### Indian Summer Monsoon – An Overview: Structure, Variability, and Predictability

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# Himalayas

- (Blanford, Founding Head, IMD- 1875); High Himalayan snow cover and deficient Indian summer monsoon
- Major drought/famine: 1877, 1899
- Walker (Director General, IMD, 1904
  -1924) Discovered Southern Oscillation







# Major Droughts over India

1877, 1899, 1918





# Great Famine of 1876-78 (India)

All India Monsoon Rainfall:-29%Drought Area:670,000 km²Estimated Deaths (Wikipedia):5.5 – 8.2 millionGovernance:British Rule(Lord Lytton exported food from India to England)

About 13 million people died in China

*Late Victorian Holocausts* (2001) by Mike Davis *El Nino Famines and the Making of the Third World* 







# SST Anomaly (°C) for DJF 1877



Courtesy of Lakshmi Krishnamurti







# Outline

- 1. Structure & Variability of Monsoon
- 2. Predictability of Monsoon
- 3. The Tale of Two Monsoons: 1972 & 1997
- 4. Seasonal Prediction: Challenges in Bridging the Gap Between Potential Predictability and Skill of Predictions
- 5. Prospects for the Future





#### Xie/Arkin JJAS 79-97 Precip Climo (mm/day)



GE N





# Monsoon

 Monsoon is derived from the Arabic word "Mausim" meaning "season", although generally defined as a system of winds characterized by a seasonal reversal of its direction.





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### **Theoretical Explanation of Monsoon**

#### **Extension of Axisymmetric Theory of Hadley Circulation to Include Local (land) Forcing**

The critical condition for the development of an angular momentum conserving meridional circulation (viz monsoon) is the existence of an extremum of angular momentum in the thermal equilibrium state (Plumb and Hou, 1992). Emanuel (1995) showed that assuming a moist adiabatic lapse rate, the threshold may be written as:

$$\frac{\partial}{\partial \phi} \left[ \frac{\cos^3 \phi}{\sin \phi} (T_s - T_t) \frac{\partial s_b}{\partial \phi} \right] = -4\Omega^2 a^2 \cos^3 \phi \sin \phi,$$

where  $\phi$  is the latitude, *a* is the radius of the earth,  $\Omega$  is the angular velocity of the earth, *s<sub>b</sub>* is the subcloud moist entropy, *T<sub>s</sub>* is the surface temperature, and *T<sub>t</sub>* is the temperature at the tropopause. Zheng (1998) veri-(Privé and Plumb, 2006 JAS)





# **Annual cycle of Rainfall over India**







### **Climatology of Sea Surface Temperature**

Hadely Center SST for 1979-2007 (°C)

DJF







## **Climatological Precipitation**

CMAP Precipitation for 1979-2007 (mm/day)



JJA

70N

DJF













Figure 2. Schematic representation of the climitological monthly mean circulation and location of the ridge (R) at 500 mb during January, April, July and October. Based on actual streamline maps published by the India Meteorological Department (1972).



# **Onset Dates for Summer Monsoon**



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#### **Monsoon Depressions**





- Mechanisms of formation, growth, and propagation of depressions
- Contributions to seasonal monsoon rainfall
- Are monsoon depressions changing due to global warming?
  - Can climate models simulate depression statistics?





# For evidence of the northward propagation: (Time-latitude plots of zonally averaged OLR and TRMM rainfall: based on daily data)







#### **Time-Latitude section of daily JJAS OLR and TRMM Rainfall**



#### 4 km Topography (m)



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#### Climatic Diagram Map of High Asia 1:4 000 000

Georg Miehe, Matthias Winiger, Jürgen Böhne



Himalayan glaciers store about 12,000 cubic kilometers of freshwater in ~15,000 glaciers and are the lifeline for millions of people (IPCC, 2007)

# **Predictability and Prediction of Monsoon**





# **Predictability in the Midst of Chaos:** Scientific Basis for Dynamical Seasonal Prediction

**Empirical Prediction:** *Regression Methods* 

Dynamical Seasonal Prediction: Source of predictability: Dynamical memory of atmos. IC + Boundary forcing (SST, SW, snow, sea ice)





