The art and science in sub-seasonal forecast system design and modelling

Yuhei Takaya

Meteorological Research Institute

Japan Meteorological Agency

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art

Craftsmanship and accumulated knowledge
in model tuning and system design

science

Scientific basis for modelling and ensemble techniques

Outline

Introduction

Challenges in S2S forecast system design

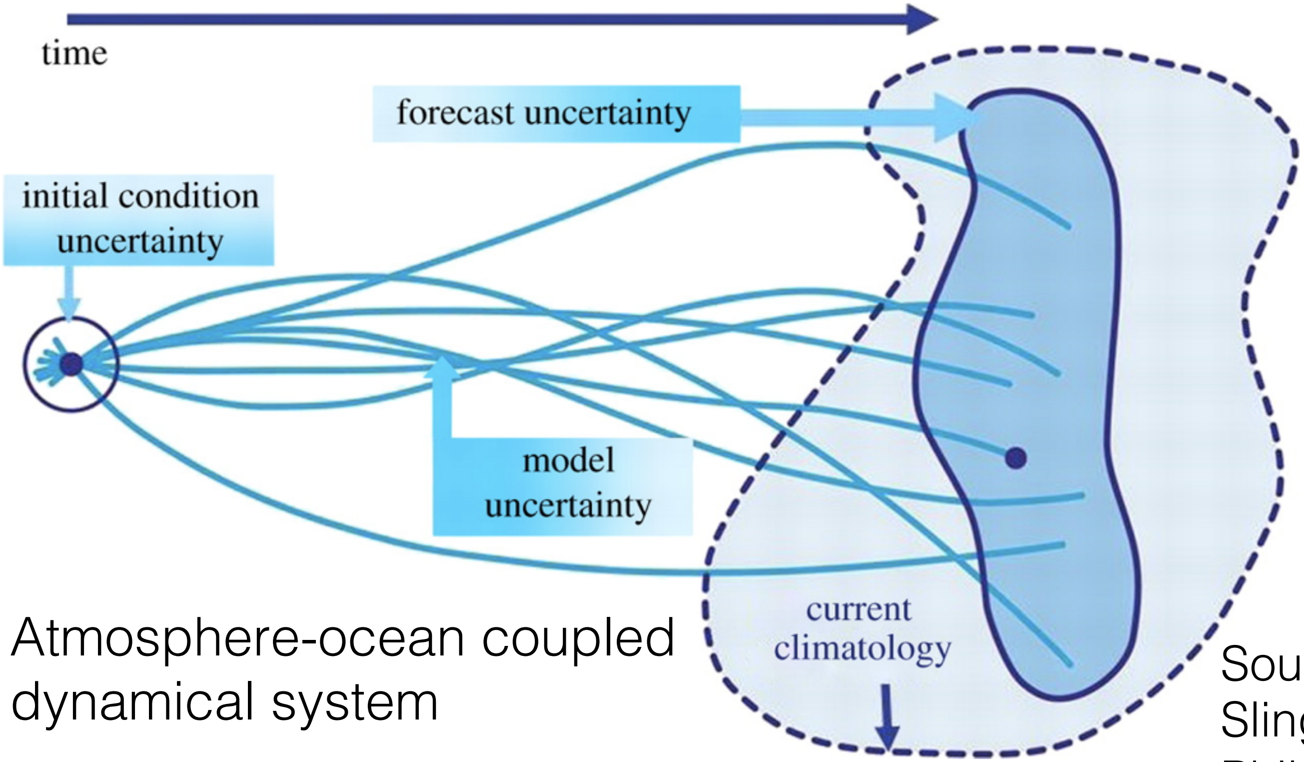
- S2S Phase 2 ensemble sub-project
- Ensemble size issue
- Forecast configurations (burst/LAF)
- Ensemble generation for Tropics & ocean

Challenges in S2S prediction modelling

- Initial shocks/drifts and system design
- MJO-teleconnection example

Summary

Introduction: Dynamical system for S2S prediction



Atmosphere-ocean coupled dynamical system

Source:
Slingo and Palmer (2011)
Phil. Trans. Roy. Soc. A

Initial condition uncertainty

Singular Vector, Bred Vector, Lagged Average Forecasting, Ensemble Transform, Ensemble Kalman Filter, etc.

Model uncertainty

Uncertainty of physics processes: multi-physics, multi-model
Uncertainty in time evolution: stochastic physics

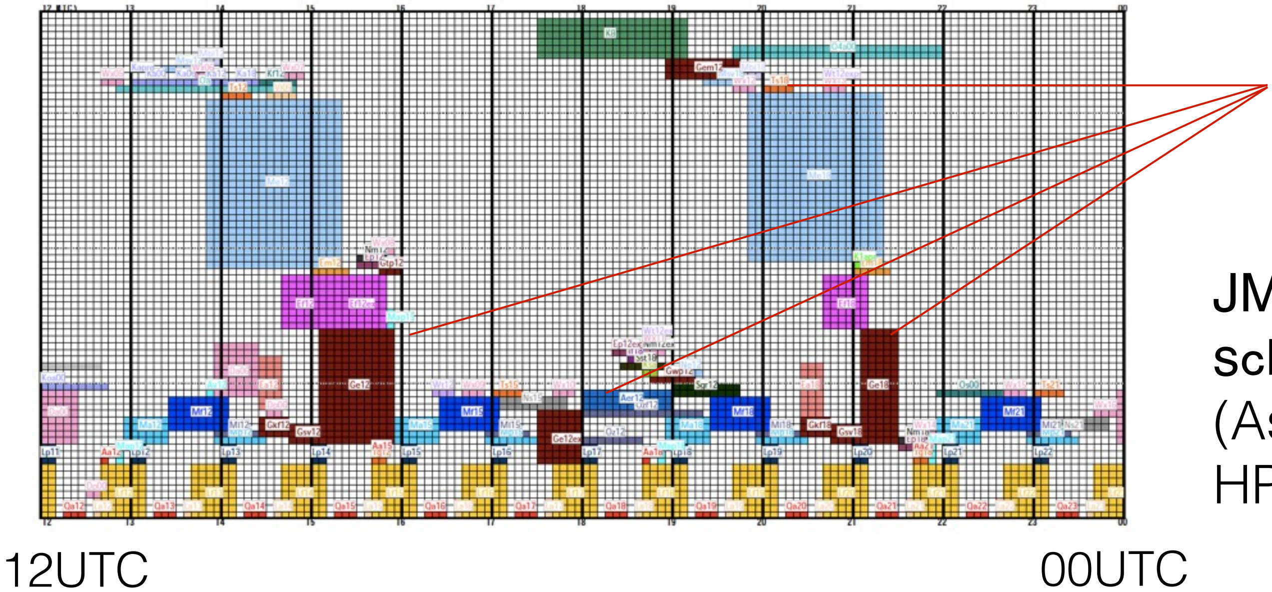
Introduction: Operational forecast systems

Requirements

- Forecast quality
- Timeliness
- Cost-efficiency

Limitations

- HPC resources
- HPC schedule
- Personpower



Global Ensemble Prediction System (subseasonal forecast system)

JMA operational suite schedule

(As of June 2018, after HPC replacement)

Challenges in S2S forecast system design

Any architectural masterpieces have careful structure design, otherwise they do not stand.

Source: wikipedia

S2S Phase 2 ensemble sub-project (science questions)

- **Optimal initial-perturbation strategies** for the sub-seasonal timescale (ens. size, burst/LAF, etc.)
- **Ocean and coupled initial perturbations** for potential skill improvements in certain regimes (e.g. MJO, tropical cyclone)
- **Over-confident predictions** due to the discrepancy between the observed and forecast spread resulting from both random and **systematic errors**
- **Understanding and representing model uncertainty** (e.g., stochastic physics) for the sub-seasonal timescale
- **Forecasting the uncertainty** in flow-dependent/non-stationary subseasonal forecasts, **spread-skill measure**. (c.f. Rodwell et al. 2018 BAMS)

S2S Phase 2 ensemble sub-project (topics)

1. Study the influence of forecast configuration strategies, including initialization strategies used in the current generation of S2S prediction systems (burst and lagged ensemble) on the forecast spread.

2. Benchmark the spread-error relationship in the current generation of S2S prediction systems.

3. Explore the impacts of coupled initial perturbations on the sub-seasonal prediction, and develop techniques of coupled initial perturbations.

