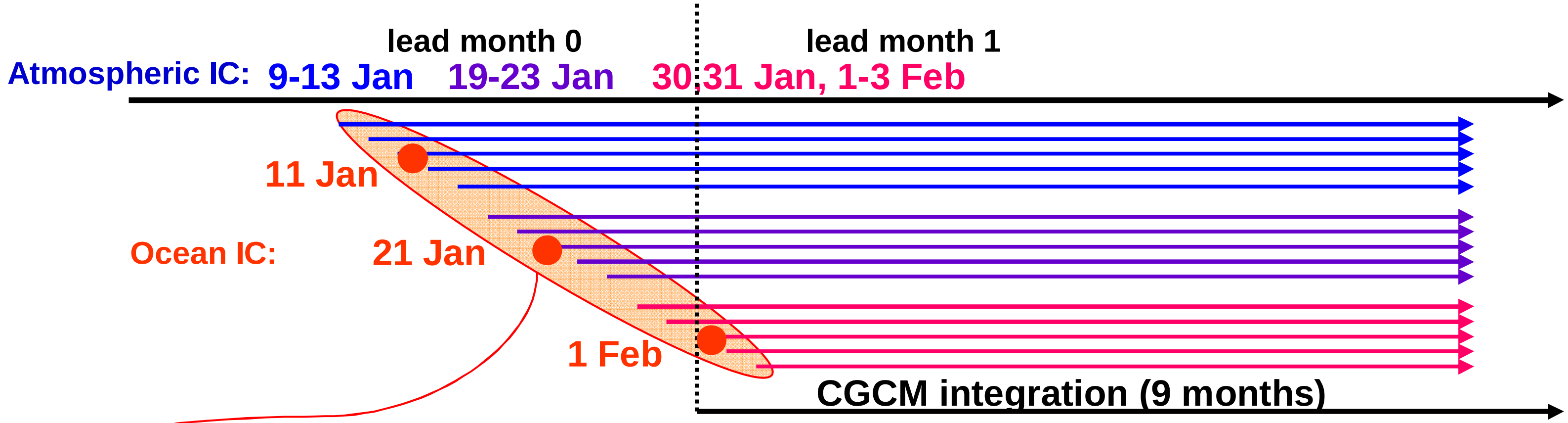
NCEP CFS forecast data

❖ The NCEP Climate Forecast System (CFS) retrospective forecast

- One-tier prediction system using CGCM
- 12 calendar months case during 23 years (1981-2003) with 9 months forecast
- 15 ensemble members with different initial condition with lead time

Institute	AGCM	Resolution	OGCM	Resolution	Initial conditions	
					Atmosphere	Ocean
NCEP	NCEP perational global sepctral model (GFS)	T62 64 Levels	MOM 3.0	$1^{o}X1/3$ to 1^{o} 40 Levels	NCEP/DOE AMIP R2	GODAS (Behringer et al. 2005)

❖ CFS prediction procedure (three segments IC)

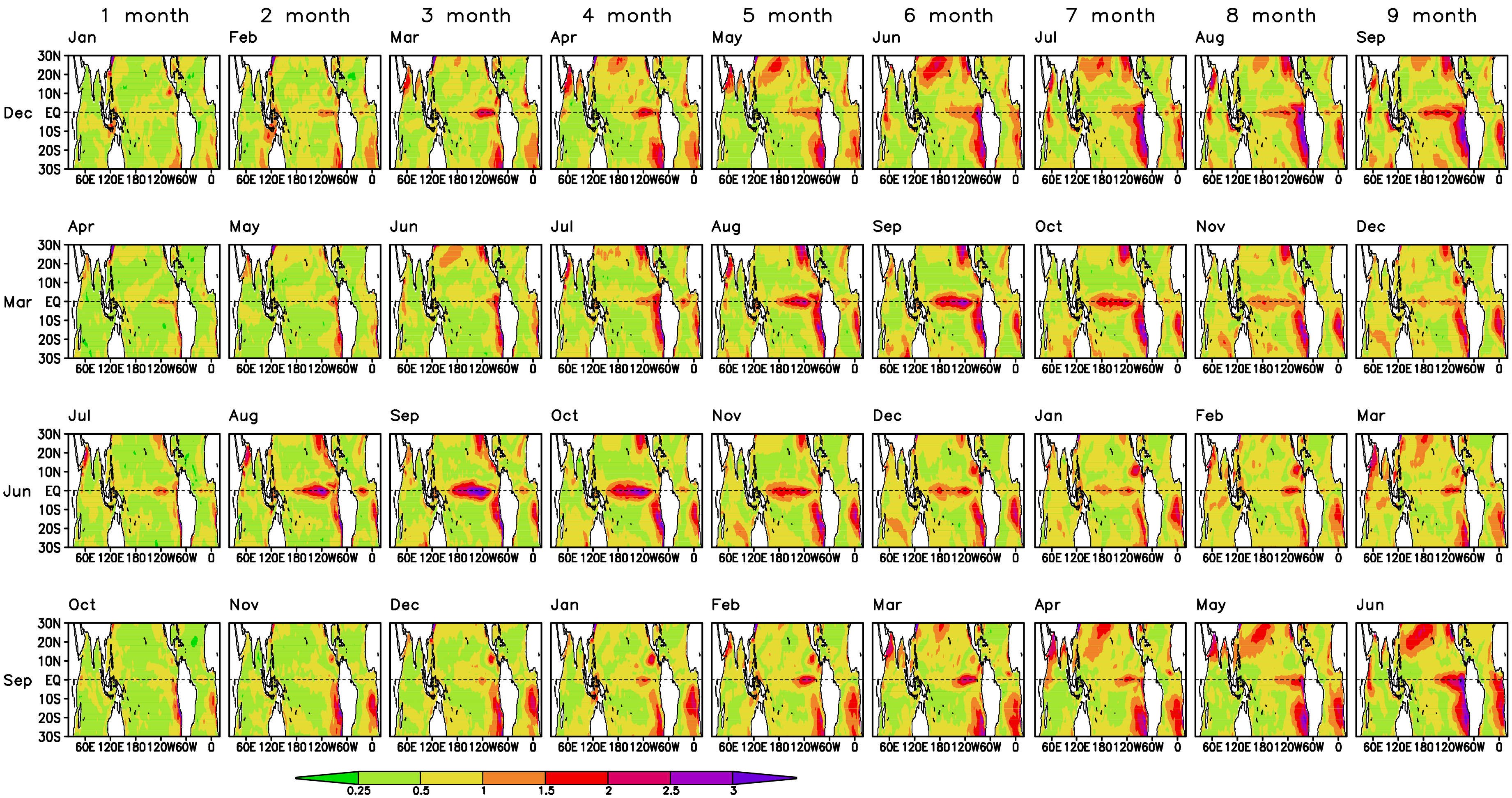


15 ensembles with 3 segments

Initial condition : Atmosphere NCEP/DOE AMIP Reanalysis 2: +2,+1,0,-1,-2 day from ocean IC

OCEAN NCEP GODAS: 11^{th} of 21th lead month 0 , 1^{st} of lead month 1

Total error of ensemble mean SST: 1 to 9 lead month

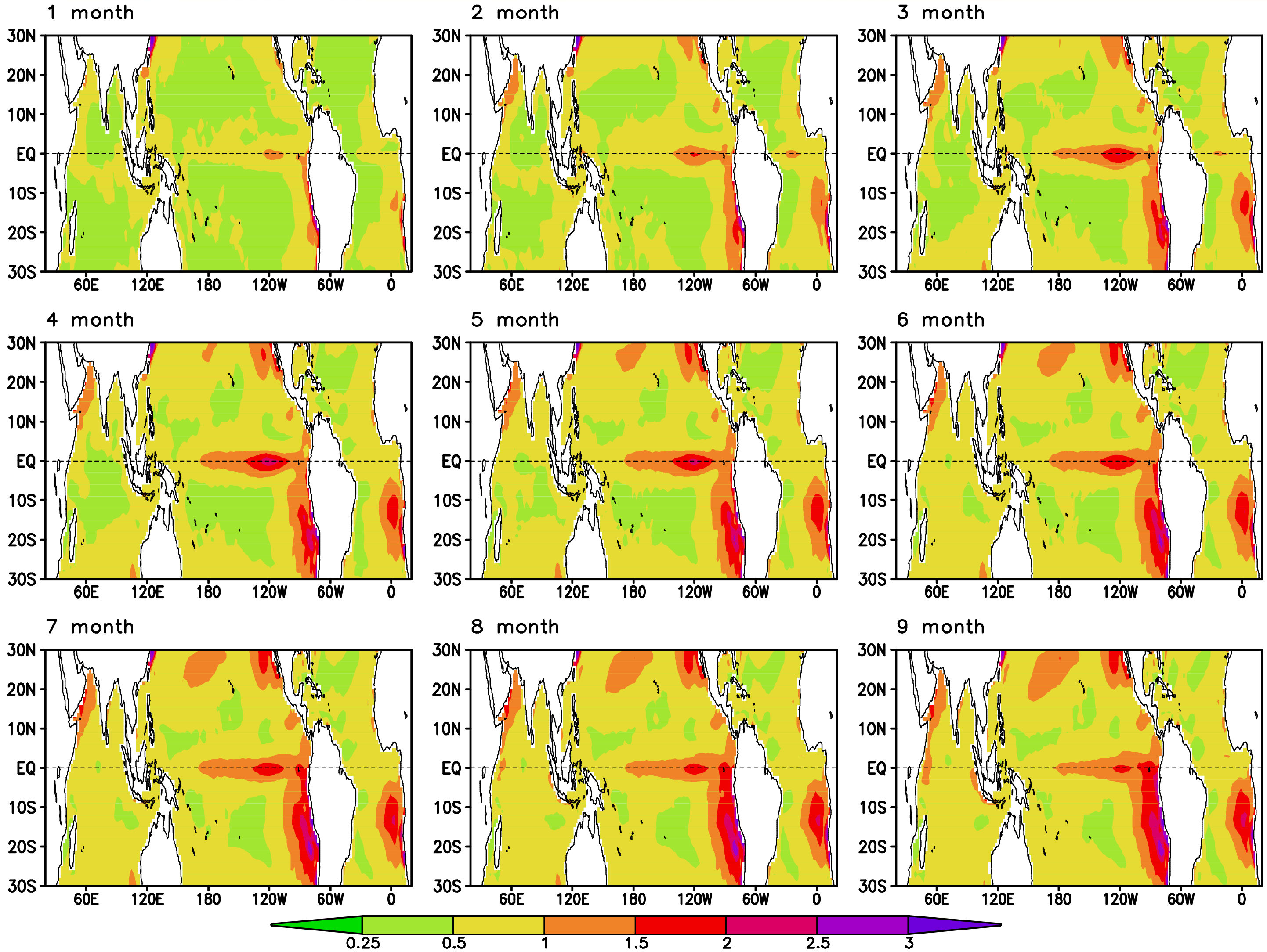


▪**Systematic error** $E_{jk} = \sqrt{\frac{1}{I}\sum_{i=1}^{I}(\overline{M}_{ijk} - O_{ik})^2}$

I : year (I=23)
j : initial condition
k : lead month (real month)

where $\overline{M}_{ijk} = \frac{1}{H}\sum_{h=1}^{H} M_{ijkh}$ *h: ensemble (H=15)*

Total error of ensemble mean SST following to lead month

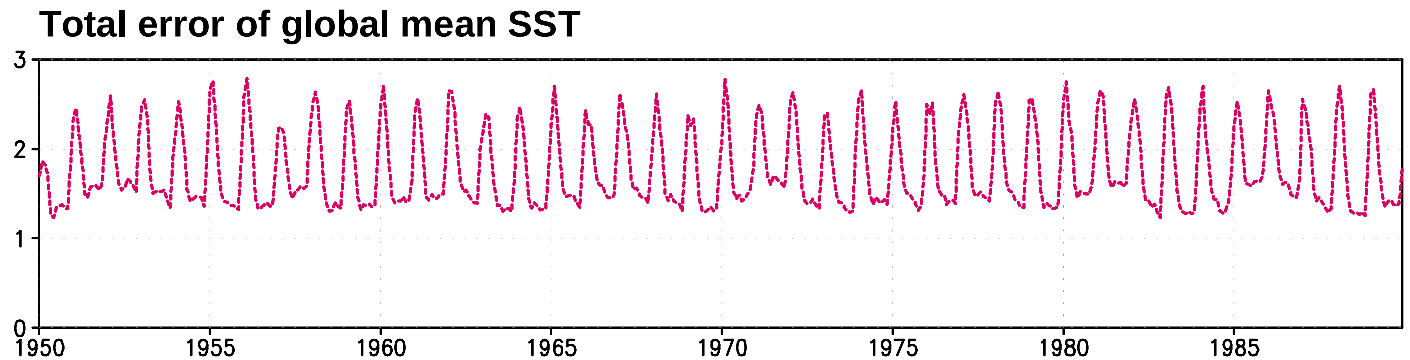


▪**Systematic error** $E_k = \sqrt{\frac{1}{J}\frac{1}{I}\sum_{j=1}^{J}\sum_{i=1}^{I}(\overline{M}_{ijk} - O_{ik})^2}$