### Sources of Predictability (Signal) and Processes Limiting Predictability (Noise)

	<u>Signal</u>	<u>Noise</u>
Weather: 1-10 Days	Initial conditions (IC) of atmosphere; prescribed boundary conditions at Earth's surface (SST, land (L), soil wetness, sea ice, snow, etc.	Turbulence, instabilities, errors in IC's
Intraseasonal Variations: 10 - 100 Days	IC of atmosphere and upper-ocean and land; convection dynamics interaction; A-O interaction	Weather variations
Seasonal to Interannual Variations: 100 – 100 Days	IC of A, O, L, and A-O-L interactions	Weather and intraseasonal variations
Climate Change	Human effects (Greenhouse Gases, land-use changes)	ENSO, decadal and multidecadal variations, volcanoes





# Influence of Boundary Condition (SST, Soil Wetness, Snow, etc.)







Change in SST Produces Changes in Evaporation, Precipitation, and Moisture Flux Convergence

# $\Delta$ SST $\rightarrow \Delta E, \Delta \tilde{V}, \Delta P$

# $\boldsymbol{\delta} \mathsf{P} = \boldsymbol{\delta} \mathsf{E} - \boldsymbol{\delta} (\int \nabla \cdot \tilde{\mathsf{V}} \mathsf{q})$

Change in Change in Precipitation Evaporation Change in Moisture Flux Convergence

**20-30%** 

70-80%





### **Mechanisms for Boundary-Forced Seasonal Predictability**

Large-scale persistent anomalies in SST, soil wetness, snow, etc. create a deep and persistent heat source anomaly (SST); The heat source anomalies in turn force atmospheric circulation anomalies locally and remotely.

Boundary-forced Atmospheric Circulation Anomalies  $\delta(BC) \rightarrow \delta(Q) \rightarrow \delta(Circulation)$ (5-10 days) (10-30 days)

Change in SST Produces Changes in Evaporation, Precipitation, and Moisture Flux Convergence

 $\Delta$  SST  $\rightarrow \Delta E, \Delta \tilde{V}, \Delta P$ 

 $\delta P = \delta E - \delta (\int \nabla \cdot \widetilde{V} q)$ 

Change in Precipitation

Change in n Evaporation Change in Moisture Flux Convergence

20-30%

70-80%





#### **Analysis of Variance:** F as a measure of predictability E is ensemble size (e = 1,2,3 - - - E); Y is total years (y = 1,2,3 - - - Y); P is the predicted variable

Measure of predictability is

$$F = E \frac{\hat{\sigma}_{S}^{2}}{\hat{\sigma}_{N}^{2}}$$

Ratio of Signal and Noise Variance

where

$$\hat{\sigma}_{S}^{2} = \frac{1}{Y-1} \sum_{y=1}^{Y} \left( \overline{P}_{y} - \overline{\overline{P}} \right)^{2}$$
Signal Variance  
$$\hat{\sigma}_{N}^{2} = \frac{1}{Y(E-1)} \sum_{y=1}^{Y} \sum_{e=1}^{E} \left( P_{y,e} - \overline{P}_{y} \right)^{2}$$
Noise Variance  
$$\overline{P}_{y} = \frac{1}{E} \sum_{e=1}^{E} P_{y,e}$$
$$\overline{\overline{P}} = \frac{1}{Y} \sum_{y=1}^{Y} \overline{P}_{y}$$

For samples drawn independently from the same normal distribution, and for Y = 46 and E = 9, the 5% significance threshold of F is 1.40



Please find the value of F from the F distribution table for a significance threshold.



500

## Ratio of Signal to Noise Variance for JJAS Rainfall for Four Climate Models NASA, NCEP, CCSM3, GFDL

JJAS Total Precipitation Signal to Noise Ratio IC:May



F for JJAS Precip in ECMWF

25

20

15

9

F for JJAS Precip in IFM–GEOMAR



F for JJAS Precip in UK Met Office



- 3.5

90

F for JJAS Precip in Meteo–France



F for JJAS Precip in CMCC-Bologna



F for JJAS Precip in Multi-model Anomaly







# If monsoon has high predictability, why is the skill of operational predictions so low?





### The Southern Oscillation





Rasmusson, 1984



### To predict monsoon, we must predict ENSO first

(ENSO has large amplitude after the monsoon season)



#### DelSole and Shukla (2012)

•Canonical Correlation Analysis (CCA) for 1880-1959 for May SST & Indian Subdivisional rainfall. (No Skill)

•CCA: May SST and all India rainfall (1880-1959):

•No skill in independent sample for 1960-2005.