4. Investigate the impact of stochastic parameterizations for the sub-seasonal prediction.

Objectives

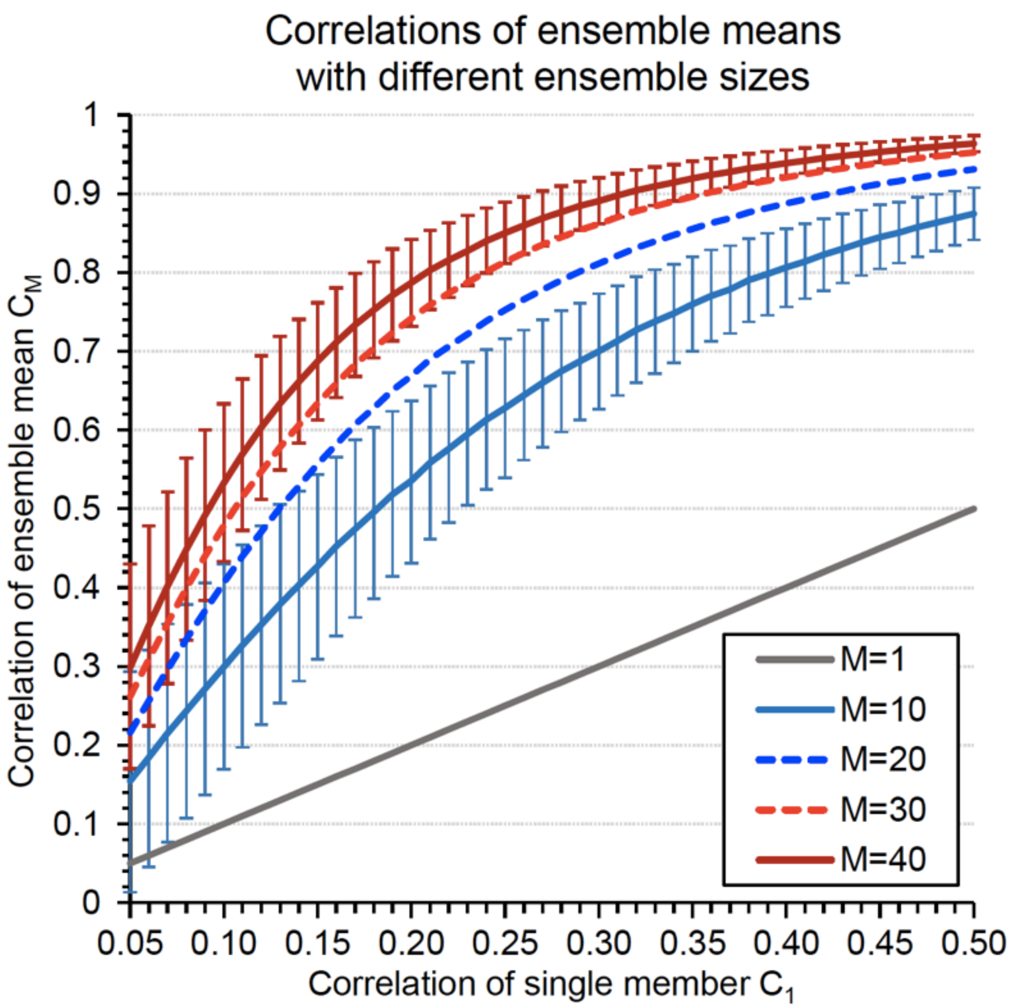
To investigate the ensemble size effects on ensemble mean predictive skills and uncertainty range of the skill assessment.

Method

10,000 sets of Monte Carlo simulations with 50 independent samples (cases) were made. The samples were generated by the Box-Muller's method. The skill dependency on ensemble size was analyzed.

Takaya in prep. S2S book
c.f. Kumar et al. (2009)

Ensemble size issue



The whiskers indicate the intervals of 1 σ.

Larger ensemble size, higher scores

Larger score gain in modest forecast skill.

Score gain getting saturated in large ensemble size (M>40)

Larger ensemble size, more robust estimate of statistics

cf. Kumar (2009)
Murphy (1988)

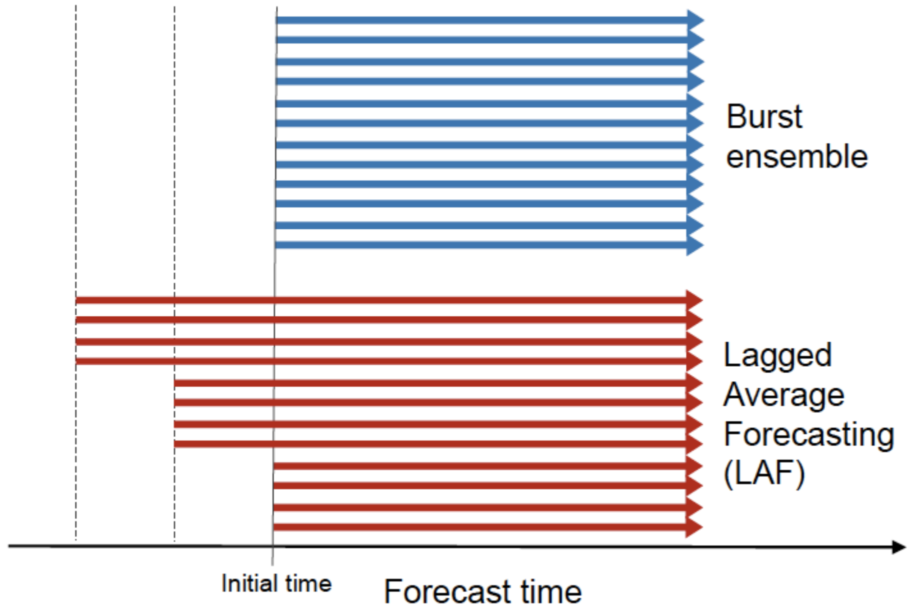
Forecast configurations (burst/LAF)

Burst ensemble:

All ensemble start from the same initial time

LAF ensemble:

LAF approach divides whole ensemble into chunks with different initial time



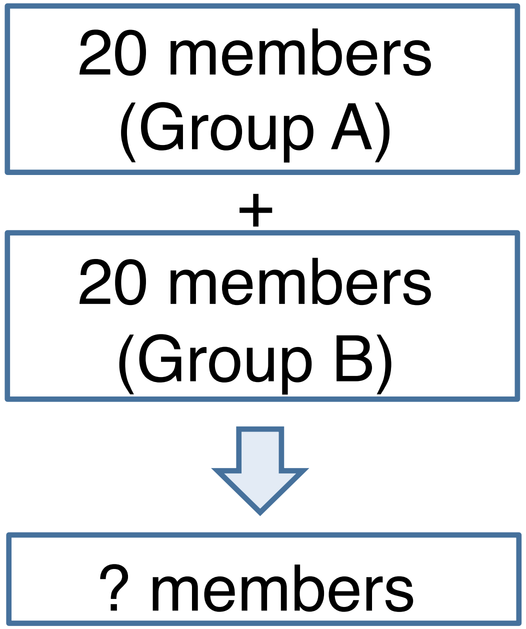
Advantages

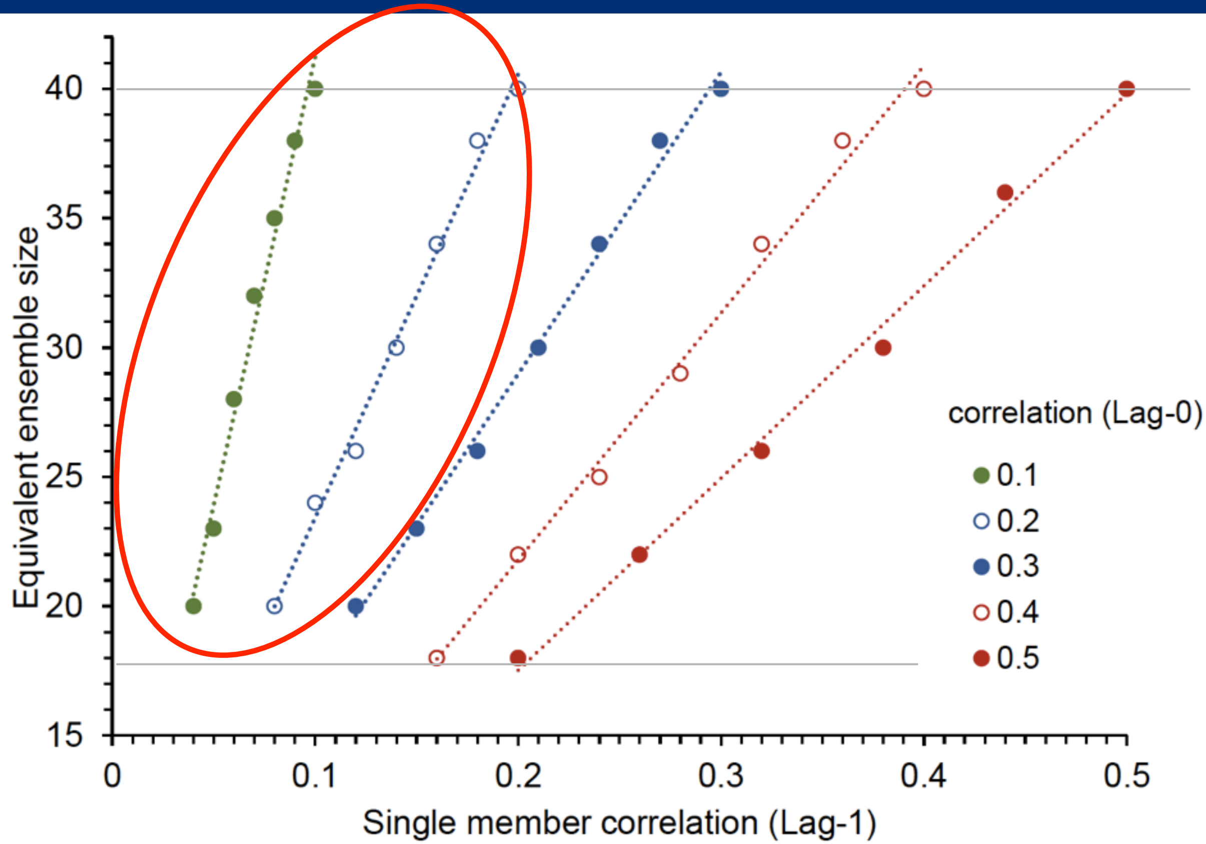
Less computational costs at the same time, updated forecasts available

