# Sub-seasonal to Seasonal (S2S) predictions of the Asian summer monsoon: Current status and future directions

Yuhei Takaya\*, Hong-Li Ren, Frederic Vitart and Andrew W. Robertson

\*Japan Meteorological Agency, Meteorological Research Institute



Seventh WMO International Workshop on Monsoons (IWM-7) 22-26 March 2022

# Outline

- Data archives for the sub-seasonal to seasonal (S2S) prediction studies
- Performance of S2S prediction systems: current status and its evolution

Seasonal prediction

 Dominant drivers for the ASM variability and representation of their responses in the models

Subseasonal prediction

- Prediction skill of Boreal Summer Intraseasonal Oscillation and Indian rainfall
- Future challenges
- Summary

# Data archives for the sub-seasonal to seasonal prediction studies

Data archives for the sub-seasonal to seasonal prediction studies

# **Sub-seasonal prediction**

# WWRP/WCRP Sub-seasonal to Seasonal Prediction Project (S2S)

Vitart et al. 2017 BAMS

12 models: BoM, CMA, CNR-ISAC, CNRM (Meteo France), ECCC, ECMWF, HMCR, IAP-CAS, JMA, KMA, NCEP, UKMO

4

http://www.s2sprediction.net/

### The Subseasonal Experiment (SubX)

Pegion et al. 2019 BAMS

7 models: NCEP-CFSv2, EMC-GEFS, ECCC-GEM, GMAO-GEOS, NAVY-ESPC, RSMAS-CCSM4, ESRL-FIM

http://cola.gmu.edu/subx/

Data archives for the sub-seasonal to seasonal prediction studies

## Seasonal range prediction WCRP CHFP, NMME, C3S, ENSEMBLES, APCC MME, DEMETER

### WCRP Climate-system Historical Forecast Project (CHFP)

Tompkins et al. 2017 BAMS

https://www.wcrp-climate.org/wgsip-chfp

### North American Multi-Model Ensemble (NMME)

Kirtman et al. 2014 BAMS

https://www.ncei.noaa.gov/products/weather-climate-models/north-american-multi-model

https://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/

### **Copernicus Climate Change Service (C3S)**

Models: CMCC, DWD, ECCC, ECMWF, JMA, Met Office, Meteo-France, NCEP

https://climate.copernicus.eu/seasonal-forecasts

### Performance of seasonal prediction systems: current status and its evolution

Numerous studies have investigated model performance in representing the ASM. (Kang et al. 2002, Rajeevan et al. 2012, Sperber et al. 2013…) This study (as a part of WGSIP project) updates the current status and address its evolution.

### Precipitation climatology (JJA) in seasonal prediction models

CMAMlo shfp

JMAMRI-CGCM1 CHFP

MPT-ESM-LR CHEP

[mm/d]

150W

CHFP



cf. Kang et al. (2002), Sperber et al. (2013), Rejeevan et al. (2012)

#### C3S (1993-2016)

#### Precipitation climatology of C3S models

## cmcc\_3 dwd 2







meteo france 7























ukmo 600









ecmwf F



ima 2

### Precipitation bias (JJA) in seasonal prediction models

### C3S MME(1993-2016) vs GPCP2.3

#### MME



cf. Kang et al. (2002), Sperber et al. (2013), Rejeevan et al. (2012), Choudhury et al. (2021)

C3S (and CMIP) models share a common bias pattern for precipitation.

- Excessive rainfall over the tropical western North Pacific and North Indian Ocean
- Deficient rainfall around coastal East Asia (Meiyu rainfall) and South Asia.

\* Please note that GPCP and CMAP analyses present a significant difference.

### Pattern correlation of precipitation climatology (JJA) 40E-180, 40N-10S

9



The latest models (C3S) have higher ability to reproduce the climatological pattern of observed precipitation compared with the models a decade ago (CHFP). Almost all of the C3S models have higher pattern correlations than the median of the CHFP models.

### A decade of progress (added value of C3S over CHFP): Pattern correlation of precipitation climatology (JJA, 40E-180, 40N-10S)

10



Almost all the latest models have higher ability to reproduce the climatological pattern of observed precipitation compared with the previous models of each center. Pattern correlations of the climatological precipitation over the ASM region exceed 0.8 in some models.

### Pointwise temporal correlation skill for JJA precipitation (Estimated skill with infinite members, $C_{\infty}$ )



CMAMIo shfp (1979-2008)

(1982-2009)

20N





poama p24a (1980-2009)

CCCma-CanCM3 CHFP (1979-2008



CHFP





poama p24b (1980-2009)



poama p24c (1980-2009)



GloSea5\_sitl (1996-2009)





mcc 3 (1993-2016)

cmcc 35 (1993-2016)





iwd 2 (1993-2016)

dwd 21 (1993-2016)







MME(C3S)







meteo france 7 (1993-2016)









The dependence of skill scores on ensemble size makes it difficult to compare the skill of different systems. Therefore, here the estimated correlation skill of infinite member ensemble (Murphy, 1988) is shown. \* MME(C3S) presents the correlation skill of the multi-model ensemble mean (not  $\boldsymbol{C}_{\infty}$ ).