I : year (I=23)
j : initial condition (J=12)
k : lead month

where $\overline{M}_{ijk} = \frac{1}{H}\sum_{h=1}^{H} M_{ijkh}$ *h: ensemble (H=15)*

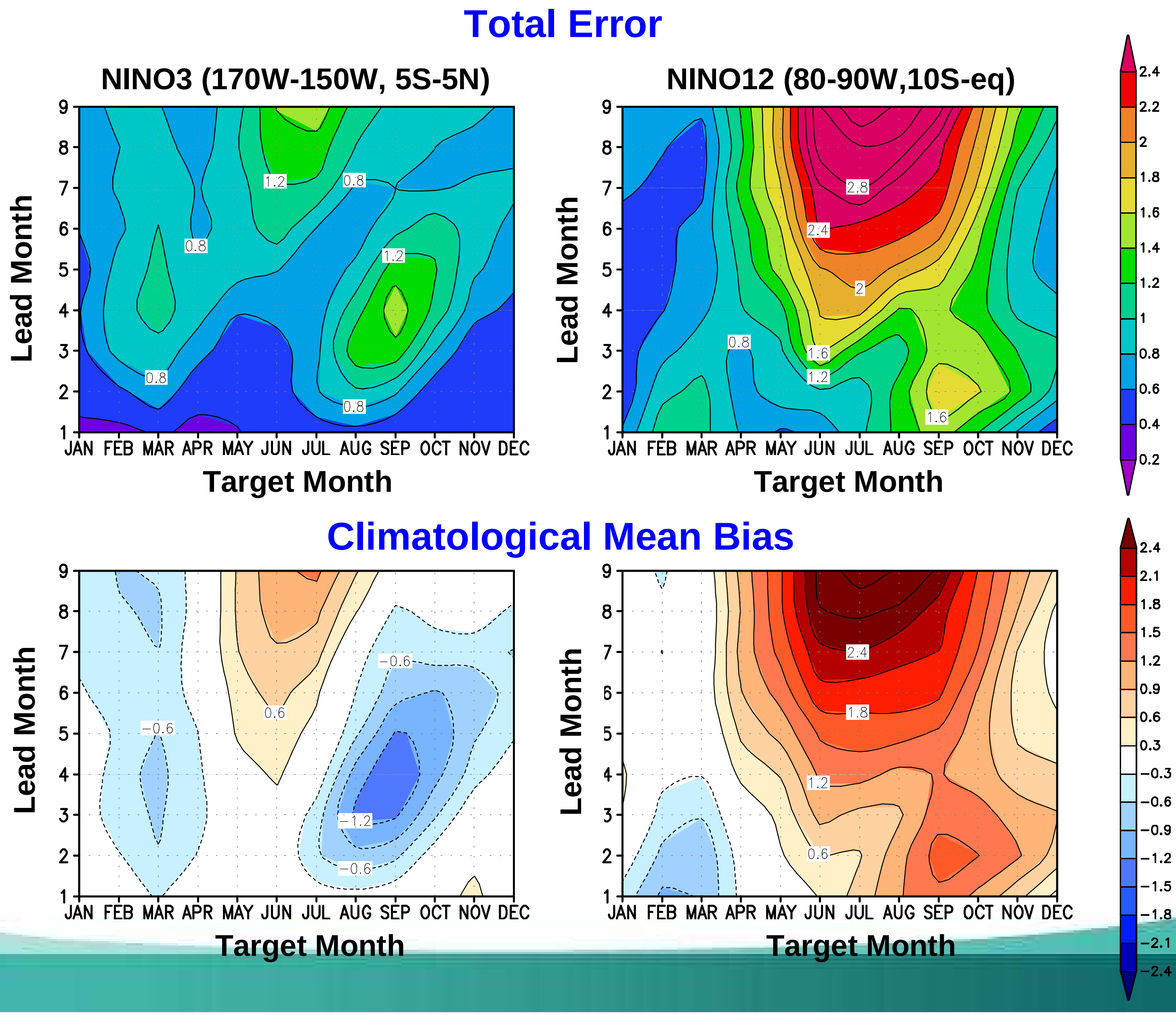
Total error in CFS 52-year simulation



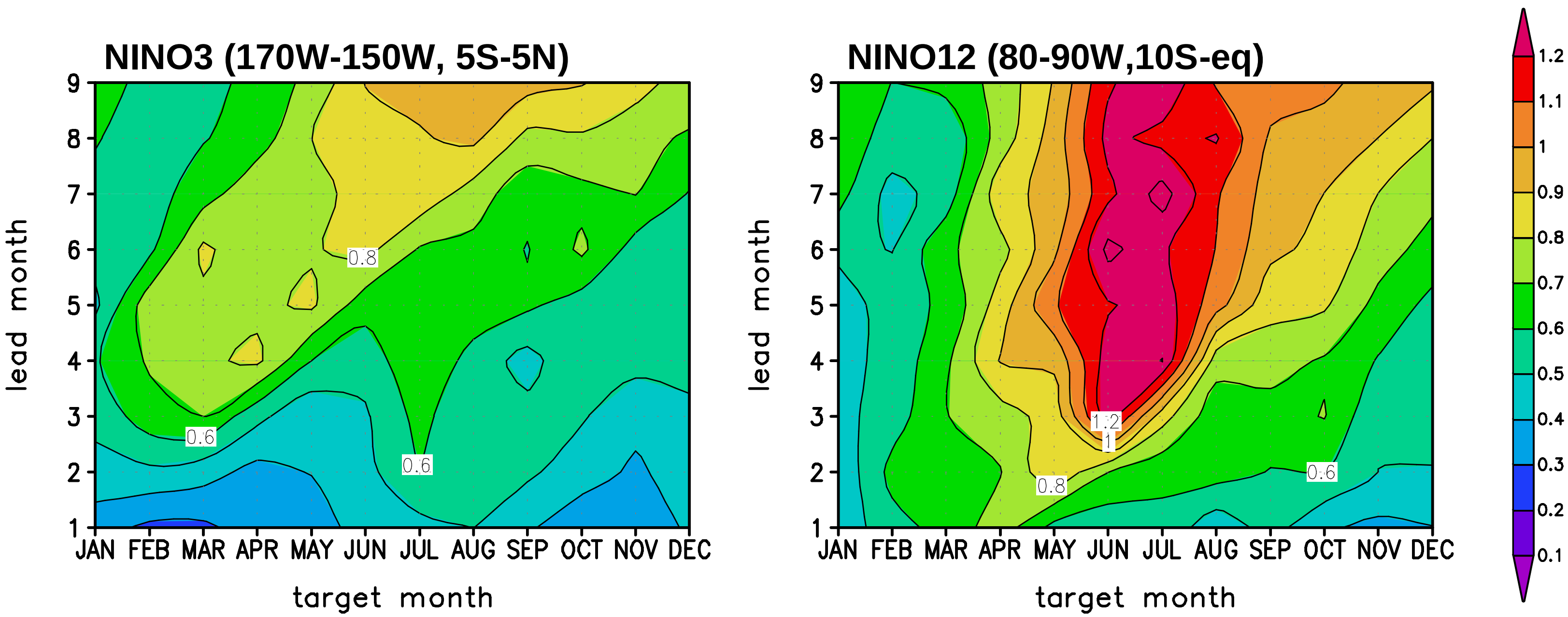
- **Departure from HadSST climatology during 1950-1999**

- **It shows dramatic increase of error only occurs during first few months and after that there is interannual variability of error but no sign of constant error growth.**

Total error of monthly NINO indices



RMSE of anomalous monthly NINO indices



▪ RMS error between observed and simulated anomalies after subtracting the 23-yr climatological annual cycle of monthly mean

▪ Even though the magnitude of the RMS error is smaller due to removal of the systematic component of the error, it still shows clear spatial and seasonal structure.
▪ The slant to the right indicates an increase of RMS error with respect to lead month, with a maximum value in late spring and summer starting from winter initial conditions. This feature of forecast error is the well-known "spring barrier" .
▪ Different from the NINO3 index, the RMS error is dominated by the seasonality with a large maximum value in late spring to summer and a relatively weak dependence on lead time.

Sources of Forecast Error

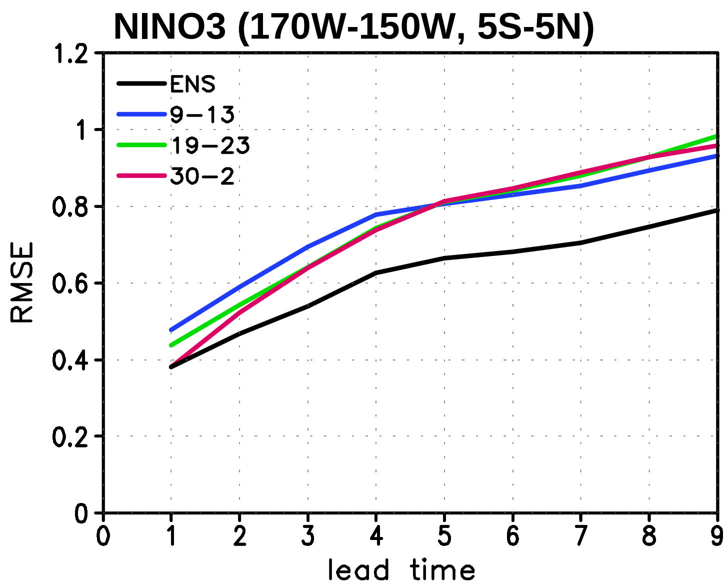
Forecast Error

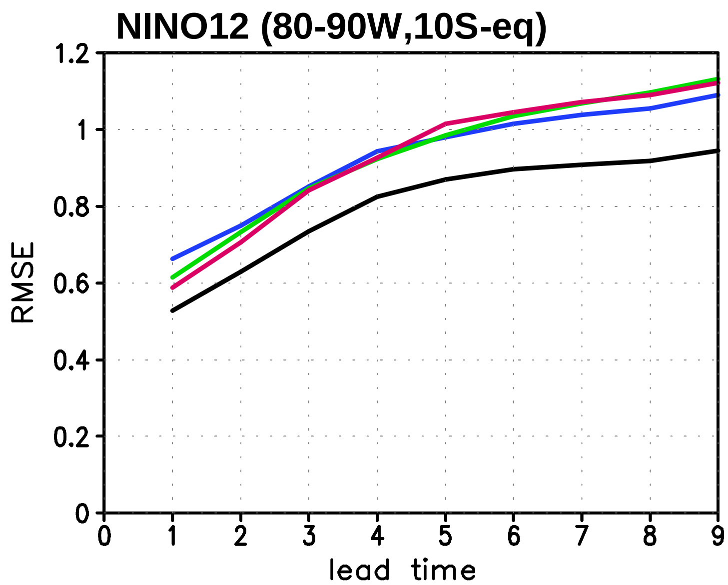
❑ From amplitude and phase of ENSO
→ amplitude of SST anomalies with respect to ENSO phase

❑ From observation
→ Imperfect initial condition

❑ From model errors
→ mean error, phase shift, different amplitude, and wrong seasonal cycle, etc

Forecast Error distinguished by Initial Date

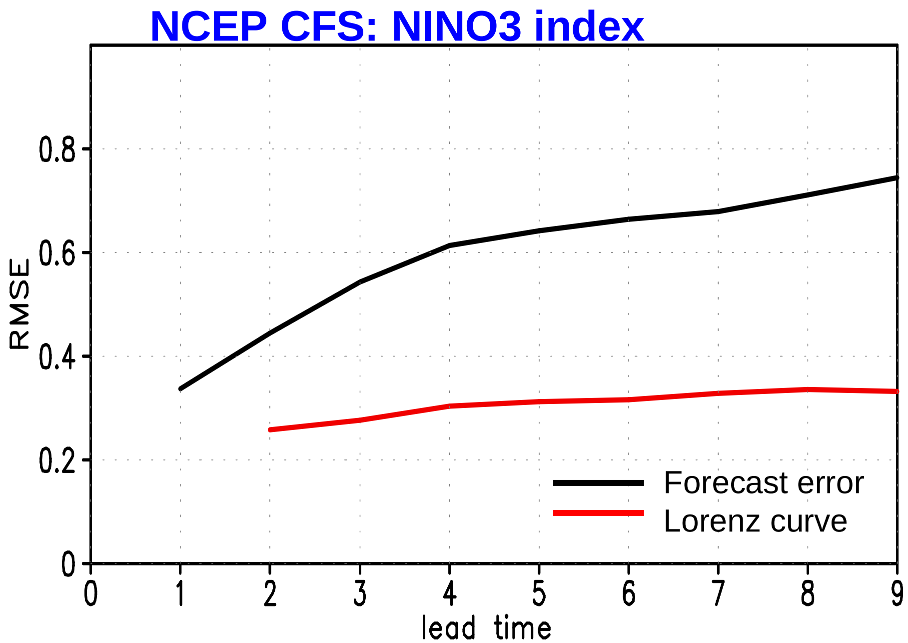




- To clarify the effect of initial condition associated with exact initial lead time, 3 segments following to the experimental design are considered.
- For example, for February 1 initial condition, 9-13 means 9Jan to 13Jan (blue), 19-23 means 19Jan to 23Jan (greed), and 30-3 means most recent initial conditions (red)
- Here, 12 initial condition cases are averaged during 1981-2003.