Disadvantages

Lower skills due to skill degradation with a longer lead time

LAF ensemble effects in idealized experiment





The LAF effects are sensitive to the forecast skill.
For subseasonal forecasts, it is not so efficient as the seasonal prediction.

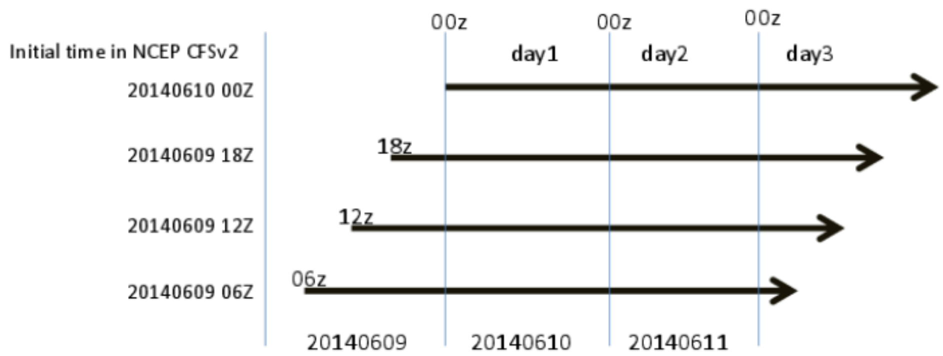
We could improve this results with a post-process for multi-leadtime. (e.g., Dabernig et al. 2016 MWR)

LAF ensemble effects (subseasonal forecast case) (1/2)

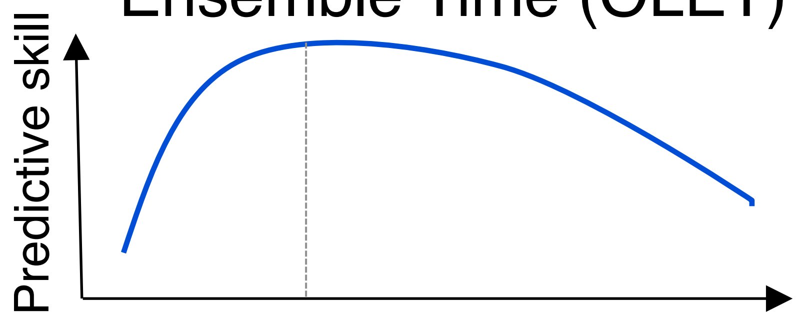
How efficient are different ensemble size and LAF settings?

Total ensemble size

Ensemble size of each initial time						
4	4	8	12	16	20	24
3	3	6	9	12	15	18
2	2	4	6	8	10	12
1	1	2	3	4	5	6
Number of Lag ensemble (Lagged ensemble lead time)	0	1	2	3	4	5



Optimal Lagged Ensemble Time (OLET)



Number of Lag ensemble

LAF ensemble effects (subseasonal forecast case) (2/2)

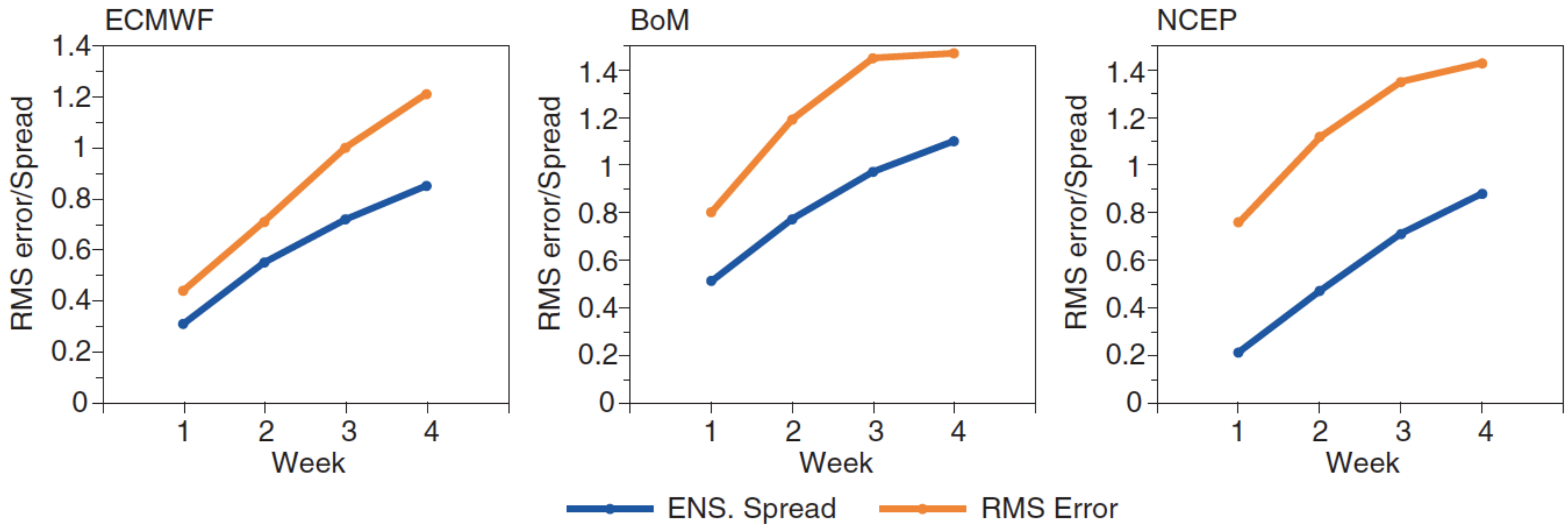
Variables	Land 2mT (W3-W4)		850-hPa T (W3-W4)		500-hPa GPH (W3-W4)	
	60N-60N	30N-30S	60N-60N	30N-30S	60N-30N	30S-60S
ACC OLET (day)	2	1	2	2	1	2
Opt ACC (gain %*)	0.18 (4)	0.19 (3)	0.22 (5)	0.28 (4)	0.15 (5)	0.19 (7)

* ACC gain was defined difference between OLET ACC and 0-lag 1-member ACC.

Optimal lagged ensemble time (OLET) was defined as a LET which gives the best ACC.

The LAF ensemble approach improves subseasonal forecast skills, but its optimal LAF period is much shorter than that for seasonal forecasts (Chen et al. 2013). Efficiency of the LAF approach is difficult to assess using currently available hindcast data.

Over-confident characteristics of MJO prediction



Source: Vitart (2017)

What are problems?
Ensemble techniques, models, or simply too large forecast errors?