Correlation between NINO3 and All–India JJAS Rainfall 1880–2010



Month of NINO3





# **Reforecasting the ENSO Events in the Past 57 Years** (1958-2014)

Bohua Huang<sup>1</sup>, Chul-Su Shin<sup>1</sup>, J. Shukla<sup>1</sup>, Lawrence Marx<sup>1</sup>, Magdalena A. Balmaseda<sup>2</sup>, Subhadeep Halder<sup>1</sup>, Paul Dirmeyer<sup>1</sup>, James L. Kinter III<sup>1</sup> (to appear, J of Climate)

Initial Conditions (ICs) 1958-1978 1979-2014 **Atmosphere ERA-40** Land NASA GLDAS2 4 members **CFSR** (The first 4 days of each **CFSR** month) (January 1, 1979, April 1, 1979, Sea Ice July 1, 1979, October 1, 1980) 5 members\* Ocean **ORA-S4** 

\* Perturbed through ocean data assimilation.

20 total ensemble members




#### **57 Years of Reforecasts:**

## No secular changes in ENSO predictability



Huang et al. 2017





### **Obs. and Forec. OND Nino 3.4 (April IC)**



MASON



TOPOPO



### Obs. and Forec. JJAS Precip. Anom. (10-25N, 70-90E)

Obs. Mean: 8.3 mm/d; Forec. Mean: 6.7 mm/d; ACC = 0.31



Coupled A-O models now show statistically significant skill in predicting Indian Summer Monsoon rainfall; But not good enough for many societal applications





### In Spite of Large Biases in Simulated SST, Predictions of SST Anomalies Have Some Skill in Some Cases

Small Skill in Predicted SST is Enough to Give Statistically Significant Skill in Predicted Monsoon Rainfall

That is why statistical models using April/May SST to predict JJAS monsoon rainfall have no skill, but coupled models with April/May initial conditions of A & O have statistically significant skill





### Reforecasting 1972-73 & 1997-98 ENSO and Monsoon

### **ENSO - Monsoon Teleconnections:**

# Sometimes they work marvelously, and sometimes they fail miserably.

### The tale of two ENSOs: 1972 – 1973 1997 – 1998





### **1972-73 El Nino Devastated Peruvian Fisheries; Caused Severe Drought Over India**







Guano Mountain (1860) in Peru – 60 ft tall





#### ENSO & ISMR for JJAS 1972 and 1997 1972 1997 (b) 1997 (a) 1972 60N -60N -40N 🏳 40N · 20N -20N EQ-EQ · 20S -1 .... 20S -40S-40S-60S · 60S -60W 1200 120E 60W 60E 180 12'0W 60E 120E 180 -2 -0.5 -0.2 0.2 0.5 1.5 2 3 4 5 -1.5 -1 JJAS 1997 - 23% JJAS 1972 + 2% from 1871-1990 mean (-23%)

 $\frac{1}{10}$   $\frac{1}{10}$ 

Rainfall Normalized Departure from 1871–1990 mean Rain >= 2. SD 1. <= Rain < 2. SD 1. <= Rain < 2. SD .5 <= Rain < 1. SD -.5 < Rain <= -1. SD -1. < Rain <= -2. SD

Rain <= -2. SD



### **1997 JJAS Rainfall Anomalies Over India**





#### **Observed and Forecast SST Anomalies for April and October IC (CFSv2)**

#### Case Studies: Strong Warm Events

Yellow shading indicates the period of each event. The 1972-73 event terminated earlier than the 1997-98 event.

This is an example of rapid drop of skill after March in the earlier period.