- **Both of indices, clear separation is only found for the first one to two months lead.**

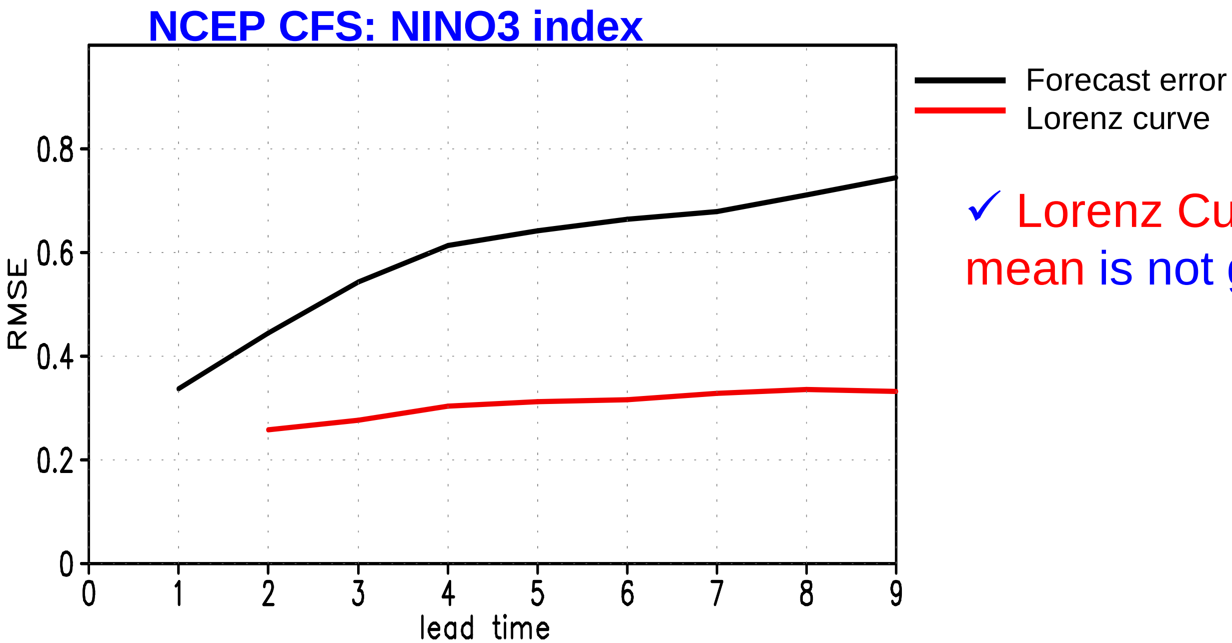
Forecast Error and Lorenz Curve of Ensemble Mean in CFS



To calculate the error growth for CFS following Lorenz' (Lorenz curves), which means that we will take one month forecast and two month forecast validated same time and see how the error grows with time.

Forecast error: **lower bound of predictability, skill of "current" forecast**
Lorenz curve: **upper bound of predictability (lower bound of error), growth of initial error defined as the difference between two forecasts valid at the same time (Lorenz 1982)**
→estimated from monthly mean data by assembling the locus of the RMS difference between the one-month and two-month lead forecasts for the first target month, the RMS difference between the two-month and three-month lead forecasts for the second target month, and so on.

Forecast Error and Lorenz Curve of Ensemble Mean in CFS

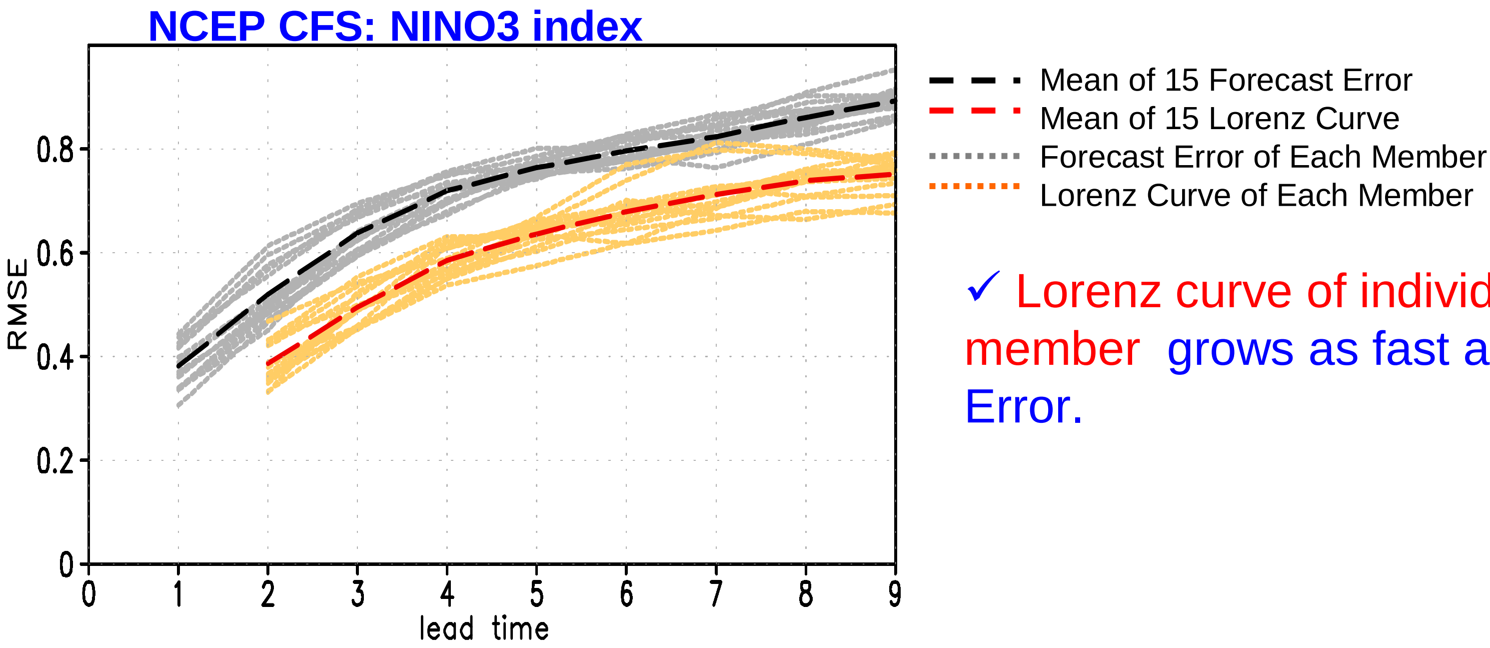


✓ Lorenz Curve of Ensemble mean is not growing

Forecast error: **lower bound of predictability, skill of "current" forecast**
Lorenz curve: **upper bound of predictability (lower bound of error), growth of initial error defined as the difference between two forecasts valid at the same time (Lorenz 1982)**

➢ **Here, Lorenz curve is calculated the difference of two forecasts with same target month and different initial time done by same model. Therefore it can be said as perfect model error growth.**

Forecast Error and Lorenz Curve of Each Member in CFS



✓ Lorenz curve of individual member grows as fast as Forecast Error.

→ **At month one, fifteen different values of error correspond to fifteen members' ensemble because each one has been integrated for different length of time.**

→ **The growth rate of forecast error is almost same as Lorenz curve. This means this model has very fast error growth.**

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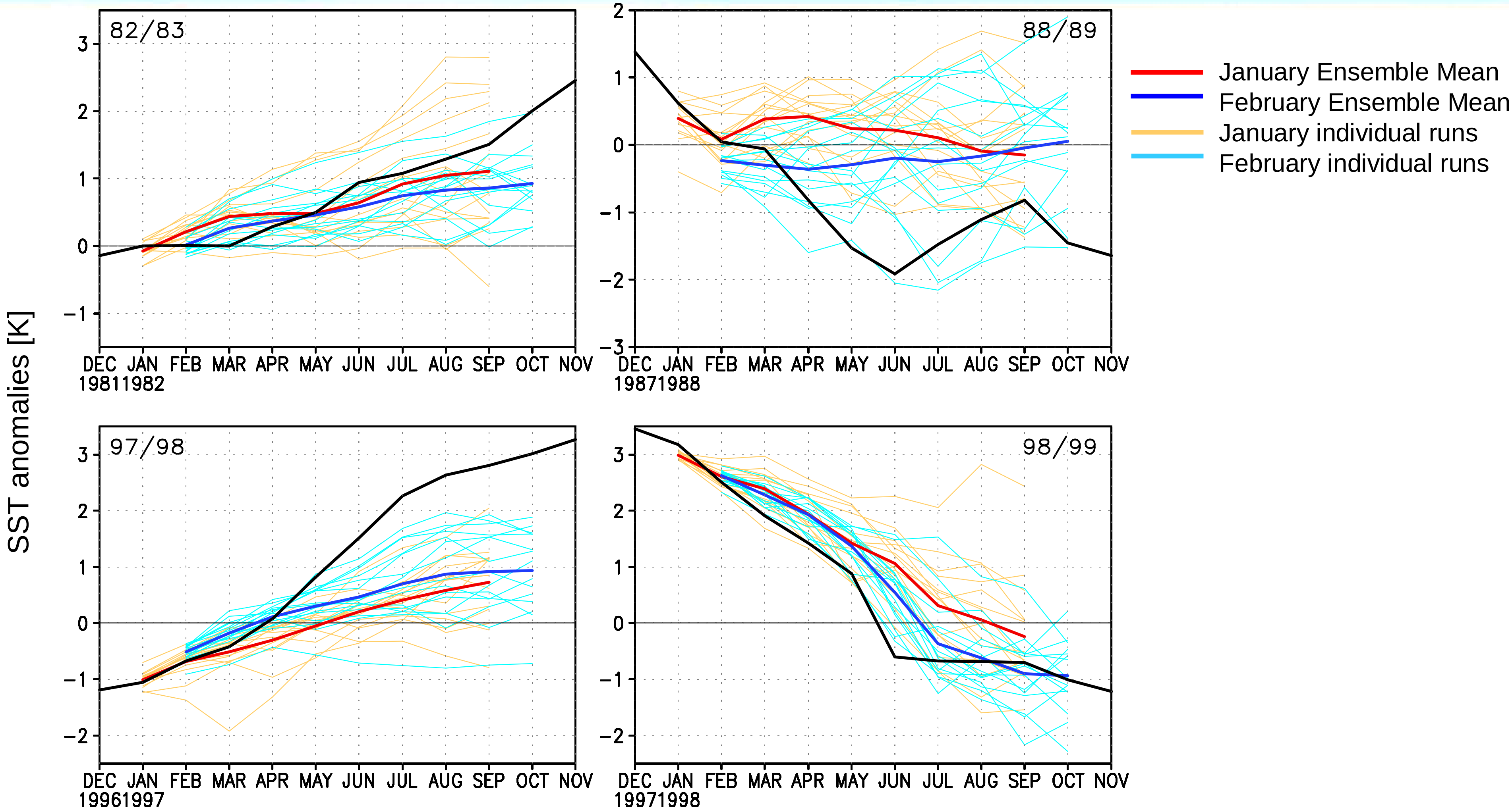
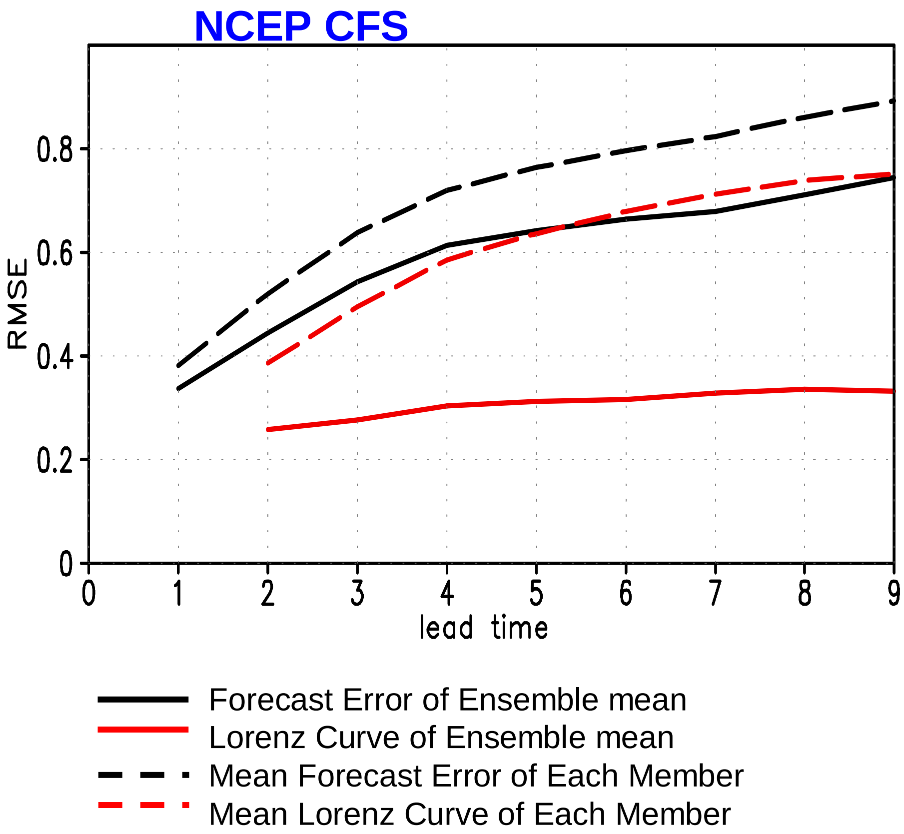
Examples: 4 ENSO growth cases of NINO3 index in CFS