Ensemble generation for Tropics, ocean

Challenge: Ensemble generation for MJO, ISO, A-O coupled variabilities

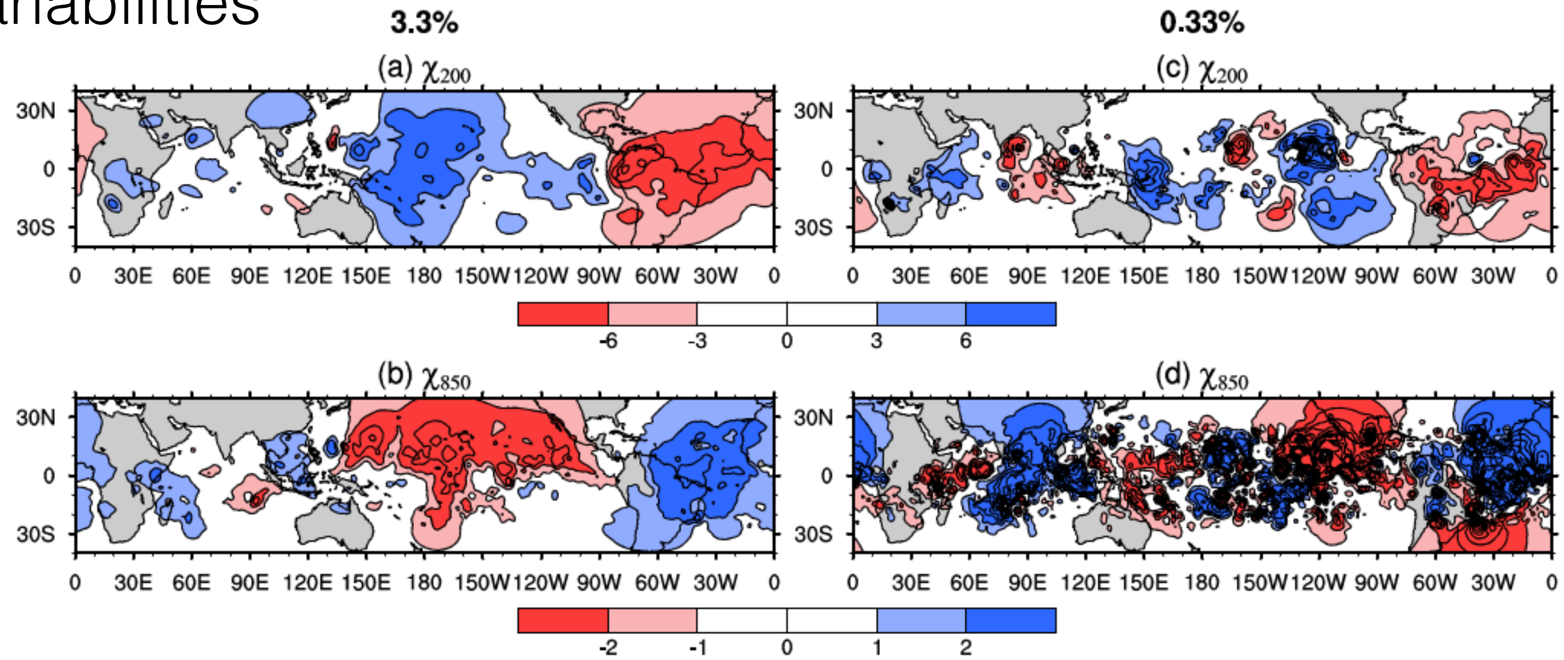
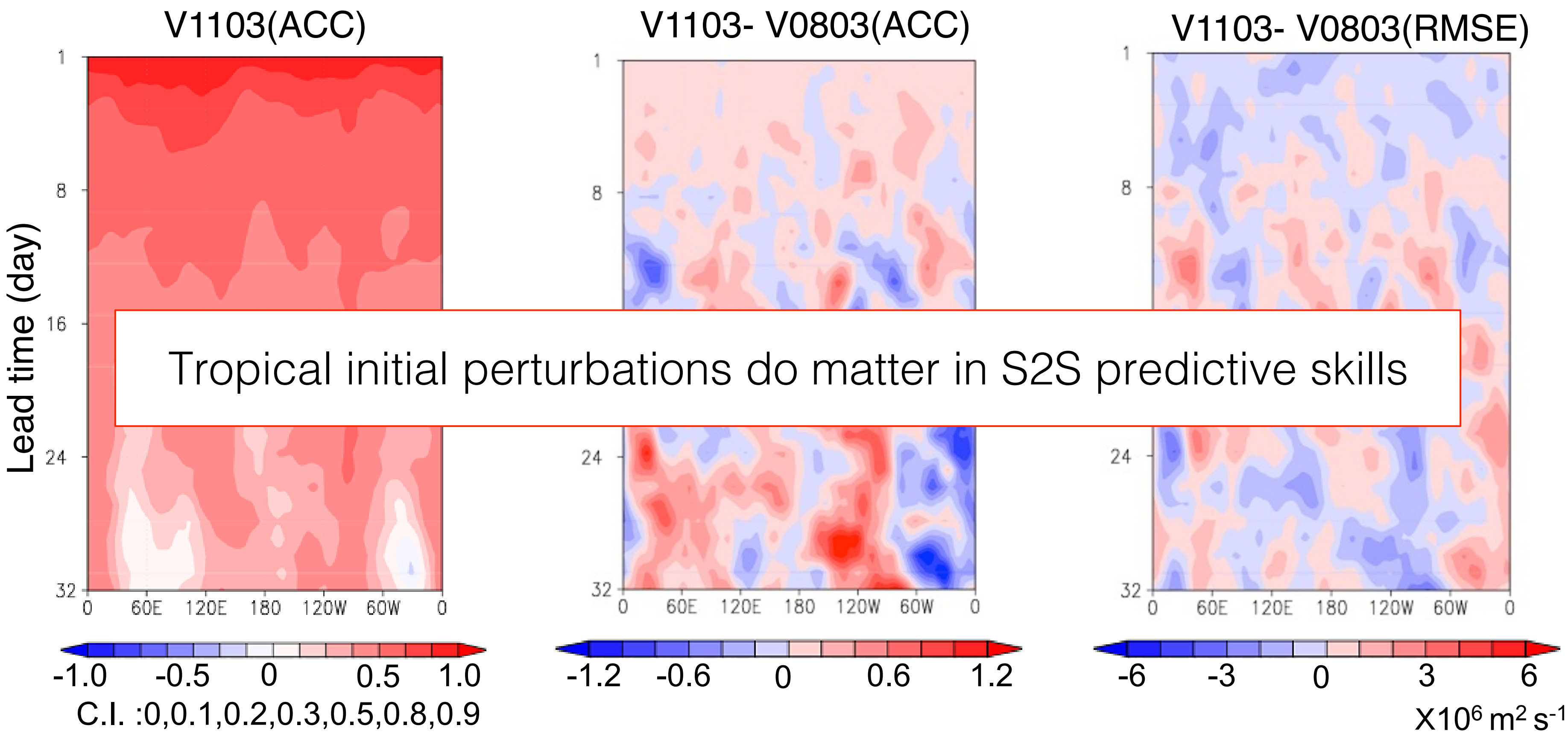


Figure 2. Snapshots of (a, b) 200-hPa and (c, d) 850-hPa velocity potential fields of tropical bred vectors on 26 November 2003. The left (right) plots show tropical bred vectors with rescaling factor of 3.3% (0.33%) of the climatological RMS variance of the 200-hPa velocity potential. Amplitudes of these bred vectors are normalized. Positive (negative) values indicate convergence (divergence). The contour intervals for the top (bottom) plots are 3×10^5 m^2 s^{-1} (1×10^5 m^2 s^{-1}).

Source: Chikamoto et al. (2007)

Ensemble generation for Tropics, ocean



Tropical initial perturbations do matter in S2S predictive skills

V1103: EPS w/ tropic BGM
V0803: EPS w/o tropic BGM

Averaged over 10N-10S

Miyaoka and Takaya（2011）MSJ meeting

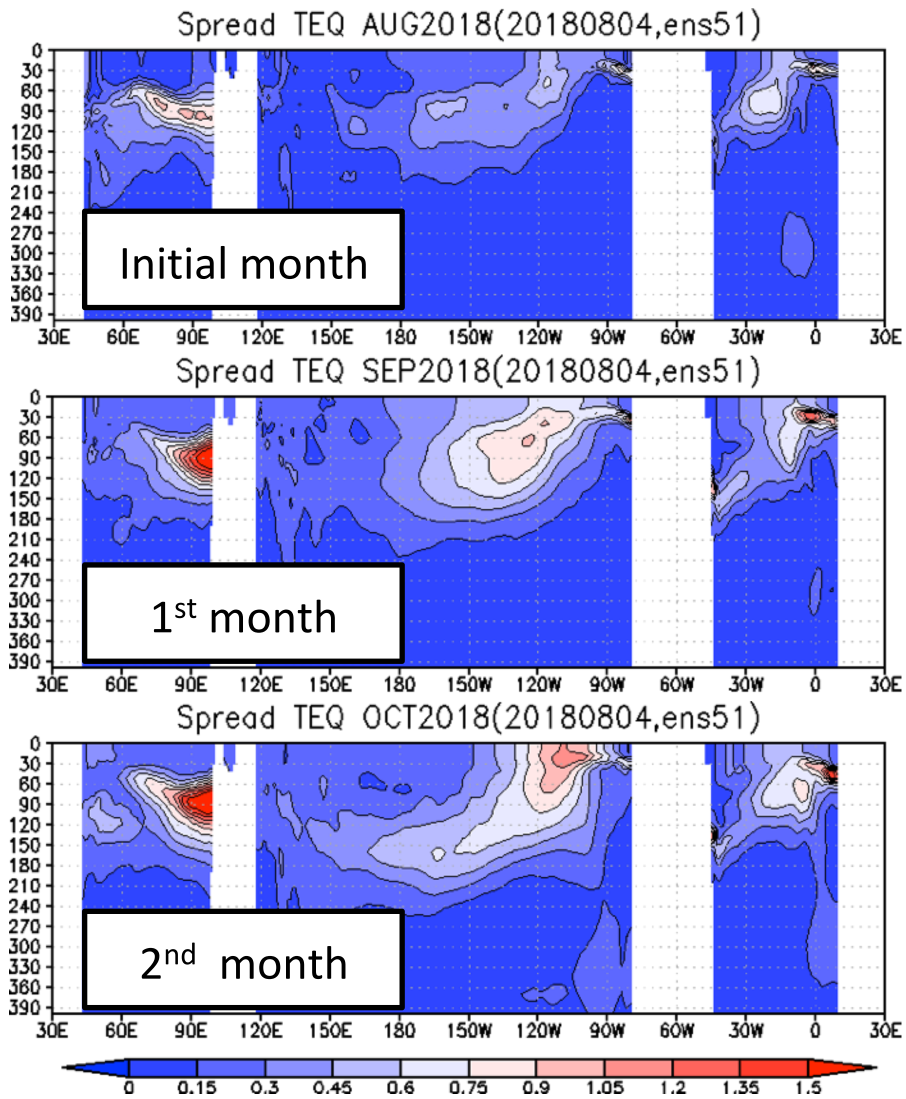
Perturbation evolution of subsurface temperature