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#### **Observed and Predicted SST Anomalies for 1972-74**



Mason



#### **Observed and Predicted SST Anomalies for 1997-99**







### **CFSv2** Forecast JJA mean SSTA and Precip. (April IC)





### Forecast (April 72, IC) and Observed (IMD) Rainfall Anomalies for JJAS 1972 (mm/day)

#### **Observed IMD**

#### Forecast CFSv2

Anomalies of the Indian monsoon rainfall in 1972 [mm/day]



#### **CFSv2** Forecast JJA mean SSTA and Precip. (April IC)



### JJAS India Rainfall for 1972 &

Model, 99, 2005 Model, 99, 200







## Challenges in Bridging the Gap Between Predictability and Prediction of Monsoon

- Large model biases: improving the fidelity of models
- Improving the initial conditions of ocean and land
- Realistic simulation of tropical diabatic heat sources (IOD)





## **Climate Modelers' Good Luck**

- In spite of large systematic errors, climate models can capture part of the short-term climate variability, and therefore can produce a skillful seasonal forecast.
- Puzzle: model errors, although large in amplitude, do not seem to interact strongly with the real signal, and therefore a systematic bias correction can be used to produce seasonal forecasts.





#### SST Bias in 5 Month Forecasts (CFSv2), 1979-2014, I.C. April, 1













#### **1997 Diabatic Heating Anomaly (W/m<sup>2</sup>)** (Based on Observations)



Jang, Y. and D. M. Straus, 2013: Tropical Stationary Wave Response to ENSO: Diabatic Heating Influences on the Indian Summer Monsoon. J. Atmos. Sci., 30, 193-222.





#### Pacific Only vs. Pacific + Indian Ocean (1997 ENSO)



The Pacific heating and cooling associated with 1997/98 El Nino produced a weaker monsoon circulation (drought!) over India. However, the superposition of Pacific El Nino and Indian Ocean warming produced a normal monsoon circulation over India.





### Pacific Only vs. Pacific + Indian Ocean



### Pacific Only vs. Pacific + Indian Ocean 1997 ENSO

- The Pacific heating and cooling associated with 1997/98 El Nino produced a weaker monsoon circulation (drought!) over India.
  However, the superposition of Pacific El Nino and Indian Ocean warming produced a normal monsoon circulation over India.
- Response:Psi/ wind at 850hPa



Response: Psi/ wind at 850hPa 30N 15N ΕQ 15S · 30S 40E 60E 80E 100E 120E 140E 160E 180 -4 -3 -2 -0.50.5

## **Some Broad Conclusions & Suggestions**

- In spite of large model bias, ENSO has significant predictability. Model biases seem to influence ENSO growth and decay.
- In spite of improved ocean observations during the recent decades, skill is comparable between 1958-78 and 1979-2014.
- Current models and assimilation systems are unable to take full advantage of enhanced ocean observations.
- Need for mechanistic process-based experiments to understand the limitations in predicting characteristics of individual ENSO events and their global impacts (viz monsoons).





## Summary

- In spite of large model bias, ENSO has significant predictability
- After 50 years of climate modeling, models have begun to show some skill in prediction of seasonal mean rainfall over India. This skill comes almost entirely from skill in prediction of tropical SST (ENSO).
- Realistic simulation of SST and diabatic heat sources in West-Pacific & IO appear to be important for accurate seasonal mean monsoon rainfall prediction, and intraseasonal variations during the monsoon season.
- The lack of skill in monsoon forecasts is not due to intrinsic limits of predictability.





## **THANK YOU!**

### **ANY QUESTIONS?**





### Indian Ocean Dipole

#### Positive Dipole Mode



Negative Dipole Mode





Vinayachandran et al. 2010, JASGEORGE







#### Forecast JJA Vertical Velocity (omega) for 1972 and

**1997** Anomalies of JJA mean Vert. Velocity [0.01Pa/s] (CFSv2, April IC) (a) 1972



### Correlation Coefficient between Nino 3.4 SSTA and Observed Precip for JJAS (1981-2010)



Ravi P. Shukla & Huang (2015)





#### **CFSv2** Forecast JJA mean SSTA and Omega (April IC)







#### FIVE HIGHEST MONSOON RAINFALL



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Fig.9.7(h) Synoptic charts 0300 GMT 10 July 1968.

GE N TY

•



Correlation between observed and predicted JJAS all-India rainfall for hindcasts in the ENSEMBLES data set for the period 1960-2005. All-India rainfall in dynamical models is defined as the total land precipitation within 70E – 90E and 10N – 25N.

Last row shows empirical prediction using observed May NINO3.

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## A Breakthrough in Monsoon Prediction (~ 2010)

After 50 years of climate modeling, coupled ocean-atmosphere models began to show some skill in prediction of seasonal mean rainfall over India.