- ✓ In January forecast and February forecast, ensemble mean is similar to each other that is why Lorenz curve is flat.
- ✓ Of course, ensemble spread is increasing in both but ensemble mean remains same.
- ✓ However the difference between each member is quite large range even more than 4 degree.

Forecast Error and Lorenz Curve of Each Member in CFS



✓ **Lorenz Curve of Ensemble Mean is not growing**

→ Initial error growth is saturated within two months.

→ After that, error growth is following the identical model error for all initial cases. For NINO3 index, it will be the error of model ENSO dynamics.

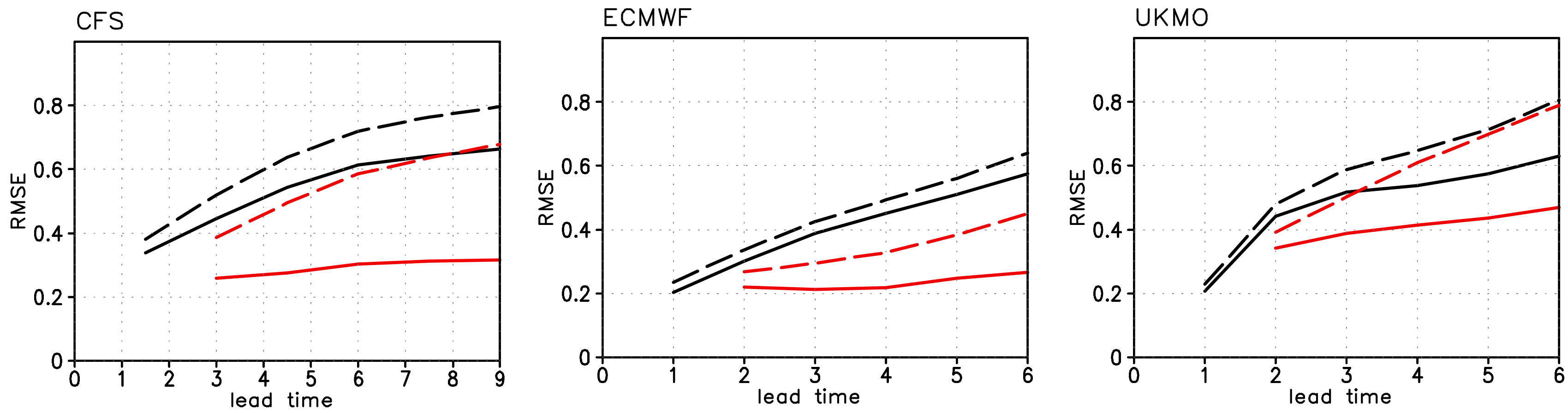
✓ **Lorenz Curve of Individual Member grows as fast as Forecast Error.**

→ CFS has large ensemble spread due to instability of coupled system.

✓ **Biggest improvement of ENSO prediction can be obtained by cutting the first month forecast error.**

Forecast Error and Lorenz Curve in CFS

NCEP CFS **ECMWF** **UKMO**



Forecast Error of Ensemble Mean
Lorenz Curve of Ensemble Mean
Mean of Forecast Error of Each Member
Mean of Lorenz Curve of Each member

✓ **This is the not the property of only CFS, but all the three models here show flat Lorenz curve for ensemble mean.**

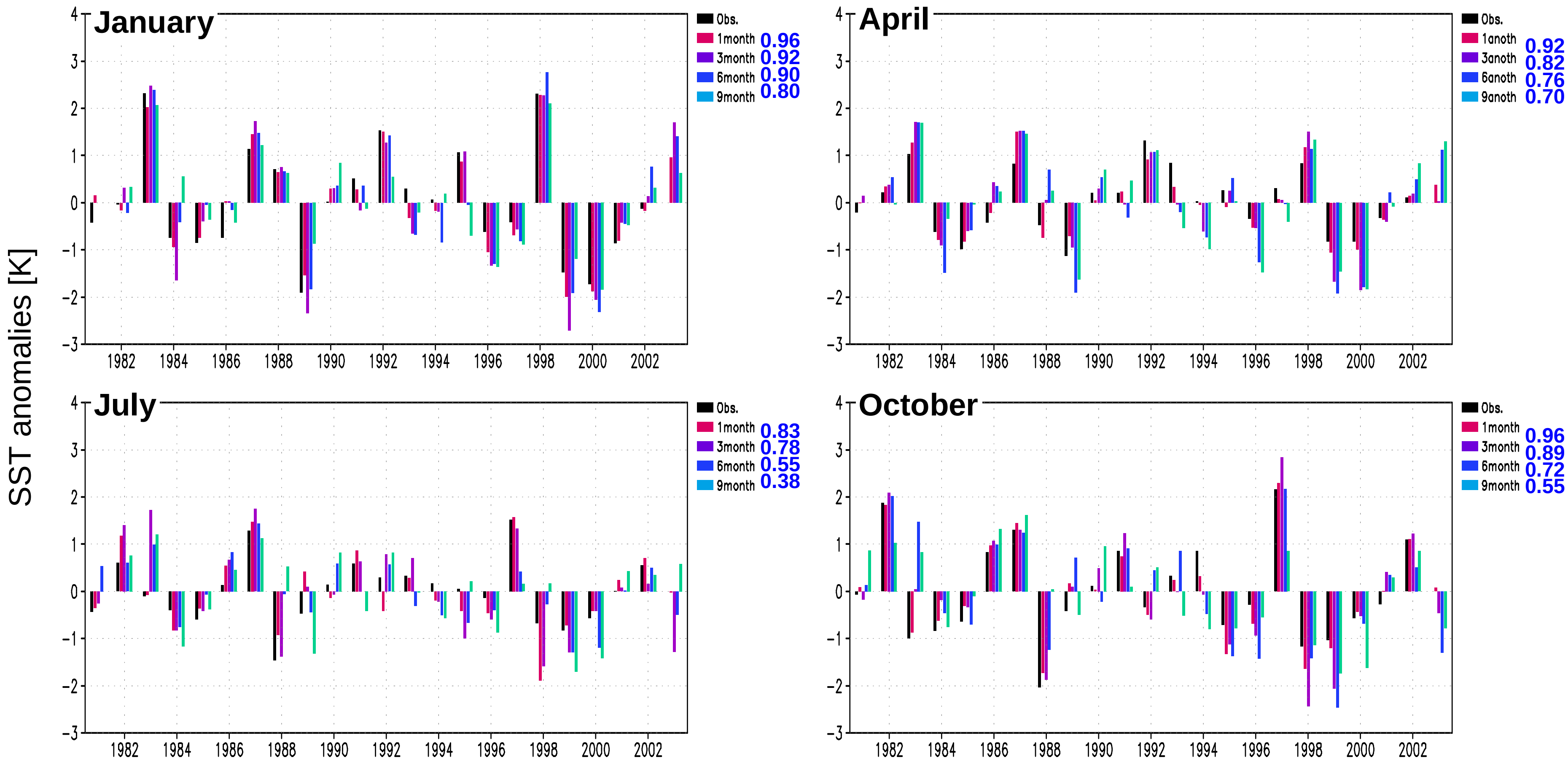
✓ **However, ECMWF model seem to have more potential to improve prediction, because the Lorenz curve of individual members does not grow as fast as forecast error curve.**

UKMO dada from Malcolm MacVean, and ECMWF data from Tim Stockdale

The Influence of Model Deficiency on the Forecast Skill

- ❑ **Forecast skill as a function of ensemble size in NCEP CFS**
- ❑ **Forecast error with respect to lead month**
- ❑ **Model errors in NCEP CFS focusing on ENSO events**

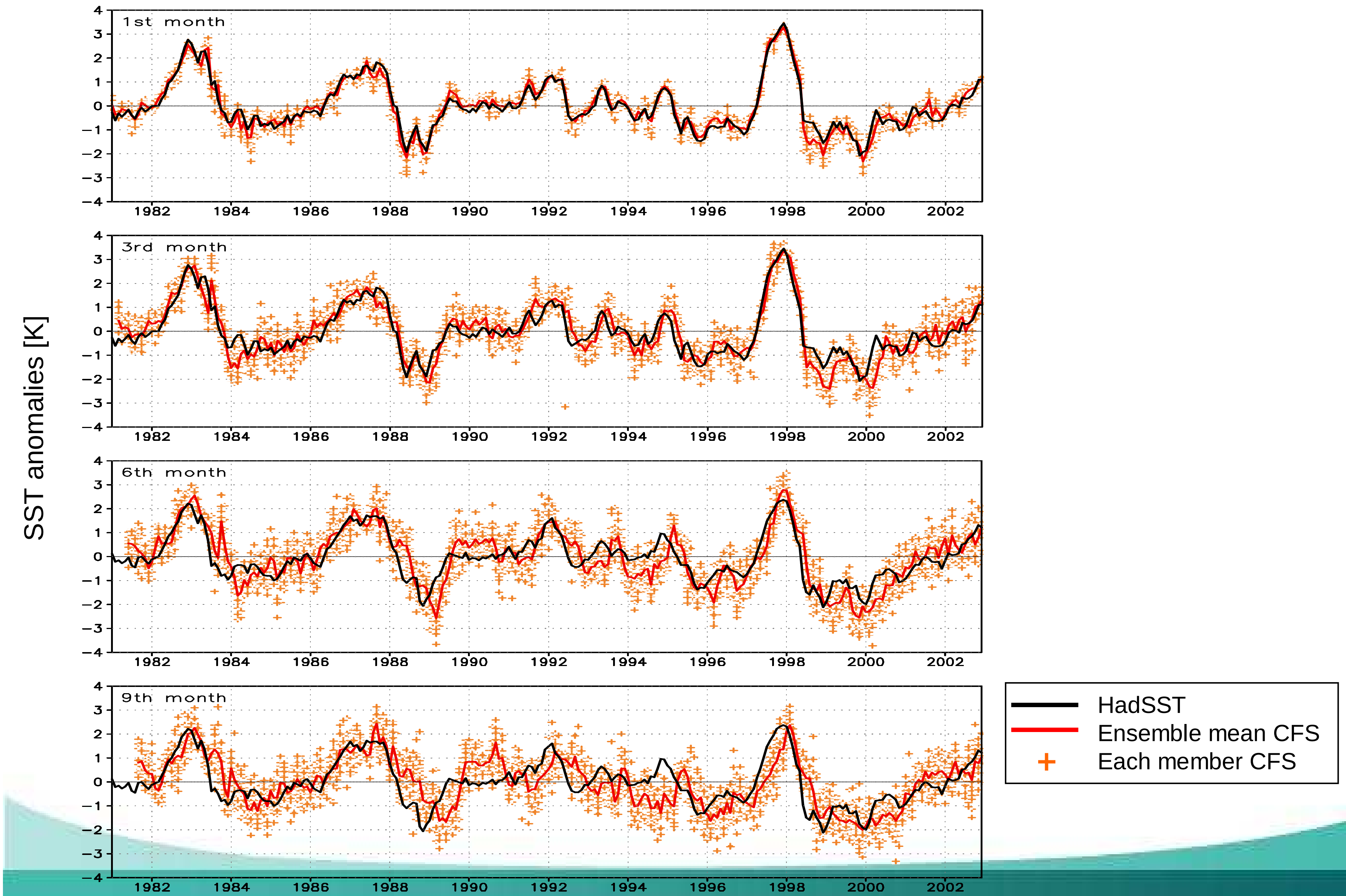
Interannual NINO3 Index with respect to Lead Month in CFS