JMA ensemble generation
for seasonal predicition

Atmoshperic
perturbed forcing
(Tropic bred vector)

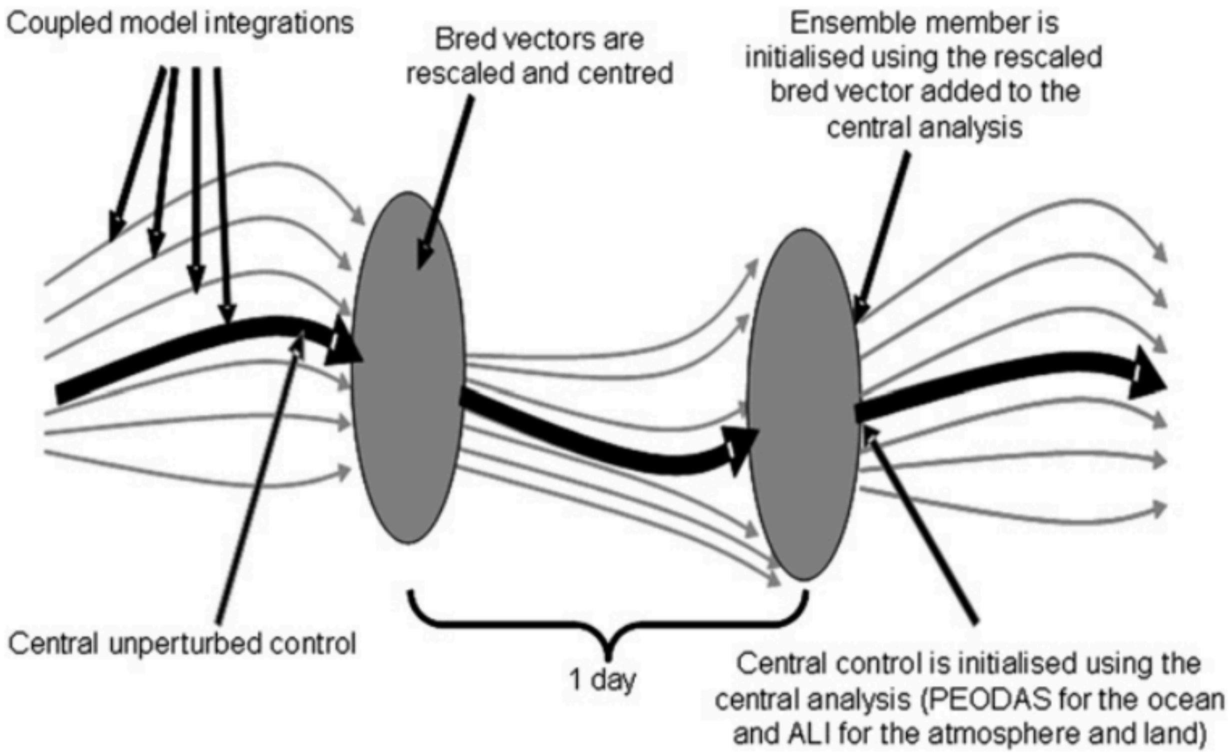
Ocean model

Perturbations



Ensemble generation for Tropics, ocean

Coupled ensemble generation



Source: Hudson et al. 2013

Work in progress at MRI/JMA

Challenges in S2S prediction modelling

Seamless (unified) model development

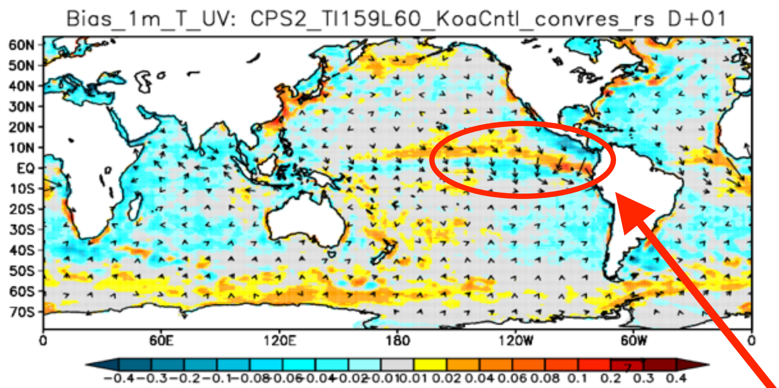
Subseasonal prediction modelling is
“buttering one's bread on both sides”?

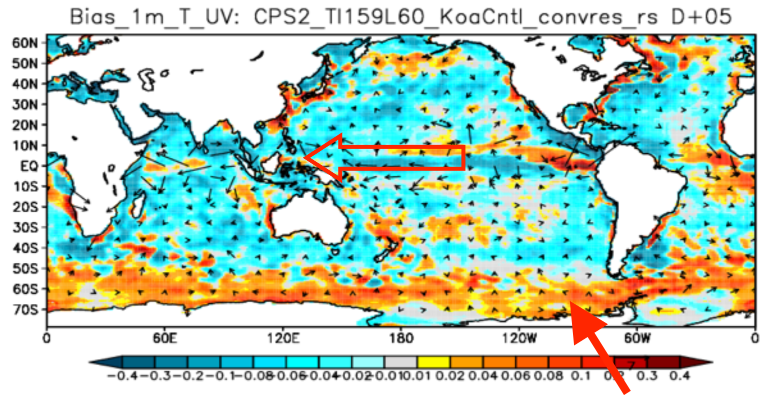
The S2S prediction requires models having **more accurate predictive skill from week to subseasonal time ranges** as well as **smaller model biases.**

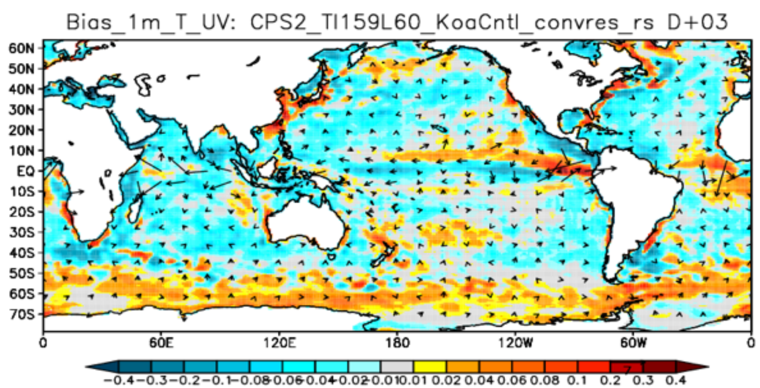
Initialization shocks/drifts and system design

Ocean initialization shocks and model drifts appear in a short time scale.

Biases of temperature and velocity at 1-m depth







Biases against MOVE-G2 ocean analysis forced by JRA-55 fluxes during 5 June 2016-5 June 2017.