# **Summary** of Results not shown

- There is significant unrealized seasonal predictability.
  (*dilemma*: theoretical predictability of monsoon is high, but prediction skill is low)
- Ocean initial conditions import for skillful seasonal prediction.
- Realistic Land ICs enhance weekly-monthly predictions (high resolution land rainfall data required)
- Model predictability depends on model's fidelity to simulate climate.





# **Predictive Understanding**

**Prediction Skill and Predictability as a Metric of Understanding** 

- To enhance predictive understanding, a vigorous, collaborative, and simultaneous effort is needed for model development, predictability research, and seamless prediction of weather and climate. Diagnostic evaluation and prediction must be an integral part of model development.
- A multi-institutional (multinational) enhanced research effort and computational infrastructure is needed to develop the next generation of high fidelity climate models for improved climate predictions.
- Advances in NWP did not come by some major theoretical or conceptual breakthrough; it came by comprehensive, persistent, and simultaneous efforts in prediction, model development and predictability research by a team of qualified scientists.

(A similar effort for Dynamical Seasonal Prediction is needed.)





El Nino and the Southern Oscillation A Scientific Plan	U.S. Participation in the TOGA Program A Research Strategy	<b>TOGGA</b> A Review of Progress and Future Opportunities	
1983	1986	1990	
1991	1994	1996	
PROSPECTS FOR EXTENDING THE RANGE OF PREDICTION OF THE GLOBAL	Gobal Ocean-Atmosphere-Land System for Predicting Seasonal-to-Interannual Climate	Learning to Predict Climate Variations Associated with El Niño and the Southern Oscillation	

**ATMOSPHERE** 

Accomplishments and Legacies of the TOGA Program

#### **Analysis of Variance:** F as a measure of predictability E is ensemble size (e = 1,2,3 - - - E); Y is total years (y = 1,2,3 - - - Y); P is the predicted variable

Measure of predictability is

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Ratio of Signal and Noise Variance

where

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For samples drawn independently from the same normal distribution, and for Y = 46 and E = 9, the 5% significance threshold of F is 1.40



Please find the value of F from the F distribution table for a significance threshold.









After FGGE: Skill of NWP has steadily improved



**After TOGA:** No significant improvement in seasonal prediction of regional circulation and rainfall by coupled climate models.

- Inaccurate simulation of non-ENSO heat sources
- Large biases in climate models











#### Sources of Predictability (Signal) and Processes Limiting Predictability (Noise)

	<u>Signal</u>	<u>Noise</u>
Weather: 1-10 Days	Initial conditions (IC) of atmosphere; prescribed boundary conditions at Earth's surface (SST, land (L), soil wetness, sea ice, snow, etc.	Turbulence, instabilities, errors in IC's
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Climate Change	Human effects (Greenhouse Gases, land-use changes)	ENSO, decadal and multidecadal variations, volcanoes





# **Baroclinic Development:**

#### 7.1 Hydrodynamic Instability

"Specifically, we discuss the role of dynamical instability of the mean flow in accounting for the growth of synoptic-scale disturbances."

"A zonal-mean flow field is said to be hydrodynamically unstable if a small disturbance introduced into the flow grows spontaneously, drawing energy from the mean flow."

"Under normal conditions of static stability the wavelength of maximum stability is about 4000km, which is close to the average wavelength for mid-latitude synoptic systems."



An Introduction to Dynamic Meteorology by Holton & Hakim (2013)





#### Dynamical Predictability: Beyond Weather Predictability of Planetary Waves and Synoptic Waves

- 1. Largest Variance in Low Frequency Long Waves
- 2. Longer Predictability for Planetary Waves



















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#### **Obs. and Forec. SST Anomalies for JJA (April IC)**





## **Observed JFM SST anomalies for 1998 and 2016**







## **CFSv2** Forecast JJA mean SSTA and Precip. (April IC)





## **CFSv2** Forecast JJA mean SSTA and Precip. (April IC)





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# ENSO & ISMR for JJAS 1972 and 1997



# Forecast (April 72, IC) and Observed (IMD) Rainfall Anomalies for JJAS 1972 (mm/day)



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### **Obs. and Forecast SST Anomalies for April and Oct. IC (CFSv2)**

#### 1971-1974







## **CFSv2** Forecast JJA 1972 mean Precip. anomaly (April IC)





## **Tibetan Plateau**







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