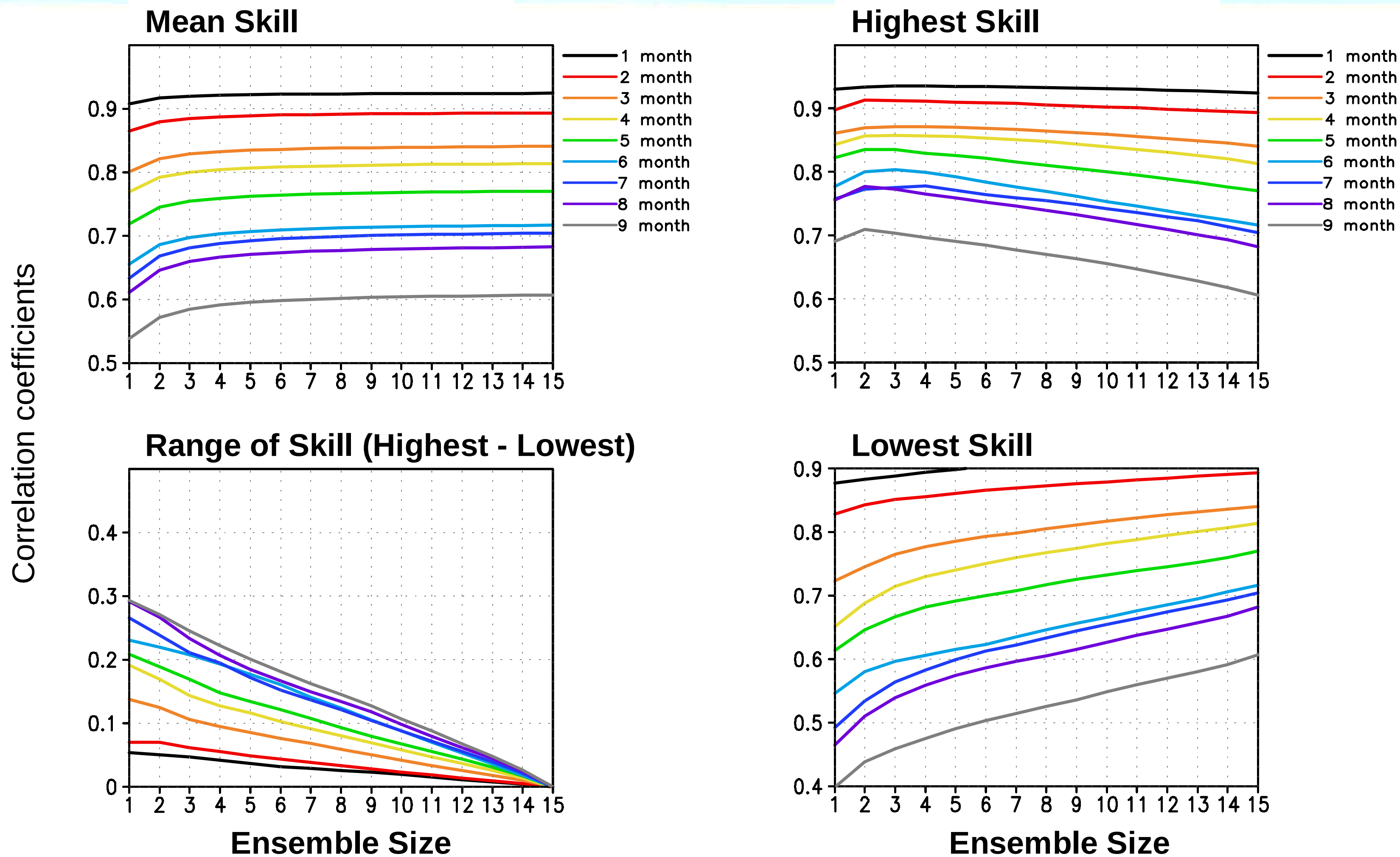
Anomaly correlation coefficients

Target month	1 month	3 month	6 month	9 month
Jan	0.96 (Dec)	0.92 (Oct)	0.90 (Jul)	0.80 (Apr)
Apr	0.92 (Mar)	0.82 (Jan)	0.76 (Oct)	0.70 (Jul)
Jul	0.83 (Jun)	0.78 (Apr)	0.55 (Jan)	0.38 (Oct)
Oct	0.96 (Sep)	0.89 (Jul)	0.72 (Apr)	0.55 (Jan)

Interannual NINO3 Index with respect to Lead Month



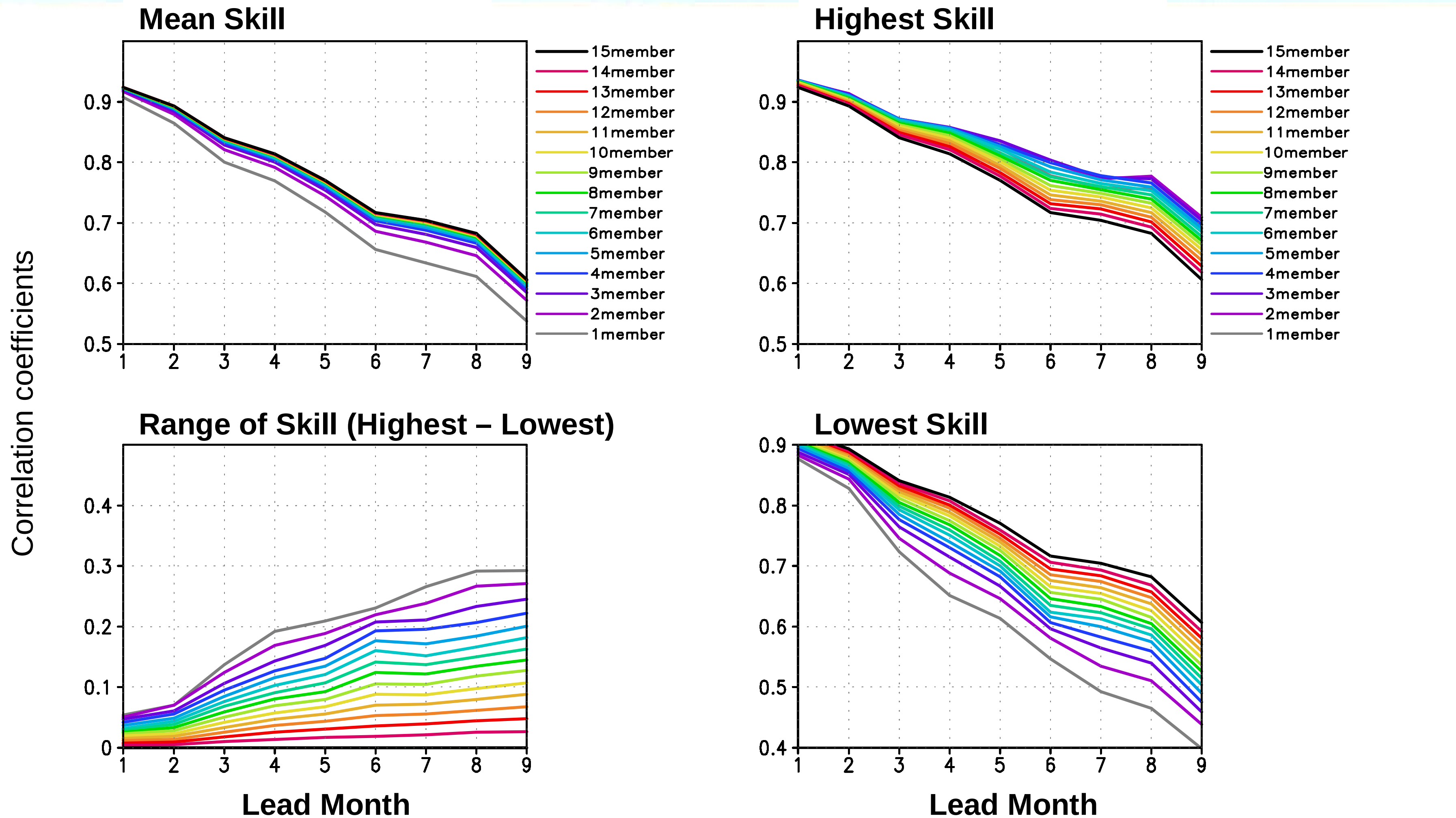
Forecast skill as a function of ensemble size



→ **Forecast skills are calculated for all possible combinations with respect to ensemble size**
→ **Mean skill denotes average of correlation coefficients for all possible combinations**
→ **Range of skill means highest skill minus lowest skill**

Ensemble size	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Possible combinations	15	105	455	1365	3003	5005	6435	6435	5005	3003	1365	455	105	15	1

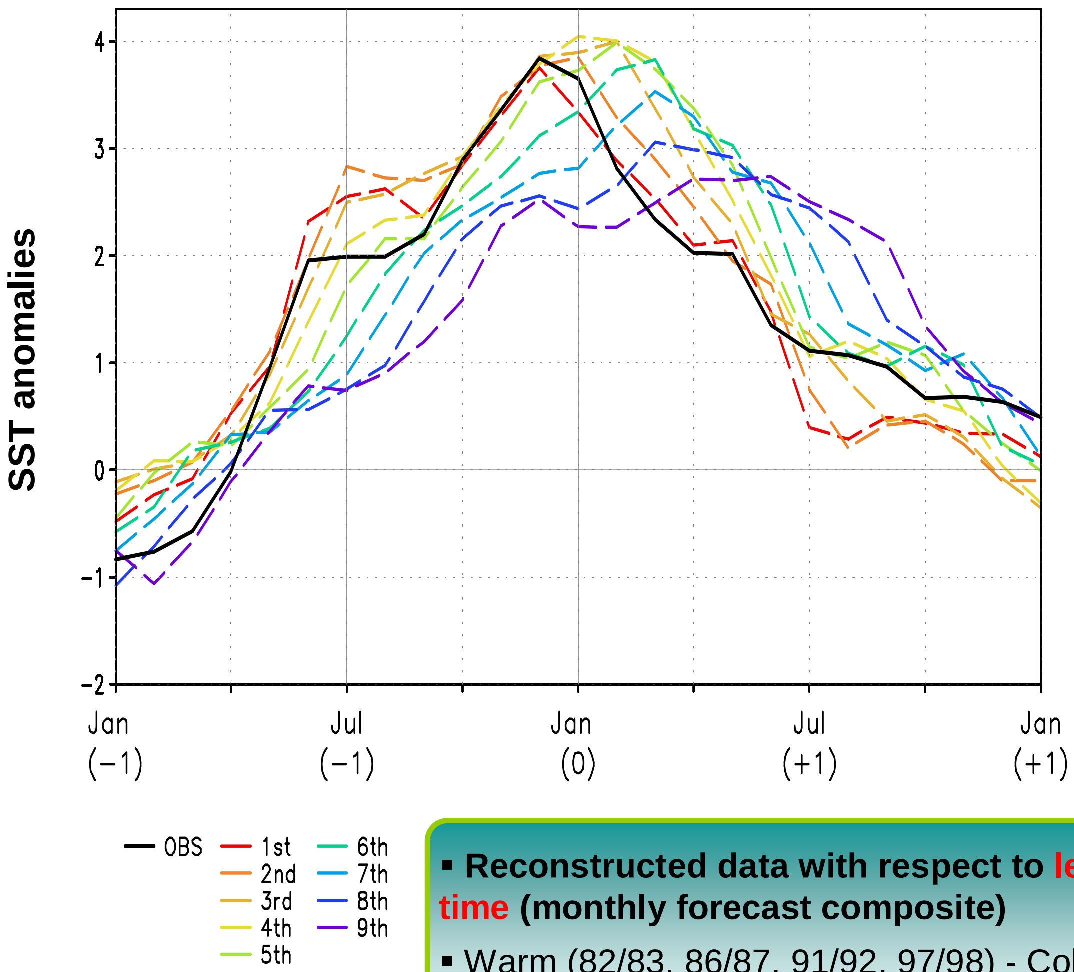
Forecast skill as a function of lead month