Courtesy T. Komori@CPD/JMA

Initialization shocks/drifts and system design

Causes of Initialization shocks

(1) An imbalance of surface fluxes due to insufficient communication between the model components in the initial condition calculation

(2) The use of different models, different versions, or different configurations of the forecast model

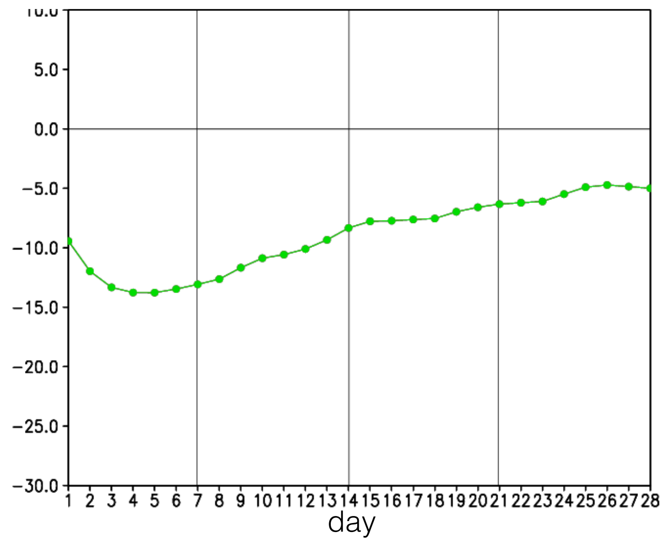
(3) Removal of bias correction terms in the model components in the beginning of the forecast

Mulholland et al. (2015)

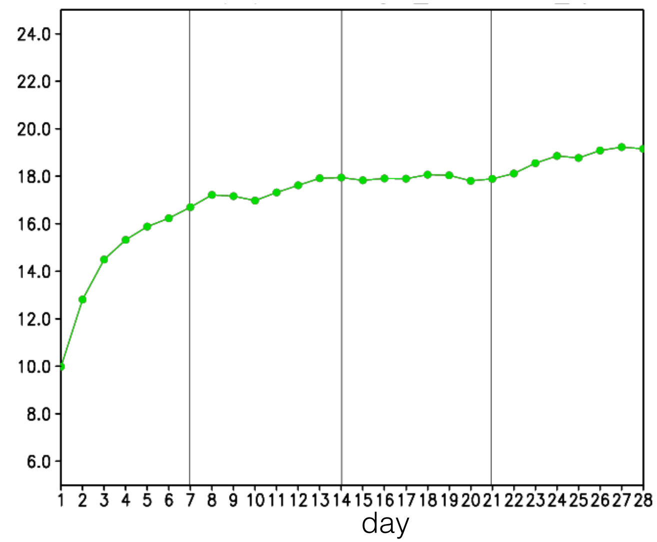
➡ Possible solution: coupled data assimilation

Initialization shocks/drifts and system design

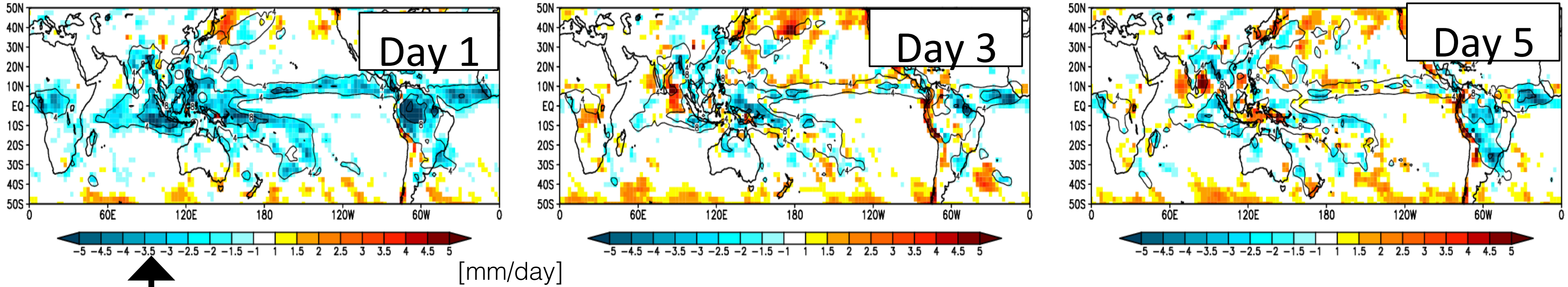
Z500 bias（Trop）against JRA55



Z500 RMSE（Trop）against JRA55



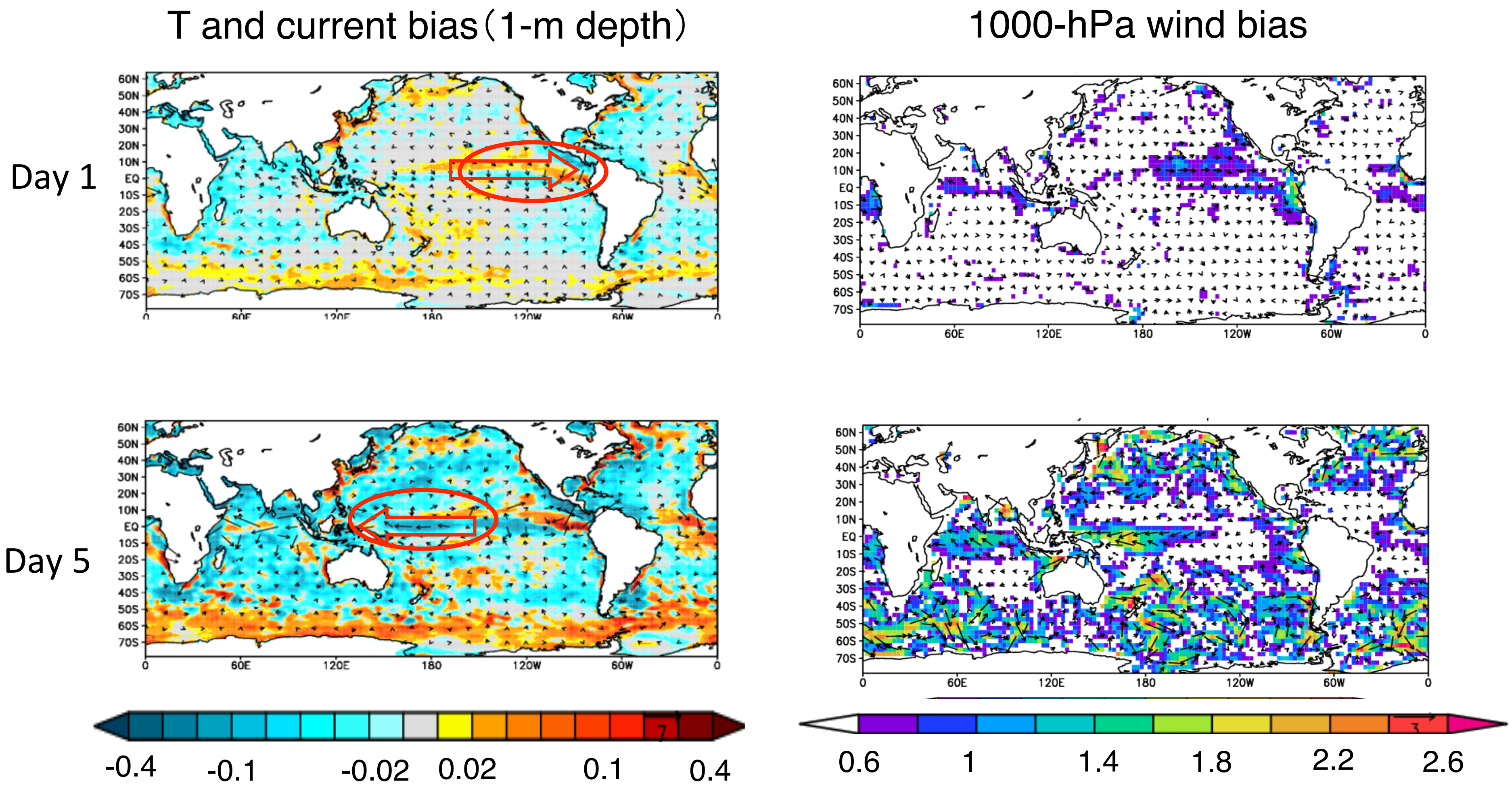
Precip bias against TRMM Multi-satellite Precipitaion Analysis