#### C<sub>3</sub>S

A decade of progress: Area averages of temporal correlations ( $C_{\infty}$ ) 12 for JJA precipitation (40E-180, 40N-10S)\*



The latest models (C3S) have higher ability to predict the interannual variability of precipitation over the ASM region than the models a decade ago (CHFP). Almost all of the C3S models have higher averaged correlation than the median of the CHFP models.

\* Negative correlations were set to zero when the area averages were computed.

A decade of progress: Area averages of temporal correlations ( $C_{\infty}$ ) for JJA precipitation (40E-180, 40N-10S)\*

13



Almost all the latest models have higher ability to predict the interannual variability of JJA precipitation than the previous models of each center.

### Predictable regions of JJA precipitation

Number of models that have expected correlation skills ( $C_{\infty}$ ) exceeding 0.3

CHFP (16 models)



4

C3S (11 models, 1996-2016)



8

9

7

(Potentially) predictable regions:

3

2

Tropical western North Pacific, Maritime Continent (Indonesia), Arabian Sea, eastern and western Indian Ocean, Ganges region, south part of Indian subcontinent, Central China-Japan (Meiyu-Baiu region), coastal regions of Indochina Peninsula

6

\* Please note that higher prediction skill can be obtained after area averaging.

5

# Dominant drivers for the ASM variability and representation of their responses in the model (seasonal prediction)

### Dominant climate drivers and predictability sources for ASM



Figure made by Y. Takaya, similarly to that presented in Meehl et al. 2020

\* In the ESM prediction, most components are initialized, so all the phenomena are initial value problems, but here I show the slowly-varying phenomena as boundary value problems for the atmosphere following a traditional convention.

### Dominant coherent variability of ASM

Simultaneous and delayed influence of ENSO

ENSO mode

COBE\_GPCP (1979-2016)





IPOC mode

COBE\_GPCP (1979-2016)

сf. Mi

Mishra et al. (2012) *PNAS* Wang et al. (2013) *PNAS* Wang et al. (2015) *Clim. Dyn.* Xie et al. (2016) *AAS* 

VAR SST: 17.5%, PR: 20.5%

VAR SST: 10.7%, PR: 6.7%



Heterogeneous correlation maps of SVD analysis for SST and precipitation in JJA colors: precipitation (CI: 0.2) contours: SST (CI: 0.2)

### Dominant coherent variability of ASM



Heterogeneous correlation maps of SVD analysis for SST (contours) and precipitation (colors) in JJA

SVD analysis for JJAS precip. and SST (1900-2008)

Mishra et al. (2012) PNAS

cf. Webster et al. 1998, Krshna Kumar et al. 2005, and many others

A prominent pattern of year-to-year variability in Indian Summer Monsoon Rainfall Vimal Mishra, Brian V. Smoliak, Dennis P. Lettenmaier, and John M. Wallace, Proc. Nat. Aca. Sci., Vol. 109, No. 19 Copyright(2012) Dominant coherent variability of ASM providing the predictability



The dominant coherent variability of the ASM gives rise to the seasonal predictability.

### Representation of the coherent variability modes

### ENSO mode (obs)

#### COBE\_GPCP (1993-2016)



color: precipitation contour: SST (CI:0.2 [K])

Results of SVD analysis for SST and precipitation in black box. heterogeneous regression maps

#### cmcc\_3 (1993-2016)



cmcc\_35 (1993-2016)



ecmwf\_5 (1993-2016)



#### dwd\_2 (1993-2016)



#### dwd\_21 (1993-2016)



jma\_2 (1993-2016)



meteo\_france\_6 (1993-2016)



meteo\_france\_7 (1993-2016)



ncep\_2 (1993-2016)



ukmo\_14 (1993-2016)



ukmo\_600 (1993-2016)



-0.9 -0.7 -0.5 -0.3 -0.1 0.1 0.3 0.5 0.7 0.9

All latest models capture overall ENSO influence on large scale precipitation. cf. Krishna Kumar et al. (2005) Some (not all) reasonably capture regional rainfall pattern (e.g., South Asia). failure of AGCM,

### Representation of the coherent variability modes

### IPOC mode (obs)

#### COBE GPCP (1993-2016)



color: precipitation contour: SST (CI:0.2 [K])

Results of SVD analysis for SST and precipitation in black box. heterogeneous regression maps

#### cmcc 3 (1993-2016)



#### cmcc 35 (1993-2016)



ecmwf 5 (1993-2016)



#### dwd 2 (1993-2016)



#### dwd 21 (1993-2016)

SCF:13.0

jma\_2 (1993-2016)



#### meteo france 6 (1993-2016)



meteo france 7 (1993-2016)



ncep 2 (1993-2016)



#### ukmo 14 (1993-2016)



21

ukmo 600 (1993-2016)



-0.9 -0.7 - 0.5 - 0.3 - 0.10.1 0.3 0.5 0.7 0.9

Representing IPOC mode seems to be more difficult than ENSO mode, but the majority of models represent the observed pattern. Some models present IOD-like pattern (presumably due to model bias).