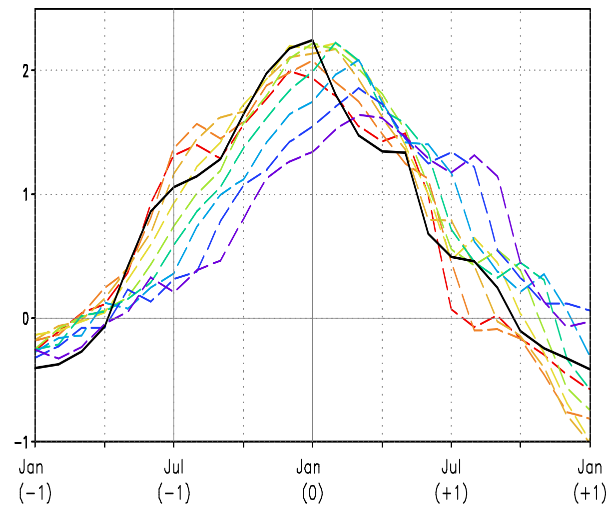
→ **The icrease of lead month give us more obvious statistics showing constant drop of skill with increase of ensemble spread for mean, high and low skill case.**

Observed and Simulated NINO3 Index

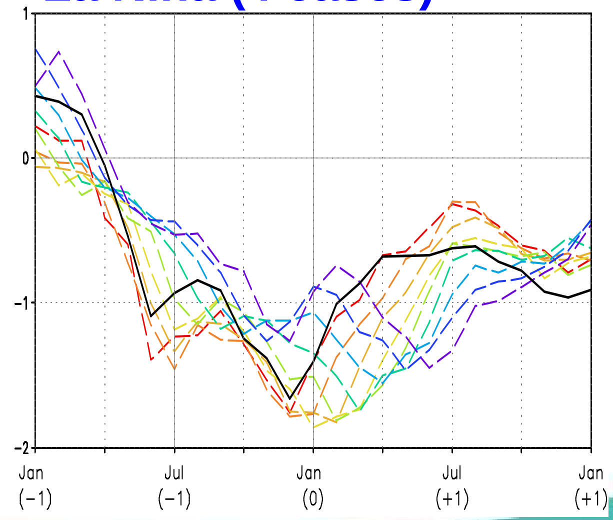
Warm minus Cold composite



El Nino (4 cases)



La Nina (4 cases)



- **Reconstructed data with respect to lead time (monthly forecast composite)**
- Warm (82/83, 86/87, 91/92, 97/98) - Cold (84/85, 88/89, 98/99, 99/00) composite

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NCEP CFS 52-yr long run

→ To investigate the property of this model without influence of initial condition, long run simulation is analyzed and compared with forecast data.

long run

- **52-year simulation**
- **Analyzing last 50 years (50-yr climatology is subtracted)**

[Courtesy of *K. Pegion* in COLA]

forecast

- **1981-2003 period**
- **15 members**
- **12 calendar months**
- **9 months lead**

Sources of Forecast Error

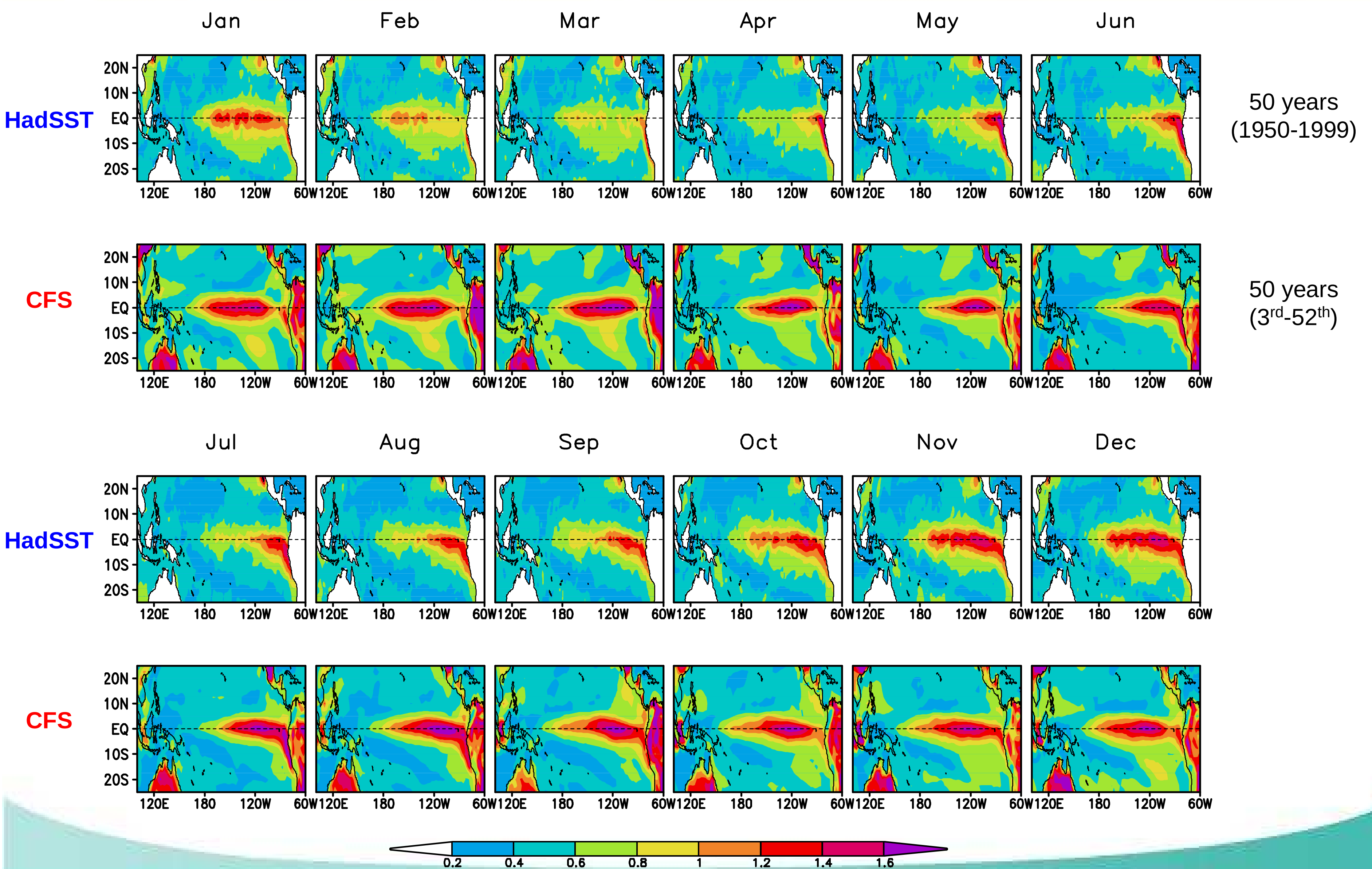
Forecast Error

❑ **From amplitude and phase of ENSO**
→ **amplitude of SST anomalies with respect to ENSO phase**

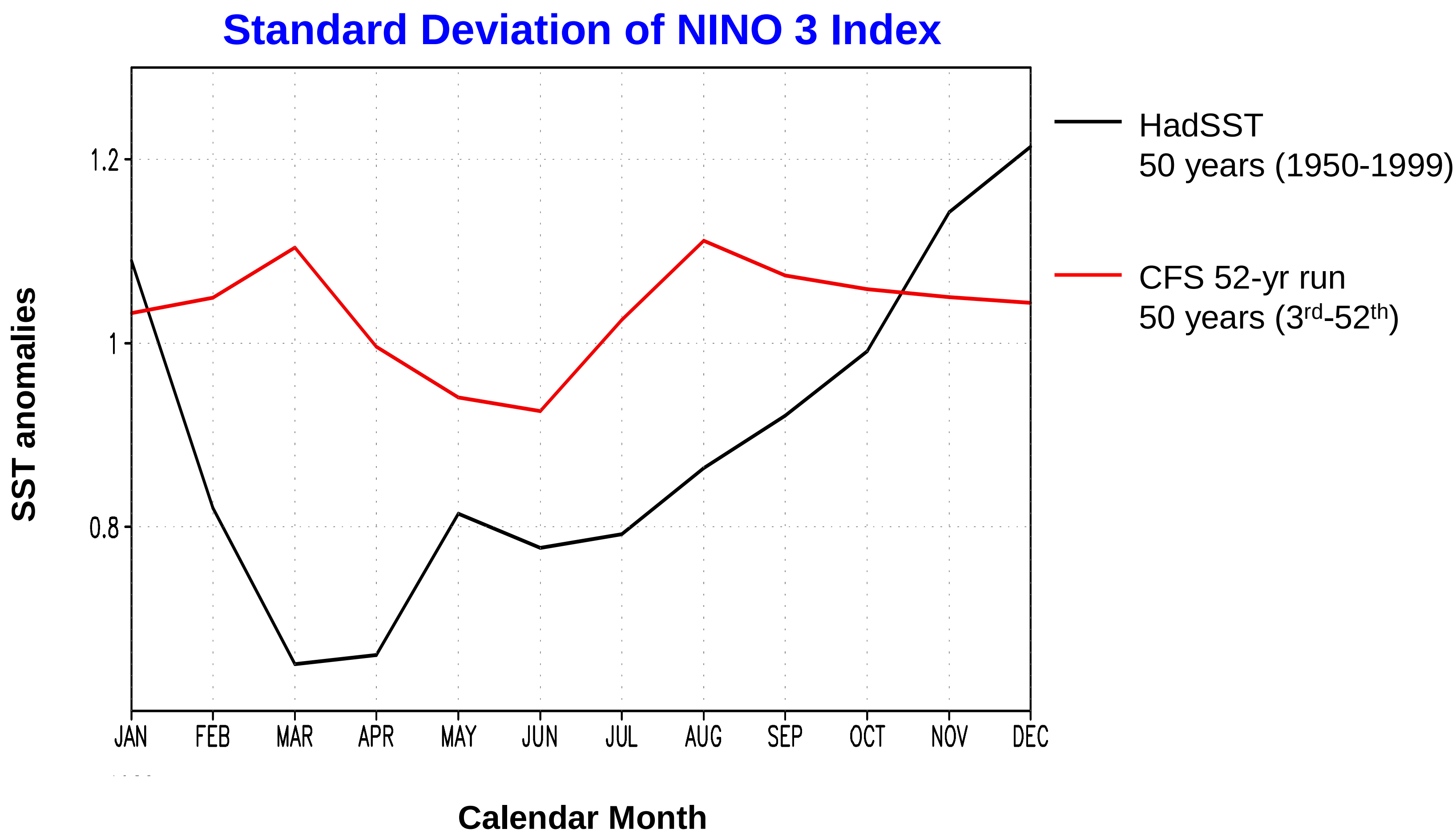
❑ **From observation**
→ **Imperfect initial condition**

❑ **From model errors**
→ **mean error, phase shift, different amplitude, and wrong seasonal cycle, etc**