Spin-up due to lack of initialization of cloud/convection properties

Courtesy T. Komori@CPD/JMA

Initialization shocks in ocean model



Challenge of modeling, analysis and observations

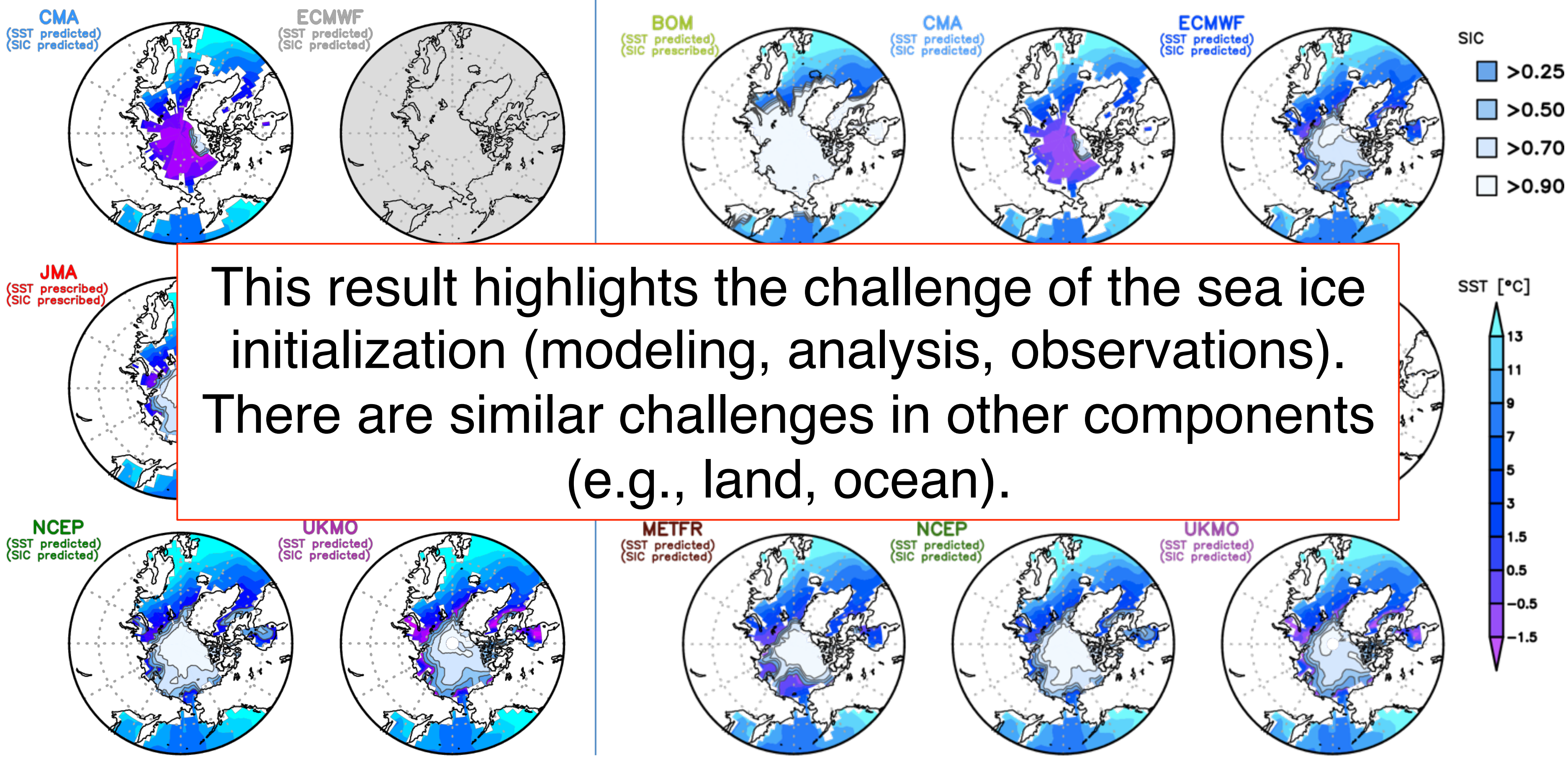
Courtesy T. Komori@CPD/JMA

Sea ice initialization

Arctic SST & Sea Ice Concentration (ensemble mean)

Initial: 2018.07.18, week1

Initial: 2018.07.19, week1



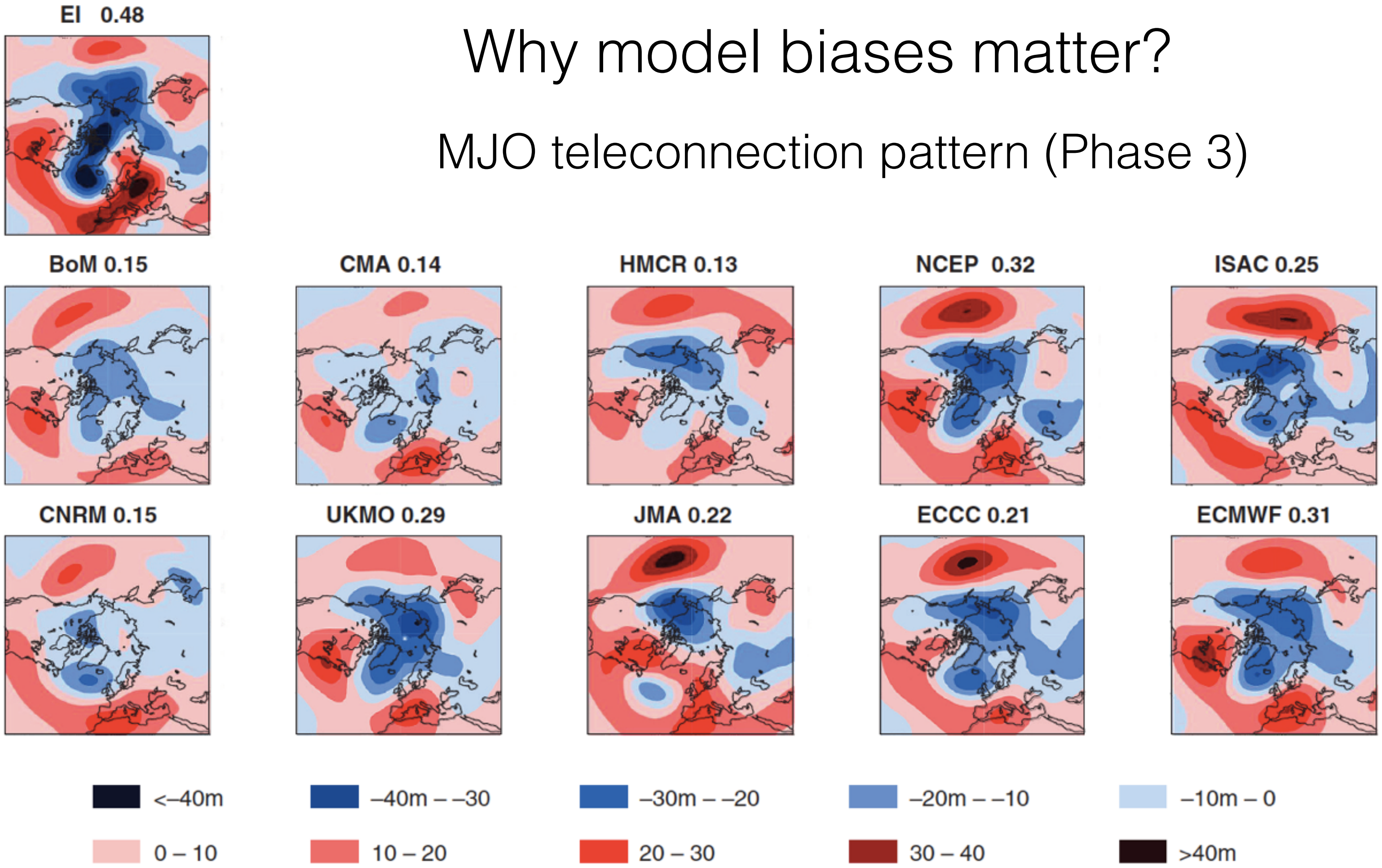
This result highlights the challenge of the sea ice initialization (modeling, analysis, observations). There are similar challenges in other components (e.g., land, ocean).

Source: S2S museum, Courtesy Dr. Mio Matsueda

Model drift: MJO-teleconnection example

Why model biases matter?

MJO teleconnection pattern (Phase 3)



Source: Vitart (2017) QJRMS

Model drift: MJO-teleconnection example

MJO related teleconnection errors are caused by

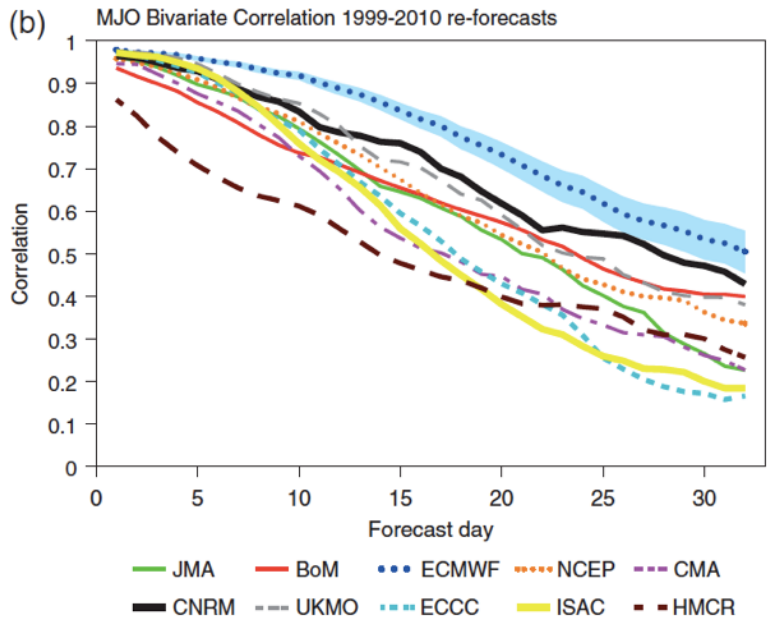
(1) MJO errors:

phase, amplitude, tropical forcing (Rossby wave source)