### Representation of precipitation climatology and prediction skill



A good relationship between the pattern correlation of precipitation climatology and precipitation prediction skill.

However, plots of the C3S models scatter. What do make the skill difference?

Pattern correlation of precipitation climatology (40E-180,40N-10S)

\*Precipitation prediction skill: Area averages of temporal correlation for JJA precipitation (40E-180, 40N-10S, estimated skill with 50 members)

### Representation of teleconnections and prediction skill



Pattern correlation of NINO3.4 teleconnection

Pattern correlation of IOB SST teleconnection

\*Precipitation prediction skill: Area averages of temporal correlation for JJA precipitation (40E-180, 40N-10S, estimated skill with infinite members). The teleconnections are regressed patterns against NINO3.4 and IOB SSTs.

The skill difference is attributable to the ability or lack thereof to represent the ENSO-rainfall teleconnection.
→ Improving representation of the coherent variability and teleconnections is a key for seasonal ASM prediction.

cf. Jain et al. (2019) Clim. Dyn. for Indian rainfall

# Dominant drivers for the ASM variability and representation of their responses in the model (subseasonal prediction)

# **IRI Real-Time Probabilistic Forecasts Based on SubX**

#### Precipitation Forecast issued Jul 23, 2021 (Week 3+4) Hindcast Week 3+4 RPSS Skill



Previous forecasts can be viewed through the control bar menu. The weeks 3-4 forecast (i.e. the 14-day target period, 16 to 29 days after the forecast is issued) is also available. New forecasts are issued weekly on Fridays.

> Issued every Friday in Real Time Based on 3 NOAA SubX models: CFSv2, GEFS, ESRL-FIM Calibrated using extended logistic regression



Some positive skill over northern South Asia. The forecast on the left verified over parts of South and SE Asia

http://iridl.ldeo.columbia.edu/maproom/Global/ForecastsS2S/



S2S forecasts are now a reality. However, hindcast skill is still low, which emphasizes the need for future improvement.

### Boreal Summer Intraseasonal Oscillation (BSISO) in S2S models



EOF modes of daily OLR (shadings; units: Wm<sup>-2</sup>) and zonal 850 hPa wind (vectors; units: ms<sup>-1</sup>) anomalies from ERA-Interim/NOAA during May-October for the 12-year period of 1999–2010.

Jie et al. (2017) QJ

BSISO is considered to be the dominant subseasonal variability that gives the subseasonal predictability. BSISO is more difficult to predict/simulate than MJO in winter.



Bivariate Anomaly Correlation as a function of lead time for BSISO1 and BSISO2 between ERA-Interim and forecasts from S2S models during May-October for the 12-year period 1999–2010

Jie, W., Vitart, F., Wu, T. and Liu, X. (2017), Simulations of the Asian summer monsoon in the sub-seasonal to seasonal prediction project (S2S) database. Q.J.R. Meteorol. Soc., 143: 2282-2295. (CC BY 4.0)

### Subseasonal prediction skill of ASM is associated with BSISO skill

## Forecast skill (ROC area) of precipitation over India in ECMWF model

Bivariate correlation of MJO indices



A significant improvement of forecast skill scores with time was observed, especially in the last 5 years, possibly due to the increased horizontal resolution from 60 to 35 km.

#### Courtesy: Dr. Frederic Vitart

### Future challenges

- Improving Inter-basin interaction and its influence on ASM
  - Slow/fast decaying ENSO
  - ENSO flavor (CP/EP-ENSO)
  - Model bias and IOD
- Improving subseasonal prediction skill of BSISO and associated variability
- Process-based understanding of model errors of the S2S prediction models
- User-oriented forecast information (e.g., monsoon onset for agriculture)

Further improvement of the S2S prediction skill is needed.

### Take-home messages

- This study overviewed the performance of the seasonal prediction of the ASM using multi-model forecast archives.
- Seasonal prediction models present steady progress of the predictive capability of the ASM over a decade.
- The latest models reasonably represent the coherent atmosphere-ocean coupled variability of the ASM and its associated regional variability of precipitation.
- Better representing the climatology of precipitation and ENSO-related teleconnection patterns of precipitation is fundamental for improving the seasonal prediction skill of the ASM.
- Subseasonal prediction of ASM is challenging, however prediction skill of ISM rainfall has increased together with the improvement of BSISO skill.
- The multi-model subseasonal prediction is now established. Further improvement of the prediction skill is needed.

# Thank you for your attention.