Monthly Standard Deviation of SST Anomalies in 52-yr long run

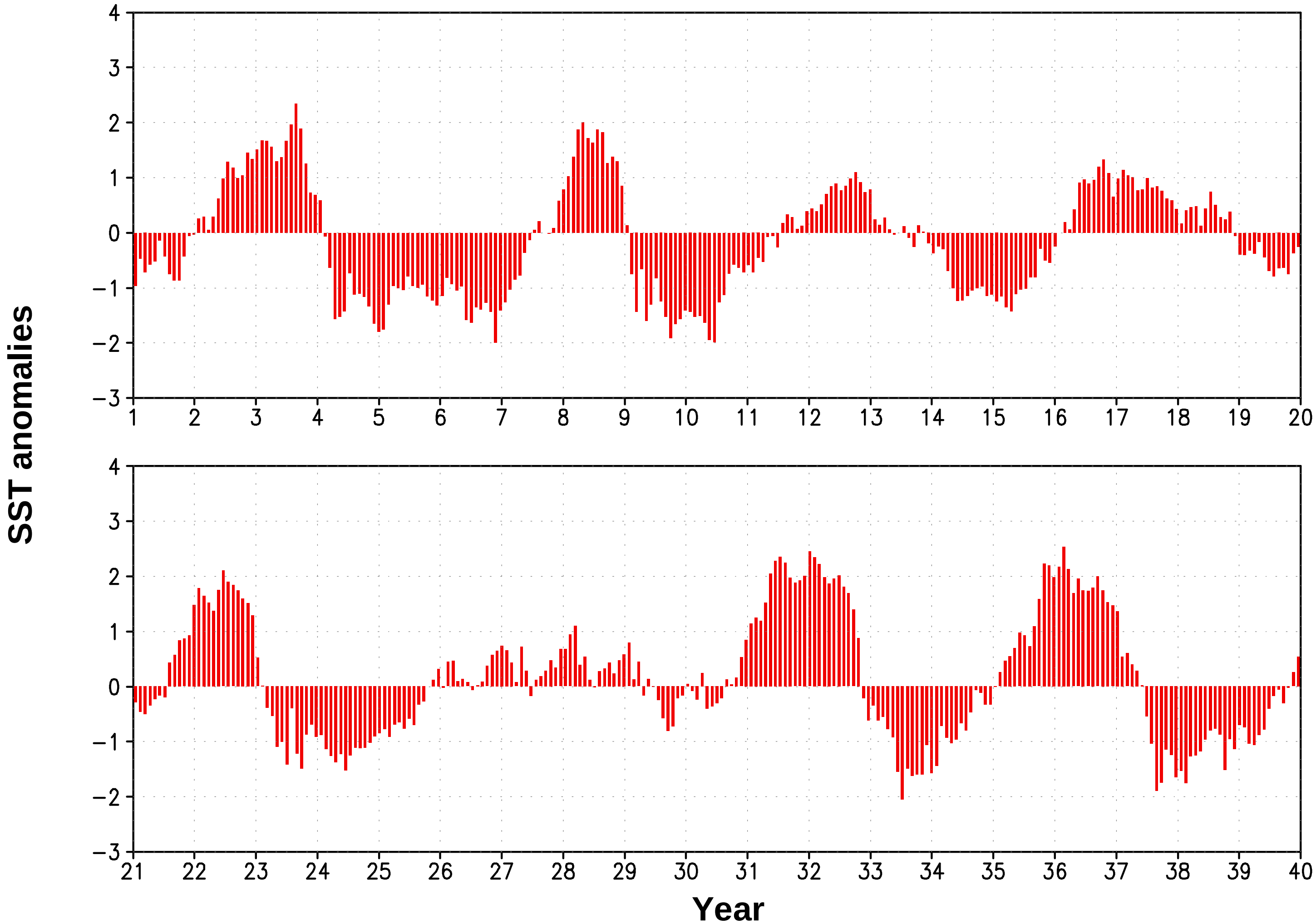


Monthly Standard Deviation of SST Anomalies



→ **Observation has maximum variance in December and weak variance in spring and summer, while model show larger variance in March and August different from observation.**

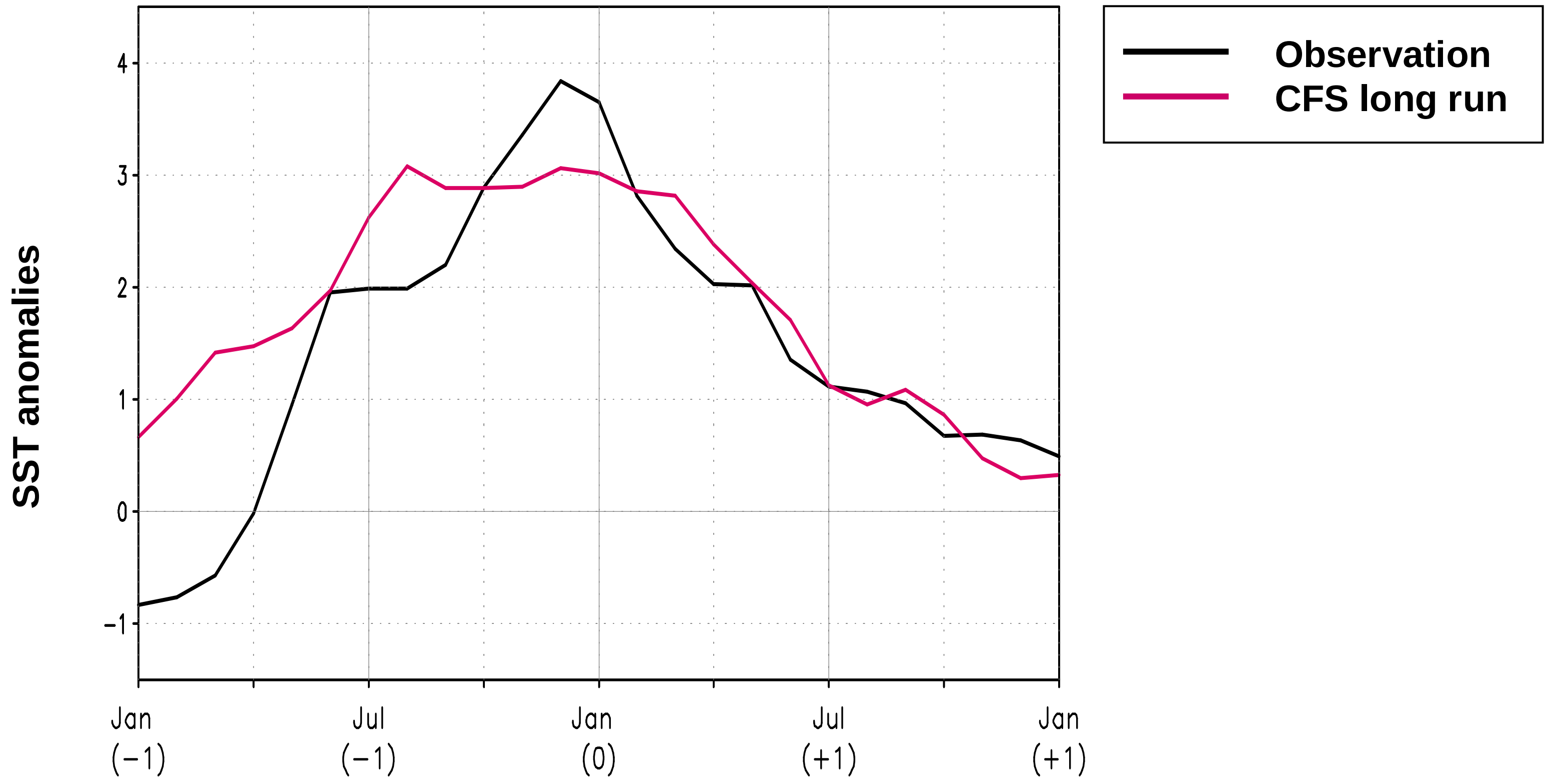
Simulated interannual NINO3 Index in CFS 52-yr long run



- Model has so regular and long ENSO cycle with 5 to 6 year period.
- Associated with this long life cycle, the peak of ENSO is frequently shown in summer time.
- Therefore, this model shows large error during summer.

NINO3 Index in CFS 52-yr simulation

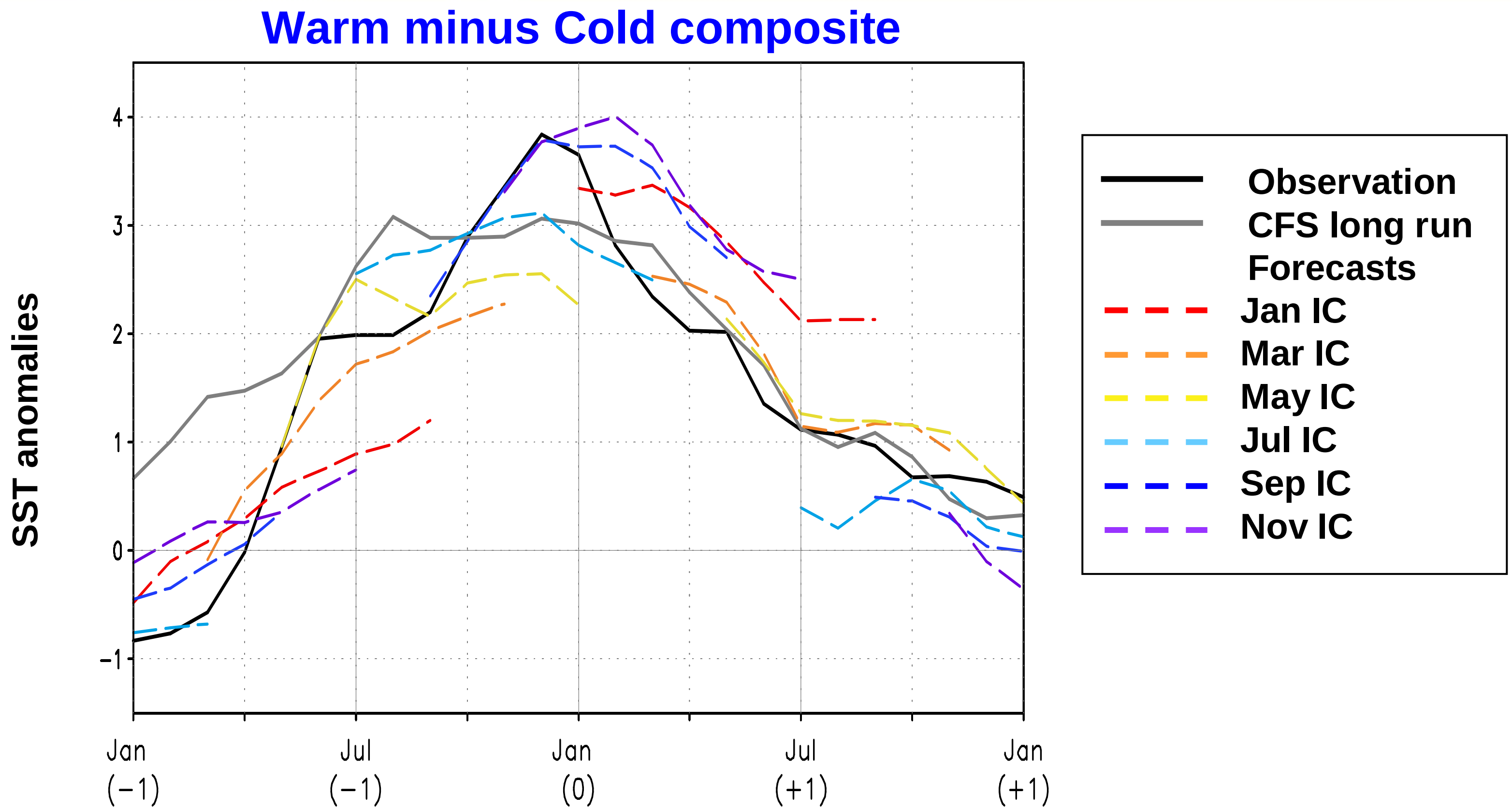
Warm minus Cold composite



- For observation, Warm composite (82/83, 86/87, 91/92, 97/98) - Cold composite (84/85, 88/89, 98/99, 99/00)
- For CFS 52-yr run, 7 cases for El Nino and 12 cases for La Nina based on one standard deviation definition of DJF Nino3 index

- As expected, simulated ENSO cycle show early and slow evolution
- And it has wrong peak in summer and winter peak is weaker than observed.
- Decay looks more similar to observation but it is also slowly progressing than observed beca use the peak of ENSO is smaller than observation.