Hoskins and Karoly 1981, Yasui and Watanabe 2010

(2) Mean state errors of circulations : wave guide, Rossby wave propagation

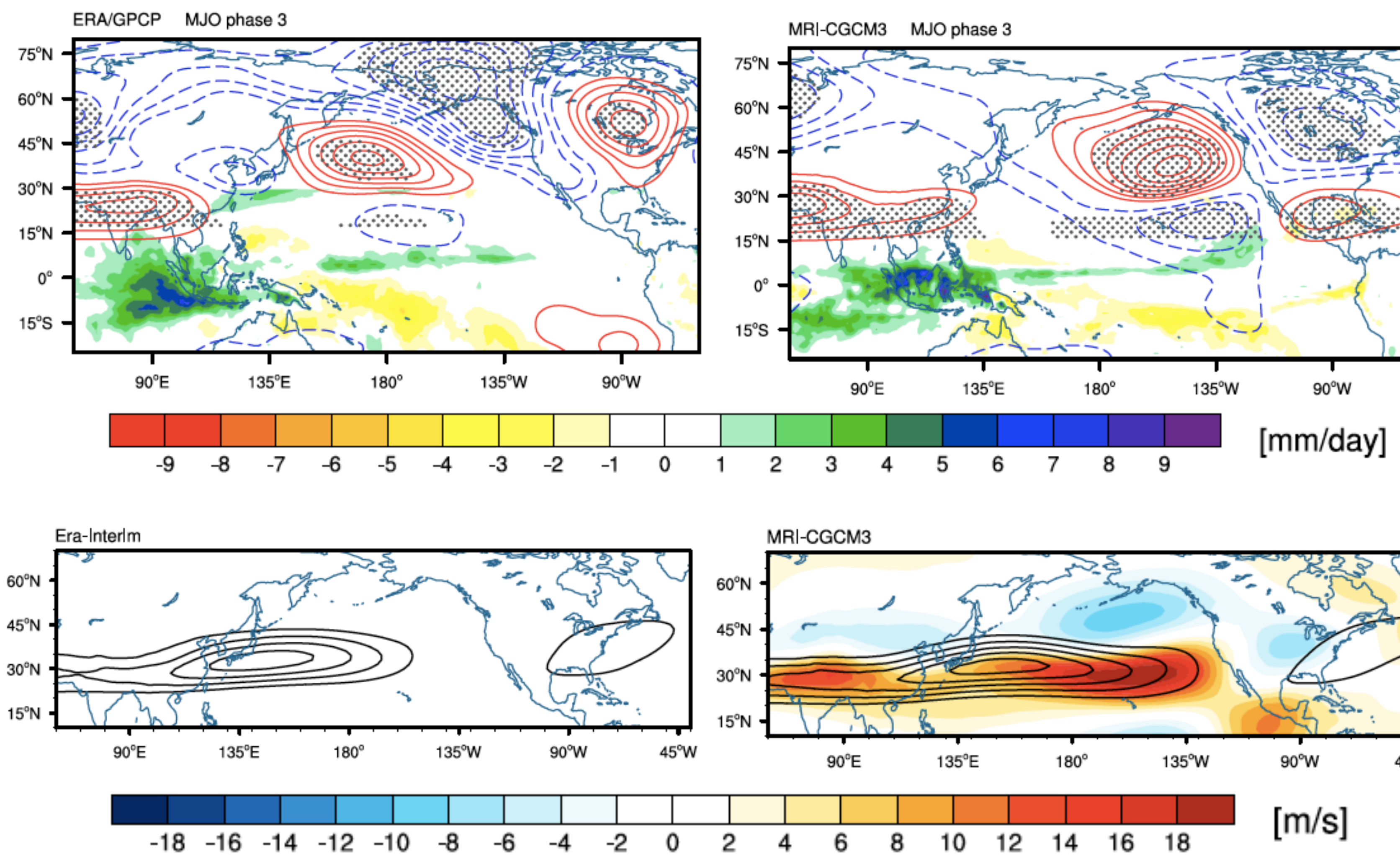
Hoskins and Ambrizzi 1993, Ting and Sardeshmukh 1993



Source: Vitart (2017) QJ

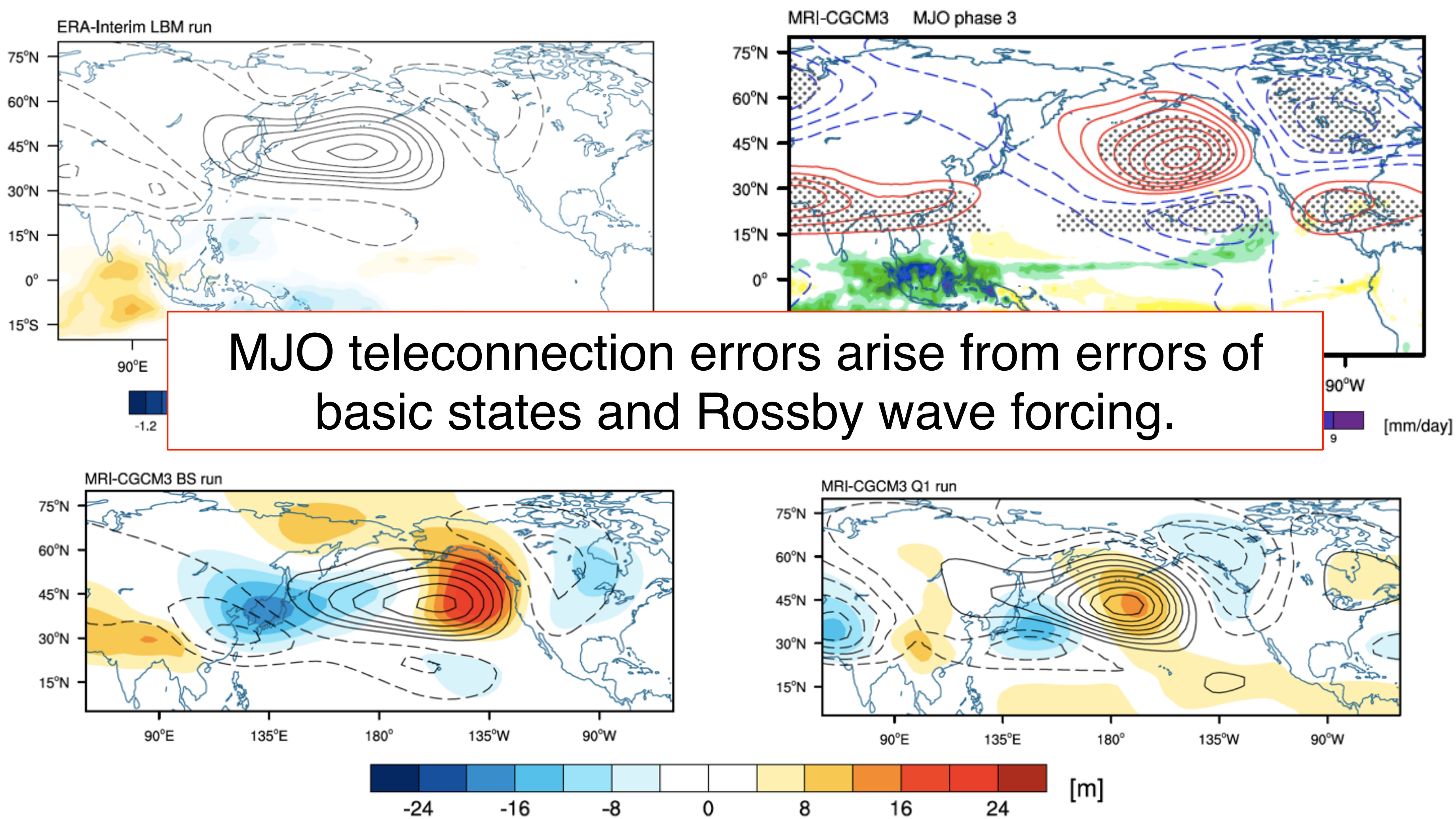
cf. Henderson et al. 2017 *J. Clim.*

Model drift: MJO-teleconnection example



Source: Henderson et al. 2017 *J. Clim.*

Model drift: MJO-teleconnection example



MJO teleconnection errors arise from errors of basic states and Rossby wave forcing.

Source: Henderson et al. 2017 *J. Clim.*

Summary

- Ensemble strategies have great impacts on S2S predictive performance.
- LAF ensemble adds skills, but its efficacy is not high compared with that for the seasonal prediction.
- Ensemble strategies for coupled models and Tropics need to be further studied.
- Initialization of coupled models (sea ice, land, etc.)
- S2S predictions suffer from initial shocks and model drifts, reducing these errors is an outstanding modelling challenge for S2S prediction.