NINO3 Index in CFS forecasts

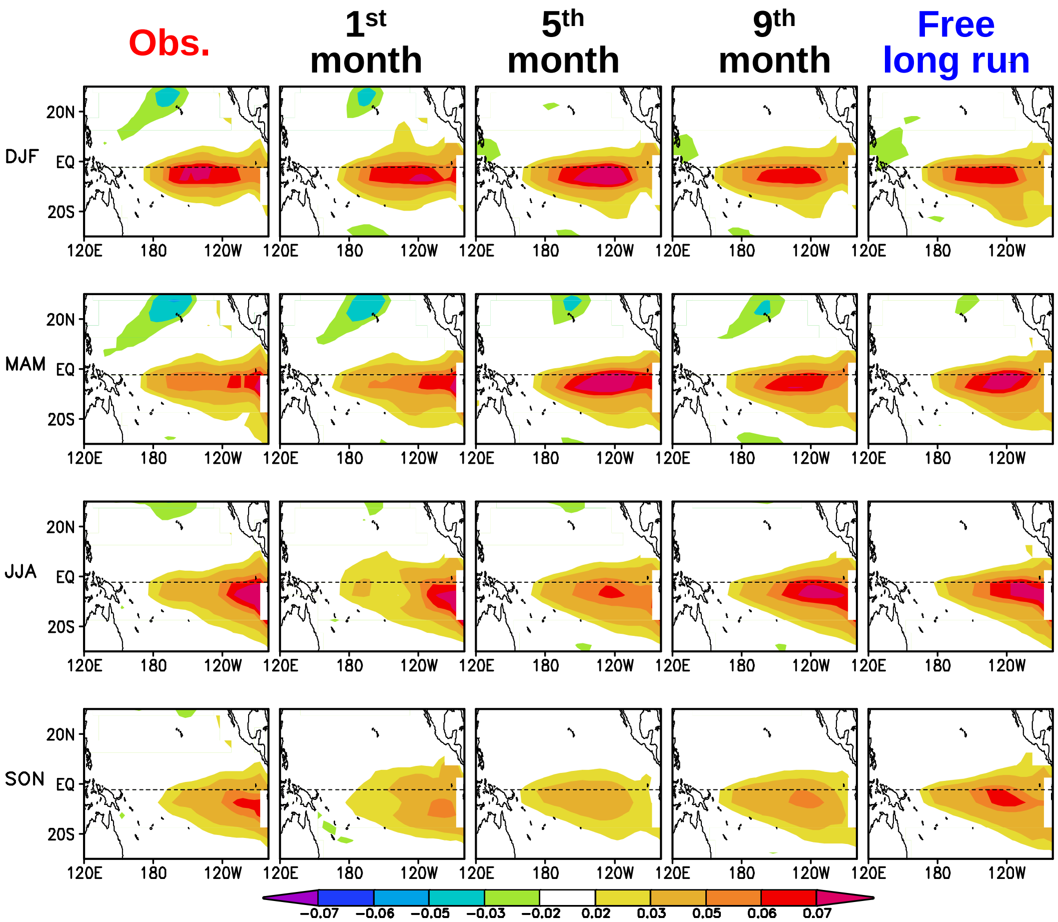


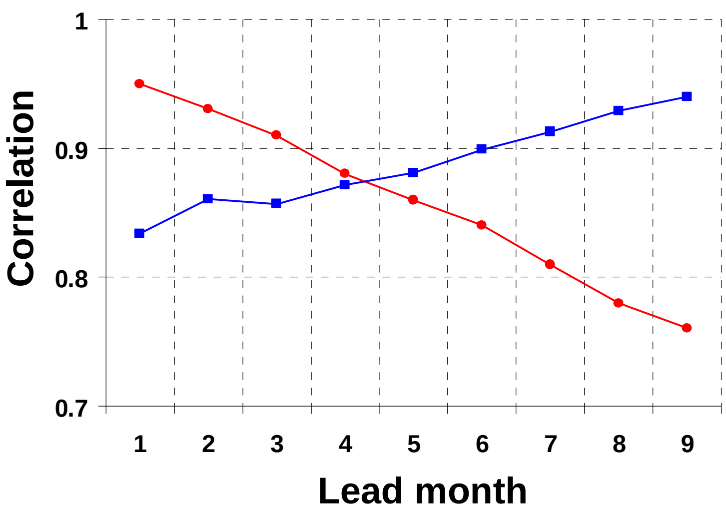
- Warm composite (82/83, 86/87, 91/92, 97/98) - Cold composite (84/85, 88/89, 98/99, 99/00)
- Dashed lines are 9 months forecast warm minus cold composite of six initial condition cases.

- On the basis of this analysis, forecasted ENSO can be considered in the sense of model ENS O property.
- For initial few months, simulated ENSO show good accordance with observed feature.
- However, after that, slow evolution of this model is clear with respect to lead time, and it gene rates the phase shifted feature in previous plot.

Modal Analysis using SEOF with respect to Lead Month

1st mode SEOF of SST (Low frequency mode)





Temporal correlation of PC timeseries with observation

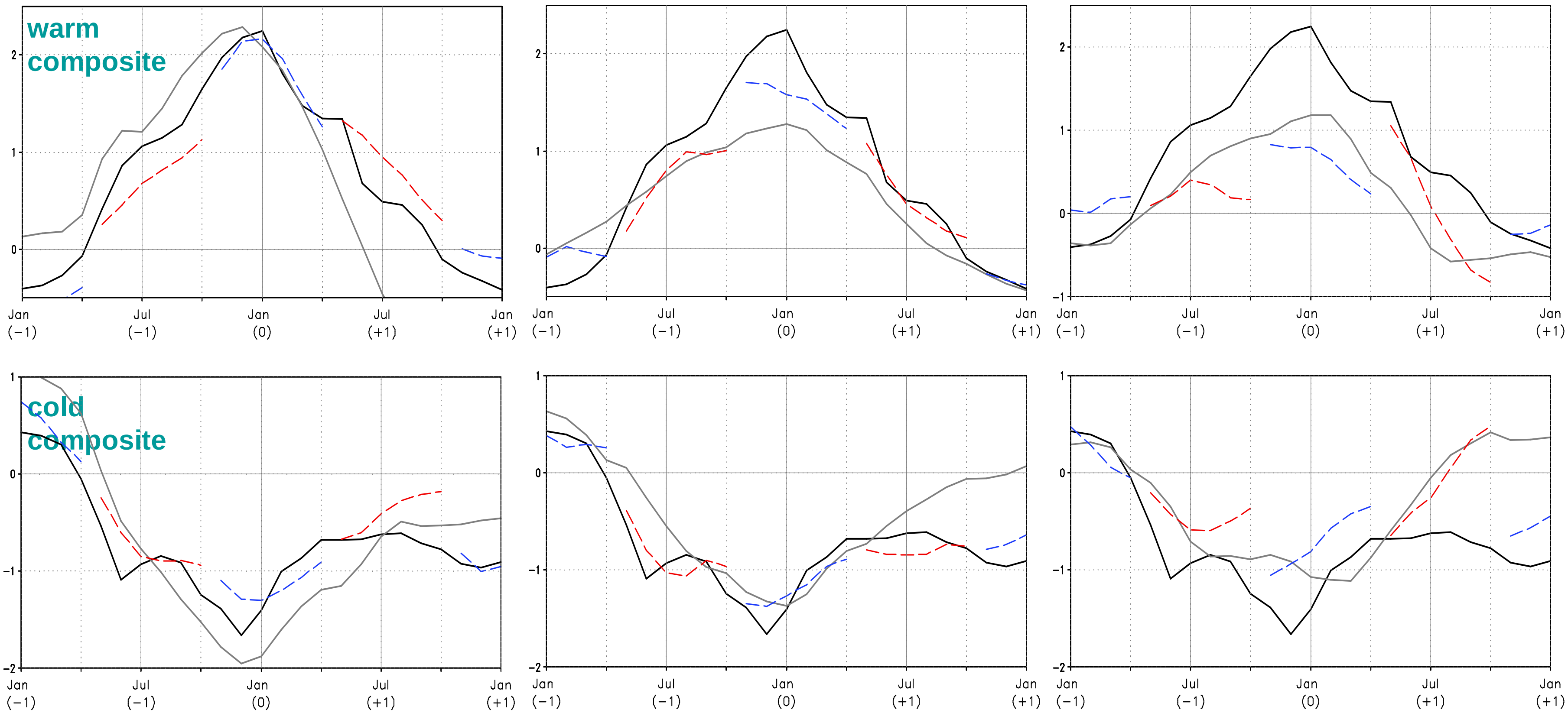
Pattern correlation of eigenvector with free long run

Experimental Design

	long run	forecast	
PRCGC SINTEX	• 202-year simulation • Analyzing last 200 years (200-yr climatology)	• 1982-2004 period • 9 members • May, Nov IC • 6 months lead	Luo *et al*. 2005
SNU	• 175-year simulation • Analyzing last 140 years (140-yr climatology)	• 1960-2001 period • 6 member • May, Nov IC • 6 months lead	Kug *et al*. 2005
UKMO	• 80-year simulation • Analyzing 80 years (80-yr climatology)	• 1980-2001 period • 9 members • 4 calendar months • 6 months lead	
NCEP CFS	• 52-year simulation • Analyzing last 50 years (50-yr climatology)	• 1981-2003 period • 15 members • 12 calendar months • 9 months lead	Saha *et al*. 2005

NINO3 Index in forecasts: SINTEX and SNU case

UKMO SINTEX SNU



80-yr long run
10 case El Nino
10 cases La Nina

Observation
long run
MAY forecast
NOV forecast

200-yr long run
34 case El Nino
32 cases La Nina

140-yr long run
24 case El Nino
26 cases La Nina

Obs.: Warm composite (82/83, 86/87, 91/92, 97/98) - Cold composite (84/85, 88/89, 98/99, 99/00)

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Summary (1)

- Overall forecast skill in 12 coupled GCMs is assessed. Strong ENSO cases are more predictable than weak cases. Growth phase of both warm and cold events is more predictable than decay phase. Normal events are far less predictable than warm and cold events.

- In ENSO forecasts in NCEP CFS, constant phase shift with respect to lead month is so clear by using monthly forecast composite data. And this feature is related with model properties having long life cycle with different peak shown in long run case.
- In SINTEX, SNU, UKMO GCM, common behavior both in long run and forecast is also investigated.

- Systematic errors of couple models is major factor in limiting predictability: mean error, phase shift, different amplitude, and wrong seasonal cycle, etc.
- Therefore, investigation of the model capability in long simulation is also important to understand the behavior of forecast error.

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Summary (2)

- Error growth of coupled GCMs is investigated.

→ In coupled GCMs, initial error growth is saturated within two months. After that, error growth is following the identical model error for all initial cases. Therefore, Lorenz curve of ensemble mean is not growing.

→ Lorenz curve of individual member grows as fast as forecast error because CFS has large ensemble spread due to instability of coupled system in CFS.

→ ECMWF seem to have more predictability, because the Lorenz curve of individual members does not grow as fast as forecast error curve.

- Finally we can draw the same conclusion as Lorenz did for weather forecasting, which is that the best way to improve the weather forecast beyond day 1 is by improving the first day forecast (Lorenz 1982). Similarly, biggest improvement of ENSO prediction can be obtained by reducing the first month forecast error.

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Thank You !

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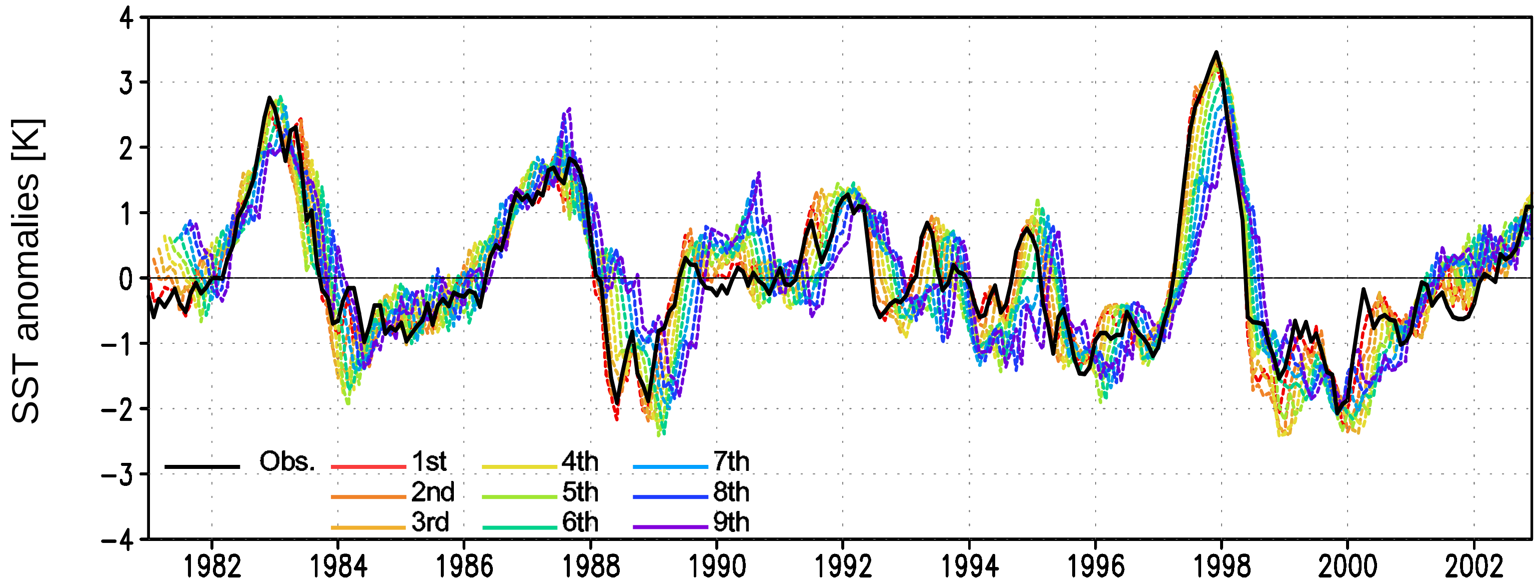
Observed and Simulated NINO3 Index



- **Reconstructed data with respect to lead time (monthly forecast composite)**
- **Black denotes observation, and red to purple rainbow colors are for ensemble mean simulation composed by lead month.**